ESSAYS ON PROACTIVE DETECTION OF COLLUSION, EX POST ANALYSIS OF COMPETITION POLICY ACTIONS, AND ESTIMATING OVERCHARGE

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Essays on Proactive Detection of Collusion, Ex Post Analysis of Competition Policy Actions, and Estimating Overcharge

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Abstract

This work is an empirical analysis of collusion by using a private consumer level data set in a setting where no a priori knowledge of collusion exists. This study benefits from spatial variation in the data. For identification, the relation between price and local market power under different assumptions of conduct is central. Accordingly, first, using a simple theoretical background I provide some theoretical intuition for the measure of local market power used in this work. Second, while controlling for demand and cost shifters and using OLS and GMM, I estimate pricing equations to explore if market patterns are more consistent with collusion or competition. Results suggest that consistent with a regime switch from collusion to competition, stable relations in the market are disrupted after month seven. Third, I estimate the hypothetical overcharge associated with this finding. To this aim, first, I employ the techniques frequently used in collusion retrospectives; second, I propose importing empirical strategies from merger retrospectives. Adopting the techniques that are used widely in merger retrospectives to collusion involves either using i) *basic difference-in-difference framework* where locations characterised by monopolistic pricing even in competition are set as the control group for the counterfactual of regime switch; or, ii) *difference-in-difference framework with treatment intensity*, where the regime switch is treated as a treatment, which, at each location, produces heterogeneous effects that is inversely proportional to the level of local market power the provider enjoys at that location. I find that overcharge estimates using alternative methodologies range in $7.48 - 13.98\%$. Furthermore, results suggest that if the spatial dynamics are ignored, estimation leads to undercompensation in regions where the market powers of dominant competitor and potential competitor converge; overcompensation in regions where the market powers diverge. Finally, to address the inference problems associated with spatial dependency across observations and difference-in-difference methodology, I apply various remedies proposed in the literature. The findings are robust to alternative methods of inference.

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Introduction

Before 1990's, competition policy was an area primarily driven by law. This trend changed with the new millennia, and policy gradually became more economics imbued. Neven (2006) provides a case in point; between 1995 - 2004 the annual growth of firms providing competition economics consulting was around 25-30% (pp. 748-749). Another case in point is from Alexander Italianer, former Director General of DG Competition of European Commission; when speaking in a conference in 2010, he told the audience: *"This is where we are at today. Competition cases are an intricate combination of legal arguments backed by solid economic analysis. The interplay between law and economics has never been greater. And the Courts acknowledge this and welcome this interplay. I see this trend going forward and developing across competition law instruments**".

Within the domain of competition economics I am primarily interested in empirical analysis of collusion. When it comes to collusion, conventional wisdom is that the role of the empirical economist is at the post ruling period; the assessment of the impact of an already proven collusion. There is no role for the economist in the process of evidence gathering, or triggering an investigation; detection is reserved for leniency, the promise of immunity from penalties in the case of self-reporting. Not surprisingly, many economists have issues with this demarcation; they are worried that leniency might not be enough in desisting and deterring cartels with highest profitability. Consequently, they propose *complementing* leniency with proactive detection, detecting cartels using economic analysis.

This work is an *empirical analysis of collusion*; in particular its *detection* and *estimating the overcharge* associated with it, in a setting where *no a priori knowledge of collusion exists* by using a *consumer level data set*. However, I also extend to rich literature of *mergers*, in particular to studies that estimate the impact of a merger *ex post*, using postmerger data. In this literature, typically consumer level data is used and refined identification strategies are employed; therefore, they offer some inspiration for estimating overcharge.

This study benefits from spatial variation in the data. For identification, the relation between price and local market power under different assumptions of conduct is central. Accordingly, in the first chapter, using a simple theoretical background I

*Charles River Associates 2010 Conference, Brussels, http://ec.europa.eu/competition/speeches/text/sp2010_09_en.pdf

provide some theoretical intuition for the measure of local market power used in this work.

The second chapter introduces the main data set, and other sources of data; informs about processing and refinement of the data; presents the variables employed in empirical analysis. Moreover, it introduces simple markers designed to flag suspicious patterns in the market. Application of some of these markers suggest that consistent with a regime switch from collusion to competition, stable relations in the market are disrupted after month seven.

In third chapter, I take on the suspicious patterns identified around month seven, and investigate further, while I control for demand and cost shifters; I explore if observed patterns are more consistent with collusion or competition. For this purpose, one particularly important work in the literature is Bresnahan (1987) who suggests that if there is price competition, for the products that have a close substitute, the price would converge to marginal cost; while in collusion, price and cost would diverge.

The *first major contribution of this dissertation* to the literature is taking the premise in Bresnahan (1987) – centring on the relationship between price and local market power in identifying regime switch – that is defined on an heterogeneous product / product characteristics space setting to an homogeneous product / geographic space setting. In this study, local market power is taken to vary at each location according to cost difference between potential competitor and dominant competitor at that location. Consequently, estimation centres on explaining pricing behaviour, and particularly its relation with indicator of local market power. Using Ordinary Least Squares (OLS) and Generalized Method of Moments (GMM), and via interacting a two level factorial variable, the dummy for suspicious first seven months, with market power indicators, two different pricing equations are estimated; one for first seven months, and the other for after month seven. Findings indicate that i) at locations where market power of provider and the closest rival converge, there is a large price difference between two periods; ii) at locations where the provider has large market power, price in both periods converge; iii) before month seven, local market power indicator is positively but only linearly related to price; iv) after month seven, local market power indicator is both linearly and quadratically related to price; providers suffer large price cuts to serve buyers that are gradually closer to the closest rival. These findings are interpreted as further evidence for a regime switch from collusion to competition. The results also suggest that level of market power each provider has on a buyer is very important in the assessment of the impact of collusion on price, which is explored further in estimating overcharge.

Fourth chapter presents the literature on *ex post evaluation of competition policy actions* in order to identify empirical strategies that might be used in estimating the overcharge associated with the hypothetical collusion. First, I explore the literature associated with ex post analysis of collusion. Some popular reduced form strategies involve *before and after*, *dummy variable approach*, *forecasting*, *yardstick* and *difference-in-difference*. In search of additional empirical strategies, next I turn to merger retrospectives; I observe that the literature using a reduced form

approach almost always use difference-in-difference and frequently use consumer level data. A comparison of collusion retrospectives and merger retrospectives that use difference-in-difference suggest that two lines of literature are unexpectedly disconnected; compared to merger retrospectives, collusion retrospectives are in earlier stages of development; merger retrospectives which use spatial variation in identification, provide great insight to collusion retrospectives. Inspired from methodologies used in merger retrospectives, I propose two alternative identification strategies to identify the impact of a regime switch from collusion to competition: i) *basic difference-in-difference* which involves using *home markets* – locations characterised by monopolistic pricing even in competition, hence are unaffected by the regime switch – as the control group for the counterfactual of regime switch; and capturing the impact of the treatment, as a deviation of price in *home markets* from price in *overlapping markets*; ii) *difference-in-difference with treatment intensity*, which involves interpreting the regime switch as a treatment, which, at each location, produces heterogeneous effects that is inversely proportional to the level of local market power the provider enjoys at that location.

Chapter 5 brings these methodologies to data. Empirical objective in this chapter is to estimate the hypothetical overcharge. To this aim, first, I employ the techniques frequently used in collusion retrospectives: before and after, indicator variable approach, forecasting. Overcharge estimates using these three methodologies are respectively 9.26 %, 11.14–13.98 %, 8.05–11.46%. Second, I use empirical strategies imported from merger retrospectives. Basic difference-in-difference specifications suggest that the variation in overcharge is strongly related to difference-in-difference coefficient which captures the impact of the treatment. It is shown that the impact of the regime switch is conservatively estimated in the interval of $7.48 - 11.25\%$. I also show that if the provider's market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of degree of exposure to the "treatment", market power variations might lead variations in the price predicted for competition counterfactual, consequently variation in overcharge estimate as high as 11.89 %. This constitutes *second major contribution of this dissertation* to the literature. To my knowledge, this is the first collusion retrospective that uses spatial variation in determining control groups, and that takes on regime change within a treatment intensity framework. Findings indicate that if the spatial dynamics are ignored, and single overcharge estimation is made, estimation leads to; undercompensation in regions where the market powers of dominant competitor and potential competitor converge; and overcompensation in regions where the market powers diverge.

Finally, to address the inference problems associated with spatial dependency across observations and difference-in-difference methodology, I apply various remedies proposed in the literature. These include i) imposing an error structure using Conley standard errors, ii) changing the level of variation in the data, iii) using effective number of clusters rather than actual number of clusters in defining critical values, and iv) wild cluster bootstrap. The results are robust to alternative methods of inference.

Chapter 1

Setting the Theoretical Background

1.1 Introduction

In this work, the relation between price and local market power under different assumptions of conduct is central. Variation in local market power is used both in identifying the regime switch; and estimating overcharge. The objective of this chapter is to provide some theoretical intuition for the measure of local market power used in this work, and to set a theoretical background. Note that this is different than developing a fully-fledged theoretical model.

The nature of the industry and of the data (detailed information on which is provided in the next chapter) suggest that I should take on a spatial setting. I centre on the relationship between price at which a provider meets demand at a particular location and market power that provider can exercise at that particular location. This, in turn relates to both the proximity of alternative providers that could serve that location, and the nature of competition in the market at that location specifically whether the market is monopolised, cartelised or competitive. Implicit in this spatial setting is the idea of price discrimination - so a given provider will potentially charge different price to consumers at different locations. In this setting, I highlight an important characteristic of the market. Under collusion, collusive agreement ensures that each provider enjoys undisturbed market power at each location. However, under competition at the locations where cost difference across providers disappears, price under competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, price in both regimes will be similar; consequently, regime switch would have a small impact on price. It follows that the impact of regime switch on price is inversely proportional to the local market power of the provider under competition. Building on this, I propose approximating local market power variations via an indicator of local cost differences. For location l, I suggest using

$\Delta_j^l = d_{kl} - d_{jl}$, a measure of relative proximity; the distance between the closest rival k and location l, d_{kl}, net off the distance between provider j and location l, d_{jl}.

Background Literature: The spatial competition first modelled in Hotelling (1929)[1] is a linear one dimensional market with two sellers, each producing one homogeneous product. There is no price discrimination, and the major prediction was that sellers will tend to cluster at the centre, being only marginally different[2].

Hoover (1937) is the first one to combine price discrimination and spatial setting of Hotelling (1929). Hoover (1937) offers three conditions for price discrimination. First is the absence of any returns for arbitrage[3]. Second is the ability to observe the location of the buyers[4]. Third is the optimal scale to be large, resulting in concentration of production in certain locations[5]. If this is not the case, production will be dispersed and geographical advantages will erode. *"...material producing industries with standardized commodities (p.189)"* satisfy these criteria. Some example industries are iron, steel, oil, cement, furniture, lumber, ready mixed concrete, plywood, fertilizer and sugar[6]. Hoover (1937) points that in these markets, competition has two primary dimensions, price and distance.

Following Hobbs (1986), in this setting, under a delivered pricing scheme,

$$p_{jl} = \min\left(p_{jl}^m, \quad t_k d_{kl} + C_k\right) \tag{1.1}$$

where t_k is the unit transportation cost, and C_k is the production cost of the closest rival provider k; d_{kl} is the distance of provider k to location l; p_{jl} and p_{jl}^m are actual price and monopoly price provider j charges at location l. This is a formal representation of the well-known characteristics of spatial price discrimination. Market is characterized by a Bertrand competition at each location. The price charged to each customer c by firm j at each point is the minimum of monopoly price and minimum price the least cost firm k can charge. Consequently, competitive

[1] Some models follow Salop (1979) framework of circular city.

[2] d'Aspremont et al. (1979) revisit this theorem and show that this result does not hold under quadratic formulation of distance.

[3] Arbitrage is only possible under "perfect spatial price discrimination" (see, Braid (2008)), in which consumers within a region are further discriminated according to their types. Consequently, favoured buyers might have resale opportunities.

[4] See also MacLeod et al. (1988). Hamilton and Thisse (1992) characterize price discrimination as *"primarily an informational problem (p. 176)"*. They suggest that if demand is inelastic and consumer locations are unobservable firms would not prefer to discriminate. On the other hand, if firms have full information on customer locations, they would price discriminate at equilibrium (Thisse and Vives, 1988, p.124-25).

[5] Also see, Capozza and Van Order (1978). Note that large scale might have other implications for pricing. Firms might try to avoid underutilization. In such a case, downturns in the market would be associated with fierce competition and price wars, e.g. McBride (1983). This leads some empirical studies, e.g. Rosenbaum and Sukharomana (2001), to model cost structure as dependent on capacity utilization.

[6] See, Hoover (1937); Lederer and Hurter (1986); Vogel (2011)

pressure from rivals is stronger in the border regions. Since these regions are more distant to the provider and closer to rivals, they are expected to be characterised by lower price.

Later studies expanded into game theory setting. Typically, pricing is taken in a multistage process, and as conditional on earlier stages. An example of this is Vogel (2011) that divides the market process into four consecutive stages: entry, location, pricing and consumption. The characteristics of the equilibrium are refined by backward induction. Even when pricing is contingent on entry and location, optimal pricing still involves a Bertrand competition at each location. Hurter and Lederer (1985); Lederer and Hurter (1986), improves Hoover (1937) setting by allowing *complete information*. At the first stage, firms chose locations. Second stage is the revelation stage. Third is pricing and fourth is payoff. They suggest that optimal pricing would be determined by the cost structure of the high cost firm, product being served by the low cost firm. MacLeod et al. (1988) expands by allowing *multiple plant ownership*. Firms first decide on whether to enter into the market. If they do, they decide on the number of plants and where to operate them. After choosing the locations, they set a price schedule. Equilibrium price is characterised as a Bertrand outcome at each location; marginally below the cost of the second low cost firm[7]. Hamilton and Thisse (1992) modify the setting; instead of single price, *a contract* is offered to consumers. The intuition behind the pricing behaviour remains the same.

Recall that this study centres on the relation of *price* with local market power of the provider, which is determined by local relative costs of provider and the least cost rival. Past theoretical evidence suggests that constructing the framework as multistage might not contribute to the insight regarding this particular relation. Moreover, the dataset covers only 18 months, a relatively short period of time to analyse entry/exit decisions. Consequently, in setting the theoretical background, I employ a static framework; in which providers make pricing decisions given their exogenously determined presence in the markets, capacities, own location choices, locations of rivals and buyers.

The theoretical background is to be set in a number of stages. To fix ideas I start with a very simple text-book model[8]. Second, I discuss some generalizations within the basic framework. Third, I consider a very general setting.

1.2 The Simplest Model

Consider the case where there are two identical firms located at either end of a line of length $L = 1$. Both firms produce a homogeneous product, and have identical

[7] Hamilton et al. (1989) also arrive at similar conclusions.

[8] After all, *"the linear spatial model is a first step at generalizing economic models to deal with markets that exist in more dimension: three if one interprets 'space' in a literal sense. (Martin, 2010, 109)"*

constant unit cost of production $c \geq 0$. There are no capacity constraints.

At each point on the line there is a demand for this product represented by the demand function $Q(p)$ where $Q \geq 0$ is the quantity bought and $p \geq 0$ is the price at which the commodity is sold. Given the nature of the product that underpins the empirical analysis, assume that this the commodity is a necessity; so, demand is strictly positive for all $p \geq 0$ and, in addition, has the standard property of being strictly decreasing in price. In addition, in order to have well-defined monopoly equilibria it is assumed that there is a price range for which demand is elastic[9]. Let $p^m(\chi) > \chi$ be the price that would be set by a monopolist that is serving demand $Q(p)$ with constant unit cost, $\chi > 0$. From standard theory $p^m(\chi)$ is a strictly increasing function of χ. Also let $\pi^m(\chi) = (p^m(\chi) - \chi)\, Q(p^m(\chi))$ be the profit earned by a monopolist that is serving demand $Q(p)$. By the envelope theorem monopoly profit is a strictly decreasing function of χ.

The market operates under delivered pricing, so firms deliver the product to consumers and can charge different price to different consumers depending on their location. Consumers have no market power. For simplicity, assume that both firms have the same constant transport cost per unit distance, $t > 0$. Consequently the effective unit cost to firms 1 and 2 of meeting demand originating at a distance $0 \leq d_1 \leq 1$, from firm 1, f_1, and consequently a distance $d_2 = 1 - d_1$ from firm 2, f_2 - is

$$\chi_j = c + td_j, \quad j = 1, 2 \tag{1.2}$$

Figure 1.1 illustrates. The dashed lines $\overline{c_j \chi_j}$ show how units cost vary for both providers as d_1 increases from 0 to 1. The solid lines $\overline{p_j^m p_j^m}$ show the price that each form would charge at each location were it a monopolist at that location, and how these vary as d_1 increases from 0 to 1. For simplicity these are shown as straight lines parallel to the cost lines.

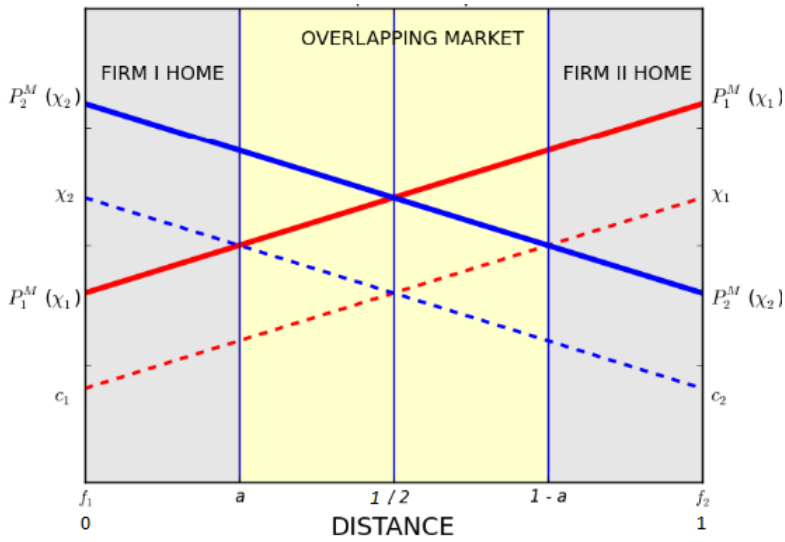
Consider demand that arises at a distance d_1, $0 \leq d_1 \leq 1$ from firm 1, with the costs of two firms in serving this location given by Equation 1.2. We can make the following, increasingly strong definitions of each firm's competitive position at this location:

Definition 1.2.1. For two firms $j, k = 1, 2$ and $k \neq j$, firm j is

- a *potential competitor* for serving the demand at this location if $\chi_j \leq p_j^m(\chi_k)$
- the *dominant competitor* for serving the demand at this location if $\chi_j \leq \chi_k$,

[9]Here, an explicit assumption is that at each location the provider applies a single price (potentially varies spatially but uniform at each location) for every unit bought. Consequently, nonlinear pricing, which may imply a higher payoff to provider, is ruled out. In the case of nonlinear pricing, an important consideration should be the replicability of the provider's offer by other providers. To the extend that provider's offer can be observed and matched by competitors, the intuition in single price should extend to nonlinear pricing. In our case, single pricing assumption is realistic given the nature of trade in the industry studied in the empirical chapters.

Figure 1.1: Two Firm Spatial Competition



- an *effective monopolist*[10] for serving the demand at this location if $p_j^m(\chi_k) \leq \chi_k$

Moreover,

- set of locations in which firm j is an *effective monopolist* is the *home market* of firm j
- set of locations in which there is at least one *potential competitor* is the *overlapping market*[11] between *potential competitor* and *dominant competitor*.

Clearly a firm is an *effective monopolist* at a location if and only if it has no *potential competitor* at that location. It follows that we can split the market up into 4 segments as illustrated in Figure 1.1. Firm 1 is a *potential competitor* for all consumers located between 0 and $1-a$; the *dominant competitor* for all consumers between 0 and $\frac{1}{2}$; an *effective monopolist* for consumers between 0 and a. Analogously firm 2 is a *potential competitor* for all consumers located between a and 1; the *dominant competitor* for all consumers between $\frac{1}{2}$ and 1; an *effective monopolist* for consumers between $1-a$ and 1.

Now, under two alternative assumptions about the nature of competition in the market consider the implications for pricing behaviour.

[10]For a similar definition, see, (Thisse and Vives, 1988, p.125-6). They define the market area in which any firm can meet non-zero demand as 'the potential market', and the firm having a lower market price then the marginal cost of the all possible rivals as having 'a monopoly position" (p.125-6).

[11]Thisse and Vives (1992) use the term "overlapping market area" (p.255-6).

1.2.1 Bertrand Competition

From standard analysis it follows that:

- at those locations where firm j is an *effective monopolist* firm j will supply the market at a price $p_j^m(\chi_j)$

- at those locations where firm j is the *dominant competitor* but not an *effective monopolist*, $\chi_j \leq \chi_k \leq p_j^m(\chi_j)$, firm j will serve the market at a price χ_k.

So, under *Bertrand Competition*, we see that, for $j, k = 1, 2$ and $j \leq k$,

- Firm j will serve the market for which it is *the dominant competitor*, i.e. $\chi_j \leq \chi_k$.

- The price j sets for serving a customer in this market and located at a distance d_j from j will be

$$p_j^{comp} = \min\left(p_j^m(\chi_j, \chi_k)\right) = \min\left(p_j^m(c + td_j), (c + t(1 - d_j)\right) \tag{1.3}$$

which is just the standard result as reported in 1.1 above.

So firm 1 will serve the market between 0 and $\frac{1}{2}$ and firm 2 will serve the market between $\frac{1}{2}$ and 1. The price set by firm 1 will be $p_1^m(\chi_1)$ for consumers located between 0 and a and, so a strictly *increasing* function of d_1, but will be χ_2 for all consumers between a and $\frac{1}{2}$ and so a *decreasing* function of d_1. So under Bertrand Competition the price charged by each firm across the market it serves will be an inverse U-shape with respect to the distance between the provider and the buyer.

We can express this in a rather different way by introducing the following definition under Bertrand Competition, for those locations in which provider j is the *dominant competitor*, we say that j's market power, $\left(\mu_j^{comp}\right)$, at a location that is a distance d_j from it is given by,

$$
\begin{aligned}
\mu_j^{comp}(d_j) &= \begin{cases} 1 & \text{if } \chi_k \geq p_j^m(\chi_j) \\ \frac{\chi_k - \chi_j}{p_j^m(\chi_j) - \chi_j} & \text{if } \chi_j \leq \chi_k \leq p_j^m(\chi_j) \end{cases} \\
&= \begin{cases} 1 & \text{if } \chi_k \geq p_j^m(\chi_j) \\ \frac{(c+td_k)-(c+td_j)}{p_j^m(\chi_j) - \chi_j} & \text{if } \chi_j \leq \chi_k \leq p_j^m(\chi_j) \end{cases} \\
&= \begin{cases} 1 & \text{if } \chi_k \geq p_j^m(\chi_j) \\ \frac{t(d_k - d_j)}{p_j^m(\chi_j) - \chi_j} & \text{if } \chi_j \leq \chi_k \leq p_j^m(\chi_j) \end{cases} \\
&= \begin{cases} 1 & \text{if } \chi_k \geq p_j^m(\chi_j) \\ \frac{t(1-2d_j)}{p_j^m(\chi_j) - \chi_j} & \text{if } \chi_j \leq \chi_k \leq p_j^m(\chi_j) \end{cases} \qquad (1.4)
\end{aligned}
$$

So, market power lies between 0 and 1. It is constant and equal to 1 when firm j is an *effective monopolist*. However, when firm k is a *potential competitor* it is an increasing function of χ_k- so the more costly it is for rival k to serve a given location the higher is firm j's market power - but consequently decreases sharply with d_j.

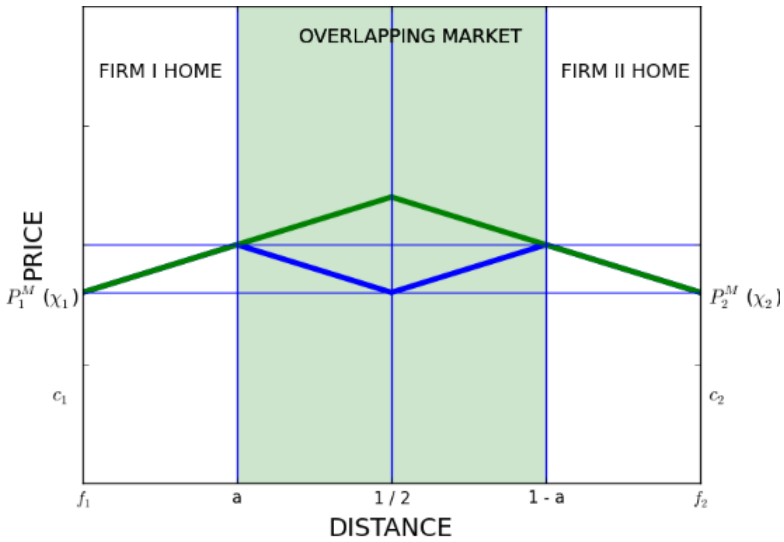
We can combine Equations 1.1 and 1.4 to get

$$
\begin{aligned}
p_j^{comp}(d_j) &= \chi_k \\
&= \frac{\chi_k \left(p_j^m(\chi_j) - \chi_j\right)}{\left(p_j^m(\chi_j) - \chi_j\right)} \\
&= \frac{\chi_k p_j^m(\chi_j) - \chi_j p_j^m(\chi_j) + \chi_j p_j^m(\chi_j) - \chi_k \chi_j}{\left(p_j^m(\chi_j) - \chi_j\right)} \\
&= p_j^m(\chi_j) \frac{\chi_k - \chi_j}{\left(p_j^m(\chi_j) - \chi_j\right)} + \chi_j \frac{\left(p_j^m(\chi_j) - \chi_k\right)}{\left(p_j^m(\chi_j) - \chi_j\right)} \\
&= \mu_j^{comp}(d_j) p_j^m(\chi_j) + \left(1 - \mu_j^{comp}\right) \chi_j \qquad (1.5)
\end{aligned}
$$

So, for all locations served by firm j the price it charges under Bertrand competition is just a weighted average of its monopoly price and the cost of serving that location, with the weight given by its market power at that location.

Figure 1.2 summarizes the pricing pattern in competition and collusion in this simple framework. In one dimensional *competitive* market with delivered pricing structure, it is reasonable to expect initially a linear and monotonically increasing relation between provider distance and price. As we travel from provider to rival, initially we

Figure 1.2: Price Patterns in the Market under Collusion and Competition



are travelling within the *home market* of the provider. Rival firm has no incentive to extend operations to this region. Nevertheless, as the provider extends its operations further – into the *overlapping market*, proximity to the rival matters because the rival firm has an incentive to serve this area. The closer the operations are extended to rival, the higher is the price cut provider needs to make to keep the buyers[12]

1.2.2 Collusion

Now suppose firm 1 and firm 2 form a cartel via explicitly colluding. Since our interest is in explaining pricing behaviour conditional on being in a cartel rather than the decision to form a cartel, I will take it that firms are explicitly colluding; meaning that the cartel exists, and, if detected and successfully prosecuted by the Competition Authority, it will pay a fixed penalty $F \geq 0$[13]. So its objective is simply to maximise joint gross profit across all locations, which requires that

[12]Effects of proximity to rivals on pricing has long been recognized in the literature. As captured by Hoover (1937),
"The effect of the presence of rival points of supply is, of course, to make the demand for the goods of each seller more elastic than it would be if his location were the only one in the field. But the effect is not spread evenly over any one seller's market area. Near the outer margins of this area he is most vulnerable, while in the neighbourhood of his own location he may be able to raise prices as far as local competition allows and still keep them below what it would cost his distant competitors to deliver in that territory (p.187)."

[13]Katsoulacos et al. (2015) provide a critical assessment of the design of monetary punishments in the antitrust enforcement in a non-spatial context. One aspect of the analysis is the impact of penalty regime on the collusive price. In the case of fixed penalty regime, collusive price is the monopoly price. Since the fine translates as a fixed cost to the conspirators, it does not affect pricing. Same result holds if penalty regime depends on profit. If penalty regime depends on revenue, collusive price is higher than the monopoly price. If penalty regime depends on overcharge, collusive price is lower than the monopoly price. In this work, to ensure monopoly pricing in collusion, a fixed monetary penalty is assumed.

both firms maximise joint gross profit at each location. Since monopoly profit is strictly decreasing function of χ, this means that the cartel should let the *dominant competitor* at each location act as a monopolist. For those parts of the market where a firm is an *effective monopolist* this will happen anyway even under Bertrand competition. For those parts of the market where a firm is a *dominant competitor* but not an *effective monopolist* this outcome could be achieved by having the rival firm committing itself to either refusing to serve that market, or quoting a price above the *dominant competitor*'s monopoly price.

So, under a cartel we see that, for $j = 1, 2$

- Firm j will serve the market for which it is the *dominant competitor*,

- The price it sets for serving a customer located at a distance d_j from it will be

$$p_j^{cartel} = p_j^m \left(c + td_j\right) \tag{1.6}$$

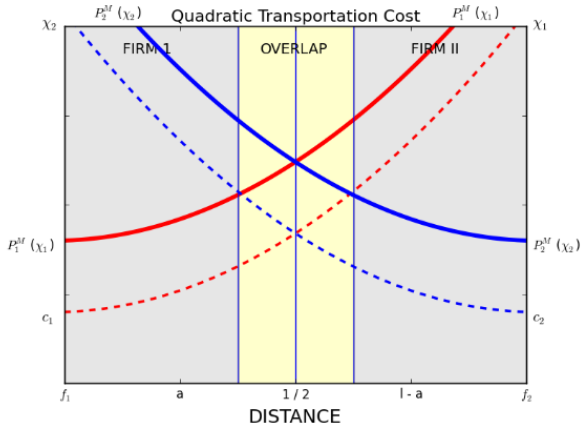
and so is a *strictly increasing* function of d_j, the distance between the provider and the customer.

Once again a somewhat different way of saying that, under a cartel, for those locations in which it is provider j that is the *dominant competitor*, so that $\chi_j \leq \chi_k$, its market power under collusion at distance d_j is given by;

$$\mu_j^{cartel}(d_j) = \begin{cases} 1 & \text{if } \chi_k \geq \chi_j \\ 0 & \text{otherwise} \end{cases} \tag{1.7}$$

Recall that Equation 1.5 sets out the relation between price the firm charges and its market power under competition as a weighted average of its monopoly price and the cost of serving that location, with the weight given by its market power at that location. Since collusive strategy provides undisturbed market power to provider at every location; combining Equations 1.5 and 1.7, would collapse pricing equation into 1.6. It follows that even though the collusive strategy did not include an explicit agreement on price, the effect of a cartel by adjusting the market power of each of its members in those parts of the market in which they would otherwise have faced real competition is monopoly pricing at each location. So we have the following result:

Figure 1.3: Quadratic Transportation Cost



i. Each firm serves exactly the same market under both Bertrand Competition and collusion.

ii. Under a cartel, market power is constant and equal to 1 throughout a firm's market, so price is necessarily increasing in distance between the provider and the customer.

iii. Under competition, market power declines sharply the further a customer is from the provider, leading to an inverse U-shaped relation between the equilibrium price and the distance between the provider and the customer.

1.2.3 Immediate Extensions

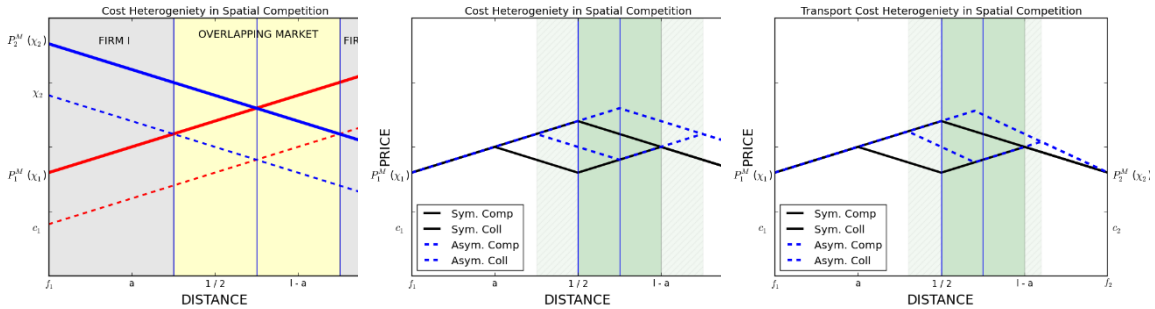
The theoretical framework considered so far involves some very strong assumptions. I now briefly consider the implications of dropping some of them while retaining the basic framework of two firms located at either end of a line.

(i) Linear transport cost. If transport cost is given by some increasing function of distance then, given the assumption that the commodity is a necessity, positive amounts will be sold at all locations. Given symmetry, each firm will serve half the market. This is displayed in Figure 1.3, in which the transportation cost is quadratic in distance.

$\overline{c_j\chi_j}$ illustrate how units cost vary along with d_j, $\overline{p_j^m p_j^m}$ show the price that each firm would charge at each location had it been monopoly supplier at that location, and how these vary with d_j[14]

[14]Functional form of transportation cost has been highly debated in the literature. d'Aspremont et al. (1979) suggest that quadratic transportation cost assumption leads to maximum

Figure 1.4: Cost Heterogeneity



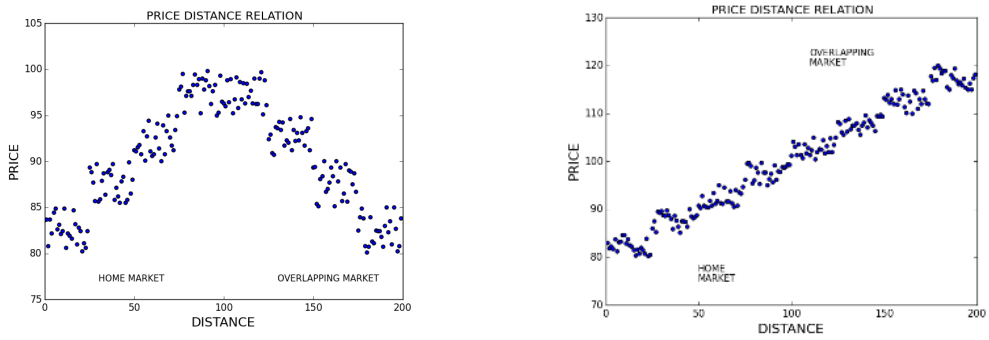
(a) (b) (c)

(ii) Symmetric Firms. Provided that the asymmetry is not too great, we can allow the firms to differ in their unit cost of production and in their unit transportation cost. Each firm will still have a part of the market for which it is an *effective monopolist*. However, as shown in Figure 1.4, cost side heterogeneity leads to asymmetrical market allocation. Left panel depicts market allocation when production cost of f_2 is 50 % higher than f_1. $\overline{c_j \chi_j}$ maps the cost of serving at each location thus, the minimum price. Similarly, $\overline{p_j^m p_j^m}$ maps the monopoly price that provider would prefer to charge at each location. Higher production cost makes it more difficult for f_2 to undercut f_1, easier for f_1 to undercut f_2. This expands *home market* of f_1 in the expense of home market of f_2. As the centre panel shows, *overlapping market* shifts, but the behaviour within remains the same. In competition period, firms undercut each other at low market power locations. The panel on the right shows the case if heterogeneity in cost is related to unit transportation cost. *Overlapping market* rotates but the pattern within is again not affected.

(iii) Customer Heterogeneity. Up to now, two sources of variation within price have been mentioned: increase in price due to higher transportation cost and decline in price due to proximity to rivals. Clearly, this deterministic representation is incomplete. For example, large buyer size might translate as lower price. The motivation for giving price concessions (say in the form of quantity discounts / rebates) to large buyers might be particularly strong for industries in which scale matters. Moreover, some factors unobservable to researcher might also be influential in price; some examples are financial stability of the buyer, default risk, road quality, the duration of the provider-buyer relation. Variations in price might be due

differentiation. This contrasts with Hotelling (1929) conclusion of minimum differentiation. In this debate of linear vs quadratic, I side with Davis and Garcés (2009) "Each case is clearly special and therefore restrictive". When the distance in question is not literal, or not a cost actually borne, but signifies a deviation from an optimal choice as in the setting of Davis (2006) – movie theatre competition, it might be more intuitive to use a nonlinear specification. On the other hand it might be more intuitive to use a linear specification in the setting of Miller and Osborne (2014) - price discrimination in cement markets, in which transportation cost is a significant part of the price, and determines profitability directly.

Figure 1.5: Customer Heterogeneity



(a) Competition

(b) Collusion

to observable/unobservable heterogeneity related to these "other" factors. Thus, it is more realistic to expect stochasticity in pricing. At each location, imagine there is a stochastic factor, ϵ_{jc}, specific to each provider–buyer pair. Figure 1.5 illustrates price–distance relation for a hypothetical provider in one dimensional world, assuming the distribution governing the stochasticity at each location is constant across the market.

After inclusion of heterogeneity, under competition, price now has three sources of variation: i) An increasing trend in price over distance at the locations where the provider is an *effective monopolist*, ii) Declining trend in price over distance at the locations where the provider is the *dominant competitor*, iii) Provider–buyer specific heterogeneity due to observable/unobservable factors. Right panel depicts collusion. In collusion, only first and third sources of variation are present in price.

1.3 General Case

1.3.1 Bertrand Competition

Consider a spatial industry with j producers and l buyers located at distinct locations. Parties have full information about distance between buyers and all potential providers. There are no capacity constraints. In this case, we have no restrictions with regards to number of dimensions in the market. $Q_l(p)$ represents the demand at each location with the same properties in one dimensional case. $p^m_{jl}(\chi_{jl})$ represents the monopoly delivered price a firm would desire to charge at each location while serving demand $Q_l(p)$ with cost $\chi_{jl} > 0$. $p^m_{jl}(\chi_{jl})$ is a strictly increasing function of χ_{jl}. Similar to one dimensional case, cost is characterised by an interaction of unit production cost and transport cost.

$$\chi_{jl} = f\left(c_j, t_{jl}, d_{jl}\right), \qquad j = 1, 2...J \tag{1.8}$$

For example, assuming total transportation cost is governed by $T_{jl}(d_{jl})$, the average transportation cost per unit of travel would be $t_{jl} = \frac{T_{jl}}{d_{jl}}$. Then, χ_{jl} would be $\chi_{jl} = c_j + t_{jl}d_{jl}$.

The definitions in one dimensional case with respect to competitive position of a firm at each location can be amended as follows:

Definition 1.3.1. For firms $j, k = 1, 2...J$, and for k, $\chi_{kl} = \min \chi_{(-j)l} \left(c_{-j}, t_{(-j)l}, d_{(-j)l}\right)$, firm j is

- a *potential competitor* for serving the demand at this location if $\chi_{jl} \leq p^m_{kl}(\chi_{kl})$
- the *dominant competitor* for serving the demand at this location if $\chi_{jl} \leq \chi_{kl}$,
- an *effective monopolist* for serving the demand at this location if $p^m_{jl}(\chi_{jl}) \leq \chi_{kl}$

It follows that

- at those locations where firm j is an *effective monopolist*, firm j will serve the market at a price $p^m_{jl}(\chi_{jl})$,
- at those locations where firm j is the *dominant competitor* but not an *effective monopolist*, $\chi_{jl} \leq \chi_{kl} \leq p^m_{jl}$, firm j will serve the market at a price χ_{kl}.

So, under Bertrand Competition we see that for firms $j, k = 1, 2...J$, where $\chi_{kl} = \min \chi_{(-j)l}$,

- Each location l will be served by the firm j, satisfying,

$$\chi_{jl} \leq \chi_{kl} \tag{1.9}$$

- Price firm j sets for serving a customer located at location l will be

$$p^{comp}_{jl} = \min\left(p^m_{jl}(\chi_{jl}), \chi_{kl}\right) \tag{1.10}$$

So for the locations at which firm j is an effective monopolist, $p^m_{jl}(\chi_{jl}) \leq \chi_{kl}$, price will be a (strictly increasing) function of χ_{jl}. However, for the locations at which j is the dominant competitor, $\chi_{kl} \leq \chi_{jl} \leq p^m_{kl}(\chi_{kl})$, price is a function of χ_{kl}. This brings us to the relation between local market power of provider j and local relative costs. Modifying Equation 1.5 to the general setting, given provider j, the *dominant competitor*, and provider k, $\chi_{kl} = \min \chi_{(-j)l}$ where $j = 1, 2...J$; under Bertrand Competition, firm j's market power at location l is characterised by

$$\mu^{comp}_{jl} = \begin{cases} 1 & \text{if } \chi_{kl} \geq p^m_{jl}(\chi_{jl}) \\ \frac{\chi_{kl} - \chi_{jl}}{p^m_{jl}(\chi_{jl}) - \chi_{jl}} & \text{if } \chi_{jl} \leq \chi_{kl} \leq p^m_{jl}(\chi_{jl}) \end{cases} \tag{1.11}$$

It is easy to see the dynamics of the relation between $\mu_{jl}^{comp}(\chi_{jl}, \chi_{kl})$ and d_{jl}. Recall that for any firm j, $\chi_{jl} = f(c_j, t_{jl}, d_{jl})$. Assuming, unit production cost is independent of distance travelled[15], $\frac{\partial c_j}{\partial d_{jl}} = 0$; and per unit cost of transportation is independent of own distance travelled, and distance travelled by the rival[16], $\frac{\partial t_{jl}}{\partial d_{jl}} = 0$, $\frac{\partial t_{jl}}{\partial d_{kl}} = 0$,

$$\frac{\partial \mu_{jl}^{comp}}{\partial d_{jl}} = \frac{\left[\frac{\partial(\chi_{kl}-\chi_{jl})}{\partial d_{jl}}\left(p_{jl}^{m}(\chi_{jl}) - \chi_{jl}\right)\right] - \left[\frac{\partial(p_{jl}^{m}(\chi_{jl})-\chi_{jl})}{\partial d_{jl}}(\chi_{kl} - \chi_{jl})\right]}{\left(p_{jl}^{m}(\chi_{jl}) - \chi_{jl}\right)^2}$$

$$= \frac{\frac{\partial \chi_{kl}}{\partial d_{kl}}\frac{\partial d_{kl}}{\partial d_{jl}} - \frac{\partial \chi_{jl}}{\partial d_{jl}}}{p_{jl}^{m}(\chi_{jl}) - \chi_{jl}} - \frac{\left[\frac{\partial(p_{jl}^{m}(\chi_{jl})-\chi_{jl})}{\partial d_{jl}}(\chi_{kl} - \chi_{jl})\right]}{\left(p_{jl}^{m}(\chi_{jl}) - \chi_{jl}\right)^2} \tag{1.12}$$

Note that two forces are in motion. Let us start with the second term in Equation 1.12. This centres on the impact of cost increases on monopoly mark-up. Assuming at each location, a well-defined monopoly price exists, and monopoly profit is non-zero; if cost increases are passed on one-to-one in the form of equally higher monopoly price, meaning $\frac{\partial p_{jl}^{m}(\chi_{jl})}{\partial \chi_{jl}} = 1$, then,

$$\frac{\partial p_{jl}^{m}(\chi_{jl}(c_j, t_{jl}, d_{jl}))}{\partial d_{jl}} = \frac{\partial p_{jl}^{m}}{\partial \chi_{jl}}\frac{\partial \chi_{jl}}{\partial d_{jl}} = \frac{\partial \chi_{jl}}{\partial d_{jl}}$$

will hold. In this case, this term will cancel out.

We are more interested with the first term. In addition to χ_{jl}, any incremental change in distance might also affect χ_{kl}. This is intuitive as, incremental change in distance might affect on the cost of the minimum cost rival. Thus, this term captures the relative change in delivered cost of provider in relation to the minimum cost rival. For example, consider a marginal increase in distance served for provider j. Market power of j, would be higher at the latter location only if expansion of operation increases χ_{kl} relatively more than χ_{jl}; alternatively, if $\frac{\partial \chi_{kl}}{\partial d_{kl}}\frac{\partial d_{kl}}{\partial d_{jl}} > \frac{\partial \chi_{jl}}{\partial d_{jl}}$.

Finally, regarding price - market power relation, which is captured by Equation 1.4 in one dimensional case, little changes. If $\chi_{kl} \geq p_{jl}^{m}(\chi_{jl})$, j has undisturbed market power, hence prices monopolistically. If, $\chi_{jl} \leq \chi_{kl} \leq p_{jl}^{m}(\chi_{jl})$, then by same

[15] One example of unit production cost being dependent on the distance would be additional inputs, e.g. preservative chemicals, being used in the products shipped further away.

[16] Independence of t_{jl} from distance travelled by rival, d_{kl}, is straightforward. Independence of t_{jl} from d_{jl} involves the assumption that *distance* related economies of scale associated in transportation is marginal. Regarding the industry and the geography studied in this work, this is a mild assumption; as, transportation is done primarily by land, via standard size trucks, and over relatively short distance.

derivation

$$p_{jl}^{comp}\left(\chi_{jl},\chi_{kl}\right)=\chi_{kl}$$

$$=\mu_{jl}^{comp}\left(\chi_{jl},\chi_{kl}\right)p_{jl}^{m}+\left(1-\mu_{jl}^{comp}\left(\chi_{jl},\chi_{kl}\right)\right)\chi_{jl} \tag{1.13}$$

Thus, price charged is still a weighted average of monopoly price a firm is willing to charge and the cost of serving that location, with the weight given by its market power at that location.

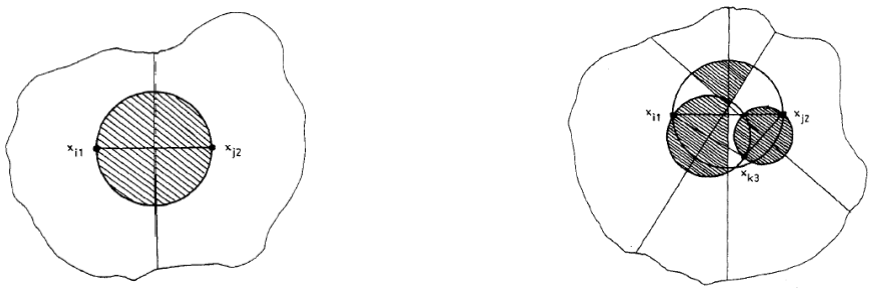
An Application in Two Dimensional World - Competition

In a two dimensional world, let $f_j = (x_f^j, y_f^j)$ refer to coordinates of independent facilities controlled by different undertakings[17]. $c_l = (x_c^l, y_c^l)$ refers to coordinates of independent buyers. Euclidean distance between buyer l and provider j is $d_{jl}(c_l, f_j)$. Equation 1.11 suggests that price cuts are conditional on the competitive pressure from rivals. In one dimensional models, by construction, as provider - buyer distance increases, rival - buyer distance decreases. As a result of competitive pressure, market power falls. However, in two dimensional setting we cannot anticipate a negative relationship between price and provider - buyer distance. MacLeod et al. (1988) illustrate this. Consider two firms (left panel) operating on an irregular grid as shown in the following figure. As we travel away from x_{i1}, the increase in competitive pressure from x_{j2} is only relevant for the shaded area. For the rest of the plain, there would not be an increase in competitive pressure. Right panel introduces a third firm, x_{k3}. The area where price declines with distance is now irregular. Therefore, it is hard to suggest a straightforward relationship. It remains a fact that firms suffer higher transportation cost as more distant locations are served. In some cases, the heightened competition outweighs this effect. In some other cases it does not.

The role of relative proximity in market power can be shown algebraically. Assume that the firms have constant, linear and symmetrical transportation cost and unit cost of production. Given $\chi_{kl} = \min \chi_{(-j)l}$, where $j, k = 1, 2...J$; Equation 1.11 suggests,

[17]The term undertaking forms the basis of competition law in distinguishing different entities that are independently liable from a competition law perspective. In this regard, critical element is the control over the undertaking. Undertakings are distinct only if they are distinctly controlled. For example, two production plants registered under different legal names, but controlled by the same board, are part of the same undertaking. Similarly in this study, "undertaking" refers to production facilities that are commonly controlled. See, Jones (2012) for a discussion in legal context.

Figure 1.6: Rivalry in Two Dimensional World



(a) Two firms (b) Three firms

Source: Figure 2 in MacLeod et al. (1988).

$$\mu_{jl}^{comp}(\chi_{jl}, \chi_{kl}) = \begin{cases} 1 & \text{if } \chi_{kl} \geq p_{jl}^{m}(\chi_{jl}) \\ \frac{\chi_{kl}-\chi_{jl}}{p_{jl}^{m}(\chi_{jl})-\chi_{jl}} & \text{if } \chi_{jl} \leq \chi_{kl} \leq p_{jl}^{m}(\chi_{jl}) \end{cases}$$

$$= \begin{cases} 1 & \text{if } \chi_{kl} \geq p_{jl}^{m}(\chi_{jl}) \\ \frac{(c+td_{kl})-(c+td_{jl})}{p_{jl}^{m}(\chi_{jl})-\chi_{jl}} & \text{if } \chi_{jl} \leq \chi_{kl} \leq p_{jl}^{m}(\chi_{jl}) \end{cases}$$

$$= \begin{cases} 1 & \text{if } \chi_{kl} \geq p_{jl}^{m}(\chi_{jl}) \\ \frac{t\left(d_{kl}-d_{jl}\right)}{p_{jl}^{m}(\chi_{jl})-\chi_{jl}} & \text{if } \chi_{jl} \leq \chi_{kl} \leq p_{jl}^{m}(\chi_{jl}) \end{cases}$$

$$= \begin{cases} 1 & \text{if } \chi_{kl} \geq p_{jl}^{m}(\chi_{jl}) \\ \frac{t(\Delta_l^j)}{p_{jl}^{m}(\chi_{jl})-\chi_{jl}} & \text{if } \chi_{jl} \leq \chi_{kl} \leq p_{jl}^{m}(\chi_{jl}) \end{cases} \tag{1.14}$$

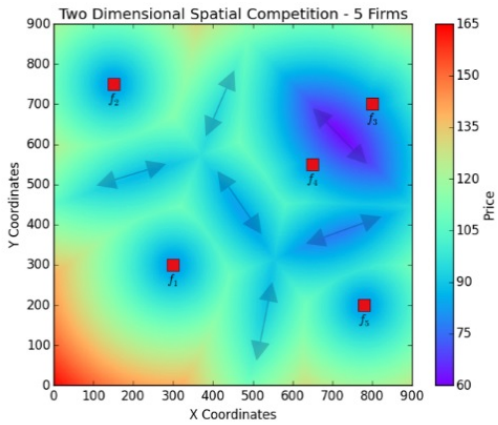
where,

$$\Delta_l^j = \min d_{kl} - d_{jl} \tag{1.15}$$

Therefore, local market power of each provider will be proportional to its relative proximity.

Figure 1.7 illustrates the functioning of a hypothetical market defined on a 900×900 Cartesian plane under Bertrand competition. The market structure is exactly the same as Figure 1.2. Therefore assume that firms are symmetrical both in production and transportation cost. Consumers have no market power and firms can price discriminate. Market operates under delivered pricing. Again for simplicity, firms add a constant mark-up to cost if they are monopolists. The parametrization is identical with the one dimensional case. $f_j = (x_f^j, y_f^j)$, marks the coordinates of the independent facilities controlled by different undertakings. The graph displays price in a colour scale as indicated on the right. Blue values correspond to lowest; red values correspond to highest price.

Figure 1.7: Spatial Competition in Two Dimensional World



In the areas where the provider is an *effective monopolist*, no other rival can restrict its pricing. At these locations, market power is maximum and price increases with distance linearly. On the other hand, at locations in which the competitiveness of *potential competitor* and *dominant competitor* converge, market power of provider is lower and providers need to price cut. The increase in competition creates some price rifts in the market.

1.3.2 Collusion

Assume that j firms decide to collude and form a complete cartel. The objective of the cartel is to maximise joint gross profit. Since the profit at each location is a decreasing function of χ_{jl}, the collusive returns will be maximized if cartel lets *dominant competitor* at each location act as a monopolist. Therefore, in case of a complete cartel formed by j firms, $j, k = 1, 2...J$, and k satisfies $\chi_{kl} = \min \chi_{(-j)l}$,

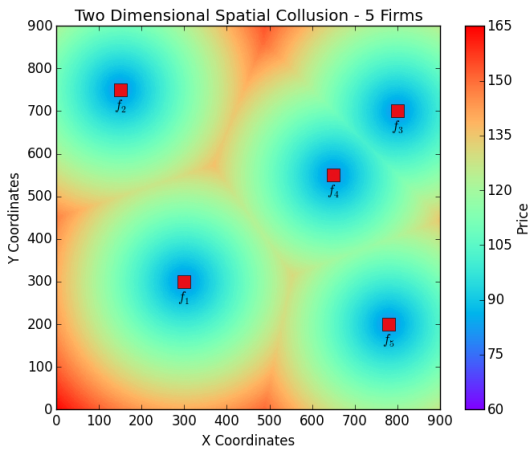
- Firm j will serve location l if
$$\chi_{jl} \leq \chi_{kl} \tag{1.16}$$

- The price at each location l will be
$$p_{jl}^{cartel}\left(\chi_{jl}\right) = p_{jl}^{m}\left(\chi_{jl}\right) \tag{1.17}$$

Incorporating the collusive strategy, the price at each location l can alternatively be represented as,
$$p_{jl}^{cartel} = \min\left(p_{jl}^{m}\left(\chi_{jl}\right)\right) \tag{1.18}$$

Note that each firm is operating where it is a *dominant competitor*. Since collusive agreement ensures against the risk of being undercut, the market power of firm j at

Figure 1.8: Spatial Collusion in Two Dimensional World



any location l is characterized by,

$$\mu_{jl}^{cartel} = \begin{cases} 1 & \text{if } \chi_{kl} \geq \chi_{jl} \\ 0 & \text{otherwise} \end{cases} \tag{1.19}$$

Consequently, $\frac{\partial \mu_{jl}^{cartel}}{\partial d_{jl}} = 0$.

Similar to earlier case, to see the effects of collusive strategy on price, Equations 1.19 and 1.13 should be combined. Cartel, by setting market power to unity in 1.13, collapse pricing function to Equation 1.17. Thus, even though collusive strategy does not include an explicit agreement on price, it results in monopoly pricing.

An Application in Two Dimensional World - Collusion

Figure 1.17 illustrates the functioning of the market under collusion. Under the assumption of constant, linear and symmetrical transportation and production costs, pricing is characterised by,

$$p_{jl}^{cartel} = \min p_{jl}^{m} \left(c + td_{jl}\right) \tag{1.20}$$

For every provider, price increases linearly in all directions. Market power is governed by Equation 1.19 and maximised at every location due to cartel agreement.

Note that locations with the lowest price under competition, the regions of price rifts, now have the highest price. Therefore, a possible regime switch is very likely to affect these regions. On the other hand, areas that correspond to *home market*, e.g. the corners of the plain, have the same colour. A possible regime switch is unlikely to affect these regions.

1.3.3 Defining the Variable of Interest

$$\Delta_l^j = \text{Distance of the Closest Rival from location } l-$$

$$\text{Distance of Provider from location } l$$

Δ_l^j can be identified as a "relative proximity based local market power measure" for each realized transaction. It measures market power of the provider at location l, as a function of relative proximity of provider and the closest rival to that particular location. The provider is expected to enjoy a market power associated with and proportional to this value. For each provider-location pair it is constant across time.

For each transaction,

- Large positive values mean that provider is the closest firm to the customer (home market).
- Large negative values mean that provider is serving to a customer closer to its closest rival (home market of the rival).
- Values around zero mean that both firms are good alternatives for the buyer (overlapping market).

1.4 Conclusion

In this chapter, I provide some theoretical intuition for the measure of local market power used in this work. I centre on the relationship between price at which a provider meets demand at a particular location and market power that provider can exercise at that particular location. This, in turn relates to i) the proximity of alternative providers that could serve that location, and ii) the nature of competition in the market at that location - specifically whether the market is monopolised, cartelised or competitive. I highlight an important characteristic of the market. Under collusion, collusive agreement ensures that each provider enjoys undisturbed market power at each location. However, under competition at the locations where cost difference across providers disappears, price under competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, price in both regimes will be similar; consequently, regime switch would have a small impact on price. It follows that the impact of regime switch on price is inversely proportional to the local market power of the provider under competition. Building on this, I propose approximating local market power variations via an indicator of local cost differences. For location

l, I suggest using $\Delta_j^l = d_{kl} - d_{jl}$, a measure of relative proximity; the distance between the closest rival k and location l, d_{kl}, net off the distance between provider j and location l, d_{jl}.

Chapter 2

Data and Screening

2.1 Introduction

This chapter, first, presents the main data set, other sources of data, and the processing and the refinement of the data. Second, it introduces the variables (and the intuition behind these variables) employed in the empirical chapters 3 and 5, the empirical objectives of which, at this stage, can be generalized to the analysis of firm pricing decisions, and particularly, the relation of these decisions with the measures of market power in a spatial setting. Third, it introduces alternative methodologies of simple data analysis, called "screening" or "collusive markers", which are designed to flag suspicious patterns in the market in understanding if further inquiry into the market is warranted. Application of some of these markers, e.g. evolution of average price; price variation; distance; relative proximity of provider and the closest rival; correlation of price with distance of closest rival; and correlation of price with number of rivals, indicate that consistent with a regime switch from collusion to competition, stable relations in the market were disrupted after month seven.

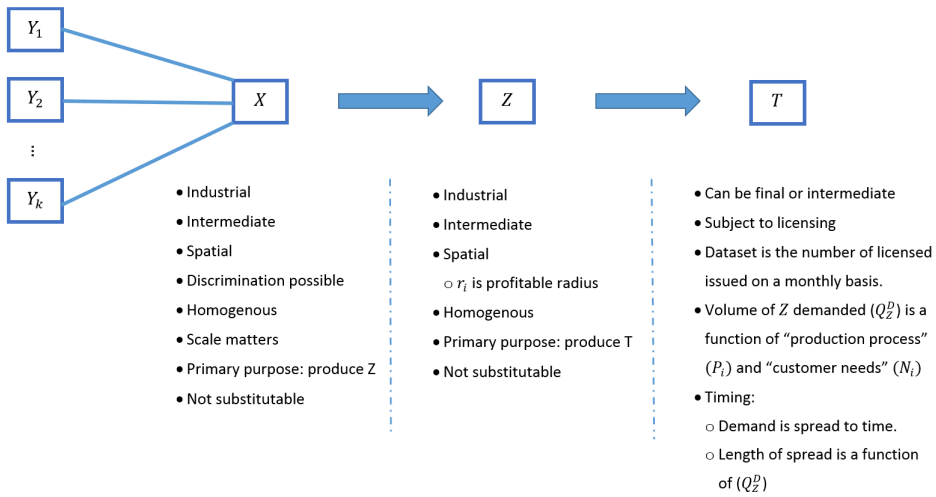
2.2 Sources of Data and Construction of the Data Set

This study, even though it uses multiple sources of data, builds on a consumer level data set of monthly transactions for provider-buyer pairs in a certain region. Data set does not originate from a cartel investigation; thus, there is no information with regards to existence of a cartel, how it operates or what its coverage is. Access to dataset is granted by TCA under confidentiality terms. Terms require masking the identities of the providers and customers; the regions they makes sales to / operate in; date of the sales; costs; and details about the products concerned. Even though terms do not dictate concealment of the industry, for now it will be concealed

(henceforth, product **X**). However, some information relevant for economic analysis should be provided.

- Product is homogeneous. The scope for branding is limited. Firms are not exclusively producing X, but it has a big share in their revenues.
- The sales are bulky in quantity. The transportation cost constitutes an important part of the delivered price.
- Scale is important. Marginal production cost fall as output is expanded.
- The product is an intermediate product. Thus, producers may choose to integrate upwards or downwards. Figure 2.1 summarizes the relation of product X with downstream and upstream products.

Figure 2.1: Product Attributes, X, Z, and T



- Facilities differ in complexities. Some operate like assembly plants, while others are more sophisticated.
- In distribution, vertical agreements are occasionally preferred; but they are not the norm.

This study benefits from three different sources of data: regional demand data, data reported by undertakings, and distance information provided by web mapping. Next section outlines the data processing and refinement for each one.

2.2.1 Regional Demand

The primary purpose of X, is to produce Z; primary purpose of Z is to produce T. Alternatively speaking, any production of T, creates a demand for Z. Any

production of Z creates a demand for X. Given the input-output relation, T production is the ultimate source of demand, hence ultimate source of demand variation. Therefore it is possible to capture regional demand fluctuations affecting X, by incorporating T into analysis. To this aim, around each Z location, "relevant" T production over time is monitored; consequently, first source of data draws from T production.

Figure 2.2: Spatial Production Patterns in X, Z and T

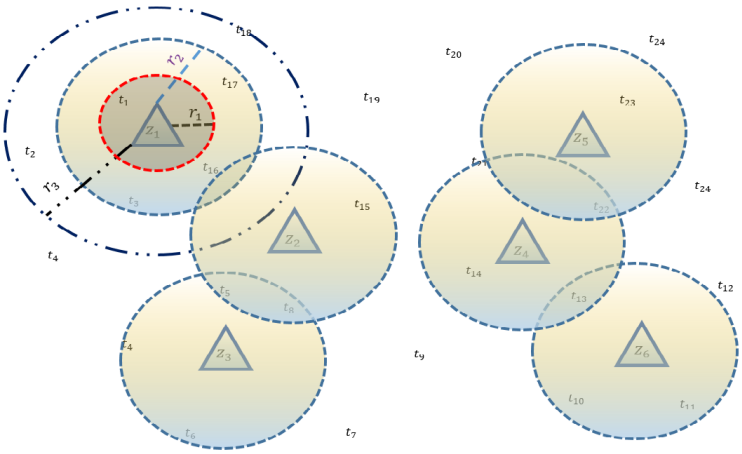


Figure 2.2 illustrates the spatial relation between X, Z and T. Let t_i refer to the volume of T production at each center. z_i corresponds to the locations to which X is delivered (henceforth, X locations). The assumption employed here is $z_i = x_i$. This means, consistent with its primary purpose, all the shipments to these locations have been used in the production of Z. In the figure, r_i marks the limit distance within which it is considered viable to supply Z from. It is initially set to $\bar{r}$, an industry rule of thumb.

Two defining features of T is the customer needs N, and the production process P. They together define the volume of T produced at each location, hence quantity of Z required, Q_Z^D. Production of T is subject to licensing. Licenses are provided at the district level[1]. This includes monthly volume of T production, Q_{npdt}, in a breakdown of customer needs $n = 1, 2, ...\bar{N}$, production process $p = 1, 2, ...\bar{P}$, month $t = 1, 2, ...\bar{T}$ and district $l = 1, 2, ...\bar{L}$.

Producers of T do not prefer to supply Z from providers that are far away. Alternatively speaking, only T production in a reasonable radius can create demand for each Z production. To identify "relevant" T locations that might be associated with each Z location, distance between Z locations and T locations should be retrieved.

T production data is at district level. Therefore, first, the coordinates of all districts are manually retrieved from Google Maps. Even though within a given district, T

[1]Perhaps a better term might be "district plus" as, data has information on districts and counties. According to Turkish administrative system, from specific to general, ordering of administration regions is neighbourhood, district, county, province.

production can be anywhere, distance is calculated in reference to a single point. As the first choice, the coordinates of a public building, e.g. municipality, hospital, post office, are used. If no public building is registered in the Google Maps in that district, a central location is arbitrarily chosen. Ambiguity about exact coordinates of T production inevitably causes some measurement error. However, since the districts are small, error is expected to be negligible. Second, coordinates of X locations are identified. Third, in connection with Google servers, a matrix of point to point driving distances between each district and each X location is constructed in an automated manner. After retrieving the distance information, building on nearby T activity, three different regional monthly demand indices are constructed: For each X location, first measure is the aggregate monthly T volume that is in $\bar{r}$ units of driving distance; second measure uses $0.8\bar{r}$ as the cut-off; third measure uses $0.6\bar{r}$.

Not surprisingly, the demand for T exhibits seasonality and is prone to calendar effects. To strip seasonal effects off, first option is using an indicator variable for each calendar month. Benefit of this approach is that fixed effects capture seasonality, not only from demand side, but also from supply side. However, there are two drawbacks: first, data is not long time wise; as it spans 18 months, only 6 calendar month indicators would be nonzero more than once. Second, employing calendar month fixed effects means forcing an additive seasonal structure on data. Second option is seasonally adjusting the demand data first and using adjusted data in the estimation. This allows experimenting with more flexible seasonal patterns. However, (i) any supply side seasonality in X production would not be captured, (ii) as the process would be sensitive to outliers, identification of seasonal patterns would be challenging with disaggregated data[2].

Table 2.1: Seasonal Adjustment

	n_2p_2	n_1p_2	n_1p_1	n_2p_1	Total
Log Transformed	Yes	Yes	Yes	Yes	Yes
Model Fitted	$[(0,1,1)(0,0,0)]$	$[(0,1,1)(0,1,1)]$	$[(0,1,1)(0,1,1)]$	$[(0,1,1)(0,1,1)]$	$[(0,1,1)(0,1,1)]$
Calendar Effects	Yes	Yes	Yes	Yes	Yes
pvalue	0.0007	0.0000	0.0000	0.0000	0.0000
Seasonality (*pvalue*)	ISNT	ISP	ISP	ISP	ISP
Stable seasonality (FS)	0.1809	0.0000	0.0000	0.0000	0.0000
Kruskal - Willis (W)	0.1028	0.0000	0.0000	0.0000	0.0000
Seasonality Assuming Stability (T)	0.1507	0.0000	0.0000	0.0000	0.0000
Evolative Seasonality (FM)	0.2107	0.3994	0.7459	0.2285	0.0000
Residual Seasonality (R) (F Stat)	1.43	0.31	0.64	0.71	1.22
	FS	No Seasonality. Monthly averages are not different			
	W	No Seasonality. Monthly averages are not different			
H_0	FM	Seasonal effect across years is not different			
	T	Seasonality is not present			
	T	Residuals do not have seasonality			

As a solution, data is stripped of seasonal effects at the aggregated level, and in proportion to each district's weight in unadjusted data, aggregated adjusted data is disaggregated to districts. This works as follows: First, a weight $\omega_{\bar{n}pdt}$

[2]Potential differences in seasonal patterns across different customer needs N and production process P combinations make the task more challenging.

is calculated for each district, d, month, t, and n, p combination. This bases on i) seasonally unadjusted monthly district level volume, Q_{npdt}, ii) total monthly unadjusted volume, $\sum_d Q_{\bar{n}\bar{p}dt} = Q_{\bar{n}\bar{p}t}$, so that $\omega_{\bar{n}\bar{p}dt} = \frac{Q_{\bar{n}\bar{p}dt}}{\sum_d Q_{\bar{n}\bar{p}t}}$. Next, unadjusted aggregated data is adjusted at aggregated level for each combination of n, p, where $n, p = (1,1), (1,2), (2,1), (2,2)$. After retrieving seasonally adjusted aggregate series $\tilde{Q}_{\bar{n}\bar{p}t}$, district level seasonally adjusted series are calculated via interacting district weights with seasonally adjusted aggregate data, $\tilde{Q}_{\bar{n}\bar{p}dt} = \omega_{\bar{n}\bar{p}dt}\tilde{Q}_{\bar{n}\bar{p}t}$. This process is iterated, for three different radii; $r_i = \bar{r}, 0.8\bar{r}, 0.6\bar{r}$.

Table 2.1 provides information about some diagnostics and seasonality tests. Since T information is publicly available, we are not restricted with the sample period. Seasonal adjustment builds on eight years of monthly data (96 months) of T production[3]. For the seasonal adjustment *Demetra* is used as the software. It compares alternative models and suggests the most suitable model to the data basing on information criterion measures. It also reports many diagnostic tests automatically which are informative about the nature of seasonality. As seasonal adjustment method, *TRAMO-SEATS* of Gomez and Maravall (1996) is used. ISNT stands for "identifiable seasonality is not present", ISP refers to "identifiable seasonality is present". The results indicate that the seasonal pattern, when present, follows a multiplicative structure, thus series are log transformed. In many cases an *ARIMA* model of $[(0,1,1)(0,1,1)]$[4] has the highest likelihood[5]. Residuals do not exhibit seasonality, indicating the model does a good job in removing seasonality. Calendar effects are consistently significant across subgroups. Findings indicate that n_2p_2 is in stark contrast to other n, p combinations. Both Freidman test, which is concerned with if subsamples in a sample are governed by the same distribution, and Kruskal-Wallis test, which compares subsample means, do not find evidence for seasonal patterns. Since there is no evidence for seasonality for Q_{22dt}, series have only been adjusted for $n, p = (1,1), (1,2), (2,1)$. Final regional demand index, $(t_{\bar{n}\bar{p}lt})$, is an aggregation of seasonally adjusted indices $n, p = (1,1), (1,2), (2,1)$, and unadjusted index $n, p = (2,2)$ into a single index.

2.2.2 Undertaking Data

Second source of the data set is the reported figures from undertakings and covers 18 months. These include information about

- Providing facility (origin of production)

[3]In the estimations in Chapter 3 and 5, only data spanning 18 months is used.

[4]$[1-L][1-L^{12}]Q_m = [1+\gamma_1 L][1+\gamma_1 L^{12}]e_m$ where Q is quantity, m is month, e is the error term and L is the lag operator. This model is also called as the airline model following Cleveland and Tiao (1976) that study airlines.

[5]Three years in data exhibit more volatility than remaining 5. If volatile years are excluded, $[(0,1,1)(0,1,1)]$ has the highest likelihood in all specifications. If volatile years are included N_1P_1 has different form $[(1,0,0)(1,0,0)]$. For the sake of consistency I use $[(0,1,1)(0,1,1)]$ in all specifications.

- Type of the product
- Destination county
- Distance of the facility to the buyer's location as reported by undertakings
- Identity and type of the customer (vertical relations, buyer's line of business)
- Total revenue, quantity and transportation cost (if any) in each transaction
- Monthly unit price of some inputs
- Information on the rebates and discounts, if any is provided to consumers and how they are set.

One problem encountered with handling the dataset is a structural one. The data set is fairly old and the access is provided to the rawest format of data. This necessitates doing serious refinement where interaction with the original providers of data is not possible[6].

Dataset contains revenue and volume for each transaction but not the price. There are some observations with zero quantity, zero revenue or no customer identity[7]. These transactions have been omitted. The transaction price is found by dividing total revenue to total quantity. If multiple transactions are reported at customer/location/provider/month level, these transactions are aggregated by taking quantity weighted average. To give coefficients a more intuitive interpretation, price is normalized with average price in the competitive period.

There are two types of sales. Some sales are delivered to buyer's location by the providers. Consequently, the revenue reported includes the freight as well. In some other sales, product is picked up by customers at the origin of production. Consequently, freight is not included in the invoiced revenue. To assure conformity between two types of sales, all sales have been converted into delivered sales. This has been preferred instead of the other way around for two reasons: First, delivered sales are more frequent in the dataset, even though the difference in frequency is small (8 %). Second, the assumption done by opting for delivered pricing is that any buyer is equally efficient in transporting the product with the producing firms. This is more reasonable then the assumption that the transportation cost reported by all firms are as they actually realize -not diverging from actual transportation cost.

Undertakings report transportation cost differently. For any consumer c located at l, provider j, month t and transaction i,

$$TC_i = v_i d_{jl} t_{jt} \tag{2.1}$$

[6]However, this have been considerably mitigated by the helpful inputs of the experts at the TCA.

[7]The observations omitted in this sort is % 0.4 of the sample.

would hold where TC_i is the total transportation cost incurred at the transaction i, v_i is the volume of transaction, d_{lj} is the distance between provider j and location l and t_{jt} is the transportation cost for provider j per unit of volume per unit distance in month t. Some undertakings report TC_i, v_i, and d_{jl}; some others report v_i along with d_{jl} and t_{jt}; and some others report v_i, d_{jl}, t_{jt}. The conversion of mill price has been done by benefiting from transportation cost calculations of one of the firms which reports t_{jt} for each month. As transportation is highly standardized, I do not expect monthly unit transportation cost to differ greatly across undertakings, hence use that monthly figure for all undertakings $\left(t_{jt} = t_{\bar{j}t} = t_t\right)$. Following transformation is used in converting prices that do not include transportation cost to calculate counterfactual delivered price.

$$p_i = \frac{REV_i + v_i d_{jl} t_t}{v_i} \tag{2.2}$$

where REV_i refers to revenue reported from transaction i. Price is then the ratio of revenue including actual or potential freight to total quantity[8].

Some of the revenue / volume figures are flawed, as they suggest prices equal to zero or infinity[9]. In some cases it is straightforward to detect the source of anomaly, e.g. skipping / adding a decimal, or reporting the transportation cost as the price. In these cases corrections have been done. Regarding less straightforward cases, following rule of thumb is applied: i) If there is one other entry for that customer in the same month, that value is taken as the price of both shipments. ii) If there are multiple, the average price of non-anomalous entries is used as the price of the anomalous entry. iii) If there are none, the average of first month before and first month after is taken as the price. iv) If the anomalous entry belongs to the last month, the average of two preceding months is used; if it belongs to the first month, the average of two proceeding months are used. Inspection of the data showed that sale reports of one undertaking are inaccurate for one month. For these cases, the price of the shipment is taken equal to the price in proceeding month[10].

Regarding the customer location, in some cases no province information is present. These transactions have been omitted[11]. For some other cases, province is provided without accompanying county information. These transactions are taken to be destined to the administrative centre of the province[12]. In some cases, county names

[8]For delivered sales of some undertakings, it is difficult to understand whether the reported revenue already includes the transportation cost or transportation cost should be added on top of that revenue figure. For the undertakings where there is a doubt, to understand whether the revenue already includes the freight or not, the transactions are analysed on customer/location/provider basis to see if any one customer demanded both delivered and mill sales from a certain location, in the same month. In this case it becomes easier to understand whether the reported figures already include freight. A separate log outlining the decision making process is kept in the process, which may be provided upon request.

[9]The observations omitted this sort is % 0.3 of the sample.

[10]The observations in this category is % 0.1 of the sample.

[11]The observations omitted this sort is % 0.4 of the sample.

[12]The observations in this category is % 1.1 of the sample.

are reported as province names or are matched with incorrect provinces. These cases have been corrected with the assumption that the most specific information, the county, is accurate.

The dataset includes customer identity information. This information is first used in distinguishing transactions within a vertically integrated undertaking, or transactions across rival undertakings (consumers). These two types of transactions are omitted from the analysis and the attention is confined to what we may think of as "commercial sales", sales destined to third parties. Second, I use customer identity information in approximating customer size. In the assessment of the customer size, transactions from all providers are taken into account. Since, the same customers are not always registered under the same name across different providers, first task is harmonizing customer identities. In many cases, the difference is simply related to using abbreviations or differences in spelling. For these cases, taking name, province, county, customer type information together it is not difficult to identify the same customers registered under different names[13]. Customers with different identities are taken independent from each other[14].

Finally, we have information about buyer's line of business, and presence of any vertical relation between the buyer and provider. In this work, to analyse the potential impact of vertical relations on price, an indicator variable, which marks the transactions between provider and a vertically related buyer, is constructed.

2.2.3 Web Mapping Data, Distance and Coordinates

There are two possible alternative distance measures. First is based on the coordinates of competitors and/or centre for commercial activity (i.e. city, town) and calculating the Euclidian distance between competitors and/or centres. In the literature, this approach is more frequently preferred when distance covered is conceptualized as a time loss for the consumer[15]. Some examples in this fashion are: McManus (2007) analysing coffee consumption around University of Virginia, Davis (2006), studying spatial competition in movie theatres, Dafny (2009) taking on the effects of hospital mergers, and Pinkse et al. (2002) focusing on spatial competition patterns in wholesale gasoline[16]. Second measure is using the driving distance. This is preferred when transportation cost is literal and competitiveness declines with

[13] 39 % of the customers are registered similarly enough to indicate they might be identical, for 29 % of which similarity in names is also supported by consistency in province, county, customer type information. For 10 %, the similarity in the names of the customers is not supported by other available information, these customers are taken independent from each other.

[14] It should be noted that the methodology used here is an imperfect reflection of the customer side. Customer name, location and customer type are poor measures of assessment of control, which in essence a fairly complex task.

[15] Clark and Houde (2013); Lewis (2008) are some exceptions where covered distance is considerable, yet Euclidian distance is preferred.

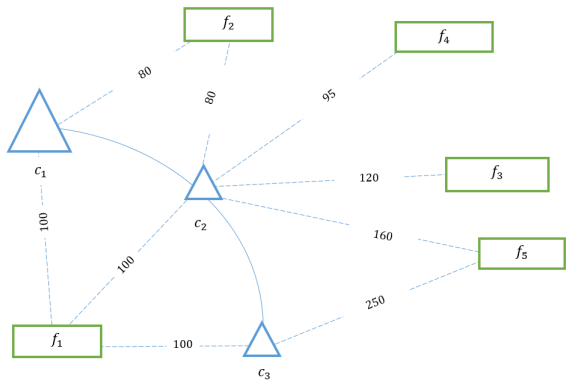
[16] Thomadsen (2005) studies fast food consumption and uses a combination of both shortest route and Euclidean Distance. If the outlet is in a shopping mall Euclidean distance is used, if not shortest route is used.

each extra mile. Some examples are Bajari and Ye (2003) for construction projects, Harrington et al. (2015); Miller and Osborne (2014) for cement markets, and Houde (2012) for retail gasoline[17]. Since our case is similar to the second one, in this study, driving distance is preferred in all estimations.

Recall that the variable of interest in this study is the relative proximity of provider and the closest rival. First step in calculating this measure is retrieving distance of provider and all rivals to each location. Methodology is similar to that in retrieving regional demand data. First the coordinates of the production facilities, and coordinates of the buyers' counties are obtained via satellite imagery applications. Next, in connection with Google servers, a matrix of point to point driving distances between each provider and each county is constructed in an automated manner[18]. It should be noted that the distance matrix is not constructed only for the production facilities from which the transaction data is coming from. It also includes neighbouring facilities that might be a competitive restraint.

After forming the distance matrix, second step is identifying the closest rival, calculating the distance of the closest rival to the location, and the measure of relative proximity. This is done consistently with the notion of undertaking. Consequently, facilities owned by the same undertaking are not expected to compete with each other. Figure 2.3 depicts a hypothetical case. c_l corresponds to location of buyers. f_j corresponds to location of five independent providers.

Figure 2.3: An Example Two Dimensional Plane



$d_{jl}(c_l, f_j)$ corresponds to distance between customer l and provider j Computation of the closest rival for a transaction from f_1 to c_2 would be formalized as,

$$Closest_{c_2}^{f_1} = min\left(d_{22}(c_2, f_2), d_{32}(c_2, f_3), d_{42}(c_2, f_4), d_{52}(c_2, f_5)\right) \tag{2.3}$$

Note that this would imply $\Delta_{c_2}^{f_1} = d_{22}(c_2, f_2) - d_{12}(c_2, f_1) = 80 - 100 = -20$. On

[17]Houde (2012) goes one step further and take traffic flows into consideration as well. One optimal route minimizing travel time is defined for every consumer in a given traffic zone.

[18]For a similar application of using web mapping as a data source, see, Bajari and Ye (2003).

the other hand, if f_1 and f_2 are controlled by the same undertaking, then,

$$Closest_{c_2}^{f_1} = min\left(d_{32}(c_2, f_3), d_{42}(c_2, f_4), d_{52}(c_2, f_5)\right). \tag{2.4}$$

This would imply $\Delta_{c_2}^{f_1} = d_{32}(c_2, f_3) - d_{12}(c_2, f_1) = 95 - 100 = -5$.

Distance information and spatial distribution of providers and customers are also used in calculating the number of rivals in a defined radius, $\bar{d}$, around each buyer. Following the Figure 2.3, first consider all five facilities are controlled by different undertakings. Regarding a transaction between f_1, and c_2, the rivals within 100 km would be f_2 and f_4; number of rivals would be 2. However, if f_1, and f_2 are controlled by same undertaking, the only rival within 100 km would be f_4, and number of rivals would be 1; if all f_1, f_2, f_3 are controlled by the same undertaking, there would not be any rivals in 100 km, and number of rivals would be 0.

2.2.4 Variables

In this part the variables that are used in the empirical chapters, Chapter 3, proactive detection of collusion, and Chapter 5, estimation of the overcharge are presented. Naturally, since the empirical objectives of the two chapters differ, empirical strategy and methodology differs; consequently the variables employed in the estimation also differs. However, at this point, to understand the intuition behind the variables used in these two chapters with different empirical strategy and methodology, it is sufficient to consider the commonality in two different empirical objectives at the very general level: This is *analysing firm pricing decisions, and particularly relation of these decisions with measures of local market power measures, in a spatial setting,*. In both empirical chapters, where necessary I am revisiting the intuition of these variables.

The relation between pricing and local market power is at the centre of the analysis. Local market power variations are captured by Δ_l^j, the relative proximity of the provider and its closest rival at each location, and $\left(\Delta_l^j\right)^2$. The intuition is, after controlling for observables, $\Delta_l^j = \min(d_{kl}) - d_{jl}$ approximates to $\chi_{kl} - \chi_{jl}$, the cost difference between potential competitor and dominant competitor at each location.

The pricing behaviour when competing with a single rival vs. multiple rivals, should differ. Therefore, in the literature, it is common to include the number of rivals in a defined radius to capture the impact of non-local competition. Some examples in this fashion are: Thomadsen (2005) and the number of fast food restaurants within 2 miles, Harrington et al. (2015) and the number of cement providers within 150 km, Dafny (2009) and the number of hospitals within 5 miles, and finally Houde (2012) and the number of gasoline stations within 5 miles. In this study, number of rivals in a defined radius (NBR_{jlc}) is used as a control variable as well[19].

[19]The radius chosen is, volume weighted average provider distance or formally $\bar{d} = \frac{\sum\sum_{lj} v_i d_i}{N_t \bar{V}_t}$.

One important source of heterogeneity is supply side factors. Nature of the data makes it possible to associate transactions with production facilities. Therefore, any heterogeneity in cost structures that are constant over time is captured by facility fixed effects.

Another time invariant supply feature put forward in the literature relates to multiplant ownership. In assessing the risk of vertical foreclosure in concrete and cement markets in US, Hortaçsu and Syverson (2007) find that multiplant ownership is efficiency enhancing in distribution of products: *"...deliveries ... typically ordered on very short notice by consumers at different locations, can be made more efficiently, by having a dispatch office that substitutes production and delivery among firm's several local plants (p. 252)"*. This improvement in efficiency should be more pronounced when scale matters also in production; providers may also switch production from one plant to another to rationalize production. To account for such distribution and/or production related efficiencies, I employ an indicator variable; it marks the presence of a nearby additional X facility owned by the same undertaking within a defined radius[20].

Time varying supply side features do not constitute a major concern. The reason is the nature of variation in the data. Measures of local market power and price vary over customer/location/provider/month basis, thus, has considerable variation within each month. On the other hand, capacity utilization or cost realizations (i.e. wages, energy, and other inputs) vary over provider/month basis and has similar trends across undertakings. This limits the size of any potential omitted variable bias on the coefficients of market power measures. However, some specifications employ energy price and capacity utilization as controls, while some others use month fixed effects to control for time varying factors.

Turning to the demand side, main source of heterogeneity suggested in the literature is the brand related effects. Nevo (2000a,b, 2001) suggests that brand fixed effects go a long way in controlling for factors (like quality) that are observable to the consumer/producer but not observable to the researcher. Similarly, Lewis (2008) favours a high/low quality division which captures brand recognition of the firm and loyalty of customers in gasoline markets. Studying bottled water, Bonnet and Dubois (2010) find evidence for strong brand effects on top of manufacturer effect. In our setting, via employing facility fixed effects, manufacturer effects are controlled. Any brand effect on top of manufacturer effect is assumed to be negligible. This should be a reasonable assumption; as, homogeneity of products limits returns for further brand making.

In incorporating demand fluctuations into the analysis there are three options. First is using transaction volume directly as a control[21]. This is only legitimate if quantity is exogenous. An illustration of this would be Houde (2012) with the assumption of *"consumer has inelastic demand for gasoline. In this representation consumption is split between heterogeneous consumption needs and a common fixed*

[20]Radius is the same as it is in number of rivals. See, Footnote 19.

[21]This issue is thoroughly examined in Chapter 3.

quantity (p.2156).". Another example is Harrington et al. (2015), analysing the collusive patterns in cement. Building on procurement data, in which, list price, and discounts are separately observed, empirical strategy involves using volume as a control. Naturally, in assessing exogeneity, nature of the available data should also be taken into account. Nevo (2000b) points that when transaction level data is concerned, strategy might involve an explicit assumption of exogeneity. Baum (2006) suggests that, transaction data may imply a price taking consumer (p.186). However, as data gets more aggregated, endogeneity issue becomes more problematic.

Second option is using instruments. In this case, demand shifters might be employed in identifying the coefficients of transaction volume in pricing equation within an instrumental variables framework using 2SLS or GMM. Third option is employing demand shifters directly in a reduced form setting using OLS.

In this study, some specifications take on the assumption of exogeneity of transaction volume (v_{jltc}), and employ transaction volume (and other volume related controls) directly in identifying the regime switch (Chapter 3). However, despite the inelasticity of demand for product X, and nature of data set (consumer level transaction data) in line with Nevo (2000b), these estimates are interpreted with caution. In identifying regime switch, regional demand indices building on seasonally adjusted T license data are used as instruments ($t_{\overline{npl}t}$), $\left(t_{\overline{npl}(t-1)}\right)$, $\left(t_{\overline{npl}(t-2)}\right)$, $\left(t_{\overline{npl}(t-3)}\right)$, $\left(t_{\overline{npl}(t-4)}\right)$ for transaction volume within an IV framework, which allows exploring the impact of exogeneity assumption. In estimating the overcharge, regional demand indices are directly employed in reduced form setting as controls.

Two other demand side controls are (i) contractual obligations (vertical agreements), (ii) size of the consumer. Providers might be willing to offer more favourable conditions to the buyer, if the buyer is vertically related. This effect is controlled by an indicator variable marking the presence of a contractual relation between each buyer-provider pair. There are two variables indicating buyer size. First is an indicator variable (γ_c^{large}) marking the buyers in top 5 %[22]. Second one is aggregated volume of all purchases in 18 months ($\bar{V}_{lc}$) for each buyer/location pair. Like transaction volume, this variable suffers from potential endogeneity issues. Similarly, in some specifications, $\bar{V}_{lc}$ is employed directly as a control; in some others, aggregate T license information, $t_{\overline{nptl}}$ is used as an instrument for $\bar{V}_{lc}$ in an IV framework; in some others $t_{\overline{nptl}}$, is employed directly in reduced form setting as a control.

To summarize, following is the list of variables used:

Price (p_{jltc}): Price of commercial sales (excludes transactions within an undertaking or across undertakings) for the transaction between provider j, to customer c, at location l, in month t. Price is calculated using $p_{jltc} = \frac{REV_{jltc}}{v_{jltc}} \frac{100}{\bar{p}}$ where REV_{jltc} is total revenue; v_{jltc} is the transaction volume. In some cases, providers or buyers prefer mill sales. To homogenize the type of sales, mill sales have been converted to delivered sales via Equation 2.2. Also to give the coefficients more

[22]Excludes transactions within an undertaking or across undertakings.

intuitive interpretation, price is normalized by the quantity weighted average price in competitive period, $\bar{p}$[23].

Local market power indicator, as a measure of relative proximity $\left(\Delta_l^j\right)$: Calculated as the difference between driving distance from the rival closest to location l and driving distance from provider j to location l[24]

Delta squared $\left(\Delta_l^j\right)^2$: Square of Δ_l^j to capture nonlinearities.

Number of rivals in a defined radius (NBR_{jlc}): Total number of rivals in a defined radius. The radius chosen is the 'volume weighted average provider distance'. It captures the impact of deviations from localized competition on market power.

Volume (v_{jltc}): Volume of transaction.

Buyer size $\left(\bar{V}_{lc}\right)$: Total volume of X transactions for each buyer, over 18 months.

Facility fixed effects (γ^j): To control for time-invariant unobservable features at facility level, each facility is identified with an indicator variable.

Large buyer $\left(\gamma_c^{large}\right)$: Indicator variable marking top 5 % of the buyers in terms of total volume of purchases.

Collusion $\left(\gamma^{coll}\right)$: It is a dummy variable indicating collusive regime. It is equal to 1 for the first 7 months.

Competition (γ^{comp}): It is a dummy variable indicating competitive regime. It is equal to 1 for the months 8 to 18.

Own facility nearby $\left(\gamma_{jl}^{own}\right)$: An indicator variable marking presence of one (or more) nearby extra production facilities controlled by the provider.

Vertical relations $\left(\gamma_{jc}^{vertical}\right)$: An indicator variable marking vertical relation between provider and buyer.

Energy index (EI_{jt}): Index value that bases on the reports of undertakings about their monthly unit energy price for the most commonly used form of energy.

Capacity Utilization (U_{jt}): Capacity utilization of facility j at time t.

T license $\left(t_{\overline{nptl}}, t_{\overline{nplt}}\right)$: Seasonally adjusted volume of new T licenses at district level. In some specifications monthly level (and its lagged values), in others 18 months aggregated volume is used.

[23] $\bar{p} = \sum_l \sum_j \sum_c \sum_{t=8}^{18} \frac{p_{jltc} v_{jltc}}{\sum_l \sum_j \sum_c \sum_{t=8}^{18} v_{jltc}}$

[24] To ensure visibility of coefficient estimate for $\left(\Delta_l^j\right)^2$ in four digits after the decimal sign, in empirical chapters instead of Δ_l^j, and $\left(\Delta_l^j\right)^2$, I use $0.1 * \Delta_l^j$, and consequently, $0.01 * \left(\Delta_l^j\right)^2$ as covariates.

2.3 Data Analysis and Collusive Markers

2.3.1 Collusive Markers, and Related Literature

In a well-known strand of research[25] , Professor Joseph Harrington analyses how cartels operate. Guided by theory and enforcement experience, the aim is providing rules of thumb for isolating suspicious patterns in the market. These rules of thumbs are widely referred as "collusive markers" or "Harrington markers", and flag the possibility of a regime switch. Some examples are: a steady period of high price followed by a decline; structural changes in pricing; a high correlation in pricing behaviour across competitors; a change in relation of price and cost; reduction of variation in price, product characteristics or quality; elimination of discounts; price increases accompanied by declining imports; and stability in the market shares.

Collusive markers have low data requirements. They are intuitive and the economic analysis involved is not necessarily complicated. Their purpose is "screening" the market in deciding if more detailed analysis is required. However, since they are only designed to flag the *possibility* of collusion, risk of type 1 and 2 errors are considerable[26]. In this part, the literature on screening for collusion is presented.

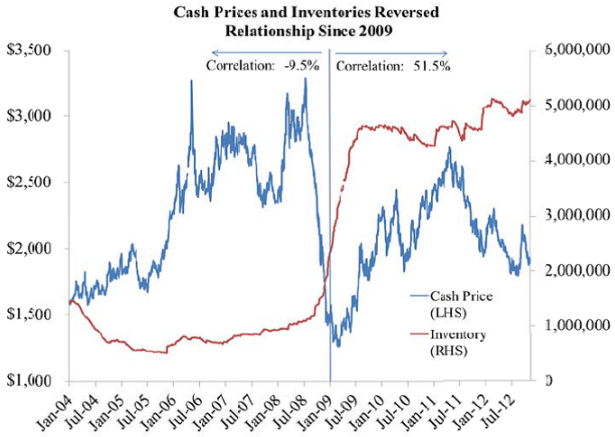
Abrantes-Metz (2013a) focuses on aluminium market, where large customers (primarily producers of canned beverages and drinks) express their concerns about activities of metal warehouses, which recently have been taken over by investment banks. Metal warehouses are accused of creating bottlenecks in the market. Figure 2.4 depicts the evolution of the relation between inventory accumulation and price in the market. Vertical line marks the warehouse takeovers. Before warehouse takeovers, the correlation between inventory accumulation and price is weak and negative. After the takeovers the correlation changes sign, and inventory accumulation is associated with higher price. Similar breaks are also found in other markers, e.g. the relation between cost of warehousing and inventory accumulation; the relation between cost of warehousing and price. Abrantes-Metz (2013a) suggests that findings warrant antitrust scrutiny or some regulatory action in the market.

In screening for collusion, Giles (2007) proposes an unconventional methodology known as the Benford's Law; if any data set is naturally occurring, the distribution

[25] Harrington (2006b,c, 2008)

[26] Yet, ironically, all the successful attempts of detecting collusion so far are studies of this sort. This is a good example for divergence of needs of policy making, and the incentives in academic research. Regarding policy making, it is not necessarily the case that the most sophisticated analysis is the best. Competition policy stands on the intersection of economics, and other fields, particularly law. At the heart of the case for proactive detection there is an assumption: Upon detecting suspicious patterns, it is possible to launch an investigation. However in many jurisdictions investigations require legal consent. On one hand, in order to convince decision makers, the findings in the detection process should be reliable enough, and reliability usually comes with more complex economic analysis. On the other hand, since decision to investigate is taken by non-economists, making the analysis more complex might, (i) make communication more difficult, (ii) increase the time requirements. It is difficult to say where the optimum is.

Figure 2.4: Inventory Holdings and Prices in Aluminium



Source: Figure 1 in Abrantes-Metz (2013a).

of first and second digits can be predicted. Some examples for compatibility with Benford's Law are *"areas of lakes, lengths of rivers, and molecular weights of compounds (p.157)"*. In the field of economics, returns from Dow-Jones stocks, Standard and Poor indices, price in European stock markets are found compatible with Benford's law[27].

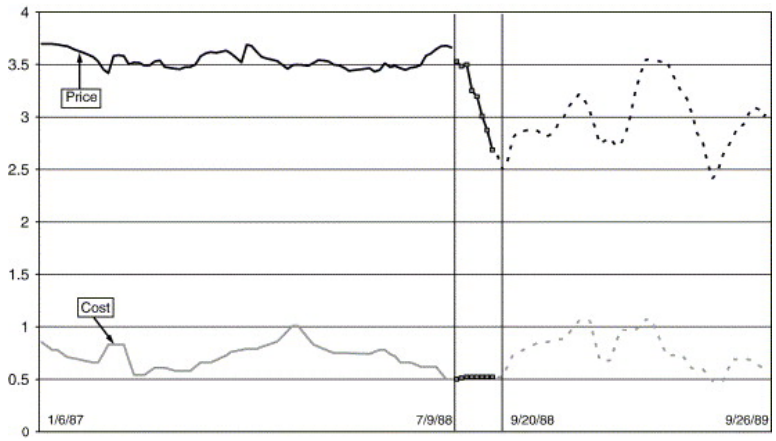
Giles (2007) points out that collusion can be taken as an anomaly, a non-natural intervention to naturally occurring data process. Consequently, it should be possible to detect bid rigging by monitoring the deviation of the actual bids from the distribution predicted by Benford's Law. In Giles (2007), bidding behaviour in *ebaY* for the professional football tickets is taken on as an example. Observed bidding data is in compliance with Benford's Law, which is consistent with competitive bidding.

To isolate suspicious patterns in retail gasoline market in the Western Australia between 2004-2012 Rauch et al. (2013) also use Benford's Law. Since the price data in retail petroleum is confined to an interval, it is the difference between retail price and wholesale terminal price that is compared with Benford's Law predictions. First step is assessing compatibility of the aggregate market data with the law in the long run. Results suggest that data frequencies roughly agree with Benford's law predictions. In the second stage, the analysis is repeated for each undertaking. Results suggest suspicious deviations from the Benford's Law. Particularly for one undertaking, British Petroleum, the deviations are the most visible. Third step centres on the relation between the size of deviation and some collusive markers. Results indicate that except two years, 2009 and 2012, stations with greater deviation have higher average margins, lower variance in margins, fewer price changes, fewer price declines and low variance in market price. These findings are interpreted as potential *"circumstantial evidence of explicit collusion between companies (p.19)"*.

[27]See, (Giles, 2007, p.158) for a summary of literature

Probably one of the most commonly used marker is the *variance screening* developed by Abrantes-Metz et al. (2006). At the first part of the analysis, the study centers on a prosecuted bidding ring that was operational in frozen fish procurements of US Department of Defence in 1984-1989. Figure 2.5 illustrates the price and cost patterns for one type of fish, perch, in 1987-1989. First vertical line corresponds to one member of the ring leaving the cartel; second vertical line corresponds to start of the legal proceedings. Before the breakdown of the cartel, the price of frozen perch is high and relatively stable. Following the collapse of the collusion, despite average price falls by 16 %, standard deviation increases by 263 %, which gives a coefficient of variation increase of 332 %. In the second part of the analysis, Abrantes-Metz et al. (2006) explore the pricing patterns in Louisville gasoline market in which there is no prior information about any collusion. Monitoring pricing patterns of 279 gas stations, they look for "pockets" exhibiting high price, low price variation. Results suggest there are no clusters of gasoline stations that provide a meaningful pattern of collusion.

Figure 2.5: Perch Price and Cost, 1987-1989



Source: Figure 1 in Abrantes-Metz et al. (2006).

The proposition of Abrantes-Metz et al. (2006) to analyse first two moments of price has took a hold in the literature. A small empirical literature that centre on price variation has emerged.

Blanckenburg et al. (2012) study 11 European cartels and find that in seven of them variance is significantly lower in collusion periods. Bolotova et al. (2008a) explore patterns in Citric acid and Lysine cartels. Results suggest that in both cases, there are significant price increases; however, in lysine cartel price increase has been coupled with decline in variance, but in citric acid cartel with increase in variance. Esposito and Ferrero (2006) follow the footsteps of two documented cartels in Italy, motor fuels; and personal care and baby food products. Using scanner data, price variation in supermarkets and pharmacies are analysed. Results exhibit considerable regional heterogeneity; suspicious patterns are present in all regions but they are more concentrated in central and southern regions.

Heijnen et al. (2015); Jiménez and Perdiguero (2012); Vickers and Ziebarth (2014)

incorporate price variation analysis within a broader framework.

Heijnen et al. (2015) study Dutch retail gasoline industry, particularly the patterns in price variation with the objective of isolating some clusters of outlets with suspicious price variation. A station is defined suspicious if it is at 5% of the stations with the least price variation. Any two suspicious stations that are h kilometres apart are regarded to be in the same cluster, along with non-suspicious stations that are in the same radius. Final step is assessing the randomness of each cluster, basing on the distribution of suspicious and non suspicious stations. The cluster that is least likely to occur, is identified as "should be investigated". The stations in this cluster are removed and the analysis is iterated until no suspicious cluster is detected.

Vickers and Ziebarth (2014) study the response of the macaroni industry to the National Industry Recovery Act (NIRA). Branded as "elimination of cutthroat competition for the sake of fair competition", NIRA is a temporary relaxation of antitrust rules in US as a response to the Great Depression. The questions asked in the study is, whether the official declaration of turning a blind eye to collusion had an impact on firm behaviour. To this aim, three markers are employed. If there is collusion: i) price would be less responsive to the changes in the cost, ii) price variation would decline, and iii) price persistence (measured as the autocorrelation in price) would increase. Results suggest that the act weakened the relation between price and cost; as, correlation declined from 0.66 to 0.52. Moreover following the act price dispersion declined significantly, as estimates for the fall is around 20-33 %[28]. Third, after NIRA, price persistence falls to one third of former levels. It is also noted that, all these patterns are more pronounced on the big firms in the industry which would be the usual suspects for collusion.

Jiménez and Perdiguero (2012) focus on price variation and price levels, however incorporates two benchmarks. First benchmark is for monopolistic behaviour. Canary Islands, are a collection of seven islands of various size, and in two of them there is only one gasoline station. Price levels and variation in these markets are taken to represent monopoly. Second benchmark is for competition. Price level and price variation for a maverick brand are taken as the competitive benchmark. The question is, two ends of the scale being defined as such, where do the gasoline markets on oligopolistic islands locate? The results suggest that behaviour of oligopolistic firms is closer to monopolistic firms.

2.3.2 Preliminary Analysis of Data

Figure 2.6 illustrates the price trend in the market. Left panel depicts the evolution of monthly average price (in the form of a price index) by weighting each transaction with the volume. Right panel presents non-weighted values.

[28] Vickers and Ziebarth (2014) suggest that this change in price variation cannot be traced back to factors of the cost as the cost variation is same before and after NIRA.

The price is relatively stable until month 7; then, it collapses without any sign of recovery. In a period of one year, it suffers a decline of almost 30 %. The average price in month 7–17 is 9.7% lower than the price average in the preceding months. This period is also marked with considerably higher variation in price. Standard deviation of price after month 7 is 34.9 % higher than the preceding period, while the coefficient of variation is 49.3% higher.

Figure 2.6: Monthly Price

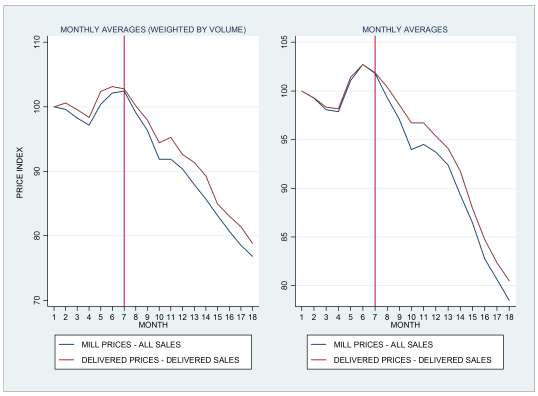
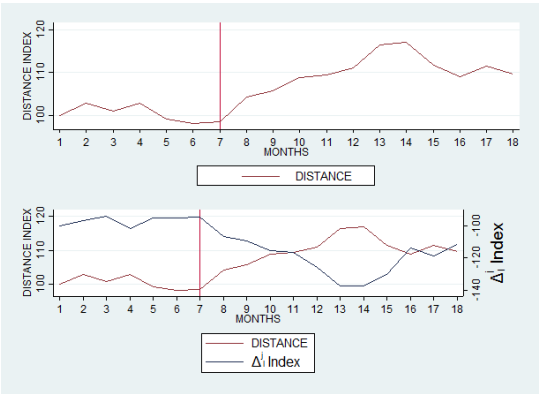


Figure 2.7 illustrates the evolution of monthly average distance between provider and buyer. Month 7 marks the lowest average distance; after month 7, providers serve regions further away. Within a couple of months, the average distance increases 15 %. The direction of this expansion is also important. This is captured by the index of relative proximity measure, Δ_l^j, which bases on the difference between *provider distance to buyer* from *the distance of the closest rival to buyer*. Similarly, it seems that initial stability in this measure is disrupted similarly in month 7. The index value is negative and increases in absolute value. Meaning that, firms extend their activities to regions closer to their rivals.

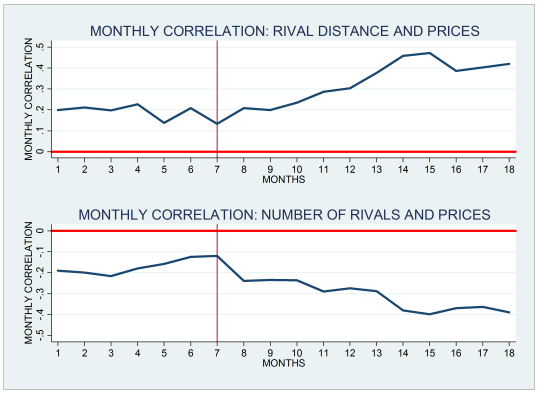
Figure 2.7: Distance of Operations



Serving customers closer to rivals necessitates price reductions. First panel in Figure 2.8 takes on this relationship. It illustrates the evolution of the correlation between transaction price and the distance of the closest rival to buyer each month. After month 7, the correlation between price and rival distance gradually increases;

expansion of operations is increasingly associated with price cuts. Second panel centres on the correlation between price and *the number of rivals around the buyer in a defined radius*; they are negatively correlated. Until month 7 the association of two variables shows a stable pattern. Similarly, the correlation increases in absolute terms in later months.

Figure 2.8: Price-Rival Distance & Price-Number of Rivals Correlation



Findings indicate that month 7 might represent a structural break in the form of regime switch from collusion to competition. In the next chapter, using proactive detection methodologies, this possibility is explored in greater detail.

Chapter 3

Proactive Detection: An Empirical Application in a Spatial Setting with Market Power Heterogeneity

3.1 Introduction

Competition policy draws its legal justification from competition law. Legal rules bans the undertakings from certain conducts, and defines the penalties they face if they do not comply. Within the borders of these prohibitions and penalties, the decision makers i.e. court, competition authority, evaluate the facts and the arguments of parties and form a decision. In a way, this decision is what gives cartel its existence; it is difficult to talk about a cartel without any legal ruling. Any legal ruling that say a cartel does/does not exit, builds on a prosecution; which requires willingness to investigate on the law enforcement side, which in turn depends on the available evidence. Some rare cases aside, the conventional wisdom in the competition policy is that economics have no role in the process of evidence gathering, or triggering an investigation. This is enshrined by the phrase "you can't catch a thief with an economist[1]". Rather, in "thief-catching", policy makers around the world prefer relying on "the thieves themselves". Today in many jurisdictions, leniency[2] is the primary tool to detect collusion. The role of the economist is confined

[1]This phase is credited (Schinkel, 2013, p.4) to Scott D. Hammond, Deputy Assistant Attorney General for Criminal Enforcement in US Department of Justice. See, the presentation done by Scott D. Hammond in October 2005, in OECD Prosecutor's Programme Working Party https://www.justice.gov/atr/speech/ten-strategies-winning-fight-against-hardcore-cartels.

[2]Leniency is granted by the competition authority in exchange for cooperation. EU antitrust regulations allow any firm that is part of a cartel to step up and acknowledge its participation in a collusive scheme; provide a detailed description of the collusive agreement i.e. coverage, duration, participants; and present any evidence it has. In return, if EU Commission does not have enough evidence prior to the application and the applicant is the first, an immunity from fine is granted. If the applicant firm is not the first to come forward, then instead of an immunity, a reduction is granted. The amount of reduction is 30–50 % for the second firm, 20–30% for the third firm, and

to the post ruling period; the assessment of the impact of an already proven collusion, which most probably is "detected" by a leniency application.

Not surprisingly, many economists have issues with this demarcation[3]. They find the overreliance to self-reporting troublesome; in particular, they are worried that leniency might not be desisting and deterring the cartels with highest member loyalty; these with highest profitability. Consequently, it is better to *complement* leniency with other tools; to this end, they propose proactive detection methodologies, detecting collusive activity by using economic analysis in the absence of no prior information about the cartel.

Harrington (2008) describes the proposed methodology: The economist, similar to what a *"detective"* would do in pursuing a case, adopts a sequential analysis. The first step is *"screening"*. The aim in this stage is flagging markets that are *"worthy of close scrutiny (p.214-215)"*.

Building on collusive markers proposed by Harrington (2006a,c, 2008), in Chapter 2, I conduct a simple analysis of data. Findings indicate that consistent with a regime switch from collusion to competition, stable relations in the market were disrupted after month seven. I take this as a suspicious pattern to be investigated further.

In the sequential analysis of Harrington (2008), if no suspicious pattern is identified in the screening, there is no basis for further investigation. If some suspicious patterns are identified, the law enforcement has two options. First, is triggering an *ex-officio* investigation with the available information[4]. Second, is asking the economist to go to the second stage, *"the verification"*. In this stage the aim is to *"systematically exclude competition as an explanation for observed behaviour and gather evidence in support of collusion"*. The difference between screening and verification is this: *Whereas screening may entail studying price patterns, verification requires controlling for demand and cost factors and any other variables necessary to distinguish between collusion and competition. (p.215)"*. If the verification stage suggests patterns are consistent with competition, no further investigation is carried on. If not, authorities may trigger an ex-officio investigation. Harrington (2008) also suggests there might be a third stage, *"the prosecution"*; providing economic evidence *"to persuade a court or some other administrative body that there has been violation of law"*. This stage is essentially *"verification with different standards (p.215)"*, and is uncharted waters, as, in no jurisdiction, economic evidence is seen sufficient to establish guilt[5].

In this chapter, I take on the suspicious patterns identified around month seven,

20% for the subsequent firms. See, http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52006XC1208(04).

[3]See, Abrantes-Metz (2013b); Schinkel (2013).

[4]At this point I presume that it is possible to trigger an *ex-officio* investigation, which typically would be more plausible if collusion is only an administrative offence. If collusion is a criminal offence, obtaining legal consent using economic evidence might be practically impossible.

[5]Note that this is different than damages proceedings where the impact of the conduct on price is estimated, after the guilt is established by a court decision.

and investigate further, while I control for demand and cost shifters. Building on the theoretical framework laid on in Chapter 1, I explore if observed patterns are more consistent with collusion or competition.

In devising the empirical strategy, I consult to the empirical literature concerned with the identification of collusion. The literature in this area can be grouped into three: studies basing on *data analysis*, works making *regime comparison*, and studies *tracking collusive strategy*. As covered in Chapter 2, data analysis is primarily used to identify suspicious markets, firms or periods. In some works, similar to this one, it is used as a first stage in a multi stage analysis. Regime comparison entails either (i) making estimations alternative regime assumptions and competing them in terms of likelihood, or (ii) estimating a single pricing/bidding equation assuming competition, and tracking the left over patterns in the unexplained portion. Tracking collusive strategy involves testing a specific type of correlation across the behaviour of rivals that arises as a result of the collusive strategy cartel employs or is suspected to employ.

One particularly important work in the literature for our purposes is Bresnahan (1987) who suggests that if there is price competition, for the products that have a close substitute, the price would converge to marginal cost; while in collusion, price and cost would diverge. He tests this theory in explaining drastic changes in US automobile industry in 1955, by taking this year as a temporary price war in the context of a longer collusion.

This study contributes first to the literatures of *detecting collusion using consumer level data*, and *empirical analysis of price discrimination*. However, more important contribution of this work is taking the premise in Bresnahan (1987) – centring on the relationship between price and local market power in identifying regime switch – that is applied to an heterogeneous product / product characteristics space setting to an homogeneous product / geographic space setting. In geographical space, local market power varies at each location according to cost difference between potential competitor and dominant competitor at that location. In this study, estimation centres on explaining pricing behaviour, and particularly its relation with Δ_l^j, relative proximity of the provider and its closest rival to the buyer. The idea is that after controlling for factors influential in pricing[6], Δ_l^j acts as an indicator of variations in local market power measure, the cost difference between potential competitor and dominant competitor at each location. Using OLS and GMM and via interacting a two level factorial variable, the dummy for first seven months, with market power measures, two different pricing equations are estimated; one for first seven months, and the other for after month seven. To my best knowledge, there is no work with similar methodology in homogeneous product / geographic space setting.

Findings indicate that i) at locations where market power of provider and the closest rival converge, there is a large price difference between suspected collusion period

[6]Controlling for all factors influential in pricing is naturally not possible; however, as part of future work, I plan to study other confounding factors.

and competition period; ii) at locations where the provider has large market power, price in both periods converge; iii) in suspected competition period, local market power indicator is both linearly and quadratically related to pricing; providers suffer large price cuts to serve buyers that are gradually closer to the closest rival; iv) in suspected collusion period, local market power indicator is positively but only linearly related to price, and the linear relation is much weaker than that in competition. These findings are interpreted as further evidence for a regime switch from collusion to competition. The results also suggest that level of market power each provider has on a buyer is very important in the assessment of the impact of collusion on price, which is explored in detail in Chapter 5.

This chapter is organized as follows: Next section discusses the motivation in proactive detection, and previous episodes of successful detection. Third section introduces the literature, empirical strategy methodology, and contribution of this work to the literature. Fourth section presents the estimations. Final section concludes.

3.2 A Brief Assessment of Proactive Detection: The Motivation and the Outcome

3.2.1 Motivation for Proactive Detection

Today in many jurisdictions leniency is the primary tool to detect collusion. Leniency has delivered many cartels worldwide. However, after a recent roundtable[7], OECD suggested that enforcement might be improved if it is complemented by other tools. The concern is, leniency might fall short of desisting and deterring "high-quality" cartels.

> *...what type of cartel is typically brought up by a leniency application? ... [T]he less well-organized ones. Or old-and-dying cartels that lost most of their profitability and so their stability. ... [S]ophisticated active cartels, certainly those that formed with the leniency programs being a reality ... can only exist because they found ways in which to avoid being destabilized by the lure of leniency... [W]hen agency resources are limited, it is doubtful whether they should be spend mostly on bringing these tail-end leniency cartels, since it means that other cartels, in particular more sophisticated and profitable ones ... cannot be discovered, and in some cases also cannot be investigated when a suspicion does exist (Schinkel, 2013, p.259).*

The decision to collude is the outcome of an assessment of relative pay-offs in

[7]See, www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf.

collusion and competition[8]. The most successful cartels have the broadest pay-off gap between competition and collusion, thus have the highest member loyalty. It follows that success of leniency on a specific cartel, depends on profitability of cartel; in other words, leniency is dependent on internal dynamics of the cartel (Abrantes-Metz, 2013b, p.228).

In this debate, whether leniency systematically fail to deliver high quality cartels or not, one line of experimental economics literature is particularly relevant. These works focus on the relation between leniency and deterrence, and test two competing arguments[9]:

i. The urge of being first to report (also known as "the race to the courthouse") destabilize the cartels, increase probability of detection and make collusion <u>less</u> likely.

ii. As anyone can apply for leniency at any time, the credibility of retaliations increase. Moreover, expected fines might be reduced if firms can apply leniency taking turns. As a result, incentive to collude is fortified, and collusion is <u>more</u> likely.

Literature, despite not centring on cartel quality, does answer relevant questions like "what is the relative level of price?" or "what is the relative cartel stability?" in collusion, if i) leniency is allowed, and ii) leniency is not allowed. Table 3.1 summarizes the related findings.

Most of the studies have findings that justify the concerns about the quality of cartels. Under leniency, cartels are more resilient, and characterised by higher price[10]. However, this should be interpreted with some caution for at least two reasons. First, leniency and antitrust policy are imperfectly modelled in these studies. Institutions like damages[11], or leniency plus[12] are not incorporated. Fines are either set to 10 % of turnover – the maximum fine limit – or are fixed at a constant

[8]This assessment involves weighing the expected cost of collusion (fines, damages, reputation loss) and probability of detection on one side, the expected net profits from collusion on the other.

[9]See, Hinloopen and Onderstal (2014), p.318.

[10]The findings by Hinloopen and Soetevent (2008) and Bigoni et al. (2015) either justify absence of quality issues, or provide a case for increasing fines rather than investing in improving the detection rate.

[11]Damages are compensation claims of parties that are harmed by collusion. More formally damages may be defined as "*...compensation for actual loss (damnum emergens), for gain of which that person has been deprived (loss of profit or lucrum cessans), plus interest.*" See, http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.L_.2014.349.01.0001.01.ENG, Article 12.

[12]"Leniency plus" refers to a further fine reduction granted to the applicant if the applicant reveals another collusion in a distinct market. See, http://ec.europa.eu/competition/international/multilateral/template.pdf, Footnote 5.

Table 3.1: Some Experimental Works and Relevant Findings

Work	**Relevant Finding**
Apesteguia et al. (2007)	For the subset of cases in which self-reporting happens, the price is not necessarily the maximum price. However, for the subset of cases in which self-reporting does not happen, market price is the maximum price. There is no cartel pricing below the maximum price.
Bigoni et al. (2012)	"What does not kill us makes us stronger": Average collusive price is higher in treatment with self-reporting in relation to treatment without self-reporting. Also, when probability of detection and the level of fines increase, under leniency, collusive price increases even further.
Dijkstra et al. (2011)	Cartels formed under leniency are able to make larger price increases.
Hinloopen and Onderstal (2014)	Treatment with no leniency: cartel is less stable, and collusive price is lower.
Hinloopen and Soetevent (2008)	The level of collusive price is similar in all cartels. If there is leniency, collusive price is lower; survival probability of cartels is lower.
Bigoni et al. (2015):	Let us assume leniency causes overburdening in competition authority and this reduces deterrence. The best way to overcome this problem is increasing the fines. Increasing probability of detection will not have the desired effect.

value[13]. Second, since market structure does not vary within an experiment[14], only one market can be tested at a time. It is difficult to generalize findings under one market structure to other market structures.

[13]In EU anti-cartel enforcement, the fine setting would start by determination of a basic fine. This is 30 % of the revenue from relevant sales multiplied by the number of years, plus 15-25 % entry fee for cartels. Then, first, aggravating factors are considered i.e. offender is a repeat offender, or a ring leader. Second, mitigating factors are considered i.e. offender has a limited role, or cooperated with authorities beyond legal requirements. 10 % threshold applies on the world turnover of the entire undertaking. Naturally, in many cases, 10 % only constitutes a hypothetical threshold. See, "Guidelines on the method of setting fines imposed pursuant to Article 23(2)(a) of Regulation No 1/2003", available at http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52006XC0901(01)&from=EN.

[14]Only a limited number of market structures have been used in experimental literature. These are Bertrand competition with homogeneous goods, Bertrand competition with product differentiation, English type oral auction and first price sealed auction.

Nevertheless, from a policy making perspective, assuming there are inherent quality issues in leniency, it should not be provoking to suggest that these issues might be mitigated by complementing leniency with proactive detection. The more successful a cartel, the greater is the divergence between competition and collusion. This means that the likelihood of a successful cartel to pop-up in the radar is higher (Abrantes-Metz, 2013b, 228)[15].

In the following part, some of successful episodes of proactive detection is explored.

3.2.2 Episodes of Proactive Detection

Probably the most well-known case of successful proactive detection is the National Association of Securities Dealers Automated Quotation (NASDAQ) market studies by Christie et al. (1994); Christie and Schultz (1994). The aim is analysing competitiveness of NASDAQ. The market is subject to free-entry and exit, and there are multiple dealers operational at any given time.

Christie and Schultz (1994) study the bid-ask spreads of 100 most traded stocks in 1991. These stocks are compared with similar 100 stocks from New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). In NASDAQ stocks, odd eight quotes (quotes ending with $\frac{1}{8}, \frac{3}{8}, \frac{5}{8}, \frac{7}{8}$ of a dollar) are suspiciously rare. On the other hand, for the similar stocks in AMEX and NYSE, the bids are distributed more evenly to odd and even eights. Results suggest,

- A quarter of the spreads in NYSE/AMEX is $\frac{1}{8}$, while the ratio is 10 percent for NASDAQ. More than 30 % of the spreads in NASDAQ is $\frac{4}{8}$, while this is 5% in NYSE. This implies a minimum spread of $\frac{2}{8}$ for each transaction in NASDAQ.
- 66 % of the NASDAQ firms have no[16] quotations with the lowest spread, $\frac{1}{8}$. Only 2 % of the NYSE/AMEX firms have no quotations with the lowest spread.
- In NASDAQ, in the subset of stocks that are rarely quoted in odd eights, average duration time for odd eights is less than 2 minutes, while average duration time for an even quote time is 20-35 minutes. On the other hand, in the subset of stocks that routinely use odd eights, the average duration time of an odd- eight quote and even-eight quote is similar.

Christie and Schultz (1994) find that the distribution of dollar spreads in NASDAQ and other stock exchanges are fundamentally different (p.1819), and conclude,

[15]Note that cartels might strategically attempt to fly under the radar. However, this means the cartel is no more equally "successful". A less pronounced benefit of proactive detection is better quality dawn raids. Guidance about nature, length, type, coverage or parties of a cartel may help to target the dawn raids effectively (Bos, 2009, p.110).

[16]Less than 4%.

"While this article does not provide conclusive evidence of tacit collusion among market makers, we are unable to offer any other plausible explanation for the lack of odd-eighth quotes (p.1835)."

Upon making their findings public at 24th of May 1994, Professors William Christie and Paul Schultz immediately became famous[17]. On 26th of May *the Los Angeles Times*[18] and on 27th of May *the Wall Street Journal*[19] covered potentially collusive practices in NASDAQ.

After the news became public, the behaviour of the NASDAQ dealers changed drastically. Christie et al. (1994) show that,

- Inside spread narrows within a couple of trading days.
- Percentage of odd-eight quotes for the most popular stocks jumps from less than 3 %, to 40 %. Within these odd-eight quotes, highest share is one-eight spread with almost 70 % share.

Christie et al. (1994) comment on these findings as follows, *"the change in the inside spread for these stocks may reflect the breakdown of implicit agreements among market makers to post quotes exclusively on even eighths for these issues. (p.1853)"*

Department of Justice (DOJ) launched an investigation in the summer of 1994, eventually reaching a settlement with 24 dealers in July 1996 including big names like *Goldman, Sachs & Co.*, *J.P. Morgan Securities Inc*, *Lehman Brothers Inc.*, *Merrill, Lynch, Pierce, Fenner & Smith Inc.* and *Morgan Stanley & Co. Inc.* DOJ publicly acknowledged the role of Christie and Schultz (1994) and Christie et al. (1994) by announcing *"The Department's investigation began in the summer of 1994, shortly after the publication of an economic study by Professors William Christie of Vanderbilt University and Paul Schultz of Ohio State University about the NASDAQ market*[20]". The follow-up law suits following the case were settled around 1 billion dollars in December 1997[21].

A similar episode is related to the London Interbank Offered Rate (LIBOR), the interest rate to be charged by member financial institutions for lending. The rate is computed by taking an average of some mid ranking quotes, ignoring the highest and lowest ones[22]. Figure 3.1 summarizes the patterns in *LIBOR* and alternative indicators of cost of borrowing in 2007-2008. Interest rate is marked on the left axis.

[17]For an account of events form Professor William Christie's view, see, https://www.youtube.com/watch?v=h6IruE_sMsw.

[18]Along with Milwaukee Journal, Detroit News and others.

[19]Along with Boston Globe, Atlanta Constitution and others.

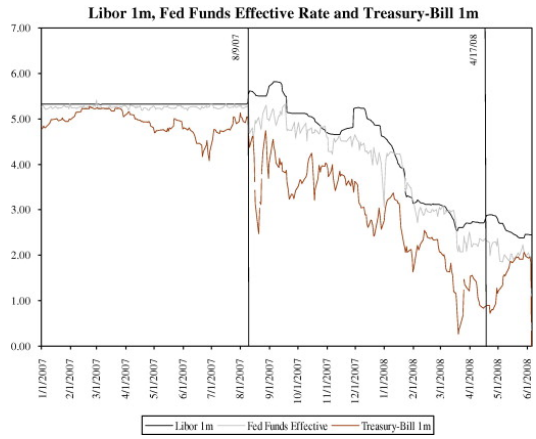
[20]See, https://www.justice.gov/archive/opa/pr/1996/July96/343-at.html.

[21]For a map of the legal process, also see, http://www.wsj.com/articles/SB916082557328717000 and http://www.economist.com/node/111273.

[22]Exact method of calculation depends on the currency. For example, for GBP derivatives, 16 institutions submit bids and the rate is the average of mid 8 quotes, after discarding highest and lowest 4 quotes. See, https://www.theice.com/iba/libor.

The horizontal lines mark two structural breaks in the market: First is the date (September 2007) of the joint announcement of European Central Bank, Federal Reserve, and Bank of Japan about a coordinated intervention. Second is the date (April 2008) of the announcement of British Bankers Association to investigate. The figure suggests that starting from August 2006, *LIBOR* is virtually constant on average until August 2007. Between September 2007 and April 2008, *LIBOR* plunges, and remains systematically higher than alternative indicators of cost of borrowing. After April 2008, *LIBOR* stabilizes and converges with alternative indicators of cost of borrowing.

Figure 3.1: Trends in *Libor* and Other Rates



Source: Figure 1 in Abrantes-Metz et al. (2012)

Abrantes-Metz et al. (2011) explore the suspicious stability in the market before September 2007, using Benford's Law. Since *LIBOR* is sticky in the first digit, they track the compatibility of the second digit with Benford's Law. First finding is that in the long-run (between 1987-2005), second digit distribution of *LIBOR* is compatible with Bedford's Law predictions. Later, to identify deviations in the short run, they monitor *LIBOR* on a rolling six month basis. The results indicate,

- Until January 2006, data complies with Benford's Law.
- Starting from February 2006, for a period of 18 months (until August 2007), data deviates from Benford's Law.
- Between August 2007 and December 2007, second digit behaviour is again compatible with Benford's Law.
- After oscillating between convergence and divergence until April 2008, the data diverges from Benford's Law once again between May 2008 and October 2008.

The results are interpreted as follows,

> *The behavioural departures of LIBOR from the expected path, in particular a path that LIBOR had followed for at least the prior 20 years, raise questions regarding the integrity and quality of its rate signals coming from individual banks and cry out for an answer. Based on our evidence, biased signals coming from the individual banks (agent aggregation bias), rate manipulation or collusion appear as one likely answer (p.897).*

In June 2012, US Department of Justice announced that it reached an agreement with Barclays Bank PLC, regarding *LIBOR*. Settlement is related to the following conduct: *"certain Barclays traders communicated with traders at other financial institutions, including other banks on LIBOR and EURIBOR panels, to request LIBOR and EURIBOR submissions that would be favourable to their or their counterparts trading positions*[23]*"*. European Commission in 04.12.2013 announced that it has fined banks participating in the interest derivatives industry by a total of 1.49 billion Euros for two different collusive activities: one (EURO LIBOR) covering September 2005 and May 2008, and the other one (JPY LIBOR) covering 2007-2010 http://europa.eu/rapid/press-release_IP-13-1208_en.htm.

Abrantes-Metz and Sokol (2012) comment on this as follows:

> *The alleged Libor collusion and manipulation is something that antitrust authorities or the banks themselves could have detected had they used econometric screens. ... What explains the lack of adoption of screens by the DOJ is that it, like many organizations, is slow to respond to changes. However, in a world of uncertainty, organizations may copy other organizations, as competition will eliminate inferior ideas (p.16).*

Estrada and Vazquez (2013); Mena-Labarthe (2012) and country contribution from Mexico in 2013 OECD roundtable[24] tell a successful detection story from Mexico. Mexican Social Security Institute (IMSS) applied to Mexican Competition Authority (CFCE) about suspicions regarding Medical Procurements. Using a dataset provided by the *IMSS*, *CFCE* analysed i) distribution of auctions across bidders, ii) convergence of market shares, iii) profit margins, iv) the effects of new entry on the bidding behaviour.

Data suggests that the winning bids are exactly the same in some auctions over and over. Moreover, the market shares display patterns consistent with bid rotation. Figure 3.2 illustrates the evolution of monthly market shares in three categories of drugs over time. Market shares start from initially very divergent values, and then converge. Shares remain convergent until two simultaneous events happen in the market (marked by vertical lines in 2006): i) a policy change in the bidding

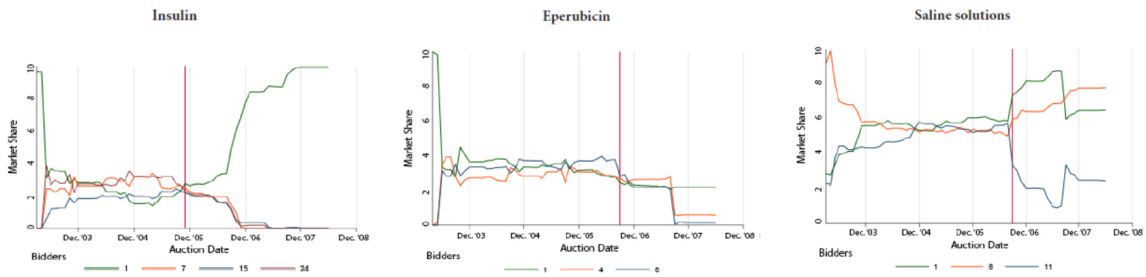
[23]See, https://www.justice.gov/opa/pr/barclays-bank-plc-admits-misconduct-related-submissions-london-interbank-offered-rate-and

[24]See, www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf, pp.155-160.

mechanism - a change away from small regional procurements to nationwide large procurements - ii) aggressive new entry in the market. This change acts as a structural break, and market shares diverges again.

Findings are interpreted as evidence indicating that a cartel might be in place before 2006; then it might be disrupted by the structural changes. Building on these findings *CFCE* launched an investigation. The investigation process provided the legal evidence documenting the coordination among the firms. In January 2010, the investigation ended. Seven pharmaceutical firms have been fined for bid rigging in procurement of two different products.

Figure 3.2: Bidder Market Shares in *CFCE* Investigation



Source: Figure 2 in Estrada and Vazquez (2013)

Similarly, in July 2016, COMCO/WEKO had a rulling regarding 8 construction companies and imposed a total fine of 5 million CHF. According to 2016 Annual Report of COMCO/WEKO[25] "*The companies had agreed on bids and determined who was to be awarded contracts in connection with several hundred invitations to tender ... between 2002 and 2009. The investigation began in April 2013 with searches of premises, largely based on a statistical analysis of* [public tender protocols (Offertöffnungsprotokollen)]. *As part of the arrangements that were uncovered, the companies had until mid-2009 met regularly for market assessment meetings. At these meetings ... The eight companies discussed the projects that they were each interested in. If they reached agreement, a decision was taken on which company should be awarded the contract. The other companies submitted bids offering their services at higher prices (p.5).*". The case at hand is the product of a long term project of *COMCO/WEKO* that is launched in 2008. The aim was developing a screening tool that has modest data requirements, can be applied simply, and is reliable. Imhof et al. (2016) presents the *COMCO/WEKO* multi stage framework. First stage aims to single out the suspicious firms and/or auctions. To this aim, first variance screening is used. Second marker, called "relative distance", is designed to capture phantom bidding. It is the ratio of the difference between two lowest bids to standard deviation of losing bids. In the case of phony bids, the ratio takes a large value, while in the case of competitive bidding it approximates to 1. Second stage looks for some regularity in the observed suspicious patterns. Third stage centres on geographical distribution of the suspicious activity. Fourth stage aims to identify potential non-members of the cartel.

[25] https://www.weko.admin.ch/dam/weko/en/dokumente/2017/Jahrespressekonferenz{%}202017.pdf.download.pdf/Jahresbericht_2016_englisch.pdf

There is reason to believe that proactive detection may be a reality of antitrust policy in the near future as research is growing fast; research and policy interaction might provide considerable improvements; and awareness of consultancy firms is increasing[26]. Similar optimism is shared by Harrington (2006a):

> *For sceptics who think that screening cannot work, I have two responses. First, screening is used for various other forms of illegal activity such as tax evasion, insider trading on security markets, and credit card fraud. It appears to be working there. Though the available data is much greater in those cases than it would generally be for someone screening for collusion, this leads me to my second point. We have never really tried to engage in cartel screening. Solutions to challenging problems are not found until we seriously apply ourselves to solving them. The sceptics may ultimately be right but their views reflect a pessimistic assessment based on the existing body of knowledge. Innovation is the creation of new knowledge and, by its definition, is not anticipated. Who knows what innovations in screening methods may arise once we apply ourselves. So, I intend to ignore the sceptics until after we've seriously tried to develop and implement methods for screening (p.38).*

In the next section, literature on proactive detection of collusion is explored[27].

3.3 Literature

The works in this field are quite diverse in methodology, strategy and complexity. It is possible to evaluate existing research in three subsections: studies basing on *data analysis*, works making *regime comparison*, and studies *tracking collusive strategy*. Since both in Chapter 2 and in previous subsection data analysis literature is presented, in this section they are not introduced again. This section focusses on the works in the latter two categories.

It should be noted that it is not always straightforward to classify works between detection literature and estimation of damages literature, because some works aspire to do both. In these cases, when a judgement needs to be made, own positioning of the paper, the literature it covers, and the gravity of the analysis are taken into account. To avoid repetition, I refrain from covering works that are better suited to damage/overcharge estimation in Chapter 4.

[26] See, http://www.globaleconomicsgroup.com/antitrustcompetition-policy/aluminum-market-dislocation-evidence-incentives-and-reform, and http://www.oxera.com/Latest-Thinking/Agenda/2013/Hide-and-seek-the-effective-use-of-cartel-screens.aspx

[27] For another evaluation of literature from a more sceptical view see, Doane et al. (2015).

3.3.1 Regime Comparison

There are two defining factors for the works that use regime comparison. First, is the *information set* researcher has. Some studies track the behaviour of prosecuted cartels (Jakobsson (2007); Porter and Zona (1993, 2003, 1999)). In this case, in identifying the regime switch, the researcher may benefit from the information available from proceedings, e.g. identity of cartel members, nature of collusive agreement, cartel's duration. Some others, like this work, track cases with no prior knowledge of cartel activity. In this case, first, suspicious time periods, regions, or firms are identified. Next, suspicious patterns are compared to non-suspicious patterns (Aryal and Gabrielli (2013); Padhi and Mohapatra (2011)). Second, is the *methodology*. One approach is estimating a competitive pricing equation and applying it first to competing firms, then to colluding firms, with the expectation that if there is collusion, pricing equation will only explain behaviour of competing firms (Porter and Zona (1993, 1999)). Another is estimating multiple pricing equations, one of which is collusive, and racing the equations in terms of likelihood (Baldwin et al. (1997); Banerji and Meenakshi (2004); Bresnahan (1987)). Also common is, estimating a competitive pricang equation, and monitoring the correlation in the unexplained portion across competitors (Bajari and Ye (2003); Jakobsson (2007); Padhi and Mohapatra (2011)). Almost all the works making regime comparison look at on bidding markets.

Porter and Zona (1993) study a bidding rigging that was active in Long Island highway construction projects and operated by phantom bidding. The identity of the winner is determined in ring meetings held before each auction. Designated firm submits a serious bid, while other bids are complementary. The collusion is partial, in the sense that there is a competitive fringe. The aim is identifying collusive behaviour via comparing the level and the ranking of bids of prosecuted firms, with those of the fringe. Results suggest that the level of bids for the fringe is well explained by competitive bidding equation; bids are primarily determined by factors of cost, such as capacity utilization, or proximity. However, the same bidding equation does a poor job in explaining the bidding behaviour of the ring. Regarding the ranking of the bids, findings are similar: For the fringe, bid ranking is determined by the cost rankings; while for the ring, bid ranking and cost ranking are unrelated.

Porter and Zona (2003, 1999) focus on tenders for milk procurement in Ohio school districts. Demand is insensitive to price. Production is scattered. Firms have similar suppliers, inputs, and technology, and symmetrical production cost. Transportation cost is important for competitiveness, and competition is localized.

Three milk producers in Cincinnati have been accused of bid rigging. Two of them applied for leniency and pleaded guilty while the third pleaded innocent. The case eventually was settled, and did not go to court. Collusion spanned 1980-90, with two brief interruptions, one in 1983-1984, another in 1989. Collusive strategy is customer allocation; members of the ring submit only phantom bids for the school

districts that are being served by one of the other members. Ring members submit competitive bids only against distant rivals which are located outside the Cincinnati area. Porter and Zona (2003) expect that *"Since competition is localized, prices will fall to competitive levels only in areas where there is a sufficient number of local competitors. Distant competitors are disadvantaged by transportation cost and can only limit price increases to a certain extent. The competitive significance of each supplier is directly related to its relative distance from the school district (pp.217-8)"*. Since all three firms are located in Cincinnati, the relative proximity of the rivals to school districts is similar. In competition, this pushes price towards the cost. In collusion, ring members have the opportunity to drive up the price, as they are constrained only by competition from distant rivals. Behaviour of the control group shows that the likelihood to bid is a declining function of distance. Firms almost never bid for a district more than 75 miles away, while they bid for every other auction that is at almost zero distance. Regarding the level, bids increase with distance. The closest supplier has some market power, but this quickly erodes.

Porter and Zona (1999) analyse two issues related to bidding: decision to participate in an auction and the level of the bid. The strategy is similar to Porter and Zona (1993): Taking the behaviour of the non-participating firms (control group) as the competitive behaviour, and comparing it to the behaviour of the colluding parties.

The methodology in comparing the behaviour of ring members and the control group is as follows: For each defendant, the defendant bidding data is added to the control group data and the estimation is made by assuming first, the defendant has no difference in the likelihood of bidding from the control group; second, the likelihood of bidding is different for the defendant. Same methodology is applied on the level of bids, and the findings are similar; bidding equation for each defendant is different than the bidding equation for control group.

At the next step, the consistency of behaviour of defendants with collusive strategy is explored. Results suggest that in comparison to the control group, the defendants have higher likelihood to serve further away. Also the level of the bid is a declining function of distance. This is consistent with the collusive strategy, which should produce high price in Cincinnati, at the heart of collusion; and low price on the boundaries. This pattern is only disrupted with the interruptions to collusion, the price wars, which are characterised by a fall in Cincinnati price. Finally, the independence of the defendant firm behaviour from identity of rivals is formally tested. If all firms are competing, information about a bidder (either participation to the auction or bid level) should not have any explanatory power in predicting whether another firm is also participating or its bid. However if the defendants are using phantom bidding as the prosecution suggests, their decisions (both participation to the auction and bid level) should be positively correlated. The results are consistent with collusive behaviour; unexplained part is highly positively correlated across defendants. The correlation is present both in decision to participate and the level of the bid.

Banerji and Meenakshi (2004) examine wheat procurement in Northern India.

Primarily concerned with process of price formation, and its efficiency, they also explore the possibility of collusion among asymmetrical buyers. If present, the hypothesized form of collusion is a bid rotation among three big buyers, which together control 45 % of the trade; if collusion is in effect, in each auction, one ring member is competing against a set of small firms. However, if competition is in effect, all large players are expected to participate in the auction. Basing on the bidding data, two models, one for collusion and one for competition, are estimated. Collusive model outcompetes the competitive model in terms of likelihood statistics and fit to the data.

Bajari and Ye (2003) look at highway maintenance auctions in US. They propose following test for assessing if firms are competing. First, after controlling common features governing bidding, the bidder behaviour should be independent from each other. This *conditional independence*, in practice corresponds to retrieving bid equations for each bidder, then monitoring the correlation between residuals in the bidding equations between bidders in a pairwise manner. Results suggest that one pair of firms violates conditional independence. Second condition of competitive bidding is *exchangeability*. Identities of the rivals in an auction should be inconsequential in determining the bid; it should be governed by relative costs. This, in practice, corresponds restraining the sample to two firms and testing parameter equality in bidding equation in a pairwise manner. Results suggest another pair fails to satisfy exchangeability. Conditional independence and exchangeability tests suggest three alternative explanations. First, all the firms are competing. Second, the firms violating conditional independence are colluding. Third, the firms violating exchangeability are colluding. To assess the likelihood of these explanations, Bajari and Ye (2003) compare three estimations made under these three assumptions. Findings suggest that competitive model not only outcompetes the collusive models in terms of likelihood measures; but results of competitive model are more compatible with the actual cost and mark-up levels in the industry.

Bajari and Ye (2003) provide a good self-critique of the empirical strategy. Since the strategy involves, controlling all the factors related to bidding behaviour and monitoring the left out correlation in the residuals, misspecification, or uncontrolled factors might lead to correlation in the residuals (p.983, FN21). Jakobsson (2007) points out a couple of other issues. First, if suppliers procure inputs from each other (or from a common source), this should introduce some dependencies in bidding that might are not captured by observables. Second, testing behaviour of bidders pairwise might make interpretation difficult if cartel is composed of more than two firms. Third, if there is a competitive fringe, strategic considerations might introduce dependencies. Strategy of the fringe might differ when facing some member of the cartel vs. when facing non-members.

Systematic framework developed in Bajari and Ye (2003) has been applied by others to other settings. An example is Padhi and Mohapatra (2011) that apply conditional independence and exchangeability tests to Indian roadwork procurement data. Another example is Jakobsson (2007), investigating the bidding patterns in asphalt paving auctions in Sweden. The study tracks a legal case. Nine firms have

been prosecuted for price fixing and market allocation in 1990's. Jakobsson (2007) examines if the bidding behaviour violates the conditional independence. The results suggest high pairwise correlation in the residuals of the bidding equations for eight out of nine prosecuted firms[28].

Aryal and Gabrielli (2013) develop an intuitive test to detect collusion. If bidders are colluding, their mark-up should be higher relative to that in competition. For example, if the same bid observed in both competitive and collusive regimes, it must be because the cost is lower in the collusive regime. However, note that cost is unobservable; but using structural estimation techniques it is possible to infer it under alternative conduct assumptions[29]. In that case, to identify collusion, researcher can test if the cost inferred under competition assumption and cost inferred under collusion assumption have identical distributions.

The test is applied on data from Californian Highway procurement auctions[30]. At the first stage, to identify suspicious behaviour, bidders that violate conditional independence and exchangeability are identified via a reduced form equation. These pairs are marked as suspicious. Later cost is inferred first under assumption of competition, and then under assumption of collusion. The result is in favour of competition; it is not possible to reject the equality of the distributions. They view this divergence in the verdict as *"highlight[ing] potential pitfalls of inferring collusion based only on reduced form tests (p.26)."* There are a couple of comments to be noted about this conclusion.

First, Bajari and Ye (2003) methodology simply asks *"Is there left over relation between bidders' mark-ups even after observable factors that are influential in bidding are controlled?"*. It is the answer "No" that provides a concrete evidence; after controlling for observable factors, there is no proof of dependency in bidding behaviour across firms. As discussed above for the answer "Yes" there may be multiple explanations, only one of which is collusion; some others are presence of an omitted variable, misspecification or interdependencies among firms. Second, it is not clear how (actual or alleged) failure of Bajari and Ye (2003) to distinguish between competition and collusion can be generalized all empirical strategies that employ reduced form techniques. Third, the structural estimation also comes with a cost: structural rigidity. The estimates might be severely biased if the assumptions about conduct are not realistic, or the issue of how to address the time spent travelling from one conduct to another is not addressed[31].

[28] Lundberg et al. (2015) using an updated version of the same data set, builds on the empirical strategy by including probability to collude to the analysis.

[29] Structural estimation techniques are analysed in detail in Chapter 4.

[30] Before applying it on data, Aryal and Gabrielli (2013) do Monte Carlo simulations; results suggest that the test is picking up collusion. The test is applied on publicly available auction data, about which there is no a priori information regarding presence of a collusion.

[31] See, Peters (2006) for an assessment of sensitivity of structural estimation to assumptions about the conduct.

3.3.2 Tracking the Collusive Strategy

Differing from the works in the previous group, works in this group do not test the presence of *any* correlation across rivals. Instead they test a *specific* type of correlation: the collusive strategy cartel employs or is suspected to employ.

Ishii (2009) develops a test for a specific type of collusive strategy; keeping a score of *"favours"* in the form of "letting the rival to win". Cartel members expect to have a proper return for the favours they do, i.e. winning in the future. In this scheme, before any auction the most likely winner is the firm which did the most favours in relation to favours it received.

The study takes on compensation consulting market[32] in Okinawa using publicly available data and with no a priori knowledge of collusion. There are some suspicious patterns in bidding behaviour. With the exception of a couple of cases, such as non-Okinawian firms being present, the winning bids are clustered very close to reserve price with little variance. Ishii (2009) proposes estimating likelihood to win, using observables that should influence bidding behaviour, e.g cost indicators, level of competition, along with a score variable that captures pairwise balance sheet of "favours" of firms to each other. Under competition, the score should capture nothing. Likelihood to win should be determined by relative cost and level of competition. Under hypothesized collusive strategy, score should signal the most likely winner. The findings suggest that the effect of score is significant and very strong while observables that should influence bidding behaviour have little effect and/or insignificant.

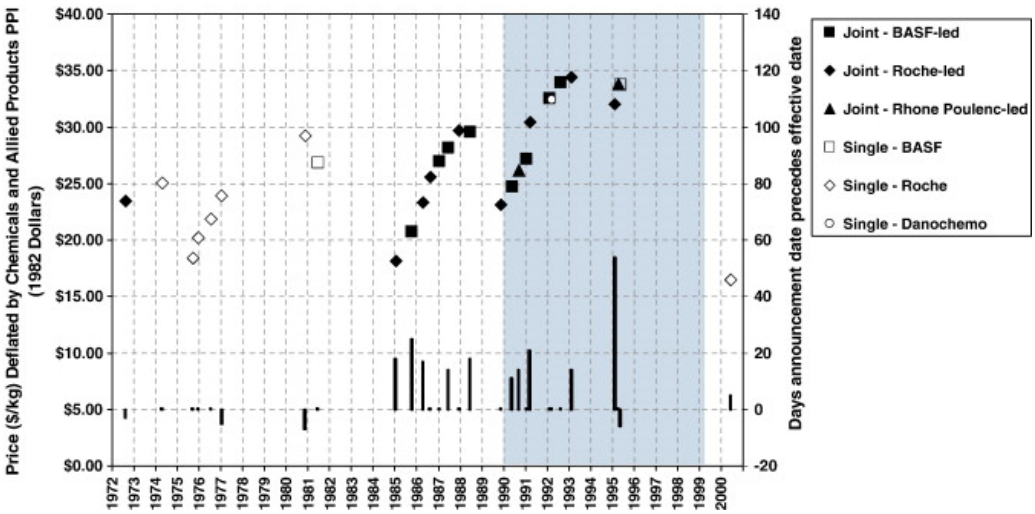
One of the most frequently studied cartels in competition economics is Vitamins cartel. On a global scale, vitamin producers adopted market sharing arrangements and fixed the price during September 1989 - February 1999. Prosecution in EU ended with Commission fining eight vitamin producers a total of 855.22 million Euros[33]. Figure 3.3 illustrates some patterns in price announcements in Vitamins industry.

There are two features of price announcement behaviour that is consistent with a regime switch. First, before 1985, price is announced by the market leader unilaterally, while after 1985 price announcements become joint. Second, before 1985, advance price announcement does not occur, while after 1985, it is a common practise. Building on this finding, Marshall et al. (2008) formally estimate the likelihood of a price announcement using demand and cost shifters, i.e. price of oil, exchange rate; and the variable of interest, time elapsed since the previous adjustment (time lag). The idea is that if the firms are competing, price announcements would be determined by demand and cost shifters, not by time lag. On the other hand if firms are colluding, price increases would be determined by the regularly held cartel meetings, and price and time lag would be closely related.

[32] To be more specific, the market under investigation is consulting services extended to parties whose property has been subject to compulsory purchase by public authorities.

[33] http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32003D0002

Figure 3.3: Price Announcements of Producers of Vitamin A



Source: Figure 1 in Marshall et al. (2008).

Findings suggest that after 1985 price is primarily governed by the time lag. It is noticeable that even though parties pleaded guilty for post 1990, the structural break in price announcement behaviour goes back to 1985. This is interpreted as a potential sign of under enforcement, meaning five years of cartel not being penalized[34].

Conley and Decarolis (2016) develop a way to detect collusion in average price auctions (APA), and apply it public road works auctions in Italy. In APA auctions, the auctioneer, rather than making the price as the first criterion, eliminates too high and too low quotes and awards the auction to the bidder closest to the average of "reasonable" bids.

In APA setting, if firms are not allowed to submit multiple bids, all firms bidding the reserve price is an equilibrium. No profitable deviation is possible, as price cutting would guarantee being eliminated, while increasing price will render your bid invalid. However, if firms can submit multiple bids (via shadow companies or colluding), they can both "pilot" the average, and have some control over the identity of the winner. The methodology proposed is designed to detect if the bidders are trying to pilot the mean[35]: If the firms are coordinating, their co-occurrence in auctions should not

[34]However, this is not the only explanation. It might be the case that what had started as coordinated effects or tacit collusion in 1985 might have evolved into explicit collusion over time. Some players might have communicated their incentive to coordinate by adopting a strategy that would clearly be unprofitable in a competitive regime, such as advance announcement. In this case, adopting the unprofitable strategy works as a *"...device that produces the commonly held belief among firms that they will collude (Harrington (2012) FN 16, 24 and p.658)"*, or *mutual understanding mechanisms.*

[35]One of the conclusions drawn is very provocative, it is suggested that auctioneer might prefer to allow collusion as it provides a lower price, *"it is not obvious that bidder coordination should always be sanctioned. We present the case of a market in which bidder coordination reduces the procurement cost for the auctioneer relative to an environment where firms compete...[t]hus our results argue against any automatism in antitrust activity (p.37)"*.

be random. Once factors influential in the participation and bidding decisions are taken into account, they should be appearing together in auctions unusually often. Bid level may also be used to identify collusion in a similar manner. It is possible to compare impact of the coordination on the auction outcome, with a group of non-suspicious firms with similar characteristics.

Conley and Decarolis (2016) first apply their methodology to a prosecuted public road work bidding ring in Turin. The prosecution implicates eight different cartels. The test captures seven of them, only missing the cartel that was least frequently operational. Next, the test is applied to Northern Italy public road works, for which there is no legal evidence of collusion. Results suggest, 30 % of the auctions show signs of coordination.

Bos and Schinkel (2009) develop a framework to detect a specific form of collusion, basing point pricing[36]. The collusive strategy is pricing the product as if it has been transported from an agreed on specific location, independent of actual origin. The providers retain the difference between invoiced transportation cost, and the incurred transportation cost.

The methodology builds on a forensic technique, geographic profiling, which is used in identifying the most likely area a criminal resides in, basing on the locations of multiple crime scenes. This is applied to collusion as follows: If a cluster of firms are colluding via basing point pricing, to allow sizeable gains, the location of the base (or bases) should be far from the cluster. If the firms in the cluster are competing, at each point, the price any provider can charge is capped with the minimum price a rival can offer. Therefore, base should fall within the neighbourhood of the cluster. It follows that by estimating the location of the base, it is possible to flag base point pricing.

Hüschelrath and Veith (2014) follow the German cement cartel prosecution. In 2003, German Competition Authority (*Bundeskartellamt*) imposed fines amounting to 660 million Euro[37] to cement producers[38]. Collusion involves market allocations and quotas, and covers 1990s. Figure 3.4 illustrates the price patterns. First vertical line marks the deviation of a discontent member, and *de facto* collapse of cartel. Second vertical line marks the beginning of the investigation, and formal collapse of the cartel. Cartel period is characterised by an initial steady increase in price. This is followed by price stability. Following the collapse of the cartel, price falls sharply.

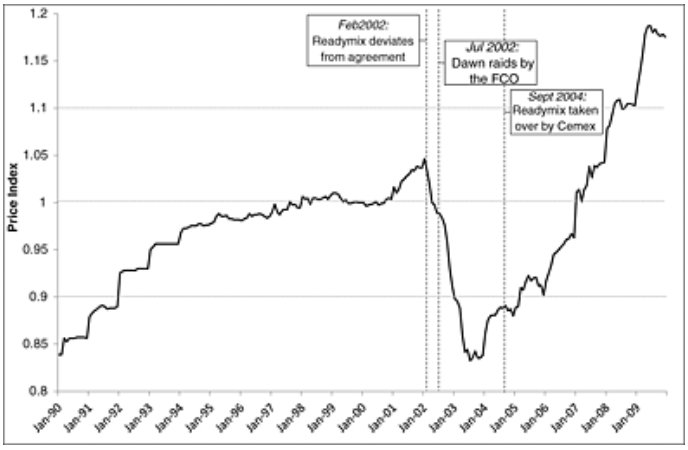
Hüschelrath and Veith (2014) offer a methodology with which consumers (using only own procurement data) can detect cartels without the involvement of competition authority. Building on a very detailed transaction dataset of 16 consumers with various providers, for each customer, they hypothesize a two stage analysis. At the first stage, customer is expected to do a structural break analysis. Results

[36]For an example antitrust case see *FTC vs. Cement Institute, et al., 333 U.S. 683 (1948).*

[37]In appeal, the fines were reduced to 329 million Euro.

[38]http://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2003/14_04_2003_Bu%C3%9Fgeld_Zementkartell_eng.html

Figure 3.4: German Cement Cartel



Source: Figure 1 in Hüschelrath and Veith (2014)

suggest that only two customers fail to identify a structural break. At the second stage, basing on the information in first stage, each customer is expected to run a multivariate regression. Findings indicate 80 % of customers would be able to detect collusion.

3.4 Empirical Strategy and Contribution

Findings so far suggest that consistent with a regime switch from collusion to competition, stable relations in the market were disrupted after month seven. In this chapter, I investigate further, and explore if observed patterns are more consistent with a regime switch.

Followed by Bajari and Ye (2003); Jakobsson (2007); Padhi and Mohapatra (2011), one frequently used empirical strategy is estimating a pricing equation for competition. If the competition is present, conditional on controlling all common factors, residuals should be independent across firms. However, in our case, this assumption is problematic for at least two reasons. First, producers purchase inputs and final products from each other. This inevitably introduce dependencies in error terms across rivals. Second, in bidding markets, where this methodology is widely applied, typically researcher has access to *reserve price*, which partly controls for unobservable factors. Since here there is not a similar measure that would reduce the risk omitted variable bias, the risk of dependency in error terms increases further. Neglected dependencies in error terms might lead to false positives, concluding for collusion even if the firms are competing.

Another alternative is using structural estimation techniques[39]. It is possible to

[39]Structural estimation is more widely employed in damage estimation rather than proactive detection. Chapter 4 presents a detailed presentation of structural estimation methodologies, their merits and drawbacks.

construct two structural models, one for collusion and one for competition, and see which model is a better fit to the data. However, note that if a regime switch is present within 18 months, then, there will be an episode of collusion, a transition period, and a period of competition. Not knowing the length of the transition, or its dynamics makes structural analysis challenging.

Followed by Jakobsson (2007); Porter and Zona (1993, 2003, 1999), another frequently used empirical strategy is estimating a competitive pricing equation and applying it first to competing firms, then to colluding firms, with the expectation that if there is collusion, pricing equation will only explain the behaviour of competing firms. Alternatively, as in, Baldwin et al. (1997); Banerji and Meenakshi (2004); Bresnahan (1987), researcher can estimate multiple pricing equations, one of which is collusive, and race them in terms of likelihood.

In devising the empirical strategy, I give special importance to Bresnahan (1987) who suggests that if there is price competition, for the products that have a close substitute, the price would converge to marginal cost; while in collusion, price and cost would diverge.

Bresnahan (1987) studies pricing behaviour in US automobile industry. In relation to proceeding and preceding year, in 1955, the total output in the US automobile industry is higher, and the price is lower. Sales concentrate on small size and lower value cars. In an attempt to understand the dynamics behind this change in 1955, Bresnahan (1987) looks at supply side and tests an interesting hypothesis: 1955 is a temporary price war within a larger context of collusion.

As illustrated in Figure 3.5, assume marginal cost is increasing with the automobile quality, the x-axis. Demand is characterised by heterogeneity in preferences; each individual has a different desired set of characteristics. Differences in preferences taken together with the menu of prices, lead to different purchasing patterns at the optimum. Therefore, it is unlikely for models with very distinct product characteristics to influence each other‘s demand. It follows that distant models have zero, neighbouring models have non-zero cross price elasticities.

Y-axis, informs about the cost and the price. Let each number on the x-axis correspond to a different model. First assume that models 1, 2, 4, 5 are produced by firm A, and model 3 is produced by firm B. Also assume that in terms of product characteristics, the closest two models are 2 and 3. If firm A and B are competitors, then as a result of high cross price elasticity between model 2 and 3, the mark-up would be low. On the other hand, if i) firm A and B are controlled by the same undertaking, or, ii) A and B are colluding, the degree of substitution between models 2 and 3 is irrelevant for the determination of mark-up. It follows that the impact of regime switch is most pronounced on models 2 and 3. Bresnahan (1987) has following proposition:

> *The intuition of why competitive and collusive behaviours are distinct in such a model is straightforward. If firms compete on price, price will*

Figure 3.5: Cost and Mark-Up in Collusion and Competition, Bresnahan (1987)

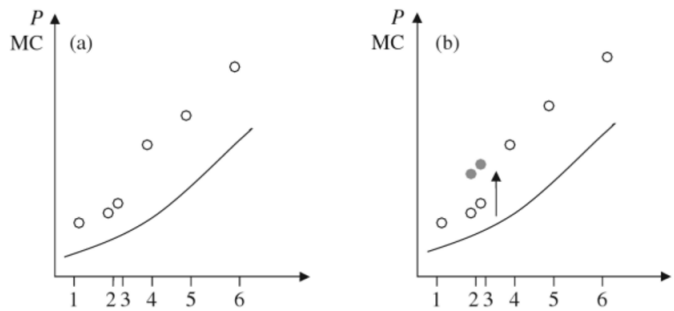


Figure 6.5. Expected outcomes under (a) competition and (b) collusion. *Source*: Authors' rendition of figure 2 in Bresnahan (1987). (a) Under competition, products with close substitutes produced by rivals get very low markups over MC. (b) Under collusion, close substitutes produced by rivals get much higher markups over MC.

Source: (Davis and Garcés, 2009, p.341).

> *be near marginal cost for those products for which a close, competitive substitute exists. If firms are setting price by some (tacitly) collusive means, then $P - MC$ for one firm's products will not depend crucially on whether their close substitutes are sold by competitors or by the firm itself. ...Thus even when marginal costs are taken to be unobservable, competitive and collusive conduct can be discerned from the movements in industry and firm price and quantity (p.458).*

I, similar to Bresnahan (1987), centre on the relationship between price and market power, under different regimes. The difference between two works is, Bresnahan (1987) is specified in product characteristics space, and market power varies on product characteristics. My work is specified on geographical space and market power varies on locations. Estimation centres on explaining pricing behaviour, and particularly its relation with $\Delta_l^j = \min(d_{kl}) - d_{jl}$, relative proximity of the provider and its closest rival to the buyer. The idea is that after controlling for factors influential in pricing, Δ_l^j approximates to local market power measure, the cost difference between potential competitor and dominant competitor at each location, $\chi_{kl} - \chi_{jl}$. Via interacting a two level factorial variable (the dummy for collusion) with market power measures, two different pricing equations are estimated for each regime using OLS and GMM. In this process, dynamic effects (i.e. entry/exit, location choice or investment) are ignored. This primarily stems from data structure. Data set covers 18 months; this is relatively short for dynamic considerations.

To my best knowledge, there is no work with similar methodology in homogeneous product / geographic space setting. One example of similar motivations is Baldwin et al. (1997), looking at timber removal auctions in US. Primary aim is to understand the presence of collusive patterns from 1975 to 1981 in Pacific Northwest, a region marked with low winning bids. The empirical objective is comparing alternative explanations for low bids, collusion vs. supply shifters. Collusion probability is modelled as a function of bidder proximity, defined as an indicator variable if

the highest two bidders are in the same county. Results suggest that the bidder proximity is borderline insignificant. Baldwin et al. (1997) claim that if instead of a local proximity index (proximity dummy) a global index was available, this would *"produce a significant improvement of the collusive model, thereby strengthening final conclusions (pp. 684-5)."* This finding is encouraging for the design of empirical strategy here, and the variable of interest, Δ_l^j.

Additionally this study contributes to proactive detection literature via using consumer level data. In competition economics, rather than assessment of collusion, transaction data more commonly is used in the assessment of mergers - for which Chapter 4 and Appendix 3 provide a summary of literature. Let alone proactive detection, there are only a handful of studies that focus on collusion in broader sense and use consumer level data. In this mini-literature, the most common objective is overcharge estimation. Some examples are Hüschelrath et al. (2016) who estimate the overcharge related to German cement cartel using a private data set; Kamita (2010) who estimate the impact of antitrust immunity granted to Hawaiian airlines on price; Laitenberger and Smuda (2015) who estimate the overcharge related to European detergent cartel using a private data set; McCluer and Starr (2013) who estimate the overcharge related to Marshfield/Blue Cross Blue Shield case in US using a private data set; and Nevo (2001) assessing the allegations of collusive pricing behaviour in ready to eat cereal industry. These works are discussed in more detail in the next chapter. Another empirical study of collusion that use consumer level data is Harrington et al. (2015) who focus on the cartel stability issues in German cement cartel. In the study, the empirical objective is illustrating differences in the behaviour of the discontent member and other members in a reduced form framework. However, the work with most similar empirical objective to this work is Hüschelrath and Veith (2014) - see, Section 3.3.2 - who also focus on German cement cartel. There are two differences in two works: First, this work does not centre on a prosecuted cartel. Second, in this work, empirical strategy does not involve the assumption of parameter equality across regimes for the variables of interest, hence is more flexible.

This study contributes to a handful[40] of empirical studies in the area of price discrimination in spatial setting. I believe taking on a spatial price discrimination framework is particularly important in order to embed the proactive detection into anti-cartel enforcement. Theory suggests if the arbitrage opportunities are limited, scale matters, consumer locations are observable, transportation is costly, price and location are the only determinants of competitive power; producers can spatially price discriminate. Some example industries are iron, steel, oil, cement, furniture, lumber, ready mixed concrete, plywood, fertilizer and sugar. The methodology developed here, can be directly applied to any of these industries. It should be noted that, these industries have a long record of antitrust violations; possibly because collusion is very profitable. Recall that main argument for proactive detection is complementing leniency where it is most likely to fail, detection of the most

[40] *"...the existing empirical literature does not address spatial discrimination despite the long and litigious history of discrimination in the industry (Miller and Osborne, 2014, p.222)".*

profitable cartels. Therefore, the framework in this paper is a good starting point, as it can immediately be applied in any of these potentially problematic sectors.

3.5 Estimation

3.5.1 OLS Estimation

Table 3.3 presents the OLS estimates. This involves estimating,

$$p_{jltc} = \alpha_0 + \alpha_1\gamma^{coll} + \alpha_2\gamma^{coll}\Delta_l^j + \alpha_3\gamma^{coll}\left(\Delta_l^j\right)^2 + \alpha_4\gamma^{coll}NBR_{jlc} + \alpha_5\gamma^{comp}\Delta_l^j + \alpha_6\gamma^{comp}\left(\Delta_l^j\right)^2$$

$$+ \alpha_7\gamma^{comp}NBR_{jlc} + \sum_j \theta_j\gamma^j + \sum_p \lambda_p z_{jltc}^p + \sum_k \rho_k\chi_{jltc}^k + \upsilon_{jltc} \tag{3.1}$$

where t is month, j is provider, l is location, c is consumer; z_{jltc}^p refers to demand shifters; χ_{jltc}^k refers to supply shifters; θ_j refers to provider fixed effects; and dependent variable, p_{jltc} is the delivered price. Results are reported for six different specifications. The estimations are done by gradually adding control variables, keeping the main idea: Measures of market power, Δ_l^j, $\left(\Delta_l^j\right)^2$, and NBR_{jlc} interact with regime indicators, $\gamma^{coll}, \gamma^{comp}$, and two different pricing equations, one for each regime, are estimated.

In all specifications dependent variable is the delivered price charged by provider j, to customer c, at location l, in month t, p_{jltc}. Besides interactions of regime indicators and market power indicators, all specifications include, a constant, facility fixed effects, γ^j; an indicator variable marking the regime switch, γ_t^{coll}; and an indicator variable marking presence of a vertical relation between provider and buyer, $\gamma_{jc}^{vertical}$. Baseline specification includes an indicator variable marking large buyers, γ_c^{large}. Specification 2 adds, γ_{jl}^{own}, the indicator variable marking presence of multiple nearby production facilities of the provider. Specifications $3-6$ extend Specification 2, each by adding a different control. Specifications 3 and 4 add demand side controls; Specification 3 controls for transaction volume, v_{jltc}; Specification 4 controls for buyer size via using total transaction volume, $\bar{V}_{lc}$, rather than γ_c^{large}. Specifications 5 and 6 add supply side controls; Specification 5 controls for capacity utilization[41], U_{jt}; Specification 6 controls for energy price index[42], EI_{jt}.

The estimations in this chapter build on heteroscedasticity robust White standard

[41] Utilization values are not available for 5 % of the observations, thus this specification bases on slightly less observations then first four specifications.

[42] Compared to Specification 5, energy index value is not available for an additional 1.5 % of the observations.

Table 3.3: OLS Estimates

		(1)	(2)	(3)	(4)	(5)	(6)
		Baseline	(1)+ Own Facility	(2)+ Buyer Size	(2)+ Volume	(2)+ Utility	(2)+ Energy
Δ_j^l							
	γ_t^{comp}	0.5739***	0.5963***	0.6140***	0.6129***	0.5941***	0.6045***
		(0.0432)	(0.0427)	(0.0424)	(0.0425)	(0.0439)	(0.0427)
	γ_t^{coll}	0.2209***	0.2274***	0.2429***	0.2483***	0.2146***	0.2157***
		(0.0462)	(0.0455)	(0.0452)	(0.0450)	(0.0472)	(0.0459)
$(\Delta_j^l)^2$							
	γ_t^{comp}	0.0241***	0.0240***	0.0252***	0.0252***	0.0247***	0.0244***
		(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
	γ_t^{coll}	-0.0036*	-0.0040*	-0.0023	-0.0026	-0.0041*	-0.0045**
		(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
NBR_{jlc}							
	γ_t^{comp}	-2.2726***	-2.2243***	-2.2539***	-2.2634***	-2.3427***	-2.2464***
		(0.2161)	(0.2133)	(0.2132)	(0.2134)	(0.2205)	(0.2132)
	γ_t^{coll}	-0.5948***	-0.6015***	-0.7218***	-0.7111***	-0.7172***	-0.5557***
		(0.2061)	(0.2048)	(0.2031)	(0.2040)	(0.2140)	(0.2055)
$\gamma_{jc}^{vertical}$		-0.6874	-0.8542*	-0.3822	-0.4408	-0.4055	-0.8443*
		(0.4891)	(0.4854)	(0.4856)	(0.4853)	(0.5601)	(0.4862)
γ_t^{coll}		8.5669***	8.6725***	8.6777***	8.8061***	9.1892***	10.1274***
		(0.5513)	(0.5434)	(0.5412)	(0.5421)	(0.5902)	(0.6768)
γ_c^{large}		-4.2383***	-4.3811***			-4.3169***	-4.3822***
		(0.4810)	(0.4804)			(0.5084)	(0.4791)
γ_{jl}^{own}			4.6334***	4.9119***	4.8030***	3.5905***	4.6044***
			(0.6797)	(0.6788)	(0.6871)	(0.8614)	(0.6775)
$\bar{V}_{cl}$				-0.0000***			
				(0.0000)			
v_{jltc}					-0.0484***		
					(0.0051)		
U_{jt}						-1.8341*	
						(1.0125)	
EI_{jt}							0.0639***
							(0.0160)
Constant		Yes	Yes	Yes	Yes	Yes	Yes
γ^j		Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.4726	0.4770	0.4793	0.4764	0.4812	0.4783

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. γ_t^{coll} indicates collusive, γ_t^{comp} indicates competitive regime. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_c^{large} indicates large buyers. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. γ^j refers to provider fixed effects. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. v_{jltc} is the transaction volume. $\bar{V}_{lc}$ is total transaction volume. U_{jt} is capacity utilization. EI_{jt} is energy price index. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

errors. Consequently, even though error variance is allowed to vary, error terms are assumed to be independent, $E[u_i u_j] = 0$. However, since demand for the

product is governed by spatial dynamics, independence assumption would be unrealistic, particularly for observations coming from neighbouring locations. Any ignored dependency of this sort should lead to underestimation of standard errors, overestimation of test statistic, and overrejection. In this chapter, despite its limitations, I stick to White standard errors. There are two reasons for this. First, opting for White standard errors makes the implementation of GMM very straightforward. Second, in this chapter, for the empirical outcome, the choice of standard error structure is inconsequential. To expand on this; as thoroughly discussed in Chapter 5, the most frequently used remedy in addressing dependency across error terms is using clustered standard errors. This involves defining observations coming from nearby locations as a cluster, and letting $E[u_i u_j] \neq 0$ for the observations within the same cluster; while, retaining independent error term assumption for observations from different clusters[43]. Note that in this chapter, empirical strategy involves comparing the parameters governing the relation between price and measures of market power across two time periods, competition period and collusion period. Findings suggest estimated difference is so large that the choice of standard error structure becomes inconsequential in deciding if the parameters are equal across regimes. This is illustrated in Table 3.4 for measures of local market power, Δ_l^j, $\left(\Delta_l^j\right)^2$. Basing on Specification 2, parameter equality across regimes is tested under different standard error structures, i.e. White standard errors, standard errors clustered at customer level, standard errors clustered at county level, standard errors clustered at province level. Naturally, clustering affects inference. The standard errors quadruple, estimates become less precise, and confidence intervals widen. However, the hypothesis tests still favour parameter inequality across regimes.

Table 3.4: Clustering

$H_0 = \beta_1 - \beta_2 = 0$				
Δ_l^j				
	None	Customer	County	Province
Difference	0.3637	0.3637	0.3637	0.3637
Standard Error	0.020	0.0801	0.0872	0.0873
t-stat	6.99***	4.54**	4.17***	4.17***
$(\Delta_l^j)^2$				
Difference	0.0286	0.0286	0.0286	0.0286
Standard Error	0.0026	0.0044	0.0046	0.0056
t-stat	11.07***	6.58***	6.23***	5.20***

Going back to the estimation results in Table 3.3, findings suggest that vertical relations do not matter for pricing. The point estimate is small and insignificant

[43]See, Section 5.2.2 for inference issues, cluster robust variance estimator, the conditions for its consistency and other potential remedies.

across all specifications[44]. If present, any preferential treatment for vertically related buyers is marginal. This is not surprising, as using distribution channels is not the norm in the industry. In contrast, being a large buyer translates as lower price. A buyer in top 5 % in terms of total procurement volume would enjoy $4.1 - 4.7$ % lower price. Note that the same effect is captured also by Specification 4, where large buyer dummy is replaced with total volume of purchases.

Specification 2 suggests that the effect of multiplant ownership is also significant. However, in contrast to hypothesis of Hortaçsu and Syverson (2007) that multiplant ownership brings distributional efficiencies, and eventually lower price, OLS estimation suggests that multiplant ownership brings higher price. Note that the estimate varies in size across specifications; $2, 3$ and 6 suggest a point estimate around $4.6 - 4.9$ % with similar precision. Point estimates in specifications 4 and 5 are lower and less precise. The estimate is lowest in Specification 5, which controls for capacity utilization. This suggests that coefficient estimate might be capturing effects related to volume.

Specification 5 suggests that 1 % increase in capacity utilization leads to 1.8 % reduction in price. Yet, again the effect is very imprecise, only significant at 10 % level. In contrast, Specification 6 suggests a precise point estimate for the energy index; energy price has a pass through of 6.4 %. As expected, the impact of including supply shifters on the coefficient of market power measures is marginal.

Specification 3 incorporates transaction volume. In this study, we give particular importance to relation between transaction volume and market power at each location. To see why, initially, assume transaction volume is not a function of price (price taker customer), but price is a function of transaction volume; so that following is the *true* model

$$p_i = \alpha_0 + \alpha_1 \Delta_i + \alpha_2 v_i + \alpha_3 \chi_i + \alpha_4 z_i + e_i$$

where i refers to transaction, z_i, and χ_i are demand and cost shifters, satisfying $E[\Delta_i \chi_i] = 0$ and $E[\Delta_i z_i] = 0$. Note that if the *estimated* model is

$$p_i = \delta_0 + \delta_1 \Delta_i + \delta_2 \chi_i + \delta_3 z_i + \zeta_i$$

the omitted variables formula suggests that linear projection coefficient for Δ_i would

[44]This result might also partially be governed by measurement error. During refinement of data the impression was that the categorization of customers was not accurate in every case.

be

$$\delta_1 = \frac{E[\Delta_i p_i]}{E[\Delta_i^2]},$$

$$= \frac{E[\Delta_i(\alpha_0 + \alpha_1\Delta_i + \alpha_2 v_i + \alpha_3\chi_i + \alpha_4 z_i + e_i)]}{E[\Delta_i^2]}, \tag{3.2}$$

$$= \alpha_1 + \alpha_2\frac{E[\Delta_i v_i]}{E[\Delta_i^2]} + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]}$$

and, the consequence of leaving v_i out of the model should be an additional bias of $\alpha_2\frac{E[\Delta_i v_i]}{E[\Delta_i^2]}$.

Note that it is difficult to assess $E[\Delta_i v_i]$. Since returns at high market power locations are higher then returns at low market locations, particularly when capacity utilization is high, providers might choose to limit their bulky operations to closer regions.

As seen in Specification 3, plugging transaction volume directly as a regressor suggest a precise but small impact of transaction volume on pricing. Among the variables of interest, the impact is most pronounced on the nonlinear effects related to Δ_l^j in the collusion period. Coefficient of quadratic term is no longer significant at 10 %, and in comparison to Specification 2, point estimate drops 40 %, although it is not possible to make an inference about how informative this drop is.

The estimates for local market power indicator are robust to the inclusion of other control variables, particularly in the competitive regime. In competition, lowest and highest point estimates are 6 % apart for linear effects, and 4 % apart for nonlinear effects. The point estimates are lowest in the baseline model, and gradually increase as more variables are added. In the collusion period, in all specifications nonlinear effects are weak in absolute terms and significant at 5 % only for Specification 6. Note that regime switch first affects the price via regime change indicator, γ_t^{coll}. This may be interpreted as the immediate impact. Basing on Specification 2, the estimate is 8.9 %. Second, regime switch affects price via its interaction with Δ_l^j, $(\Delta_l^j)^2$ and NBR_{jlc}. OLS estimates suggest that the relation between price and measures of market power is distinctly different across regimes. Responsiveness of price to market power, as captured by the coefficients of market power measures, is much higher in competitive regime. In fact, using estimates from Specification 2, and calculating average price predicted at the expected values of covariates in two regimes, the effect of regime switch increases to 12.7 %.

Results suggest that presence of more rivals is associated with lower price, both in competition and collusion; however, in the latter case, the effect is small and imprecise. In collusion, the presence of an additional rival has $0.60 - 0.72$ % downward effect on price. In competition, point estimate almost triples is more precise; it rises to $2.22 - 2.34$ %, while lower bound of confidence interval is above 1.8 %.

However, before elaborating on the findings further, we need to reconsider how transaction volume is incorporated into the analysis.

In general form, volume and price are simultaneously determined as they interact with, local market power measure Δ_i, observable exogenous demand and cost shifters features (z_i, χ_i), and unobservable shocks (e_i, μ_i). Take the following system in the unrestricted form,

$$\begin{aligned} p_i &= \alpha_0 + \alpha_1\Delta_i + \alpha_2 v_i + \alpha_3\chi_i + \alpha_4 z_i + e_i, \\ v_i &= \beta_0 + \beta_1\Delta_i + \beta_2 p_i + \beta_3\chi_i + \beta_4 z_i + \beta_5 t_i + \mu_i \end{aligned} \tag{3.3}$$

where t_i to corresponds to exogenous demand shocks with no impact on supply. This implies following reduced form equation for volume,

$$\begin{aligned} v_i &= \beta_0 + \beta_1\Delta_i + \beta_2(\alpha_0 + \alpha_1\Delta_i + \alpha_2 v_i + \alpha_3\chi_i + \alpha_4 z_i + e_i) \\ &\quad + \beta_3\chi_i + \beta_4 z_i + \beta_5 t_i + \mu_i \\ v_i(1-\beta_2\alpha_2) &= (\beta_0 + \beta_2\alpha_0) + (\beta_1 + \beta_2\alpha_1)\Delta_i + (\beta_3 + \beta_2\alpha_3)\chi_i \\ &\quad + (\beta_4 + \beta_2\alpha_4)z_i + \beta_5 t_i + (\beta_2 e_i + \mu_i), \\ v_i &= \gamma_0 + \gamma_1\Delta_i + \gamma_2\chi_i + \gamma_3 z_i + \gamma_4 t_i + \frac{\beta_2 e_i}{(1-\beta_2\alpha_2)} + \frac{\mu_i}{(1-\beta_2\alpha_2)} \end{aligned} \tag{3.4}$$

where, $\gamma_0 = \frac{\beta_0+\beta_2\alpha_0}{(1-\beta_2\alpha_2)}, \gamma_1 = \frac{\beta_1+\beta_2\alpha_1}{(1-\beta_2\alpha_2)}, \gamma_2 = \frac{\beta_3+\beta_2\alpha_3}{(1-\beta_2\alpha_2)}, \gamma_3 = \frac{\beta_4+\beta_2\alpha_4}{(1-\beta_2\alpha_2)}, \gamma_4 = \frac{\beta_5}{(1-\beta_2\alpha_2)}$.

and for price,

$$\begin{aligned} p_i &= \alpha_0 + \alpha_1\Delta_i + \alpha_2(\beta_0 + \beta_1\Delta_i + \beta_2 p_i + \beta_3\chi_i + \beta_4 z_i + \beta_5 t_i + \mu_i) \\ &\quad + \alpha_3\chi_i + \alpha_4 z_i + e_i \\ p_i(1-\beta_2\alpha_2) &= (\alpha_0 + \alpha_2\beta_0) + (\alpha_1 + \alpha_2\beta_1)\Delta_i + (\alpha_3 + \alpha_2\beta_3)\chi_i + \\ &\quad (\alpha_4 + \alpha_2\beta_4)z_i + \alpha_2\beta_5 t_i + (e_i + \alpha_2\mu_i) \\ p_i &= \delta_0 + \delta_1\Delta_i + \delta_2\chi_i + \delta_3 z_i + \delta_4 t_i + \frac{\alpha_2\mu_i}{(1-\beta_2\alpha_2)} + \frac{e_i}{(1-\beta_2\alpha_2)} \end{aligned} \tag{3.5}$$

similarly, $\delta_0 = \frac{\alpha_0+\alpha_2\beta_0}{(1-\beta_2\alpha_2)}, \delta_1 = \frac{\alpha_1+\alpha_2\beta_1}{(1-\beta_2\alpha_2)}, \delta_2 = \frac{\alpha_3+\alpha_2\beta_3}{(1-\beta_2\alpha_2)}, \delta_3 = \frac{\alpha_4+\alpha_2\beta_4}{(1-\beta_2\alpha_2)}, \delta_4 = \frac{\alpha_2\beta_5}{(1-\beta_2\alpha_2)}$.

First, it is straightforward to see, since v_i and p_i both depend on e_i and μ_i, it is not possible to have a consistent estimate for v_i if price is simply regressed on it. This is the well-known simultaneity bias. One solution for this is employing an exogeneity assumption. One way of doing this is considering consumers as price takers. In that case, v_i is allowed to be determined by factors other than price. In Equation 3.3, this would correspond to setting $\beta_2 = 0$. Alternatively, one might assume v_i to be orthogonal to all observables, implying $\beta_1, \beta_2, \beta_3 = 0$. As mentioned earlier, some studies using customer level data, benefit from an assumption of exogeneity of either form.

> *In most studies that use consumer-level data, the correlation between the regressor and the error term ... is usually ignored. ... This correlation might still be present, for at least two reasons. First, even though consumers take prices and other product characteristics as given, their optimal choice from a menu of offerings could imply that econometric endogeneity might still exist (Kennan, 1989). Second, unless enough control variables are included, common unobserved characteristics, could still bias the estimates (Nevo, 2000b, p.544).*

However, since in this study we are concerned with the relation of price and measures of market power, if this relation is not affected, endogeneity induced bias via v_i may be regarded as a minor setback. Formally, the impact of plugging v_i directly into pricing equation on Δ_i can be traced as follows:

$$\begin{aligned}
\frac{E[\Delta_i p_i]}{E[\Delta_i^2]} &= \frac{E[\Delta_i(\alpha_0 + \alpha_1\Delta_i + \alpha_2 v_i + \alpha_3\chi_i + \alpha_4 z_i + e_i)]}{E[\Delta_i^2]} \\
&= \alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} \\
&+ \alpha_2 \frac{E[\Delta_i(\gamma_0 + \gamma_1\Delta_i + \gamma_2\chi_i + \gamma_4 z_i + \beta_5 t_i + \frac{\beta_2 e_i}{(1-\beta_2\alpha_2)} + \frac{\mu_i}{(1-\beta_2\alpha_2)})]}{E[\Delta_i^2]} \\
&= \alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2\gamma_1 + \frac{\beta_2\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \frac{\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i\mu_i]}{E[\Delta_i^2]}
\end{aligned}$$

Inserting γ_1 and adding and subtracting $\alpha_2\beta_1$ and $\alpha_2\frac{E[\Delta_i\mu_i]}{E[\Delta_i^2]}$,

$$
\begin{aligned}
\frac{E[\Delta_i p_i]}{E[\Delta_i^2]} &= \alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2 \frac{\beta_1 + \beta_2\alpha_1}{(1-\beta_2\alpha_2)} + \alpha_2\beta_1 - \alpha_2\beta_1 + \\
&\frac{\beta_2\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \frac{\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} + \alpha_2\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} - \alpha_2\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} \\
&= \alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2\beta_1 + \alpha_2\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} + \left(\alpha_2\frac{\beta_1 + \beta_2\alpha_1}{1-\beta_2\alpha_2} - \alpha_2\beta_1\right) + \\
&\frac{\beta_2\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \left(\frac{\alpha_2}{1-\beta_2\alpha_2} - \alpha_2\right)\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} \\
&= \alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2\beta_1 + \alpha_2\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} + \alpha_2\beta_2\delta_1 + \frac{\beta_2\alpha_2}{1-\beta_2\alpha_2}\frac{E[\Delta_i e_i]}{E[\Delta_i^2]} \\
&+ \frac{\beta_2\alpha_2^2}{1-\beta_2\alpha_2}\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]} \qquad (3.6)
\end{aligned}
$$

Equation 3.6 illustrates that in a simultaneous system, any relation between regressor and error structure, say in the form of an omitted variable, multiplies throughout the system and inflates the bias by extra terms. Also note that the intuition behind price taking customer is more visible in 3.6. Setting $\beta_2 = 0$ is sufficient to eliminate the inflation coming from the interplay of variable of interest and error structure. In this case 3.6 will be limited to $\alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2\beta_1 + \alpha_2\frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]}$. Assuming further, β_1, and $\beta_3 = 0$, the expression is reduced to OLS estimate, $\alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]}$.

Therefore, the consequence of imposing restriction in a supply demand system will be determined by how realistic this restriction is within that system. For example, within an established buyer/seller relation, buyers might ask discounts for large shipments. Also, if the returns to scale is increasing, providers might have motivations to give discounts. Moreover, from a dynamic perspective, if signing large customers now increases the chances of serving them later, providers might be inclined to give price concessions. Thus, for these reasons or others[45] if the suspicion is α_2 and β_2 might not be very small, it is best to refrain from restricted form.

Fortunately, in this study, it might be possible to assess the consequence of imposing $\beta_2 = 0$. First let us consider transaction volume. Recall that t_i is a demand shifter, with no impact on supply. Using the variation in t_i, and the corresponding variation in price, it is possible to estimate sensitivity of pricing to transaction volume. To

[45] As quoted from Nevo (2000a) above, these all can be characterised as "common unobserved characteristics". Also see, Angrist and Pischke (2009) for endogeneity and bad controls.

see that formally, note that in an IV framework, where $\gamma_4 = \frac{E[v_i p_i]}{E[t_i^2]}$ and $\delta_4 = \frac{E[t_i p_i]}{E[t_i^2]}$,

$$\frac{\delta_4}{\gamma_4} = \frac{\frac{E[t_i p_i]}{E[t_i^2]}}{\frac{E[v_i p_i]}{E[t_i^2]}} = \frac{E[t_i p_i]}{E[v_i p_i]} = plim(\hat{\alpha_2}) = \frac{\frac{\alpha_2 \beta_5}{1-\beta_2\alpha_2}}{\frac{\beta_5}{1-\beta_2\alpha_2}} = \alpha_2 \tag{3.7}$$

Second, let us consider the variable of interest. In an IV setting, using the moment conditions from the exogenous variable, initially first stage is estimated. Next using fitted values, price equation is retrieved. Therefore, price equation would look like,

$$p_i = \alpha_0 + \alpha_1 \Delta_i + \alpha_2 \hat{v_i} + \alpha_3 \chi_i + \alpha_4 z_i + e_i$$

In this case, the coefficient for Δ_i would be characterised by

$$\frac{E[\Delta_i p_i]}{E[\Delta_i^2]} = \frac{E[\Delta_i(\alpha_0 + \alpha_1 \Delta_i + \alpha_2 \hat{v_i} + \alpha_3 \chi_i + \alpha_4 z_i + e_i)]}{E[\Delta_i^2]}$$

Orthogonality of the instrument to the error structure assures that any relation between regressor and error structure is not multiplied throughout the system. Then the estimate can converge to $\alpha_1 + \frac{E[\Delta_i e_i]}{E[\Delta_i^2]} + \alpha_2\beta_1 + \alpha_2 \frac{E[\Delta_i \mu_i]}{E[\Delta_i^2]}$ without an outright rejection of simultaneity.

Next, within an IV setting, a similar estimation is made and the consequences of imposing exogeneity assumption is assessed.

3.5.2 GMM Estimation

Estimation strategy is identical to 3.1; measures of market power, interact with regime indicators, $\gamma^{coll}, \gamma^{comp}$, and two different pricing equations, one for each regime, are estimated. Difference between OLS and GMM is the introduction of transaction volume as a control in an IV framework. Recall that products X, Z and T are linked in an input-output chain. The primary purpose of X, is to produce Z. Primary purpose of Z is to produce T. Alternatively speaking, any production of T (recall that we refer T production at location l at time t as $t_{\overline{nplt}}$), creates a demand for Z. Any production of Z creates a demand for X[46].

Here, the objective is using aggregate monthly T volume that is within a radius of r_i as an instrument for X activity at each X location in a GMM framework. This is consistent with other works in the literature, e.g. (Brander and Ross, 2006, p.353), (Röller and Steen, 2006, p.331), (De Roos, 2006, 1090-1), (Hüschelrath et al., 2013, pp. 111-2)), where output data from vertically related industry is used to identify pricing equation in the manner described above[47]. $t_{\overline{nplt}}$ satisfies both conditions of

[46] See, Figures 2.1, and 2.2.

[47] X, T relation has also been used in the literature in IV framework in identifying pricing

being a good instrument[48]. First, there is the strong relation between X production and $t_{\overline{np}lt}$; X demand is almost entirely governed by $t_{\overline{np}lt}$; consequently, $t_{\overline{np}lt}$ is *relevant*[49]. Second, even though X demand is governed by, $t_{\overline{np}lt}$; this relation is one directional. The weight of X, in production of T is marginal, and fluctuations in $t_{\overline{np}lt}$ are typically governed by macroeconomic aggregates. Consequently, $t_{\overline{np}lt}$ is *valid*[50].

Initially, r_i is set to $\bar{r}$, an industry rule of thumb which marks the limit distance within which it is profitable to ship Z; later, I experiment with alternative values, $0.6\bar{r}, 0.8\bar{r}$. Since the information about T volume (T Index, $t_{\overline{np}dt}$) is coming from the license information about production to be made, initially, in addition to current value, four lagged values (license information in the preceding months) are also included. Results suggest that periods immediately following licensing do a poor job in explaining variations in X volume. Eventually, a model with two instruments, $t^{-2}_{\overline{np}dt}$ and $t^{-4}_{\overline{np}dt}$, is identified.

Table 3.5 summarizes the first set of results. In all specifications dependent variable is delivered price charged by provider j, to customer c, at location l, in month t, p_{jltc}. Beside interactions of regime indicators, and measures of market power, all specifications employ an indicator variable marking the presence of an additional nearby facility controlled by the provider, γ^{own}_{jl}; an indicator variable marking the regime switch, γ^{coll}_{t}; and an indicator variable marking presence of a vertical relation between provider and buyer, $\gamma^{vertical}_{jc}$. Specification 7 is a slightly modified form of baseline OLS regression as it does not include any variable capturing the buyer size. Specification 8 adds the transaction volume, which is potentially endogenous. Specification 9 provides an IV solution to the endogeneity problem. In this specification, instead of the moment condition used in OLS, $E[v_i e_i]$, the moment condition building on the instrument, $E[t_i e_i]$ is used.

In a GMM estimation[51] the aim is to minimize objective function, defined as,

$$Q(\beta) = \left(\frac{1}{N}\sum_i t_i e_i\right)' W \left(\frac{1}{N}\sum_i t_i e_i\right) \tag{3.8}$$

where W is the weighting matrix. W should be defined as the sample correspondent of $E[t_i e_i e_i t_i']$, which is

$$\hat{S} = \frac{1}{N}\sum_i \hat{\mu_i}^2 t_i t_i' \tag{3.9}$$

We face a cyclicality. Estimation of β requires $\hat{S}$, which requires $\hat{\beta}$.

equations. At this point, I am not citing specific examples to keep the industry undisclosed.

[48]See, Davis and Garcés (2009) (p.442-444) for a discussion about conditions of a good instrument.

[49]Also known as rank condition, and typically is formalized as $E[t_i v_i] \neq 0$.

[50]Also known as exclusion restriction, and typically is formalized as $E[t_i e_i] = 0$.

[51]See, Baum et al. (2003, 2007), and Hansen (2016), pp.280-3.

Table 3.5: GMM Estimates - I

		(7)	(8)	(9)	(10)	(11)	(12)
		(1)- Large Buyer	(7)+ Volume	2sGMM	IGMM	CUE	(7)+ Buyer Size
Δ_j^l							
	γ_t^{comp}	0.6114***	0.6129***	0.6265***	0.6265***	0.6331***	0.6175***
		(0.0426)	(0.0425)	(0.0510)	(0.0510)	(0.0554)	(0.0427)
	γ_t^{coll}	0.2459***	0.2483***	0.2703***	0.2703***	0.2784***	0.2392***
		(0.0453)	(0.0450)	(0.0536)	(0.0536)	(0.0583)	(0.0455)
$(\Delta_j^l)^2$							
	γ_t^{comp}	0.0251***	0.0252***	0.0259***	0.0259***	0.0259***	0.0254***
		(0.0020)	(0.0020)	(0.0028)	(0.0028)	(0.0031)	(0.0021)
	γ_t^{coll}	-0.0025	-0.0026	-0.0034	-0.0034	-0.0037	-0.0019
		(0.0021)	(0.0022)	(0.0030)	(0.0030)	(0.0033)	(0.0022)
NBR_{jlc}							
	γ_t^{comp}	-2.4307***	-2.2634***	-0.9470**	-0.9468**	-0.5567	-2.0249***
		(0.2118)	(0.2134)	(0.4328)	(0.4328)	(0.4955)	(0.2474)
	γ_t^{coll}	-0.8425***	-0.7111***	0.3599	0.3603	0.6884	-0.5655**
		(0.2020)	(0.2040)	(0.4242)	(0.4243)	(0.4929)	(0.2270)
$\gamma_{jc}^{vertical}$		-0.2917	-0.4408	-1.6679**	-1.6684**	-2.0994**	-0.4994
		(0.4846)	(0.4853)	(0.7680)	(0.7680)	(0.8826)	(0.5053)
γ_t^{coll}		8.6480***	8.8061***	10.0244***	10.0246***	10.2979***	8.7162***
		(0.5440)	(0.5421)	(0.7374)	(0.7375)	(0.8186)	(0.5467)
γ_{jl}^{own}		4.3564***	4.8030***	8.2526***	8.2527***	8.9707***	5.6312***
		(0.6907)	(0.6871)	(1.1944)	(1.1945)	(1.3532)	(0.7846)
v_{jltc}			-0.0484***	-0.4278***	-0.4278***	-0.5301***	
			(0.0051)	(0.0887)	(0.0888)	(0.1025)	
$\bar{V}_{lc}$							-0.0001***
							(0.0000)
Constant		Yes	Yes	Yes	Yes	Yes	Yes
γ^j		Yes	Yes	Yes	Yes	Yes	Yes
$F(2, N)$				17.183	17.183	17.183	101.193
$GMM(C)$				40.255	40.255	33.742	4.334
J				7.929	7.969	6.880	NA
RPT		10.77	16.76	24.06	NA	21.37	13.46

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. γ_t^{coll} indicates collusive, γ_t^{comp} indicates competitive regime. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. γ^j refers to provider fixed effects. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. v_{jltc} is the transaction volume. $\bar{V}_{lc}$ is total transaction volume. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In Specification 9, this problem is addressed by separating the estimation into two stages. First, an initial matrix is used to estimate $\hat{\beta}$. This is used to retrieve initial $\hat{e}_i$, to be used in computation of an initial $\hat{S}$. Basing on initial $\hat{S}$, $\hat{\beta}$ is re-estimated. Using updated values, $\hat{S}$ takes its final form. Specification 10 employs a similar strategy, but does not stop at two stages, keep estimating and re-estimating until both $\hat{\beta}$ and weighting matrix converge[52]. Finally, Specification 11 overcomes the

[52]Known as iterated GMM estimator.

cyclicality by changing the optimization problem. Estimation of weighting matrix is internalized to optimization. Thus, instead of Equation 3.8,

$$Q(\beta) = \left(\frac{1}{N}\sum_i t_i e_i\right)' W(\beta) \left(\frac{1}{N}\sum_i t_i e_i\right) \tag{3.10}$$

is estimated by numerical optimization[53].

Results suggest that choice of estimator has no effect on coefficients of Δ_l^j and $(\Delta_l^j)^2$. The patterns in OLS survive GMM estimation[54]. Linear term is significant in both regimes. It is larger in competitive regime, and more precise. Quadratic term is only significant for competition. Estimates in OLS and GMM are very close, suggesting little contamination for Δ_l^j from endogeneity. In IV setting, the coefficient for number of rivals is smaller for competition period; GMM point estimates are less then half of OLS point estimates.

Second set of specifications are summarized in Table 3.6. All specifications, follow Specification 9; while controlling for multiplant ownership, vertical relations, and production facility fixed effects, regime indicators are interacted with measures of market power. However, there are small differences across specifications as they test the sensitiveness of results to assumptions employed in the construction of the instrument.

Recall that Z, similar to X, is costly to transport. Consequently, demand for Z (and eventually demand for X), which originates from T production, is regional. Thus, empirical strategy involves using T activity within a defined radius, r_i. Specifications 9, and $13 - 14$, focus on spatial variation and use alternative radii as the cut-off point for r_i to explore the consequences of cut-off decision. Specification 15 focuses on product variation, and instead of index of aggregated T production, it uses only index of highly processed T products (N_1P_2, N_2P_2). Specification 17 adds month fixed effects to Specification 9 in order to capture the impact of unobservable time varying shifters. Specification 16 uses seasonally unadjusted data along with month fixed effects to explore if the findings are affected from seasonal adjustment methodology.

Findings suggest that estimates for Δ_l^j and $(\Delta_l^j)^2$ are robust to the choice of cut-off point, using highly processed products as demand shifters, inclusion of month fixed effects, or using seasonally unadjusted demand indices. The difference across estimates is marginal at best. However, an interesting finding is about, Ramsey/ Pesaran Taylor test statistic. Also known as RESET adjusted for IV setting, the test aims to detect functional misspecification in the form of neglected nonlinearities[55]. To this aim, upon estimation, dependent variable is regressed on the squares of

[53]Continuously updated estimator.

[54]Convergence in GMM and OLS estimates should not be surprising. As De Roos (2006) points out, when variations in market patterns are governed by changes in firm behaviour, rather than demand and cost considerations, IV and OLS estimates are more likely to converge (p.1094).

[55]See, Baum et al. (2007) (pp. 497-8) for RESET in IV setting.

optimal forecast values[56]. Specifications $16-17$ suggest that there is no evidence of neglected nonlinearities if month dummies are involved. This is important, because nonlinearities associated with indicator of local market power has a central role in this study. High value of RESET test statistic in estimations in Table 3.5 indicates presence of left over nonlinearities in the residuals. Rejection of left over nonlinearities after introducing month fixed effects suggests that nonlinearities are time varying rather than spatial, hence not related to indicator of local market power.

Even though, sensitivity of pricing to transaction volume is not at the centre of this work; some interesting patterns emerging from the estimation should be noted. First is the gradual increase in the responsiveness as the cut-off radius is increased. Recall that in interpreting results from an IV estimation, there are two approaches. First is *global*. This is essentially choosing an appropriate instrument with the assumption of homogeneity in the population, i.e. patterns across different subgroups in the population are not distinct. In this case, the results are interpreted informative about the characteristics of the population in general. Second approach is *local*. Assume there are multiple instruments available. Different instruments give different estimates. In this approach, this variation is taken informative locally. Each instrument reflects the effect on the group it is most likely to represent (compliant subgroup).

In our setting, when the radius is fixed to $0.6\bar{r}$, T production only within this radius is used to instrument demand for X. The compliant population in this case would be (i) *producers of X who produced X, as a result of T production within $0.6\bar{r}$ radius of Z producers they serve.* However when the radius is increased to $\bar{r}$, in addition to (i), compliant population would include (ii) *producers of X who produced X, as a result of T activity within $\bar{r}-0.6\bar{r}$ radius of Z producers they serve.* It may be that Z producers consider serving distant T locations if transaction volume is big enough. Yet, distant locations are characterised by higher transportation cost. Thus, serving distant locations might only be possible with "better that usual" X procurement conditions (e.g. lower X price). If X producer knows that operations of Z producer within $\bar{r}-0.6\bar{r}$, is contingent on better terms, a price concession might be given, as for X producer, less profit would be an improvement from no profit. Thus, it is intuitive to think sensitivity of pricing to transaction volume for transactions in (i) and (ii) should differ. The increase in coefficient of v_{jltc} in absolute terms as the radius is expanded might be capturing this heterogeneity. Also note that when nature of the product varies (instead of the aggregated index, index of highly processed T products is used, i.e. Specification 14), there is little impact on the estimate for transaction volume. Given product homogeneity, this is also intuitive.

Basing on Specification 9, Figure 3.6 illustrates the predicted effect of Δ_l^j in two regimes. Recall that $\Delta_l^j = \min(d_{kl}) - d_{jl}$ should approximate to $\chi_{kl} - \chi_{jl}$, the cost difference between potential competitor and dominant competitor at each location. Moreover, higher positive values of Δ_l^j should represent transactions in *home market*,

[56]Pesaran-Taylor version uses optimal values.

Table 3.6: GMM Estimates - II

		(9)	(13)	(14)	(15)	(16)	(17)
		Radius = r	Radius = 0.8r	Radius = 0.6r	N1P2 N2P2	No S. Adjustment	(13)+ Month
Δ_j^l							
	γ_t^{comp}	0.6265***	0.6242***	0.6173***	0.6295***	0.6063***	0.6104***
		(0.0510)	(0.0468)	(0.0432)	(0.0487)	(0.0443)	(0.0466)
	γ_t^{coll}	0.2703***	0.2630***	0.2551***	0.2699***	0.2770***	0.2827***
		(0.0536)	(0.0494)	(0.0457)	(0.0513)	(0.0480)	(0.0502)
$(\Delta_j^l)^2$							
	γ_t^{comp}	0.0259***	0.0257***	0.0256***	0.0257***	0.0252***	0.0254***
		(0.0028)	(0.0025)	(0.0021)	(0.0026)	(0.0023)	(0.0025)
	γ_t^{coll}	-0.0034	-0.0032	-0.0029	-0.0030	-0.0030	-0.0031
		(0.0030)	(0.0027)	(0.0023)	(0.0028)	(0.0026)	(0.0028)
NBR_{jlc}							
	γ_t^{comp}	-0.9470**	-1.3291***	-1.8987***	-1.0973***	-1.5979***	-1.3407***
	γ_t^{coll}	0.3599	0.0364	-0.3998	0.2145	-0.0497	0.1462
		(0.4242)	(0.3627)	(0.2649)	(0.3668)	(0.3286)	(0.3702)
$\gamma_{jc}^{vertical}$		-1.6679**	-1.2996*	-0.7847	-1.6037**	-0.6908	-0.9090
		(0.7680)	(0.6649)	(0.5366)	(0.6941)	(0.5826)	(0.6497)
γ_t^{coll}		10.0244***	9.6944***	9.1649***	9.7195***	15.0511***	15.3270***
		(0.7374)	(0.6606)	(0.5776)	(0.6838)	(0.6782)	(0.7256)
γ_{jl}^{own}		8.2526***	7.2333***	5.7743***	7.6399***	6.6455***	7.3077***
		(1.1944)	(1.0706)	(0.8444)	(1.0593)	(0.9011)	(0.9966)
v_{jltc}		-0.4278***	-0.3142***	-0.1555***	-0.3742***	-0.2791***	-0.3518***
		(0.0887)	(0.0776)	(0.0510)	(0.0704)	(0.0669)	(0.0748)
Constant		Yes	Yes	Yes	Yes	Yes	Yes
γ^j		Yes	Yes	Yes	Yes	Yes	Yes
γ^t		No	No	No	No	Yes	Yes
$F(2, N)$		17.183	15.959	22.785	12.719	17.376	17.017
$GMM(C)$		40.255	19.363	4.920	28.098	17.502	32.407
J		7.929	9.019	14.920	41.0274	8.687	4.321
RPT		10.77	20.15	15.87	17.72	1.24	0.84

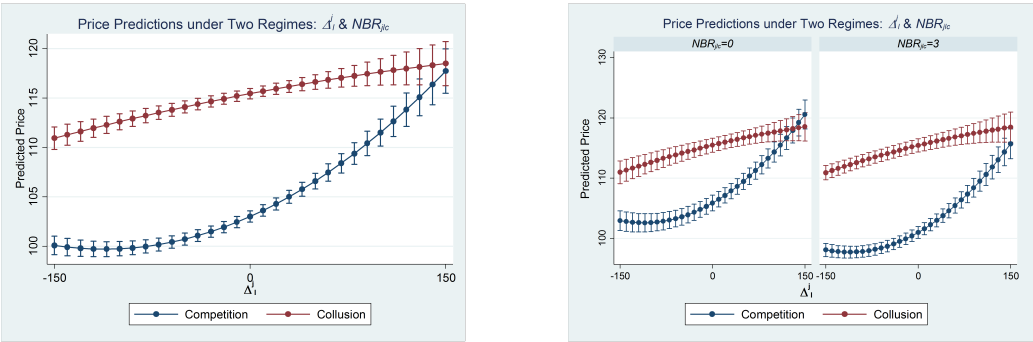
Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. γ_t^{coll} indicates collusive, γ_t^{comp} indicates competitive regime. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. γ^j refers to provider fixed effects. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. v_{jltc} is the transaction volume. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

large negative values should refer to transactions destined to rival *home market*. Values around zero should refer to *overlapping market*. Regarding the relation between price and measures of local market power, there are four empirical findings.

First relates to the size of the predicted gap between competition and collusion around the neighbourhood of zero – *overlapping markets*. In fact, setting $\Delta_l^j = 0$, and all other covariates to mean, price impact of the regime change is predicted to be 12.4 %[57]. Second, for high values of Δ_l^j (*home market*), predicted price converges

[57]Bases on Specification 9.

Figure 3.6: Estimated Relationship between Price and Δ_l^j



(a) Price and Δ_l^j

(b) Price, NBR_{jlc} and Δ_l^j

across regimes. In these regions, market power of the incumbent provider is already high; thus, explicit collusion should not lead to further notable increases in price. These are illustrated in Figure 3.7.

Third empirical finding is about how spatial variation in local market power is related to spatial variation in price. As elaborated in Chapter 1, under competition spatial distribution of price is a function of relative costs of *dominant competitor*, and *potential competitor*.

- In *home market*, *dominant competitor* is an effective monopolist; rivals do not constrain its pricing; hence, market power is at maximum. Note that there is still variation in price. Price should increase with distance at *home market* due to higher transportation cost.
- In *overlapping market*, as *dominant competitor* serves locations that are less costly for *potential competitor*, market power of *dominant competitor* declines, and price falls.

Spatial distribution of price over locations with varying degrees of market power is illustrated in the Figure 3.8a, and Figure 3.8b.

Note that Δ_l^j is the relative proximity of dominant competitor and potential competitor to each location, and is designed to reflect cost differences, hence the local market power variation. Consequently, price should be declining sharply with Δ_l^j, if it mimics local market power accurately. Figure 3.8c depicts that estimated relation between Δ_l^j and the price is consistent with the expectations. This suggests that Δ_l^j might actually be capturing local market power variations. Providers suffer considerable price cuts to extend their operations to regions where they are not protected by cost advantages. The more disadvantaged they are relative to least cost rival, the larger is the required price cut - an effect captured by quadratic term.

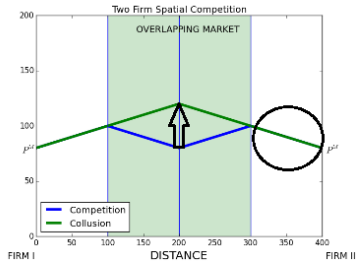
Under collusion, cartel, by adjusting the market power of its members in those parts of the market in which otherwise would have been competition, allows its

members to price monopolistically at each location. Consequently, price increases with distance in all directions. In this case, Δ_l^j should not be capturing any market power related effects, as each provider, independent of its level of cost relative to rival has undisturbed market power. This is illustrated in Figure 3.9a, and 3.9b. This brings us to our fourth empirical finding: interestingly, estimation suggests a significant relation between Δ_l^j and price also in collusion. The point estimate for the linear term is much smaller and the coefficient for quadratic term is not significant. Not finding large effects is hardly surprising. There is no reason for firms to make drastic changes in pricing, when collusion ensures against being undercut. However, the question arises: what does Δ_l^j capture if not market power? The most intuitive answer would be cheating. The theoretical framework above depicts a perfect collusion. Nevertheless, voluntarily or involuntarily firms might extend their operations, infringing the collusive agreement. Marshall and Marx (2012) comment on this as follows:

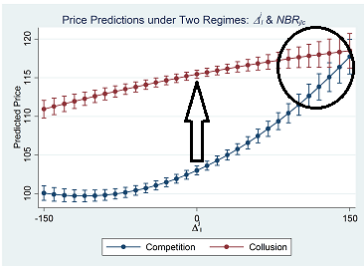
> *"Specifically, if the cartel has agreed to a price, then each cartel member will consider whether it can secretly offer some buyers a slightly lower price, and thereby capture additional sales and additional profits. ... It is not necessary for a cartel to deter all secret deviations in order to be profitable. Some amount of secret deviations may occur and might be tolerated by cartel. ...From the perspective of cartel, the implications of unintentional deviations and secret deviations are quite different. ... Mistakes are quickly acknowledged by upper management, they fall in the realm of unintentional deviations and can be addressed through reallocations. ... Mistakes can happen, but successful collusive structures typically specify methods by which redistributions can be made to correct mistakes (pp.105-6 & 128)."*

An intentional deviation would entail a price cut to convince the consumer to purchase from the cheating party. This behaviour is probably more associated with *overlapping markets*, because the pay-off associated with under cutting declines as cheater serves customers closer to rival. Similarly, one might also expect unintentional deviations to be more common on *overlapping market* rather than *home markets*; as the incumbent producer would be dominating his own *home market*, confusion about customers in this region is less likely.

Figure 3.7: Market Power and Price: Home Market and Overlapping Market

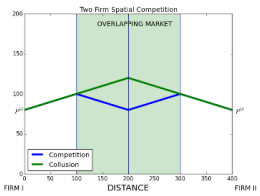


(a)

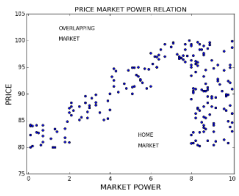


(b)

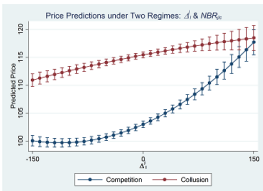
Figure 3.8: Interpreting Price, Distance and Market Power Relation in Competition



(a) Theoretical Relation: Price and Distance



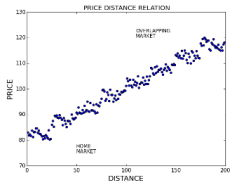
(b) Expected relation: Price and Market Power



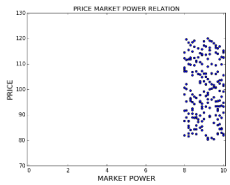
(c) Estimated Relation: Price and Δ_l^j

- **Theoretical prediction**: Large price difference between collusion and competition at locations where both *dominant competitor* and *potential competitor* are equally good options for customers.
- Locations with higher positive values of Δ_l^j should represent transactions in *home market*, large negative values should refer to transactions destined to rival *home market*. Values around zero should refer to *overlapping market*.
- **Theoretical prediction**: Price should converge across regimes in *home market*.
- **Empirical finding 1**: Large differences in price across regimes when $\Delta_l^j = 0$.
- **Empirical finding 2**: At locations with large Δ_l^j, price in both regimes converge.
- **Theoretical prediction**: Price increases with cost of provider in *home market*; price falls in *overlapping market* even though cost increases.
- Price decline in *overlapping market* is related to gradual decline in local market power of *dominant competitor*.
- Δ_l^j is designed to capture local market power effect by relating relative distances of the provider and the best alternative to each location.
- **Empirical finding 3**: Market power is significant in competition, both linearly and quadratically. Providers suffer large price cuts to serve customers closer to rivals.

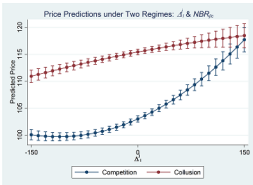
Figure 3.9: Interpreting Price, Distance and Market Power Relation in Collusion



(a) Theoretical Relation: Price and Distance



(b) Expected relation: Price and Market Power



(c) Estimated Relation: Price and Δ_l^j

- **Theoretical prediction**: Price increases with cost in all directions.
- If firms are colluding, the link between measures of market power and pricing is broken. It is the collusive agreement that assures maximum market power at each location.
- Δ_l^j is designed to capture local market power variations by relating relative distances of the provider and the closest rival to each location. Hence, under collusion, it should capture nothing.
- **Empirical finding 4**: In collusion, market power is positively but only linearly related to price. The relation is much weaker than that in competition, but is significant.

3.6 Conclusion

In this chapter, building on the theoretical framework in Chapter 1, I take on the suspicious patterns identified in Chapter 2 that are consistent with a regime switch in the market from collusion to competition. Controlling for demand and cost shifters, I investigate these patterns further, and explore if observed patterns are more consistent with collusion or competition.

In devising the empirical strategy, I consult to empirical literature concerned with the identification of collusion, particularly Bresnahan (1987). Consequently, in this study, estimation builds on explaining pricing behaviour, and particularly its relation with Δ_l^j, relative proximity of the provider and its closest rival to the buyer. The idea is after controlling for factors influential in pricing, Δ_l^j acts as an indicator of variations in local market power measure, the cost difference between potential competitor and dominant competitor at each location. Findings indicate that i) when market power of provider and the closest rival converge, there is a large price difference between suspected collusion period and competition period ii) at locations where the provider has large market power, price in both periods converge, iii) in suspected competition period, local market power indicators are both linearly and quadratically related to pricing; providers suffer large price cuts to serve buyers that are gradually closer to the closest rival, iv) in suspected collusion period, local market power indicator is positively but only linearly related to price, and the linear relation is much weaker than that in competition. These findings are interpreted as

further evidence for a regime switch from collusion to competition. The results also suggest that level of market power each provider has on a buyer is very important in the assessment of the impact of collusion on price, which is explored in detail in Chapter 5.

Chapter 4

Ex Post Evaluation in Competition Policy: Damages, Mergers and a Bridge between Two

4.1 Introduction

This chapter presents the literature on *ex post evaluation of competition policy actions* (henceforth, retrospectives). Retrospectives typically take a competition policy action after the action has been taken, and empirically identify its impact on a variable of interest, i.e. price, output, quality. Table 4.1 illustrates how frequently different competition policy areas are studied in retrospectives; they almost exclusively cover mergers[1] and collusion[2].

The objective of this chapter is exploring the literature surrounding ex post evaluation of competition policy actions in order to identify empirical strategies that might be used next chapter, in estimating the overcharge associated with

[1]In this work, I ignore the distinction between mergers and acquisitions. In the application of competition law, the assessment of transactions that change concentration in the market, base on the concept of "change of control". Consistent with policy practice, here I refer to any transaction that lead to a change of control as a "merger".

[2]Article 101 of EU treaty prohibits *"all agreements between undertakings, decisions by associations of undertakings and concerted practices which may affect trade between Member States and which have as their object or effect the prevention, restriction or distortion of competition within the internal market."* Therefore, Article 101 is not exclusively about collusion; but also vertical agreements, and other types of horizontal agreements, e.g. horizontal cooperation agreements. However, in this chapter, I focus only on ex post studies of collusion and mergers.

[3]Event studies use financial market information (typically stock prices) and estimate the impact of a competition authority decision basing on the appreciation / depreciation in the stocks of the involved undertaking(s) around the decision time. Some examples for collusion are Bosch and Eckard (1991); Günster and van Dijk (2016); Thompson and Kaserman (2001).

Table 4.1: Ex Post Evaluation Literature by Policy Area[3]

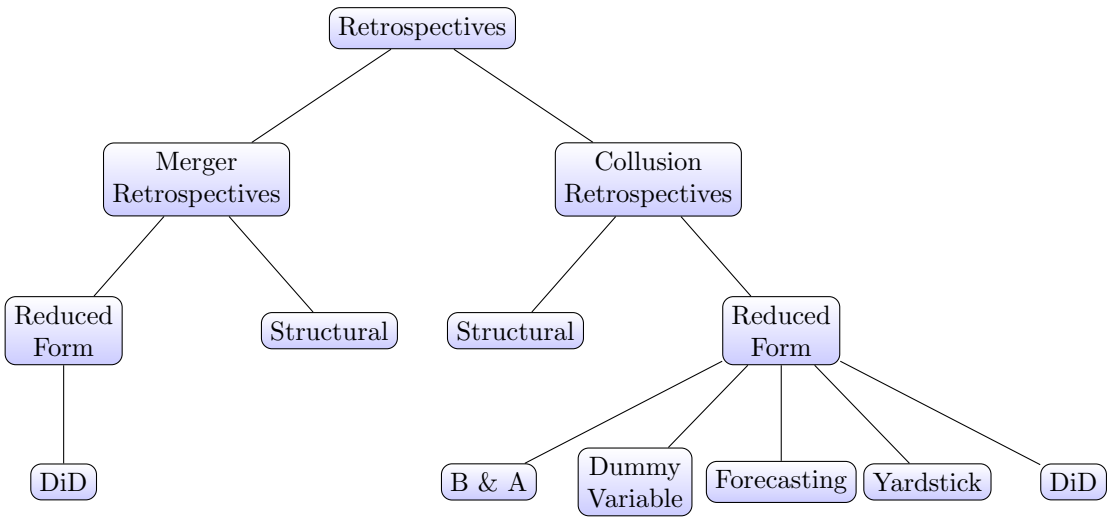
	Methodology	Academic Literature	CAs
Enforcement			
Merger control	Simulation	Extensive	Extensive
	Event Studies	Extensive	Some
	DiD etc.	Extensive	Some
Cartels/Article 101	Simulation	Some	Few
	Event Studies	Some	Few
	DiD etc.	Some	Some
Abuse/Article102	Simulation	Few	None
	Event Studies	None	None
	DiD etc.	Few	None
Non-enforcement			
Advocacy	None	None	Few
Compliance	None	None	None
Consumer Education	None	None	None

Source: Table 2 in Davies and Ormosi (2012).

the hypothetical collusion identified in Chapter 3. To this aim, first, I look at the literature associated with ex post analysis of collusion (henceforth, collusion retrospectives).

As illustrated in Figure 4.1, collusion retrospectives (Appendix 2 provides a detailed record) can be taken into two main groups. First group of works use structural estimation. This most commonly involves estimating demand parameters and inferring price cost margins under different conduct assumptions. Second group of works use reduced form strategy of varying complexity. This might involve *before and after*, simple comparison of patterns in the dependent variable before and after the regime switch; *dummy variable approach*, identifying the impact of collusion using an indicator variable while controlling for demand and cost shifters; *forecasting*, estimating the parameters for demand and cost shifters only for competition period and forecasting the counterfactual of collusion using these parameters; *yardstick* and *difference-in-difference* (henceforth, DiD), comparing the market affected from collusion to a similar yet unaffected market.

Figure 4.1: Ex Post Analysis of Competition Policy Actions[4]



[4] B & A stands for before and after, DiD stands for difference-in-difference. Before and after

In search of empirical strategies to be used in estimating overcharge, next I turn to merger retrospectives. Similar to collusion retrospectives, merger retrospectives can be broadly taken into two categories; structural estimation and reduced form estimation. However, differing from collusion retrospectives, reduced form merger retrospectives almost always use DiD (see, Table 4.1, and Appendix 3), and frequently use customer level data. Due to compatibility in methodology and data, I also provide an account of reduced form merger retrospectives, along with discussions about merits and limitations of DiD in this context. A comparison of DiD based collusion retrospectives and merger retrospectives leads to following conclusions: i) Two lines of literature are unexpectedly disconnected. ii) Compared to merger retrospectives, collusion retrospectives are in a stage of infancy. iii) Merger retrospectives provide great insight to collusion retrospectives. iv) In particular, merger retrospectives that study mergers with spatial nature offer (so far unexploited) empirical strategies and identification techniques that can be replicated in studying the effects of collusion in similar setting. Inspired from methodologies used in merger retrospectives, I propose two alternative identification strategies to identify the impact of a regime switch from collusion to competition: i) using *home markets* – locations characterised by monopolistic pricing even in competition, hence are unaffected by the regime switch – as the control group for the counterfactual of regime switch (continuation of cartel and associated monopolistic pricing in *overlapping markets*); consequently, capturing the impact of the treatment, as a deviation of price in *home markets* from price in *overlapping markets*. ii) interpreting the regime switch as a treatment, which, at each location, produces heterogeneous effects that is inversely proportional to the level of local market power the provider enjoys at that location.

This chapter is organized as follows: Next section presents collusion retrospectives – excluding DiD studies – and methodologies employed. Third section introduces DiD methodology, and presents collusion retrospectives, and merger retrospectives that use DiD in comparison with each other. Fourth section outlines the proposed methodology. Fifth section offers a critical evaluation of the proposal. Final section concludes.

4.2 Collusion Retrospectives: Methodology and Literature

This section, introduces alternative methodologies (with the exception of DiD) employed in collusion retrospectives, and associated literature. However, before this introduction, some cautionary remarks should be made: First, in classifying the literature, I prefer a slightly modified version of Davis and Garcés (2009) - structural estimation on one side, and reduced form estimation techniques, i.e.

is essentially not an estimation, but a simple comparison. It is included among reduced form techniques only for practical purposes.

before and after, dummy variable approach, forecasting, yardstick and DiD, on the other (pp. 352-368). This differs from the classification in more recent works, which commonly follow Oxera (2009) - comparator based, financial analysis based, market structure based. Second, the literature I cover is not confined to damage estimation. Occasionally, I extend to price wars, historical cartels, supply management programs (also known as marketing orders) and market power estimations[5]. Third, even in many cases it is possible to generalize the methodology, I exclude limited literature on estimation of damages related to other infringements, i.e. vertical restraints abuse of dominance/monopolization)[6]. Fourth, at the risk of being repetitive, I should iterate the cautionary remark in Section 3.3; it is not always straightforward to classify works between detection literature and damages literature, as some works aspire to do both. In these cases, when a judgement is to be made, own positioning of the paper, the literature it covers, and the gravity of the analysis are taken into account. However, to avoid being repetitive further, I refrain from covering the works I covered in Chapter 3.

Verboven and van Dijk (2009), illustrate the intuition in damage estimation as follows[7]. Suppose there are two parties, each active on a different level of the same production chain: buyers (plaintiffs), and providers (defendants). Buyers purchase product x from providers and have the following profit function:

$$\pi = pq_b - C\left(w, q_b\right) \tag{4.1}$$

where p is the price of the product buyers sell, q_b is the output of the same product, $C\left(w, q_b\right)$ is the cost which for simplicity can be taken to be only a function of q_b and input price, w. The providers form a cartel and make an infinitesimal price increase, dw. Ignoring second order effects, Verboven and van Dijk (2009) track the impact of this small price overcharge on buyer profit in order to *"highlight key channels"* via which equation 4.1 is affected.

$$\begin{aligned}\frac{d\pi}{dw} &= \frac{d\left(pq_b\right)}{dw} - \frac{dC\left(w, q_b\right)}{dw} \\ &= \frac{pdq_b}{dw} + \frac{q_b dp}{dw} - \frac{\partial C\left(w, q_b\right)}{\partial w} - \frac{\partial C\left(w, q_b\right)}{\partial q_b}\frac{dq_b}{dw}\end{aligned}$$

Multiplying both sides by dw and using Shepard's Lemma to relate change in cost

[5]At this point Connor (2014) deserves a special mention. In an attempt to provide a data set for overcharge estimations Connor (2014) refers to about 60 studies that have an econometric dimension, which serve as a solid starting point.

[6]For more information, see, Davies and Ormosi (2012); OECD (2016).

[7]See, p.463.

to input demand q_x, $\frac{\partial C(w,q_b)}{\partial w} = q_x$.

$$d\pi = q_b dp + p dq_b - \frac{\partial C(w, q_b)}{\partial w} dw - \frac{\partial C(w, q_b)}{\partial q_b} dq_b$$

$$= -q_x dw + q_b dp + dq_b \left(p - \frac{\partial C(w, q_b)}{\partial q_b} \right) \tag{4.2}$$

Consequently, Verboven and van Dijk (2009) identify three channels via which cartel's infinitesimal price increase can affect buyers' profits. First channel is *price overcharge effect*; it captures the impact of cartel overcharge on the procurement cost. Second is the *pass-on effect*; it captures the extent plaintiff manages to pass cost increases to its own customers. Third is the *output effect*; it captures any decline in profits due to reduced volume of production.

Estimation of all three effects is only possible within a structural framework. In contrast, in a typical reduced form setting, the second and third effects are ignored. Empirical estimation centres on estimating the impact on price – *the price overcharge effect*, or simply *overcharge*. Next, I am going to present the methodologies and the literature on structural estimation and reduced form estimation respectively.

4.2.1 Structural Estimation of Damages

This subsection takes the structural estimation literature under three groups: (i) works that use perfect competition in forming benchmark, (ii) works that use imperfect competition in forming a benchmark, (iii) works that estimate damages within a dynamic framework. This subsection concludes with a short discussion about feasibility of applying structural estimation in the next chapter.

Perfect Competition as the Benchmark: Estimating a System of Equations

First set of works employ the assumption that in the absence of collusion, market would be characterised by perfect competition. In this line of literature, supply is modelled as a function of price and supply shifters; demand is modelled as a function of price and demand shifters. In a simultaneous equations framework, demand and supply together determine the equilibrium price and quantity, which form the competitive benchmark. Damages are measured as the divergence from this benchmark (Brander and Ross, 2006, p.347-349).

An example is Normann and Tan (2014), tracking the West German high voltage cable industry in 1958–1990. In 1958–1974, German high voltage cable industry

was subject to competition law like any other industry. In 1975, an exemption from antitrust law was granted to the industry, with the hopes that this would promote efficiency gains and technological progress. The exemption was taken back in 1985, and the industry was returned to the jurisdiction of competition law. In the study, the empirical strategy is identifying the impact of exemption using annual data. Supply, demand, profit and capacity equations are estimated in a simultaneous equation setting. Results suggest that annual impact of cartel on price is 16–19 %. As a result of the inelastic demand, the impact on quantity was much smaller, 2%. The findings do not indicate any efficiency gains, or technological progress during the exemption period, only a wealth transfer from consumers to producers.

Another example isBrännlund (1989), exploring the impact of monopsonic practices of pulpwood producers on sawtimber and pulpwood markets in Sweden using 1954–1984 data. Sawtimber is used as an input in furniture, and production is characterised by many small scale firms. Pulpwood is used for production of pulp and eventually paper; pulp production is characterised by fewer firms. During the period under investigation pulpwood producers either use a common procurement office, or openly collude. Empirical objective is exploring the direct impact of monopsonist practices directly on the pulpwood market, and indirectly on the sawtimber market.

Since pulpwood is already characterised by monopsony, empirical strategy is modelling the market that would be under the counterfactual of collusion; in this case, perfect competition. To identify the impact in both pulpwood and sawtimber markets, two markets are modelled in interaction with each other within a simultaneous equations framework. Results suggest that transition from monopsony to perfect competition would translate as 28 % increase in pulpwood production and 78 % increase in price. Higher price would lead to reallocation of capacity to pulpwood, which in turn would bring a contraction of sawtimber production. The estimates for sawtimber market suggest 10 % reduction in the volume, and accompanying 18 % increase in price.

Some others example using this methodology include Hausman (1980, 1984) and Tan (2009) exploring the coal industry in 17th and 18th century in UK; Shepard (1986), studying SMP employed by orange producers in California and Arizona; French and Nuckton (1991), focusing on a raisin SMP.

In this methodology there are three challenges. First, simultaneity is a challenge for identification. Estimation requires using exogenous demand variations to identify supply side, and using exogenous supply variations to identify demand side. Finding exogenous shifters is not an easy task. Second, results are sensitive to the functional form. Even though linearity or log linearity are considered as reasonable approximations, estimations typically include sensitivity analysis to various functional forms. Third, accuracy of damage estimation relies on perfect competition being the counterfactual. If market instead is characterised by imperfect competition, estimates would overestimate the impact of collusion (Brander and Ross, 2006, p.347-349). This brings us to second group of works in the literature; the studies accommodate some degree of market power in the benchmark for

competition.

Departing from Perfect Competition

In this line of literature, the analysis typically starts with the estimation of demand. On the supply side, ideally one would like to work with marginal cost, which exceptional cases aside, is not observable. Some use average cost as an approximation. Others acknowledge its unobservability, and infer it.

Probably the most well-known example of this approach is Nevo (2001). Empirical objective is to assess the competitiveness of ready to eat cereal (RTEC) industry which is commonly believed to be collusive. At the first stage, using customer level data, and employing discrete choice estimation techniques[8], demand is estimated. Upon retrieving parameters from demand side, at the second stage, price cost margins are inferred under three different assumptions regarding conduct: (i) firms are making single product profit maximization, and their profits are entirely determined by their ability to differentiate themselves from rivals; (ii) firms are competing under portfolio effects, and their profits are also a function of their ability to offer a brand portfolio; (iii) top 25 brands are joint profit maximizers, and their profits are determined by the collusion. Results suggest under first two assumptions margins go as high as 42 %; while in collusion expected margin would be 72%. At the final stage, an observed indicator of actual margins is compared with, the inferences from three different models. Proposed collusive conduct (collusion among top 25 brands) is rejected[9].

Another example is Asker (2010), studying a bidding ring of collectable stamp dealers that were operational from late 1970s to late 1990s. Cartel employs an innovative collusive strategy. Parties hire an agent, in this case a taxi driver. Before each auction[10], the agent collects quotes from all ring members about their true valuation of each lot. This is the "knock-out" auction within the ring. When the auction actually takes place, the ring is represented by the agent. Agent is bounded by the maximum bid in knock-out session b^r. If the auction concludes with a price higher than the knock-out session, the ring loses the auction. If the auction concludes with a price lower than the knock-out session, the ring wins the auction and pays b^f. There is a profit for the ring that is equal to $b^r - b^f$. Table 4.2 illustrates the distribution of this profit among members of the ring. For example assume that ring wins the auction for 6750$; and also assume that in knock-out session, three ring members reported valuations higher than 6750$. The ring members who report valuations below the winning bid get nothing. Each member of the ring, except the winner, that reported a valuation higher than the winning bid receives a side payment from the winner. The payment increases with own knock-out bid

[8] Nevo (2001) follows Berry et al. (1995) in demand estimation.

[9] For another work with a similar methodology also see Mariuzzo et al. (2009) which study Irish Automobile industry.

[10] The auctions are English auctions.

Table 4.2: Side Payments Example

Knockout auction	Bid ($)	Sidepayment
Bidder A	9,000	$-\left(\frac{7{,}500-6{,}750}{2}\right)-\left(\frac{8{,}000-7{,}500}{2}\right)=-625$
Bidder G	8,000	$+\left(\frac{7{,}500-6{,}750}{2}\right)\times\frac{1}{2}+\left(\frac{8{,}000-7{,}500}{2}\right)=437.50$
Bidder B	7,500	$+\left(\frac{7{,}500-6{,}750}{2}\right)\times\frac{1}{2}=187.50$
Bidder J	5,100	0
Target auction price	6,750	

Source: Table 1 in Asker (2010).

and decreases with the number of bidders that reported a valuation higher than the winning bid. The winner takes the item.

Data contains information from both actual auctions and knock-out auctions. Impact of the cartel is identified in two different models. First model interprets the knock-out auctions as the true valuation of the cartel members. In this interpretation, if the cartel was not present, the price in an auction won by the ring would have been the second highest valuation in knock-out auction; thus, in this case the overcharge is equal to the difference between the auction price and second highest knock-out bid. This estimate is considered as the "naive estimate", as it ignores that side payments increase with own knock-out bid, which creates an incentive to overbid. Second model embeds the collusive strategy in a structural framework. Findings suggest significant overbidding behaviour, which mitigates the collusive harm by increasing the winning bid. True damages are significantly (around 50 %) less than the naive estimates. Cartel also harms the non-member rivals by forcing them to inflate their bids. Damages suffered by non-member rivals are equal to the damages suffered by sellers.

Some other examples using this methodology include De Roos (2006), exploring lysine cartel; Igami (2015), which studying International Coffee Arrangement - a supra national cartel.

There are three challenges in this approach. First, estimation is difficult to communicate to a non-professional audience, which makes it less popular in a court hearing. Second, in this approach, estimation requires explicit imposition of a conduct assumption (Bresnahan, 1989, 1010-16). Consequently, accuracy of damage estimation critically relies on the accuracy of the imposed market structure. Third, competition is most frequently defined within a static framework. Ignoring features of the market that relates to dynamic competition might lead to inaccurate estimates. This brings us to third group of works in the literature; the studies that accommodate dynamic considerations into the analysis.

Estimation in a Dynamic Setting: Switching Regression Models

Works in this group focus on a long time frame and incorporate dynamic considerations – most frequently incentive to cheat – into the analysis.

One of the most well-known studies in this fashion is Porter (1983). The aim is empirically testing Green and Porter (1984) which works as follows: Under repeated interaction, each firm sets the output, and observes the market price, which naturally is the result of demand and output decisions of all firms. Under collusion, firms cannot differentiate negative demand shocks, from cheating. To deter cheating, colluders employ a trigger price which is less than collusive price. If price is below the trigger, they revert to Cournot for a fixed time period. If price is above the trigger, they adhere to collusion. Incentive compatibility condition dictates that cheating can only happen if the expected cheating pay-off (net of Cournot) in one period, is larger than the expected stream of profits foregone by triggering a regime change. Cartel can influence members' decision to cheat by adjusting the trigger price and/or length of punishment period. Therefore, collusive strategy might be a self-enforcing equilibrium.

Note that transposing to a dynamic setting has strong implications. First, two behavioural outcomes that differ entirely from a static point of view, collusion and competition, may actually be two occasional outcomes of the same long run process. Second, price war is the result of the inability of the firms to distinguish demand shocks from cheating. Then it follows that what governs price wars might be demand shocks. Note that it is not necessarily only negative demand shocks that destabilize collusion. Any improvement in market conditions that pushes the output towards static collusive levels, increases the returns to cheating at the same time. To maintain incentive compatibility, cartel must increase either the punishment period or the trigger price (Porter, 1983, pp. 301-302).

Porter (1983) seeks to identify the occasional switches between competition and collusion in an historical cartel, Joint Executive Committee (JEC). Cartel is formed by railroad companies shipping grain from Chicago to the East Coast. JEC, predates the Sherman Act, so it is well-documented. Using a switching regression model with two regimes, collusion and competition periods are identified, and supply and demand parameters are estimated. The estimates suggest that price predicted by dynamic collusion is between price predicted by static collusion and Cournot. Under collusion, total revenue is 11 % higher than competitive levels[11][12].

Working on OPEC pricing in 1973–2004, Almoguera et al. (2011) build on Porter (1983) by incorporating a competitive fringe. The findings indicate that OPEC

[11]There is reason to believe these are conservative estimates. Ellison (1994) builds on Porter (1983) by incorporating serial correlation on demand side and Markov structure in transition between collusion and punishment. The estimates suggest that the impact of collusion is higher than previously believed (p. 42-43).

[12]For another work with similar methodology see Grant and Thille (2001), which focus on gas lamb oil trust in Ontario Canada in the 19th century.

is better characterised as a non-cooperative Cournot game, which is occasionally interrupted by collusion rather than the other way around. Similarly, Fabra and Toro (2005) use daily data from Spanish electricity market in 1998 build on Porter (1983), by modelling a Markov transition between collusion and punishment[13] and by experimenting with alternative triggers: market share, concentration (HHI), revenue and average market price.

Applicability of Structural Estimation

On the plus side, structural estimation has many strengths. First, since data from competitive periods/regions is not necessary to estimate competitive benchmark, it has low data requirements. Second, it allows researcher to experiment with multiple market structures. Third, it allows estimating *price overcharge*, *output effect*, and *pass-on effect* separately. Consequently, regarding any change in conduct, it makes a welfare assessment possible (Brander and Ross, 2006, p.349-351).

However, as mentioned above these strengths are coupled with some challenges. Above I mentioned identification issues associated with simultaneity of demand and supply; sensitivity of results to functional form; difficulty in communicating to a non-professional audience; sensitivity of results to conduct assumption; impact of ignoring dynamic considerations on the estimates. In our setting, there are some other factors that complicate usage of structural estimation techniques. First, data set is consumer level transaction data. This means market power of providers vary; consequently, assuming perfect competition and estimating system of equations would not be appropriate. Second, data set spans 18 months. This includes a collusive period, a transition period, and presumably a competition period. However, it is not straightforward to identify if transition is complete; or, if so when it had been complete (and competition started).

As a result of these complications, I do not engage in structural estimation, and leave it as a potential direction for future research. Rest of the analysis focus on reduced form estimation techniques.

4.2.2 Reduced Form Methodologies

In reduced form analysis, the aim is estimating the impact of on price (the overcharge effect, or simply overcharge). Output effect, and pass on effect are ignored. Overcharge is approximated by

$$OR_t = \frac{p_t^m - p_t^c}{p_t^c} \tag{4.3}$$

[13] Similar to Ellison (1994).

where OR_t is the overcharge rate p_t^m is the observed collusive price, p_t^c is the price that would have prevailed in the absence of collusion, or *but-for price*. Since p_t^c is the only unknown, for this approximation to work, an accurate prediction of p_t^c must be made.

Next four subsections present alternative approaches in reduced form estimation; namely, before and after, dummy variable approach, forecasting and yardstick method. DiD methodology and literature are explored in the next chapter in comparison with merger retrospectives.

Before and After

Before and after uses only time series of the cartelized product. First, collusion and competition periods are identified. If collusion covers *t-j* and *t*, estimate for the *but-for price* – price that would have been observed in the market absent the collusion – bases on price from *t-j-k* to *t-j-1* and/or from *t+1* to *t+l*. Typically, as the estimate, average price in the competitive period(s) is (are) used. As Davis and Garcés (2009) point out, it is difficult to suggest that there is a great deal of economics involved in before and after, since demand and cost shifters are not controlled for[14]. It should rather be perceived as a simple approximation, which might be significantly biased unless demand and supply are exceptionally stable (p.354-56). Moreover, if there are multiple episodes of competition and collusion, it might be difficult to modify the analysis[15].

An example of this approach is Notaro (2014), estimating the overcharge in pasta cartel in Italy. Italian competition authority, *AGCM*, fined pasta producers for a total of 12.5 million Euros. AGCM claimed that using cost shocks as a cover, pasta producers agreed to fix the list price during October 2006 – March 2008. In the study, basing on monthly industry level data in 2000 – 2009, the impact of the cartel on price is estimated. Naturally, this requires identifying the impact of the cost increases and regime switch. In the study, before and after analysis corresponds to comparing the average price in cartel period and competition period. The difference in two periods is approximately 15 %.

Another example is Nelson (1993), studying the second hand police car auctions in New York City. Police cars are renewed after certain age and mileage; the old cars are sold. The study tracks an alleged conspiracy in these auctions. As the case is settled in early stages of investigation, there is no information with regards to exact form of coordination, or to the identities of colluders. However, an initial screening suggests that March–May 1990 is the most suspicious period. Data set includes winning bid, reference price, number of firms, and quality measures are available for 340 vehicles sold at 13 auctions in January 1990 – May 1991. Additionally a

[14] Friederiszick and Röller (2010) and Maier-Rigaud and Schwalbe (2013) consider dummy variable approach and forecasting as special cases of before and after method. I follow Davis and Garcés (2009) (and majority of the literature) and consider each of them separately.

[15] See Davis and Garcés (2009), Figure 7.3.

measure of expected price ("book value"), which base on price of similar car models, is available for each auction. In the study, before and after is used as one of the methods to estimate overcharge. Average price–expected price ratio in competition period is multiplied by average expected price in collusion period to give but-for price estimate.

Some other examples in the literature include Bolotova et al. (2008b); Howard and Kaserman (1989).

Dummy Variable Approach

In dummy variable approach[16], using all the available data (t-j-k to t+l) price, p_i, is regressed on control variables i.e. demand and cost shifters z_i, χ_i; and a variable of interest r_i, an indicator variable marking collusive periods.

$$p_i = \alpha_0 + \alpha_1 z_i + \alpha_2 \chi_i + \alpha_3 r_i + v_i \tag{4.4}$$

The coefficient of the indicator variable, α_3, is interpreted as the impact of collusion on price. The dummy variable approach is an improvement over before and after method, as it includes demand and cost controls. Its validity does not depend on a specific structural form. It is intuitive and easy to communicate (Brander and Ross, 2006, p.353). However it still involves relatively strong assumptions: The regime switch is instant. The impact of collusion on price is captured exclusively by a dummy variable. The set of variables and how they affect the price are identical across regimes[17] (Nieberding, 2006, p.368-69).

Some of these assumptions can easily be relaxed. Parameter equality across regimes can be addressed by interaction dummies. The impact of the instant regime switch assumption can be mitigated by introducing transition dynamics. Some challenges are more difficult to address. First, identification requires data from both infringement and non-infringement periods. Data should ideally be spanning a relatively short period of time, as time period under investigation expands, structural features of the market that is assumed to be constant are susceptible to change. At the same time, data should include variation high enough to make precise identification possible. Second, it is known that cartels have phases. Ability to increase price might differ within the life span of the cartel. Averaging out the impact might give imprecise estimates. Third, collusion is known to be proceeded by unsustainably harsh periods of competition, price wars[18]. In that case using the precartel price to form the competitive benchmark is likely to lead to underestimation of but-for price, and overestimation of harm. Similarly, using postcartel period might also be problematic. The experience of explicit collusion

[16] Also known as indicator variable approach.
[17] Known as the assumption of parameter equality across regimes.
[18] Such as a punishment phase in a dynamic collusion model.

might make tacit collusion easier, and the effect of collusion might stay on the market (Brander and Ross, 2006, p.351-55)[19].

An example of this approach is Cramton and Schwartz (2002), tracking the Federal Communication Commission (FCC) electromagnetic spectrum licenses. FCC auctions are structured as simultaneous bidding in multiple rounds. At each round, parties submit bids or update their bids for the blocks[20] they are interested. Bidding continues until the round in which no single bid is increased. When bidding ends, licenses are granted to highest bidders. It is claimed that six firms have been practising *code bidding* in 40% of the auctions: The last three digits of the bids of these six bidders were carrying a message to co-conspirators about licence numbers they should withdraw from. Receiving the message, other members stopped being aggressive in the indicated license. In the study, estimating the impact of code bidding on the winning bid is one of the empirical objectives. To this aim, a variation of the dummy variable approach is used. Winning bid is regressed on the variable of interest, an indicator variable implying presence of code bidding; and control variables, i.e. regional demographics, regional income, competition in the auction. Results suggest that colluders maintained 27–36 %[21] reductions in the winning bids in relation to non-coordinating parties.

Another example is Asmat (2016), studying the DRAM cartel. Investigation was triggered by an immunity application form a cartel member, and ended with a settlement agreement. The infringement involved information sharing and price coordination, and covered July 1998-June 2002[22]. As part of the settlement, the parties agreed to pay a total of 330 million Euros[23].

Asmat (2016) analyses the impact of the conduct on products that are at different stages in their product-cycle. DRAM industry, similar to many high-tech industries, introduces products in successive "generations". Over time, innovation leads to improvement, e.g. faster processing, higher storage; so, new generations replace older ones. The production is characterised by learning by doing; the cost in the next period is partly determined by the level of output this period. It is hypothesized that under these conditions, collusion in newer generations is more difficult to sustain: Incentive to cheat is present in every cartel, as colluders might prefer to trade higher gains in this period with a stream of potential high gains in the future. However, in newer generations, the incentive to *cheat* is fortified, as cheating also providers a strategic edge in the next period in the form of lower cost in relation to rivals. Interestingly, in contrast to newer generations, in older generations, the incentive to *collude* is fortified. Collusion is easier to sustain in older generations; it not only

[19] Brander and Ross (2006) also suggests that tacit collusion may also be facilitated by damages claims following prosecution. If cartel members anticipate that damage estimates depend on postcartel pricing (more aggressive postcartel pricing leads to lower estimates for but-for price, and higher overcharge) a tacit collusion might emerge in postcartel period to keep the price above competitive level (p.355).

[20] Geographical areas.

[21] See, page 11.

[22] http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52011XC0621(03).

[23] http://europa.eu/rapid/press-release_IP-10-586_en.htm?locale=en.

allows higher returns in the older generation sales, but also transfers some part of the total demand to newer generations. Under learning by doing, this translates as lower cost in the next period. It follows that collusion might be characterized by some form of partial collusion: colluding in older generations and competing in newer generations.

Using firm level quarterly data covering 1988–2011 and 11 different generations, the impact of collusion on quantity and price are explored using dummy variable approach. Results support theoretical predictions: For *older generations*, collusion reduces the output sold. After the collapse of the cartel in 2002, trend reverses and output expands. The impact of collusion on price is estimated as 25 %. Regarding *newer generations*, sales increase with transition to collusion. This is accompanied by a reduction in price. The estimates for the price reduction goes as high as 70 %.

Some other examples in the literature include Bolotova et al. (2008b); Boshoff (2015); Hausman (1980, 1984); Howard and Kaserman (1989); Hüschelrath et al. (2013, 2016); Laitenberger and Smuda (2015); Madhavan et al. (1994); Mncube (2014); Nelson (1993); Notaro (2014).

Forecasting

Forecasting, is proposed in response to the limitations of dummy variable approach. Assume a cartel is active from *t-j* to *t* and both price and control variables are observable from *t-j-k* to *t+l*. In a typical forecasting exercise, at the first stage, price is first regressed on control variables using the data from *t-j-k* to *t-j-1* and/or from *t+1* to *t+l* in a reduced form setting[24]. Parameters retrieved from this regression are treated as parameters governing pricing behaviour under competition. At the second stage, parameter estimates interact with independent variables in the collusive period. This gives predicted values for the price that would have been observed under the competition counterfactual.

As an improvement over the dummy variable approach, there is no assumption of parameter equality across regimes. Since the estimation involves only parameters in competition, forecasting remains agnostic about the parameters in collusion. Note that, since there is no parameter equality across regimes, the impact of collusion is not confined to the coefficient of dummy variable. Moreover, in forecasting, the consequences of instant regime switch assumption might be mitigated by the choice of competition period. Finally, since the aim is estimating the competitive benchmark, adherence to collusive agreement over time is also less relevant. Improvements suggest that the forecasting estimates should be less biased. True that may be; there is a cost. Limiting the available data to competitive period reduces precision of estimates. Choosing between two methods involves a trade-off

[24]Technically, if only postcartel data is used to establish competitive benchmark, more precise term would be backcasting. However, literature rarely makes this distinction. See Nieberding 2006, p.369 or Werden et al. 1991, p.343 for this distinction.

between unbiasedness and efficiency (Howard and Kaserman, 1989, p.381).

An example is Lee and Hahn (2002) tracking the impact of 1997 financial crisis on collusive incentives in South Korea. Prior to the crisis, common understanding was, the construction industry is highly collusive. The crisis had a great impact on the construction sector. In one year, construction industry shrank by 37 %. Collusive incentives were replaced with survival instincts; many firms exited and remaining ones started to compete to stay in the market. The empirical objective is assessing the likelihood of a regime switch from collusion to competition and assessing the impact of this regime change on price. Using bidding data from 63 firms active in construction projects during 1995–2000, Lee and Hahn (2002) first identify two distinct regimes: precrisis (collusion), and postcrisis (competition). Price before crisis is 13 % higher than the price after. Second stage is the overcharge estimation. Basing on data from competitive period, they forecast but-for price for the collusion period. Results suggest that cooperation in the construction sector increased price 14.3–16.3 %.

Another example is Boshoff (2015) tracking the bitumen cartel active in South Africa. The competition law in South Africa was adopted in 2000; prior to which, bitumen firms were running a legal cartel. After collusion being illegal, firms adopted a more discrete approach. They used industry association as a medium of coordination. Association determined a pricing formula to regulate the changes in wholesale price. South African Competition Authority fined bitumen producers 68 million South African Rand. The forecasting analysis corresponds to first retrieving coefficient estimates using country level data from a panel of other countries, then interacting these estimates with values of South African independent variables.

Some other examples in the literature include Howard and Kaserman (1989); Lee (2000); Nelson (1993); Notaro (2014).

Yardstick Method

Yardstick method requires identifying a market i) similar in terms of market structure, demand conditions, and cost structure, ii) not suffering from collusion. This might be a similar product in the same geographical market or the same product in another geographical market. If a market satisfying these two conditions is identified, it might be easier to control for demand and cost shifters (Davis and Garcés, 2009, p.360). Another benefit of yardstick approach is that it might help dating the start (end) of conspiracy by identifying the time when parallelism in benchmark market and affected market ceased (re-emerged) (Brander and Ross, 2006, p.346).

An example is Carlton et al. (1995), studying the antitrust case that surrounds the Ivy League Schools and Massachusetts Institute of Technology (MIT). In May 1991, US Department of Justice (*DoJ*) announced that an antitrust case had been filed against 8 Ivy League schools and MIT. *DoJ* claimed that these universities

regularly met in "Overlap Meetings" and in these meetings they were agreeing on how to determine the size of family contribution and the scholarship[25]. Carlton et al. (1995) explore *DoJ* allegations and investigate if the conduct had any impact on the price using yardstick method. By tracking 225 private and public schools in 1984–1990, the behaviour of the defendants is compared to the behaviour of the rest of the colleges. Price is regressed on many factors, including participation to Overlap Meetings. The results suggest that price differences across schools are primarily governed by structural features, e.g. public vs. private, quality, and income level of the enrolled students. Participation to Overlap Meetings has no significant impact on price.

Another example is Lee (2000), focusing on school milk auctions in Dallas Forth Worth in 1980s. Eleven firms were prosecuted of bid rigging; nine reached a settlement with the state. In order to estimate the overcharge Lee (2000) suggests a fusion of forecasting and yardstick. Recall that forecasting requires modelling competitive behaviour and retrieving parameters using competitive period data. Using these parameters but-for price is retrieved. However, Dallas Forth Worth data does not have enough observations in competition period. Parameters in competition period are retrieved using data from San Antonio, which has a similar market structure but is not contaminated with collusion. Comparing actual price and but-for price, the overcharge estimate ranges in 9.3–15.45 %, averaging 11.74 %.

However, the most popular yardstick methodology is DiD, which is explored in the next section.

4.3 *Ex Post* Analysis and Difference-in-Difference

The intuition of DiD methodology within the framework of *ex post* analysis is best illustrated by Ashenfelter et al. 2009, (pp. 6-9). Consider following pricing relation in the treated market,

$$p_t^T = \delta_0^T + \gamma_t^T + \delta_1 \gamma_t^{post} + \upsilon_t \tag{4.5}$$

where p_t^T is the price in the treatment market at time t, δ_0^T is the intercept; γ_t^T captures any factor that impact pricing over time (i.e. demand, cost shifters); γ_t^{post} is an indicator for posttreatment period. Equation implies that at any time t, price in the treated market is determined by three factors: i) initial price level, δ_0^T; ii) time varying factors that influence price, γ_t^T; iii) treatment, γ^{post}. Without properly controlling time varying factors, it is not possible to estimate δ_1 consistently.

One way of controlling time varying factors is including them into the model. If the

[25] https://www.justice.gov/archive/atr/public/press_releases/1991/325032.pdf.

researcher believes that the time varying factors are related to observable demand shocks, z_t and cost shifters, χ_t in the following way,

$$\gamma_t^T = \alpha_0 + \beta_1 z_t + \beta_2 \chi_t + \epsilon_t \tag{4.6}$$

by plugging z_i and χ_i into Equation 4.5, it is possible to identify the impact of the treatment in the treatment market. Resulting pricing relation in this case is the same with the one in the dummy variable approach, Equation 4.4. Note that consistency of δ_1 critically rests on the assumption of $E\left[\upsilon_t \gamma_t^{post}\right] = 0$; all time varying factors that might impact pricing and change around the treatment time are controlled. If not, δ_1 fails to capture exclusively the impact of the treatment; it also captures other treatments hidden in υ_t.

Another way of controlling time varying factors is using a control market. Sticking to the Ashenfelter et al. (2009) terminology, consider a control market in which price is determined by

$$p_t^C = \mu_0^C + \mu_t^C + \mu_1^C \gamma_t^{post} + \vartheta_t \tag{4.7}$$

where p_t^C is the price, in control market at time t; μ_0 is the intercept; μ_t^C captures any time varying factor; and γ_t^{post} is an indicator for posttreatment observations. In this case, using difference in price across markets and difference in price before and after treatment, it is possible to eliminate the impact of time varying factors on price and to identify the impact of the treatment if

- Two markets have similar demand and cost conditions[26], implying $\gamma_t^T - \mu_t^C = 0$,
- Control market is not affected from the treatment, implying $\mu_1 = 0$.

4.3.1 Collusion Retrospectives and Difference-in-Difference

Collusion retrospectives, on top of any challenges associated with reduced form techniques, highlight two challenges specific to DiD. First is the increased data requirements. In addition to the treatment market, now the researcher needs data from the control market as well. Note that not any market can be a control market. It must have similar demand and cost conditions, yet must be unaffected from the treatment (Hüschelrath et al., 2013, p. 103). Second challenge is disentangling the impact of the treatment and the co-occurring factors. Therefore, the researcher must be sure about absence of any unobservable co-occurring factor that is affecting the treatment market uniquely and having an impact on price. (Coatney and Tack

[26]Similarity in demand and cost conditions is not considered as sufficient by some. I am going to revisit this issue later.

2014, p. 431, Oxera 2009, p. 61). In other words, for identification, it might be an improvement not to rely on $E\left[\upsilon_t \gamma_t^{post}\right] = 0$ only if, $E\left[\gamma_t^{post}\left(\gamma_t^T - \mu_t^C\right)\right] = 0$.

A typical DiD specification would look similar to,

$$p_i = \alpha_0 + \alpha_1 z_{st} + \alpha_2 \chi_{st} + \alpha_3 \gamma_t^{post} + \alpha_4 \gamma_s^{treated} + \alpha_5 \gamma_t^{post} \gamma_s^{treated} + \epsilon_i \tag{4.8}$$

where, the treatment is the regime switch; z_{st} refers to demand shifters; χ_{st} refers to cost shifters; γ_t^{post} is an indicator variable that marks posttreatment observations; and $\gamma_s^{treated}$ marks the treated observations, the locations affected from the regime switch. Consequently, α_3 captures the impact of unobservable factors that change over time, while α_4 captures the impact of unobservable time-invariant differences between treated and not treated regions. α_5 is the coefficient the researcher is after; it captures average treatment effect, the impact of the regime change. Some examples in the literature using this specification would include Erutku and Hildebrand (2010); Hüschelrath et al. (2013); Laitenberger and Smuda (2015); McCluer and Starr (2013).

An example collusion retrospective with DiD is McCluer and Starr (2013), studying the *Marshfield/Blue Cross Blue Shield (BCBS)* case. Marshfield offers multispecialty physician services. BCBS offers health care plans. In 1994, BCBS went to court, and accused Marshfield and its rivals of market allocation and price fixing. McCluer and Starr (2013) describe the economic analysis done by BCBS consultants. Marshfield and 8 surrounding counties are defined as the treatment market. Rest of the Wisconsin is defined as the control market. Estimation is done using BCBS individual claims data. After controlling for the differences across individual characteristics, i.e. sex, age, marital status; the differences in insurance plans, i.e. comprehensiveness of the plan, type of the employer; and the differences in county characteristics, i.e. income, unemployment rate, population growth, findings suggest that around 50 % of the price increase in the treatment market is associated with collusion.

Another example is Laitenberger and Smuda (2015), studying the European detergent cartel. They use transaction data in estimating overcharge. First, dummy variable approach is employed. This involves estimating independent pricing equations for each group of competitors (colluders, private brands, and independent manufacturers), while controlling for product characteristics, retailer specific features and demand and cost shifters, and capturing the impact of collusion by an indicator variable. The results suggest that cartel increased price 6–7 %. Private labels followed the cartel and increased their price 2.6 % in an umbrella pricing fashion, but independent brands did not. Basing on these findings at the second stage DiD is used. In this, independent manufacturers, whose behaviour is relatively less contaminated by the cartel, are taken as the control group. DiD estimates are around 6-7 %, similar to dummy variable approach estimates.

Another frequently used specification, is a variation of Equation 4.8.

$$p_i = \alpha_0 + \alpha_1 z_{st} + \alpha_2 \chi_{st} + \alpha_3 \gamma_t^{post} \gamma_s^{treated} + \sum_t \beta_s \gamma^s + \sum_t \delta_t \gamma^t + \upsilon_i \tag{4.9}$$

Here, γ_t^{post} and $\gamma_s^{treated}$ are replaced with location and time fixed effects, γ^s, γ^t. Some examples in the literature using this specification would include Coatney and Tack (2014); Kamita (2010).

Kamita (2010) studies airline market in Hawaiian archipelago, in particular the impact of the antitrust immunity given to two incumbents in July 2002. Hawaiian archipelago is compared with two different control markets: (i) these with similar cost structure, i.e. West Coast flights; (ii) these with similar demand structure, i.e. East Coast flights. Estimations suggest that list price increased 48–129 % as a result of the immunity. However the effective price (net of discounts) increased 10–18 %. High price stretches to 2.5 years after immunity expires.

Some other collusion retrospectives in the literature that use DiD include Coatney and Tack (2014)[27]; Erutku and Hildebrand (2010); Hüschelrath et al. (2013, 2016).

4.3.2 Merger Retrospectives and Difference-in-Difference

Even though there had been previous attempts to analyse the impact of mergers, the popularity of merger retrospectives increased in early 2000s. There are at least two reasons for this.

First is the poor performance of the US Government in challenging hospital mergers in 1990's. Fales and Paul (2014) provide a detailed record of government's defeats in courts[28]. In many cases, the courts ruled in favour of the defendants on the grounds that government failed to i) establish product market, ii) establish geographical market, iii) show emergence of market power after merger, or iv) show anticompetitive effects. Conducting merger retrospectives was one of the measures FTC took in order to convince courts on the effects of mergers[29]. FTC staff published three papers[30] (Haas Wilson and Garmon, 2011; Tenn, 2011; Thompson, 2011). In fact, following retrospective analysis, one of the mergers – Evanston/Highland Park – has been successfully challenged and the transaction was modified after it was closed[31]. Second reason for the increased popularity of merger retrospectives is the

[27] Coatney and Tack (2014) study the impact of an antitrust investigation, rather than a cartel.

[28] See, Figure 1, p. 33 for a summary.

[29] Other measures included more selective challenging, modernization of geographical market definition, and developing a new theory of harm building on bargaining power of hospitals and insurance companies.

[30] For a brief summary of the merger retrospectives in FTC regarding hospitals, see, Farrell et al. (2009).

[31] This is particularly interesting because parties reported the merger under Hart–Scott–Rodino Act (1976), and government took no action. Consequently, parties closed the transaction. FTC challenged the case retrospectively 3 years after closure. Modification to the transaction involved

emergence of empirical evidence, e.g. GAO (2004); Hastings (2004), which associate merger activity in petroleum industry with price increase. FTC took the evidence seriously, and conducted many petroleum merger retrospectives, e.g Taylor et al. (2010) (in reply to Hastings (2004)); Hosken et al. (2011); Silvia and Taylor (2013); Simpson and Taylor (2008); Taylor and Hosken (2007)[32]. The retrospectives rapidly spilled over to other industries in collaboration with great names in the program evaluation literature such as Orley Ashenfelter[33]. Next part presents this literature and the methodologies with an emphasis on the empirical strategy employed. I take merger retrospectives in three groups: i) conventional merger retrospectives, ii) merger retrospectives that use spatial variation in identifying treatment and control groups, iii) merger retrospectives that take a treatment intensity approach.

Conventional Merger Retrospectives

It is safe to say that merger retrospectives are most frequently conducted in petroleum industry. The list includes Hosken et al. (2011)[34], Jiménez and Perdiguero (2014)[35], Kreisle (2015)[36], Silvia and Taylor (2013)[37], Simpson and Taylor (2008)[38], Taylor and Hosken (2007)[39] [40]. There are a large number of common features across these studies. Treatment market is chosen from regions which are most adversely affected from the merger. This is followed by a thorough evaluation of treatment market conditions, i.e. sources of supply; distance to supply; potential outages, and capacity constraints; presence of merging parties; intensity of rivalry; local formulation of gasoline; local environmental regulations. Next, the market that best approximates to the conditions in the treatment market is taken as the control market. Typically, Oil Price Information System (OPIS) data is used[41]. At the wholesale level, this involves refiner specific price quotes; at the retail level, this involves transaction data from stations accepting fleet cards. The empirical strategy is regressing the price difference between treatment and control markets on an indicator variable, which marks the treatment time, and other indicator variables

a behavioural commitment; each Evanston hospital was required to negotiate separately with insurance companies. See, Fales and Paul (2014) for details (pp. 31-32, FN. 14-15).

[32]FTC publishes a yearly paper in *Review of Industrial Organization*, themed "Economics at the FTC" summarizing the input FTC Bureau of Economics provided to antitrust enforcement. It is also possible to track the wave of merger retrospectives in petroleum and hospitals in 2005, 2006, and 2009.

[33]See, Ashenfelter and Hosken (2010); Ashenfelter et al. (2013, 2014, 2009).

[34]UDS/Tosco merger.

[35]DISA/Shell merger.

[36]Western Refining/Giant Industries merger.

[37]Sunuco/El Paso and Valero/Promcor mergers.

[38]Marathon Ashland/Ultramar merger.

[39]Marathon/Ashland merger.

[40]Hastings (2004); Hastings and Gilbert (2005); Houde (2012); Pennerstorfer and Weiss (2013); Taylor et al. (2010) are also petroleum merger retrospectives. They are explored in the upcoming sections.

[41]Jiménez and Perdiguero (2014), study a European merger, hence do not use OPIS data.

for calendar months[42]:

$$p_i^T - p_i^C = \alpha_0 + \alpha_1 \gamma_t^{post} + \sum_m \beta_m \gamma^m + \upsilon_i \tag{4.10}$$

In this specification, p_i^T is the price in treatment market, p_i^C is the price in control market, γ^m represents calendar month and captures seasonality, γ_t^{post} is an indicator variable marking the posttreatment observations, hence the variable of interest. Generally separate estimations are made for wholesale vs. retail, regular gasoline vs. diesel, or branded vs. unbranded.

In hospital merger retrospectives (Haas Wilson and Garmon (2011)[43], Thompson (2011)[44], Tenn (2011)[45]) empirical strategy is similar; analysis centres on the provision of general acute care services for inpatients, in particular the relation between hospitals and the insurance companies. Retrospectives are concerned with the impact of increase in hospitals' bargaining power on price. They typically use individual level claims data provided by insurance companies. Merging parties are taken as the treatment group; hospitals of similar nature[46] in the rest of the state constitute the control group. Empirical strategy is identifying the impact of the merger via regressing price on a variable of interest; hospital fixed effects; and a set of controls, i.e regional demographics, and insurance plan characteristics, hospital characteristics[47].

Definition of treatment and control groups is similar in airline merger retrospectives (Kwoka and Shumilkina (2010)[48], Gayle (2008)[49], Luo (2014)[50], Dobson and Piga (2013)[51]). Routes unaffected from the merger – these in which merging parties do

[42]Occasionally some controls are employed as well. Taylor and Hosken (2007) use crude oil price, Simpson and Taylor (2008) use indicator variables marking pipeline raptures. Jiménez and Perdiguero (2014) follow a more conventional DiD specification, like Equation 4.8, and use transport cost and gasoline price as control.

[43]Evanston Northwestern Healthcare/Highland Park Hospital, and Provena St. Therese Medical Centre/Victory Memorial Hospital mergers in Chicago.

[44]Summit Hospitals/Sutter Hospitals merger in San Francisco, California.

[45]New Hanover Regional Medical/Cape Fear Memorial Hospital merger in North Carolina.

[46]If merging parties are teaching hospitals, the control group is composed of teaching hospitals. Similarly, large hospitals, hospitals with residential programs are compared with similar hospitals. Federal hospitals, and hospitals that were party to another recent merger are eliminated from the control group.

[47]Tenn (2011); Thompson (2011) prefer a less conventional multi stage approach. At the first stage, price is regressed on a set of controls, and a set of indicator variables each marking a quarter and hospital combinations. At the second stage, for each hospital, price change from pretreatment to posttreatment is calculated. This is done by taking the averages of the posttreatment and pretreatment quarter effects respectively, and subtracting the latter average from the former. At the final stage, price change is regressed on an intercept and an indicator variable marking merging parties. The coefficient of the indicator variable is interpreted as the impact on price.

[48]USAir/Piedmont merger.

[49]Delta/Continental/Northwestern codeshare agreement.

[50]Delta/Northwestern merger.

[51]Ryan Air/Buzz and Easy Jet/Go Fly mergers.

not operate together – are taken as the control. Methodology involves regressing price on a variable of interest and a set of controls, e.g. flight characteristics, route characteristics, airport characteristics, or demographics, using a specification similar to Equation 4.8

FMCG[52] merger retrospectives (Friberg and Romahn (2015)[53], Tenn and Yun (2011)[54], Ashenfelter and Hosken (2010)[55], Weinberg (2011)[56], Weinberg and Hosken (2013)[57] differ from other retrospectives as competition is defined on product space. Consequently, merging party products are taken as the treatment group[58]. Ashenfelter and Hosken (2010); Weinberg (2011); Weinberg and Hosken (2013) take private label products as the control group; Friberg and Romahn (2015); Tenn and Yun (2011) take rivals that are not affected by the merger as the control group. In the analysis, scanner data is used. Ashenfelter and Hosken (2010) employ a specification similar to

$$p_i = \alpha_0 + \alpha_1 \gamma_t^{post} + \alpha_2 \gamma_t^{post} \gamma_s^{treated} + \sum_{ct} \beta_{cs} \gamma^{cs} + \sum_m \delta_m \gamma^m + \upsilon_i \tag{4.11}$$

for product s, city c, time t, calendar month m where, γ^{cs} is city-product fixed effect. γ_t^{post} is an indicator marking postmerger observations. γ^m is an indicator for calendar month and captures seasonality. $\gamma_s^{treated}$ marks merging party products. Other FMCG retrospectives also follow similar specifications[59]. Friberg and Romahn (2015); Weinberg (2011) replace γ_t^{post} with time fixed effects[60]. Weinberg and Hosken (2013) add cost indicators (price for crude petroleum for motor oil merger, and price of corn syrup for maple syrup merger) as controls.

Some other examples in the literature that use similar methodology are Aguzzoni et al. (2014), looking at a merger of two videogame outlets, Game/Gamestation, in

[52]FMCG can be defined as products that are geared towards household consumption and typically consumed, and replaced rapidly, e.g. foodstuffs, cosmetics, cleaning products, and drugstore products. See, http://europa.eu/rapid/press-release_IP-15-5375_en.htm.

[53]Carlsberg/Pripps merger in Sweden.

[54]Pfizer/Johnson & Johnson merger.

[55]Quaker State/Pennzoil, Log Cabin/Mrs. Butterworthy, Guinness/Metropolitan, Always/Tambrands, General Mills/Chex mergers.

[56]Always/Tambrands merger.

[57]Quaker State/Pennzoil, and Log Cabin/Mrs. Butterworthy mergers.

[58]Friberg and Romahn (2015) track a case that involves divesture. Consequently, in addition to merging parties, the divested brand, and the third party acquiring the divested brand are also taken as part of the treatment group. Tenn and Yun (2011) are primarily concerned with the performance of divested brands. Therefore treatment group is the divested brands.

[59]An application of a similar empirical strategy to another industry is done by Ashenfelter et al. (2013), studying a merger of two producers of home appliances, Whirlpool/Maytag, using scanner data. The merger reduces the number of domestic producers from four to three. Parties considerably overlap in the production of cloth washers, dryers, dishwashers, and refrigerators. These appliances constitute the treatment group. The overlap is little to none in the production of freezers, cooktop, oven, and ranges. These appliances constitute the control group.

[60]Friberg and Romahn (2015) use aggregated data, so they employ only product fixed effects.

the UK; Calomiris and Pornrojnangkool (2005) studying a banking merger in US, Bank Boston/Fleet; DGComp (2015) focusing on in mobile telecommunications, T-Mobile/Telering merger in Austria, and T-Mobile/Orange merger in the Netherlands.

Using Spatial Variation

Some works in the literature use spatial variation in identifying the impact of the merger. An example is Hastings (2004), studying regional effects of a petroleum merger, Thrifty/ARCO, using a private data set that provides station level information, i.e. individual characteristics and posted price. Empirical objective is identifying the impact of elimination of an independent brand, Thrifty, on the other stations. Naturally, this requires a local analysis; elimination of Thrifty stations would have an effect on the behaviour of another station only if that station was close to a Thrifty station before the merger. The stations that were in close proximity to a Thrifty station before the merger constitute the treatment group. On the other hand, merger will have no impact in regions where there were no Thrifty stations before merger. The stations in these regions constitute the control group. Hastings (2004) identify the impact of merger via

$$p_i = \alpha_0 + \alpha_1 \gamma_{st}^{contract} + \alpha_2 \gamma_{st}^{comp} + \sum_{ct} \beta_{ct} \gamma^{ct} + \sum_{s} \delta_s \gamma^s + \upsilon_i \tag{4.12}$$

where s is station, c is city, t is month. γ^{ct} refers to city time fixed effects. γ^s refers to station fixed effects. $\gamma_{st}^{contract}$ is an indicator variable that controls for a contractual change. γ_{st}^{comp} is the variable of interest; it is an indicator variable marking the stations which were competing with a Thrifty station before the merger. For control stations, the indicator takes value 0 both before and after the merger. For treatment stations, it takes value 1 before the treatment, and 0 after the treatment. The findings suggest that the merger had significant effect on retail price; stations that were previously competing with independent brands to raise price 5 cents per gallon, which corresponds to 50 % of retail margins (Taylor et al., 2010, p.1269). Methodology offered in Hastings (2004) has been employed in similar settings by others. First study is a work by FTC staff and primarily is about replicating the methodology in Hastings (2004) using a more comprehensive dataset. Taylor et al. (2010) suggest that the impact of the merger on price was marginal at best. Second study Houde (2012) focus on regional effects of another petroleum merger, acquisition of Sunoco bu Ultramar, in Quebec City Canada, using a private data set that provides station level information, i.e. individual characteristics, posted price. Houde (2012) builds on Hastings (2004) via estimating a separate treatment effect for the merging parties, and competitors[61].

Another example is Aguzzoni et al. (2016), studying Waterson/Ottakar merger in the UK retail book market, and Argentesi et al. (2016) studying C1000/Jumbo merger in

[61] See, p. 2172.

Dutch retail grocery market have similar empirical strategy. First step is identifying the regions affected from the merger. Employing market definitions used by the competition authority, the geographic markets in which parties were competing with each other before merger (overlap regions) are identified. In these regions, after the merger, the number of competitors drops by one. In other regions (non-overlap regions), number of competitors remains unchanged. Using a matching approach, overlap regions (treatment markets) are matched with non-overlap markets on the basis of demand indicators, i.e. demographics, social and economic indicators; measures of competition, i.e. number of rivals, regional HHI; or cost indicators, i.e. housing price. Finally, the impact of merger is identified by regressing price on a variable of interest, indicators of demand and cost, and measures of competition in a conventional DiD specification. Findings indicate that neither Jumbo/C1000, nor Waterson/Ottokar merger had an impact on price.

Final example I cover here is Allen et al. (2014), studying an undisclosed merger in the Canadian mortgage market, using insurance administration data at contract level. In regions where activities of merging parties overlap, the merger reduces the number of available lenders by one. These locations are taken as treatment market. On the other hand, in other regions where only one or none of the merging parties is present, the merger has no impact. These locations are taken as control market. Naturally, the impact of the merger depends on the number of remaining lenders in the market. To homogenize the treatment effect, Allen et al. (2014) limit the treatment and control regions to areas in which borrowers have 5-8 lender options. In the study, three different DiD estimations are done. First specification is a variant of Equation 4.9, where dependent variable, transaction mortgage rate net of government bond rate, is regressed on a variable of interest, region and time fixed effects, and a set of controls, i.e. borrower income, credit score, residential status of the borrower, existing debt, the price of the property, loan to value indicators[62]. Second specification interacts the controls with posttreatment indicator and adds linear and quadratic time trends. Third, Allen et al. (2014) combines DiD and matching, where the markets are matched with four closest neighbours on the basis of propensity score. Findings indicate a small increase in mortgage rates, 6 basis point, associated with the merger[63].

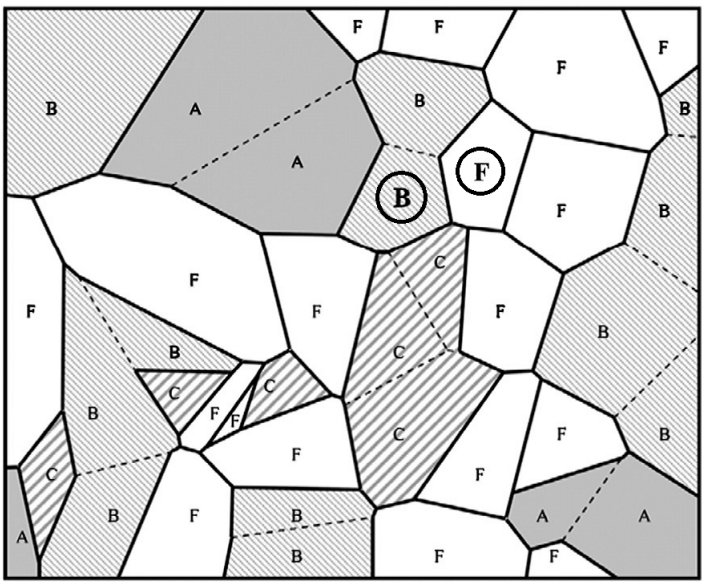
Treatment Intensity

As the examples given so far illustrate, the works that use spatial variation to identify the impact of a merger, benefit from this variation in the determination of treatment and control groups. Outlets of the parties to the transaction, and their close competitors are considered "treated", while further away regions are considered "not treated". Little attention is paid to the variations in the intensity

[62]See, Table D2 in online appendix.

[63]This corresponds to 5 Canadian Dollars increase in monthly payments for a mortgage of 150,000 Canadian Dollars. Considering the analysis is confined to areas with 5-8 lender options, small size of the estimate should not be surprising (p. 3379).

Figure 4.2: Spatial Clusters



Source: Figure 2 in Pennerstorfer and Weiss (2013).

of the treatment within the treated regions. The assumption here is that two outlets, one located right across the street to merging party outlet, and the other right on the border separating treated and not treated regions; both receive the same treatment. Works in this part challenge this assumption, and exploit variations in the intensity of treatment.

Pennerstorfer and Weiss (2013) study regional effects of an Austrian petroleum merger, acquisition of Arai by BP, using a public data set that provide station level information, i.e. individual characteristics, posted price. The idea is that the distribution of treatment effect might be governed by the distribution of the stations, and the identity of merging parties. Consider five gasoline stations in one dimensional world that are controlled by three rival undertakings A, B, C. Let the researcher be interested with the impact of a merger between A and C. If before merger the sequence of the stations is $A_1 - B_1 - C - B_2 - A_2$, after the merger, the intensity of the competition will be unchanged. Instead, if the sequence of the stations is $B_1 - A_1 - C - A_2 - B_2$, after the merger, as a result of clustering of A stations, only $B_1 - A_1$, and $A_2 - B_2$ will be competing with each other. In two dimensional world, Pennerstorfer and Weiss (2013) propose measuring clustering as follows: Consider in the market, there are three undertakings with multiple stations, A, B, C, and a number of independent stations, F, each belonging to a different undertaking. Let the stations be distributed as illustrated in Figure 4.2.

Spatial clustering around each station i is measured by an index, $SC_i \equiv \sum_{m_i} \frac{k_{m_i i}}{M_i} / N_i$, where, $k_{m_i i}$ refers to number of stations in any cluster m_i; M_i refers to number of clusters; N_i refers to number of adjacent stations. To understand the index better, let us follow the example in Pennerstorfer and Weiss (2013): the circled station B, has six adjacent neighbours; meaning $N_i = 7$. Seven stations are

distributed on five clusters (two independent – one cluster each, and clusters of two B, three C, one A); meaning $M_i = 5$. Employing the formula, the spatial clustering around circled B station is $SC_i = \frac{\frac{2}{5}+\frac{1}{5}+\frac{3}{5}+\frac{1}{5}+\frac{2}{5}}{7} = \frac{9}{35}$. If the independent station that is circled in the figure is acquired by one of the multi station undertakings, the index value changes. The size of the change depends on the identity of the acquiring undertaking (and the distribution of stations). If the acquiring firm is B, total number of clusters falls by one and size of SC increases. If the acquiring firm is A, change in SC is zero because A does not have any stations neighbouring the acquired independent station (p. 665).

In this context, the treatment group is defined as the stations with a change in clustering index; the control group is defined as the stations with no change in clustering index. Empirical methodology builds on Hastings (2004). Specification used in estimation is a variation of

$$p_i = \alpha_0 + \alpha_1 \gamma_{st}^{BP} + \alpha_2 \gamma_{st}^{comp} + \alpha_3 SC_{st} + \sum_t \beta_t \gamma^t + \sum_s \delta_s \gamma^s + \sum_l \lambda_l z_{st} + \upsilon_i \quad (4.13)$$

where s is station, t is time. γ^t refers to time fixed effects. γ^s refers to station fixed effects. z_{st} refers to time variant station characteristics, i.e. amenities in the station, size of the station, working hours, land price; and regional characteristics, i.e. number of commuters, tourism indicators, population density. γ_{st}^{BP} marks stations subject to merger. γ_{st}^{comp}, as in Hastings (2004), indicates station s was competing with an Arai station premerger. SC_{st} is the variable of interest. *"The change in spatial clustering can be considered a treatment' effect of a change in a continuous variable indicating if and to which extent a location is affected by the merger (p.665)"*. The findings provide valuable insight. Results suggest that even though the impact of the merger in overall price level is insignificant, there are sizeable local increases in price.

Choné and Linnemer (2012) study the effects of a merger of two Paris carpark operators, GTM and Vinci, using a public data set providing outlet specific information, i.e. individual characteristics, posted price. Choné and Linnemer (2012) note that the approach in Hastings (2004) involves a separation of the stations into two groups: treatment, the outlets that were close to acquired stations before the merger; and control, the stations that were not close to an acquired station. However, this is simply an approximation; as in this approach only first order effects are considered. Treatment effects can pass on to other stations, in particular those in close proximity to the acquired stations. Including stations that are somewhat affected from the treatment into the control group contaminates the control group and leads to inconsistent estimates.

Assume there are six outlets l, i, j, m, n, o, controlled by five undertakings $(i, m), (j), (l), (n), (o)$, as marked with + signs in Figure 4.3. r marks the limiting

distance that a rival can influence the behaviour of another rival. Consider a merger of (i, m) and (j). Outlets of the merging parties that were competing with each other before the transaction (outlets that are in r radius of each other), are directly exposed to the merger. These outlets are defined as "exposed of degree zero", $E^0(r)$. Outlets that are not directly exposed to the merger themselves, but are competing with an outlet that is directly exposed are defined as exposed of degree one, $E^1(r)$. The outlets that are not $E^1(r)$ themselves, but are competing with an $E^1(r)$ outlet are defined as exposed of degree two, $E^2(r)$, and the iteration goes on. Finally, $F^k(r)$, corresponds to the outlets that are exposed at order k or less. For instance, $F^1(r)$ refers to the subset of $E^0(r)$ outlets, i, and j; and $E^1(r)$ outlets, m, and l. The premise is that the risk of contamination of control group is minimized if the outlets that are not exposed to the merger at any order, the subset of outlets in $1 - F^k(r)$, constitute the control. In the Figure 4.3 these are outlets n, and o. Accordingly, depending on what the researcher is interested in, treatment group may include either only firms that are directly exposed to merger, $E^0(r)$; or firms that are exposed of higher orders $F^k(r)$. Choné and Linnemer (2012) offer three valuable insights about this methodology. First, it is straightforward to use the methodology for "*any event that affects particular group of outlets*". Second, the methodology can easily be generalized the product space. Third, via estimating a separate treatment effect for each degree of exposure, $E^1(r), E^1(r) ... E^\infty(r)$, if "*competitive interactions are simple enough*", the researcher might capture the "treatment intensity" (pp. 637-639).

The estimation builds on a simple specification

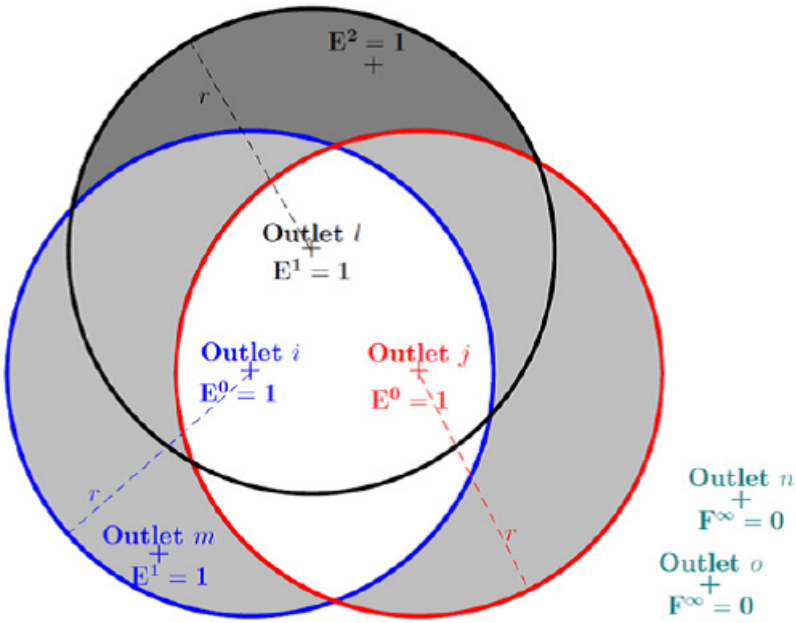
$$p_i = \alpha_0 + \alpha_1 \gamma_s^{treated} \gamma_t^{post} + \sum_t \beta_t \gamma^t + \sum_s \delta_s \gamma^s + \upsilon_i \tag{4.14}$$

where s is outlet, t is time. γ^t refers to time fixed effects; γ^s refers to outlet fixed effects. γ_t^{post} marks posttreatment observations. $\gamma_s^{treated}$ marks the treated group, either $E^0(r)$ or $F^k(r)$. Findings are provocative. If degree of exposure is ignored, i.e. control group includes outlets that are indirectly exposed to the merger, the impact of merger on price is insignificant. If control group is composed exclusively of the outlets that are not exposed to merger at any order, results suggest 3 % price increase.

4.4 Forming a Bridge between Collusion and Merger Retrospectives

In this section, drawing from theoretical framework and identification techniques employed in merger retrospectives, in a DiD setting, an alternative empirical strategy to estimate collusive overcharge is proposed. Even though, in the next chapter this proposed strategy is applied, discussion in this section should be taken in the broader context of estimating overcharge in a spatial setting. Issues specific to the application

Figure 4.3: Degree of Exposure



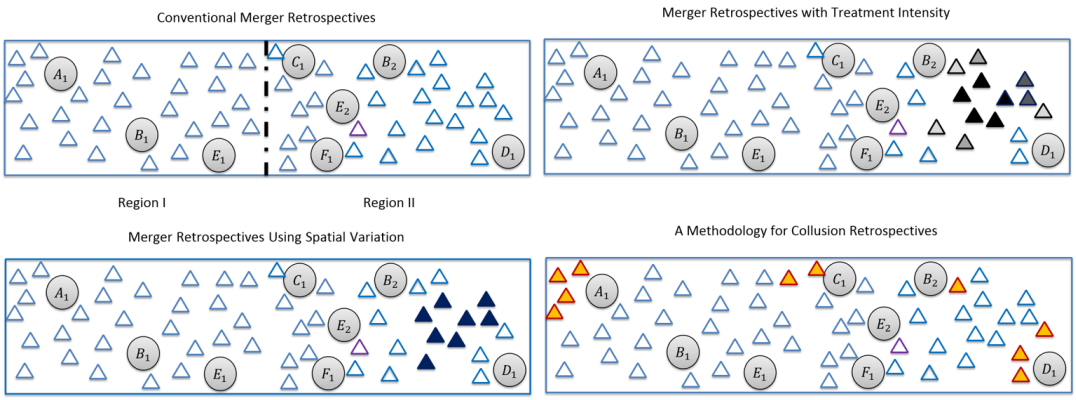
Source: Figure 1 in Choné and Linnemer (2012).

carried on in Chapter 5 are covered in that chapter. It should also be stressed that strategy proposed here should be thought as an addition to the existing strategies, rather than as a strategy replacing existing ones.

DiD is very frequently employed in merger retrospectives. Merger retrospective literature, in its "extensive" state, offers powerful insights for the collusion retrospectives, which, in comparison, is at its infancy. Primary reason of this divergence is data availability. Merger proceedings are more transparent in nature. Parties would like to convince both the authorities and the public that they are not doing anything wrong. Therefore, after the merger has been concluded, they are more willing to disclose their analyses, which typically rely on consumer or transaction level data, and employ more refined empirical strategies. On the other hand, collusion proceedings are held more private. Since damage proceedings are contingent on an infringement decision, i.e. decision of an authority that finds the parties guilty, the discussion is not about if parties had done something wrong; rather, it is about the damage associated with that action. Therefore, after a damage litigation, parties are less willing to disclose their analyses. This is a setback for the collusion retrospectives; the analysis is confined to either publicly available data or the third party data, which in turn has a natural toll on the set of available empirical strategies to be used, and/or industries to be studied. In our case, however, availability of consumer level data makes importation of estimation strategies from merger retrospectives possible.

DiD involves comparing two markets; one is subject to the treatment and the other is not. Upper left panel of Figure 4.4 illustrates the empirical strategy in a *conventional*

Figure 4.4: Comparing Methodologies



merger retrospective. Suppose there are seven facilities controlled by five different undertakings in two neighbouring regions. Assume, B_1 is acquired by undertaking E. A conventional merger retrospective would start by setting a control market, such as Region II, which is not too far away so that demand and cost conditions differ, but not too close so that there is a risk of spill over. The impact of merger is identified using the deviation of price in Region I from Region II. This empirical strategy is frequently employed in retrospectives studying hospital mergers, e.g. Haas Wilson and Garmon (2011); Tenn (2011); Thompson (2011); or, retrospectives studying mergers in petroleum industry, e.g. Hosken et al. (2011); Silvia and Taylor (2013); Simpson and Taylor (2008); Taylor and Hosken (2007). If the competition in the market is on the product space, empirical strategy is modified; in this case, comparison is not between affected regions and unaffected regions; but, between affected brands and unaffected brands, e.g. Ashenfelter and Hosken (2010); Friberg and Romahn (2015); Tenn and Yun (2011); Weinberg (2011); Weinberg and Hosken (2013). Alternatively, if the data has rich spatial variation (preferably at outlet level), it is possible to *use spatial variation in the determination of treatment and control groups*. An example of this is illustrated in lower left panel of Figure 4.4. In the same market, this time assume that D_1 is acquired by undertaking B. In this approach, outlets of the parties to the merger, and their close competitors are considered "treated", while further away regions are considered "not treated". This is similar to taking coloured triangles as the treatment group, and rest as the control group. The impact of merger is identified using the deviation of price in two groups. This is the empirical strategy in Aguzzoni et al. (2016) in studying retail book market; Argentesi et al. (2016), in studying retail grocery; Allen et al. (2014), in studying mortgage services; and Hastings (2004); Houde (2012); Taylor et al. (2010) in studying retail gasoline. Finally, since some outlets are affected from the treatment more than others, third option is *using the variation in the intensity of treatment in identification*. An example of this is illustrated in upper right panel of Figure 4.4. Consider again the example of D_1 being acquired by undertaking B. Let the colouration in the triangles reflect the intensity of the treatment on each outlet, which is governed by the distribution of the outlets, providers and the identity of merging parties. By employing a continuous variable indicative of variation in local

treatment intensity – a variable that changes only due to treatment and proportional to the intensity of treatment at that location – it is possible to identify the impact of the merger. Pennerstorfer and Weiss (2013), studying changes in local concentration index in retail gasoline market; and Choné and Linnemer (2012), studying variations in degree of exposure to merger car park market are examples in this fashion.

It is possible to use empirical strategies in merger strategies as an inspiration in identifying the impact of a regime switch from collusion to competition. The theoretical framework suggests that *home markets*; locations characterised by monopolistic pricing even in competition, are unaffected by the regime switch. These regions are governed by monopolistic behaviour both before and after the treatment. On the other hand, *overlapping markets*, which would have been characterised by collusive pricing if the collusion was sustained, are now characterised by competitive pricing. Consequently, I first propose using uninterrupted monopolistic behaviour in *home markets* as the counterfactual of the regime switch in *overlapping markets*. Lower right panel of Figure 4.4 illustrates the proposed strategy. In the same market, consider that a complete cartel was operational. Then a regime switch occurs and cartel brakes down. My first proposal involves taking the coloured triangles - outlets that would have been subject to monopolistic pricing both in competition, and counterfactual of the regime switch, the continuation of the cartel - as the control group; while taking other outlets as the treatment group.

Also note that the theoretical framework suggests that under collusion, collusive agreement ensures that each provider enjoys undisturbed market power at each location. However, under competition price within overlapping markets is proportional to market power each provider enjoys at a given location, which in turn is proportional to difference in cost across providers. At the locations where cost difference disappears, market power of the provider is low, and price under competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, market power of the provider is also high. Consequently, price in both regimes will be similar and regime switch would have a small impact on price. It follows that within *overlapping markets*, the impact of regime switch on price – the size of the overcharge – is inversely proportional to the market power of the provider under competition. Building on this, secondly I propose estimating the overcharge in a treatment intensity framework. I interpret regime switch as a treatment which produces heterogeneous effects at each location that is inversely proportional to difference in cost across providers at that location. In that regards, to approximate cost difference at location l, I use a measure of relative proximity, Δ_j^l; the distance between the closest rival k and location l (d_{kl}) net off the distance between provider j and location l (d_{jl}); so that $\Delta_j^l = d_{kl} - d_{jl}$.

4.5 Managing Expectations: A Critical Analysis of the Proposed Approach

In merger retrospectives, criticisms[64] towards DiD is thoroughly discussed. Next, these criticisms are taken under three headings: i) Atheoretical nature of DiD and the choice of counterfactual, ii) Problems and solutions in choosing control, iii) Exogeneity of treatment. In the discussion of *merits and limitations of DiD in the context of merger retrospectives*, finding consensus occasionally becomes challenging. To provide a balanced view, when there are conflicting views – particularly relevant for i) and iii) – first, I provide highlights of the arguments of both sides. Second, (where applicable) I provide remedies proposed in the literature to address potential limitations. Finally, I link the discussion that is defined in the context of merger retrospectives with the empirical strategy proposed to estimate overcharge, to understand if proposed limitations are mitigated or aggravated in the latter context. This section concludes with a brief discussion about the applicability of the proposed methodology in other settings.

Atheoretical Nature and the Choice of the Counterfactual

One of the most common criticism towards DiD is the lack of a formal model of competition or collusion. This criticism targets both at general methodology, and at the identification of control group (OECD, 2016, p.50). Following, Davies and Ormosi (2012): *"Since much depends on evaluation of the nature of the counterfactual, this means that a key part of the methodology-identifying an appropriate control group-is also atheoretical. As such, there is a danger that the choice of counterfactual (control group) is constrained by "what is out there", that is, the best of a set of alternatives, none of which is entirely appropriate (p.781)."*

It should also be noted that, some view lack of theoretical foundation as a strength. DiD is data driven. Some prefer *results being determined by "what is out there"* over results being determined by *"untestable theoretical assumptions"*(Davies and Ormosi, 2012, p. 781). Lack of a structural framework also has other benefits; it lowers data requirements; it allows the analyst to remain agnostic about the market structure or the conduct and circumvents the complexities regarding from multiple equilibrium (OECD, 2016, p.50).

The proposal here sits in between "atheoretical" and "atheoretical". It is true that this work does not include a fully fledged model[65]; however, proposed empirical strategy still gets its inspiration from simple theoretical intuition.

[64] In this chapter, I am limiting the discussion to issues of consistency. Issues of inference are taken in Chapter 5.

[65] It should be stressed that even though this work does not build on a fully fledged theoretical model, this should not be taken as a prescription. One possible direction for future work is employing a more complex framework to be used in construction of a counterfactual in a spatial setting.

Problems and Solutions in Choosing Control

In merger retrospectives, typically non-merging rivals, or regions or products that are not affected from the merger[66] constitute the control group. If the merger has a geographical dimension, meaning that competition is local, it is common to compare price in the treatment region with price in a region that is close enough to be affected from the same demand and cost shocks, but far enough so it is sheltered from the treatment. In this case, the challenge is managing this proximity tension (Ashenfelter et al. 2009, p.9, Werden 2015, pp. 289-290)[67]. Using non-merging rivals is more frequently preferred if competition is on the product characteristics space. This case also has its challenges. Every horizontal merger creates some "externality" on the rivals, which affect their pricing behaviour. Ignoring this externality would be too "naive" (Nevo and Whinston 2010, p.74). In realization of this limitation, with the hope that externalities would be least prominent for "private label products", this group of products are frequently used as the control group. However, not everyone is convinced that this is a good idea. Nevo and Whinston (2010) suggest that, building control group on private labels might be particularly problematic if the marginal cost is not constant, private label producers have some market power, or they strategically interact with branded products (p.74). Ashenfelter and Hosken (2010) warn that branded goods, and private label products might be disproportionately affected from income shocks (p.437). Davies and Ormosi (2012), basing on their experience in United Kingdom supermarket industry, find the premise of irrelevance of externalities for private label products "highly contestable" (p. 782).

Another challenge in choosing control is that similarity of demand and cost conditions is a necessary condition of compatibility between treatment and control markets; yet, it is not a sufficient condition. In this regard, similarity of *level of competition* and *institutional features* in treatment and control markets are also important.

Simpson and Schmidt (2008) show that two markets facing exactly the same demand and cost shifters might perform differently if they have different propagation mechanisms. As a case in point they employ simple case of linear demand and constant non-zero marginal cost; in this case, any cost shock would have full pass through in perfect competition, and partial pass through in monopoly. Therefore, to ensure compatibility with treatment market, control market should be chosen so that the *level of competition* in both markets are similar; consequently, the same shocks are propagated similarly. Preceding literature also held this perspective. Davies and Ormosi (2012); Jiménez and Perdiguero (2014); Ulrick and Sacher (2015); Werden (2015) acknowledge the propagation issue in reference to Simpson and Schmidt

[66] See, OECD (2016), pp. 48-49 for some examples.

[67] A similar tension exists in choice of posttreatment period. On one hand, researcher would like to capture both short and long term effects of the treatment, hence would prefer to keep the posttreatment period long. On the other hand, as the time period extends, there is an increased risk of structural change in either treatment or control market which would threaten the compatibility of two markets (Davies and Ormosi, 2012, p. 780).

(2008). Similarly, in exploring the impact of a merger in Canadian mortgage market, Allen et al. (2014) restrict the sample to borrowers having 5-8 alternative potential lenders; in tracking the impact of a bank merger, Calomiris and Pornrojnangkool (2005) estimate a distinct impact for each borrower group that face varying number of potential lenders.

To see the importance of *institutional features*, contractual relations in gasoline markets (see, Hastings (2004); Taylor et al. (2010)) is a good example. In gasoline, it is common for the wholesalers (refinery level) to be also active in retail (station level). There are multiple types of contracts governing the relation between wholesalers and retailers, and each imply different levels of control of the former, on the latter. On one end, there are stations owned by the wholesalers. These are under direct control of the wholesalers. On the other end, there are independent stations. In this case, relationship between retailer and wholesaler is confined to procurement. A merger between two wholesalers both active in the retail level, typically have three impacts at retail level: i) One rival is eliminated. ii) Retail stations that belong to acquired firm are rebranded. iii) New contracts are drafted between the merged entity and the stations that were originally working with the acquired wholesaler. Typically, merger retrospectives are concerned about estimating the impact of the elimination of the rival. However, it is challenging to identify this impact when there are multiple treatments[68].

Fortunately, literature also offers i) some tools to assess if compatibility of treatment and control group is at risk, ii) potential remedies if there are compatibility issues.

In the *assessment of the degree of compatibility issues*, the first methodology suggested is complementing DiD with demand estimation. If estimation reveals that the cross-price elasticities between control and the treatment brands are low, risk of contamination should not be high (Friberg and Romahn, 2015, p. 5). Second methodology is conducting a formal test of compatibility of treatment and control markets[69]. This involves testing if the treatment and control groups have a "common trend[70]" in pretreatment period[71]. As in Friberg and Romahn (2015)[72] and Weinberg and Hosken (2013), this might involve simply regressing price on a set of time invariant fixed effects and trend variables, while allowing trends to vary across treatment and control groups. Consider a merger in a market which competition is in product space; formal test builds on

[68]Variation in institutional structure is not the only reason for multiplicity of treatment. Another merger preceding the merger of interest might be distorting estimates (DGComp, 2015, p. 66).

[69]See, Aguzzoni et al. (2016); Ashenfelter et al. (2013); DGComp (2015); Friberg and Romahn (2015); Weinberg and Hosken (2013).

[70]Also referred as treatment and control groups have parallel trends. In this work, both concepts should be thought interchangeable.

[71]In some other retrospectives, common trend assessment is confined to an eyeball approach; evolution of price over time is plotted for treatment and control groups and a judgement is made about similarity of two plots.

[72]See, Appendix Table 2, p. 15.

$$p_i = \alpha_0 + \alpha_1 t \gamma_s^{treated} + \alpha_2 t \gamma_s^{control} + \alpha_3 \gamma^c + \upsilon_i \tag{4.15}$$

In this specification, s refers to brand, c refers to cities/regions, γ_i^c refers to city/region fixed effects, $\gamma_i^{treated}$ and $\gamma_i^{control}$ refer to treatment and control groups, and t is a linear time trend. Estimation uses only pretreatment data and is followed by a formal test of $\alpha_1 = \alpha_2$.

Alternatively, as in Ashenfelter et al. (2013) a more general specification might be employed (p.252):

$$p_i = \alpha_0 + \alpha_1 t \gamma_t^{pre} + \alpha_2 t \gamma_t^{pre} \gamma_s^T + \alpha_3 t \gamma_t^{post} + \alpha_4 t \gamma_t^{post} \gamma_s^T + \sum_j x_{sj}^T \beta_j^T + \sum_h x_{sh}^C \beta_h^C + \upsilon_i \tag{4.16}$$

where, j refers to treated products; h refers to control products; s refers to product; and t refers to time. In this specification, γ_t^{pre}, and γ_t^{post} are pretreatment and posttreatment indicators; γ_s^C marks the control group; γ_s^T marks the treatment group; and x_{sj}^T, x_{sh}^C are controls for treatment and control groups respectively, i.e. product characteristics, brand. There are three differences between Equation 4.15 and 4.16. The latter i) employs controls rather than fixed effects, ii) allows parameter estimates for control variables to vary across treatment and control groups, iii) use both pretreatment and posttreatment data. The estimation is followed with a formal test of $\alpha_2 = 0$

Finally, as in Ashenfelter et al. (2013) it is possible to employ time fixed effects rather than trends.

$$p_i = \alpha_0 + \sum_j x_{sj}^T \beta_j^T + \sum_h x_{sh}^C \beta_h^C + \sum_l \sigma_l \gamma_l^t + \sum_l \delta_l \gamma_l^t \gamma_s^T + \upsilon_i \tag{4.17}$$

In this specification, γ_l^t is time fixed effect. Estimation uses both pretreatment and posttreatment data, and is followed by a formal test of $\delta_l = 0$ for pretreatment periods, both jointly and marginally.

When it comes to *addressing potential compatibility issues*, one proposition is using other techniques from treatment effects literature, such as propensity score matching, e.g. Aguzzoni et al. (2016); Allen et al. (2014); Argentesi et al. (2016); Dobson and Piga (2013); or synthetic cohorts, e.g. DGComp (2015). *Propensity score matching* builds on modelling the probability of being treated, the propensity score, using observable characteristics of treated and untreated participants. For each treated participant, control group is customized by the propensity score. *Synthetic cohort* is the process of constructing a hypothetical control group, when none of the available alternatives are good enough. Artificial control is established

by weighting untreated participants, where the weights are chosen to minimize the pretreatment distance between the treatment group and the synthetic control (OECD, 2016, pp. 47-48).

Note that in a merger retrospective research objective is identifying the impact of collusion on price. In a DiD setting, this requires taking a good control market that would serve as the counterfactual of no merger. Two necessary conditions for a good control market are similarity in demand and cost conditions to treatment market, and being unaffected by the merger. However, as mentioned earlier, these conditions might fall short of ensuring compatibility between treatment and control markets if propagation of the shocks are dissimilar in two markets. Risk of difference in propagation mechanisms increase along with the degree of deviation between level of competition in treatment and control markets.

It should be noted that complications associated with differences in propagation mechanism should be less worrying for the proposed methodology. In the proposed framework, the regime change from collusion to competition is taken as the treatment. The propagation mechanisms in i) *overlapping markets* before treatment (in collusion), ii) *home markets* before treatment, iii) *home markets* after the treatment, and iv) the counterfactual of the collapse of collusion, the continuation of the cartel; all are characterised by monopolistic behaviour. Therefore local variations in competition and market power should be immaterial for price determination.

Note that there are two implicit assumptions in this approach: First is the similarity of monopolistic behaviour under collusion and monopoly. This equality might not hold if price is also governed by strategic considerations. Second is the homogeneity in the enforcement of collusive strategy at each location. Even though, in theory, price in all regions is governed by collusive agreement, in practice, there might be voluntary and involuntary deviations from the agreement. This might cause deviations of average competitiveness in *overlapping* and *home markets* in effect[73].

Exogeneity of Treatment

In merger retrospectives, treatment exogeneity assumption is challenged on two different levels. First, some question the exogeneity of *the decision to merge*. The argument is as follows: Treatment effects literature is quasi-experimental; hence the results should ideally be drawn from randomized control trials. However, it is difficult to consider mergers random. Merging is one of many possible reactions of market participants to the events that happened, are happening, or expected to happen (Nevo and Whinston, 2010, p. 74). In the words of Werden (2015):

> *DiD estimation is widely applied by economists to 'natural experiments',*

[73]It should also be noted that in collusion retrospectives it might be easier to modify empirical strategy for any violation of these assumptions, as the retrospectives typically proceed a court case. Case file might include some assessment about strategic concentrations; or presence of deviations from agreement, and the time period and the locations they concentrate on.

> *like mergers, which lack the randomization and careful control of laboratory experiments. Researchers typically assume the 'unconfoundedness' of a natural experiment. With merger retrospectives, this means that no unobserved determinant of price was part of the rationale for merger. For example, it means that the acquiring firm did not act on information unavailable to the econometrician indicating that the acquired firm was about to enjoy higher price. Violation of the unconfoundedness assumption causes the estimate of the merger effect to be biased. Researchers applying DiD estimation to natural experiments argue that the conditions under study 'approximate the conditions of a controlled experiment', but critics often are sceptical ... Mergers, ... offer only non-randomized, uncontrolled experiments (p.289)*[74].

Second, some question exogeneity of the *identity of merging parties*. The critics suggest that firms might have preference for some firms over the others. It is difficult to think "selection into the treatment group" as random (OECD, 2016, p.47). In the words of Dafny (2009)

> *... most observational or reduced-form analyses of the impact of mergers fail to address fundamental selection problems arising from the fact that mergers are not randomly assigned. These studies typically compare outcomes of merging firms with those of nonmerging firms. The resulting estimates suffer from a classical selection problem, as merging firms are likely different from nonmerging firms in unobserved ways that affect the outcomes of interest. ... any omitted factor that is correlated with the outcome measure as well as with the probability of a merger will generate biased estimates of the impact of a merger. (p. 524).*

In this context, Dafny (2009) gives the example that a financially distressed firm, be it party to the merger or not, is more likely to cut cost and reduce price. Consequently, it is difficult to claim that cost cuts, and price reductions that happened after merger, would not have happened in the absence of merger.

Despite being heavily criticized, the assumption of exogeneity is employed by many. However some justify the exogeneity assumption via conditions specific to the studied merger. For example De Nijs (2012) claims that *"The operation to merge GTM with Vinci took place in December 2000. It aimed at constituting a world leading group in construction and associated services. The merger was therefore exogenous for the Parisian parking garage market, because Vinci and GTM did not merge for their park activity. Importantly, this means that there is no selection bias for merging parking garages (p.929)"*. More relevantly for our purposes Hastings (2004), suggests that *"Thrifty Oil Company was a privately held company. The owner was 75, and decided to retire and sell the company's retail assets to ARCO.*

[74] FN 10 is merged with the text.

ARCO saw this as a good opportunity to expand market share (FN.9, 320)", and takes elimination of Thrifty as "locally exogenous". Later, assessing methodology of Hastings (2004), Nevo and Whinston (2010) suggest that considering *"circumstances of the acquisition"*, it is reasonable to take the merger *"exogenous to the local market"* as merger is *"unlikely to be correlated with any unobserved factors that would have changed prices in markets containing Thrifty stations differently from prices in markets without them (p.73)."*

When it comes to collusion, a case for both sides might be made. On one hand, similar to mergers, collusion (or its breakdown) might be considered as a conscious response to changing market conditions, hence it might be taken endogenous. On the other hand, competition and collusion might be considered as two occasional outcomes of the same long run process, e.g. Green and Porter (1984). In this interpretation, breakdown of collusion would be governed by inability to identify if low price is a result of unfavourable demand conditions or a rival cheating, which in turn is governed by exogenous shocks[75]. However, when it comes to the proposed methodology, as Nevo and Whinston (2010) comment, it should be more reasonable to assume exogeneity if empirical methodology employs local variations in identifying the impact of regime switch; the likelihood of regime switch to be correlated with any unobserved factor that would have changed price in the treatment market differently from price in the control market is not very high. Consequently, *"it is plausible to treat changes in spatial concentration in a local submarket as an exogenous shock to a rival stations' pricing decision, after controlling for fixed time and station-level effects (Pennerstorfer and Weiss, 2013, p. 662, FN 5)"*.

Applicability to Other Settings

Regarding the applicability of the proposal in other settings, the nature of the competition in the market is very important. In our setting, product is homogenous, competition is spatial; consequently, it is the relative proximity of alternative providers that governs the decisions of buyers. It follows that in any other homogenous product / geographic space setting the analysis should be immediately applicable conditional on the availability of a comparable that set (consumer level information on price; indicators of local market power; demand and cost shifters). However, note that the empirical strategy relies on using high market power regions as the counterfactual of collusion. This involves two inherent assumptions. First, there are some locations, at which local market power is high enough, so they can serve as counterfactual for collusion. If the level of market power - even at the locations it is presumably highest – is not high enough compared to market power under collusion, overcharge estimate would be downward biased. Second, observable indicators of local market power are sufficiently good reflection of actual market power provider enjoys at each location. For example, if buyers have countervailing power, observable features may overstate the market power of the provider. Alternatively, if the provider installs customer specific investment at the

[75] In addition to Green and Porter (1984), also see, Jones and Sufrin (2016) (p.656).

premises of some buyers, this may act as switching cost; consequently, the observable features might understate market power of the provider.

It is possible to generalize the empirical strategy to heterogeneous product / product characteristics space setting. As Bresnahan (1987) suggests, even if competition is in product characteristics space, providers will have heterogeneous market power over different products in the product line they offer. Sticking to the automobile industry that Bresnahan (1987) studies as an example, one can think of automobile manufacturer Volkswagen. When it comes to mainstream models such as Golf or Polo, it is plausible to think the competition would be high, i.e. there are a number of other manufacturers producing models with similar characteristics. On the other hand, market power of Volkswagen on a model like Beetle would be much higher. Consequently, in estimating the impact of a regime switch from collusion to competition on low market power models - Golf, Polo – high market power models – Beetle – may be used as the counterfactual. However, it must be admitted that as competition gets more multidimensional (as it might be in product characteristics space) identifying control and treatment groups would be more challenging.

Chapter 5

Estimating Overcharge: An Empirical Application in a Spatial Setting with Market Power Heterogeneity

5.1 Introduction

In competition policy, compensation claims for the collusive harm in the form of "the actual loss" – *damnum emergens* – and/or "the foregone profits" that would have been obtained in the absence of collusion – *lucrum cessans*[1] are called *damages*. In many legal jurisdictions consumers are allowed to make private claims if they prove they have been adversely affected. Consequently, an infringement decision triggers legal proceedings and a debate forms about the magnitude of this harm. In jurisdictions with a well-established legal culture of private litigation, e.g. US, compensation payments can reach substantial amounts. Table 5.1 illustrates the importance of damage proceedings in deterring cartel activity via providing a breakdown of the monetary sanctions in *Vitamins*[2] cartels. In US, private claims cost cartel members more than the twice of the government prosecution. In Canada, there is an even split between fines and private claims.

[1]For legal context, see, http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.L_.2014.349.01.0001.01.ENG.

[2]For legal context, see, EU Commission decisionhttp://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32003D0002.

[3]Table note: *Source: Connor (2006c, Table 17A) To allow for the opportunity cost of capital (i.e. the absence of prejudgement interest), fines and settlements are adjusted downward by the US prime interest plus 1 % from the midpoint of the conspiracy to the year the cartel was fined; then from the latter year, the figure is raised to $ 2005 using producer price index of the appropriate region. i) The EU assigns by product, but most other fines and settlements are allocated by the affected sales of the product and then within the product by company market share. US Private is conservative. Converted C$1 to US$ 0.826 ii) includes private settlements for single damages to*

Table 5.1: Real Monetary Sanctions by Product[3]

Product Market	U. S. Govt.	U.S. Private	Canada[b]	Europe	Rest of the World	World
			2005 U.S. dollars[a]			
Beta carotene	52.4	118.9	8.2	52.7	0	232.2
Canthaxanthin	1.1	2.6	0.17	51.1	0	55.0
Biotin (H)	0	42.1	0	0	0	42.1
Choline chloride (B4)	2.4	43.0	4.58	35.4	0	85.5
Folic acid (B9)	0	6.6	0	0	0	6.6
Vitamin A	74.8	232.9	16.7	69.1	4.68	400.6
Vitamin B1	0	14.5	0	0	0	14.5
Vitamin B2	19.5	38.0	2.7	32.9	0	93.1
Vitamin B3	22.9	30.7	2.36	0	0	56.0
Vitamin B5	20.9	50.9	4.55	58.4	0.08	134.9
Vitamin B6	0	13.4	0	0	0	13.4
Vitamin B12	0	3.1	3.12	0	0	6.27
Vitamin C	111.9	218.6	18.1	51.0	3.74	405.3
Vitamin D3	0	0	0	24.7	0	24.7
Vitamin E	202.2	509.7	32.4	106.3	4.85	857.9
Premixes	168.5	348.5	52.5	0	0	569.6
Total	676.6	1673.8	145.6	481.7	13.36	2991.1

Source: Table 13.2 in Connor (2007).

In a legal proceeding, typically, plaintiffs and defendants are both active in the same production chain, but on different levels; plaintiffs are the buyers of products provided by the defendants. Both sides make predictions about *the world that would-be* in the absence collusion. The difference between the actual, and predicted counterfactual is presented as the impact of collusion. Naturally, plaintiffs would like to present this difference as large as possible while defendants would like to present it as small as possible.

The impact of the cartel on buyers' profit, or the damage, can be decomposed into three effects: The impact of the collusion on price, or the *overcharge effect*, is the additional payment buyer makes for each input procured. *Output effect* captures the decline in profits due to production foregone associated with higher input price. *Pass-on effect* is the recovery in buyers' profits due to passing some of the rise in input price to price of the product. In reduced form analysis, empirical estimation centres on estimating the overcharge, ignoring other components of damage. This work, follows the literature, and confines estimations to overcharge.

Empirical objective of this chapter is to estimate the hypothetical overcharge related to a possible collusion[4]. To this aim, first, I employ the techniques frequently used in collusion retrospectives: before and after, indicator variable approach, forecasting. Overcharge estimates using these three methodologies are respectively 9.26 %, 11.14–13.98 %, 8.05–11.46%. Second, I import empirical strategies from merger retrospectives. I initially estimate the overcharge using basic difference-in-difference (DiD) by benefiting from spatial variation. I take regime switch as a treatment;

direct and indirect purchases that account for 51 % of the total.

[4]The term hypothetical overcharge draws on Nelson (1993) who study a similar case.

identify the buyer-provider pairs that would be least affected from the switch (the pairs that are most likely to be characterised by monopoly pricing even under competition) as the control group; I estimate the impact of the treatment, as a deviation of price in high market power regions from price in low market power regions before and after the treatment. Next, I estimate the overcharge in a treatment intensity framework. I interpret the regime switch as a treatment, which produces heterogeneous effects at each location that is inversely proportional to the level of local market power the provider enjoys at that location.

To my knowledge, this is the first collusion retrospective that i) uses spatial variation in determining control groups, ii) takes on regime change within a treatment intensity framework. This allows going beyond reporting a single overcharge estimate, and commenting on spatial distribution of overcharge, particularly the impact of variations of market power at each location on the overcharge at that location.

Basic DiD specifications suggest that the variation in overcharge is strongly related to DiD coefficient. It is shown that the impact of the regime switch is conservatively estimated in the interval of $7.48 - 11.25\%$. I also show that if the provider's market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of degree of exposure to the "treatment", market power variations might lead variations in the price predicted for competition counterfactual, consequently variation in overcharge estimate as high as 11.89 %. These findings suggest that if the spatial dynamics are ignored, and single overcharge estimation is made, estimation leads to; undercompensation in regions where the market powers of dominant competitor and potential competitor converge; and overcompensation in regions where the market powers diverge.

Finally, to address the inference problems associated with spatial dependency across observations and DiD methodology, I apply various remedies proposed in the literature. These include i) imposing an error structure using Conley standard errors, ii) changing the level of variation in the data, iii) using effective number of clusters rather than actual number of clusters in defining critical values, and iv) wild cluster bootstrap. Results are robust to alternative methods of inference.

This chapter organized as follows. Next section outlines the empirical strategy. Third section introduces inference issues related to DiD methodology and spatial nature of the data, and potential remedies in addressing these issues. Fourth section presents the estimations done by before and after, dummy variable approach and forecasting. Fifth section presents DiD estimations. Final section concludes.

5.2 Empirical Strategy, Methodology and Contribution

In this chapter, empirical objective is to estimate the hypothetical overcharge related to a possible collusion. To this aim, in the first stage, I use techniques that are frequently used in collusion retrospectives. First, I employ before and after method. This involves a simple comparison of the average price in collusion period and average price in competition period, and using the latter as but-for price. However, there is not a great deal of economics involved in before and after, since demand and cost shifters are not controlled for. Second method, dummy variable approach, introduces demand and cost shifters into the analysis. Price is regressed on a variable of interest (r_i), an indicator variable marking observations in the collusion period; and control variables i.e. demand shifters, z_i; cost shifters, χ_i. Formally,

$$p_i = \alpha_0 + \alpha_1 z_i + \alpha_2 \chi_i + \alpha_3 r_i + v_i \tag{5.1}$$

The coefficient of the indicator variable, α_3, is interpreted as the impact of collusion on price.

Note that there are implicit assumptions in this approach. First, it is possible to capture the impact of regime change solely by the indicator variable. Second, the set of variables and how they affect price are identical in both regimes. Third method, forecasting, relaxes these assumptions. In a typical forecasting exercise, at the first stage, price is first regressed on control variables using only data from competition period in a reduced form setting. Parameter estimates are treated as representative of pricing behaviour under competition. At the second stage, estimates are interacted with independent variables in the collusive period. This gives predicted price that would have been observed under competition.

At the second stage, I import empirical strategies from merger retrospectives.

The theoretical framework suggests that *home markets*; locations characterised by monopolistic pricing even in competition, are unaffected by the regime switch. These regions are governed by monopolistic behaviour both before and after the treatment. On the other hand, *overlapping markets*, which would have been characterised by collusive pricing if the collusion was sustained, are now characterised by competitive pricing. Consequently, adopting the methodology in merger retrospectives, I first propose using uninterrupted monopolistic behaviour in *home markets* as the counterfactual of the regime switch in *overlapping markets*[5]. I estimate the

[5] An issue of importance is related to the difference in counterfactual in this chapter and that in Chapter 3. Here, for low market power regions, the counterfactual of regime switch – continuation of collusion – comes from the behaviour in high market power regions; if the market power is high enough, I take the pricing behaviour under competition and under collusion close enough to each other. In Chapter 3, in search of a regime switch, I explore suspicious patterns before month 7. At each location, under competition I expect to find strong relationship with price and

overcharge using basic difference-in-difference (DiD) by benefiting from spatial variation. I take regime switch as a treatment and identify the buyer-provider pairs that would be least affected from the switch (the pairs that are most likely to be characterised by monopoly pricing even under competition) as the control group. This involves using a specification similar to

$$p_i = \alpha_0 + \alpha_1 z_{lt} + \alpha_2 \chi_{lt} + \alpha_3 \gamma_t^{post} + \alpha_4 \gamma_l^{treated} + \alpha_5 \gamma_t^{post} \gamma_l^{treated} + \epsilon_i \tag{5.2}$$

where, z_{lt} refers to demand shifters; χ_{lt} refers to cost shifters; γ_t^{post} is an indicator variable that marks posttreatment observations; and $\gamma_l^{treated}$ marks the locations affected from regime switch. Consequently, α_5 is the coefficient of interest; it captures average treatment effect, the impact of the regime change.

Also note that the theoretical framework suggests that under collusion, collusive agreement ensures that each provider enjoys undisturbed market power at each location. However, this differs from competition under which price within overlapping markets is proportional to market power each provider enjoys at a given location, which in turn is proportional to difference in cost across providers. At the locations where cost difference disappears, market power of the provider is low, and price under competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, market power of the provider is also high. Consequently, price in both regimes will be similar and regime switch would have a small impact on price. Building on this, secondly I propose estimating the overcharge in a treatment intensity framework. I interpret regime switch as a treatment which produces heterogeneous effects at each location that is inversely proportional to difference in cost across providers at that location. In that regards, to approximate cost difference at each location, I use Δ_j^l.

To my knowledge, this is the first collusion retrospective that i) uses spatial variation in determining control groups, ii) takes on regime change within a treatment intensity framework. This allows going beyond reporting a single overcharge estimate, and commenting on spatial distribution of overcharge, particularly the impact of variations of market power at each location on the overcharge at that location. This study also adds up to the developing literature on empirical studies of collusion using consumer level data (see, section 3.4). Finally, as discussed in the next part, this study attempts to connect empirical studies of collusion with the literature that proposes remedies for the inference issues which are stemming from spatial nature of data and DiD methodology.

local market power measure. Under collusion, I expect finding no (or weak) relation between price and local market power. Therefore, benchmark for competitive pricing comes from simple theoretical reasoning regarding competitive pricing; benchmark for collusive pricing comes from simple theoretical reasoning regarding collusive pricing.

5.2.1 Evidence of Collusion

Findings in previous chapters suggest that pricing behaviour in first seven months is more consistent with collusion; pricing behaviour after month seven is more consistent with competition. For the sake of brevity, here I simply take it that a regime switch has happened in month seven. In the upcoming sections, I estimate the hypothetical overcharge using various reduced form techniques with this prior.

5.3 Inference Issues and Remedies

In this part, potential risks to inference due to nature of the data and the methodology are presented, and some remedies in minimizing their impact are discussed.

The estimations in earlier chapters, use heteroscedasticity robust White standard errors. This means that even though error variance is allowed to vary, error terms are assumed to be independent from each other, $E[u_i u_j] = 0$. However, considering demand for the product is governed by *spatial dynamics*, assuming independence across observations coming from neighbouring locations may be unrealistic. Another source of dependency across observations is due to *variation in the data*. Recall that data has *consumer* $\times$ *facility* $\times$ *location* $\times$ *month* breakdown. However, our key variable, indicator of local market power is invariant to customer identities and have limited variation over time. This means "*our unit of observation is more detailed than level of variation* (Bertrand et al., 2004, p. 254)".

Bertrand et al. (2004) points to other challenges. They suggest that invalid inference might be particularly relevant for *DiD methodology*. They point that in DiD, variable of interest, DiD indicator, typically changes very little over time; it is a string of zeros for untreated observations, and a string of zeros followed by a string of ones for the treated observations[6]. In an attempt to illustrate inference issues in DiD, Bertrand et al. (2004) embark on an empirical exercise. Using 900.000 observations spanning 21 years and 50 US states, the impact of a randomly allocated placebo policy is tracked. Results suggest that if the changes in the treatment status is permanent, DiD indicator is significant in 67 % of the cases, providing a case for over-rejection. The rejection rate drops to 5 % if the changes in the treatment status are not permanent (treatment is turned on and off).

In their paper they also offer some remedies to inference issues, and using Monte Carlo simulations, they assess the effectiveness of these remedies. They suggest, limiting the level of variation in data, e.g. eliminating time dimension; parametric solutions, e.g. imposing a structure on error terms; allowing arbitrary correlation within clusters; and wild cluster bootstrapping. Results suggest that imposition of

[6]They also suggest two other aggravating factors; these are using long time series, and using dependent variables that suffer from severe autocorrelation.

a structure on error terms still leads to considerable over rejection (around 20 %). Bootstrapping and allowing arbitrary correlation within clusters performs well when number of clusters is large. In cases with small number of clusters, both solutions work less admirably.

In our case, the dependency in error terms is spatial. A remedy to address dependency of this kind is offered by Conley (1999). Taking on a Euclidean spatial setting, each observation about an agent with a specific location s_i is regarded as a realization of a random process. Around each location there are unobservables, potentially affecting observations at that location, and at other nearby locations. Therefore, distance between two locations s_i, s_j also informs about the proximity to common unobservables. In Conley setting, observations from nearby locations are allowed to be highly correlated; as locations grow further apart, the dependency decays in a linear manner and eventually becomes zero after a cut-off distance. Conley standard errors fit well to our setting.

In order to calculate Conley standard errors, Stata code by Hsiang (2010) is used. In this process, first challenge is extracting the spatial distribution of observations and their distance from each other. Recall that in our setting, distance measure is driving distance. However, Hsiang (2010) uses the Euclidean distance measured from actual coordinates. Therefore as a first step, coordinates of X delivery locations are retrieved. Second challenge is defining the cut-off distance beyond which observations may be comfortably considered independent. Since X is used in production of Z, and since transportation of Z is not viable after $\bar{d}$, it makes sense to use $\bar{d}$ as the cut-off value. However, $\bar{d}$ threshold is defined in driving distance. Unless two points are connected by a perfect straight line with no elevation change, driving distance will always be greater than the Euclidean distance. Therefore to approximate equivalent value of $\bar{d}$ in Euclidean space, first, average driving distance, $\bar{d}$, and average Euclidean distance in X transactions, $\bar{d}_e$, are calculated[7]. Note that the divergence between two measures of distance is determined primarily by factors such as topography or road network. It is reasonable to assume that, Z producers are subject to the same road network and same topography. Consequently, adjusting $\bar{d}$, by the deviation of two distance measures in X transactions should serve as a fair approximation. This adjustment gives the threshold value $\bar{d}_e$, to be used in calculating standard errors, where $\bar{d}_e = 0.71\bar{d}$. It should be stressed that this measure is used only as a cut-off to mark potentially dependent observations that we are not comfortable assuming $E[u_i u_j] = 0$. Estimations still employ measures of driving distance.

Hsiang (2010) also allows defining an autocorrelation process. It is reasonable to assume $E\left[u_{it} u_{j(t-17)}\right] = 0$ where t refers to month, even though they are at the same location. However, since such imposition potentially lowers the standard errors, in order to assess the most risky situation, no autocorrelation structure is imposed.

A second remedy is employing clustered standard errors that allow arbitrary correlation within clusters. The researcher is happy to assume that $E[u_i u_j] = 0$

[7] All averages are volume weighted.

for observations that belong to different clusters, but is less willing to make the same assumption for observations in the same cluster. Following Cameron and Miller (2015), in this case, variance of the estimate of β – $\hat{\beta}$ – can be formalized as

$$V_{clu}\left[\hat{\beta}\right] = \frac{\left(\sum_i \sum_j x_i x_j E\left[u_i u_j\right] \mathbb{1}\left[i,\ j \textit{ are in the same cluster}\right]\right)}{\left(\sum_i x_i^2\right)^2} \tag{5.3}$$

where $y_i = \beta x_i + u_i, \quad i = 1...N$ and $\mathbb{1}[]$ is an indicator function that equals to 1 if condition [] is satisfied, 0 if not. Then an estimate for the variance would be

$$\hat{V}_{clu}\left[\hat{\beta}\right] = \frac{\left(\sum_i \sum_j x_i x_j \hat{u}_i \hat{u}_j \mathbb{1}\left[i,\ j \textit{ are in the same cluster}\right]\right)}{\left(\sum_i x_i^2\right)^2} \tag{5.4}$$

It is easy to see that the estimate is heteroscedastic robust as well, as White‘s heteroscedastic robust variance estimate is the special case of single observation in every cluster. In studies with a spatial aspect, clusters are typically countries, cities, markets or regions (pp.320-21). Similarly, in our setting, the level of clustering is county level; there are more than 100 distinct counties.

Cameron and Miller (2015); Carter et al. (2017) provide a technical discussion of the properties of the CRVE, and track the evolution of the relevant literature. Accordingly, asymptotics of the CRVE kick in via number of clusters, G, rather than number of observations, N. Hence consistency requires first $G \to \infty$. Considering that typically 50 clusters are considered sufficient (Cameron and Miller, 2015, p.341), in our case, one would not expect any consistency issues. This judgement however might be premature; because, another requirement for the consistency of CRVE is cluster homogeneity, particularly, cluster size equality. Since the dataset is consumer level transaction data, there is considerable heterogeneity in cluster sizes. In order to elaborate on implications of this, we need to take a closer look on the relationship between heterogeneity in cluster size and consistency of CRVE.

Heteroscedasticity robust variance estimator employs the assumption that $E\left[u_i u_j\right] = 0$; consequently, the error covariance matrix, $E[uu']$, is diagonal with N potentially distinct values. In CRVE error covariance matrix becomes block diagonal; within each cluster (or block) there is another error covariance matrix with extra non-zero values (Baum et al., 2003, p.3). Following the example in Carter et al. (2017), consider the case of 20 observations evenly split into two clusters. In heteroscedasticity robust estimator, there would be 20 potentially distinct terms; in CRVE there would be potentially 110 distinct terms. Consequently, CRVE estimates are greater. Cameron and Miller (2015) decomposes this inflation in CRVE for the regressor k via, τ_k, variance inflation factor. Formally,

$$\tau_k = 1 + \rho_{x_k}\rho_u \left(\frac{V\left[N_g\right]}{\bar{N}_g} + \bar{N}_g - 1 \right) \tag{5.5}$$

where ρ_{x_k} is within cluster regressor correlation, ρ_u is within cluster error correlation, $\bar{N}_g$ is average cluster size, and $V\left[N_g\right]$ is the variance in cluster size. If the number of clusters is large enough, asymptotics kicks in and CRVE is consistent. However, with finite number of clusters, as $V\left[N_g\right]$ increases, it is more difficult for asymptotics to kick in. Alternatively, to see this point, one can go back to example in Carter et al. (2017). If 20 observations are split into two clusters, one of 19 observations, and one of 1 observation, there will be 191 potentially distinct terms, an addition of 61 terms compared to the case with the even cluster size. It is difficult to claim asymptotics will kick in equally fast in both cases[8].

Carter et al. (2017) and Lee and Steigerwald (2017) (henceforth CSSL) propose a method to assess the impact of the disproportionate cluster sizes on inference. As Equation 5.5 shows, the impact of clustering on inference depends on three factors; cluster size, within cluster error covariance and the covariate correlation. They develop a sample specific measure which takes these three factors into account and scales down the actual number of clusters, and returns a measure of effective number of clusters. Accordingly, for G clusters, the effective number of clusters G^* is

$$G^* = \frac{G}{1+\Gamma} \tag{5.6}$$

where Γ is the correction factor as following holds:

$$\Gamma = \frac{1}{G}\sum_{g=1}^{G}\left(\frac{\gamma_g - \bar{\gamma}}{\bar{\gamma}}\right)^2$$

$$\gamma_g = a_k' \left(X'X\right)^{-1}\left(X_g'\Omega_g X_g\right)'\left(X'X\right)^{-1} a_k$$

$$\bar{\gamma} = \frac{1}{G}\sum_{g=1}^{G}\gamma_g$$

In this setting, Ω_g is within cluster error covariance matrix for cluster g, and a_k' is a selection vector of length k incorporating hypothesis being tested, i.e. in testing $\beta_k = 0$, it is $k-1$ values of 0 followed by a single 1. In the case of $\gamma_g = \gamma$, $\Gamma = 0$ and $G^* = G$ (Lee and Steigerwald, 2017, p.3-4). CSSL claims that it is G^* that

[8]CSSL also note that a similar problem might arise in the case that clusters are equal sized but a cluster level covariate takes the same value across some of the clusters (Carter et al., 2017, 2), e.g. a DiD indicator where treatment is given to all observations in the cluster or not given at all.

governs the validity of inference, not G, or number of observations N. Therefore, conventional hypothesis testing with CRVE should be used only if G^* is high enough for asymptotics to kick in (Carter et al., 2017, p. 1).

However, there is one problem; within cluster error covariance matrix is unobservable. CSSL propose estimating G^* by assuming perfect within cluster error correlation via replacing error covariance matrix with an $n_g \times n_g$ matrix of 1s. This gives the *feasible* effective number of clusters, G^{*A}; formally,

$$
\begin{aligned}
G^{*A} &= \frac{G}{1+\Gamma^A} \\
\Gamma^A &= \frac{1}{G}\sum_{g=1}^{G}\left(\frac{\gamma_g^A - \bar{\gamma}^A}{\bar{\gamma}^A}\right)^2 \\
\gamma_g^A &= a_k' \left(X'X\right)^{-1}\left(X_g' I_g I_g' X_g\right)' \left(X'X\right)^{-1} a_k \\
\bar{\gamma} &= \frac{1}{G}\sum_{g=1}^{G}\gamma_g^A
\end{aligned}
\tag{5.7}
$$

Note that using G^{*A} allows the researcher to assess the worst case scenario: perfect error correlation within clusters. If even under worst case, G^{*A} is large enough for asymptotics to kick in, conventional critical values can comfortably be used for hypothesis testing (Lee and Steigerwald, 2017, p.4-5).

As case studies, CSSL compute the effective number of clusters in two well-known papers in Labour Economics literature: i) Krueger (1999) that studies the STAR experiment[9], ii) Hersch (1998) that studies the impact of injury risks on wages. In STAR experiment standard errors are clustered at classroom level, and there are 318 classrooms. Employing Equation 5.7 CSSL find that $G^{*A} = 192$. In Hersch (1998) standard errors are clustered at industry level, and there are 211 industries. CSSL calculate $G^{*A} = 19$. Results suggest that seemingly large number of clusters might not always guarantee valid inference.

Recall that G^{*A} depends on hypothesis being tested, and covariates in the specification. In our setting, calculations using CSSL method[10] indicate that for key variables G^{*A} is in the interval of $6 - 40$, more frequently in the interval of $10 - 15$. Therefore, we cannot comfortably use CRVE with the hope that asymptotics to kick-in. Consequently, I now turn to the literature surrounding the issue of inference

[9]Student teacher achievement ratio (STAR) experiment is conducted in 1980's in Tennessee, US. Via randomly allocating teachers and students to different class sizes, the aim was quantifying the relation between class size and academic success (Angrist and Pischke, 2009, 17-24).

[10]I express my sincere gratitude to Chang Hyung Lee, and Douglas G Steigerwald of University of California, Santa Barbara for sharing Stata code *"clusteff"* with me. I also thank Chang Hyung Lee for his comments and ideas during our correspondence.

with few clusters.

First remedy offered in the literature to address inference problems associated with few clusters is using critical values basing on $t\left(G^{*A}\right)$ or $t\left(G^{*A}-1\right)$. The intuition is straightforward: CRVE asymptotics kick in via number of clusters under cluster homogeneity. Cluster heterogeneity pulls down the effective number of clusters. Then it seems reasonable to rely on effective number of clusters instead of actual number in hypothesis testing (Cameron and Miller, 2015, p. 348) (MacKinnon and Webb, 2017, p. 236).

Second method proposed is wild cluster bootstrap. Suppose we are interested with the hypothesis, $\beta_k = 0$. The methodology is as follows: First, estimate the equation using OLS without any restriction. Then calculate t-stat, t_k, using CRVE. Second, impose the hypothesis $\beta_k = 0$, and run the restricted regression. Retrieve restricted coefficient estimates and residuals, $\tilde{\beta}$, and $\tilde{\epsilon}$. Next, form a bootstrap sample of size B by iteration. This sample follows the following data generating process

$$y_{ig}^{*j} = X_{ig}\tilde{\beta} + \tilde{\epsilon}\upsilon_{ig}^{*j} \tag{5.8}$$

where j is the number of iteration, g is cluster, υ_{ig}^{*j} is a random variable that takes value either 1 or -1 with equal probability, and y_{ig}^{*j} is bootstrap dependent variable. At the last step, using the newly formed bootstrap sample, estimate the unrestricted equation again and retrieve t-stat, t_k^{*j}. Bootstrap p-value is measured by the proportion of number of iterations with $|t_k^{*j}| > t_k$, to total number of iterations, B (Cameron and Miller, 2015, p. 344) (MacKinnon and Webb, 2017, p. 235).

It should be noted that, even though the strongest motivation for calculating wild cluster bootstrap calculations is guarding against any risks to inference stemming from few effective clusters, incorporation also has additional benefit of improving inference when there are few treated or few untreated clusters. MacKinnon and Webb (2017) investigate the performance of alternative methodologies, CRVE, $t\left(G^{*A}\right)$ and wild cluster bootstrap using simulations for a sample of 50 clusters and 2000 observations by varying, i) within cluster covariate correlation, ii) within cluster error correlation, iii) cluster size and iv) number of treated clusters. Results suggest that CRVE performs less admirably when number of treated, not treated clusters are small, but wild bootstrap performs less admirably only if they are very small[11].

In computing the wild cluster bootstrap p-values, I use Stata code by MacKinnon and Webb (2017)[12]. It is not only compatible with later versions of Stata; but also

[11] CRVE works well if number of treated clusters are higher than 17 and lower than 33, while wild bootstrap performs well if number of treated clusters are higher than 7 and lower than 43 (p.241).

[12] I express my gratitude to James G. Mackinnon of Queen's University, and Matthew D. Webb of Carleton University for making their code publicly available. I also thank Matthew D. Webb for his comments during our correspondence.

allows embedding i) Hsiang (2010) code for calculating Conley standard errors, ii) Lee and Steigerwald (2017) code for effective number of clusters, iii) calculating $t\left(G^{*A}\right)$ critical values suggested by MacKinnon and Webb (2017) and Cameron and Miller (2015).

5.4 Estimating Overcharge Using Techniques in Collusion Retrospectives

5.4.1 Before and After

In this part, the impact of the cartel on price is approximated by before and after method. This involves comparing average price in competition and collusion periods. Recall that in this study consumer level data is used. p_{jltc} represents the delivered price charged by provider j, to customer c, at location l, in month t scaled by the quantity weighted average price in competitive period, $\bar{p}$[13].

Figure 5.1a shows the evolution of price over time. Seventh month, marked by the vertical line, represents the end of collusive period. Quantity weighted monthly average price[14] is represented on the y-axis. Blue horizontal line is the average price in competition period[15]. Orange marks the minimum price in this period. Figure 5.1a shows that average price in collusive period is 12.28 % higher than competitive period average.

In order to explore spatial distribution of overcharge, before and after method is slightly modified. Recall that data set includes information about location of the customer, l, and customer identity, c. First, (c, l) pairs, for which at least one transaction is reported both before and after the regime switch are identified. Second, for each (c, l) pair, the divergence between quantity weighted average price[16] in collusive and competitive periods are calculated separately as,

$$OVCH_{\bar{cl}} = 100\frac{p_{\bar{cl}}^{r=1} - p_{\bar{cl}}^{r=0}}{p_{\bar{cl}}^{r=0}} \tag{5.9}$$

where j is provider, t is month, $r = 1, 2$, $r = 1$ marks collusive regime, $r = 0$ marks competitive regime.

Figure 5.1b, illustrates the distribution of overcharge. The mean and median are respectively 9.26 % and 8.24 %. However, spanning an interval of -7.84 - 38.84 %, overcharge shows considerable variation.

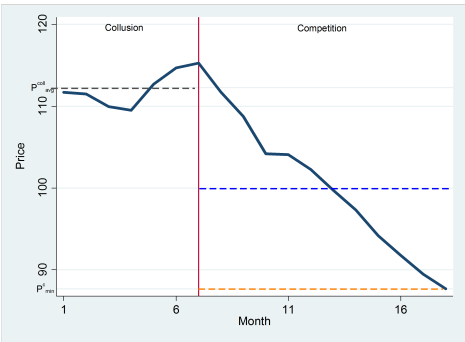
[13] $\bar{p} = \sum_l \sum_j \sum_c \sum_{t=8}^{18} \frac{p_{jltc} v_{jltc}}{\sum_l \sum_j \sum_c \sum_{t=8}^{18} v_{jltc}}$.

[14] $p_t = \sum_l \sum_j \sum_c \frac{v_{jclt}}{\sum_j \sum_c \sum_l v_{jclt}} p_{jclt}$.

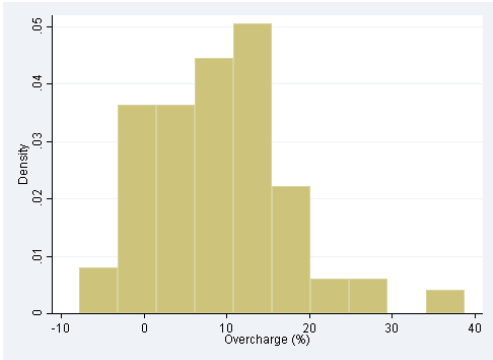
[15] Since the price is normalized with average competitive price, this is equal to 100.

[16] $p_{\bar{cl}}^r = \sum_j \sum_t \frac{v_{\overline{clr}jt}}{\sum_j \sum_t v_{\overline{clr}jt}} p_{\overline{clr}jt}$.

Figure 5.1: Before and After Method



(a) Average Price Patterns



(b) Overcharge Distribution

5.4.2 Dummy Variable Approach

A conventional dummy variable approach would follow a specification similar to Equation 5.1. This involves the assumption that the impact of collusion is captured exclusively by a dummy variable. The set of variables affecting the price and the way they affect price are identical in both regimes. Some examples are Cramton and Schwartz (2002); Hüschelrath et al. (2016); Laitenberger and Smuda (2015); Nelson (1993). Similarly, in this work, specifications (1) - (4) adopt this simplistic approach.

Some works in the literature relax the assumption of parameter equality. Typically this is done by expanding the specification in Equation 5.1 by interacting regime indicators with some of the regressors. Naturally in these cases, reporting the intercept shift alone would be insufficient, as regime change also impacts price via its interaction with covariates. Therefore, it is common to fix the values of the covariates to expected values and report a single overcharge estimate[17]. Some examples are Boshoff (2015); Kamita (2010); Madhavan et al. (1994); Mncube (2014); Notaro (2014). Specifications (5), (6) adopt this approach, in which indicators of market power, Δ_j^l, $(\Delta_j^l)^2$ and NBR_{jlc}, interact with a two level factorial variable, the dummy for collusion, and two different reduced form pricing equations, one for each regime, are estimated.

[17]See, Kamita (2010); Madhavan et al. (1994); Notaro (2014).

In all specifications, dependent variable is the delivered price charged by provider j, to customer c, at location l, in month t, p_{jltc}. All specifications include a constant and facility fixed effects, γ_j. Standard errors are clustered at county level. Specifications 3, 4 also employ cluster fixed effects. As controls, all specifications employ indicator of local market power and its square, Δ_l^j, and $\left(\Delta_l^j\right)^2$; number of rivals in a defined radius, NBR_{jlc}; distance between provider and buyer, d_{jl}; an indicator variable marking presence of a vertical relation provider and buyer, $\gamma_{jc}^{vertical}$; an indicator variable marking presence of an additional nearby facility controlled by the provider, γ_{jl}^{own}; index for the price of most commonly form of energy, EI_{jt}; and indices tracking regional demand, $t_{\overline{npl}(t-i)}$ where $i = 1, 2, 3, 4$, or $t_{\overline{nptl}}$. Variable of interest is the indicator variable marking collusive regime, γ_t^{coll}. Table 5.2 presents the results. Last row presents the overcharge estimates. Since in specifications 1-4 the impact of regime switch is captured entirely by γ_t^{coll}, overcharge estimates for these specifications are equal to parameter estimates for γ_t^{coll}. In specifications 5-6, regime switch indicators interact with Δ_l^j, $\left(\Delta_l^j\right)^2$, NBR_{jlc}. In these specifications the impact of regime switch on price, is captured by comparing predicted price in competition and collusion after fixing all covariates to sample averages.

EI_{jt}, d_{jl}, $\gamma_{jc}^{vertical}$, are most frequently insignificant across specifications. Any relation between these covariates and price does not survive allowing arbitrary within cluster correlation. Demand indicators are frequently significant. All specifications suggest large price difference associated with a regime switch. Findings indicate that overcharge estimates are in the interval of 11.14-13.98 %. Specifications 5, 6 also suggest that the impact of collusion varies greatly depending on the market power of the provider at each location. In competition period, there are strong nonlinearities between local market power indicator Δ_l^j and price; in collusion period $\left(\Delta_l^j\right)^2$ is not significant. Similarly, Δ_l^j and, NBR_{jlc} are significant across all specifications, with the exception of 4, 5. Since Δ_l^j and, NBR_{jlc} have little variation over time, in specifications 5, 6, their impact on price is captured by cluster fixed effects. Results suggest that under competition providers suffer considerable price cuts in serving locations that are closer to rivals, and locations in which there are greater number of rivals. However, under collusion, relation of market power indicators and price is much weaker, with no nonlinear component. It follows that the price that would serve as the but-for price, and consequently overcharge estimates building on but-for price, vary along with market power indicators.

Recall that there are potential inference issues stemming from potential spatial dependency across observations. In specifications 1-6 this was addressed via using clustered standard errors and allowing arbitrary correlation among observations

[18]**Notes for Table 5.2**: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. γ_t^{coll} indicates collusive, γ_t^{comp} indicates competitive regime. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance. NBR_{jlc} is number of rivals. U_{jt} is capacity utilization. EI_{jt} is energy price index. d_{jl} is distance. $t_{\overline{npdt}}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{npdt}}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5.2: Dummy Variable Approach Estimates[18]

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
γ_t^{coll}	12.0679***	11.6355***	11.1350***	11.2561***	8.9590***	10.0651***
	(0.9070)	(0.8756)	(0.8425)	(0.8324)	(1.2780)	(1.2576)
$\gamma_{jc}^{vertical}$	-0.0213	-0.2875	0.0028	0.2836	0.1175	-0.2851
	(1.5013)	(1.4347)	(1.5050)	(1.6978)	(1.6652)	(1.4086)
γ_{jl}^{own}	3.6074	4.9434**	5.7404***	4.3393	4.1914	4.9162***
	(2.3548)	(1.9140)	(1.8478)	(3.0967)	(3.0817)	(1.8753)
d_{jl}	-0.0037	-0.0047	-0.0283***	-0.1029*	-0.0961*	-0.0056
	(0.0204)	(0.0190)	(0.0093)	(0.0556)	(0.0567)	(0.0190)
EI_{jt}	0.0330	0.0360*	0.0110	-0.0182	0.0003	0.0629***
	(0.0199)	(0.0196)	(0.0204)	(0.0258)	(0.0254)	(0.0194)
U_{jt}	-2.1194**					
	(0.8117)					
Δ_l^j	0.4312*	0.4464**		-0.4168		
	(0.2357)	(0.2220)		(0.4133)		
$\left(\Delta_l^j\right)^2$	0.0147***	0.0146***		0.0199*		
	(0.0055)	(0.0055)		(0.0108)		
NBR_{jlc}	-1.9339***	-1.3502*		-0.9930		
	(0.5860)	(0.7244)		(2.3104)		
$t_{\overline{nptd}}$		-0.0790				-0.0815
		(0.0724)				(0.0725)
$t_{\overline{np}dt}$			0.1707***	0.0405	-0.0013	
			(0.0366)	(0.0610)	(0.0598)	
$t_{\overline{np}dt}^{-1}$			-0.0960***	-0.1981***	-0.2258***	
			(0.0339)	(0.0538)	(0.0506)	
$t_{\overline{np}dt}^{-2}$			-0.1820***	-0.3040***	-0.3395***	
			(0.0255)	(0.0486)	(0.0481)	
$t_{\overline{np}dt}^{-3}$			-0.3801***	-0.4981***	-0.5329***	
			(0.0285)	(0.0563)	(0.0546)	
$t_{\overline{np}dt}^{-4}$			0.1338***	-0.0163	-0.0695	
			(0.0277)	(0.0530)	(0.0542)	
$\gamma^{comp} \times \Delta_l^j$					-0.2345	0.5883**
					(0.4332)	(0.2287)
$\gamma^{coll} \times \Delta_l^j$					-0.6290	0.2046
					(0.4072)	(0.2241)
$\gamma^{comp} \times \left(\Delta_l^j\right)^2$					0.0275***	0.0258***
					(0.0104)	(0.0057)
$\gamma^{coll} \times \left(\Delta_l^j\right)^2$					0.0007	-0.0029
					(0.0122)	(0.0064)
$\gamma^{comp} \times NBR_{jlc}$					-1.6143	-1.9957**
					(2.3762)	(0.7816)
$\gamma^{coll} \times NBR_{jlc}$					0.3508	-0.3371
					(2.3089)	(0.7683)
R-squared	0.4588	0.4562	0.4574	0.5874	0.6030	0.4716
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	No	No	No	Yes	Yes	No
Overcharge	12.0679	11.6355	11.1350	11.2561	13.4608	13.9754

within the same cluster. Some other remedies include using CRVE standard errors; imposing an error structure; limiting the level of variation, e.g. collapsing data to lesser number of dimensions; using feasible effective number of clusters rather than actual number of clusters in defining critical values; and making wild cluster bootstrap. Table 5.2 summarizes this information for the variable of interest, γ_t^{coll} indicator. First four rows presents the inference using clustered standard errors, as in Table 5.2. Fifth and sixth rows present G^{*A} calculated via CSSL, and p-value associated with $t\left(G^{*A}\right)$. Seventh row presents Conley standard errors assuming that dependency across observations decays linearly with distance. Final row presents p-values using wild cluster bootstrap. Each of the three panels refers to different level of data aggregation. Upper panel uses the same aggregation as used so far; each transaction corresponds to a transaction in month t, to customer c, located at l, by provider j. Middle panel keeps the month, provider and location dimension, but eliminates customer dimension via aggregation. Lower panel further eliminates the provider dimension and leaves month and location. It should be noted that aggregation might necessitate a redefinition of the variable if that variable is affected from that aggregation. This should be clarified with an example. In the case of no aggregation, data is $t \times l \times j \times c$, $\gamma_{jc}^{vertical}$ is an indicator variable marking presence of a vertical relation provider and buyer. If data is aggregated to eliminate consumer dimension, so that data is $t \times l \times j$, then instead of an indicator variable, a continuous variable vr_{jlt} is used; for each provider j, at location l, in month t, this is defined as the ratio of total volume of transactions that go through a vertically related buyer to total volume of transactions. If the data is further aggregated to $t \times l$ level, the variable used is vr_{lt}; this is defined as the ratio of total volume of transactions that go through a vertically related buyer to total volume of transactions at location l, in month t. When necessary, the same adjustment is made to other variables as well.

Results are robust to changes in inference strategy; γ_t^{coll} is strongly significant with clustered standard errors, with Conley standard errors, with wild cluster bootstrap, or using critical values from feasible effective number of clusters.

5.4.3 Forecasting

First step in forecasting is to estimate pricing equations for competition period and retrieving parameters governing that period while employing *only* competition period data. Formally this corresponds to estimating an equation in the following form

$$p_{jltc} = \delta_0 + \sum_p \lambda_p z_{jltc}^p + \sum_k \rho_k \chi_{jltc}^k + e_{jltc}$$

where, p_{jltc} is the delivered price charged by provider j, to customer c, at location l, in month t; δ_0 is the intercept; z_{jltc}^p, and χ_{jltc}^k are respectively demand and supply

Table 5.3: Inference – Regime Change Indicator, Dummy Variable Approach

		(1)	(2)	(3)	(4)	(5)	(6)
$t \times l \times j \times c$	*Coeff.*	12.067 9	11.635 6	11.288 2	11.256 1	8.959 0	10.065 1
	Clustered s.e.	0.907 0	0.875 6	0.833 6	0.832 4	1.278 0	1.257 6
	t-stat	13.305 7	13.288 1	13.541 0	13.523 0	7.010 1	8.003 4
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	22.139 3	27.330 0	26.045 7	47.583 7	45.920 8	27.668 8
	p-value, G^{*A}	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	Conley s.e.	1.798 2	1.580 0	1.372 9	1.195 1	1.141 6	1.304 2
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
$t \times l \times j$	*Coeff.*	11.384 3	11.042 0	10.757 9	10.923 6	8.403 2	9.191 7
	Clustered s.e.	0.875 5	0.787 2	0.768 7	0.745 5	1.051 2	1.135 6
	t-stat	13.003 1	14.027 7	13.994 5	14.653 5	7.993 7	8.094 5
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	24.916 7	26.588 3	26.018 2	61.958 8	53.171 0	22.462 2
	p-value, G^{*A}	0.000 0	0.000 0	0.000 0	0.061 6	0.247 6	0.000 0
	Conley s.e.	1.639 4	1.432 1	1.290 5	1.077 3	1.013 9	1.210 8
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
$t \times l$	*Coeff.*	11.223 3	9.601 3	9.409 0	10.547 4	7.697 2	7.841 5
	Clustered s.e.	1.457 1	1.467 7	1.471 2	1.312 1	1.547 8	1.773 6
	t-stat	7.702 4	6.541 6	6.395 4	8.038 5	4.972 9	4.421 2
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	27.682 4	29.192 3	28.566 7	73.581 8	62.642 5	34.915 0
	p-value, G^{*A}	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 1
	Conley s.e.	1.255 2	1.205 0	1.198 1	1.080 0	0.952 9	1.229 9
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7

Notes: Each panel corresponds to different level of aggregation in data. In each panel, the coefficient of interest is regime change indicator. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

shifters. At the second step parameter estimates, $\hat{\delta}_0, \hat{\lambda}_k, \hat{\rho}_k$, are interacted with the values of covariates in the collusion period. This gives the prediction for the but-for price, the price that would have been observed if competition was in effect.

In all specifications dependent variable is p_{jltc}. All specifications include a constant and facility fixed effects, γ^j. Standard errors are clustered at county level. Specification 4 also employs cluster fixed effects. As controls, all specifications employ an indicator variable marking presence of a vertical relation provider and buyer, $\gamma_{jc}^{vertical}$; an indicator variable marking presence of an additional nearby facility controlled by the provider, γ_{jl}^{own}; distance between provider and buyer, d_{jl}; index for the price of most commonly form of energy, EI_{jt}; and indices tracking regional demand, $t_{\overline{npl}(t-i)}$ where $i = 1, 2, 3, 4$, or $t_{\overline{nptl}}$. Table 5.4 presents the results. Average overcharge implied by the estimates is primarily governed by the variables of interest that are indicative of market power, the indicator of local market power and its square, Δ_l^j, and $\left(\Delta_l^j\right)^2$; and number of rivals in a defined radius, NBR_{jlc}.

The estimates for d_{jl}, $\gamma_{jc}^{vertical}$, are most frequently insignificant across specifications. For EI_{jl}, γ_{jl}^{own} evidence is mixed; the estimates are significant in some specifications, insignificant in others. However, the estimated effect is imprecise, as standard errors are large. $t_{\overline{npl}(t-i)}$ do a fine job in explaining pricing. All specifications suggest large price difference associated with a regime switch. Findings indicate that overcharge estimate is in the interval of 8.05-11.46 %. However, it is characterised by considerable variation. This is shown in Figure 5.2 by calculating overcharge for each provider-location pair via modifying Equation 5.9 with replacing forecast price, $\hat{p}_{\bar{cl}}^{r=0}$, as the but-for price.

$$OVCH_{\bar{cl}} = 100\frac{p_{\bar{cl}}^{r=1} - \hat{p}_{\bar{cl}}^{r=0}}{\hat{p}_{\bar{cl}}^{r=0}} \tag{5.10}$$

Going back to Table 5.4, findings suggest that in competition period there are strong nonlinearities between indicator of local market power, Δ_l^j, and price. Consistent with findings in dummy variable approach, Δ_l^j and, NBR_{jlc} are significant, with the exception of Specification 5, in which their impact on price is captured by cluster fixed effects. Findings imply that a considerable part of the of the variation displayed in Figure 5.2 is related to varying levels of market power at different locations. This is shown more clearly in Table 5.5, where Δ_l^j, and NBR_{jlc} are fixed to certain values, where increases in Δ_l^j, and decreases in NBR_{jlc} imply a progressively increasing market power on the side of the provider. All other covariates are fixed at sample averages. Findings indicate that variations in market power measures alone may lead to variation in price predicted for the competition counterfactual as high as % 11.99.

Table 5.6 summarizes the findings from alternative methodologies used to ensure inference is valid. For each specification, two sets of computations, one for Δ_l^j, and one for $\left(\Delta_l^j\right)^2$ are presented. Computations involve G^{*A}, p-values associated

Table 5.4: Forecasting Estimates

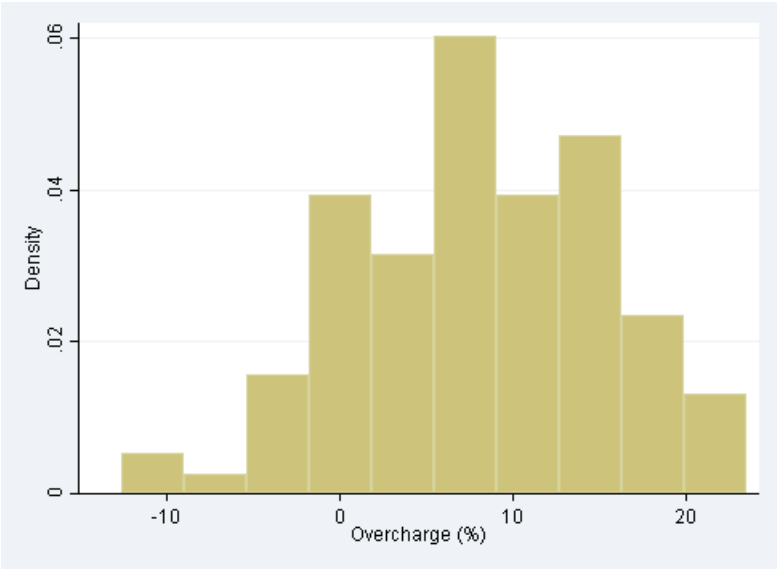
	(1)	(2)	(3)	(4)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
Δ_l^j	0.4128*	0.4322*	0.4653**	0.0256
	(0.2381)	(0.2258)	(0.2162)	(0.5830)
$\left(\Delta_l^j\right)^2$	0.0219***	0.0219***	0.0222***	0.0223*
	(0.0055)	(0.0054)	(0.0055)	(0.0120)
NBR_{jlc}	-2.5710***	-1.8116**	-1.3405*	-0.4971
	(0.6359)	(0.8245)	(0.7988)	(3.1891)
$\gamma_{jc}^{vertical}$	-1.3240	-1.5091	-1.2587	-0.2815
	(1.6426)	(1.4709)	(1.4612)	(1.7862)
γ_{jl}^{own}	2.9018	5.0018**	5.2504**	4.6793
	(2.6472)	(2.0664)	(2.0470)	(3.7098)
d_{jl}	-0.0158	-0.0168	-0.0156	-0.0619
	(0.0211)	(0.0197)	(0.0186)	(0.0727)
EI_{jt}	0.0798***	0.0958***	-0.0036	-0.0297
	(0.0246)	(0.0259)	(0.0235)	(0.0324)
$t_{\overline{npdt}}$			0.1596	-0.1746
			(0.0992)	(0.1638)
$t_{\overline{npdt}}^{-1}$			-0.4028***	-0.5179***
			(0.1228)	(0.1057)
$t_{\overline{npdt}}^{-2}$			0.4701***	0.1606
			(0.0956)	(0.0986)
$t_{\overline{npdt}}^{-3}$			-1.5880***	-1.5811***
			(0.1357)	(0.1282)
$t_{\overline{npdt}}^{-4}$			1.1140***	0.5399***
			(0.1331)	(0.1698)
U_{jt}	-2.6227**			
	(1.0702)			
$t_{\overline{nptd}}$		-0.1051		
		(0.0826)		
R-squared	0.3870	0.3880	0.4373	0.5606
Constant	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes
Cluster FE	No	No	No	Yes
Overcharge (%)	11.459	11.1636	8.2018	8.0558

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance. NBR_{jlc} is number of rivals. U_{jt} is capacity utilization. EI_{jt} is energy price index. d_{jl} is distance. $t_{\overline{npdt}}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{npdt}}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5.5: Predicted Price for Various Degrees of Market Power, Forecasting

Δ_l^j	-10	-10	-10	-5	-5	-5	0	0	0	5	5	5	10	10	10
NBR_{jlc}	2	1	0	2	1	0	2	1	0	2	1	0	2	1	0
$\hat{p}$	100.6	101.9	103.2	101.2	102.6	103.9	103	104.3	105.7	105.9	107.2	108.6	109.9	111.2	112.6

Figure 5.2: Distribution of Overcharge, Forecasting



with $t\left(G^{*A}\right)$, Conley standard errors, and p-values using wild cluster bootstrap for different level of aggregations[19] of data. Inference strategy in this case matters to an extent for the significance of the linear term. With the exception of Specification 4, in which linear effects are captured by cluster fixed effects, p-value associated with Δ_l^j goes as high as 0.16; but more frequently is below 0.10; in many cases is below 0.05. For the quadratic term, p-value is never higher than 0.10, but most frequently, lower than 0.01. I interpret these findings as there is a risk of invalid inference, but that risk is not very high.

5.5 Difference-in-Difference

For DiD, first important step is construction of an *appropriate counterfactual*, which requires description of the world if the treatment did not happen. Here, we are tracking the impact of a regime switch from collusion to competition. In coming up with the appropriate counterfactual for identifying the impact of the regime switch, I use theoretical intuition. Some locations, *home markets*; are characterised by high provider market power. These locations are governed by monopolistic pricing both in collusion, and competition; hence, are not affected from the treatment, the regime switch. On the other hand, *overlapping markets*, which would have been characterised by collusive pricing if the collusion was sustained, are now characterised by competitive pricing. Consequently, I first propose using uninterrupted monopolistic behaviour in *home markets* as the counterfactual of the regime switch (continuation of the collusion) in *overlapping markets*.

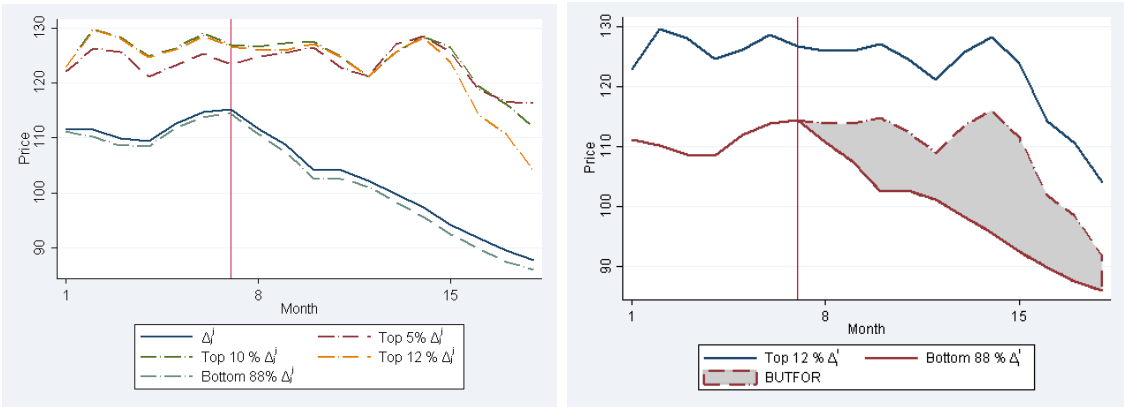
[19]Recall that aggregating data to $t \times l$ necessitates a redefinition of Δ_l^j. In $t \times l$ aggregation, I take volume weighted average Δ_l^j at location l, in month t. This is the reason for the divergence of absolute values of coefficient estimates (first line) in first two panels and panel three.

Table 5.6: Inference – Measures of Local Market Power, Forecasting

		Specification 1		Specification 2		Specification 3		Specification 4	
		Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$
$t \times l \times j \times c$	*Coeff.*	0.412 8	0.021 9	0.432 2	0.021 9	0.465 3	0.022 2	0.025 6	0.022 3
	Clustered s.e.	0.238 1	0.005 5	0.225 8	0.005 4	0.216 2	0.005 5	0.583 0	0.012 0
	t-stat	1.733 9	3.980 9	1.914 6	4.053 8	2.152 7	4.005 6	0.043 9	1.857 8
	p-value	0.085 5	0.000 1	0.057 8	0.000 1	0.033 2	0.000 1	0.965 1	0.065 5
	G^{*A}	10.006 1	18.176 5	10.653 6	10.653 6	10.830 1	17.721 3	13.135 9	14.128 2
	p-value, G^{*A}	0.113 6	0.000 9	0.082 8	0.002 0	0.054 8	0.000 9	0.965 7	0.084 2
	Conley s.e.	0.178 9	0.002 9	0.173 4	0.002 8	0.155 8	0.002 8	0.255 8	0.005 3
	p-value, wild BS	0.127 4	0.005 3	0.098 0	0.004 0	0.055 4	0.002 7	0.988 3	0.117 4
$t \times l \times j$	*Coeff.*	0.376 0	0.020 3	0.387 5	0.020 4	0.390 1	0.020 4	−0.369 8	0.023 8
	Clustered s.e.	0.243 1	0.005 5	0.231 3	0.005 5	0.228 8	0.005 7	0.516 8	0.012 9
	t-stat	1.546 8	3.719 5	1.675 2	3.732 1	1.705 2	3.571 2	−0.715 4	1.844 3
	p-value	0.124 5	0.000 3	0.096 4	0.000 3	0.090 6	0.000 5	0.475 7	0.067 5
	G^{*A}	32.603 4	14.654 1	30.898 5	30.898 5	30.991 0	13.758 8	13.753 4	15.082 1
	p-value, G^{*A}	0.131 6	0.002 1	0.104 0	0.000 8	0.098 2	0.003 1	0.486 3	0.084 9
	Conley s.e.	0.152 3	0.002 5	0.151 3	0.002 4	0.139 8	0.002 5	0.230 4	0.005 2
	p-value, wild BS	0.142 7	0.004 0	0.113 4	0.002 7	0.108 0	0.002 7	0.518 2	0.136 0
$t \times l$	*Coeff.*	1.684 8	0.033 5	1.772 3	0.036 0	1.743 1	0.035 6	1.531 1	0.036 3
	Clustered s.e.	0.326 6	0.010 4	0.363 3	0.011 6	0.359 6	0.011 6	0.859 8	0.015 4
	t-stat	5.158 8	3.231 1	4.878 4	3.099 1	4.846 8	3.077 1	1.780 8	2.363 2
	p-value	0.000 0	0.001 6	0.000 0	0.002 4	0.000 0	0.002 6	0.077 3	0.019 6
	G^{*A}	23.266 4	5.725 1	24.015 5	6.451 1	24.038 5	6.449 5	11.833 3	8.017 0
	p-value, G^{*A}	0.000 0	0.019 1	0.000 1	0.019 2	0.000 1	0.019 8	0.100 6	0.045 7
	Conley s.e.	0.150 4	0.003 9	0.157 5	0.004 2	0.147 9	0.004 2	0.521 4	0.007 4
	p-value, wild BS	0.001 3	0.026 7	0.002 0	0.022 0	0.002 0	0.022 0	0.111 4	0.076 7

Notes: Each panel corresponds to different level of aggregation in data. In each panel, the coefficient of interest is either Δ_l^j, relative proximity measure, or its squared. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

Figure 5.3: Evolution of Price in Home and Overlapping Markets



(a) Evolution (b) Impact

Here, main challenge is drawing the border between *home markets* and *overlapping markets*. Theoretical framework suggests that local market power of a provider is governed by its local relative cost. Unfortunately, the cost at each location is not observable. However, distance of each provider to each buyer is observable. Building on relative proximity of a provider and its closest rival to each buyer, it is possible to identify buyer-provider pairs in which provider has considerable transportation cost advantage in comparison to even its closest rival. With this reasoning, I use a measure of relative proximity, Δ_j^l; the distance between the closest rival k and location l (d_{kl}) net off the distance between provider j and location l (d_{jl}); so that $\Delta_j^l = d_{kl} - d_{jl}$. Figure 5.3 presents the evolution of market average price and average price in transactions with top 5 % 10 %, and 12 % Δ_j^l. It is easy to see that price in these transactions remained on high range longer, and when it finally felt, it did not fall as much as the average price.

In the rest of the section, the transactions at the top 10% of Δ_j^l, and these at the top 12 % are used as two different *home market* candidates. Note that it is difficult to claim that observations with top 10 %, and 12 % Δ_j^l are unaffected from the regime switch. Especially considering that it is the divergence in *total* cost not transportation cost that governs market power, the nullification of transportation cost advantages by disadvantages in production cost is possible. It follows that defining *home market* purely on a relative proximity measure, may lead to inclusion of some transactions that should be in *overlapping market* into *home market*. However, note that even if that is the case, this would make the overcharge estimates more conservative.

Also note that the theoretical framework suggests that under collusion, collusive agreement ensures that each provider enjoys undisturbed market power at each location. However, under competition price within overlapping markets is proportional to market power each provider enjoys at a given location, which in turn is proportional to difference in cost across providers. At the locations where cost difference disappears, market power of the provider is low, and price under

competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, market power of the provider is also high. Consequently, price in both regimes will be similar and regime switch would have a small impact on price. It follows that within *overlapping markets*, the impact of regime switch on price – the size of the overcharge – is inversely proportional to the market power of the provider under competition. Building on this, secondly I propose estimating the overcharge in a treatment intensity framework. I interpret regime switch as a treatment which produces heterogeneous effects at each location that is inversely proportional to difference in cost across providers at that location. In that regards, to approximate cost difference at each location, I use Δ_j^l.

Another important issue for the DiD estimation is *identifying compatibility issues* across treatment and control groups. In addition to a simple eye-ball approach, this involves testing formally if the treatment and control groups have a "common trend" in pretreatment period. This is done in the next section.

Finally, literature favours a discussion regarding *exogeneity of treatment*, the regime switch. A potential risk here is related to the decision to collude (alternatively decision to stop colluding); one can claim, this decision can never be taken to be exogenous, it is a as a conscious response to changing market conditions. Even though this is a very legitimate concern, two factors make this concern less relevant to the case at hand. First factor is the local nature of the analysis. As recognized by the literature, e.g. De Nijs (2012); Hastings (2004); Nevo and Whinston (2010); Pennerstorfer and Weiss (2013), decision to collude is not likely to be correlated with unobserved factors at the local level[20]. Second, there is some evidence that collapse of the cartel may be related to negative demand shocks. Recall that X demand is governed by movements in T preliminary analysis of data suggest that the collapse of the cartel is occurring in the middle of contraction in the T activity. Considering fluctuations in T are typically governed by macroeconomic conditions rather than local conditions in X market, risk of treatment endogeneity diminishes further.

5.5.1 Testing for Common Trend

At the core of DiD sits the assumption that control group is a good representation for the counterfactual of no treatment in the treated group; absent the treatment, the trend in the outcome variable will be the same in both groups. One way of assessing this is monitoring the trends of outcome variable in treatment and control groups before treatment, and see if they are similar. This might involve a

[20]To give a more formal perspective, note that decision to collude can be thought to have two dimensions, i) identities of colluding undertakings (j) and ii) timing of collusion (or its termination) (t). Also note that time dimension of the data is short (18 months), and number of undertakings is small. On the other hand, variable of interest, DiD coefficient, is an interaction of overlapping market indicator, $\gamma_{jl}^{overlap}$, which is defined on provider (j) times location (l) basis, with γ_t^{post} which is defined over time (t) basis. Differences in the level of variation between potential source of endogeneity ($j \times t$) and variable of interest ($j \times l \times t$) makes the risk small.

simple visual comparison; evolution of outcome variable is plotted for treatment and control groups and a judgment is made about similarity of two plots prior to the treatment. Alternatively, a formal test may be employed[21]. In that regards, Friberg and Romahn (2015)[22] and Weinberg and Hosken (2013), offer simply regressing price on a set of time invariant fixed effects and trend variables, while allowing trends to vary across treated and untreated groups, and then formally testing similarity in trends. Rewriting Equation 4.15,

$$p_i = \alpha_0 + \alpha_1 t \gamma_b^{treated} + \alpha_2 t \gamma_b^{control} + \alpha_3 \gamma^l + \upsilon_i$$

Recall that in this specification, b refers to brand; l refers to cities/regions; γ^l refers to city/region fixed effects; $\gamma_b^{treated}$ and $\gamma_b^{control}$ mark treatment and control brands retrospectively; and t is linear time trend. Estimation uses only pretreatment data and is followed by a formal test of $\hat{\alpha}_1 = \hat{\alpha}_2$.

Table 5.7 presents the results of the application of this test to *overlapping* and *home markets*. Specifications $1-2$ take top 10 % of Δ_j^l as the *home market*, while $3-4$ take top 12 % as the *home market*. Specifications $1, 3$ use county fixed effects; $2, 4$ use province fixed effects. All specifications employ facility fixed effects. In our setting, treatment and control groups are marked by $\gamma_{jl}^{overlap}$, and γ_{jl}^{home} respectively; consequently, hypothesis tested is $H_o : \gamma_{jl}^{overlap} \times t = \gamma_{jl}^{home} \times t$. As indicated in the last two rows, I fail to reject trend equality in *home* and *overlapping markets* in all specifications.

In testing common trend assumption, Ashenfelter et al. (2013) favours a more general specification, where in addition to fixed effects also controls are employed; parameter estimates are allowed to vary across treatment and control groups; and both posttreatment and pretreatment data is used. Rewriting Equation 4.16,

$$p_i = \alpha_0 + \alpha_1 t \gamma_t^{pre} + \alpha_2 t \gamma_t^{pre} \gamma_b^T + \alpha_3 t \gamma_t^{post} + \alpha_4 t \gamma_t^{post} \gamma_b^T + \sum_j x_{bj}^T \beta_j^T + \sum_h x_{bh}^C \beta_h^C + \upsilon_i$$

Recall that in this specification, j refers to treated brands, i.e. parties to the merger; h refers to control brands, i.e. private brands; b refers to brand; t is time; γ_t^{pre}, and γ_t^{post} are pretreatment and posttreatment indicators; γ_b^T marks the treatment group; and x_{bj}^T, x_{bh}^C are controls for treatment and control groups, i.e. product characteristics. Estimation is followed by a formal test of $H_o : \hat{\alpha}_2 = 0$; failure to reject H_o is interpreted as an evidence for trend equality between treatment and control groups.

[21] See, Aguzzoni et al. (2016); Ashenfelter et al. (2013); DGComp (2015); Friberg and Romahn (2015); Weinberg and Hosken (2013).

[22] See, Appendix Table 2, p. 15.

Table 5.7: Tests for Common Trend Assumption - I

	(1)	(2)	(3)	(4)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma_{jl}^{overlap} \times t$	0.6822***	0.7031***	0.6550***	0.6835***
	(0.1225)	(0.1190)	(0.1248)	(0.1185)
$\gamma_{jl}^{home} \times t$	0.6542*	0.6155*	0.8676**	0.7688**
	(0.3552)	(0.3641)	(0.3455)	(0.3223)
Constant	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes
Cluster FE	Yes	No	Yes	No
Province FE	No	Yes	No	Yes
$H_o : \gamma_{jl}^{overlap} \times t = \gamma^{home} \times t$				
F Stat	0.00	0.04	0.28	0.05
p-value	0.9448	0.8333	0.5952	0.8181

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_{jl}^{home} is home market. t is time trend. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5.8 presents the results of this test. Specifications $1-3$ take top 10 % of Δ_j^l as the *home market*, while $4-6$ take top 12 % as the *home market*. All specifications use a constant, facility fixed effects, county fixed effects. $1, 4$ use only fixed effects. $2, 5$ add controls. $3, 6$ add demand indices. With the exception of Specification 1, I fail to reject trend equality in *home* and *overlapping markets* in all specifications.

As a final alternative, Ashenfelter et al. (2013) suggest to employ time fixed effects rather than trends, while still allowing estimates to vary across treatment and control groups. Rewriting Equation 4.17

$$p_i = \alpha_0 + \sum_j x_{bj}^T \beta_j^T + \sum_h x_{bh}^C \beta_h^C + \sum_l \sigma_l \gamma_l^t + \sum_l \delta_l \gamma_l^t \gamma_b^T + \upsilon_i$$

Recall that in this specification, γ_l^t is time fixed effect. Estimation uses both pretreatment and posttreatment data, and is followed by a formal test of $\delta_l = 0$ for pretreatment periods, both jointly and marginally. Table 5.9 summarizes the findings. Specifications $1-3$ take top 10 % of Δ_j^l as the *home market*, while $4-6$ take top 12 % as the *home market*. All specifications use a constant and facility fixed effects. $2-5$ also employ cluster fixed effects. $2, 5$ add controls. $3, 6$ add demand indices. Findings suggest that even though in some specifications it is possible to find some deviations between *overlapping markets* and *home markets*, more frequently, the month fixed effects in two markets do not deviate significantly in the pretreatment period. Table 5.9 also presents test statistics for joint significance

Table 5.8: Tests for Common Trend Assumption - II

	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_t^{pre} \times t$	-0.3320	0.3532*	0.3964*	-0.1984	0.3497*	0.3608*
	(0.2152)	(0.2125)	(0.2160)	(0.2171)	(0.1967)	(0.2020)
$\gamma_t^{pre} \times \gamma_{jl}^{overlap} \times t$	0.4865**	0.0853	0.0203	0.3425	0.0949	0.0634
	(0.2399)	(0.2254)	(0.2263)	(0.2505)	(0.2140)	(0.2190)
$\gamma_t^{post} \times t$	-0.8919***	-0.7408***	-0.7605***	-0.8448***	-0.7552***	-0.8045***
	(0.1848)	(0.1584)	(0.1511)	(0.1842)	(0.1709)	(0.1699)
$\gamma_t^{post} \times \gamma_{jl}^{overlap} \times t$	-1.1875***	-1.4237***	-1.3663***	-1.2398***	-1.4067***	-1.3131***
	(0.2016)	(0.1763)	(0.1719)	(0.2029)	(0.1957)	(0.1957)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Demand Controls	No	No	Yes	No	No	Yes
Cluster	County	County	County	County	County	County

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_t^{pre} is pretretment; γ_t^{post} is posttretment; t is time trend. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

of month fixed effects. With the exception of the specifications that only use fixed effects, I fail to reject joint significance.

The results from three different strategies in testing common trend suggest that prior to treatment the trends in treatment and control markets were statistically "common". Consequently, I now proceed to DiD estimations.

5.5.2 Estimations

At the most basic level, DiD estimation bases on

$$p_i = \alpha_0 + \alpha_1 \gamma_t^{post} + \alpha_2 \gamma_l^{treated} + \alpha_3 \gamma_t^{post} \gamma_l^{treated} + \upsilon_i \tag{5.11}$$

where γ_t^{post} marks posttreatment observations, $\gamma_l^{treated}$ marks treated observations. $\gamma_t^{post} \times \gamma_l^{treated}$ is the variable of interest, as it captures the effect of the treatment on the treated. However, in practice, researcher either employs some controls, i.e. demand, cost shifters, z_{lt}, χ_{lt}; or, time and cross-section specific fixed effects, γ^l and or γ^t[23].

Fixed Effects Specifications:

In this part, estimations are conducted within a fixed effects framework. This involves estimating

$$p_{jltc} = \alpha_0 + \alpha_1 \gamma_{jl}^{overlap} \gamma_t^{post} + \sum_t \beta_t \gamma^t + \sum_l \delta_l \gamma^l + \sum_j \theta_j \gamma^j + \upsilon_{jltc} \tag{5.12}$$

in the general form. p_{jltc} is the delivered price; l refers to location; j refers to provider; t refers to month; c refers to consumer. $\gamma_{jl}^{overlap}$, marks locations that are impacted from the regime change; γ_t^{post} marks observations in posttreatment period. All specifications include a constant and facility fixed effects. Standard errors are clustered at county level. In specifications 2, 4, 7, and 9 county fixed effects are used; in 5, and 10 province fixed effects are used. In specifications 1, 3, 6, and 8, instead of location fixed effects, $\gamma_{jl}^{overlap}$ is used; similarly, in 1, 2, 6, and 7 instead of month fixed effects γ_t^{post} is used. Specifications $1-5$ set transactions at the top 10% of Δ_l^j; specifications $6-10$ set transactions at the top 12% of Δ_l^j as the control group. The coefficient of interest is α_1, the DiD coefficient. Table 5.10 presents the

[23]Some straightforward extensions include allowing parameter inequality across treated and not treated groups, e.g. Allen et al. (2014); Ashenfelter et al. (2013); Weinberg and Hosken (2013); allowing heterogeneity in treatment effects, e.g. Aguzzoni et al. (2014); Ashenfelter et al. (2013); Calomiris and Pornrojnangkool (2005); Friberg and Romahn (2015); Luo (2014); tracking multiple treatments, e.g. Silvia and Taylor (2013); or, allowing impact of treatment to vary over time, e.g. DGComp (2015); Hosken et al. (2011)

Table 5.9: Tests for Common Trend Assumption - III

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma^{m=2}$	0.5407	1.0445	1.5424	0.5336	1.3823	1.9229
	(1.3330)	(1.1803)	(1.1558)	(1.2182)	(1.1520)	(1.4193)
$\gamma^{m=3}$	1.3411	1.2617	1.3675	1.0189	1.9557	1.5083
	(1.4073)	(2.0657)	(2.1239)	(1.2790)	(1.8074)	(1.8633)
$\gamma^{m=4}$	1.1264	1.6746	1.7670	1.0457	2.4356	1.7388
	(1.4440)	(2.2541)	(2.3622)	(1.3194)	(2.0605)	(2.1277)
$\gamma^{m=5}$	2.3117	3.3943	3.7502	2.1482	3.7077	2.3170
	(1.6559)	(2.9531)	(3.1163)	(1.4932)	(2.5315)	(2.7568)
$\gamma^{m=6}$	5.8653***	7.1876**	7.5233**	4.9562***	6.9754***	6.0144**
	(1.9468)	(2.8668)	(2.9966)	(1.7735)	(2.5393)	(2.7080)
$\gamma^{m=7}$	6.1909***	6.7631**	6.9129**	5.4886***	8.6637***	7.2400**
	(2.0394)	(2.7507)	(3.0468)	(1.8537)	(2.9961)	(2.8616)
$\gamma^{m=1} \times \gamma_{jl}^{overlap}$	-2.1114	2.4722	2.9405	-2.2418	-10.3780	-20.3997*
	(3.2587)	(16.6347)	(17.0128)	(2.9278)	(12.2805)	(10.5380)
$\gamma^{m=2} \times \gamma_{jl}^{overlap}$	-3.1315	0.6398	1.7412	-3.2580	-12.5416	-22.0741**
	(3.1080)	(16.6698)	(16.7886)	(2.8041)	(12.4484)	(11.0137)
$\gamma^{m=3} \times \gamma_{jl}^{overlap}$	-4.9659	1.7928	2.8153	-4.7682*	-11.8549	-20.5663*
	(3.1278)	(16.3860)	(16.5515)	(2.7794)	(12.7726)	(10.6990)
$\gamma^{m=4} \times \gamma_{jl}^{overlap}$	-4.6279	1.8079	2.8590	-4.6754*	-11.9294	-20.3546*
	(3.0242)	(16.3682)	(16.5211)	(2.7266)	(13.0073)	(10.8636)
$\gamma^{m=5} \times \gamma_{jl}^{overlap}$	-2.7462	3.0413	2.6557	-2.6904	-10.2166	-19.0515*
	(2.9335)	(16.0414)	(16.1697)	(2.5952)	(13.0189)	(10.4611)
$\gamma^{m=6} \times \gamma_{jl}^{overlap}$	-4.7459*	0.8797	1.5654	-3.8770	-11.8117	-20.0350*
	(2.7153)	(16.0133)	(16.1341)	(2.4492)	(12.8332)	(10.3510)
$\gamma^{m=7} \times \gamma_{jl}^{overlap}$	-5.3746*	0.7423	1.8696	-4.7410*	-14.1818	-21.6767*
	(2.8339)	(16.4207)	(16.5061)	(2.5591)	(13.9923)	(11.4942)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	No	Yes	Yes	No	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Demand Controls	No	No	Yes	No	No	Yes
$H_o : \gamma^t \times \gamma_{jl}^{overlap} = \gamma^{t-1} \times \gamma_{jl}^{overlap} = 0, \quad t = 1, 2...7$						
F Stat	3.60	1.57	0.71	2.88	1.64	0.71

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. $\gamma_t^{m=i}$ is month dummy for month i. Standard errors are clustered at county level.

Table 5.10: *DiD* – Estimations with Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	-10.0142***	-8.2262***	-10.0764***	-8.1949***	-8.1117***	-9.1798***	-7.7115***	-9.1163***	-7.4871***	-7.7325***
	(1.1048)	(1.3114)	(1.1319)	(1.2786)	(1.4563)	(1.1478)	(1.3328)	(1.1874)	(1.3460)	(1.4254)
γ_t^{post}	-1.6415*	-3.2463***				-2.4858**	-3.7941***			
	(0.9464)	(1.1604)				(1.0254)	(1.2067)			
$\gamma_{jl}^{overlap}$	-4.0635		-4.0043			-3.9526		-3.7653		
	(2.9375)		(2.8520)			(2.6285)		(2.5772)		
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No	No	No
Month FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Cluster FE	No	Yes	No	Yes	No	No	Yes	No	Yes	No
Province FE	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.4418	0.5912	0.5805	0.7201	0.6307	0.4414	0.5912	0.5790	0.7198	0.6310

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_t^{post} is posttretment. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

results.

Table 5.11: Inference – *DiD* Variable, Specifications with Fixed Effects

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−10.014 2	−8.391 7	−10.076 4	−8.342 0	−8.111 7	−9.179 8	−8.339 0	−9.116 3	−8.035 3	−7.732 5
	Clustered s.e.	1.111 2	1.301 1	1.134 9	1.259 2	1.460 9	1.153 8	1.339 1	1.198 6	1.320 1	1.419 0
	t-stat	−9.012 1	−6.449 9	−8.878 7	−6.624 8	−5.552 5	−7.956 0	−6.227 5	−7.606 0	−6.086 7	−5.449 1
$t \times l \times j \times c$	*p-value*	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	15.406 7	18.678 8	15.372 2	18.679 2	5.356 3	18.636 3	21.867 0	18.461 7	21.861 9	6.335 5
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.002 1	0.000 0	0.000 0	0.000 0	0.000 0	0.001 3
	Conley s.e.	1.385 8	1.051 7	1.132 9	0.760 5	0.966 6	1.235 3	0.903 0	1.037 2	0.737 4	0.881 3
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−9.258 3	−6.438 4	−9.471 0	−6.523 1	−6.122 5	−7.873 2	−6.734 9	−7.936 7	−6.541 5	−6.070 2
	Clustered s.e.	1.311 7	1.577 6	1.295 4	1.454 4	1.566 7	1.437 7	1.827 0	1.443 3	1.658 8	1.538 4
	t-stat	−7.058 2	−4.081 0	−7.311 5	−4.485 0	−3.907 8	−5.476 1	−3.686 3	−5.498 8	−3.943 6	−3.945 7
$t \times l \times j$	*p-value*	0.000 0	0.000 1	0.000 0	0.000 0	0.000 1	0.000 0	0.000 3	0.000 0	0.000 1	0.000 1
	G^{*A}	8.309 9	22.578 5	8.312 6	22.597 6	6.383 3	10.746 9	25.972 0	10.670 4	25.988 8	7.048 5
	p-value	0.000 1	0.000 5	0.000 1	0.000 2	0.007 0	0.000 2	0.001 1	0.000 2	0.000 5	0.005 5
	Conley s.e.	1.249 4	1.021 3	0.985 6	0.750 3	0.887 4	1.157 3	0.998 5	0.960 5	0.849 2	0.892 7
	p-value, wild BS	0.000 7	0.002 0	0.000 7	0.001 3	0.004 0	0.000 7	0.000 7	0.000 7	0.000 7	0.001 3
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−10.376 2	−9.532 9	−10.211 0	−9.404 1	−8.508 6	−8.102 3	−10.248 3	−7.658 3	−9.729 1	−7.786 2
	Clustered s.e.	2.506 8	1.776 2	2.342 6	1.474 6	1.823 2	2.396 1	1.606 9	2.327 4	1.408 4	1.739 0
	t-stat	−4.139 1	−5.367 1	−4.358 8	−6.377 4	−4.666 8	−3.381 5	−6.377 8	−3.290 5	−6.908 1	−4.477 3
$t \times l$	*p-value*	0.000 1	0.000 0	0.000 0	0.000 0	0.000 0	0.000 9	0.000 0	0.001 3	0.000 0	0.000 0
	G^{*A}	6.713 9	17.066 4	6.707 2	17.112 3	9.092 4	9.079 4	21.393 7	9.031 2	21.443 7	12.005 8
	p-value, G^{*A}	0.004 8	0.000 1	0.003 7	0.000 0	0.001 1	0.008 0	0.000 0	0.009 3	0.000 0	0.000 8
	Conley s.e.	3.088 6	1.136 7	2.978 9	0.840 9	0.997 7	2.809 7	1.029 3	2.713 0	0.765 3	0.884 2
	p-value, wild BS	0.003 3	0.001 3	0.002 7	0.000 7	0.001 3	0.006 7	0.000 7	0.008 0	0.000 7	0.002 0

Notes: Each panel corresponds to different level of aggregation in data. In each panel, the coefficient of interest is DiD indicator. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

If *home market* is defined as top 10% of Δ_l^j, estimates suggest that the fall in price in *home markets* is in the interval of $1.64 - 3.79\%$. However, $8.11 - 10.08\%$ of the price decrease in the *overlapping market* can be associated to regime change. If the *home market* is defined as the top 12% of Δ_l^j, estimates for price fall in *home markets* goes up to $2.48 - 3.79\%$, while price decrease in the overlapping market that can be associated to regime change is $7.48 - 9.17\%$. Since expanding *home market* threshold implies including transactions that are progressively more competitive, this decline in coefficient estimates for DiD coefficient is consistent with the theoretical framework.

Inference problems due to spatial dependency across observations and DiD methodology are addressed by applying various potential remedies, e.g. collapsing data to fewer dimensions; imposing an error structure; using $t\left(G^{*A}\right)$ critical values; and wild cluster bootstrap. Table 5.11 summarizes this information for the variable of interest, DiD indicator, $\gamma_t^{post} \times \gamma_{jl}^{overlap}$. First four rows present the inference using clustered standard errors. Fifth and sixth rows present G^{*A} calculated via CSSL, and p-value associated with $t\left(G^{*A}\right)$. Seventh row presents Conley standard errors assuming dependency across observations decays linearly with distance. Final row presents p-values using wild cluster bootstrap. Each of the three panels refer to a different level of data aggregation.

Findings suggest that p-values calculated using clustered standard errors are in fact smaller than those with $t\left(G^{*A}\right)$, or wild cluster bootstrap. However, the difference does not affect the inference; even using alternative methodologies to calculate standard errors and p-values, the DiD coefficient is significant at conventional levels.

Employing Control Variables:

In this part, control variables are introduced. In general form, this involves estimating,

$$p_{jltc} = \alpha_0 + \alpha_1 \gamma_{jl}^{overlap} \gamma_t^{post} + \sum_p \lambda_p z_{jltc}^p + \sum_k \rho_k \chi_{jltc}^k + \sum_t \beta_t \gamma^t + \sum_l \delta_l \gamma^l + \sum_j \theta_j \gamma^j + \upsilon_{jltc} \tag{5.13}$$

where t is month, c is customer, l is location, j is provider. Note that this equation incorporates p demand shifters, z_{jltc}^p and k cost shifters, χ_{jltc}^k. Control variables include indicator of local market power, and its square, Δ_l^j, and $\left(\Delta_l^j\right)^2$; number of rivals in a defined radius, NBR_{jlc}; distance between provider and buyer, d_{jl}; an indicator variable marking presence of a vertical relation provider and buyer, $\gamma_{jc}^{vertical}$; an indicator variable marking presence of an additional nearby facility controlled by the provider, γ_{jl}^{own}; indices tracking regional demand, $t_{\overline{npl}(t-i)}$ where $i = 1, 2, 3, 4$, or $t_{\overline{nptl}}$; indices tracking energy price and capacity utilization, EI_{jt} and U_{jt}. All specifications employ a constant and facility fixed effects. Standard errors are clustered at county level. In specifications 5, 6, 11, and 12 county fixed effects,

in other specifications, $\gamma_{jl}^{overlap}$ is used. Similarly, specifications 1, 2, 5, 7, 8, and 11 use γ_t^{post}, while other specifications use month fixed effects. Specifications $1-6$ set top 10% of Δ_l^j; specifications $7-12$ set top 12% of Δ_l^j as the home market. The coefficient of interest is α_1, the DiD coefficient. Table 5.12 presents the results.

Defining *home market* as top 10% of Δ_l^j, point estimates suggest that $8.33-11.25\%$ of the price decrease in the *overlapping market* can be associated with regime switch. If *home market* is defined as 12% of Δ_l^j, point estimates range in $7.99-10.17\%$. Δ_l^j, $\left(\Delta_l^j\right)^2$, $\gamma_{jc}^{vertical}$, d_{jl} are frequently insignificant across specifications. Demand indicators are frequently significant. It is interesting to see that $t_{\overline{npl}t}^{-4}$ and $t_{\overline{npl}t}^{-3}$, $t_{\overline{npl}t}^{-2}$, $t_{\overline{npl}t}^{-1}$ have opposite signs in many specifications. However, in specifications 5, 10, where demand indicators and capacity utilization are used together as regressors, $t_{\overline{npl}t}^{-4}$ is no longer significant. Also considering, this pattern does not survive when transaction volume is included in the estimation in an IV framework[24], I do not take it as a major concern.

Table 5.13 summarizes the results from alternative methods employed for valid inference. Findings are very similar to the findings in Table 5.11. p-values calculated using clustered standard errors are in fact smaller than those with $t\left(G^{*A}\right)$, or wild cluster bootstrap. However, even using alternative methodologies to calculate standard errors and p-values, DiD coefficient is still significant at conventional levels.

Basic DiD specifications suggest that using difference in price across control and treatment markets and before and after treatment, the impact of the regime switch is conservatively estimated in the interval of $7.49-11.25\%$.

Treatment Intensity:

So far, spatial variation in the data is exploited in determining treatment and control groups. Provider-buyer pairs that are unaffected from the regime change make up the control group; pairs that are affected from the regime change make up the treatment group. This involves the assumption that two locations, one right off the *overlapping market* boundary, the other one right on the centre, have been exposed to the same treatment. In this part, this assumption is relaxed, and variation in the treatment intensity is exploited in the identification. This is done by employing a continuous variable indicative of variation in treatment intensity at each location. In order to provide the intuition behind this, I revisit Pennerstorfer and Weiss (2013). Rewriting the estimated equation,

$$p_i = \alpha_0 + \alpha_1 \gamma_{st}^{BP} + \alpha_2 \gamma_{st}^{comp} + \alpha_3 SC_{st} + \sum_t \beta_t \gamma^t + \sum_s \delta_s \gamma^s + \sum_l \lambda_l z_{st}^l + \upsilon_i$$

Recall that in this equation s is station; t is time; γ^t and γ^s are time and station

[24]See the estimations in Chapter 3.

Table 5.12: *DiD* – Estimations with Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	-11.2524***	-10.0864***	-10.0922***	-8.3757***	-10.1695***	-9.0116***	-9.0048***	-7.9884***
	(1.2072)	(1.1467)	(1.1633)	(1.2773)	(1.2737)	(1.2451)	(1.2562)	(1.2357)
$\gamma_{jl}^{overlap}$	2.7356	3.9925	4.0438		1.6979	2.9873	3.0280	
	(3.7870)	(3.1735)	(3.1644)		(2.8320)	(2.5326)	(2.5248)	
$t_{\overline{np}dt}$			0.0075	0.0150			0.0066	0.0158
			(0.0409)	(0.0442)			(0.0410)	(0.0423)
$t_{\overline{np}dt}^{-1}$			-0.1258***	-0.0916**			-0.1264***	-0.0899**
			(0.0329)	(0.0403)			(0.0328)	(0.0393)
$t_{\overline{np}dt}^{-2}$			-0.0870***	-0.0741*			-0.0862***	-0.0724*
			(0.0303)	(0.0384)			(0.0303)	(0.0375)
$t_{\overline{np}dt}^{-3}$			-0.0800**	-0.0529			-0.0799**	-0.0502
			(0.0354)	(0.0444)			(0.0354)	(0.0435)
$t_{\overline{np}dt}^{-4}$			0.1581***	0.1466***			0.1578***	0.1466***
			(0.0316)	(0.0349)			(0.0319)	(0.0344)
Δ_l^j	0.2829	0.3842	0.3917	-0.8667**	0.2590	0.3661	0.3735	-0.8767**
	(0.2660)	(0.2448)	(0.2440)	(0.3741)	(0.2506)	(0.2329)	(0.2321)	(0.3667)
$\left(\Delta_l^j\right)^2$	0.0001	0.0001*	0.0001*	0.0001	0.0001	0.0001*	0.0001*	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
NBR_{jlc}	-1.8473***	-1.3127*	-1.3592*	-2.0285	-1.8455***	-1.2963*	-1.3483*	-1.9377
	(0.5911)	(0.7207)	(0.7065)	(2.0878)	(0.5811)	(0.7185)	(0.7036)	(2.0822)
γ_{jl}^{own}	3.3845	4.7360***	4.6704***	4.4102	3.3833	4.7487***	4.6764***	4.4518
	(2.3053)	(1.7430)	(1.7532)	(2.9285)	(2.2887)	(1.7419)	(1.7519)	(2.8753)
d_{jl}	-0.0052	-0.0024	-0.0019	-0.1308**	-0.0064	-0.0032	-0.0027	-0.1305**
	(0.0201)	(0.0186)	(0.0185)	(0.0515)	(0.0202)	(0.0186)	(0.0185)	(0.0513)
$\gamma_{jc}^{vertical}$	0.0864	0.4439	0.4450	1.2296	0.0343	0.4117	0.4129	1.2655
	(1.5029)	(1.4307)	(1.4300)	(1.7369)	(1.5087)	(1.4360)	(1.4351)	(1.7413)
γ_t^{post}	-2.6253**				-3.6942***			
	(1.0425)				(1.1768)			
EI_{jt}	0.0608***				0.0591***			
	(0.0189)				(0.0186)			
U_{jt}	-1.7279**				-1.8897**			
	(0.8071)				(0.8200)			
$t_{\overline{nptd}}$		-0.0808				-0.0821		
		(0.0701)				(0.0702)		
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	No	No	No	Yes	No	No	No	Yes
Month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R-squared	0.4717	0.6049	0.6065	0.7075	0.4713	0.6040	0.6056	0.7078

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_t^{post} is posttretment. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance. NBR_{jlc} is number of rivals. U_{jt} is capacity utilization. EI_{jt} is energy price index. d_{jl} is distance. $t_{\overline{np}dt}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{np}dt}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5.13: Inference – *DiD* Variable, Specifications with Controls

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−11.252 4	−10.086 4	−10.092 2	−8.375 7	−10.169 5	−9.011 6	−9.004 8	−7.988 4
	Clustered s.e.	1.207 2	1.146 7	1.163 3	1.277 3	1.273 7	1.245 1	1.256 2	1.235 7
	t-stat	−9.321 0	−8.795 6	−8.675 7	−6.557 6	−7.984 5	−7.237 5	−7.168 5	−6.464 6
$t \times l \times j \times c$	*p-value*	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	13.421 5	14.610 4	17.640 9	19.067 6	17.324 1	18.674 7	20.866 2	22.182 1
	p-value, G^{*A}	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	Conley s.e.	1.477 4	1.033 1	1.025 3	0.751 8	1.317 3	0.983 4	0.973 9	0.705 3
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−10.665 1	−9.354 9	−9.378 1	−7.059 3	−8.959 6	−7.866 8	−7.869 5	−6.926 3
	Clustered s.e.	1.435 0	1.347 2	1.368 1	1.418 4	1.595 8	1.456 4	1.471 2	1.357 2
	t-stat	−7.432 0	−6.943 8	−6.855 0	−4.976 7	−5.614 6	−5.401 7	−5.348 9	−5.103 4
$t \times l \times j$	*p-value*	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	7.452 1	8.392 3	9.721 6	23.238 8	9.879 7	10.910 4	12.467 9	26.857 6
	p-value, G^{*A}	0.000 1	0.000 1	0.000 1	0.000 0	0.000 2	0.000 2	0.000 2	0.000 0
	Conley s.e.	1.373 4	0.945 7	0.937 5	0.701 5	1.268 6	0.960 4	0.952 6	0.758 2
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−10.718 5	−9.912 4	−9.656 0	−8.754 8	−9.074 5	−7.705 7	−7.410 5	−9.130 5
	Clustered s.e.	2.291 2	1.870 3	1.863 5	1.636 3	2.127 8	1.901 5	1.899 8	1.503 8
	t-stat	−4.678 2	−5.299 8	−5.181 7	−5.350 5	−4.264 8	−4.052 4	−3.900 6	−6.071 5
$t \times l$	*p-value*	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 1	0.000 2	0.000 0
	G^{*A}	6.522 6	6.729 3	6.895 6	17.935 1	9.296 5	9.107 5	9.300 2	23.452 8
	p-value, G^{*A}	0.002 7	0.001 3	0.001 3	0.000 0	0.001 9	0.002 8	0.003 4	0.000 0
	Conley s.e.	2.397 2	2.182 9	2.178 6	0.873 8	2.147 1	1.895 4	1.892 0	0.799 9
	p-value, wild BS	0.002 7	0.001 3	0.001 3	0.001 3	0.003 3	0.003 3	0.003 3	0.000 7

Notes: Each panel corresponds to different level of aggregation in data. In each panel, the coefficient of interest is DiD indicator. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

fixed effects; z_{st}^{l} refers to controls; γ_{st}^{BP} marks stations subject to merger; γ_{st}^{comp} indicates that before the merger, station s was competing with a station that changed ownership. Note that the impact of merger is governed by distribution of the stations and the identity of the merging parties, and it is uneven across different locations; some locations suffer large jumps in concentration, while some are only marginally affected. To capture this heterogeneity, Pennerstorfer and Weiss (2013) propose employing spatial clustering index, SC. This is a local measure of concentration that varies at each location but have no variation over time in premerger period. It changes only once, due to merger[25], and in proportion to the impact of merger at that location.

Here, I adopt the same methodology to a regime switch from collusion to competition. At the locations where cost difference disappears, market power of the provider is low, and price under competition is forced towards cost. Consequently, regime switch would have a big impact on price. If cost difference across providers is high even in competition, market power of the provider is also high. Consequently, price in both regimes will be similar and regime switch would have a small impact on price. It follows that within *overlapping markets*, the impact of regime switch on price – the size of the overcharge – is inversely proportional to the market power of the provider under competition. Building on this, I propose interpreting regime switch as a treatment which produces heterogeneous effects at each location that is inversely proportional to difference in cost across providers at that location. In that regards, to approximate cost difference, alternatively local intensity of treatment at each location, I use Δ_j^l and its squared.

However, there is a difference between Δ_l^j and spatial clustering index. The latter, by design, is unchanged in pretreatment period, and changes only due to treatment, while the former has some variation in the pretreatment period. Consequently, I modify the empirical strategy in Pennerstorfer and Weiss (2013) by using a specification of the following form:

$$p_{jltc} = \alpha_0 + \alpha_1 \gamma_t^{post} \gamma_{jl}^{overlap} \Delta_l^j + \alpha_2 \gamma_t^{post} \gamma_{jl}^{overlap} \left(\Delta_l^j\right)^2 + \sum_p \lambda_p z_{jltc}^p + \sum_k \rho_k \chi_{jltc}^k$$
$$+ \sum_t \beta_t \gamma^t + \sum_l \delta_l \gamma^l + \sum_j \theta_j \gamma^j + \upsilon_{jltc} \tag{5.14}$$

where t is month, c is customer, l is location, j is provider. γ^j γ^l, γ^t are respectively provider, county and time fixed effects. z_{jltc}^p and χ_{jltc}^k are demand and cost shifters. Note that $\gamma_t^{post} \times \gamma_{jl}^{overlap} \times \Delta_l^j$ and $\gamma_t^{post} \times \gamma_{jl}^{overlap} \times \left(\Delta_l^j\right)^2$ are zero in *home markets* before and after treatment; and in *overlapping markets* before treatment; they are nonzero only in *overlapping markets* after treatment. Specification 1, and 4 only include fixed effects and variables of interest. Specification 2, and 5 include number

[25] Pennerstorfer and Weiss (2013) also note that entry and exit may affect the index as well (FN 9).

Table 5.14: *DiD* – Estimations with Treatment Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma_t^{post} \times \gamma_{jl}^{overlap} \times \Delta_l^j$	0.6340***	0.5777***	0.6028***	0.4907**	0.6264***	0.5650***	0.5910***	0.4780**
	(0.1943)	(0.1938)	(0.1873)	(0.1895)	(0.1930)	(0.1957)	(0.1890)	(0.1922)
$\gamma_t^{post} \times \gamma_{jl}^{overlap} \times \left(\Delta_l^j\right)^2$	0.0276***	0.0287***	0.0293***	0.0312***	0.0273***	0.0280***	0.0287***	0.0306***
	(0.0084)	(0.0081)	(0.0079)	(0.0082)	(0.0084)	(0.0082)	(0.0080)	(0.0083)
$\gamma_t^{post} \times \gamma_{jl}^{overlap} \times NBR_{jlc}$		-2.1984***	-2.1750***	-2.2158***		-2.1023***	-2.0741***	-2.1090***
		(0.4890)	(0.5199)	(0.5369)		(0.4834)	(0.5072)	(0.5252)
$\gamma_{jc}^{vertical}$			1.1833	1.1039			1.2065	1.1287
			(1.7772)	(1.7259)			(1.7791)	(1.7282)
γ_{jl}^{own}			2.2294	3.6553			2.2523	3.6796
			(2.6679)	(2.4997)			(2.6725)	(2.4971)
$t_{\overline{np}dt}$			0.0019	-0.0051			0.0056	-0.0012
			(0.0418)	(0.0413)			(0.0408)	(0.0403)
$t_{\overline{np}dt}^{-1}$			-0.1027**	-0.1039***			-0.1006**	-0.1017***
			(0.0396)	(0.0389)			(0.0389)	(0.0382)
$t_{\overline{np}dt}^{-2}$			-0.0874**	-0.0918**			-0.0842**	-0.0884**
			(0.0385)	(0.0382)			(0.0379)	(0.0375)
$t_{\overline{np}dt}^{-3}$			-0.0741*	-0.0750*			-0.0712*	-0.0719*
			(0.0438)	(0.0437)			(0.0429)	(0.0428)
$t_{\overline{np}dt}^{-4}$			0.1151***	0.1098***			0.1191***	0.1139***
			(0.0379)	(0.0374)			(0.0374)	(0.0370)
d_{jl}				-0.0273**				-0.0273**
				(0.0128)				(0.0128)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.6982	0.7052	0.7072	0.7100	0.6980	0.7046	0.7066	0.709

Notes: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_t^{post} is posttretment. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. d_{jl} is distance. $t_{\overline{np}dt}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{np}dt}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

of rivals in a defined radius via interacting it with $\gamma_t^{post}\gamma_{jl}^{overlap}$ as in variables of interest. Specifications 3, 4, 7, and 8 introduce controls without any interaction. In defining *home markets*, specifications $1-4$ use top 10% of Δ_l^j; specifications $5-8$ use top 12% of Δ_l^j. Standard errors are clustered at county level. Table 5.14 presents the results.

Findings suggest that Δ_l^j and $\left(\Delta_l^j\right)^2$ have a significant impact on pricing. Estimates for $\left(\Delta_l^j\right)^2$ are very precise and inclusion of controls has limited impact. Estimates for Δ_l^j are more sensitive to inclusion of controls, in particular, inclusion of distance between provider and buyer d_{jl}. This is intuitive, as distance variable potentially captures some of the linear impact of local market power on price.

Building on the estimates in specifications 3, and 7 in Table 5.14, Table 5.15

Table 5.15: Predicted Price for Various Degrees of Market Power, Treatment Intensity

Δ_l^j	NBR_{jlc}	$10\%\Delta_l^j$	$12\%\Delta_l^j$
-10	2	101.1808	101.3545
-10	0	105.5309	105.5027
-10	1	103.3558	103.4286
-5	2	104.1948	104.3095
-5	1	106.3698	106.3836
-5	0	108.5449	108.4577
0	2	107.2088	107.2644
0	1	109.3839	109.3385
0	0	111.5589	111.4126
2.5	2	108.7158	108.7419
2.5	1	110.8909	110.816
2.5	0	113.0659	112.8901

summarizes the price predicted for competition. In this computation, Δ_l^j, and NBR_{jlc} are fixed to the values on the table, where increases in Δ_l^j, and decreases in NBR_{jlc} imply a progressive increases in market power of the provider. All other all covariates are fixed at sample averages. Next these values interact with coefficient estimates and give the predicted price for competition. Next these values interact with coefficient estimates and give the predicted price for competition. Findings indicate that if the provider's local market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of intensity of the exposure to the "treatment" (regime change) at each location, market power variations imply variations in price predicted for competition as high as 11.89 %.

Table 5.16 summarizes the results from alternative methodologies employed to ensure valid inference. It presents G^{*A}, p-values associated with $t\left(G^{*A}\right)$, Conley standard errors, and p-values using wild cluster bootstrap for different level of aggregations of data for variables Δ_l^j and $\left(\Delta_l^j\right)^2$. Findings are robust to alternative methods of inference.

To sum up, overcharge estimates are 9.26 % with before and after; 11.14–13.98 % with dummy variable approach; 8.05–11.46 % with forecasting; 7.48–10.08 % with DiD specifications using fixed effects; 7.99–11.25 % with DiD specifications that use controls. First thing to notice about the estimates is the convergence. Recall that at any time t in posttreatment period, price in the treated market is determined by three factors: i) initial price level, ii) time varying factors that influence price, iii) treatment[26]. In accurately identifying the impact of the treatment, dummy variable approach for example relies on controlling for other factors, i.e. demand and cost shifters. In this approach, consistent estimation depends on controlling all time varying factors that might impact pricing and that change around the treatment time. Formally, I referred to this as $E\left[\upsilon_t \gamma_t^{post}\right] = 0$, where γ_t^{post} is the regime change indicator, and υ_t captures the unobservables in the treatment market. On the other

[26]See, Equation 4.5.

hand, DiD adopts a different strategy; the difference in price between two markets (treated and not treated) before and after the treatment, is used in identifying the impact of the treatment. In this case, two necessary conditions for consistency are treatment and control markets having similar demand and cost conditions, and control market not being affected from the treatment. Formally, I referred to this as $E\left[\gamma_t^{post}\left(\gamma_t^T - \mu_t^C\right)\right] = 0$, where $\gamma_t^T - \mu_t^C$ corresponds to unobservables in the treatment market net of unobservables in the control market. I take convergence of results that use alternative identification assumptions as a suggestive evidence of the exogeneity of the shock, the regime switch.

Second important result is about the relation between the variation in overcharge and variation in local market power. This can be seen first via forecasting estimates. As displayed in Figure 5.2, forecasting overcharge estimates suggest considerable spatial variation; 11.99% of this variation might be explained by variations in market power. Second, if the market is divided into high market power *(home market)* and low market power *(overlapping market)* regions, DiD estimates suggest price in the former has been $7.48 - 11.25$ % higher than the price in the latter after treatment even after controlling demand and cost shifters. Third, if the provider's market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of degree of exposure to the "treatment", market power variations might lead variations in the price predicted for competition counterfactual, consequently variation in overcharge estimate as high as 11.89 %. These findings indicate that if the spatial dynamics are ignored, and single overcharge estimation is made, estimation leads to; undercompensation in regions where the market powers of dominant competitor and potential competitor converge; and overcompensation in regions where the market powers diverge.

5.6 Conclusion

In this chapter, building on the previous ones, hypothetical overcharge related to a possible collusion is estimated. In estimating the overcharge, I first use the techniques frequently used in collusion retrospectives, i.e. before and after, indicator variable approach, forecasting. A simple comparison of average price before and after the regime switch implies 9.26 % overcharge. Dummy variable approach point estimates for the overcharge range in 11.14-13.98 %; while forecasting point estimates range in 8.05-11.46%.

Second, in estimating the overcharge I find inspiration in empirical strategies that are employed in merger retrospectives. I initially estimate the overcharge using basic difference-in-difference by benefiting from spatial variation. I take regime switch as a treatment and identify buyer-provider pairs that would be least affected from the switch (the pairs that are most likely to be characterised by monopoly pricing even under competition) as the control group; and capture the impact of the treatment, as a deviation of price in high market power regions from price in low market power

Table 5.16: Inference – Measures of Local Market Power, Treatment Intensity

		Specification 1		Specification 2		Specification 3		Specification 4		Specification 5		Specification 6	
	$\left(\gamma_t^{post} \times \gamma_{jl}^{overlap}\right) \times$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$	Δ_l^j	$\left(\Delta_l^j\right)^2$
$t \times l \times j \times c$	*Coeff.*	0.634 0	0.027 6	0.577 7	0.028 7	0.490 7	0.031 2	0.626 4	0.027 3	0.565 0	0.028 0	0.478 0	0.030 6
	Clustered s.e.	0.194 3	0.008 4	0.193 8	0.008 1	0.189 5	0.008 2	0.193 0	0.008 4	0.195 7	0.008 2	0.192 2	0.008 3
	t-stat	3.263 1	3.275 3	2.980 7	3.518 1	2.589 1	3.818 9	3.245 0	3.244 2	2.886 6	3.400 4	2.487 4	3.688 9
	p-value	0.001 4	0.001 3	0.003 4	0.000 6	0.010 7	0.000 2	0.001 5	0.001 5	0.004 5	0.000 9	0.014 1	0.000 3
	G^{*A}	26.615 6	13.513 3	26.588 4	13.628 6	31.324 3	13.084 5	26.068 6	13.325 4	25.955 2	13.409 4	30.416 6	12.886 6
	p-value, G^{*A}	0.003 0	0.005 8	0.006 1	0.003 5	0.014 5	0.002 1	0.003 2	0.006 2	0.007 7	0.004 6	0.018 6	0.002 8
	Conley s.e.	0.087 6	0.003 6	0.087 7	0.003 5	0.089 8	0.003 4	0.086 3	0.003 6	0.086 6	0.003 5	0.088 8	0.003 4
	p-value, wild BS	0.005 3	0.004 7	0.010 0	0.006 0	0.018 0	0.001 3	0.005 3	0.004 7	0.010 0	0.008 0	0.020 0	0.003 3
$t \times l \times j$	*Coeff.*	0.585 3	0.025 8	0.522 3	0.026 3	0.455 9	0.028 1	0.576 8	0.025 4	0.506 9	0.025 5	0.439 4	0.027 3
	Clustered s.e.	0.234 0	0.009 8	0.227 5	0.009 1	0.213 5	0.008 9	0.234 1	0.009 8	0.231 9	0.009 3	0.218 8	0.009 1
	t-stat	2.501 7	2.640 3	2.296 3	2.887 8	2.134 9	3.171 7	2.463 8	2.594 6	2.186 0	2.748 0	2.007 8	3.010 7
	p-value	0.013 5	0.009 3	0.023 2	0.004 5	0.034 6	0.001 9	0.015 0	0.010 5	0.030 5	0.006 8	0.046 6	0.003 1
	G^{*A}	28.664 3	12.290 3	28.254 2	12.389 7	36.165 0	12.153 2	28.301 3	12.114 9	27.722 0	12.145 5	35.207 3	11.922 0
	p-value, G^{*A}	0.018 3	0.021 2	0.029 3	0.013 2	0.039 6	0.007 9	0.020 1	0.023 3	0.037 4	0.017 5	0.052 4	0.010 9
	Conley s.e.	0.086 5	0.003 5	0.084 6	0.003 3	0.086 6	0.003 2	0.085 2	0.003 5	0.084 1	0.003 3	0.086 4	0.003 3
	p-value, wild BS	0.024 7	0.016 0	0.044 7	0.019 3	0.052 7	0.007 3	0.028 7	0.017 3	0.050 7	0.023 3	0.066 7	0.010 7
$t \times l$	*Coeff.*	0.643 5	0.026 8	0.645 3	0.030 0	0.548 6	0.030 8	0.617 6	0.025 8	0.642 2	0.029 9	0.539 3	0.030 5
	Clustered s.e.	0.228 8	0.009 5	0.195 2	0.007 1	0.195 5	0.008 1	0.235 2	0.009 5	0.202 2	0.007 3	0.204 3	0.008 3
	t-stat	2.812 3	2.811 8	3.306 3	4.221 1	2.805 5	3.786 5	2.625 3	2.709 2	3.176 6	4.124 0	2.638 9	3.689 1
	p-value	0.005 6	0.005 7	0.001 2	0.000 0	0.005 8	0.000 2	0.009 6	0.007 6	0.001 8	0.000 1	0.009 3	0.000 3
	G^{*A}	24.769 9	4.283 5	24.799 3	4.522 2	32.818 3	4.659 4	22.922 8	4.186 4	23.269 9	4.467 2	30.878 8	4.640 4
	p-value, G^{*A}	0.009 5	0.044 6	0.002 9	0.010 4	0.008 4	0.014 6	0.015 1	0.051 0	0.004 2	0.011 6	0.012 9	0.016 2
	Conley s.e.	0.090 4	0.003 6	0.082 3	0.003 1	0.083 1	0.003 2	0.093 0	0.003 6	0.084 6	0.003 1	0.085 9	0.003 3
	p-value, wild BS	0.003 3	0.014 7	0.002 0	0.001 3	0.003 3	0.005 3	0.006 7	0.017 3	0.002 0	0.001 3	0.006 0	0.006 0

Notes: Each panel corresponds to different level of aggregation in data. In each panel, the coefficient of interest is interaction of DiD coefficient with either Δ_l^j, relative proximity measure, or its squared. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

regions. Next, I estimate the overcharge in a treatment intensity framework. I interpret the regime switch as a treatment, which produces heterogeneous effects at each location that is inversely proportional to the level of local market power the provider enjoys at that location. Basic DiD specifications suggest that using difference in price across control and treatment markets and difference in price before and after treatment, the impact of the regime switch is conservatively estimated in the interval of $7.48 - 11.25$ %. If the provider's market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of degree of exposure to the "treatment", market power variations might lead variations in the price predicted for competition counterfactual, consequently variation in overcharge estimate as high as 11.89 %.

Finally, to ensure inference is valid, and not affected from spatial dependencies across observations, and DiD methodology, I apply various remedies suggested in the literature. These include using CRVE standard errors; limiting the level of data variation, e.g. collapsing data to lesser number of dimensions; imposing an error structure; using critical values basing on feasible effective number of clusters; and wild cluster bootstrap. The results are robust to alternative methods of inference.

Findings indicate that overcharge displays considerable spatial variation basing on market power of provider at each location. If the spatial dynamics are ignored, estimation leads to; undercompensation in regions where market powers of dominant

competitor and potential competitor converge; and overcompensation in regions where the market powers diverge.

Conclusion

This work is an empirical analysis of collusion; in particular its detection and estimating the overcharge associated with it, in a setting where no a priori knowledge of collusion exists by using a consumer level data set.

At the first step, using simple markers proposed in the literature, I observe that consistent with a regime switch from collusion to competition, stable relations in the market are disrupted after month seven. Next, I take on these suspicious patterns, and investigate further, while I control for demand and cost shifters; I explore if observed patterns are more consistent with collusion or competition. To this aim, I take the premise in Bresnahan (1987) about centring on the relationship between price and local market power in identifying regime switch defined in an heterogeneous product / product characteristics space setting to an homogeneous product / geographic space setting. I propose taking cost difference between potential competitor and dominant competitor at that location as a measure of local market power. Consequently, estimation centres on explaining pricing behaviour, and particularly its relation with indicator of local market power. Using OLS and GMM, and via interacting a two level factorial variable, the dummy for first seven months, with market power indicators, two different pricing equations are estimated; one for first seven months, and the other for after month seven. Findings indicate that i) at locations where market power of provider and the closest rival converge, there are large price difference between two periods ii) at locations where the provider has large market power, price in both periods converge, iii) before month seven, local market power indicator is positively but only linearly related to price, iv) after month seven, local market power indicator is both linearly and quadratically related to pricing; providers suffer large price cuts to serve buyers that are gradually closer to the closest rival. These findings are interpreted as further evidence for a regime switch from collusion to competition.

The results also suggest that level of market power each provider has on a buyer is very important in the assessment of the impact of collusion on price, which is explored in detail next. Building on the previous findings, I estimate hypothetical overcharge related to a possible collusion. First, I employ the techniques that are frequently used in collusion retrospectives, i.e. before and after, indicator variable approach, forecasting. A simple comparison of average price before and after the regime switch implies 9.26 % overcharge. Dummy variable approach point estimates for the overcharge range in 11.14-13.98 %; while forecasting point estimates range

in 8.05-11.46%. Second, I import empirical strategies from merger retrospectives to collusion retrospectives. I initially estimate the overcharge using basic DiD by benefiting from spatial variation. I take regime switch as a treatment and identify the impact of the treatment, as a deviation of price in high market power regions (regions that are marginally affected from regime switch) from price in low market power regions (regions that are heavily affected from regime switch). Next, I estimate the overcharge in a treatment intensity framework. I interpret the regime switch as a treatment which produces heterogeneous effects at each location that is inversely proportional to the level of local market power the provider enjoys at that location. Basic DiD specifications suggest that using difference in price across control and treatment markets and difference in price before and after treatment, the impact of the regime switch is conservatively estimated in the interval of $7.48 - 11.25$ %. If the provider's market power at each location, as measured by relative proximity and number of rivals, is taken as an indicator of degree of exposure to the "treatment", market power variations might lead variations in the price predicted for competition counterfactual, consequently variation in overcharge estimate as high as 11.89 %. Findings indicate that overcharge displays considerable spatial variation basing on market power of provider at each location. If the spatial dynamics are ignored, estimation leads to; undercompensation in regions where market powers of dominant competitor and potential competitor converge; and overcompensation in regions where the market powers diverge. Finally, to ensure inference is valid, and not affected from spatial dependencies across observations, and DiD methodology, I apply various remedies suggested in the literature. These include using CRVE standard errors; limiting the level of data variation, e.g. collapsing data to lesser number of dimensions; imposing an error structure; using critical values basing on feasible effective number of clusters; and wild cluster bootstrap. The results are robust to alternative methods of inference.

There are two natural directions of further research. First is applying the frameworks developed here to other data sets and markets. For proactive detection, this would correspond to testing the framework developed in Bresnahan (1987) and applied here in a prosecuted case of collusion to see the degree of conversion between empirical findings and the case information. For estimating overcharge, this would correspond to applying the proposed framework in markets where competition is defined on product characteristics space. Second is adopting a structural estimation framework, and comparing implications of reduced form and structural estimations as have been done in Peters (2006); Weinberg (2011); Weinberg and Hosken (2013).

Appendix 1: Detection Literature

Work	Auction	Prosecuted	Empirical Strategy
Porter and Zona (1993)	Yes	Yes	(i) Model competitive behaviour. (ii) Apply competitive model to competitive firms. (iii) Apply competitive model to collusive firms. (iv) Test if two sets of firms behave differently.
Porter and Zona (1999)	Yes	Yes	(i) Apply (i)-(iv) in Porter and Zona (1993). (ii) Retrieve residuals from noncompetitive firms. (iii) Test for residual correlation across firms.

Work	Auction	Prosecuted	Empirical Strategy
Bajari and Ye (2003)	Yes	No	(i) Apply competitive model to all firms; and retrieve residuals and estimates. (ii) In a pair wise manner, test for residual correlation across firms. (iii) In a pair wise manner, test for symmetry in coefficients. (iv) Basing on (ii) and (iii) construct alternatives to competition. (v) Compare alternative models.
Jakobsson (2007)	Yes	Yes	Apply (i) - (ii) in Bajari and Ye (2003).
Padhi and Mohapatra (2011)	Yes	No	(i) Use various markers to identify suspicious behaviour. (ii) Apply (i) - (iii) in Bajari and Ye (2003) to verify.
Aryal and Gabrielli (2013)	Yes	No	(i) Apply (i)-(iii) in Bajari and Ye (2003) to identify suspicious firms. (ii) In a structural setting, retrieve cost estimates implied by FOCs, assuming firms are colluding. (iii) Repeat (ii), assuming firms are competing. (iv) Test if estimates from (ii) and (iii) have the same distribution.

Work	Auction	Prosecuted	Empirical Strategy
Conley and Decarolis (2016)	Yes	NA	(i) Identify a set of characteristics that are influential in participation to the auction. (ii) Identify a suspect group. (iii) Identify comparable groups with the suspect group in terms of characteristics in (i). (iv) Test the randomness of co-occurrence of the suspect group, given the behaviour of comparable group. (v) Test if the behaviour of suspect group impacts the threshold more than comparable group.
Ishii (2009)	Yes	No	(i) Construct a score variable aggregating net favours for each firm pair. (ii) Model likelihood to win as a function of this score variable and observables. (iii) In competition, score should be irrelevant.

Work	Auction	Prosecuted	Empirical Strategy
Marshall et al. (2008)	No	Yes	(i) Monitor the change in price announcements i.e. joint vs. singleton, and advance vs. immediate. (ii) Model probability of a price change as a function of observable shifters, and time elapsed since last price change. (iii) Length of time period should be irrelevant in competition.
Bos and Schinkel (2009)	No	NA	(i) Form expectations about how would firms collude if they are using basing point pricing. (ii) Repeat (i) if firms are competing. (iii) Recover the location of the base and see if the location is consistent with collusion or competition.
Hüschelrath and Veith (2014)	No	Yes	(i) Look for a structural break in pricing behaviour, e.g. sharp rise or fall. (ii) Run a reduced form equation, to identify the break.
Banerji and Meenakshi (2004)	Yes	No	(i) Build a model assuming competition. (ii) Build a competitive model assuming large buyers collude. (iii) Compete two models on likelihood measures.

Work	Auction	Prosecuted	Empirical Strategy
Bresnahan (1987)	No	No	(i) Search for odd patterns in the market, i.e. some periods are consistent with competition; some others with collusion. (ii) Fit a competitive model and a collusive model to all periods. Conduct a likelihood ratio test. (iii) In collusive periods; competition, in competition periods; collusion, should be rejected.
Firgo and Kügler (2014)	No	No	(i) Estimate the best response functions for the players. (ii) Test if strategic interaction terms are similar across different sets of competitors. (iii) Test if spatial considerations i.e. distance to rival, number of rivals are influential in pricing.
Baldwin et al. (1997)	Yes	No	(i) Estimate competitive model and competitive model with supply shifts. (ii) Estimate a collusive model and collusive model with supply shifts. (iii) Compete the different explanations via log likelihood measures.

Work	Auction	Prosecuted	Empirical Strategy
Abrantes-Metz et al. (2006)	No	No	Search for a pocket of competitors that is characterised by a combination of high price, and low price variation.
Jiménez and Perdiguero (2012)	No	No	(i) Apply Abrantes-Metz et al. (2006). (ii) As the competitive benchmark, use pricing behaviour in a market with a maverick. (iii) As the collusive benchmark, use pricing behaviour in markets with monopoly power. (iv) Compare the behaviour in the oligopolistic markets with these two benchmarks
Heijnen et al. (2015)	No	No	(i) Apply Abrantes-Metz et al. (2006) to identify suspicious firms. (ii) Use geographical market definitions to identify firms in the same market. (iii) In each market, conduct a test of randomness using proportion of suspicious firms in (i).
Esposito and Ferrero (2006)	No	Yes	(i) Apply Abrantes-Metz et al. (2006) to two cartel cases in Italy.

Work	Auction	Prosecuted	Empirical Strategy
Vickers and Ziebarth (2014)	No	No	(i) Identify a structural break. (ii) Monitor the change in the relations in the market before and after the break, i.e. price cost correlation, price variation, persistence.
Christie and Schultz (1994) Christie et al. (1994)	No	No	(i) Find anomalies in market behaviour. (ii) Look for clustering of anomalies in some time period or in some firms. (iii) Search for presence of similar behaviour in comparable markets.
Abrantes-Metz et al. (2012) Giles (2007) Rauch et al. (2013)	No	No	(i) Find anomalies in market behaviour. (ii) Use Benford's Law to detect naturalness of these occurrences. (iii) Test the significance of deviation between data and the law.
Estrada and Vazquez (2013) Mena-Labarthe (2012)	Yes	No	Using various collusive markers, search for structural breaks in firm behaviour.
Imhof et al. (2016)	Yes	No	(i) Identify suspicious firms by monitoring bid variance and distribution. (ii) Look for regularity in suspicious behaviour. (iii) Analyse geographical scope. (iv) Identify potentially competitive firms.

Appendix 2: Collusion Retrospectives

Work[a]	Cartel[b]	Prosecuted	Industry	Location	Method[c]
Almoguera et al. (2011)	Yes	No	Petroleum	OPEC	Structural
Asker (2010)	Yes	Yes	Collectible Stamp Auctions	New York	Structural
Asmat (2016)	Yes	Yes	DRAM	International	Dummy
Bolotova et al. (2008b)	SMP	No	Potato	Idaho, US	B & A Dummy
Boshoff (2015)	Yes	Yes	Bitumen	South Africa	Dummy Forecast DiD
Brännlund (1989)	Yes	No	Pulpwood	Sweden	Structural
Bresnahan (1987)	Yes	No	Automobile	US	Structural
Carlton et al. (1995)	Yes	Yes	University Fees & Aids	MIT + Ivy League	Yardstick
Clay and Troesken (2003)	HC	No	Whiskey	US	Structural

Work[a]	Cartel[b]	Prosecuted	Industry	Location	Method[c]
Coatney and Tack (2014)	Yes	Yes	Culled Cow Auctions	Monroe WI, US	DiD
Cramton and Schwartz (2002)	Yes	No	Spectrum Auctions	US	Dummy
De Roos (2006)	Yes	Yes	Lysine	International	Structural
de Vanssay and Erutku (2011)	Yes	Yes	Gasoline	Sherbrooke, Canada	Yardstick
Erutku and Hildebrand (2010)	Yes	Yes	Gasoline	Sherbrooke, Canada	DiD
Fabra and Toro (2005)	Yes	No	Electricity	Spain	Structural
French and Nuckton (1991)	SMP	No	Raisin	California, US	Structural
Genesove and Mullin (1998)	HC	No	Sugar	US	Structural
Grant and Thille (2001)	HC	No	Lamb Oil	US	Structural
Hausman (1980, 1984)	HC	No	Coal	UK	Dummy Structural
Howard and Kaserman (1989)	Yes	Yes	Sewer Construction	Undisclosed, US	B & A Dummy Forecast

Work[a]	Cartel[b]	Prosecuted	Industry	Location	Method[c]
Hoxby (2000)	Yes	Yes	University Fees & Aids	MIT + Ivy League	DiD
Hüschelrath et al. (2013, 2016),	Yes	Yes	Cement	Germany	Dummy DiD
Igami (2015)	Yes	No	Coffee	International	Structural
Kamita (2010)	AI	No	Air Travel	Hawaii, US	DiD
Lee (2000)	Yes	Yes	School Milk Auctions	Texas, US	Forecast
Lee and Hahn (2002)	NA	No	Construction	Korea	Forecast
Ma (2005a,b)	Yes	Yes	Flour	Taiwan	Structural
Madhavan et al. (1994)	SMP	Yes	Milk	US	Dummy
Mariuzzo et al. (2009)	Yes	No	Automobile	Ireland	Structural
Mncube (2014)	Yes	Yes	Flour	South Africa	Dummy
Nelson (1993)	Yes	Yes	Second Hand NYPD Car Auctions	New York	B & A Dummy Forecast
Nevo (2001)	Yes	No	Breakfast Cereal	US	Structural
Normann and Tan (2014)	AI	Yes	High Voltage Cable	Germany	Structural

Work[a]	Cartel[b]	Prosecuted	Industry	Location	Method[c]
Notaro (2014)	Yes	Yes	Pasta	Italy	B & A Dummy Forecast
Porter (1983)	HC	No	Railroad Freight	US	Structural
Shepard (1986)	SMP	No	Orange	California & Arizona, US	Structural
Laitenberger and Smuda (2015)	Yes	Yes	Detergent	EU	Dummy DiD
Tan (2009)	HC	No	Coal	UK	Structural

[a] Does not include the literature covered in Chapter 2.
[b] It takes "Yes" if a cartel is being studied. It takes "HC" if an historical cartel is studied. It takes "SMP" if a supply management program is studied. It takes "AI" if an antitrust immunity is studied.
[c] DiD refers to difference-in-difference; B & A refers to before and after.

Appendix 3: Merger Retrospectives

Work[a]	Industry[b]	Parties[c]	Treatment Group[d]	Control Group[d]
Aguzzoni et al. (2014)	Retail Video Games	Game Gamestation	Products of Merging Parties	Products of Rivals
Aguzzoni et al. (2016)	Retail Book Sales	Waterson Ottokar	Regions Both Merging Parties Are Active	Other Regions
Allen et al. (2014)	Mortgage	Undisclosed	Regions Both Merging Parties Are Active	Other Regions
Argentesi et al. (2016)	Retail Grocery	Jumbo C1000	Regions Both Merging Parties Are Active	Other Regions
Ashenfelter and Hosken (2010)	Female Hygiene Products	PG Tambrands	Products of Merging Parties	Private Labels
Ashenfelter and Hosken (2010)	Spirits	Guinness Grand Metropolitan	Products of Merging Parties	Private Labels
Ashenfelter and Hosken (2010)	Motor Oil	Pennzoil Quaker State	Products of Merging Parties	Private Labels

Work[a]	Industry[b]	Parties[c]	Treatment Group[d]	Control Group[d]
Ashenfelter and Hosken (2010)	Cereal	General Mills Chex	Products of Merging Parties	Private Labels
Ashenfelter and Hosken (2010)	Maple Syrup	Log Cabin Mrs Butterworthy	Products of Merging Parties	Private Labels
Ashenfelter et al. (2013)	Home Appliances	Maytag Whirlpool	Clothes Washers; Dryers; Dish Washers; Refrigerator	Appliances in which Merging Parties are Insignificant
Calomiris and Pornrojnangkool (2005)	Banking	Fleet Bank Boston	Consumers of BankBoston and Fleet in NE	Other Customers in NE; Other Customers in NE, CT, MA, ME, NH, RI, VT
Choné and Linnemer (2012)	Urban Car Parking	GTM Vinci	Outlets Exposed to Merger	Outlets Not Exposed
DGComp (2015)	Mobile Telecom	T-Mobile Telering	Country with Merger	11 Countries in EU
DGComp (2015)	Mobile Telecom	T-Mobile Orange Netherlands	Country with Merger	11 Countries in EU
Dobson and Piga (2013)	Airlines	Ryan Air Buzz	Routes of the Parties	Independent Routes
Dobson and Piga (2013)	Airlines	Easy Jet Go Fly	Routes of the Parties	Independent Routes
Friberg and Romahn (2015)	Beer	Carlsberg Pripps	Brands Affected	Other Brands

Work[a]	Industry[b]	Parties[c]	Treatment Group[d]	Control Group[d]
Gayle (2008)	Airlines	Delta Continental Northwestern	City-Pairs with Codeshare	Other City-Pairs Served by the Alliance
Haas Wilson and Garmon (2011)	Hospital	Evanston Highland Park	Evanston IL, Glenview IL	Chigago MSA
Haas Wilson and Garmon (2011)	Hospital	St Therese Victory Memorial	Waukegan IL	Chigago MSA
Hastings (2004)	Petroleum	Arco Thrifty	Stations Close to a Thrifty Station	Other Stations
Hosken et al. (2011)	Petroleum	Tosco Unucol	San Francisco Bay	Southern California
Hosken et al. (2011)	Petroleum	UDS Tosco	San Francisco Bay	Southern California
Houde (2012)	Petroleum	Ultramar Sunoco	Acquired Stations and Immediate Competitors	Other Stations
Kwoka and Shumilkina (2010)	Airlines	US Air Piedmont	Overlap Routes; Routes That One Party is Present the Other Is a Potential Entrant	Other Routes
Luo (2014)	Airlines	Delta Northwestern	Overlap Routes	Routes No Party Present

Work[a]	Industry[b]	Parties[c]	Treatment Group[d]	Control Group[d]
Pennerstorfer and Weiss (2013)	Petroleum	Arai BP	Locations with Increased Clustering	Locations with No Change in Clustering.
Silvia and Taylor (2013)	Petroleum	Sunoco El Paso	Philadelphia; Laurel Corridor; US Northeast	Boston, Newark; Harrisburg, Pittsburgh; Fairfax VA, Houston TX
Silvia and Taylor (2013)	Petroleum	Valero Premcor	Philadelphia; Laurel Corridor; US Northeast	Boston, Newark; Harrisburg, Pittsburgh; Fairfax VA, Houston TX
Simpson and Taylor (2008)	Petroleum	MA Ultramar	6 Counties in Michigan	South Bend IN, Elkhart Goshen IN
Taylor and Hosken (2007)	Petroleum	Marathon Ashland	Louisville KY, Covington KY; Fairfax VA, Richmond VA	Chicago; Baltimore, Norfolk, Houston
Taylor et al. (2010)	Petroleum	Arco Thrifty	Stations Close to a Thrifty Station	Other Stations
Tenn (2011)	Hospital	Sutter Summit	Oakland CA, Berkeley CA	Other CA
Tenn and Yun (2011)	Consumer Health	Johnson & Johnson Pfizer	Products of Divested Brand	Rival Products

Work[a]	Industry[b]	Parties[c]	Treatment Group[d]	Control Group[d]
Thompson (2011)	Hospital	New Hanover Cape Fear	Wilmington NC	Other NC
Weinberg (2011)	Female Hygiene Products	PG Tambrands	Products of Merging Parties	Private Labels
Weinberg and Hosken (2013)	Motor Oil	Pennzoil Quaker State	Products of Merging Parties	Private Labels
Weinberg and Hosken (2013)	Maple Syrup	Log Cabin Mrs. Butterworthy	Products of Merging Parties	Private Labels

[a] Contains works that centre on the impact of merger on price.
[b] If the merger retrospective studies multiple mergers, each merger is recorded separately.
[c] It corresponds to parties to the transaction. In some cases the merger involves purchase of a brand, rather than the entire undertaking. For these cases, the brands are shown.
[d] Treatment and control groups might refer to regions, cities, or products. In the table only core treatment and control groups are present, and only main characteristic is reported (e.g. other non-federal teaching hospitals in North Carolina is abbreviated to other hospitals in North Carolina). If there are multiple treatment, control groups that are central to the analysis, these are separated with a semicolon. Abbreviations correspond to US states.

Appendix 4: Definitions and Abbreviations

Expression	Definition
p_{jltc}	Total price charged by provider j, to customer c, at location l, in month t, calculated as $\frac{REV_{jltc}}{v_{jltc}} \frac{100}{\bar{p}}$
REV_{jltc}	Total revenue for the sales to customer c, at location l, in month t from provider j
v_{jltc}	Total volume of purchase from provider j, by customer c, at location l, in month t,
$\bar{p}$	Average price in competitive period, weighted by quantity. Calculated as $\sum_l \sum_j \sum_c \sum_{t=8}^{18} \frac{v_{jltc}}{\sum_l \sum_j \sum_c \sum_{t=8}^{18} v_{jltc}} p_{jltc}$
Δ_l^j	Measure of local market power of provider j at location l $d_{kl} - d_{jl}$, where $d_{kl} = min(d_{(-j)l})$
$\bar{d}$	Average radius of sales, calculated as $\bar{d} = \frac{\sum \sum_{lj} v_i d_i}{N_t \bar{V}_t}$
d_{jl}	Distance between provider j and location l
NBR_{jlc}	Total number of undertakings that are rival to provider j with at least one facility within $\bar{d}$ radius of location l
$\bar{V}_t$	Total volume of sales in month t
$\bar{N}_t$	Total number of sales in month t
γ^j	Facility fixed effects
γ^t	Month fixed effects
γ^l	Cluster fixed effects
χ_{jltc}	General expression for cost shifters
z_{jltc}	General expression for demand shifters

Expression	Definition
γ_t^{coll}, γ_t^{pre}	Indicates regime is collusive. Takes 1 for $t < 8$.
γ_t^{comp}, γ_t^{post}	Indicates regime is competitive. Takes 1 for $t \geq 8$.
γ_{jl}^{home}	Indicates observations at top 10 % (or 12 % in some specifications) of Δ_l^j.
$\gamma_{jl}^{overlap}$	Indicates observations that are not marked by γ_{jl}^{home}.
γ_{jl}^{own}	Additional facility indicator. Equals 1 if there is at least one additional facility of provider j within $\bar{d}$ radius of location l
$\gamma_{jc}^{vertical}$	Equals 1 if some vertical relation is reported for the buyer provider pair.
γ_c^{large}	Large buyer indicator. Equals 1 if buyer c is in top 5 % in terms of total volume of purchase
$\bar{V}_{cl}$	Total volume of purchase each buyer c at location l during 18 months. Calculated as, $\sum_j \sum_t v_{jltc}$
U_{jt}	Capacity utilization of facility j in month t.
EI_{jt}	Value of unit price index of the most frequently used source of energy for facility j, month t
Q_{nplt}	Quantity of T licensed to be produced for customer need n, and production process p, in month t around location l. Seasonally unadjusted.
$\omega_{\bar{n}plt}$	Monthly weight of location l in total volume of T production for each n, p pair. Calculated as $\frac{Q_{\bar{n}plt}}{\sum_l Q_{\bar{n}plt}}$
$\tilde{Q}_{\bar{n}pt}$	Seasonally adjusted aggregated volume of T in month t for each n, p pair.
$\tilde{Q}_{\bar{n}plt}$	Seasonally adjusted volume of T at district level. Calculated as $\omega_{\bar{n}plt}\tilde{Q}_{\bar{n}pt}$
$r = \bar{r}, 0.8\bar{r}, 0.6\bar{r}$	Radius relevant for T production
$t_{\overline{np}lt}$	Final aggregated regional monthly demand index informing seasonally adjusted T production within r_i radius. Calculated by aggregating indices $\omega_{\bar{n}plt}\tilde{Q}_{\bar{n}pt}$ for $n, p = (1,1), (1,2), (2,1)$ and the unadjusted index Q_{22dt} into a single index. The superscripts $-1, -2, -3, -4$ indicate lagged values.
$t_{\overline{nptl}}$	Aggregation of seasonally adjusted regional monthly demand indices, $t_{\overline{np}lt}$, over 18 months around location l.

Appendix 5: Additional Estimations

Table 21: DiD – Allowing Parameter Inequality, Home & Overlapping Markets[27]

$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	-14.1300***	-10.0775***	-10.0663***	-10.1090***	-14.3185***	-9.0334***	-9.0320***	-9.0428***
	(0.7486)	(1.1832)	(1.1845)	(1.2161)	(0.7473)	(1.2547)	(1.2544)	(1.2507)
$\gamma_{jl}^{overlap}$	-14.5223	9.4206	9.7156	10.5525	-22.7851**	0.7046	0.6803	1.6578
	(13.3670)	(12.5987)	(12.6491)	(14.4151)	(9.3263)	(4.8833)	(4.9371)	(10.4163)
NBR_{jlc}	-1.8781***	-1.8959***	-1.4007**	-1.4476**	-1.8551***	-1.8585***	-1.3573**	-1.4161**
	(0.5733)	(0.5363)	(0.6852)	(0.6768)	(0.5605)	(0.5318)	(0.6816)	(0.6787)
γ_{jl}^{own}	3.1130	4.0211**	4.5874***	4.5334***	3.0893	4.0232**	4.5957***	4.5330***
	(2.2776)	(1.6497)	(1.6943)	(1.7084)	(2.2599)	(1.6476)	(1.6902)	(1.7028)
$\gamma_{jl}^{home} \times \Delta_l^j$	-0.9726	0.8114	0.9123	0.9943	-0.8501	-0.5318	-0.4999	-0.3454
	(2.9459)	(2.7827)	(2.8004)	(2.9567)	(1.4571)	(1.4181)	(1.4282)	(2.0824)
$\gamma_{jl}^{overlap} \times \Delta_l^j$	0.0728	0.1657	0.1789	0.1863	0.0411	0.1534	0.1647	0.1730
	(0.2874)	(0.2536)	(0.2537)	(0.2534)	(0.2921)	(0.2570)	(0.2572)	(0.2548)
$\gamma_{jl}^{home} \times \left(\Delta_l^j\right)^2$	0.0965	0.0248	0.0190	0.0164	0.0847	0.0847	0.0824	0.0758
	(0.1436)	(0.1384)	(0.1392)	(0.1443)	(0.0827)	(0.0798)	(0.0801)	(0.1045)
$\gamma_{jl}^{overlap} \times \left(\Delta_l^j\right)^2$	0.0020	0.0039	0.0042	0.0044	0.0008	0.0032	0.0034	0.0037
	(0.0083)	(0.0077)	(0.0077)	(0.0077)	(0.0083)	(0.0078)	(0.0077)	(0.0078)
$\gamma_{jl}^{home} \times d_{jl}$	-0.0314	0.0141	0.0133	0.0172	-0.0463	-0.0171	-0.0179	-0.0141
	(0.0550)	(0.0446)	(0.0447)	(0.0520)	(0.0415)	(0.0374)	(0.0375)	(0.0456)
$\gamma_{jl}^{overlap} \times d_{jl}$	-0.0067	-0.0042	-0.0050	-0.0047	-0.0062	-0.0032	-0.0041	-0.0039
	(0.0195)	(0.0181)	(0.0180)	(0.0179)	(0.0193)	(0.0181)	(0.0180)	(0.0179)
$\gamma_{jl}^{home} \times \gamma_{jc}^{vertical}$	0.5491	0.7968	0.8108	0.7462	0.6931	0.3907	0.3509	0.4062
	(3.1935)	(2.8611)	(2.8591)	(2.9141)	(2.9742)	(2.6807)	(2.6874)	(2.7509)
$\gamma_{jl}^{overlap} \times \gamma_{jc}^{vertical}$	-0.1250	0.4026	0.4117	0.4146	-0.1474	0.4391	0.4571	0.4470
	(1.6832)	(1.5302)	(1.5263)	(1.5242)	(1.7097)	(1.5496)	(1.5453)	(1.5438)
$\gamma_{jl}^{home} \times t_{\overline{np}dt}$				-0.7190				0.0551
				(0.7745)				(0.1305)
$\gamma_{jl}^{overlap} \times t_{\overline{np}dt}$				0.0133				0.0114
				(0.0397)				(0.0398)
$\gamma_{jl}^{home} \times t_{\overline{np}dt}^{-1}$				-0.3197				-0.2679***
				(0.4663)				(0.0825)
$\gamma_{jl}^{overlap} \times t_{\overline{np}dt}^{-1}$				-0.1225***				-0.1206***
				(0.0302)				(0.0300)
$\gamma_{jl}^{home} \times t_{\overline{np}dt}^{-2}$				0.4856				-0.0040
				(0.3836)				(0.1027)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}	p_{jltc}
$\gamma_{jl}^{overlap} \times t_{\overline{np}dt}^{-2}$				-0.0859***				-0.0857***
				(0.0300)				(0.0298)
$\gamma_{jl}^{home} \times t_{\overline{np}dt}^{-3}$				0.2309				-0.1856
				(0.5982)				(0.1151)
$\gamma_{jl}^{overlap} \times t_{\overline{np}dt}^{-3}$				-0.0773**				-0.0760**
				(0.0348)				(0.0345)
$\gamma_{jl}^{home} \times t_{\overline{np}dt}^{-4}$				0.5140				0.3374***
				(0.7114)				(0.0970)
$\gamma_{jl}^{overlap} \times t_{\overline{np}dt}^{-4}$				0.1537***				0.1518***
				(0.0319)				(0.0321)
$\gamma_{jl}^{home} \times EI_{jt}$	-0.0742				-0.1370***			
	(0.0497)				(0.0522)			
$\gamma_{jl}^{overlap} \times EI_{jt}$	0.0701***				0.0764***			
	(0.0188)				(0.0187)			
$\gamma_{jl}^{home} \times U_{jt}$	1.0579				1.4034			
	(3.1305)				(2.9712)			
$\gamma_{jl}^{overlap} \times U_{jt}$	-1.8631**				-1.9954**			
	(0.8784)				(0.8772)			
$t_{\overline{nptd}}$			-0.0754				-0.0765	
			(0.0661)				(0.0660)	
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.4750	0.6064	0.6075	0.6092	0.4761	0.6056	0.6067	0.6083

[27]**Notes for Table 21**: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market; γ_{jl}^{home} is home market. γ_{t}^{post} is posttretment. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. U_{jt} is capacity utilization. EI_{jt} is energy price index. d_{jl} is distance. $t_{\overline{np}dt}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{np}dt}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

[28]**Notes for Table 23**: Dependent variable is the delivered price p_{jltc}. t is month, j is provider, l is location, c is consumer. $\gamma_{jl}^{overlap}$ is overlapping market. γ_{t}^{pre} is pretretment; γ_{t}^{post} is posttretment. $\gamma_{jc}^{vertical}$ indicates vertical relation between provider and buyer. γ_{jl}^{own} indicates presence of multiple nearby production facilities of the provider. Δ_j^l is a measure of relative distance, and is multiplied by 0.1 before regression. NBR_{jlc} is number of rivals. U_{jt} is capacity utilization. EI_{jt} is energy price index. d_{jl} is distance. $t_{\overline{np}dt}^{-i}$ refers to i^{th} lag of monthly demand index. $t_{\overline{np}dt}$ refers to aggregate T activity around a given location over 18 months. Standard errors are clustered at county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 22: Inference – *DiD* Variable, Home & Overlapping Market

$t \times l \times j \times c$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−10.077 5	−10.066 3	−10.109 0	−9.033 4	−9.032 0	−9.042 8
	Clustered s.e.	1.189 9	1.191 7	1.226 6	1.263 0	1.263 7	1.268 2
	t-stat	−8.469 1	−8.447 4	−8.241 5	−7.152 2	−7.147 6	−7.130 5
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	14.311 3	14.245 9	19.865 5	18.200 1	18.185 5	20.987 2
	p-value, G^{*A}	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	Conley s.e.	0.994 9	1.003 2	0.993 2	0.943 2	0.949 4	0.939 6
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
$t \times l \times j$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−9.351 1	−9.336 4	−9.362 8	−7.826 2	−7.824 7	−7.865 1
	Clustered s.e.	1.354 9	1.352 2	1.384 6	1.483 4	1.480 1	1.484 3
	t-stat	−6.901 8	−6.904 6	−6.762 0	−5.275 9	−5.286 7	−5.298 8
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	9.269 9	9.226 9	11.592 1	11.271 6	11.267 2	13.039 9
	p-value, G^{*A}	0.000 1	0.000 1	0.000 0	0.000 2	0.000 2	0.000 1
	Conley s.e.	0.945 0	0.954 6	0.950 2	0.952 9	0.962 1	0.970 2
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7
$t \times l$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−11.187 3	−11.182 6	−10.954 9	−8.665 3	−8.657 0	−8.407 4
	Clustered s.e.	1.736 5	1.736 9	1.758 2	1.899 1	1.900 4	1.909 4
	t-stat	−6.442 4	−6.438 2	−6.230 8	−4.562 8	−4.555 5	−4.403 1
	p-value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
	G^{*A}	8.616 2	8.607 5	8.839 0	9.539 0	9.501 9	10.266 5
	p-value, G^{*A}	0.000 1	0.000 1	0.000 2	0.001 2	0.001 2	0.001 2
	Conley s.e.	1.479 7	1.476 2	1.437 9	1.498 3	1.493 7	1.488 7
	p-value, wild BS	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7	0.000 7

Notes: Each panel corresponds to different level of aggregation in data. In each panel the coefficient of interest is DiD indicator. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

Table 23: *DiD* – Allowing Parameter Inequality, Before and After Regime Switch[28]

Variables	(1) p_{jltc}	(2) p_{jltc}	(3) p_{jltc}	(4) p_{jltc}	(5) p_{jltc}	(6) p_{jltc}	(7) p_{jltc}	(8) p_{jltc}
$\gamma^{post} \times \gamma_{jl}^{overlap}$	-3.4937	-3.8657	-4.3878*	-3.8571*	-2.6539	-3.3884	-2.9930	-2.6245
	(2.3942)	(3.2334)	(2.2317)	(2.2263)	(2.1939)	(2.7247)	(2.0931)	(2.0359)
$\gamma_{jl}^{overlap}$	-1.8398		0.5794	0.4348	-2.7226		-0.5251	-0.5888
	(3.7646)		(3.1984)	(3.1402)	(2.8489)		(2.6060)	(2.5504)
$\gamma_t^{post} \times \Delta_l^j$	0.3555	0.4576*	0.4658*	0.4896*	0.3427	0.4683*	0.4720*	0.4933**
	(0.2781)	(0.2572)	(0.2595)	(0.2576)	(0.2695)	(0.2515)	(0.2520)	(0.2496)
$\gamma_t^{pre} \times \Delta_l^j$	0.1639	0.2116	0.2428	0.2534	0.1261	0.2108	0.1975	0.2117
	(0.2666)	(0.2229)	(0.2543)	(0.2478)	(0.2553)	(0.2233)	(0.2464)	(0.2409)
$\gamma_t^{post} \times \left(\Delta_l^j\right)^2$	0.0175**	0.0191***	0.0193***	0.0198***	0.0176***	0.0198***	0.0199***	0.0202***
	(0.0073)	(0.0069)	(0.0071)	(0.0071)	(0.0067)	(0.0065)	(0.0066)	(0.0067)
$\gamma_t^{pre} \times \left(\Delta_l^j\right)^2$	-0.0017	-0.0006	0.0001	0.0006	-0.0028	-0.0007	-0.0015	-0.0008
	(0.0069)	(0.0061)	(0.0066)	(0.0066)	(0.0066)	(0.0061)	(0.0065)	(0.0064)
$\gamma_t^{post} \times d_{jl}$	-0.0064	0.0010	-0.0000	-0.0010	-0.0075	0.0005	-0.0005	-0.0015
	(0.0209)	(0.0197)	(0.0194)	(0.0189)	(0.0211)	(0.0198)	(0.0195)	(0.0189)
$\gamma_t^{pre} \times NBR_{jlt}$	-1.2434*	-1.0941*	-0.5652	-1.1944	-1.2188*	-1.0798*	-0.5085	-1.1504
	(0.6402)	(0.6181)	(0.7589)	(0.7514)	(0.6304)	(0.6208)	(0.7555)	(0.7461)
$\gamma_t^{post} \times NBR_{jlt}$	-2.2473***	-2.3323***	-1.7754**	-1.3125*	-2.2708***	-2.3581***	-1.8001**	-1.3269*
	(0.6580)	(0.6283)	(0.7553)	(0.7627)	(0.6439)	(0.6172)	(0.7471)	(0.7559)
$\gamma_t^{pre} \times \gamma_{jl}^{own}$	5.0800**	3.8212**	4.4103**	3.8236**	5.1031**	3.8138**	4.4443**	3.8494**
	(2.5617)	(1.7913)	(1.8302)	(1.8267)	(2.5341)	(1.7920)	(1.8293)	(1.8250)
$\gamma_t^{post} \times \gamma_{jl}^{own}$	2.3389	4.1455**	4.8055***	5.2527***	2.3320	4.1754**	4.8188***	5.2688***
	(2.3314)	(1.7404)	(1.7525)	(1.7769)	(2.3147)	(1.7436)	(1.7483)	(1.7732)
$\gamma_t^{pre} \times d_{jl}$	-0.0045	-0.0080	-0.0086	-0.0056	-0.0052	-0.0080	-0.0093	-0.0062
	(0.0212)	(0.0201)	(0.0202)	(0.0201)	(0.0211)	(0.0201)	(0.0202)	(0.0202)
$\gamma_t^{post} \times \gamma_{jc}^{vertical}$	-0.3441	0.9196	0.9206	0.8573	-0.3978	0.8806	0.8937	0.8329
	(1.6835)	(1.4549)	(1.4361)	(1.4240)	(1.6985)	(1.4609)	(1.4469)	(1.4344)
$\gamma_t^{pre} \times \gamma_{jc}^{vertical}$	0.3644	-0.4651	-0.4555	-0.3360	0.3559	-0.4597	-0.4689	-0.3453
	(1.5313)	(1.5180)	(1.5288)	(1.5173)	(1.5246)	(1.5124)	(1.5264)	(1.5155)
$\gamma_t^{post} \times t_{\overline{npdt}}$				0.0382				0.0351
				(0.0733)				(0.0734)
$\gamma_t^{pre} \times t_{\overline{npdt}}$				-0.1396***				-0.1368***
				(0.0507)				(0.0508)
$\gamma_t^{post} \times t_{\overline{npdt}}^{-1}$				-0.2672***				-0.2671***
				(0.0692)				(0.0692)
$\gamma_t^{pre} \times t_{\overline{npdt}}^{-1}$				-0.1228***				-0.1205***
				(0.0351)				(0.0351)
$\gamma_t^{post} \times t_{\overline{npdt}}^{-2}$				0.1080				0.1097
				(0.0685)				(0.0688)
$\gamma_t^{pre} \times t_{\overline{npdt}}^{-2}$				-0.0479				-0.0477
				(0.0323)				(0.0324)
$\gamma_t^{post} \times t_{\overline{npdt}}^{-3}$				-0.4385***				-0.4407***
				(0.0883)				(0.0887)
$\gamma_t^{pre} \times t_{\overline{npdt}}^{-3}$				0.1179***				0.1158***
				(0.0419)				(0.0417)
$\gamma_t^{post} \times t_{\overline{npdt}}^{-4}$				0.2956***				0.2955***
				(0.0811)				(0.0811)
$\gamma_t^{pre} \times t_{\overline{npdt}}^{-4}$				0.1890***				0.1865***
				(0.0400)				(0.0403)
γ_t^{post}	15.4141***				15.0440***			
	(3.8507)				(3.8022)			
$\gamma_t^{post} \times EI_{jt}$	0.0409**				0.0403**			
	(0.0196)				(0.0194)			
$\gamma_t^{pre} \times EI_{jt}$	0.2300***				0.2297***			
	(0.0231)				(0.0229)			
$\gamma_t^{post} \times U_{jt}$	-3.9104***				-4.1811***			
	(1.2727)				(1.2729)			
$\gamma_t^{pre} \times U_{jt}$	-0.7909				-0.7075			
	(1.2298)				(1.2247)			
$t_{\overline{nptd}}$			-0.0846				-0.0857	
			(0.0673)				(0.0672)	
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.4848	0.6096	0.6110	0.6163	0.4854	0.6096	0.6110	0.6164

Table 24: Inference – *DiD* Variable, Before and After Regime Switch

$t \times l \times j \times c$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−4.370 4	−4.387 8	−3.857 1	−2.950 8	−2.993 0	−2.624 5
	Clustered s.e.	2.246 0	2.244 9	2.241 9	2.111 0	2.110 2	2.051 1
	t-stat	−1.945 9	−1.954 5	−1.720 5	−1.397 8	−1.418 3	−1.279 6
	p-value	0.053 7	0.052 7	0.087 6	0.164 4	0.158 4	0.202 9
	G^{*A}	15.257 7	15.014 1	17.579 3	16.515 1	15.964 9	17.465 5
	p-value, G^{*A}	0.070 3	0.069 5	0.102 9	0.180 7	0.175 3	0.217 4
	Conley s.e.	1.786 3	1.801 7	1.764 0	1.486 3	1.494 3	1.472 1
	p-value, wild BS	0.057 4	0.054 7	0.102 7	0.182 1	0.179 4	0.216 7

$t \times l \times j$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−4.426 5	−4.481 3	−4.465 1	−2.343 5	−2.439 8	−2.451 0
	Clustered s.e.	2.594 0	2.596 9	2.582 2	2.402 5	2.402 8	2.352 7
	t-stat	−1.706 5	−1.725 7	−1.729 2	−0.975 4	−1.015 4	−1.041 8
	p-value	0.090 2	0.086 7	0.086 0	0.331 1	0.311 7	0.299 4
	G^{*A}	13.826 3	13.775 2	14.009 4	18.034 6	17.894 1	18.023 0
	p-value, G^{*A}	0.110 3	0.106 8	0.105 7	0.342 3	0.323 4	0.311 3
	Conley s.e.	1.615 6	1.617 3	1.605 0	1.528 3	1.523 1	1.522 7
	p-value, wild BS	0.099 4	0.097 4	0.099 4	0.361 5	0.341 4	0.326 1

$t \times l$	$\gamma_t^{post} \times \gamma_{jl}^{overlap}$	−5.438 4	−5.389 0	−6.175 7	−0.503 1	−0.450 3	−0.890 9
	Clustered s.e.	3.454 1	3.438 5	3.480 5	3.482 5	3.457 7	3.482 8
	t-stat	−1.574 5	−1.567 2	−1.774 4	−0.144 5	−0.130 2	−0.255 8
	p-value	0.117 7	0.119 4	0.078 2	0.885 3	0.896 6	0.798 5
	G^{*A}	10.830 2	10.846 7	10.846 3	9.981 2	9.951 6	9.959 5
	p-value, G^{*A}	0.144 1	0.145 7	0.104 0	0.888 0	0.899 0	0.803 3
	Conley s.e.	3.131 8	3.123 7	3.096 5	2.939 2	2.933 6	2.920 5
	p-value, wild BS	0.128 0	0.129 4	0.084 7	0.906 3	0.917 0	0.811 6

Notes: Each panel corresponds to different level of aggregation in data. In each panel the coefficient of interest is DiD indicator. Second row is the CRVE standard errors; third and fourth rows are associated t-statistic and p-values. Fifth row provides G^{*A}, feasible effective number of clusters of *CSSL*; sixth row provides associated p-value. Seventh row is Conley standard errors. Final row is bootstrap p-values.

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