Leniency Programmes, Competition, and Innovation

Zeina Alsharkas

Supervised by

Prof Katharine Rockett

Dr Luis Vasconcelos

A thesis submitted for the degree of Doctor of Philosophy

Department of Economics

University of Essex

May 2018

To my loving family

Abstract

This thesis addresses two different topics in the area of competition policy and innovation.

In Chapters 2 and 3, I analyse the efficiency of both national and EU leniency programmes in detecting and destabilising cartels. I use industry-level panel data to track the changes in competition intensity as leniency programmes are implemented. The success of the leniency programme is captured by an increase in competition intensity (as measured by a drop in price-cost margins). I then conduct a novel difference-in-differences DD, and a difference-in-difference-in-differences DDD, where I divide the industries according to their likeliness to form a cartel as well as their likeliness to be susceptible to cross-borders cartels. Results suggest that leniency programmes are effective both at the national and the EU level.

As the results in Chapters 2 and 3 suggest that leniency programmes are successful in increasing competition intensity, I propose leniency programme implementation as a novel instrument to study the causal impact of competition intensity on innovation in Chapters 4 and 5. Specifically, I use the exogenous variation in competition intensity resulting from leniency programmes implementation to assess the impact of competition intensity on innovation. I provide two different contributions based on firm-level data in developing countries and industry-level data in developed countries. I consider both innovation inputs (R&D expenditures) and outputs (process and product innovation). The Instrumental Variable estimates of competition intensity on innovation reveal two opposite effects: the “Schumpeterian effect” where competition is associated with lower innovation activity and the “escape-competition effect” where competition is associated with increased innovation activity.

Acknowledgments

Writing this thesis would have been a distant reality without the help and continuous support from many individuals.

Firstly, I would like to express my sincere gratitude to both of my supervisors for their detailed and constructive comments on various drafts of this thesis. I am grateful to Prof Katharine Rockett, not only for her great supervision, helpful comments and advice but also for being very supportive, kind, and always there for me throughout the PhD. Similar profound gratitude goes to Dr Luis Vasconcelos for his patience, motivation and his tremendous academic support.

Special mention goes to Prof João Santos Silva, Dr George Symeonidis, Prof Giovanni Mastrobuoni, Dr Abhimanyu Gupta and Dr Gordon Kemp for their excellent comments and feedback. I have a lot of gratitude for my board members, Dr Helen Weeds and Prof Sule Alan.

I also gratefully acknowledge the doctoral scholarship from the University of Essex. The Department of Economics has been like a family to me during my life at Essex, and therefore, I am grateful. I would like to thank the administration of the Economic Department for being helpful and supportive, especially Lorna Woollcott and Debbie Hall who were there for me whenever I needed any help or advice. I am grateful to all the participants of the Research Strategy Seminar (RSS) at the University of Essex for their feedback.

My time at Essex was made enjoyable in large part due to the amazing people I have met. I would like to thank my officemates Ozgul Bilici and Alex Donov for discussing and sharing ideas about my work and theirs, which has enriched my critical skills. A special thank goes to Eike Eser, who has been an astonishing guide and mentor, and an amazing officemate. Thanks to my friends for making this journey a wonderful one: Daniel Gonzalez Olivares, Konstantin Vasilev, Gulciman karakeçi, Duygu Ozdemir, Ruaa Alshehabi, Larissa Kersten, Katya

Alkhateeb, Marwa Alrasheed, Diana Terrazas, Leyre Gómez-Oliveros Durán, Enes Duysak, Pierre Rialland, Ali Sen, Debashrita Mohapatra and Han Zhang. A special thank goes to Yara Issa, Masar Hadla, Rasha Alshalabi, Abdulkarim Atteh, Mais Shabaan and Sofia Bounahi for going far beyond the call of duty and standing nearby me during my very difficult days. Thanks to Osamah Qaralleh and Abdullah Thalji for the sleepless nights together in the labs and for all the fun that we had.

A sincere appreciation goes to Ahmad Ekrimah for his love, support and patience. Thank you for your faithful support during all the stages of this PhD and for sharing the good and bad days with me.

Finally, but by no means least, I would like to thank my family for being close to my heart and soul even when our circumstances distanced us. Thanks to my sister Hela Al Sharkas for giving me emotional support and for being my best friend. Thanks to my aunt Hyam Ghojel and my uncle Abdulazim Adawi for their unconditional love and support. My final and foremost appreciation and love are for my mother Dr Huda Ghojel for all her love and encouragement.

Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

This thesis investigates two topics in Industrial Organisation: the efficiency of leniency programmes aimed at cartels, and the effect of competition intensity on innovation.

In Chapter 2, I investigate the efficiency of leniency programmes in detecting and destabilising cartels. These programmes allow for fine reduction or avoidance for cartel member(s) that report their cartel membership to an Antitrust Authority. The main objectives of these programmes are to deter cartels either before they occur (ex-ante deterrence) or to destabilise and detect existing ones (ex-post deterrence). Unlike earlier literature that evaluated these programmes using a sample of prosecuted cartels and left aside potentially colluding firms, this study follows Klein (2010) in using the final measure of the competitiveness in an industry as a measure of the success of the programme. Thus, the measure captures the impact of the policy on colluding firms rather than on a population of detected cartels only. The empirical analysis is based on OECD industry-level panel data from 1990 to 2007. Results show, after adopting leniency programmes, an increase in the industries' competition intensity, as measured by a drop in the price-cost margin, which suggests that national leniency programmes are effective. The results, nonetheless, are not conclusive in respect of the EU leniency programmes, which spurs further investigation. Despite the fact that Chapter 2 does not fall into a single observation dilemma, it does not distinguish between potentially colluding and non-colluding firms in the sample. In other words, not all industries are expected to benefit from the programme in the first place, as it is unlikely that firms form a cartel in some industries. Thus, the programme might be irrelevant to them. This caveat is tackled in the next chapter.

In Chapter 3, I account for the fact that the impact of the leniency programmes relies heavily on the industry structure. Hence, I look deeper at the structure of industries that I have in the sample. I group industries according to their "likeliness" to form a cartel into "likely" and “unlikely” colluders. This is identified after looking at certain characteristics that make an industry susceptible to cartelisation. I expect that “likely” colluders exhibit a different behaviour than “unlikely” colluders. I capture this by employing a difference-in-differences identification strategy. The treatment group is the industries that are susceptible to cartelisation “likely colluders", and, here, I track the change in behaviour with and without leniency programmes. This group should exhibit changes when the programmes are introduced if they are effective. This effect is compared against the control group of industries where there should be no cartels in any case; thus, leniency is unlikely to make any difference. This latter group is the "unlikely colluders", where there should be no effect at all of the leniency, as no cartels will arise. Hence, the treatment and control groups should exhibit different PCM changes, as only one of the groups should be affected by leniency programmes. I further account for the fact that the EU supranational leniency programmes may be irrelevant to some cartel cases. Therefore, I classify the industries into national and EU markets by checking whether the relevant market for an industry is typically national or whether it extends at least to a significant part of the EU. I expect that industries that extend to a significant part of the EU are susceptible to cross-borders cartels and thus the EU leniency programmes are relevant to them. I estimate a difference-in-difference-in-differences (DDD) model where the “national market” industry group forms a control group within the treatment group “likely colluders”. The DDD captures two potential confounding effects: changes in the competition intensity in "likely" industries across industries that are not susceptible to cross-borders cartels as well as the changes in competition intensity in both types of industries “likely” and “unlikely” within the EU. Difference-in-difference (DD) and difference-in-difference-in-differences (DDD) estimates suggest that both national leniency and EU programmes fulfil their goal in increasing the competition intensity within and industry. However, results exhibit sensitivity to the way in which I group industries into “likely” and “unlikely” candidates. Therefore, I can conclude that leniency programmes are effective in increasing the competitiveness in "likely" industries, only under the assumption that the classification of the industries is accurate.

Chapter 4 turns into a different topic. I assess the impact of competition intensity on firms' innovative behaviour in developing countries. The major concern in this relationship is the potential endogeneity problem in the competition intensity measure. Given the results obtained in Chapters 2 and 3 and suggested the exogeneity of these programmes, I propose to instrument for competition intensity using the exogenous variation in the implementation of leniency programmes. Thus, I establish a causal relationship between competition intensity and innovation outputs, as measured by product and process innovation. Instrumental Variables estimates reveal a negative impact of competition intensity on firms' innovation behaviour in countries which implemented the leniency programme, and they were actually affected by this programme (the compliers). This result is consistent with the strand of literature where more intense competition leads to less innovative activities, which is known as the "Schumpeterian effect". However, one concern in this analysis is that it is based on self-reported measures that may be subjective as they reflect the respondent's knowledge and understanding of the survey question. Therefore, I investigate this relationship further in Chapter 5.

Chapter 5 complements the analysis in Chapter 4. I analyse the impact of competition intensity on innovation at the industry-level in OECD countries. Here, I focus on innovation inputs rather than outputs. I employ both R&D intensity and R&D expenditures as measures of innovation effort. I use both national and EU leniency programmes as instruments to establish a causal relationship between competition intensity and innovation. Conversely to Chapter 4, I find a positive impact of competition intensity on innovation which suggests that more intense product market competition incentivises firms to innovate to maintain or improve their market position, as known as the "escape-competition effect". Chapters 4 and 5 suggest higher level of competition boosts the innovative activities in economies that are close to the technological frontier whereas it does not appear to be conducive to innovation in countries where the economic growth depends on imitating and adapting technologies from the developed world.

Chapter 2 An Empirical Investigation of the Effect of Leniency Programmes on Competition Intensity

This chapter investigates the efficiency of leniency programmes in detecting and destabilising cartels by evaluating their effect on their final aim, which is to increase industries' competition intensity. The existing empirical literature is not conclusive, as it is based only on a population of discovered cartel cases and so ignores potentially colluding firms. Where the increase of the number of prosecuted cartel cases is used as a measure of the effectiveness of leniency programmes, the effects of the efficiency of such a policy and the existence of a greater pool of cartels from which prosecutions are derived are confounded. After a review of the relevant literature, I propose several approaches to evaluate leniency programmes. I implement an approach that is close to that of Klein (2010) to disentangle the effects of efficiency and change in the pool of potential cartel cases. The empirical analysis is based on OECD industry-level data from 1990 to 2007. Estimates show an increase in the industries' competition intensity (measured by the drop in the price-cost margin) after adopting leniency programmes, which suggests that these programmes are effective. This chapter forms a prelude to a more developed analysis in the following chapter, where I implement a difference-in-differences methodology to get a more precise measure of the effectiveness of these programmes.

Keywords: Cartel, Leniency Programmes, Antitrust
JEL Classification: K21, K42, L4

2.1 Introduction

Firms in cartels may protect themselves from the competitive pressure to introduce new products, improve quality, and keep prices down by controlling prices or dividing markets (European Commission, 2012). As a result, consumers may end up paying more for lower quality. Indeed, cartelisation of firms is considered a major threat to competition and so has attracted both laws proscribing this behaviour and prosecutions. The European Commission, for example, stated that cartels are illegal and, in effect, has imposed heavy fines on firms found to be involved in cartels.[1]

At the same time, detecting and destabilising cartels is a challenge for competition policy. It is not easy to determine if a cartel is occurring using publicly available information, and it is not cheap to obtain and analyse confidential information. In response, antitrust authorities in many countries have used leniency programmes as a way to detect and destabilise cartels, although the precise design of these programmes has varied.[2] Under leniency programmes, (certain) cartel members who denounce their cartel are allowed to avoid a fine or at least are granted a fine reduction. While this clearly creates incentives for members to destabilise their cartels, it also potentially increases the incentives to join cartels, since the future anticipated fine is potentially reduced. Hence, leniency programme design is a difficult balancing act, suggesting that the effectiveness of these programmes in reducing cartel occurrence might not be assured.

To analyse the effectiveness of leniency programmes, one must first explain their aims. Their main objective is to reduce cartel behaviour. This objective could be divided into two parts, however, of *ex-ante* and *ex-post* cartel reduction. The former refers to preventing cartels before they occur while the latter refers to detecting and prosecuting existing ones (Spagnolo

[1] Antitrust authorities have set up leniency programmes for cartel members that denounce their collusive agreements. More detailed leniency legislation will be described in section 2 of this chapter. Official statistics can be found at the following website: http://ec.europa.eu/competition/cartels/overview/faqs_en.html

[2] For example, these practices were revised in the USA in 1993 and in the European Union in 1996 as I shall describe in section 2 of this chapter

2008). Past work evaluating the effectiveness of these programmes has encountered difficulty in capturing both of these aims. Much of the previous literature deals with prosecuted cartels and leaves aside potentially colluding firms. In other words, researchers largely built their studies around the duration and the number of successfully prosecuted cartels.[3] This confounds the effects of the programme itself and the changes in the number of potential prosecutions.

In this chapter, I evaluate leniency programmes, capturing both the deterrence and destabilisation effects. I first replicate and then extend the model proposed by Klein (2010), who neatly finesses this issue by choosing the final competitiveness of the industry as his "success" measure instead of earlier measures that could only be observed for detected cartels (hence underestimating the deterrence effect). In other words, I intend to capture the magnitude of both effects when combined, although my work does not separate out their relative importance.

This chapter is structured as follows. Section 2 reviews the theoretical and the empirical literature on leniency programmes. Section 3 describes the empirical model I use for the analysis. The model in this chapter mimics the work of Klein (2010) before extending it in the next chapter. In section 4, I present the data used in the analysis and the descriptive statistics, pointing out some drawbacks in the data and proposing various approaches to deal with these. Sections 5 and 6 discuss the results. Section 7 briefly concludes.

2.2 Related Literature on Leniency Programmes

The term "leniency programme" refers to a system allowing fine reduction or avoidance for members of cartels who report cartel existence or activity. For example, the US 1993 corporate leniency programme notice is summarised in *"The Division has a policy of according leniency to corporations reporting their illegal antitrust activity at an early stage, if they meet certain conditions. Leniency means not charging such a firm criminally for the activity being*

---

[3] Some previous work includes Brenner (2009), Miller (2009), Bigoni et al. (2009), Hamaguchi et al. (2009) and Hinloopen and Soetevent (2008). A more complete review of the literature follows in section 2.

reported…"- The US Department of Justice ("DoJ").[4] Hence, these are tools aimed at both cartel deterrence (*ex-ante*) and destabilisation of existing cartels (*ex-post*). Initial programmes in the USA dated back to 1978 but became more vigorous after reforms in 1993 that allowed for fine avoidance for a party that denounced a cartel. Followed by the success[5] of the USA leniency policies, the EU introduced a similar programme in 1996, and it was later strengthened in 2002. The UK, Korea, and New Zealand also followed with their versions of leniency (OECD 2002).

The old US leniency programme in 1978 was criticised for not being very transparent. It left prospective applicants with uncertainty about the outcome of their application as the amount of fine reduction was discretional, and it was not automatic that reporters would be granted leniency. The US DoJ revised the programme significantly in 1993, making the award of complete amnesty automatic, conditional on no investigation having begun or having been started but with little information accumulating to date. In other words, leniency would be granted automatically in cases where the information revealed was new to the authorities. Also, under this new policy, amnesty was granted to whoever cooperated with the investigation from the applicant firm (directors, officers or employees). Overall, the main changes in the leniency programme in 1996 were to increase its generosity and transparency, extend coverage, and create positive rewards.[6]

Under the 1978 US policy, few firm applications for leniency were made. Between 1998 and 2002, however, the number of applications multiplied twentyfold. The total fines were over $1.5 billion. This evidence, as it followed the introduction of the new leniency policy of 1993,

[4] The US Corporate Leniency Policy is retrieved from the US Department of justice at*https://www.justice.gov/atr/corporate-leniency-policy*

[5] The achievements of the USA leniency policies are described by the Department of Justice staff in a report available at *http://www.justice.gov/atr/public/criminal/index.html* , as well as in international reports by the OECD (2002, 2003).

[6] Amnesty Plus programmes, which were introduced at this point, provided a net reward to cartel members (firms/managers) who reveal a new cartel.

was interpreted as suggesting that the new policy was more effective[7] than the previous one since the nature of the changes were a guaranteed amnesty and high sanctions that it would be natural to "pin" the change in effectiveness on this.

The European Commission ("EC") followed the US DoJ in adopting a leniency programme in 1996. Similarly to the US, the first EU programme was not effective for the same reasons, i.e., not transparent, not automatic, and uncertain. The EC revised their programme in 2002, making adjustments informed by the success of the US leniency programme of 1993.

Spagnolo (2006) notes the common features between the US 1993 and EU 2002 leniency programmes. Firstly, only the first party to report is eligible for full amnesty in both. Secondly, the second reporting party can still receive a reduced form of amnesty in both systems: the rewards are higher if the report takes place before the beginning of an investigation and decreases as the investigation continues. The difference is that, in the EU, the second party that collaborates may obtain a partial reduction in sanctions if it provides additional information that is valuable to prosecution, while, in the US, firms that do not report first can still obtain reductions in sanctions by pleading guilty. Hence, the conditions for later party rewards differ across the two jurisdictions.

According to the OECD (2002, 2003), and since the introduction of leniency programmes in the US, a non-negligible number of cartels have been detected and successfully prosecuted; before 1993, an average of one application for leniency per year was made. After 1993, up to three applications were made per month, a twenty-fold increase on average. Fines have been levied against cartel members and jail sentences have been served in many cases. In the light of this evidence of success, Australia, the European Union, Germany, France, New Zealand, Korea, the UK, and other countries have adopted leniency programmes. Table 2.1 provides information

[7] A dramatic increase in leniency applications was observed, as I have reported in the text (OECD 2002, 2003). This is not, of course, the only metric of effectiveness that one could have nor is it definitive, since it does not control for the possible rise in underlying cartel activity from which this pool was drawn. More will be said about this later in the chapter when I discuss the methodology.

on when national leniency programmes have been enacted across the OECD, which I will use in the empirical analysis. The table also shows whether a country is affected by the first EU leniency programme in 1996 or by its revision in 2002. Countries that joined later than 2002 fell under the latter of these.

2.2.1 Theoretical literature

Theoretical models analyse the role of leniency programme design on self-reporting. These models suggest that leniency programmes could be used as an effective tool to detect and destabilise cartels; however, the design of the programme potentially affects its ability to reduce cartel activity. Hence, the literature has examined both designs where only the first cartel member to report obtains a fine reduction, while other papers have focused on less strict programmes. The following section will discuss different features of these models and explain how they generate different results.

Leniency programmes are not the sole province of competition policy, as pointed out by Spagnolo (2004), who analyses a stylized dynamic model of leniency programmes in which there is a discounted infinitely repeated game between either oligopolistic industries or criminal organisations. He assumes that the players are risk-neutral agents. He draws a parallel between criminal and industrial cartels, relying heavily on the law enforcement literature on destabilising organised crime. The paper starts by analysing a benchmark where the optimal law enforcement policy in the absence of leniency programmes is derived. He shows that collusive or criminal agreements are more difficult to sustain when the antitrust agencies commit publicly not to penalise unduly agents who defect from their collusive or criminal behaviour. This destabilises cartels as it encourages collusive agents to defect from their agreement, knowing that they will not be penalised for their past collusive behaviour. Later, in the same paper, Spagnolo analyses alternative leniency programme designs in the model to capture their respective effects on the collusive game. He distinguishes between two designs of leniency programmes, namely "courageous" and "moderate" programmes. While the former offers positive rewards to the whistle-blower, the latter only allows for a reduction or exemption from fines. He finds that the rewards must not be too generous, as cartel members can simply exploit them to over-report and so pocket the fines. In other words, it can be optimal to form a cartel solely to report it and obtain compensation. Of course, while generous schemes do poorly at deterrence, they do well at *ex-post* destabilisation for the same reason. That is, sufficiently generous leniency programmes lead to two opposite effects that policymakers should note when designing the leniency scheme. The first is that a generous leniency programme may induce firms to agree to collude and report each period to profit from the rewards of the system (i.e. exploit the system and at the same time make the cartel problem worse; *ex-ante*). The second effect is that generous leniency programmes might increase the cartel agents' incentive to report information and hence increase cartel detection and deterrence *ex-post*.

Spagnolo (2004) concludes that the optimal scheme rewards the first reporter only because allowing the other reporting agents to obtain leniency will make it exploitable, in the same sense that is described earlier (i.e. they will be increasing the value of their agreement by reporting their misbehaviour in every period they collude). Moreover, optimal leniency design should maximise fines to reduce the expected value of collusive behaviour and to finance and offer higher rewards to the first agent who reports information. In other words, by compensating only the first agent, the "best of both worlds" can be obtained whereby a large compensation for destabilisation can be given (since only a single agent receives it), while there would be little incentive to form a cartel just to collect the fine if only a single (and *ex-ante* unidentified) agent receives any benefit.[8] Indeed, when fines are exogenously constrained to be very small, the optimal policy rewards the first reporting agent with the sum of the fines imposed on other cartel

[8] This, of course, ignores any complex plans to divide up the first reporter's payment.

agents so that the system is self-financing but concentrates all the effect on a single agent. Noting that such a scheme may not be politically and institutionally feasible because voters might not approve of rewarding reporters, Spagnolo then analyses a more realistic programme that caps fines and rewards but still provides some effectiveness; this analysis generates a constrained optimal “moderate” leniency programme, where rewards are not available, and fines are bounded to be non-negative. In the process, he isolates three distinct effects that a “moderate” programme may have that induce reporting: a “protection from fines effect”, a “protection from punishment effect” and an effect of the “riskiness” of bad behaviour. The first effect suggests that implementing a “moderate” leniency programme constricts colluders’ incentives if the reduced fines are lower than the expected fines from not reporting. The second effect occurs when a “stick-and-carrots” punishment strategy exists, where the punishment for repeated wrongdoers is higher than those who colluded for the first time. Thus, this increases the fines and lowers the expected profits from future collusion. The last effect suggests that “moderate” leniency programmes have a deterrence effect partly because they strictly increase the riskiness of entering or maintaining a collusive agreement. This is because, as explained by DoJ officials, leniency programmes generate breakdowns in trust between cartel members. The riskiness increases more when the programme is restricted to the first reporting party because the “first comer” rule generates a rush to report.

Aubert et al. (2006) provide some policy support for Spagnolo’s analysis. They comment that recent revisions (2002 in the EU and 1993 in the US) to leniency programmes have provided full amnesty for the first reporter, in line with Spagnolo's results. Unlike the settings of Spagnolo’s (2004) model, Aubert et al. (2006) distinguish between colluding individuals and organisations. They compare the effect of leniency programmes which offer a fine reduction to more generous ones, *“bounty schemes”*, that offer positive rewards (a fraction of the collected fines) to the confessors. They argue that systems which provide positive rewards to both firms and individuals are more effective in deterring collusion than the ones that simply offer a reduction in fines. In a model where, in contrast to Spagnolo, the probability of investigation is exogenous, Aubert et al. (2006) examine a benchmark case that looks like a relatively standard infinitely repeated model of collusion (where collusion is the equilibrium they focus on) and compare this to the same cartel under a leniency programme. A leniency programme that only reduces fines allows participants to reduce the cost of the assumed “random audits” by reporting. This means that leniency programmes will be effective precisely when fines are high since the incentive to report is to avoid this “audit cost”. Of course, when fines are high, the incentive to collude is small anyway. If rewards are possible for whistle-blowers too, the authorities are less constrained in the incentives they offer, and so it is clear that a greater overall effectiveness can be obtained. However, they point to some inefficiencies associated with such rewards such as restricting information exchange and cooperation between competing firms under the fear of false strategic reporting by rival firms. However, this issue could be tackled by introducing fines for false-reporters that aim to harm competitors. Aubert et al. (2006) also explain the puzzling fact that colluding firms may keep “hard” and possibly incriminating information about their cartel behaviour even at the risk of being caught by the antitrust agencies. The authors suggest that this is because firms may want to have evidence to use if they apply for leniency and potentially fine reduction in the case of an exogenous shock, such as productivity shock that leads to a cartel breakdown. As this model’s conclusions echo some of Spagnolo’s general points in a contrasting framework, it lends strength to his conclusions. Specifically, leniency programmes that offer positive rewards deter collusive behaviour more effectively in comparison to those programmes that only offer reduction or exemption from fines.

Motta and Polo (2003) analyse a more restricted framework compared to Spagnolo, assuming that collusion must be sustained with grim trigger strategies and that a reporting firm cannot be punished for colluding. Unlike the previous models of both Spagnolo (2004) and

Aubert et al. (2006), Motta and Polo (2003) limit their model to address leniency programmes that offer only a reduction in fines. Their main concern is to address whether inducing cartel agents to apply for leniency once an investigation is opened can improve welfare. They assume that the antitrust authority has limited resources that could be used for detection and prosecution activities. Given this budget constraint, the antitrust authority is unable to prevent *ex-ante* collusion. The Antitrust authority only obtains a conviction with some probability rather than "for sure" when an investigation is instigated. Under these settings, they show that leniency programmes are indeed effective as they increase the probability of interrupting the collusive behaviour and reducing the investigation time; hence, saving the Antitrust authority's resources.

Chen and Harrington (2007) also look at the setting of the reward that a leniency programme could offer, comparing between leniency programmes which grant the first confessor a total immunity from fines rather than a partial reduction in fines. Unlike the earlier mentioned works (except Motta and Polo, 2003), Chen and Harrington (2007) relax the assumption of the fixed probability of detection and prosecution without leniency programmes. Chen and Harrington (2007) introduce an oligopoly stage game, where each stage is a Prisoners' Dilemma, to measure the impact of antitrust or competition policy on collusion. Their result in a dynamic model is that the effectiveness of leniency programmes on deterrence depends on the design of the programme: a stronger leniency programme (where all penalties are waived to the first firm to come forward) deters cartels significantly, but softer leniency programmes (offering partially reduced fines) can make collusion easier compared to programmes which do not offer leniency at all. I explain the intuition of this as part of the review of the Harrington (2008) paper, which is a slightly different version of this analysis, as the latter approach does a particularly good job at diagnosing the underlying effects of leniency programmes.

Harrington (2008) breaks down the theoretical effects of leniency programmes into three different factors, which help to flesh out the effects present in the earlier Chen and Harrington's paper. Similar to the approach provided by Chen and Harrington (2007), the model examines the implication of leniency programmes in the context of a repeated Prisoners' Dilemma.

Harrington (2008) introduces three ways in which a leniency programme influences the frequency of collusion; the "Deviator Amnesty Effect", the "Cartel Amnesty Effect" and the "Race to Courthouse Effect". There is a positive destabilisation effect when fines fall for reporters, which he dubs the Deviator Amnesty Effect. It works through the payoff to cheating on the collusive agreement: a firm both undercuts the collusive price and gets the reduction in fines under leniency when it "cheats". Hence, as the payoff to cheating rises, the cartel is more difficult to sustain. In other words, the "destabilisation effect" increases. There is also, however, a negative "deterrence effect" as the anticipated punishment for cartels falls under leniency, which he dubs the Cartel Amnesty Effect. This effect works through the expected payoff to colluding, i.e., colluding firms know that they can use leniency programmes in the future when the probability of detection is high. This means that the incentive to collude rises, as firms can use a leniency programme to decrease the size of penalty if they are caught colluding. More leniency (i.e., a greater payoff to reporting) raises the expected payoff from continuing to collude (because it reduces the penalty for being found out). Harrington notes that while it may be an equilibrium for all firms to report with each receiving a payoff for doing so with some small probability, it may also be an equilibrium for none to and for the collusive agreement to simply continue. This latter outcome may Pareto dominates the former one when the leniency programme only grants amnesty to a single first reporter since the overall payoff to reporting is almost unaffected by leniency when amnesty is granted only to a single firm. Clearly, as the leniency programme becomes more generous, the non-reporting equilibrium becomes less stable. The third effect is Race to the Courthouse Effect which makes sustaining collusion more difficult by enhancing the payoff to the first cheater only. In this case, each firm will rush to the antitrust agency to decrease the extent to which it will be punished, hoping to be the first to arrive (and receive amnesty) rather than the second to arrive and receive a penalty. The Deviator Amnesty Effect and the Race to Courthouse Effect illustrate the effect of destabilising cartels while Cartel Amnesty Effect tends to stabilise the cartel.

Harrington (2008), in his review of the literature, comments that both the Deviator Amnesty Effect and the Cartel Amnesty Effect have been present in other work. These effects generate the result that increased leniency may increase the incentive to cheat (if the first of the two effects is the main driver of the model) or increase the incentive to collude (if the second of the two effects is the main driver). Harrington has a richer model that nests much of the former work. He allows the two forces to interact, and at the same time allows for the third force. In particular, his model allows the probability of detection to vary, which can match the data better: while in many of the earlier models (except Motta and Polo), it is always the equilibrium to report, as a matter of fact, we observe that cartels continue to form. This requires some equilibrium to be derived where at times firms choose to form the cartel despite leniency. This is a very appealing feature of Harrington's model.

Overall, then, the theoretical work suggests that leniency should work, and that it works better if leniency is more generous and if it gives some priority to rewarding early reporters. Harrington (2008) notes that existing programmes differ considerably in design and that new programmes are being introduced continuously so that empirical work on the design and success of the various programmes is called for. I now turn to discuss this work.

2.2.2 Empirical literature

Harrington (2008) concludes with an exhortation to empirical work. Some have followed in due course. As I noted in the previous section, the theoretical models separate out the effects of leniency programmes into destabilisation and deterrence. Brenner (2009)[9] echoes this division by tracking 61 prosecuted cartel cases in the EU between 1990 and 2003, distinguishing between short and long-term effects. Since he only looks at detected cartels, Brenner's short-term analysis focuses exclusively on destabilisation effects. More precisely, the short-run (deterrence) effects of the EU 1996 leniency programme are related to information revelation (reporting), as well as investigation and prosecution costs reduction. OLS regression analysis suggests that the leniency programme increased information revelation, as measured by an increase in the size of imposed fines per firm in cases where some firms cooperated under the 1996 leniency programme relative to other cases, by about €31 million. This finding is in line with Motta and Polo (2003) and Spagnolo (2004). Moreover, he finds a significant impact of leniency programmes on the reducing cartel investigation and prosecution costs, as measured by the reduction in the duration of the investigation (the period between detecting the cartel and reaching a decision). His results suggest that, on average, after imposing the 1996 leniency programme the duration of the investigation drops by a year and a half. The long-term effects in Brenner's framework are associated with the deterrence of collusive behaviour. To capture the long-run effects,[10] he infers a hazard rate of cartel stability based on pre-leniency cartel activities and then tests whether post-leniency activities were significantly different. His hazard model, then, aims to reveal whether those cartels being created under similar conditions break down more easily in the presence of a leniency programme. Using the duration of detected cartels as a measure of cartel stability, Brenner's results suggest no significant deterrence effect of implementing the leniency programme in 1996. This suggests that, despite the sharp rise in the number of convicted cartel cases after implementing the leniency programme in 1996, there is not sufficient evidence that

[9] To test the effect of leniency programmes on the level of fines and the investigation cost, Brenner runs different linear regressions for each of the following dependent variables: the amount of fines imposed by the European Commission before the reduction of leniency is applied, the amount of fines after deducting a leniency discount and lastly the cost of investigation. He uses a dummy for leniency programmes as an explanatory variable, which takes a value of one if the case was formally subject to the leniency programme from 1996.

[10] The dependent variable is the hazard rate of the agreement's breaking and the explanatory variable is a dummy for the existence of a leniency programme.

cartels become more less likely to form. He presents a graph of the empirical density of detection across time showing that the number of detected cartels does not back up his hypotheses as it does not show an immediate increase in the number of detected cartel cases after the implementation of the leniency policy but rather with a time lag of four years. At the same time, the long-term detection rates do not fall below the initial levels. Stephan (2005) empirically assesses the success of the 1996 leniency notice in the European Union in discovering horizontal cartel cases. He shows that three-quarters of the convicted cartel cases under the 1996 leniency programme are a result of investigations that were held previously (cartels such as Lysine, Citric Acid, and Vitamins) or simultaneously (such as the Methylglucamine cartel) by the US DoJ, which exercised a more effective leniency programme. Moreover, 67 percent of the cartels that were successfully uncovered by the leniency programme in 1996 were operating in one industry only, namely the chemical industry. Therefore, the firms' applications for leniency in the EU, followed by the introduction of the leniency in 1996, might have only reflected the natural consequence of cartels' failing due to the conditions in the market in which they are operating.[11]

Miller (2009) focuses on detection rates in a way that is equivalent to the short-term portion of Brenner's analysis. He studies the introduction of the new US leniency programme in 1993 for 342 distinct cartels between 1985 and 2005 in the US. He finds a way to overcome the "single observation" dilemma, where information on detected cartels only is used, by estimating his theoretical model and inferring the discovery rate using information on the filed violations of Section 1 of the Sherman Act. To obtain a valid inference on existing cartels from discovered cartel cases, his model assumes that the probability of formation, detection and dissolution is exogenous and the antitrust authority discovers all cartels with equal probability. In other words, he infers a discovery rate from pre-existing cartel cases, assuming that the "average" rate applies

[11]For example, the failure of the Carbonless Paper cartel was due to the decline in the market for the self-copying paper in the face of new technology that led to so little benefit from continuing to collude that a firm was tempted to apply for leniency. The Belgian Brewers cartel failed because of the decrease in demand, overcapacity and pressure from the retailers, which preceded the application for leniency. The thesis is that it is a reduction in the benefit of staying in the cartel rather than the reduction in fine or any reward that prompted these firms to report.

to all his individual cartels. His empirical methodology relies on a reduced-form Poisson regression to test whether implementing the leniency programme deters cartels and enhances their detection rates. He captures the deterrence effect of the leniency programme by an immediate increase in the cartel convictions following the policy. The enhanced deterrence effect of leniency is captured by a later drop in cartel discoveries below the pre-1993 levels. Results indeed suggest that there was a brief "rush to the courthouse" after introducing the leniency programmes, but after that there was a lull, resulting in lower detection rates than before the introduction of the programme. Furthermore, the results of his method of moment's estimation argue strongly for the effectiveness of the 1993 leniency. The cartel formation rate drops by 59 percent compared to pre-leniency levels, while the detection rate increased by 62 percent, assuming no change in underlying cartel formation rates.

As noticed from the previously mentioned literature, the deterrence effect of leniency programmes is not well addressed in any of the models we have seen so far. In all of them, it appears that there is no account taken of external events that could raise the rate of cartel formation. Evenett et al. (2001) argue, however, that the rise in the overall rate of detection in the EU after 2000 is possibly due to the economic and political changes at the time of the analysis. In the nineties, the barriers of trade decreased between national markets within the European Union. At the same time, many industries experienced trade liberalisation that was followed by the cross-border market entry. This gave an opportunity to establish new EU wide cartels. Given the fact that the average detected the duration of a cartel is 6 or 7 years, the increase in the number of discovered cartels in 2000 might just coincide with a natural break in an institutional and economic setting which occurred 6 or 7 years earlier. This was not adequately controlled for in the work of Brenner (2009) as he only controls for the duration of the cartel, the number of countries covered by the cartel, as well as the amount of trade affected by the cartel. Miller (2009) controls for GDP growth, the budget of the antitrust authority and the total fines imposed.

The previously mentioned papers rely on detected cartels, which clearly do not reflect any direct measure of pool growth. Analysing discovered cartels alone may, then, underplay deterrence and so lead to a biased view of the effectiveness of leniency programmes. Building on work by Buccirossi et al (2013), who study the general impact of antitrust policy, Klein (2010) suggests a more direct measure of the success of leniency programmes: with fewer cartels overall in a sector, it should be the case that the sector is, overall, more competitive after implementation than before. Indeed, it matters little "how" the leniency programme attains this, as the outcome will improve a lot of consumers regardless of the reasoning that goes on in the mind of competitors. In this sense, it neatly skirts the issue of balancing the positive and negative effects of leniency programmes. I intend to build on this insight in my work.

2.3 Empirical Model

I wish to analyse the effect of leniency programmes, taking into account pool formation. Therefore, I use the final measure of the success of the leniency programme as my dependent variable. In particular, I link competition intensity to leniency programmes, following the framework used in Klein (2010). I study both the national and the EU-wide leniency programmes. I start by replicating Klein's method but using my (different) data, which is the focus of this preliminary chapter. This is to get a baseline to which I will compare my modified methodology in Chapter 3. Following Klein, then, the main objective of this chapter is to analyse the efficiency of leniency programmes in both deterring cartels and destabilising them. Therefore, I employ price-cost margin ("PCM") as an index for competition intensity, and the "outcome" variable for the purposes of whether competition policy's goal of improving consumer surplus is attained. I expand on this in the next chapter in order to improve the method of detecting the effects of leniency alone.

Following Klein (2010), then, the basic equation I want to estimate is the following:

$$Ln\ (Y_{i,j,t}) = \beta_L Leniency_{j,\ t-1} + \beta_p Policies_{j,t-1} + \beta_x ln(X_{i,j,\ t-1}) + \varepsilon_{i,j,t}\ ; \qquad (1)$$

where $Y_{i,j,t}$ is the measure of competition intensity (taken to be price-cost margin), *Leniency* is an indicator (0,1) of whether a leniency programme is in place, *Policies* is a vector of other policies in place (such as single market programme, EU East enlargement, new EU members and leniency in neighbouring countries). $X_{i,j,\ t-1}$ is a vector of control variables, both at the industry- and country-level and $\varepsilon_{i,j,t}$ is a random error term. The subscript *i* refers to industry, *j* refers to the country, and *t* refers to year. The error is a composite, comprising time dummies φt and country-industry specific fixed effects $\omega_{i,j}$ and a remaining random error with mean zero $u_{i,j,t}$, so that:

$$\varepsilon_{i,j,t} = \omega_{i,,j} + \varphi_t + u_{i,j,t}$$

Due to data availability, the industries that I consider in the analysis are mostly manufacturing rather than service-providing industries: 69.57 percent of the sample is from manufacturing while 30.43 percent from service industries.

While there are econometric issues that I address below to reduce endogeneity bias, once this is done a negative and significant value for the coefficient of *Leniency* would not only indicate that leniency programmes are effective in the sense of making an industry more competitive, but also that they are effective considering the aggregated effects of all the various effects identified in the earlier literature on both deterrence and destabilisation. Hence, a finding of leniency programme effectiveness in this model indicates an overall positive balance of the various effects of leniency programmes for welfare, measured as the level of effective competition in the sector (and so reflecting consumer surplus). In the end, this is what should matter for policy-makers, by answering the question of whether this sort of programme "works" overall. One could object to the methodology of this chapter on the grounds of not controlling for all other factors. For example, this methodology does not take into consideration that the existence or lack of a leniency programme should be largely irrelevant for some industries and not for others. In Chapter 3, I propose a modified model to address this issue so I temporarily do not address this question here. A further interesting question would be whether the cost of the programme is justified, given the consumer surplus benefits that I measure, but this is also left aside for the time being.

There are several econometric concerns even with the basic approach of this chapter, as I have mentioned, which I now address. First, omitted variable bias is likely to be a significant issue in these estimations. Time-invariant factors are captured by including industry and country fixed effects whereas time-variant factors are captured by including a set of control variables that are sought to have an impact on the competition intensity. Second, I address the endogeneity between the existence of the leniency programme and the existence of underlying cartels: leniency programmes are undertaken voluntarily by a country so they should only be observed where they are likely to "pay off". This endogeneity can be tackled by using lagged values of *Leniency*. In other words, if a high PCM tends to generate leniency programmes, using a lagged value can counteract this unless policy-making is unusually forward-looking, which I view as unlikely in general. In the light of the earlier models, using lagged values tend to capture long-term effects. This, alongside with the entire methodology where leniency programmes can both deter cartels and destroy existing ones, supports the long-run interpretation.

Admittedly, however, using lagged values of leniency as a regressor is an imperfect control for endogeneity. I would certainly do better to have data from countries that have had such programmes imposed on them rather than signing up voluntarily, but I do not have information that could generate this kind of data. This will be addressed and discussed further in section 6 where I use a subsample of countries that did not already have a national programme when the European programmes were imposed.

Klein (2010) tackles endogeneity by both introducing a two-year lag of leniency variables and employing an instrumental variable approach. Unlike Klein, however, I only introduce a one-year lag to account for reverse-causality, as two-year lag is a long period in which many economic changes could occur. As for political variables, Klein introduces two sets of political variables to instrument for leniency programmes. The first set of instruments reflects the tendency of elected political parties for the role of governments' economic planning. The other set of instruments captures the size and importance of a country's welfare state. The choice to use these variables is based on a previous literature by Besley and Case (2000), Duso and Roller (2003) and Duso and Seldeslachts (2010). In their work, they find that political variables determine the policy outcomes. Buccirossi et al. (2013) also employ political variables to instrument for competition policy indicators. Klein also considers the implementation of leniency in other OECD countries as an instrument for the national leniency programme.

My more general concerns about the ability of this method to isolate the contribution of leniency programmes to overall price-cost margins will be dealt with and discussed in more depth in the next chapter. For the moment, however, I mainly focus on a version of the model that replicates rather than improves on existing work. My purpose here is to establish a baseline to be able to judge the impact of my modified methodology on the existing "state of the art".

2.4 Data and Descriptive Statistics

I estimate the model on a sample of 22 industries in 23 OECD countries over the period 1990-2007.[12] The countries included in the analysis are Austria, Belgium, Canada, Czech Republic, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Korea, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, United Kingdom and the United States. The selection was mainly guided by data availability and for comparability with Klein's work.[13] Some information is missing in these countries. My empirical strategy, in general, is to keep this

[12] In Table 2.10, I re-estimate the whole sample from 1990 to 2009. My results also show no significance.
[13] My selection of industries and countries follows Klein's (2010) data. However, my timeframe runs from 1990 to 2007.

data as it is rather than attempt to fill in missing data by means of extrapolation or otherwise guessing values. Nevertheless, there are a few instances where I complete the data following techniques used in earlier work, and I point this out when I perform any such operation. Both national-level data and industry-level data are used.

The main data source is the OECD Structural Analysis Database (STAN), which provides industry-level data on both manufacturing and service industries. I limit the analysis to industries for which sufficient information is available, which are mainly in manufacturing; 16 industries are from manufacturing while only seven are from services. Variables at the industry-level such as the industry's capital formation, imports, the industry's value added and the industry's gross output are taken from STAN. Information at the national level includes inflation rates. Interest rates data is taken from the OECD Key Economic Indicators database, and the OECD Reference Series database. Information on leniency programmes is taken from national antitrust authorities.

Overall, I have an unbalanced panel of 23 industries and 23 countries over 1990 and 2007. Table 2.4 provides a summary for all the variables I use and their sources. In the next section, I introduce the main variables that I employ in my regressions. I start by presenting the dependent variable, and then I move to discuss the main explanatory variable, leniency programmes, and my control variables. Then I move on to present some descriptive statistics.

2.4.1 Dependent variable

My dependent variable is competition intensity. This could be measured using different proxies, such average profitability, the Lerner index and market share measures. While the PCM is a popular measure of competition intensity in the literature, some authors point that PCM is not a theoretically robust measure (Amir, 2002; Bulow and Klemperer, 1990; Rosenthal, 1980 and Stiglitz, 1989). They present models where more intense competitive pressure increases PCM rather than lowering it because it might reflect inefficient firms exiting the market. Therefore, Boone (2008) proposes measuring the competition intensity based on firms' profit. He shows that this measure of competition is monotone in competition under different conditions[14] which suggest that it is more theoretically robust than other measures such as PCM, market concentration, and market shares. Roeger (1995) proposes that average profitability is equivalent to price-cost margin (PCM) under the assumption of constant returns to scale, where marginal cost is equal to average cost. Griffith et al. (2010) point out that, while theoretically PCM is not necessarily the best measure since constant returns to scale may not hold for the industry in question, as a practical matter it may be the best measure of competition that is available across countries that allows for an international comparison.

I face similar restrictions on data availability and so will use average profitability as the measure of competitive intensity. I am aware, as Griffith et al. (2010) point out, that there is a drawback in using average profitability as a measure of competitive intensity because it assumes constant returns to scale. This measure could be biased upwards (downwards) in the presence of decreasing (increasing) returns to scale. Given that industry structure does not change very quickly over time, however, this bias should be captured by including country-fixed effect in my regression. Including year dummies capture any common trends across countries. To measure competition intensity at the country-industry level, I construct a measure of the average level of profitability for manufacturing industries using the OECD STAN database, which provides information at the two-digit industry level in each country on value-added, labour, and capital stocks.

[14] Where competition is strengthened as a result of a fall in entry barriers as well as for the case where increased competition is due to more intense interaction between firms.

Following the previous literature as I have mapped it out above[15], my measure of competitive intensity, average profitability, is computed as the industry's value-added as a share of the industry's labour and capital costs:

$$PCM_{i,j,t} <=> Profitability_{i,j,t} = \frac{Value\ Added_{i,j,t}}{Labour\ Cost_{i,j,t} + Capital\ Cost_{i,j,t}};$$

where all variables are in nominal prices, and the subscripts *i*, *j*, and *t* correspond to industry, country and time respectively. I collect information on each industry's value-added and industry's labour cost from the OECD STAN database. Value-added[16] and labour costs are available in the data, whereas capital cost is not available. To construct an approximation for the capital cost for my purposes, I multiply gross fixed capital by a capital cost factor, which is described below. Gross fixed capital is available in OECD STAN database; however, it is not available for all countries. Gross fixed capital formation is, nevertheless, more widely available. Hence, where necessary, I approximate gross fixed capital by applying the perpetual inventory method to the gross fixed capital formation and the industry's gross output.[17] Multiplying gross fixed capital by a capital cost factor, which is an accumulation factor, allows moving from stock to flow. The capital cost factor is also not available in the data. The capital cost factor would normally be equal to the risk-free interest rate plus an industry's average depreciation rate minus the relevant country's annual inflation rate.[18] I estimate this cost factor, then, from publicly available data. I capture the risk-free interest rate by using the US long-term interest rate from the OECD Reference Series. Hence, I implicitly assume a unique world interest rate and free capital flow. Each industry's capital depreciation is the average capital consumption over the

[15]As a measure competition intensity, many previous studies use the PCM, as an equivalent to average profitability, for the main arguments which I have discussed in the text: Griffith et al. (2010), Griffith et. al (2007), Martins et al. (1996), Klein (2010) and Buccirossi (2013).

[16] As in Klein (2010), Griffith et al. (2007), Griffith et. al (2010), I use value added rather than sales due to data availability.

[17] This method follows Griffith et al. (2007), Griffith et al. (2010), Klein (2010) and Buccirossi (2013).

[18] I based my method here on the previous literature such as Griffith et al. (2010), Griffith et. al (2007) and Klein (2010).

capital employed.[19] Capital consumption is available on OECD STAN, but it is only available for a small subset of countries of rather different sizes. Since the countries in the sample tend to be large, I want to avoid choosing a rate that is derived from small economies. I view the rate of Germany as a closer match; thus, using this as the unique value for my work.[20] For industries not available in the German data in the OECD STAN database, I use the average of all industries available. For missing observations in German data, I use cross-country means of other countries in the same year and industry.

2.4.2 Explanatory variables

Leniency programme: National leniency programmes implementation is the main explanatory variable. I obtain information on leniency programmes from the homepages of national antitrust authorities. I use information on these programmes from the European Competition Network's (ECN) definition to prevent confusion with the several revisions of very heterogeneous leniency programmes. As in Klein (2010), the final indicator of leniency programme that I consider in the estimate assumes that the first confessor receives "full" immunity.[21] To capture the existence of such a leniency programme, I construct a dummy variable that takes a value of one in the year in which the programme is adopted onward. I introduce a lag in this measure to account for potential endogeneity that arises from the reverse-causality.

First and Second European Union Leniency Programme: I include two more dummy variables that capture whether an industry is affected by the European supranational leniency programmes. The first dummy variable captures whether a country is affected by the first EU leniency programme in 1996[22]and the second dummy captures its revision in 2002.[23] I also introduce a lag

---

[19] As calculated in Klein (2010).
[20] To ensure the robustness of the measure, I employ country's interest rate, rather than assuming that all countries face the same interest rate. The results show no sensitivity.
[21] I do not consider the leniency programmes that they only allow for partial reduction in fine, such as the US-1978.
[22] See EC 1996 notice on the non-imposition or reduction of fines in cartel cases at: *http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:31996Y0718(01)*.

in these to dummies to account for potential reversed-causality. The main distinction between these two programmes is the improved transparency and certainty in the second programme. That is, the second programme is clearer and more detailed in the conditions of providing any level of fine reduction. Including these two dummies account for the fact that EU competition policy works in harmonised and parallel pattern to every EU national one. According to the EC, a cartel member has the right to report his cartel behaviour either to his national authority or to the European Commission. For cartels that are purely national in their character, once a case is reported to the EC, the leniency or prosecution would be pursued under national law. According to the ECN, cross-border cartel members can only benefit from leniency if they apply to every relevant authority that could pursue a case against them. However, having an application filed at the EC protects the applicant from being pursued by the national authority for a limited time (until completing his application), based on providing limited oral information.

Leniency programmes in neighbouring countries: I control for whether there are spillover effects due to the existence of cross-border cartels. I introduce a dummy variable which indicates whether the countries' OECD neighbours implemented leniency programmes. This variable is especially relevant to strongly interrelated economies, such as those in the EU. Where economies are related, and cartels may span national boundaries, there may be effects of cartels detected or deterred in neighbouring countries. However, one potential issue when including this variable is that the EC programmes go hand in hand with the bordering programmes. That is, a firm in a cross-border cartel must apply for a leniency from all the national authorities that it is guilty

---

[23] See the EC 2002 notice on Immunity from fines and reduction of fines in cartel cases at: *http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52002XC0219(02).*

under, as well as the EC. As such, bordering programmes and EU programmes may be collinear.[24] However, I include that in the model for reasons of comparability with Klein (2010).

2.4.3 Control variables

GDP growth: I include national GDP growth to control for variation in my measure of competition intensity, namely PCM, which is strongly affected by business cycles. I introduce a one year lag in this control. Nekarda (2013), assesses cyclicality for PCM with GDP and shows a positive correlation. Moreover, Gali et al. (2007) report a positive correlation between PCM and GDP. Rotemberg and Woodford (1999) note that there is a cyclical component of GDP and PCM; the mark-up peak was found to occur before the business cycle in their work. More precisely, the correlations are positive for all leads and current values, indicating that an increase in the mark-up signals a current and forthcoming increase in GDP; it becomes negative for lagged values, though, meaning that a current decrease in GDP signals an upcoming increase in mark-ups. GDP growth is taken from OECD Reference Series, and it is measured in billions of units of national currency. Admittedly, including year fixed-effects in the panel setting of my data is sufficient to capture the business cycles. Nevertheless, I include this for comparability reasons with Klein's (2010) results.[25]

Import penetration: I control for an industry's openness by import penetration. I control for openness on the assumption that it is correlated with competition policy and so may affect PCM. The correlation between these two variables is 0.03. Furthermore, the relationship between import penetration and PCM might be negative as greater openness to international competition is likely to constrain the exercise of market power (as found in the previous literature; Levinsohn (1993), Harrison (1994), Grether (1996), Djankov and Hoekman (2000)). I calculate import

[24] Surprisingly, the correlation between the existing bordering programmes and the first EU leniency programme is 0.1, while its correlation with the second EU programme is 0.05. However, this is a time dummy rather than an indicator of the convergence between these programmes.

[25] The results show no sensitivity when removing the GDP growth from the regression.

penetration by dividing total imports by value added. I introduce a lag in this measure. Information on imports and value added comes from the OECD STAN database, which contains data disaggregated by industry.

EU enlargement controls: since the EU's East enlargement in 2004 affects competition intensity in all European markets, I control for this by using a dummy variable for all member states after 2005. I also add another dummy for new EU members, which entered in 2004.[26]

Legal system: I introduce a legal system measure to control for non-linearities in the effectiveness of competition policy. Based on Buccirossi et al. (2013), I include a legal system as both a control variable and as an interaction with leniency programmes. Buccirossi et al. (2013) results suggest that competition policy is more effective when the quality of the legal institutions is high. They show that it is higher in countries with German and Scandinavian legal origins compared with those of French legal origin. This finding is in line with La Porta et al. (2008) who classified legal systems into four subdivisions: English, French, German and Scandinavian. They claim that a country's legal system correlates highly with economic outcomes. Hence, I will focus on indicators of legal origin and see how they interact with competition policy, especially with leniency programmes. In the regression analysis, the omitted category is the Scandinavian legal system.

To summarise, this chapter aims to replicate the method proposed by Klein (2010) with my version of the data and including different proxies. I follow the fixed-effect and the instrumental variable strategies in his paper for comparability. I propose estimating a subsample of countries in which the leniency programmes were imposed exogenously by the EU, which is distinct from his work as a robustness check. The next chapter will attempt to improve on the methodology.

---

[26] Czech Republic, Hungary, Poland and Slovak Republic.

2.4.4 Descriptive statistics

Table 2.1 shows the date at which countries adopted a leniency programme. The table is taken from Klein (2010). The US is the first country that adopted a leniency programme in 1993. After five years, the UK adopted a leniency programme in 1998. After that, many countries have adopted a national leniency policy, as is also shown in the table. The second column illustrates whether a country was affected by the first EU leniency programme in 1996. The third column shows whether a country was affected by the revision of the leniency programme in 2002. For the countries that only became EU member states in 2004, namely the Czech Republic, Poland, and Hungary, I only consider that they are affected by the second EU leniency programme after 2004. To analyse the effectiveness of the EU leniency programmes, I limit the analysis to the EU countries. Nonetheless, I first follow Klein's work by including the EU leniency programmes in the full sample estimate while I am aware that the EU programmes are not relevant to countries outside the EU. Table 2.2 lists the OECD countries that are used in the study. I choose this sample according to data availability. Some OECD countries are missing, as there is not enough information to conduct an estimate.[27] Table 2.3 provides information on the industries used in the estimates. It can be easily observed that manufacturing industries are better represented than service industries. Again, this is due to data availability. Table 2.4 reports the preliminary statistics for the main variables discussed above, covering the period 1990 to 2007. There are 5450 observations for competition intensity, as measured by PCM. The mean is 0.17, and the standard deviation is 0.27.

2.5 Results

To assess the efficiency of leniency programmes econometrically, I test whether or not there is a negative effect of leniency programmes on the price-cost margin.

[27] I use information on European countries as well as Canada, US and New Zealand because they have relatively complete information. For any missing observations, I retain that as missing rather than filling in data by some method.

A natural starting point is to use pooled OLS regression with time, industry and country dummies to check for non-linearities and to check the interaction between price-cost margin and time-invariant variables such as leniency programmes, and legal programmes. [28] Control variables are added progressively such as GDP growth, import penetration, [29] leniency implementation in neighbouring countries, EU's ast enlargement in 2004 and legal system.

Pooled OLS estimates will be consistent if the composite error term is uncorrelated with the regressors. However, the composite error term is likely to be correlated over time for a given individual (industry-country combination). To account for the correlation within countries over time, I use cluster-robust standard errors that cluster on the country-time dimension. More fully, serial correlation in panel data for linear panel data models biases the standard errors, which lead results to be less efficient. Using robust standard errors allows me to relax the assumption that the errors are identically distributed; by using a cluster, I relax the assumption the error terms are independent of each other.

In Table 2.5, I present the basic estimation of the efficiency of leniency programmes with the log of PCM as the dependent variable, using pooled OLS regression. Column (1) reports the results of the basic model with national leniency programme as the main explanatory variable. Control variables such as GDP growth and imports penetration are added. Including all the controls together does not significantly improve the results compared to running with any one of the controls included. The key result is that the coefficient of national leniency programmes is negative at 0.168 and statistically significant at the 5 percent level. This suggests that, on average, implementing a national leniency programme decreases the price-cost margin by 16.8 percentage points.

---

[28] I use one lag for leniency programmes (and for all other policy indexes). This is to ensure that the leniency programme is in place, as it is not clear when within the year each policy was introduced, and to reduce the bias of two-way causality.

[29] GDP growth and import penetration are in logs and one lag is added.

Klein's (2010) result captures a negative at 0.0147 but a non-significant effect of leniency programme on PCM. Comparing this change of PCM after the national leniency implementation with the mean of PCM in my sample 0.19, as in Table 2.4, I find that the magnitude has decreased significantly as the leniency programmes eliminate virtually all of the PCM. The country's GDP growth has a positive but insignificant effect on PCM (Coeff. 0.0163 Std. Err 0.0295). This confirms the co-movement of GDP and markups. As in Klein, I find a positive and significant effect. However, the fact that I capture a greater magnitude of the impact of leniency programmes on PCM might be attributed to my choice of control variables and to not considering data that corresponds to the great recession.

Nonetheless, in Table 2.10, I estimate the same model with data from 1990 to 2009. Results are not significant, which is perhaps due to changes in the structural environment in the years of great recession between 2007 and 2009. I estimate a negative and significant impact of import penetration on price-cost margin. This suggests that the importance of industries' imports in the domestic economy decreases the PCM. Since pooled regression combines between and within variation[30], the interpretation of these coefficients might not be clear, however. Hence, I now move to present estimates using fixed-effects.

Column 2 details my estimate of a fixed effect model allowing for an unobserved, time-invariant industry-country effect. It allows the individual effect to be correlated with the regressors, removing the bias that would result otherwise. In my regression, then, using a fixed-effect allows me to explore the relationship between PCM and leniency programmes within an industry-country combination. Each industry might have its own individual characteristic that might or might not affect the PCM. For example, an industry might be susceptible to a cartel or

[30] Between groups describes differences across industries while within group looks at changes over time within industries ignoring differences between them. In my equation, legal system is time invariant so it will be dropped in within group estimates. Other variables used, as described in section 4, are time-variant, which allow for within group estimates.

not.[31] PCM would change more when the leniency programme is instituted if an industry is susceptible in this way.

Column 2 provides estimates of the baseline model, using PCM as a dependent variable and the same previously mentioned explanatory variables as in the first column in Table 2.5. National leniency programmes appear again to have a negative and statistically significant effect of 0.169 on PCM, which suggests that adopting national leniency increase industries' competition by 16.9 percentage points. All the other results regarding control variables are consistent with the results I previously found by using pooled OLS. The fact that the change of technique makes so little difference suggests that the OLS results are, perhaps, not biased. However, that does not appear to be convincing as the OLS assumes that the time-invariant individual effects are independent of the regressors. However, that does not seem realistic as the effect of the leniency largely depends on the unobserved time-invariant industry effect. Column (3) introduces the first EU leniency programme in 1996 and its major revision in 2002. The estimate shows consistent results with column (1); the national leniency effect stays significant with a negative effect of 0.142 on the PCM. The first EU leniency programme is associated with a significant decrease in PCM by 14.2 percentage point, while the second revision shows positive and no significance. This result contradicts with that of Stephan (2005), who suggests that the first leniency programme was not efficient in uncovering cartels, while he predicts that a more strengthened programme, such as the-2002 one, might lead to improved outcome. Having these contradictory results in the impact of the two revisions of the programmes suggests the necessity for further investigation of the efficiency of these two programmes, which I later present in Section 6.

Column (4) controls for leniency programmes in neighbouring countries. The coefficient

[31] This could be determined by looking at characteristics of an industry that tend to predispose it to cartelisation such as number of firms in the industry, barriers to entry, symmetric firms, homogeneous goods, capacity constraint, observable prices and output and the ability to change the output quickly. I investigate taking such propensities to cartelise further in the next chapter.

is negative and significant, which suggests that the existence of a leniency programme in neighbouring countries reduces the national PCM. Table 2.6 adds more control variables such as the single market programme, EU East enlargement, and new EU members. Adding these variables has only a slight effect on the significance and the magnitude of the EU leniency programmes, while national leniency continues to have a negative and significant effect on the PCM. This is surprising as the single market programme and the EU expansion represent major changes that had an impact on the European markets.

In column (4), I run the regression using the pre-2004 data only, to ensure that the first EU programme is not evaluated with a much later variable, namely new EU members in 2004. Results suggest that the first EU programme is associated with a decrease in price-cost margin by 15.2 percentage points. Having this significant effect suggests that the first EU programme has an effect indeed.[32]

In Table 2.7, I account for the importance of accounting for time lags in the leniency variables when analysing the efficiency of these programmes. I am interested in seeing whether the leniency programme effect is only temporary or whether it evolves over time. In column 1, I include the national leniency variable with no time lag. The impact of the programme is negative but not significant. Moving to columns 2 and 4, I include one and two time lags, respectively. I notice a significant and negative effect that evolves over time up to two years. This result suggests that it takes a while for firms to know and respond to the programme.[33]

Table 2.8 captures the institutional factors that control for the legal system. Since these institutional factors are time-invariant, I apply OLS estimation. As in previous regressions, national leniency has a negative and significant effect on price-cost margin. Column 1 suggests

---

[32] I investigate the efficiency of the first EU programme in 1996 further in two more ways: First, I run a pre-2002 data since the revision came in during 2002. Second, I include only EU states. The results remain significant with a slight change in the coefficients.

[33] Running the regression with the national leniency programme as well as the first and the second ones, including two-years lag, does not improve the results. The national leniency programme effect seems consistent with the previously obtained results with negative and significant impact. However, the first and the second results exhibit insignificant and coefficients with opposite signs.

that countries with the English legal system appear to have higher PCMs than other systems, all else equal. Column 2 introduces a variable which captures the interaction between national leniency and the legal origin in the country. National leniency has a negative effect, but its magnitude drops from -0.335 to -0.281. This drop in the magnitude suggests the legal origin plays an important role in determining the efficiency of the national leniency programmes. The interaction effect differs among countries with one legal system or another. Countries with the French legal system have less efficient leniency programmes compared to countries with the English legal system. The English legal system seems to have an interaction that makes the programme more efficient, as it interacts negatively with leniency, and so increases its magnitude. The interaction between English legal system and leniency programmes decreases PCM by 0.238. This result is in line with Buccurossi (2013) and La Porta et al. (2008), who report that countries with civil law (originating in Roman law) are associated with a heavier-handed regulation than in countries with common law (originating in English law) on markets and economic performance. This suggests that a country's legal institution creates an environment that affects the efficiency of leniency programmes. I can notice that the interaction term between the German legal origin and the leniency variable, as well as the interaction between the Scandinavian origin and the leniency variables are not significant.

Column (3) introduces more control variables such as the single market programme, EU 2004 East enlargement, and new EU members. The national leniency effect stays negative and significant. After the EU East enlargement, the PCM has decreased, on average, by 0.312 percentage points. This is because the size of the European market has increased, and hence it became more competitive. Unsurprisingly, the countries, which entered the European market, were affected more compared to the former members. The legal origin variables stay consistent with the results obtained in column 2. National leniency programmes seem to be more efficient in countries with the English legal system.

Column 4 adds two more variables; the first EU leniency programme in 1996 and its major revision in 2002.[34] The estimate shows consistent results with column 1 and 2; the national leniency programme stays significant with a negative effect on the PCM. The first and second EU leniency programmes, however, show conflicting coefficients. Since the results are insignificant, I cannot conclude that the EU programme was effective even though the national programmes were.

Overall, the national leniency variables seem to have a negative effect on the PCM, which suggests that these programmes are effective (given my hypothesis). This is robust given different control variables. The first and second European programmes' results are not conclusive, so I cannot say anything about them so far.[35] A more precise estimation for the European leniency programmes will be presented in the next section.

2.6 Fixed Effect estimation based on a subsample of countries

To further attempt to avoid endogeneity, I construct a subsample of the data in which leniency programmes are exogenous. In other words, I include countries that did not adopt a national leniency programme before the imposition of the EU leniency programmes in 1996 and 2002. In this case, leniency programme variables are exogenous, as the policy was imposed by the European Commission rather than the national competition authority. In this subsample, eight countries are considered; Austria, Belgium, Denmark, Finland, Germany, Italy, Luxembourg, and Portugal. Unbalanced panel data is constructed at the industry-country level. Results in Table 2.9 show the fixed effect estimation of the model using this subsample. The first column examines the effect of the first European leniency programme in 1996. Here, I could not capture

[34] I added one lag of first and second EU leniency programmes for the same reason as the national leniency programmes.

[35] I also look at the total effect and their effect in the first years after implementation, i.e., until 2004. In other words, I look into countries that had both the first and the second EU programmes until 2004. However, results show inconsistency.

a significant and negative impact of leniency programme on the PCM. The second column adds the European leniency programme major revision in 2002. A significant effect of the second European programme is not also captured in this case, either. The third column combines both the first and the second programmes. This does not significantly affect the results. The control variables seem to be consistent with the previous analysis. The single market programme affects the price-cost margin negatively. The effect of the first and the second EU leniency programmes is still ambiguous, which suggests that further investigation may be warranted.

2.7 Conclusion

In this chapter, I have evaluated empirically the effectiveness of leniency programmes in destabilising and deterring cartels. This efficiency is measured by the impact of these programmes on the price-cost margin. A successful leniency programme should ultimately deter (*ex-ante* or *ex-post*) competition harming behaviour and hence increase industry's competition intensity, and, in effect, decrease the price-cost margin. In this chapter, I adopted different estimation methods, starting from pooled OLS, and to a fixed-effects approach. OLS and fixed effect results suggest that national leniency programmes are likely to curb the exercise of market power (captured by the market price cost margin). However, I could not be conclusive about the efficiency of European leniency programmes. I looked closer at the European leniency programmes by choosing a subsample of countries in which the European leniency programmes were imposed on them before they adopted their national leniency programmes. The results suggest conflicting and insignificant results regarding their effectiveness in reducing the PCM. Obtaining conflicting results might be attributed to two reasons. Firstly, it could be the case that the EU leniency programmes capture failed cartels only, but that begs the question of why this would happen more for EU programmes than for national programmes. Another possibility is that the EU leniency programmes target cross-border cartels. When applying for leniency, a cross-border cartel member should report to the EC as well as all the national authorities that could potentially sue. Thus, the national leniency variable may capture both the impact of the EU and the national leniency programmes. For example, according to the EC, there is not any cartel case that has been transferred from the national authority to the EU since the introduction of the second EU programme until 2005, while, on the other hand, there are six cases that were transferred from the EU to the national authorities.

Secondly, the methods employed in this chapter might be wrong. This is because the key to obtain a causal inference of the impact of leniency programme on competition intensity is to control for unobserved confounding factors. An issue that is associated with the fixed effect strategy is that my regressor of interest, leniency programme policy, varies at an aggregate level, whereas my panel provides repeated observations at the industry-country level. For instance, leniency programmes may change over time but are fixed across industries within countries. However, this is not necessarily accurate as the impact of the leniency policy depends heavily on the industry structure. That is, not all industries are expected to benefit from the leniency policy at first place. Therefore, in the next chapter, I propose a difference-in-differences identification strategy to obtain a more secure evaluation of the contribution of the changes in both the EU and the national leniency system to competition. I look more deeply at the structure of the industries that I have in the sample. I divide the industries according to their “likeliness to form cartels”. I expect that industries which are “likely to form cartels” should exhibit an effect when leniency policy changes, whereas those that are not should evidence no difference. I study this using a difference-in-differences framework, obtaining contrasting results to some of this chapter’s findings.

2.8 Appendix

Table 2. 1: Leniency Implementation in OECD

Country	National Leniency	Affected by 1st EU Leniency Programme	Affected by 2nd EU Leniency Programme
Australia	2003		
Austria	2006	X	X
Belgium	2007	X	X
Canada	2000		
Chile	2009		
Czech Republic	2001		2004
Denmark	2007	X	X
Finland	2004	X	X
Estonia	2010		2004
France	2001	X	X
Germany	2006	X	X
Greece	2006	X	X
Hungary	2003		2004
Iceland	2005		
Ireland	2001	X	X
Italy	2007	X	X
Japan	2006		
Korea	2002		
Luxembourg	2004	X	X
Mexico	2006		
Netherlands	2002	X	X
New Zealand	2000		
Norway	2004		
Poland	2004		2004
Portugal	2006	X	X
Slovak Republic	2001		2004
Slovenia	2010		2004
Spain	2008	X	X
Sweden	2002	X	X
Switzerland	2003		
Turkey	2009		
United Kingdom	1998	X	X
United States	1993		

The Czech Republic, Hungary, Poland and the Slovak Republic joined the EU in 2004. Therefore, the EU leniency revision is only considered to be in place since 2004. The definition when a leniency program is effectively in place orients on the first reform implementing an ECN equivalent leniency programme.

Table 2. 2: Countries and Observations

Country	Frequency	Percent	Cumulative
Austria	375	6.87	6.87
Belgium	288	5.27	12.14
Canada	182	3.33	15.48
Czech Republic	127	2.33	17.8
Denmark	317	5.81	23.61
Finland	326	5.97	29.58
France	217	3.97	33.55
Germany	369	6.76	40.31
Greece	206	3.77	44.08
Hungary	137	2.51	46.59
Ireland	214	3.92	50.51
Italy	278	5.09	55.6
Korea	7	0.13	55.73
Luxembourg	216	3.96	59.69
Netherlands	372	6.81	66.5
New Zealand	68	1.25	67.75
Norway	324	5.93	73.68
Poland	127	2.33	76.01
Portugal	108	1.98	77.99
Spain	264	4.84	82.82
Sweden	279	5.11	87.93
United Kingdom	352	6.45	94.38
United States	307	5.62	100
Total	5,460	100	

Table 2. 3: Industries and Observations

Industry	Frequency	Percent	Cumulative
Fishing, fish hatcheries, fish farms and related services	237	4.34	4.34
Other mining and quarrying	89	1.63	5.97
Food products and beverages	195	3.57	9.54
Tobacco products	192	3.52	13.06
Wearing apparel	206	3.77	16.83
Leather, leather products and footwear	231	4.23	21.06
Wood and products of wood and cork	301	5.51	26.58
Printing and publishing	286	5.24	31.81
Coke, refined petroleum products and nuclear fuel	240	4.4	36.21
Chemicals and chemical products	274	5.02	41.23
Rubber and plastic products	291	5.33	46.56
Other non-metallic mineral products	284	5.2	51.76
Fabricated metal products, except machinery and equipment	267	4.89	56.65
Machinery and equipment	300	5.49	62.14
Electrical machinery and apparatus, n.e.c.	251	4.6	66.74
Radio, television and communication equipment	257	4.71	71.45
Medical, precision and optical instruments	247	4.52	75.97
Other transport equipment	261	4.78	80.75
Manufacturing n.e.c.	181	3.32	84.07
Electricity, gas, steam and hot water supply	182	3.33	87.4
Research and development	168	3.08	90.48
Other business activities	201	3.68	94.16
Public admin. and defence - compulsory social security	319	5.84	100
Total	5,460	100	

Table 2. 4: Variables Preliminary Statistics

Variable	Description	Source	Obs	Mean	Std. Dev.
PCM	Value Added/(Labour Cost+Capital Cost)	Analysis of OECD STAN	5,450	0.170456	0.277432
National Leniency	Dummy (0,1)	National Antitrust Authority	5,460	0.271429	0.444737
1st EU Leniency Programme	Dummy (0,1)	European Commission	5,460	0.566484	0.495606
2nd EU Leniency Programme	Dummy (0,1)	European Commission	5,460	0.211172	0.408178
Leniency in Neighbour Countries	Dummy (0,1)	National Antitrust Authority	5,460	0.070513	0.256033
GDP Growth		OECD Reference Series	5,153	2.915669	2.018767
Import Penetration	Imports/Value Added	Analysis of OECD STAN	4,716	3.599158	27.08058
English Legal System	Dummy (0,1)	La Porta et al.	5,460	0.247253	0.431454
German Legal System	Dummy (0,1)	La Porta et al.	5,460	0.398352	0.489603
Scandinavian Legal System	Dummy (0,1)	La Porta et al.	5,460	0.118865	0.323659
French Legal System	Dummy (0,1)	La Porta et al.	5,460	0.235531	0.424369
Single Market Programme	Dummy (0,1)	European Commission	5,460	0.44011	0.496446
New EU Member	Dummy (0,1)	European Commission	5,460	0.035531	0.185135
EU East Enlargement 2004	Dummy (0,1)	European Commission	5,460	0.780952	0.413639

Table 2. 5: Leniency Programmes Basic Estimations

	(1) ln(PCM) Pooled OLS	(2) ln(PCM) Fixed Effects	(3) ln(PCM) Fixed Effects	(4) ln(PCM) Fixed Effects
National Leniency (1 lag)	-0.168**	-0.169***	-0.142**	-0.135**
	(0.0748)	(0.0625)	(0.0652)	(0.0657)
1st EU Leniency (1 lag)			-0.182*	-0.174*
			(0.0970)	(0.0962)
2nd EU Leniency (1 lag)			0.181	0.197
			(0.130)	(0.129)
Leniency N. Country (1 lag)				-0.130**
				(0.0604)
GDP Growth (in logs,1 lag)	0.0163	0.0159	0.0193	0.0215
	(0.0295)	(0.0237)	(0.0235)	(0.0234)
Import penetration (in logs, 1 lag)	-0.132***	-0.121*	-0.122*	-0.122*
	(0.0268)	(0.0713)	(0.0707)	(0.0709)
Constant	-4.985***	-3.123***	-3.121***	-3.121***
	(0.175)	(0.0578)	(0.0577)	(0.0578)
Observations	4,150	4,150	4,150	4,150
R-squared	0.447	0.202	0.204	0.205
Industry dummies	x			
Country dummies	x			
Industry-country dummies		x	x	x
Year dummies	x	x	x	x
Number of pid		344	344	344

Robust standard errors in brackets, column 1's clustered in year-country dimension
*Significant at *** p<0.01, ** p<0.05, * p<0.1.*

Table 2. 6: Leniency and Competition Affecting Programmes

	(1) ln(PCM) Fixed Effects	(2) ln(PCM) Fixed Effects	(3) ln(PCM) Fixed Effects	(4) ln(PCM) Fixed Effects
National Leniency (1 lag)	-0.135**	-0.133**	-0.135**	-0.122*
	(0.0657)	(0.0654)	(0.0668)	(0.0735)
1st EU Leniency (1 lag)	-0.174*	-0.163*	-0.134	-0.152*
	(0.0962)	(0.0957)	(0.0944)	(0.0867)
2nd EU Leniency (1 lag)	0.197	0.198	0.103	0.131
	(0.129)	(0.129)	(0.125)	(0.119)
Leniency N. Country (1 lag)	-0.130**	-0.130**	-0.136**	-0.101
	(0.0604)	(0.0602)	(0.0600)	(0.0575)
Single Market Programme (1 lag)		-0.0588	-0.0648	-0.0665
		(0.0965)	(0.0969)	(0.0939)
EU 2004 enlargement (1 lag)			-0.263*	
			(0.149)	
New EU member in 2004 (1 lag)			-0.163	
			(0.155)	
GDP Growth (in logs,1 lag)	0.0215	0.0229	0.0238	0.0424*
	(0.0234)	(0.0233)	(0.0233)	(0.0230)
Import penetration (in logs, 1 lag)	-0.122*	-0.122*	-0.119*	-0.165*
	(0.0709)	(0.0710)	(0.0700)	(0.0960)
Constant	-3.121***	-3.117***	-2.979***	-3.152***
	(0.0578)	(0.0581)	(0.134)	(0.0631)
Industry-country dummies	x	x	x	x
Year dummies	x	x	x	x
Observations	4,150	4,150	4,150	3,502
R-squared	0.205	0.205	0.207	0.207
Number of pid	344	344	344	334

Robust standard errors in brackets.
*Significant at *** p<0.01, ** p<0.05, * p<0.1.*

Table 2. 7: Leniency and Timing

	(1) ln(PCM) Fixed Effects	(2) ln(PCM) Fixed Effects	(3) ln(PCM) Fixed Effects	(4) ln(PCM) Fixed Effects	(5) ln(PCM) Fixed Effects	(6) ln(PCM) Fixed Effects
National Leniency	-0.0604					
	(0.0661)					
National Leniency (1 lag)		-0.135**				
		(0.0668)				
National Leniency (2 lags)			-0.227***			
			(0.0686)			
National Leniency (3 lags)				-0.0912		
				(0.0673)		
National Leniency (4 lags)					-0.111	
					(0.0682)	
National Leniency (5 lags)						-0.122*
						(0.0685)
1st EU Leniency (1 lag)	-0.130	-0.134	-0.140	-0.140	-0.0889	-0.106
	(0.0939)	(0.0944)	(0.0949)	(0.110)	(0.111)	(0.115)
2nd EU Leniency (1 lag)	0.140	0.103	0.141	0.162	0.140	0.125
	(0.123)	(0.125)	(0.120)	(0.130)	(0.130)	(0.133)
Leniency N. Country (1 lag)	-0.150**	-0.136**	-0.114*	-0.0487	-0.0279	2.96e-05
	(0.0587)	(0.0600)	(0.0599)	(0.0624)	(0.0667)	(0.0720)
Single Market Programme (1 lag)	-0.0684	-0.0648	-0.0607	-0.105	-0.0921	-0.133
	(0.0968)	(0.0969)	(0.0972)	(0.112)	(0.113)	(0.120)
EU 2004 enlargement (1 lag)	-0.287*	-0.263*	-0.199	-0.288*	-0.288*	-0.291*
	(0.148)	(0.149)	(0.144)	(0.153)	(0.156)	(0.163)
New EU member in 2004 (1 lag)	-0.108	-0.163	-0.193	-0.146	-0.206	-0.247
	(0.151)	(0.155)	(0.155)	(0.175)	(0.185)	(0.201)
GDP Growth (in logs,1 lag)	0.0263	0.0238	0.0335	0.0302	0.0166	0.0125
	(0.0230)	(0.0233)	(0.0225)	(0.0267)	(0.0262)	(0.0267)
Import penetration (in logs, 1 lag)	-0.117*	-0.119*	-0.121*	-0.151**	-0.144*	-0.230***
	(0.0689)	(0.0700)	(0.0708)	(0.0749)	(0.0739)	(0.0768)
Constant	-3.017***	-2.979***	-2.961***	-2.987***	-2.915***	-2.904***
	(0.133)	(0.134)	(0.135)	(0.152)	(0.163)	(0.175)
Observations	4,150	4,150	4,150	3,410	3,169	2,935
R-squared	0.206	0.207	0.209	0.200	0.203	0.207
Number of pid	344	344	344	344	341	341
Industry-country dummies	x	x	x	x	x	x
Year dummies	x	x	x	x	x	x

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*

Table 2. 8: Leniency Programmes and the Legal System

	(1) ln(PCM) Pooled OLS	(2) ln(PCM) Pooled OLS	(3) ln(PCM) Pooled OLS	(4) ln(PCM) Pooled OLS
National Leniency (1 lag)	-0.335***	-0.281***	-0.261***	-0.255***
	(0.0876)	(0.0907)	(0.0935)	(0.0948)
English Legal System	0.380***	0.533***	0.520***	0.517***
	(0.144)	(0.147)	(0.148)	(0.148)
German Legal System	-0.0536	-0.00875	-0.245	-0.219
	(0.141)	(0.142)	(0.230)	(0.232)
Scandinavian Legal System	0.212	0.257*	0.191	0.221
	(0.153)	(0.155)	(0.203)	(0.204)
Eng. Legal Sys. x Leniency		-0.238**	-0.231**	-0.229**
		(0.0977)	(0.0947)	(0.0937)
Ger. Legal Sys. x Leniency		-0.0495	-0.0583	-0.0551
		(0.0883)	(0.0860)	(0.0843)
Sca. Legal Sys. x Leniency		0.0422	0.0200	-0.0449
		(0.244)	(0.251)	(0.256)
1st EU Leniency (1 lag)				-0.171*
				(0.0937)
2nd EU Leniency (1 lag)				0.103
				(0.113)
Leniency N. Country (1 lag)				-0.0518
				(0.0766)
Single Market Programme (1 lag)			-0.0702	-0.0394
			(0.133)	(0.133)
EU 2004 enlargement (1 lag)			-0.312*	-0.250
			(0.185)	(0.184)
New EU member in 2004 (1 lag)			-0.198	-0.198
			(0.155)	(0.156)
GDP Growth (in logs,1 lag)	0.0309	0.0222	0.0251	0.0278
	(0.0283)	(0.0287)	(0.0286)	(0.0287)
Import Penetration (in logs, 1 lag)	-0.134***	-0.132***	-0.131***	-0.131***
	(0.0269)	(0.0269)	(0.0270)	(0.0269)
Constant	-4.965***	-5.017***	-4.778***	-4.775***
	(0.204)	(0.204)	(0.273)	(0.272)
Observations	4,150	4,150	4,150	4,150
R-squared	0.450	0.455	0.456	0.457
Industry dummies	x	x	x	x
Country dummies	x	x	x	x
Year dummies	x	x	x	x

Robust standard errors in parentheses. Standard errors are clustered in year-country dimension
*Significant at *** p<0.01, ** p<0.05, * p<0.*

Table 2. 9: Subsample of EU countries

	(1) ln(PCM) Fixed Effects	(2) ln(PCM) Fixed Effects	(3) ln(PCM) Fixed Effects
1st EU Leniency Programme (1 lag)	0.218		0.219
	(0.436)		(0.437)
2nd EU Leniency Programme (1 lag)		-0.343	-0.344
		(0.590)	(0.590)
Single Market Programme (1 lag)	-0.271*	-0.272*	-0.271*
	(0.139)	(0.139)	(0.139)
GDP Growth (in logs,1 lag)	0.103**	0.104**	0.104**
	(0.0404)	(0.0407)	(0.0407)
Import penetration (in logs, 1 lag)	-0.253**	-0.254**	-0.254**
	(0.120)	(0.120)	(0.120)
Constant	-3.450***	-3.451***	-3.451***
	(0.0823)	(0.0820)	(0.0821)
Industry-country dummies	x	x	x
Year dummies	x	x	x
Observations	1,950	1,950	1,950
R-squared	0.235	0.235	0.235
Number of pid	170	170	170

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*

Table 2. 10: Leniency Programmes Basic Estimation for the Period 1990-2009

	(1) ln(PCM) Pooled OLS	(2) ln(PCM) Fixed Effects	(3) ln(PCM) Fixed Effects	(1) ln(PCM) Fixed Effects	(2) ln(PCM) Fixed Effects
National Leniency (1 lag)	-0.0810	-0.0856	-0.0690	-0.0672	-0.0784
	(0.0914)	(0.0558)	(0.0558)	(0.0556)	(0.0567)
1st EU Leniency (1 lag)			-0.0307	-0.0124	0.0359
			(0.0861)	(0.0857)	(0.0823)
2nd EU Leniency (1 lag)			0.148**	0.148**	0.00926
			(0.0578)	(0.0578)	(0.0628)
Single Market Programme (1 lag)				-0.129*	-0.135*
				(0.0749)	(0.0739)
EU 2004 enlargement (1 lag)					-0.115
					(0.110)
New EU member in 2004 (1 lag)					-0.401***
					(0.0843)
GDP Growth (in logs,1 lag)	0.00520	0.000112	-0.00238	0.000907	0.00146
	(0.0512)	(0.0149)	(0.0141)	(0.0139)	(0.0138)
Import penetration (in logs, 1 lag)	-0.0512***	-0.120***	-0.122***	-0.122***	-0.119***
	(0.0117)	(0.0370)	(0.0368)	(0.0369)	(0.0365)
Constant	-4.317***	-3.260***	-3.255***	-3.240***	-3.140***
	(0.140)	(0.0751)	(0.0739)	(0.0744)	(0.109)
Industry dummies	x				
Country dummies	x				
Industry-country dummies		x	x	x	x
Year dummies	x	x	x	x	x
Observations	7,046	7,046	7,046	7,046	7,046
R-squared	0.587	0.292	0.293	0.294	0.298
Number of id		589	589	589	589

Robust standard errors in parentheses. Column 1 is clustered in year-country dimension.
*Significant at *** p<0.01, ** p<0.05, * p<0.1.*

Chapter 3 The Efficiency of Leniency Programmes Based on Difference-in-Differences Estimation

Abstract

This chapter analyses the efficiency of both national and EU leniency programmes based on a difference-in-differences DD model by separating industries according to their likeliness to form cartels. DD results suggest that "likely" industries exhibit a drop in price-cost margins as compared to "unlikely" industries after the implementation of both the national leniency and the EU programmes. I further conduct a difference-in-difference-in-differences DDD model on EU countries, where industries are split according to their likeliness to form a cartel, as well as their likeliness to be cross-borders dealers. Results suggest that for "likely" industries that their relevant market extends to the EU, the EU leniency programmes exhibit an effect as captured by the drop in price-cost margins.

Keywords: Cartel, Leniency Programmes, Antitrust
JEL Classification: K21, K42, L4

3.1 Introduction

In the previous chapter, I analysed the efficiency of leniency programmes in detecting and destabilising cartels. I started by replicating the methodology proposed by Klein (2010) on new data drawn from the OECD for the period 1990 to 2007. Based on a panel analysis, I tracked the changes in price-cost margins when national and EU leniency programmes were introduced. The results showed a decrease in the industries' price-cost margin after the introduction of the national leniency programmes regardless of the estimation technique, control variables, and institutional settings. However, I could not conclude anything about EU programmes, as the coefficients were either insignificant or changed sign. Thus, in this chapter, I conduct a more precise estimate to investigate these results further.

As a way to investigate the efficiency of leniency programmes more thoroughly, I propose to estimate the relationship between leniency and price-cost margins using a difference-in-differences (DD) approach to construct a counterfactual of what would have occurred without the leniency programme. Not all industries are likely to form cartels: theory shows us that there are characteristics of industries that can predispose them to collusive behaviour. Hence, the existence or lack of a leniency programme should be largely irrelevant for some industries but not for others. It is not entirely clear how to divide up industries into "likely" and "unlikely" groups. One guess at the conditions that are likely to result in cartel formation could be that moderately tight oligopolies are more prone to cartel behaviour as they would include few enough participants that coordination would be possible but enough that a large profit gain from colluding still exists. As a result, one might use HHI to separate out industry groups. On the other hand, industries that have a very large number of participants might stand to gain a great deal from cartelisation even though they might face steep problems coordinating activities enough to achieve success. This might argue against using HHI as the criterion for separation. This type of ambiguity in measures of likeliness to form cartels suggests that I attempt several possible "indicators" of propensity to form a cartel. Similarly, some industries are susceptible to cross-borders cartels, and thus they are likely candidates to be affected by EU-wide laws.

If I can make such a division of the data, I can investigate the effectiveness of leniency laws using a difference-in-differences approach, as it allows me to separate out treated and control groups more carefully, whilst allowing the comparison of the two groups to help to control for various confounding factors that I may have not adequately controlled for in the previous chapter's methodology. This might give me an idea of whether leniency is at the root of changes in the price-cost margin changes or whether something else is occurring during the time period for which I am not adequately controlling. In my exercise for this chapter, industries that are susceptible to cartelisation form the "treatment group", and I will look at the change in behaviour with and without leniency programmes here. This group should exhibit changes when leniency is introduced if the programmes are effective. This effect is compared against industries where there should be no cartels in any case so that leniency is unlikely to make any difference. This latter group is the "control group", where there should be no effect of the leniency, as no cartels will arise. Hence, the treatment and control groups should exhibit different PCM changes, as only one of the groups should be affected by leniency programmes. The first challenge in this exercise is to apply criteria that adequately separate out treatment and control groups. The second challenge is to conduct the estimation and to analyse the results. Again, the point here is to take a closer look at the effect of leniency, separating out its effects from other effects that might influence price-cost margins.

The analysis takes two different steps. First, I estimate a difference-in-differences DD model to analyse the impact of the national leniency programme, separating industries between "likely" and "unlikely" candidate groups. I then estimate a difference-in-differences DD model on EU countries, also by separating industries according to their likeliness to form a cartel. Second, I estimate a difference-in-difference-in-differences model DDD on EU countries, where

I split industries according to their likeliness to form a cartel, as well as by their relevant market: EU or national markets. That is, for "likely" industries that their relevant market extends to the EU, I expect that the EU leniency programmes to exhibit an effect.

In comparison to Chapter 2, I find a significant effect of both the national and the EU leniency programmes. However, my results are sensitive to how I divide the industries into "likely" and "unlikely" candidates.

The rest of the chapter is structured as follows. In section 2, I outline the details of how industries are classified according to the likeliness to form a cartel and according to their relevant market. In section 3, I present the data. Section 4 presents the difference-in-differences general settings. Section 5 explains the empirical strategy. In section 6, I present a graphical evidence of the parallel trend. Section 7 discusses the results, and section 8 concludes.

3.2 Industries' Classification

My analysis in Chapter 2 does not reveal compelling results, as it dilutes the estimate of the effectiveness of the leniency programmes in two ways. First, it combines "likely" and "unlikely" colluders – those unlikely to collude have nothing to fear, so the programme should not affect them. This group is, however, included in the earlier estimates. Second, not all firms may be subject to the EU leniency. Therefore, in this chapter, I look into that by conducting a difference-in-difference approach to compare the effect where it should be occurring against those areas where it should not.

The main challenge is to divide the industries into *treatment* and *control* groups. Given that the natural experiments are changes in the EU and/or national leniency programmes, I suggest classifying industries into four categories, based on two criteria. The first criterion is whether an industry is susceptible to cartel formation. I determine that by identifying the industry characteristics that are linked with a greater ability/incentive to collude. The second criterion suggests dividing the industries according to their relevant market, i.e., whether it is national or whether it extends at least to a significant part of the EU. Given that the accuracy of results will depend on the accuracy of how well I can separate out the "likelies" and "unlikelies", I provide different methods, recognising that some (like HHI) are inherently ambiguous.

3.2.1 According to their "likeliness" to form a cartel

Theoretical IO literature predicts different factors that facilitate the collusive agreement. Ivaldi et al. (2007) group these factors into three categories: (i) the structural characteristics in a market (such as the number of competitors, entry barriers, the frequency of interaction, and transparency). (ii) the demand-side characteristics that concern market growth and the business cycles. (iii) the supply side characteristics (such as, whether firms are asymmetric in terms of costs and production capacities, as well as whether firms offer homogenous or differentiated products).

In more detail, firms are more likely to collude if the number of firms in the market is small. That is, with a high number of firms in the market, the same number of colluding firms receive a smaller share of the pie. Moreover, the deviation from the collusive agreement is harder to monitor as the number of firms increase in the market. The theory also predicts that cartel formation higher when entry barriers are high, which will tend to be associated with tight oligopolies.

Additionally, collusion is more likely to be sustained if there is a growth in the market demand because the current gains from deviating from the collusive agreement are lower than the future gains (Rotemberg and Saloner, 1986; Haltinger and Harrington, 1991). Collusion is easier to sustain if there is a frequent interaction between the colluding firms because it reduces the time to react and punish the deviator. Another theoretical prediction in determining collusion sustainability is suggested by Stigler (1964), Green and Porter (1984) and Arbeu et al. (1986). They argue that market transparency facilitates collusion. That is if a firm cannot observe and monitor rival's prices and sales and at the same time the market demand fluctuates randomly over time, a firm that exhibits low sales in a period of time cannot determine whether this is due to market conditions or a secret undercutting by the rivals.

In the light of the previous literature, then, I follow four approaches to divide the industries into “likely” and “unlikely” according to their likeliness to cartelisation:

1. The number of cartel convictions in an industry

Lacking a strong guide on easily available data to use to divide up groups, I use what has been actually observed in cartel behaviour. Hence, I use the number of cartel convictions as an indicator of whether the industry is or is not susceptible to cartelisation. Accordingly, I eyeball industry as a “likely” candidate if there has been a cartel discovered in the USA. Using cartel convictions in the USA rather than in Europe avoids the possibility of endogeneity of cartel convictions.

2. The “payroll effect”

Even though the theoretical literature in collusion did not discuss the employment issues as factors to hinder or facilitate the sustainability of the collusive agreement, empirical work shows that collusion is more likely to be sustained in markets where the pay per employee is relatively high. Grout and Sonderegger (2005) find empirically that employee costs per worker increase the likelihood of discovering cartels rather than not. The idea here is that, in industries where the employment costs per employee are high, the staff is paid well, which in turn reflects that the employees are privy to some form of “better knowledge” that generates higher rents for them as workers. To divide the industries into “likely” and “unlikely” based on wages, these steps are followed: I calculate first the mean for each industry separately, and then I calculate the mean for all the industries in the sample together. After that, I compare between the two calculated means. Based on this comparison, I label an industry as a “likely” candidate if the average wage in that industry is higher than the average wage in all industries.

3. R&D Activity

R&D is often employed in the literature as a measure of product differentiation, entry barriers, or cost asymmetry (Grout and Sonderegger, 2005). IO theory suggests that cartels are more likely where products are homogenous, as pointed out by Ivaldi et al. (2007). Raith (1996) studies a model where firms sell horizontally differentiated products and cannot monitor the behaviour of the rival firms, whereas they can use their own demand to make an inference on the other firm's behaviour. He concludes that it is harder to sustain collusion when firms sell differentiated products. In line with this, Symeonidis (2002a) considers a model where firms sell multiple products in a horizontally differentiated market setting. He finds that the cartel becomes less stable as the number of varieties sold by each firm increases because the gains from deviating from the collusive agreement become larger than if the firm sticks to the collusive agreement. Moreover, these theoretical predictions are supported by the fact that previous cartel convictions were captured in industries with limited degree of product differentiation. Grout and Sonderegger (2005) point to a list of industries where products are fairly homogenous and previous cartel cases took place. These are shipping industries, basic chemicals industries, currency exchange in the Eurozone, French Beef, Plasterboard, Steel Tubes, Carbonless Paper and Petrochemicals. Hence, if R&D is associated with differentiation and differentiation is associated with lower cartel stability, R&D activity can be used as a measure of propensity to collude.

When the costs are asymmetric and the quality of products differs significantly from one firm to another, collusive agreements may be harder to sustain (Hackner, 1994). When the market is asymmetric, low-cost (or high-quality) firms are harder to discipline, in comparison to the high-cost (or low-quality) ones. That is, even if the high-cost firm initiates a price war, the damage that it could impose on its low-cost rival is negligible. Indeed, it may not be plausible for a high-cost firm to affect its rival's demand as that would require imposing a price that is well below its rival's price. Again, if R&D activity is associated with asymmetric costs and that such costs are associated with difficulty in sustaining a cartel, it can be thought of as a good way to divide up industries for my purposes.

Lastly, as the low entry barriers attract competitors to enter the market, the future gains from collusion become lower and the punishment of deviating from the collusive behaviour becomes less costly. Again, the correlation between R&D and entry barriers opens the door to using it as a way to measure propensity to collude.

As discussed above, high R&D expenditures imply a high level of product differentiation, high barriers to entry, or cost asymmetry in industry. High product differentiation and cost asymmetry in the market hinder collusion; however, high barriers to entry facilitate collusion. This creates ambiguity in using R&D in classifying the "likely" and "unlikely" candidates. However, given that I analyse an industry-level data, it would not be plausible to detect cost asymmetry and product differentiation in an industry, as that would require firm-level data to detect different R&D spending. Nevertheless, I could potentially use industry-level R&D expenditures as a measure of an industry's barrier to entry. Accordingly, I follow the same steps applied above for the payroll effects. That is, if the industry's average R&D expenditures are above the average R&D expenditures in all industries, I label the industry as a "likely" candidate.

4. The HHI index

I split the sample between industries that have a high average HHI over the whole sample and those that have a low average HHI. In other words, I break out major industry groups for the entire sample in this manner rather than for a specific time period or country. Accordingly, I label an industry as "likely" if the HHI is greater than a threshold of the average HHI over the whole period and countries.

As regards the law, it does not really look into antitrust issues unless the HHI is high enough, but this is an ambiguous measure: what I would like as a method of detecting "likely" firms is a factor that makes it pay very little not to collude and pay a lot to collude. The problem with HHI is that, as concentration increases, the payoff to not colluding will tend to increase as well. This means that the payoff to *not* colluding improves, making it less likely to collude. On the other hand, having few players to participate may improve the practical side of how coordination will work. I include the HHI, but I am not sure which of these factors will dominate. If the factor that pays more to not collude dominates at the end, my classification according to HHI is not valid. That is high HHI here reflects "unlikely" rather than "likely" industries.

These factors may occur in groups. According to the data between 1990 and 2007, the correlation between USA cartel convictions and wages is positive at 0.03 (see Table 3.3). There is a small positive correlation between USA cartel convictions and R&D at 0.0057. The correlation between wages and R&D is positive 0.26. On the other hand, HHI appears to correlate negatively with USA cartel convictions, wages and R&D at - 0.47, -0.22, and -0.08 respectively. This may hint at the possibility of obtaining adverse effects according to the classification of the industries considered. Table 3.17 shows the division of industries into "likely" and "unlikely" on the following criteria used: USA convictions, wages, R&D, and the HHI index.

3.2.2 National or EU market

I classify industries into national or EU market by checking whether the relevant market for an industry is typically national or it extends at least to a significant part of the EU. Formally, I identify this by looking into the proportion of exports outside the national market. Exports data is given in US dollars. Therefore, I convert this to national currency to be able to divide it by total production, which is given by national currency. Both exports and production are given at the industry-level. First, I sum the total exports by each industry, and then I sum the output by industry. Then, I divide total exports by total output. If an industry's average is below the average of all industries, then this industry is considered as a local market. Alternatively, I assume it extends to a significant part of the EU and classifies it as an EU market.

3.3 Data

In this section, I introduce the variables used in diagnosing whether collusion is likely or not in each industry. Also, I describe briefly the other variables included in the analysis.

HHI Herfindahl index: data is obtained from a research conducted by Hoberg and Phillips (2010). The data is based on SIC codes while my original database is based on the NACE classification. The SIC classification of this data is more detailed, so I match each industry to the industry to which it would belong in the NACE classification. I then obtain the mean of all of the SIC industries that I had placed in each NACE classification level to get an estimation of the HHI for the corresponding NACE industry. This data varies across years but not across countries.

R&D Expenditures: The OECD's Analytical Business Expenditure on Research and Development (ANBERD) database yielded real R&D expenditures in national currencies, for industry-country pairs using the NACE classification that I discussed above. The variable is given in nominal values. I further construct a measure of R&D intensity, by dividing R&D expenditures from the ANBERD, as described above, by the nominal value-added in industry *i*, country *j* and year *t.* Information on value-added is obtained from the OECD Structural Analysis Database (STAN).

Exports: The STAN Bilateral Trade database provides data on exports revenue by Industry and End-use. This variable is given in US Dollars.

Cartel convictions in the US: I obtain this information from Grout and Sonderegger (2005). They provide the total number of cartels convicted by the US Department of Justice per industry, between 1994 and 2005. As the data is only available until 2005, I only use these industries as proxies for all the industries that are susceptible to cartelisation. Having no data from 2006 is less of a concern, as I am not using cartels convictions as a time-varying measure, but rather to construct an overall idea of whether an industry is prone to cartelisation, given its history.

Production: This is a yearly variable that is given as the nominal gross output per industry within a country, and it is obtained from OECD STAN. The data is given in units of national currency.

Wages and Salaries: The OECD Structural Analysis Database (STAN) provides information on wages and salaries per industry for each year in units of national currency. Wages and salaries are given at nominal prices.

Following the previous chapter, I use competition intensity (measured by the PCM) as the dependent variable. PCM is a yearly variable that is given at the industry-country level. I include national leniency and both the first and the second EU leniency programmes as the main explanatory variables. I control for GDP growth, import penetration single market programme and EU East enlargement. Table 3.2 reports the preliminary statistics for the main variables discussed above, covering the period 1990 to 2007. Table 3.1 provides information on the industries used in the estimate in this chapter. I have included few more industries to the ones of Chapter 2.

3.4 Difference-in-Differences General Settings

This chapter analyses the effect of leniency programmes implementation on industry's PCM. The maintained hypothesis is that a successful leniency policy would bring down the price-cost margin.

DD is a type of fixed effects estimation, where only one outcome is observed over the other. I can write this formally as:

$PCM_{1,i,j,t}$: PCM in industry i, country j, time t with a leniency policy in place.

$PCM_{0,i,j,t}$: PCM in industry i, country j, time t without a leniency policy in place.

Then one could assume that:

$$E[PCM_{0,i,j,t}|\ i,t] = \gamma_i + \lambda_t \quad (1)$$

In the absence of leniency programmes, PCM is determined by the sum of a time-invariant industry effect γ_i and a year effect λ_t that is common to all industries.

Let $D_{i,t}$ be a dummy that represents the treatment group where industries are susceptible to cartel behaviour and periods.

Then, assuming that the treatment effect of the leniency policy is:

$$E[PCM_{1,i,j,t} - PCM_{0,i,j,t}|i,t] = \delta \quad (2)$$

The observed PCM could be written as:

$$PCM_{i,j,t} = \gamma_i + \lambda_t + \delta D_{i,t} + \epsilon_{i,j,t} \quad (3)$$

Thus, the PCM in the "likely" industries before implementing the policy is given by:

$$E[PCM_{i,j,t}|i = likely, t = before\ LP] = \gamma_{likely} + \lambda_{before\ LP} \quad (4)$$

Whereas the PCM in the "likely" industries after implementing the policy is given by:

$$E[PCM_{i,j,t}|i = likely, t = after\ LP] = \gamma_{likely} + \lambda_{after\ LP} + \delta \quad (5)$$

Thus, the difference in PCM before and after implementing the leniency policy in "likely" industries is given by:

$$E[PCM_{i,j,t}|i = likely, t = after\ LP] - E[PCM_{i,j,t}|i = likely, t = before\ LP]$$
$$= \gamma_{after} - \gamma_{before} + \delta \quad (6)$$

Now I move to the control group, namely "unlikely" industries. The PCM before implementing the leniency programme is given by:

$$E[PCM_{i,j,t}|i = unlikely, t = before\ LP] = \gamma_{unlikely} + \lambda_{before\ LP} \quad (7)$$

whereas the PCM in "unlikely" industries after the leniency policy is:

$$E[PCM_{i,j,t}|i = unlikely, t = after\ LP] = \gamma_{unlikely} + \lambda_{after\ LP} \quad (8)$$

Thus, the difference in PCM in "unlikely" industries, before and after implementing the leniency policy is:

$$E[PCM_{i,j,t}|i = unlikely, t = after\ LP] - E[PCM_{i,j,t}|i = unlikely, t = before\ LP]$$
$$= \lambda_{after\ LP} - \lambda_{before\ LP} \quad (9)$$

The difference-in-difference strategy amounts to comparing the change in PCM in “likely” industries to the change in PCM in “unlikely” industries. And thus, the population difference-in-differences are given by:

$$E[PCM_{i,j,t}|i = likely, t = after\ LP] - E[PCM_{i,j,t}|i = likely, t = before\ LP] - E[PCM_{i,j,t}|i = unlikely, t = after\ LP]$$
$$- E[PCM_{i,j,t}|i = unlikely, t = before\ LP]$$
$$= \delta \qquad (10)$$

3.5 Empirical Strategy

The difference-in-differences and the difference-in-difference-in-differences could be estimated in a regression framework. In this section, I outline the equations employed in the empirical work.

3.5.1 Difference-in-Differences (DD)

My initial empirical identification strategy is to use the difference-in-differences (DD) analysis to identify the effect of both national and supranational leniency programmes on industries’ competitive outcomes, as measured by the price-cost margin. The success of the leniency programme is measured by a drop in the price-cost margin, as it captures both deterrence and destabilisation effects as described in the previous chapter. I classify industries as either “treatment” or “control” based on whether the industry is susceptible to cartels or not. Thus, I will also call these “likely” and “unlikely” industries according to whether they are classified as the treatment or control group. The DD specification compares the price-cost margin in “likely” industries to “unlikely” industries before and after the introduction of the leniency programme. If I detect a larger (negative) change for the likely industries than for the unlikely industries and this is statistically significant, then I will conclude that I have found proof of the effectiveness of leniency. The validity of this technique depends on whether I identify likely and unlikely industries correctly, as discussed above. In section 3.1.1 below, I present my general approach to the analysis of national leniency programmes, which includes the first dimension (likely or unlikely colluders) of my difference-in-differences analysis. In section 3.1.2 I specify the equations that I will run for the EU programmes, again isolating the first difference-in-difference dimension. In section 3.2 I explain how I combine these together to add the second dimension of the difference-in-difference analysis (likely or unlikely to benefit from EU leniency) that I envisage.

2.5.1.1 National Leniency Programmes

To gauge the success of the national leniency programmes, I estimate a difference-in-differences model of the general form:

$$PCM_{i,j,t} = \beta_1 + \beta_2 Likely_i + \beta_3 Post_{j,t} + \delta\left(Likely_i \times Post_{j,t}\right) + \beta_4 X_{i,j,t-1} + \gamma_j + \lambda_t + \epsilon_{i,j,t} \quad (11)$$

where $PCM_{i,j,t}$ is the log value of the price-cost margin for industry i in country j and time-period t; $Likely_i$ is a (0,1) dummy variable that takes a value of one for industries which are susceptible to cartel behaviour; following my classification in Section 2; $Post_{j,t}$ is a (0,1) dummy that takes a value of one from the year that a country adopts the national leniency programme onward; δ is the DD coeffecient of interest of the interaction term $\left(Likely_i \times Post_{j,t}\right)$, which measures the incremental effect of being in the likely group and being treated. I also include a set of country- and industry-level control variables $X_{i,j,t-1}$, γ_j is a country fixed effect and is a year effect that is common across treatment and control groups. Including industry-country fixed effects allows me to control for unobserved, time invariant factors that affect performance at the industry-country level. The year fixed effect allows me to control for any other yearly changes that occurred and would be commonly felt. Together, these fixed and year effects isolate the impact of the change in the leniency programme, assuming that this was the main change in the year in which the programme was implemented. As the difference-in-differences technique focuses on the difference across two groups of firms that would have been subject to various other pieces of legislation or other changes that could have occurred in the same year as the national leniency programme was implemented, this technique allows for a firmer identification of the effect of leniency alone, as long as this programme was the only one of these changes to affect the "likely" and "unlikely" groups differentially. I cluster the standard errors by country-level to deal with concerns about serial correlation. This allows for correlation among industries within the same country.

The main assumption for the DD strategy is that the price-cost margins in both the "likely" and "unlikely" industries would follow the same time trend in the absence of the leniency policy. The leniency policy induces a deviation from this common trend. Although "likely" and "unlikely" industries can differ, this difference is captured by the industry-fixed effect, which is analogous to an unobserved individual effect.

If this assumption holds true, a negative estimated coefficient indicates that the leniency programme in place is successful, as it decreases the price-cost margin in the industry for which it should be effective; $\delta < 1$. In this way, I isolate the effect of the leniency policy from "background" changes in the price-cost margin that could be due to other factors, which may be present in industries where leniency should not be effective. Graph 1 shows the PCM time trends for the control and treatment industries. "Likely" and "unlikely" industries time trends appear to be parallel to each other when dividing the sample by cartel convictions, wages, and R&D, but not when considering the HHI. Equation (12) below is the method used to calculate the difference-in-differences measurement of the effect of leniency:

$$\delta = E\left[PCM_{i,j,t} \middle| \, likely, t \geq Post_{j,t}\right] - E\left[PCM_{i,j,t} \middle| \, likely, t < Post_{j,t}\right] - E\left[PCM_{i,j,t} \middle| likely, t \geq Post_{j,t}\right] - E\left[PCM_{i,j,t} \middle| \, likely, t < Post_{j,t}\right] \qquad (12)$$

Following Ashnefelter and Card (1985) and Besley and Burgess (2004), I include a time trend for "likely" industries, $(Likely_i \times t)$. In this case, the identification of the effects of leniency programmes comes from whether such policies' changes lead to deviations from pre-existing industry-specific trends in treated industries. Equation (11) is, then, transformed into equation (13), which can be used for the trend analysis:

$$PCM_{i,j,t} = \beta_1 + \beta_2 Likely_i + \beta_3 Post_{j,t} + \delta\left(Likely_i \times Post_{j,t}\right) + \varphi(Likely_i \times t) + \beta_4 X_{i,j,t-1} + \gamma_j + \lambda_t + \epsilon_{i,j,t} \quad (13)$$

Following Autor (2003), I analyse the pre-trend by including m leads for the interaction terms to analyse the assumption on the common trend. I include lags to analyse whether the treatment effect changes over time after the treatment. Equation (14) below is the final equation for our difference-in-differences estimate:

$$PCM_{i,j,t} = \beta_1 + \sum_{\tau_j=0}^{m} \delta_{-\tau_j}\left(Likely_i \times Post_{j,t-\tau_j}\right) + \sum_{\tau_j=1}^{q} \delta_{\tau_j}\left(Likely_i \times Post_{j,t+\tau_j}\right) + \beta_2 X_{j,t-1} + \gamma_j + \lambda_t + \epsilon_{i,j,t} \quad (14)$$

where τ_j refers to the year that a country has adopted the national leniency programme, the sums allow for m anticipatory effects $(\delta_{-1}, \delta_{-2}, \dots, \delta_{-m})$ and q post-treatment effects $(\delta_{+1}, \delta_{+2}, \dots, \delta_{+q})$ for country-specific national leniency programmes. I normalize the adoption year of a national leniency to zero, i.e. $\tau_j = 0$. If the leads are (all) close to zero, the results suggest that there are not any anticipatory effects.

2.5.2.2 EU Leniency Programmes

The basic DD approach for analysing the impact of the EU's 1996 leniency policy and its revision in 2002 is to regress $PCM_{i,j,t}$ for industry i in country j and time-period t on a dummy for cartel likely industries, $LIKELY_i$, a dummy for post-EU leniency policy in 1996 ($t \geq 1996$), $POST_{1996}$, a dummy for post EU leniency policy revision in 2002 ($t \geq 2002$), $POST_{2002}$, two interaction terms $LIKELY_i \times POST_{1996}$ and $LIKELY_i \times POST_{2002}$, a set of country-level control variables $X_{j,t-1}$, γ_j is a country fixed effect and λ_t is a year effect that is common across treatment and control groups. Including country fixed effects allows me to control for unobserved, time invariant factors that affect performance at the country level. As I do not control for national leniency programmes here, these fixed and time effects also capture the effect of national leniency in the same way as the EU programmes would have been captured in these fixed and time effects for the national programme equations. Here, I am interested in the incremental effect of the EU programme alone. I cluster the standard errors by country grouping to deal with concerns about serial correlation. Equation (15) is given by:

$$PCM_{i,j,t} = \beta_1 + \beta_2 LIKELY_i + \beta_3 POST_{1996} + \beta_4 POST_{2002} + \delta_1(Likely_i \times Post_{1996}) + \delta_2(Likely_i \times Post_{2002}) + \beta_5 X_{j,t-1} + \gamma_j + \lambda_t + \epsilon_{i,j,t} \qquad (15)$$

δ_1 and δ_2 are the DD estimates of interest that capture the interaction terms between the "likely" industries and the leniency policy in 1996 and the "likely" industries and the leniency policy in 2002, respectively. I expect the negative coefficients δ_1 and δ_2 to indicate the success of the EU leniency programmes.

The DD first EU leniency programme effects are, then, given by Equation (16a):

$$\delta_1 = E\left[PCM_{i,j,t}\middle| LIKELY, t \geq 1996\right] - E\left[PCM_{i,j,t}\middle| LIKELY, t < 1996\right] - E\left[PCM_{i,j,t}\middle| UNLIKELY, t \geq 1996\right] - E\left[PCM_{i,j,t}\middle| UNLIKELY, t < 1996\right] \qquad (16a)$$

The DD second EU leniency programme effects are given by Equation (16b):

$$\delta_2 = E\left[PCM_{i,j,t}\middle| LIKELY, t \geq 2002\right] - E\left[PCM_{i,j,t}\middle| LIKELY, t < 2002\right] - E\left[PCM_{i,j,t}\middle| UNLIKELY, t \geq 2002\right] - E\left[PCM_{i,j,t}\middle| UNLIKELY, t < 2002\right] \qquad (16b)$$

I estimate equation (15) for all EU countries in the sample first and then I re-run this same specification on a subsample of EU countries in which both the first and second EU leniency programmes were imposed exogenously on these countries, i.e., before a country has implemented its national leniency programme. I assume that the EU leniency programmes treated only "likely" industries and that the price-cost margins of the “likely” and “unlikely” industries had evolved according to a common trend before introducing the leniency programmes. Hence, the OLS estimator of δ_1 and δ_2 , the coefficients of the interaction terms, are unbiased estimators of the average treatment effect on the treated industries. This could be verified by using the pre-leniency price-cost margins data to show that the trends are the same, which I shall discuss below. If this assumption is satisfied, a negative DD treatment effect would be interpreted as indicating a drop in the price-cost margins as leniency programmes are implemented.[36] One concern is that one might wish to measure the cumulative change (the effect of the entire effort) rather than individual the changes, δ_1 and δ_2. i.e., the cumulative impact of both the 1996 and 2002 programmes (compared to nothing at all). To check that, I look at the PCM before any programme was instituted versus all of them. In other words, I look at the pre-1996 versus post-2002.

However, following Ashnefelter and Card (1985) and Besley and Burgess (2004), I include a time trend for “likely” industries, $Likely_i \times t$. In this case, the identification of the effects of leniency programmes comes from whether such policies lead to deviations from pre-existing industry-specific trends in treated industries. Equation (17) is given as follows:

$$PCM_{i,j,t} = \beta_1 + \delta_1(Likely_i \times Post_{1996}) + \delta_2(Likely_i \times Post_{2002}) + \beta_2 X_{j,t-1} + \varphi(Likely_i \times t) + \gamma_j + \lambda_t + \epsilon_{i,j,t} \qquad (17)$$

[36] At this step, I only divide the industries into “likely” and “unlikely”. Later, in the DDD specifications I divide industries into likely/unlikely colluders and also according to their likeliness to be cross-border traders. Thus, the estimate would be more precise in capturing the impact of the EU programmes as I distinguish between the industries that are likely to be a subject to the EU law and the industries that are subject to the EU law.

Furthermore, following Autor (2003), I analyse the pre-trend by including *m* lags, and *q* leads for the interaction terms to analyse the assumption on the common trend. Equation (18) below is the final specification I use and is given by:

$$PCM_{i,j,t} = \beta_1 + \sum_{\tau_{1996}=0}^{m} \delta_{-\tau_{1996}}(Likely_i \times Post_{1996-\tau_{1996}}) + \sum_{\tau_{1996}=1}^{q} \delta_{\tau_{1996}}(Likely_i \times Post_{1996+\tau_{1996}}) + \sum_{\tau_{2002}=0}^{m} \delta_{-\tau_{2002}}(Likely_i \times Post_{2002-\tau_{2002}}) + \sum_{\tau_{2002}=1}^{q} \delta_{\tau_{2002}}(Likely_i \times Post_{2002+\tau_1}) + \beta_2 X_{j,t-1} + \gamma_j + \lambda_t + \epsilon_{i,j,t} \tag{18}$$

where the sums allow for *m* anticipatory effects $(\delta_{-1}, \delta_{-2}, \ldots, \delta_{-m})$ and q post-treatment effects $(\delta_{+1}, \delta_{+2}, \ldots, \delta_{+q})$ for the first and the second EU programmes. I normalize the adoption year of each of the leniency programmes to zero, i.e. $\tau_{1996} = 0$ and $\tau_{2002} = 0$.

3.5.2 Difference-in-Difference in-Differences (DDD)

I extend the previous DD specifications by looking at the "national market" industries as a control group within the treatment group, i.e. "likely" industries. In particular, I divide the markets into two groups: EU and national markets. The EU market group is susceptible to cross-border cartels, and thus the EU leniency programmes are relevant to it. The national market, on the other hand, is where national cartel cases occur, and thus they are subject to the national leniency programmes only. Therefore, the latter serves as another control group. It is worth noting that this is a matter of practice rather than a matter of policy. That is, looking back at the referral cases between the EC and the national authorities within the EU, one could observe that there have not been any referral cases from the national authorities to the EU, but not vice versa. This might indicate that even if a cartel is national in nature and applies to the EU leniency programme, the EC could refer the applicant back to the national authority.

I obtain the DDD coefficient by subtracting the DD treatment effect for the EU leniency programmes in unrelated markets (i.e., δ in the notation above) from the respective treatment effect of EU markets.

This Difference-in-Difference-in-Differences (DDD) design is intended to control for two potential confounding effects. Firstly, it controls for changes in the price-cost margin in “likely” industries across industries that are not related to the EU leniency programme. Secondly, it controls for changes in price-cost margins in both types of industries “likely” and “unlikely” within the EU. Considering Equation (11) again, it becomes:

$$
\begin{aligned}
PCM_{i,j,t} \; = \; & \beta_1 + \beta_2 LIKELY_i + \beta_3 POST_{1996} + \beta_4 POST_{2002} + \delta_1 (Likely_i \times Post_{1996}) + \delta_2 (Likely_i \times Post_{2002}) \\
& + \beta_5 (EUMarket_i \times Post_{1996}) + \beta_6 (EUMarket_i \times Likely_i) + \gamma_1 (EUMarket_i \times Post_{1996}) \\
& + \gamma_2 (EUMarket_i \times Post_{2002}) + \theta_1 (EUMarket_i \times Likely_i \times Post_{1996}) \\
& + \theta_2 (EUMarket_i \times Likely_i \times Post_{2002}) + \beta_2 X_{j,t-1} + \alpha_{i,j} + \alpha_t \\
& + \epsilon_{i,j,t} \qquad (19)
\end{aligned}
$$

where, $EUMarket_i$ is a (0,1) dummy for markets which are targeted by the EU leniency programmes, θ_1 is the treatment effect for the EU leniency programme in 1996, and θ_2 is the treatment effect for the EU programme in 2002.

Analogously, Equations (12) and (13) now become (20) and (21) respectively:

$$PCM_{i,j,t} = \beta_1 + \sum_{\tau_{1996}=0}^{m} \delta_{-\tau_{1996}}\left(Likely_i \times Post_{1996-\tau_{1996}}\right) + \gamma_{-\tau_{1996}}(EUMarket_i \times Post_{1996-\tau})$$
$$+ \theta_{-\tau_{1996}}(Likely_i \times EUMarket_i \times Post_{1996-\tau})$$
$$+ \sum_{\tau_{1996}=1}^{q} \delta_{\tau_{1996}}\left(Likely_i \times Post_{1996+\tau_{1996}}\right) + \gamma_{\tau_{1996}}(EUMarket_i \times Post_{1996+\tau})$$
$$+ \theta_{\tau_{1996}}(Likely_i \times EUMarket_i \times Post_{1996+\tau})$$
$$+ \sum_{\tau_{2002}=0}^{m} \delta_{-\tau_{2002}}\left(Likely_i \times Post_{2002-\tau_{2002}}\right) + \gamma_{-\tau_{2002}}(EUMarket_i \times Post_{2002-\tau})$$
$$+ \theta_{-\tau_{2002}}\left(Likely_i \times EUMarket_i \times Post_{2002+\tau}\right)$$
$$+ \sum_{\tau_{2002}=1}^{q} \delta_{\tau_{2002}}\left(Likely_i \times Post_{2002+\tau}\right) + \gamma_{\tau_{2002}}(EUMarket_i \times Post_{2002+\tau})$$
$$+ \theta_{\tau_{2002}}(Likely_i \times EUMarket_i \times Post_{2002+\tau}) + \beta_2 X_{j,t-1} + \gamma_j + \lambda_t$$
$$+ \epsilon_{i,j,t} \quad . \quad . \qquad (20)$$

In equation (21) I include a likely-industry time trend to the DDD estimation:

$$PCM_{i,j,t} = \beta_1 + \beta_2 LIKELY_i + \beta_3 POST_{1996} + \beta_4 POST_{2002} + \delta_1(Likely_i \times Post_{1996}) + \delta_2(Likely_i \times Post_{2002})$$
$$+ \beta_5 EUMarket_i + \beta_6(EUMarket_i \times Likely_i) + \gamma_1(EUMarket_i \times Post_{1996})$$
$$+ +\gamma_1(EUMarket_i \times Post_{2002}) + \theta_1(EUMarket_i \times Likely_i \times Post_{1996})$$
$$+ \theta_2(EUMarket_i \times Likely_i \times Post_{2002}) + \varphi\,(Likely_i \times t) + \beta_2 X_{j,t-1} + \gamma_j + \lambda_t$$
$$+ \epsilon_{i,j,t} \qquad (21)$$

3.6 Graphical Evidence of the Parallel Trend

Figure 1 illustrates the mean value of price-cost margins by year and industry group for the whole sample. The four graphs represent the splits in the sample into “likely” and “unlikely” industries according to the number of convicted cartels in the US, wages, R&D and HHI respectively. The price-cost margins appear to follow a common trend when the split is based on cartel convictions, wages, and R&D, whereas the price-cost margins according to HHI depicts a mixed pattern. The HHI measure could, however, be ambiguous as discussed earlier. Since each country has adopted its national leniency at a different point in time, I will analyse the parallel trend assumption formally in the next section using leads and lags as well as a likely-industry time trend.

Figure 2 illustrates the mean value of price-cost margins by year and industry group for the EU countries. The first vertical line illustrates the EU 1996 leniency policy while the second illustrates its revision in 2002. The common trend assumption appears to be satisfied in the four industry splits, at least for four years before implementing the first EU policy. However, a potential policy effect - as captured by lower PCM for likely industries- can be detected for "likely" versus "unlikely" industries based on the split according to the US cartel convictions and wages, but not according to the HHI. In particular, in (b) and (c), the graphs show a small drop in "likely" industries after the introduction of the first leniency programme in 1996 and a sharp convergence after its revision in 2002. Conversely, mixed policy effects are detected when classifying the industries according to HHI in the bottom right graph. The price-cost margins in "unlikely" candidates drop more than those in "likely" industries in some years and vice versa in others.

Figure 3 illustrates the mean value of price-cost margins by both year and industry group for a subsample of EU countries, where the leniency programmes were imposed upon them solely by the EU. In another word, there was no national leniency in place. In (a), (b) and (c), a potential policy effect is captured in two years after implementing the first EU policy. Again, the PCM pattern according to HHI appears to be misleading.

3.7 Results

3.7.1 DD Estimation of the national leniency programmes

Table 3.4 sets out the baseline DD results in which I compare "likely" industries and "unlikely" industries before and after implementing the national leniency programme. The coefficient of interest is the estimate of the Likely x Post (National Leniency), which is equal to one for "likely" industries after the year in which each country has implemented the national leniency programme.[37] This coefficient could be interpreted as the impact of national leniency programme on the price-cost margin. Column (1) shows the DD coefficient when using the USA cartel convictions to identify the treatment group, "likely" industries. A negative and significant effect of the national leniency programme is captured. In column (2), I identify "likely" industries according to wages. Here, the PCM drops by 11.4 percentage points after implementing the national leniency. In column (3), I use R&D expenditures to classify industries into "likely" and "unlikely". I can attribute a negative and significant effect here as well. Column (4) relies on HHI to identify "likely" industries. A positive effect is attributed to the national leniency programme, reflecting the ambiguity of this as a measure of likelihood, as described above. Table 3.5 introduces the "likely"-industry-specific time trend. The results are robust to including the industry-specific-time trend in column (1) and (3), when dividing industries according to cartel convictions and R&D respectively. No significant impact is captured when splitting according to wages. However, the direction of the effect stays negative. Thus, implementing leniency programmes appears to be associated with lower price-cost margins. The strength of the effect of the national leniency policy in this exercise appears to be greater than the results obtained in Chapter 2. However, it is worth mentioning that the impact of the programme is sensitive to the way I divide my industries.

Table 3.6 shows the national leniency programme coefficients with three counterfactual pre-treatment effects and three counterfactual post-treatment effects. This strategy is introduced by Autor (2003) who accounts for the potential violations of the parallel trend assumption. Therefore, if the leniency policy represents a true cartel treatment, one would predict no significance in the pre-leniency coefficients, while there is a significant post-treatment effect as captured by the lags.

[37] As the instrumental variable analysis in Chapter 2 suggests that the endogeneity may not be much of a problem, I do not instrument for national leniency programme in the DD analysis.

The estimates show no effect in the three years before implementing the national leniency programmes in columns (1), (2) and (3), when splitting the industries according to US convictions, wages and R&D, respectively. This suggests that there are no significant anticipatory effects, which is good news for the parallel trend assumption. In columns (2) and (3), the pre-leniency coefficients tend to switch from positive to negative quite regularly, which may indicate an uncaptured cyclic component. However, this is unlikely given that (i) the coefficients are insignificant and (ii) the time effects do not have a specific functional form. Column (1), when splitting the industries according to US convictions, shows that the national leniency programmes appear to be effective in the year of adoption, and the effect settles down after three years, with a reduction in price-cost margins by 8 percentage points. In column (3), when splitting according to wages, no impact of leniency programmes implementation on PCM is captured in the year of adoption. However, the PCM drops by 6 percentage points with a one-year lag. Column (3) shows negative and significant post-treatment effects. In Table 3.15, I estimate the impact of the national leniency programme by running separate regressions for the "likely" and the "unlikely" according to each classification. I only capture a negative and significant impact of leniency programmes on PCM for the likely industries based on the previous convictions and the R&D expenditures indicators.

3.7.2 DD Estimation of the EU leniency programmes in 1996 and 2002

Table 3.7 presents the baseline results of the DD Estimation of the EU Leniency Programmes in 1996 and 2002.[38] I use a sample of EU countries that were affected by the EU leniency implementation. The DD coefficients of interest are (Likely x Post1996) and (Likely x Post 2002). Both programmes show a significant and negative impact on the price-cost margins when splitting the sample according to cartel convictions, wages, and R&D, as shown in columns (1),

[38] I also evaluated the efficiency of both EU programmes together rather than evaluating separately the individual effect of each programme. I estimate the case where there is not any programme in place against the case where both programmes are implemented. Results are significant and very close to the estimates of the impact of the second EU programme.

(2) and (3). The magnitude is greater after implementing the second EU policy, which suggests that the impact of the leniency programme is strengthened after the revision of the programme in 2002. In Table 3.16, I estimate the impact of the EU leniency programmes by running separate regressions for likely and unlikely groups according to each classification. No significant impact is captured which may be attributed to the reduction in sample size.

In Table 3.8, I account for potential violation of the parallel trend assumption by including a likely-industry time trend. That is, likely and unlikely industries may have already followed different PCM trends before implementing the leniency policy. The results appear to be robust when controlling for industry-specific time trend, as shown in the table.

In Table 3.9, I include a lead and a lag for each of the EU leniency policies. No anticipatory effects are captured for the first EU policy in all specifications. In column (1), according to USA convictions, the impact of the first EU leniency policy is only captured with a lag. In column (2) a negative and impact of the first EU programme is captured according to wages split, with a reduction in the PCM by 8 percentage points. A greater magnitude is captured with a lag. In columns (3) and (4), no significant results are captured according to R&D and HHI.

Conversely, in columns (1), (2) and (3), there appear to be anticipatory effects for the second leniency programme before implementing the policy. Nonetheless, the existence of the anticipatory effects for the second EU programme could result from the first EU leniency programme.

To reduce potential endogeneity bias, I restrict the analysis to a subsample of EU countries in which the EU leniency was imposed exogenously as shown in Tables 3.10, 3.11, and 3.9. In other words, the subsample consists of the countries that had not adopted national leniency programme at the time when the EU programmes were implemented, and thus they were only affected by the EU policy. Thus, this assumption of exogeneity would derive from assuming that this programme would form only a small part of the decision to join the EU. Moreover, joining the EU is a very long process that occurs over many years and would likely extend beyond the legislative history of the leniency programme or its revision.

A significant impact of both programmes is captured when splitting the samples by wages and R&D; however, the result loses its significance when the sample is split by USA cartel convictions. This may be attributed to the shrinkage in sample's size.

Table 3.11 introduces a likely-industry time trend to the EU subsample. The cumulative effect of the EU leniency programmes after 2002 changes from 20 percentage points to 16 percentage points when splitting the sample by wages, and from 31 to 18 percentage points when splitting the sample by R&D. The significant effect of the first EU policy disappears. The DD coefficients remain insignificant when splitting the sample according to both cartel convictions and R&D.

Table 3.12 incorporates the common trend assumption by introducing counterfactual pre- and post-treatment effects. In all specifications, a no pre-treatment effect is captured whereas a post-treatment effect of the first programme is captured according to the split by USA convictions and wages. The cumulative effect diminishes with lags according to the USA cartel convictions, while the PCM decreases by 13 percentage points according to wages and by 17 percentage points according to R&D.

3.7.3. DDD estimation of the EU leniency programmes in 1996 and 2002

DDD Estimations of the EU Leniency Programmes are presented in Tables 3.13 and 3.14. Here I compare the PCM of likely and susceptible to cross-border cartel industries to the PCM of unlikely but susceptible to cross-border cartels industries before versus after the introduction of both the EU leniency programmes. I also estimate a DDD coefficient that compares the PCM of likely and susceptible to cross-border cartels industries to the PCM of unlikely but susceptible to cross-border cartels industries before versus after the introduction of both the EU national programmes. Here, I expect no impact of the national leniency programmes. In Table 3.13, column (1), according to USA cartel cases classification, no impact of the first EU programme is captured, whereas the cumulative effect of both EU programmes decreases the PCM by 33 percentage points in likely industries that are susceptible to cross-border activities. In column (2), according to the wages specification, the DDD estimate of both EU policies is negative and significant. In column (3), according to the R&D classification, no treatment effect is captured after the first EU programme, whereas there is a significant and negative DDD cumulative effect of both EU policies. The DDD coefficient of the treatment effect of the national leniency is insignificant in both classifications, as expected. This is interpreted as the EU programmes are relevant to likely industries that are susceptible to cross-border cartel activities. In Table 3.14, I include a likely-industry time trend to account for potential violations in the common trend assumption. The DDD coefficients of the cumulative effects of the EU programmes stay significant with a slight decrease in comparison to Table 3.13. This suggests that the treatment and the control industry groups have already followed different PCM trends before introducing the EU policy.

An interesting side finding is that the single market programme exhibits a negative and a strongly significant effect on the PCM. This result is robust and consistent among all the previous DD and DDD specifications which suggest that this programme was indeed associated with increased competition intensity. The single market programme was imposed before introducing the first EU leniency programme. Thus, the single market programme may have pre-created an appropriate legal environment for the imposition of leniency programmes by increasing the legal certainty across the EU and reducing firms' divergence in the initial adaption costs of the legal procedure. [39]

[39] For more details, see http://ec.europa.eu/competition/antitrust/proposed_directive_en.pdf.

3.8 Conclusion

As I previously emphasised, the method employed in Chapter 2 does not allow me to differentiate between industries to which leniency programmes might or might not be relevant, i.e. cartels are unlikely to exist in some industries. Also, it similarly treats all industries as if the EU leniency programmes were relevant to all them, without taking into account that not all cartel cases are likely to fall under the purview of EU leniency. The results of the first chapter suggested that the national leniency programmes increase the competitive intensity, whereas the EU programmes exhibit conflicting and non-significant results.

In this chapter, I closely looked at the structure of the industries in the data. I divided industries into those that are "prone" to cartels and those that are not. Several methods were used; these include the following: the number of previously prosecuted cartel cases within the industry, the HHI index, and other industry characteristics. Also, I divided the markets into national and EU markets. This is because the EU leniency is more relevant to some cases, whereas national leniency is relevant to some others.

Difference-in-difference estimates that I obtained by dividing the data in this way suggest that both the national leniency and EU programmes fulfil their aggregate goal of increasing competitive intensity, which I measure as decreasing the PCM within the industry. Nevertheless, one drawback in the analysis concerns the sensitivity of the results with regard to the way I diagnose "likely" and "unlikely" industries. That is, only if I assume that my classification of industries was accurate, I can conclude that leniency programmes have affected "likely" industries in the way I have described. Future work may investigate further whether the costs of leniency programmes are justified, given the consumer surplus.

The next chapters (Chapters 4 and 5) are related in some way via the subject matter, but I take a different approach. I study the relationship between innovation and competition, both at the firm- and industry-level. As the results of chapters 2 and 3 suggest that leniency and competitive intensity are related, I use leniency programmes as an instrument for the intensity of competition in the later work. This will be detailed in the following chapters.

3.9 Appendix

Figure 3.1: Mean PCM by Industry Group and Year, All Countries 1990-2007

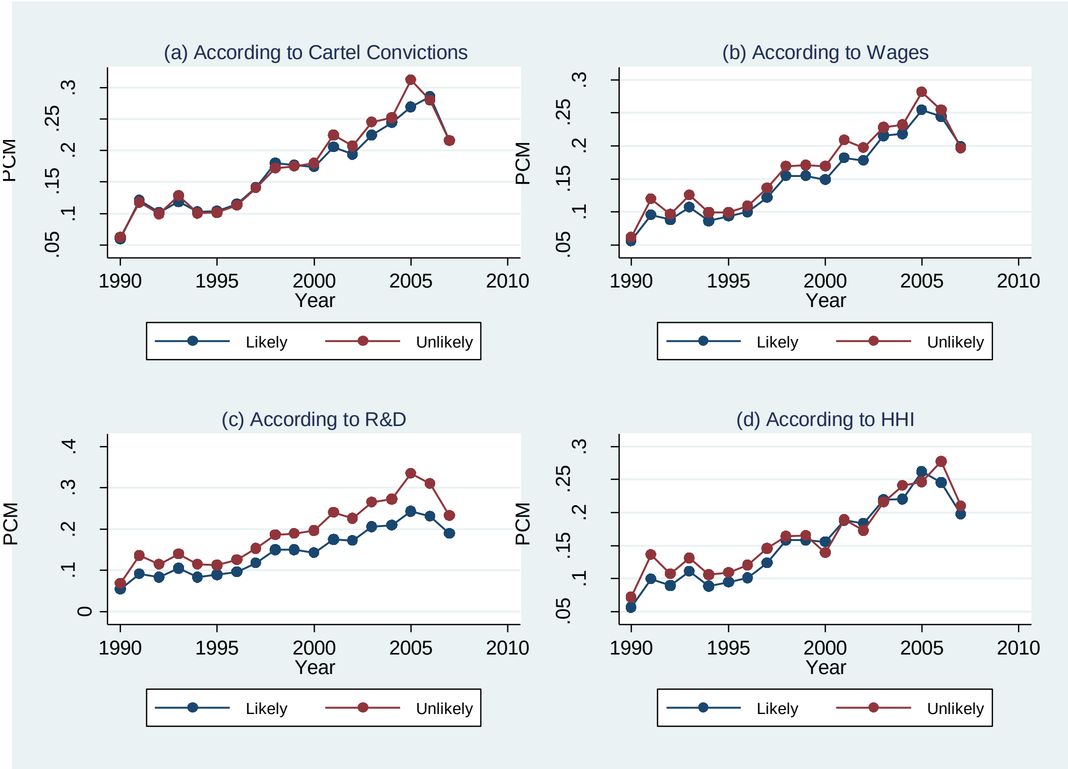


Figure 3.2: Mean PCM by Industry Group and Year, EU Countries 1990-2007

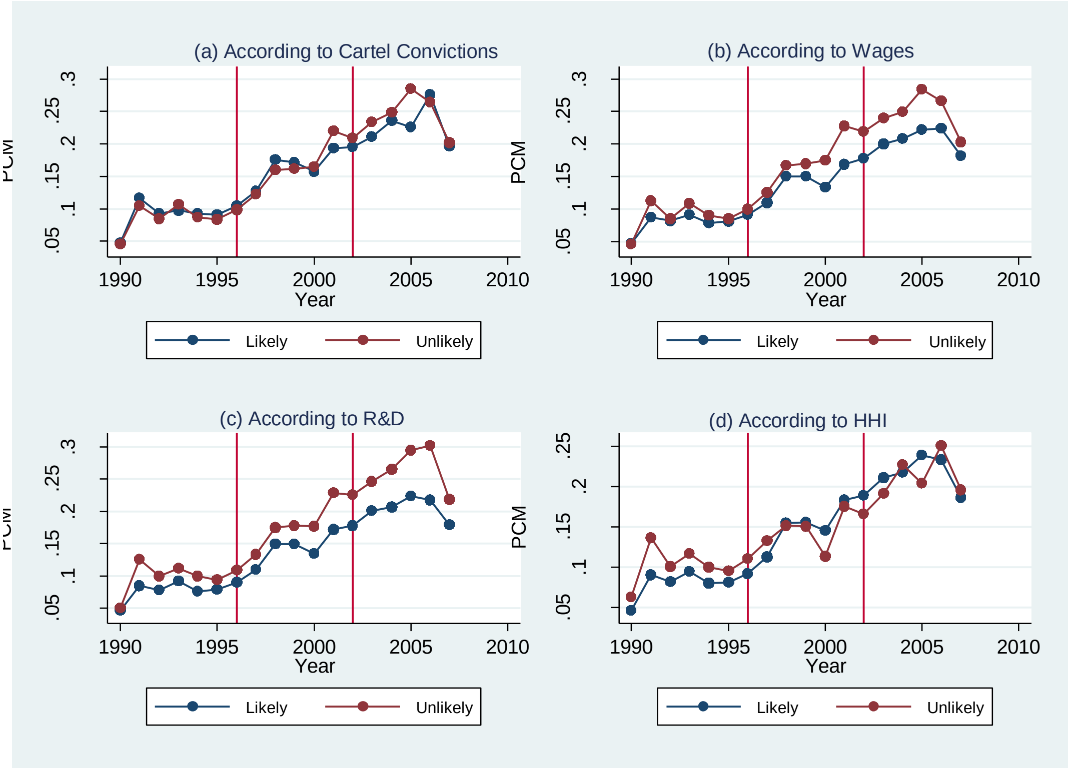


Figure 3.3: Mean PCM by Industry Group and Year, 1990-2007 (EU Countries with Exogenous EU Programmes)

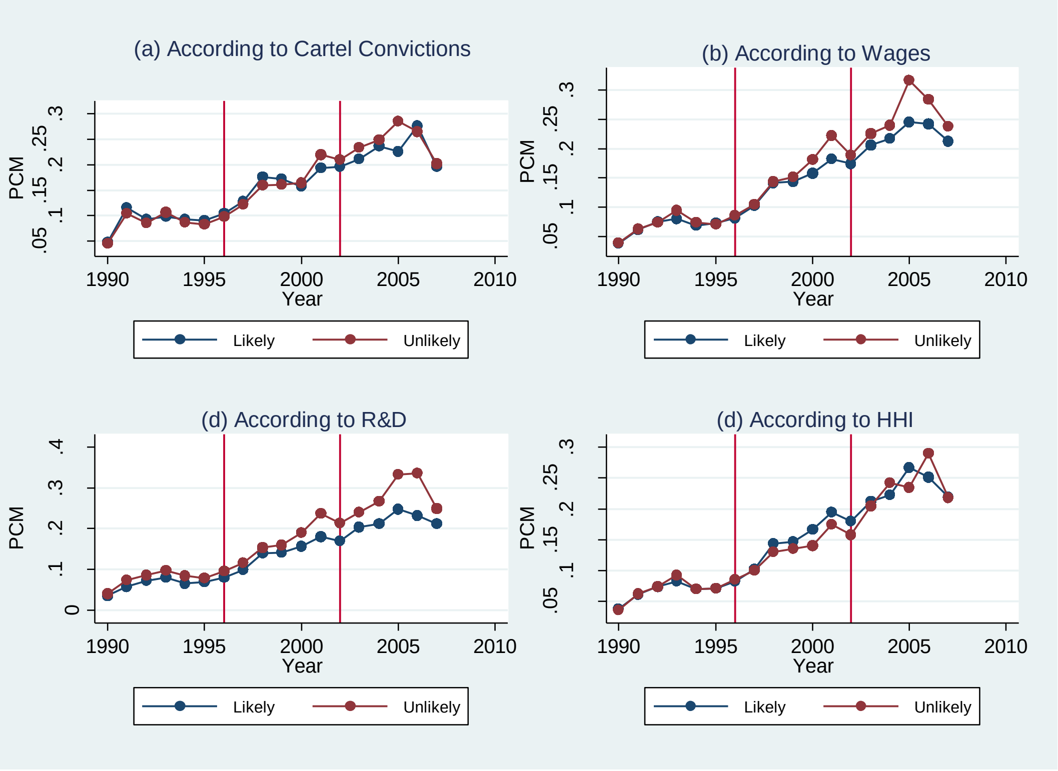


Table 3. 1: Industries and Observation

Industry	Freq.	Percent	Cum.
Fishing, fish hatcheries, fish farms and related services	259	3.62	3.62
Other mining and quarrying	112	1.56	5.18
Food products and beverages	222	3.1	8.28
Tobacco products	209	2.92	11.2
Wearing apparel	242	3.38	14.58
Leather, leather products and footwear	287	4.01	18.59
Wood and products of wood and cork	308	4.3	22.89
Printing and publishing	297	4.15	27.04
Coke, refined petroleum products and nuclear fuel	268	3.74	30.78
Chemicals and chemical products	238	3.32	34.11
Rubber and plastics products	300	4.19	38.3
Fabricated metal products, except machinery and equipment	276	3.85	42.15
Machinery and equipment	305	4.26	46.41
Electrical machinery and apparatus, n.e.c.	258	3.6	50.01
Radio, television and communication equipment	254	3.55	53.56
Medical, precision and optical instruments	244	3.41	56.97
Other transport equipment	272	3.8	60.77
Manufacturing n.e.c.	205	2.86	63.63
Electricity, gas, steam and hot water supply	191	2.67	66.3
Research and development	187	2.61	68.91
Other business activities	194	2.71	71.62
Public admin. and defence - compulsory social security	320	4.47	76.09
Building and repairing of ships and boats	175	2.44	78.53
Aircraft and spacecraft	177	2.47	81.01
Mining and quarrying of energy producing materials	224	3.13	84.13
Pharmaceuticals	256	3.58	87.71
Railroad equipment	168	2.35	90.06
Other non-metallic mineral products	320	4.47	94.53
Iron and steel	205	2.86	97.39
Non-ferrous metals	187	2.61	100
Total	7,160	100	

Table 3. 2: Variables Preliminary Statistics

Variable	Obs	Mean	Std. Dev.
PCM	7,160	0.16261	0.162268
National Leniency	7,160	0.302654	0.459439
1st EU Programme	7,160	0.547486	0.497775
2nd EU Programme	7,160	0.22081	0.414822
GDP Growth	6,721	2.831192	1.952207
Import Penetration	6,362	3.428041	20.6826
Single Market Programme	7,160	0.419832	0.493566
New EU Member	7,160	0.039525	0.194854
EU East Enlargement 2004	7,160	0.689805	0.462606

Table 3. 3: Correlation between Cartelisation Indicators

	USA	Wages	R&D	HHI
USA	1			
Wages	0.0304*	1		
R&D	0.0057	0.2650*	1	
HHI	-0.4713*	-0.2202*	-0.0763*	1

Significant at the 5% level.

Table 3. 4:DD Estimation of the National Leniency Programmes

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post (National Leniency)	-0.202*	-0.114***	-0.298***	0.327**
	(0.103)	(0.0334)	(0.0633)	(0.166)
Single Market Program (1 lag)	-0.210***	-0.194***	-0.195***	-0.195***
	(0.0720)	(0.0535)	(0.0714)	(0.0713)
New EU Members in 2004 (1 lag)	-0.152*	-0.117**	-0.114*	-0.118*
	(0.0819)	(0.0498)	(0.0636)	(0.0636)
EU 2004 enlargement (1 lag)	0.0671	0.133**	0.128	0.134
	(0.0802)	(0.0652)	(0.110)	(0.109)
GDP Growth (in logs,1 lag)	0.0285*	0.0348***	0.0357***	0.0343**
	(0.0150)	(0.0128)	(0.0137)	(0.0138)
Import penetration (in logs, 1 lag)	-0.0634**	-0.0974***	-0.0925***	-0.0972***
	(0.0288)	(0.0119)	(0.0272)	(0.0268)
Constant	-3.514***	-4.351***	-2.869***	-5.788***
	(0.165)	(0.199)	(0.263)	(0.340)
Observations	3,986	6,829	6,829	6,829
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 5: DD Estimation of the National Leniency Programmes, with Likely-Industry Time Trend

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post (National Leniency)	-0.208**	-0.0341	-0.176***	0.421**
	(0.105)	(0.0717)	(0.0621)	(0.164)
Single Market Program (1 lag)	-0.209***	-0.212***	-0.212***	-0.214***
	(0.0718)	(0.0690)	(0.0687)	(0.0685)
New EU Members in 2004 (1 lag)	-0.153*	-0.117*	-0.114*	-0.116*
	(0.0818)	(0.0650)	(0.0650)	(0.0646)
EU 2004 enlargement (1 lag)	0.0654	0.176*	0.171*	0.177**
	(0.0773)	(0.0915)	(0.0935)	(0.0905)
GDP Growth (in logs,1 lag)	0.0282*	0.0264**	0.0279**	0.0270**
	(0.0150)	(0.0132)	(0.0131)	(0.0131)
Import penetration (in logs, 1 lag)	-0.0589**	-0.0894***	-0.0884***	-0.0923***
	(0.0282)	(0.0264)	(0.0263)	(0.0259)
Constant	-6.349***	-3.776***	-1.811***	-0.534
	(2.251)	(0.259)	(0.325)	(0.672)
Observations	3,986	6,829	6,829	6,829
Likely-specific time trend	x	x	x	x
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 6: DD Estimation of the National Leniency Programmes, with Leads and Lags

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post (National Leniency) -3	-0.000341	0.0509	-0.0113	-0.0189
	(0.0489)	(0.0460)	(0.0406)	(0.0387)
Likely x Post (National Leniency) -2	-0.0177	-0.00235	-0.0326	-0.101*
	(0.0391)	(0.0462)	(0.0426)	(0.0566)
Likely x Post (National Leniency) -1	-0.0739	0.000667	0.0341	-0.0374
	(0.0647)	(0.0407)	(0.0381)	(0.108)
Likely x Post (National Leniency)	-0.141*	-0.0734	-0.232***	0.479***
	(0.0777)	(0.0596)	(0.0553)	(0.164)
Likely x Post (National Leniency) +1	-0.0648	-0.0630*	-0.104***	-0.299***
	(0.0449)	(0.0338)	(0.0325)	(0.0588)
Likely x Post (National Leniency) +2	-0.0407	-0.0585	-0.122***	-0.102***
	(0.0535)	(0.0414)	(0.0400)	(0.0371)
Likely x Post (National Leniency) +3	-0.0880**	-0.0441	-0.0309	0.00399
	(0.0444)	(0.0403)	(0.0361)	(0.0329)
Single Market Program (1 lag)	-0.235***	-0.224***	-0.222***	-0.210***
	(0.0732)	(0.0737)	(0.0732)	(0.0722)
New EU Members in 2004 (1 lag)	-0.179**	-0.105	-0.107	-0.113*
	(0.0832)	(0.0668)	(0.0667)	(0.0661)
EU 2004 enlargement (1 lag)	-0.00601	0.0841	0.0750	0.0708
	(0.0816)	(0.110)	(0.111)	(0.110)
GDP Growth (in logs,1 lag)	0.0347**	0.0379***	0.0389***	0.0410***
	(0.0147)	(0.0138)	(0.0136)	(0.0137)
Import penetration (in logs, 1 lag)	-0.0636**	-0.0975***	-0.0908***	-0.0947***
	(0.0286)	(0.0268)	(0.0272)	(0.0273)
Constant	-3.418***	-4.311***	-4.175***	-5.621***
	(0.167)	(0.231)	(0.232)	(0.354)
Observations	3,986	6,829	6,829	6,829
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 7:DD Estimation of the EU Leniency Programmes

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post1996	-0.150**	-0.212***	-0.144***	0.171
	(0.0756)	(0.0568)	(0.0548)	(0.120)
Likely x Post2002	-0.188*	-0.288***	-0.347***	0.231
	(0.0988)	(0.0650)	(0.0617)	(0.157)
Single Market Programme (1 lag)	-0.270***	-0.253***	-0.262***	-0.264***
	(0.0899)	(0.0855)	(0.0858)	(0.0874)
EU 2004 enlargement (1 lag)	-0.0928	-0.0676	-0.0706	-0.0674
	(0.0882)	(0.0656)	(0.0657)	(0.0656)
GDP Growth (in logs,1 lag)	0.0350**	0.0335**	0.0332**	0.0334**
	(0.0172)	(0.0153)	(0.0154)	(0.0155)
Import penetration (in logs, 1 lag)	-0.0639*	-0.114***	-0.105***	-0.113***
	(0.0335)	(0.0350)	(0.0335)	(0.0339)
Constant	-2.976***	-2.069***	-2.269***	-5.242***
	(0.263)	(0.226)	(0.237)	(0.411)
Observations	3,182	5,349	5,349	5,349
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 8: DD Estimation of the EU Leniency Programmes, with Likely Time Trend

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post1996	-0.152**	-0.128**	-0.0649	0.233*
	(0.0761)	(0.0567)	(0.0544)	(0.120)
Likely x Post2002	-0.191*	-0.162***	-0.232***	0.321**
	(0.100)	(0.0624)	(0.0594)	(0.155)
Single Market Programme (1 lag)	-0.268***	-0.254***	-0.259***	-0.262***
	(0.0899)	(0.0863)	(0.0862)	(0.0867)
EU 2004 enlargement (1 lag)	-0.0931	-0.0717	-0.0736	-0.0714
	(0.0881)	(0.0654)	(0.0655)	(0.0655)
GDP Growth (in logs,1 lag)	0.0346**	0.0284*	0.0284*	0.0288*
	(0.0172)	(0.0150)	(0.0150)	(0.0150)
Import penetration (in logs, 1 lag)	-0.0608*	-0.108***	-0.103***	-0.109***
	(0.0331)	(0.0341)	(0.0331)	(0.0333)
Constant	-5.037**	-1.838***	-1.251***	0.833
	(2.514)	(0.227)	(0.356)	(0.673)
Observations	3,182	5,349	5,349	5,349
Likely-specific time trend	x	x	x	x
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 9: DD Estimation of the EU Leniency Programmes, with Leads and Lags

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Policy1996-1	0.00230	0.0544	0.0792	0.0932
	(0.0582)	(0.0545)	(0.0520)	(0.0818)
Likely x Policy1996	-0.0348	-0.0822***	-0.0273	-0.0100
	(0.0401)	(0.0311)	(0.0274)	(0.106)
Likely x Policy1996+1	-0.176***	-0.202***	-0.0314	0.0296
	(0.0672)	(0.0502)	(0.0386)	(0.0533)
Likely x Policy2002-1	-0.141*	-0.280***	-0.363***	0.152
	(0.0799)	(0.0597)	(0.0716)	(0.147)
Likely x Policy2002	-0.0233	0.0362	-0.0604	0.268**
	(0.0600)	(0.0485)	(0.0410)	(0.128)
Likely x Policy2002+1	-0.00655	-0.0798*	-0.116**	0.00148
	(0.0615)	(0.0453)	(0.0463)	(0.0627)
Single Market Programme (1 lag)	-0.268***	-0.251***	-0.261***	-0.264***
	(0.0899)	(0.0853)	(0.0857)	(0.0873)
EU 2004 enlargement (1 lag)	-0.129	-0.0981	-0.104	-0.103
	(0.0834)	(0.0646)	(0.0646)	(0.0646)
GDP Growth (in logs,1 lag)	0.0334**	0.0331**	0.0322**	0.0323**
	(0.0169)	(0.0149)	(0.0150)	(0.0153)
Import penetration (in logs, 1 lag)	-0.0675**	-0.114***	-0.101***	-0.115***
	(0.0336)	(0.0360)	(0.0339)	(0.0340)
Constant	-3.009***	-2.146***	-2.086***	-2.021***
	(0.237)	(0.233)	(0.286)	(0.254)
Observations	3,182	5,349	5,349	5,349
Number of id	286	487	487	487
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 10: DD Estimation of EU Leniency Programmes, with no Endogeneity

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post1996	-0.0961	-0.190***	-0.166**	0.0245
	(0.0933)	(0.0735)	(0.0722)	(0.116)
Likely x Post2002	-0.163	-0.305***	-0.311***	0.203
	(0.113)	(0.0764)	(0.0721)	(0.184)
Single Market Programme (1 lag)	-0.330***	-0.241**	-0.261**	-0.251**
	(0.103)	(0.104)	(0.103)	(0.107)
EU 2004 enlargement (1 lag)	-0.0542	0.0266	0.0247	0.0331
	(0.0853)	(0.111)	(0.112)	(0.111)
GDP Growth (in logs,1 lag)	0.114***	0.112***	0.110***	0.112***
	(0.0211)	(0.0211)	(0.0212)	(0.0215)
Import penetration (in logs, 1 lag)	-0.133***	-0.160***	-0.148***	-0.154***
	(0.0358)	(0.0340)	(0.0335)	(0.0339)
Constant	-3.688***	-4.961***	-3.312***	-6.033***
	(0.223)	(0.302)	(0.327)	(0.374)
Observations	2,046	3,379	3,379	3,379
Number of id	166	277	277	277
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 11: DD Estimation of EU Leniency Programmes, no Endogeneity Sample with likely Time Trend

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Post1996	-0.0958	-0.0639	-0.0486	0.107
	(0.0935)	(0.0710)	(0.0695)	(0.115)
Likely x Post2002	-0.162	-0.163**	-0.188***	0.298
	(0.114)	(0.0729)	(0.0689)	(0.182)
Single Market Programme (1 lag)	-0.330***	-0.287***	-0.296***	-0.294***
	(0.103)	(0.100)	(0.0999)	(0.102)
EU 2004 enlargement (1 lag)	-0.0526	0.0707	0.0696	0.0778
	(0.0861)	(0.0958)	(0.0963)	(0.0943)
GDP Growth (in logs,1 lag)	0.114***	0.0996***	0.0987***	0.0993***
	(0.0211)	(0.0198)	(0.0198)	(0.0198)
Import penetration (in logs, 1 lag)	-0.136***	-0.136***	-0.129***	-0.133***
	(0.0365)	(0.0357)	(0.0350)	(0.0354)
Constant	-2.465	-4.287***	-2.089***	-0.432
	(2.700)	(0.348)	(0.430)	(0.881)
Observations	2,046	3,379	3,379	3,379
Number of id	166	277	277	277
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 12: DD Estimation of EU Leniency Programmes, no Endogeneity Sample with Leads and Lags

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x Policy1996-1	0.00230	0.0723	0.0547	-0.0663
	(0.0582)	(0.0722)	(0.0567)	(0.175)
Likely x Policy1996	-0.0348	-0.0416	-0.0539	-0.0232
	(0.0401)	(0.0430)	(0.0329)	(0.0718)
Likely x Policy1996+1	-0.176***	-0.208***	-0.0258	0.0113
	(0.0672)	(0.0556)	(0.0441)	(0.165)
Likely x Policy2002-1	-0.141*	-0.192***	-0.344***	0.279*
	(0.0799)	(0.0614)	(0.0654)	(0.146)
Likely x Policy2002	-0.0233	-0.00572	-0.0772	-0.114**
	(0.0600)	(0.0475)	(0.0482)	(0.0526)
Likely x Policy2002+1	-0.00655	-0.130***	-0.172***	0.0771
	(0.0615)	(0.0501)	(0.0513)	(0.0997)
Single Market Programme (1 lag)	-0.268***	-0.244**	-0.287***	-0.260***
	(0.0899)	(0.104)	(0.0868)	(0.0889)
EU 2004 enlargement (1 lag)	-0.129	0.0256	-0.0693	-0.107*
	(0.0834)	(0.112)	(0.0657)	(0.0648)
GDP Growth (in logs,1 lag)	0.0334**	0.113***	0.0268*	0.0315**
	(0.0169)	(0.0209)	(0.0154)	(0.0154)
Import penetration (in logs, 1 lag)	-0.0675**	-0.163***	-0.108***	-0.112***
	(0.0336)	(0.0340)	(0.0344)	(0.0340)
Constant	-3.009***	-2.878***	-3.452***	-5.371***
	(0.237)	(0.153)	(0.220)	(0.376)
Observations	3,182	3,379	5,349	5,349
Number of id	286	277	487	487
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 13: DDD Estimation of the EU Leniency Programmes

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x EU Market x Post1996	-0.107	-0.153**	-0.0920	0.0817
	(0.0985)	(0.0774)	(0.0686)	(0.122)
Likely x EU Market x Post2002	-0.336**	-0.361***	-0.376***	0.429
	(0.150)	(0.0934)	(0.0909)	(0.285)
Likely x EU Market x National leniency	-0.0265	0.0692	0.135	0.0701
	(0.161)	(0.112)	(0.113)	(0.275)
Single Market Programme (1 lag)	-0.311***	-0.293***	-0.297***	-0.317***
	(0.0856)	(0.0810)	(0.0820)	(0.0831)
EU 2004 enlargement (1 lag)	-0.126	-0.113*	-0.123*	-0.0928
	(0.0834)	(0.0637)	(0.0640)	(0.0664)
GDP Growth (in logs,1 lag)	0.0193	0.0247	0.0256*	0.0237
	(0.0170)	(0.0153)	(0.0155)	(0.0162)
Import penetration (in logs, 1 lag)	-0.0579*	-0.103***	-0.0966***	-0.103***
	(0.0330)	(0.0342)	(0.0329)	(0.0323)
Constant			-2.205***	
			(0.275)	
Observations	3,182	5,349	5,349	5,349
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 14: DDD Estimation of the EU Leniency Programmes with Likely-Industry Time Trend

	(1) ln(PCM) USA Cartel Convictions	(2) ln(PCM) Wages	(3) ln(PCM) R&D	(4) ln(PCM) HHI
Likely x EU Market x Post1996	-0.119	-0.183**	0.117	-0.0608
	(0.106)	(0.0869)	(0.143)	(0.0639)
Likely x EU Market x Post2002	-0.305*	-0.296***	0.371	-0.277***
	(0.176)	(0.112)	(0.304)	(0.0864)
Likely x EU Market x National leniency	-0.0470	0.0345	0.123	0.0923
	(0.171)	(0.113)	(0.265)	(0.109)
Single Market Programme (1 lag)	-0.310***	-0.289***	-0.291***	-0.320***
	(0.0853)	(0.0816)	(0.0821)	(0.0825)
EU 2004 enlargement (1 lag)	-0.132	-0.0945	-0.110*	-0.0962
	(0.0856)	(0.0653)	(0.0647)	(0.0655)
GDP Growth (in logs,1 lag)	0.0193	0.0268*	0.0210	0.0242
	(0.0171)	(0.0155)	(0.0150)	(0.0164)
Import penetration (in logs, 1 lag)	-0.0598*	-0.102***	-0.0966***	-0.105***
	(0.0328)	(0.0353)	(0.0328)	(0.0327)
Constant	-3.187***	-2.499***		
	(0.255)	(0.267)		
Observations	3,182	5,349	5,349	5,349
Year dummies	x	x	x	x
Industry-country FE	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 15: The National Leniency Programme by Industry Group

Ln(PCM)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA Convictions		Wages		R&D		HHI	
	Likely	Unlikely	likely	Unlikely	likely	Unlikely	likely	Unlikely
National Leniency	-0.0931**	-0.124	-0.0683	-0.0942	-0.0995**	-0.0583	-0.0583	-0.237
	(0.0401)	(0.122)	(0.0671)	(0.0646)	(0.0440)	(0.0651)	(0.0651)	(0.186)
Single Market Program (1 lag)	-0.164**	-0.292*	-0.163	-0.218**	-0.250***	-0.182*	-0.182*	-0.0598
	(0.0635)	(0.174)	(0.105)	(0.0943)	(0.0671)	(0.106)	(0.106)	(0.240)
New EU Members in 2004 (1 lag)	-0.182*	-0.0998	-0.0884	-0.181*	-0.177	-0.0965	-0.0965	-0.0909
	(0.104)	(0.129)	(0.0815)	(0.101)	(0.116)	(0.0758)	(0.0758)	(0.183)
EU 2004 enlargement (1 lag)	0.0197	0.161	0.170	0.0393	-0.0747	0.215	0.215	0.174
	(0.0965)	(0.137)	(0.170)	(0.106)	(0.0568)	(0.163)	(0.163)	(0.443)
GDP Growth (in logs,1 lag)	0.0244*	0.0385	0.0394**	0.0220	0.0335**	0.0350*	0.0350*	0.0387
	(0.0136)	(0.0383)	(0.0195)	(0.0196)	(0.0157)	(0.0188)	(0.0188)	(0.0436)
Import penetration (in logs, 1 lag)	-0.0437	-0.104	-0.183***	-0.0306	-0.135***	-0.0911**	-0.0911**	-0.503**
	(0.0336)	(0.0763)	(0.0417)	(0.0348)	(0.0494)	(0.0414)	(0.0414)	(0.200)
Constant	-3.014***	-3.302***	-3.658***	-3.145***	-2.983***	-3.541***	-3.541***	-3.207***
	(0.106)	(0.194)	(0.167)	(0.126)	(0.0818)	(0.164)	(0.164)	(0.369)
Observations	2,751	1,235	3,988	2,841	2,166	4,663	4,663	801
R-squared	0.616	0.263	0.197	0.395	0.641	0.158	0.158	0.150
Number of id	234	105	351	238	182	407	407	68
Year dummies	x	x	x	x	x	x	x	x
Industry-country FE	x	x	x	x	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 16: EU Leniency Programmes by Industry Group

Ln (PCM)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA Convictions		Wages		R&D		HHI	
	Likely	Unlikely	likely	Unlikely	likely	Unlikely	likely	Unlikely
First EU Leniency	-0.267	0.131	-0.172	-0.310***	0.0620	-0.230	0.235	0.225
	(0.419)	(0.213)	(0.174)	(0.103)	(0.280)	(0.222)	(0.195)	(0.287)
Second EU Leniency	0.0491	0.0888	0.0952*	0.105	0.0639	0.107	0.0478	0.253*
	(0.114)	(0.0561)	(0.0572)	(0.118)	(0.0555)	(0.0776)	(0.0462)	(0.151)
Single Market Programme (1 lag)	-0.301	-0.244***	-0.210	0.0103	-0.209	-0.353***	-0.306***	-0.0559
	(0.223)	(0.0792)	(0.139)	(0.302)	(0.133)	(0.0776)	(0.0887)	(0.262)
EU 2004 enlargement (1 lag)	-0.0606	-0.113	-0.0122	0.194***	-0.0435	-0.125	-0.0756	-0.0297
	(0.144)	(0.112)	(0.0794)	(0.0662)	(0.0777)	(0.125)	(0.0703)	(0.198)
GDP Growth (in logs,1 lag)	0.0575	0.0269*	0.0436*	0.0685*	0.0359	0.0335*	0.0381**	0.0351
	(0.0446)	(0.0153)	(0.0227)	(0.0354)	(0.0218)	(0.0173)	(0.0161)	(0.0458)
Import penetration (in logs, 1 lag)	-0.182***	-0.0504	-0.0972**	-0.0719	-0.0926**	-0.138***	-0.0807***	-0.624***
	(0.0686)	(0.0342)	(0.0410)	(0.0480)	(0.0384)	(0.0519)	(0.0284)	(0.151)
Constant	-2.873***	-3.281***	-3.517***	-4.421***	-3.297***	-2.697***	-3.208***	-2.146***
	(0.644)	(0.246)	(0.240)	(0.370)	(0.321)	(0.426)	(0.224)	(0.265)
Observations	1,010	2,172	3,375	1,480	3,618	1,731	4,717	632
Number of id	90	196	313	102	333	154	430	57
Year dummies	x	x	x	x	x	x	x	x
Industry-country FE	x	x	x	x	x	x	x	x

*Cluster-robust Standard errors on the country level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. I split the industries into "likely" and "unlikely" according the number of cartel convictions in the USA in column (1), wages in column (2), R&D expenditures in column (3) and HHI in column (4).*

Table 3. 17: The Division of Industries According to Cartelisation Indicators

Likely by USA Convictions	Unlikely by USA Convictions
Food products and beverages	Fishing, fish hatcheries, fish farms and related services
Tobacco products	Other mining and quarrying
Chemicals and chemical products	Wearing apparel, dressing and dyeing of fur
Rubber and plastics products	Leather, leather products and footwear
Fabricated metal products, except machinery and equipment	Wood and products of wood and cork
Electrical machinery and apparatus, n.e.c.	Printing and publishing
	Coke, refined petroleum products and nuclear fuel
	Machinery and equipment, n.e.c.
	Radio, television and communication equipment
	Medical, precision and optical instruments
	Other transport equipment
	Manufacturing n.e.c.
	Electricity, gas, steam and hot water supply
	Research and development
	Other business activities
	Public admin. and defence - compulsory social security
Likely by Wages	**Unlikely by Wages**
Other mining and quarrying	Fishing, fish hatcheries, fish farms and related services
Food products and beverages	Tobacco products
Chemicals and chemical products	Wearing apparel, dressing and dyeing of fur
Fabricated metal products, except machinery and equipment	Leather, leather products and footwear
Machinery and equipment, n.e.c.	Wood and products of wood and cork
Electrical machinery and apparatus, n.e.c.	Printing and publishing
Other business activities	Coke, refined petroleum products and nuclear fuel
Public admin. and defence - compulsory social security	Rubber and plastics products
	Radio, television and communication equipment
	Medical, precision and optical instruments
	Other transport equipment
	Manufacturing n.e.c.
	Electricity, gas, steam and hot water supply
	Research and development
Likely by R&D	**Unlikely by R&D**
Chemicals and chemical products	Food products and beverages
Radio, television and communication equipment	Tobacco products
Medical, precision and optical instruments	Wearing apparel, dressing and dyeing of fur
Other transport equipment	Leather, leather products and footwear
Research and development	Wood and products of wood and cork
	Printing and publishing
	Coke, refined petroleum products and nuclear fuel
	Rubber and plastics products
	Fabricated metal products, except machinery and equipment
	Manufacturing n.e.c.
	Other business activities
Likely by HHI	**Unlikely by HHI**
Other mining and quarrying	Wearing apparel, dressing and dyeing of fur
Food products and beverages	Wood and products of wood and cork
Tobacco products	Printing and publishing
Leather, leather products and footwear	Coke, refined petroleum products and nuclear fuel
Rubber and plastics products	Chemicals and chemical products
Other transport equipment	Fabricated metal products, except machinery and equipment
Manufacturing n.e.c.	Radio, television and communication equipment
Public admin. and defence - compulsory social security	Medical, precision and optical instruments
	Research and development
	Other business activities

Chapter 4 Does Competition Increase Innovation? An Empirical Assessment Using Firm-Level Data

Abstract

In this chapter, I empirically investigate the impact of competition intensity on innovation. I analyse a firm-level dataset for 1025 firms in 8 industries in 26 developing countries over the period 2002-2005. Data is obtained from The Business Environment and Enterprise Performance Survey (BEEPS). I examine two types of innovation: product and process innovation. I start the analysis with simple probit and linear probability estimation. I then use an instrumental variable approach to account for the potential endogeneity problems. Leniency programmes implementation in a country is used to provide an exogenous variation in the competition index. I find a robust positive effect of price-cost margin on innovation, which suggests that competition intensity has a negative impact on innovation. Instrumental variable results suggest that one percentage point increase in price-cost margins is associated with on average about a 0.0458 percentage points increase in the probability of product innovation and 0.0365 percentage points increase in the probability of process innovation.

Keywords: Innovation, Leniency Programmes, Competition
JEL Classification: O31, K21, L4, D41

4.1 Introduction

Innovation is widely viewed as the engine of growth in an economy. Schumpeter (1934) was a pioneer in explaining the economic growth with entrepreneurial innovation. He explains that growth is mainly driven by a sequence of quality-improving innovations, and each innovation destroys the monopoly rents generated by previous ones. Thus, higher rates of creation and destruction are associated positively with growth. Since then, several authors have incorporated innovation into their models, putting it at the heart of the growth process (Romer, 1968; Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman,1991). These models consider that investment in designing new or better commercial products is the source of long-run growth. Given the importance of innovation, it is crucial to identify its determinants. In this chapter, I analyse one of the main determinants of innovative activity, namely competition.

Theoretical studies on the impact of competition on innovation suggest three different effects. On the one hand, intense product market competition discourages innovation as it reduces the profits of successful innovators. This relation between competition and innovation is known as the Schumpeterian effect. On the other hand, product market competition induces innovation by the ample rewards for innovation leaders that escape neck-and-neck races with their rivals. This is known as the escape-competition effect. Recently, however, Aghion et al. (2005) have developed a theoretical model that combines the Schumpeterian effect with the escape-competition effect. They argue that the escape-competition effect dominates in industries where firms are technologically equal (neck-and-neck industries), whereas the Schumpeterian effect dominates in industries where there is a leading firm that is technologically ahead of other firms (leader-laggard industries).

In this chapter, I analyse the empirical relationship between competition intensity and innovation. I focus on developing countries over the period in which they first started adopting their national leniency programmes and which led to exogenous variation in the nature and the magnitude of product market competition. The primary data source for this chapter is the Business Environment and Enterprise Performance Survey BEEPS. I obtain a firm-level data of twenty-six developing countries across eight industries from 2002 to 2005. Following the literature, I consider different approaches to measure the level of a firm's innovation. First, I proxy a firm's innovation by innovation outputs. Under this approach, I use a dummy that captures whether a firm has undertaken any product innovation and similarly for process innovation. The second approach is to capture innovation inputs by the total amount of research and development (R&D) spending. To measure competition intensity, I use firms' self-reported price-cost margins. I also provide the number of competitors as an alternative measure of competition intensity. I combine the BEEPS dataset with country-level data obtained from the World Bank on GDP as well as data that I collected from the national competition authorities on the implementation of leniency programmes.

I begin the analysis of the impact of competition intensity on innovation by estimating ordinary probit and linear probability models. In all specifications of the model, I control for firm-level, industry-level and country-level characteristics which are likely determinants of firms' innovative activity. The results suggest that the probability to innovate decreases with the intensity of competition, which confirms the Schumpeterian hypothesis.

The major empirical concern in analysing this relationship is the endogeneity in the measure of competition intensity. This issue might arise from both reverse causality and omitted variable bias. Reverse causality appears to be a feature of this relationship because while market structure might affect innovation, highly innovative firms may also be more likely to dominate the market. Omitted variable bias exists as it is very likely that industries exhibit different levels of innovation activities that have no direct causal relationship with competition intensity, but rather reflect other features of the industry such as their technological opportunities and appropriability conditions. Therefore, I control for time-invariant individual heterogeneity at the industry-country level by using fixed effects. The panel structure of the data allows me to control for industry and country fixed effects which removes the bias that results from the permanent level of innovation and competition. I also exploit an instrumental variable approach, using the adoption of leniency programmes in a country as instruments for competition intensity. The inclusion of a country and time effects allows me to identify the competition effect through the the introduction of leniency programmes across countries. The idea of using leniency programmes as instruments is that their ultimate objective is to deter behaviours that reduce competition. Hence, I expect a higher level of competition to be associated with the implementation of these programmes. The exclusion restriction for my instrument is related to the fact that the imposition of a leniency programme in a country does not affect the innovative behaviour of this country.[40] Furthermore, I analyse a cross-section in which I introduce the lagged values for both competition intensity measures: price-cost margins and the number of competitors that a firm has. This allows me to account for the potential endogeneity in these measures. Overall, my findings suggest that the probability of innovation decreases with competition. The Instrumental Variable analysis suggests that a one percentage point increase in the price-cost margin increases the probability of product innovation by 0.0458 and the probability of process innovation by 0.03565. Cross-sectional results show that as the number of competitors that a firm faces increases by one unit, the probability of product innovation, process innovation and R&D investment decreases by 0.0821, 0.119 and 0.148 percentage points respectively.

I contribute to the literature on competition and innovation in three main ways. First, I focus on firm-level data in emerging countries. While this relationship was widely analysed empirically in developed economies, research on developing countries is scarce. Second, I

[40] I cannot test the exclusion restriction directly in my framework as I am using an exactly identified IV model.

provide further empirical evidence on the negative role of competition in promoting innovation in developing countries. Thus, this research adds to the empirical literature which has not been conclusive on the effect of competition on innovation. Other studies point to a positive, negative or an inverted-U relationship. Finally, I provide a novel way of addressing the endogeneity problem between competition and innovation by using leniency programmes as instrumental variables which vary by industries, countries and time.

The remainder of the chapter is structured as follows. Section 2 provides a review of both theoretical and empirical literature on innovation and competition. Section 3 presents the data, variables and descriptive statistics. Section 4 introduces the empirical model and the identification strategy. Section 5 discusses the results. Section 6 performs some robustness checks. Section 7 briefly concludes.

4.2 Related Literature on Competition and Innovation

The relationship between competition intensity and firms' incentives to innovate has received considerable attention in the literature. In this section, I first discuss the theoretical literature on the topic followed by the empirical literature.[41]

4.2.1 Theoretical literature

Schumpeter (1942) was a pioneer in studying the relationship between innovation and competition. His main hypothesis suggests that large monopoly firms are an effective engine for the economic progress. He argues that innovation is driven by the expected monopoly rents from a successful innovator and those rents decline with competition. The Schumpeterian paradigm was later opposed by Arrow (1962), who argues that the incentives to innovate are higher in a competitive market than in monopolistic conditions. That is, the pre-invention monopoly power disincentivises further innovations.

[41] For a comprehensive literature review see Aghion and Griffith (2008).

Hereafter, both theoretical models of industrial organisation and in growth theory predict that intense product market competition discourages innovation by reducing post-innovation rents. The main models of product differentiation and monopolistic competition, developed by Salop (1977) and Dixit and Stiglitz (1977), predict that increased product market competition discourages firms from entering the market (or innovating) as it reduces the post-entry rents for successful entrants. Salop (1977) captures increased competition by a decrease in transportation costs, while Dixit and Stiglitz (1997) model captures increased competition by an increase in the rate of substitutability between differentiated products. Later, these predictions were supported by endogenous growth literature where increased product market competition (or imitation) reduces monopoly rents of a successful innovator and thus reduces the productivity growth (Romer, 1986; Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1994).

Unlike the previously mentioned literature, where firms are assumed to be profit maximising, Hart (1983) incorporates agency problems and assumes that firms are run by “effort minimising” managers. Here, competition alongside with managers’ fear of liquidation and hence, of losing their jobs, act as an incentive scheme for firms to innovate. However, Scharfstein (1988) and Schmidt (1998) show that this positive role that competition plays in innovation becomes ambiguous when managers respond to monetary incentives. That is, an increased level of product market competition induces managers to exert more effort fearing from bankruptcy whereas it induces less effort as more competition reduces firms’ expected profits. Aghion et al. (1999), follow a similar line of thought by introducing “agency considerations” of Hart (1983) in an endogenous growth framework. They distinguish between profit-maximising firms and “conservative” firms, where managers only worry about preserving their private benefits and avoiding bankruptcy. Their model predicts that the Schumpeterian effect appears when firms are profit-maximising, whereas competition fosters innovation when firms are controlled by managers who solely care about staying in business.

In all the previously mentioned papers, innovations are assumed to be made only by outsiders. Instead, Aghion et al. (1997) develop a model where incumbent firms are allowed to innovate, and innovations occur "step-by-step" rather than by "leapfrogging"[42] over the current industry leader. That is, the laggard firm must first acquire the current level of technology before being a future leader. The main distinction of this model is that innovation depends on the difference between post- and pre-innovation rewards rather than on the post-innovation rewards solely.[43] The model predicts that more intense product market competition is associated with increased incentives to innovate aimed to escape competition.

In the light of the previous contradictory results, Aghion et al. (2005) develop a theoretical model in the Schumpeterian tradition to capture an inverted-U relationship between innovation and competition. They build a stylised model of an economy which consists of two types of duopolies: neck-and-neck industries where firms are technologically equal and leader-laggard industries where one firm (the leader) is technologically ahead of the other (laggard firm). In this framework, competition has two opposing effects: a Schumpeterian effect and an escaping-competition effect. The Schumpeterian effect implies that stronger degree of competition reduces profit and hence innovative activity. The escape-competition effect implies that a firm innovates to escape symmetric competition and enjoy a higher level of profits from being a leader rather than being a neck-and-neck firm. Their model shows that, in neck-and-neck industries, the competition is intense and the escape competition effect dominates the Schumpeterian effect; thus, more competition increases innovation. On the other hand, in leader-laggard industries, the Schumpeterian effect dominates the escape-competition effect; more competition may also decrease innovation as the laggard's profit may drop when catching up with the leader may drop down.

[42] The laggared firm cannot use or develop the exsisting technologies but rather leapfrog the current technology leaders.
[43] When innovations are made by outsiders, the pre-innovation profits are equal to zero.

4.2.2 Empirical literature

Existing empirical work on the relationship between competition and innovation shows diverse and conflicting results, ranging from a negative relationship to a positive or even a U-shaped relationship. Obtaining contradictory results may be attributed to two factors. First, there may be a measurement error resulting from the difficulty of finding clean and direct measures of both competition and innovation in the field data (Aghion et al., 2014). Second, different measures of market competition usually are endogenously determined by firms' innovation behaviour (Beneito et al., 2015).

A large empirical literature has been inspired by Schumpeter (1943), whose main hypothesis suggests that innovative activities are induced by large firms with monopoly power. In line with Schumpeter, Kraft (1989) analyses a cross-section of 57 West German firms in 1979 in the metal industry. He finds a strong positive effect of imperfect competition (measured by the number of competitors and entry barriers) on product innovation, as measured by the percentage of sales attributed to the introduction of new products. Crepon et al. (1998) find a positive and statistically significant effect of market power (measured by market share) on R&D intensity. Gayle (2001) confirms the Schumpeterian hypothesis using US firm-level panel data. He finds a positive relationship between industry's concentration and firms' innovation, where innovation is measured by simple or citation-weighted patent count. Carlin et al. (2004) find that facing a few number of rivals is more conducive to firm's innovation than facing many competitors.

In contrast, other authors support the escape competition effect as they find that more competition (lower concentration) is associated with more innovative activity.[44] Nickell (1996), Blundell et al. (1995) and Blundell et al. (1999) use panel data of manufacturing firms listed on the London Stock Exchange to support that more competition is good for innovation. While

[44] Other research by Porter (1990), Baily et al. (1995), Symeonidis (1996, 2002b, 2008), Galdon-Sanchez and Schmitz (2002), and Okada (2005) has also confirmed the positive effect of competition on innovation.

Nickell (1996) uses total factor productivity (TFP) as a measure of innovation, Blundell et al. (1995) and Blundell et al. (1999) use the Science Policy Research Unit (SPRU) innovation count. Both use market share, concentration, and import penetration as measures of concentration. Geroski (1990, 1995) uses industry-level data controlling for industry-level characteristics that are correlated with market structure. Based on industry-level cross-sections, Acs and Audretsch (1988a,1988b) find a negative relationship between concentration and innovation (as measured by the number of innovations introduced over the total number of employees per industry). Following the theoretical model of Vives (2008)[45], Beneito et al. (2015) test empirically the relationship between market competitive pressure and innovation using Spanish firm-level panel data for 1990-2006. They construct variables that capture competitive pressure such as product substitutability, market size and entry costs in the context of free entry. Their results show that competitive pressure spurs process innovation, but not product innovation while larger market incentivises both product and process innovation. Griffith et al. (2006) look into the effect of various reforms that are associated with the single market programme in the EU on competition intensity and the consequent effect on industries' innovation. Aghion et al. (2009) control for the endogeneity of competition (measured by firms entry) by the variation on both EU (single market programme) and the UK reforms (privatisation). Both Griffith et al. (2006) and Aghion et al. (2009) find that competition is associated with increased innovation and productivity growth.

Given the long debate over whether the relationship between competition and innovation is positive or negative, some authors reconcile the opposite lines of thought into a non-monotonic relationship between product market competition and innovation. Using panel data of UK manufacturing firms, Aghion et al. (2005) find an inverted-U relationship between

[45] Vives's (2008) theoretical framework shows that enhanced competition spurs innovation, depending on the measure of competition (product substitutability degree, market size or a decrease in entry costs) and the type of innovation (product or process).

competition, as measured by the Lerner Index or price-cost margins at the industry level, and citation-weighted counts of patents. That is, the escape-competition effect dominates for low initial levels of product market competition while the Schumpeterian effect tends to dominate at higher levels of competition. This result is in line with earlier work of Scherer (1965a, b) and Levin et al. (1985). In the spirit of the work of Aghion et al. (2005), many authors confirm their empirical results in different datasets employing different measures of competition and innovation. Tingvall and Poldahl (2006), Friesenbichler (2007) and Tingvall and Karpaty (2011) confirm this relationship between firm R&D and the Herfindahl index. Also, Friesenbichler (2007) finds this relationship is robust when measuring innovation by novel product launch indicator as an alternative measure of innovation, while Tingvall and Poldahl (2006) this result is not supported when changing the competition measure to price-cost margins.

Tingvall and Karpaty (2011) capture this relationship for both profit elasticity and the Herfindahl index as competition measures, but not for the price-cost margin. Polder and Veldhuizen (2012), confirm the inverted-U relationship between R&D investment and two different measures of competition: price-cost margins and profit elasticity[46], both at the firm-level and the industry-level. Bos et al. (2013) confirm the inverted-U relationship in the US banking industry between innovation, as measured by firms' technology gaps and the price-cost margin. Askenazy et al. (2013), elaborate the cost of innovation (cost of patenting) to the work of Aghion et al. (2005). They confirm the existence of a U-shaped relationship between R&D and Lerner index using French firm-level dataset. This relationship becomes flattered as the costs of innovation increase. This suggests that competition becomes less important in the innovation-decision when innovation costs are relatively high (in comparison to value added).

Despite the previous results, there is also work showing no relationship between

[46] Elasticity as a competition measure which is based on firms' profits was proposed by Boone (2008). Boone shows that the measure is more theoretically robust in comparison to the price-cost margin and can solve the empirical problems related to the latter.

competition and innovation. Scott (1984) uses data from 437 firms in the manufacturing industry. His results show no significant correlation between R&D intensity and market structure when controlling for industry fixed effects and firm fixed effects. Based on the same dataset as Aghion et al. (2005), Correa (2012) finds a structural break following the establishment of the United States Court of Appeals for the Federal Circuit in 1982 where the inverted-U empirical relationship found by Aghion et al. (2005) does not hold. His results suggest an unstable relationship between competition and innovation; a positive relationship only during between 1973 and1982 and no relationship during the period 1983-1994.

The above discussion highlights that there is an intense debate on the relationship between competition and innovation. In this chapter, I contribute to this debate by providing a novel instrumental variable approach to address the endogeneity issue between competition intensity and innovation. My results confirm the Schumpeterian hypothesis in which market power stimulates innovative activity.

4.3 Data

I use a sample of 1457 enterprises in 8 industries and 26 transition countries for two years 2002 and 2005. The countries included in the study are Eastern European and Central Asian countries. More precisely, the countries are Albania, Armenia, Azerbaijan, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, Macedonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Ukraine and Uzbekistan.

Analyzing the period 2002-2005 is useful because it coincides with the implementation of leniency programmes for most of the countries in my sample. Furthermore, my competition intensity indicator, the price-cost margin, is only observed in these two waves. Industries in this study are mainly from the manufacturing and retail sectors as well as from a residual stratum that includes most services sectors and construction. In particular, mining and quarrying, construction, manufacturing, transport storage and communication, wholesale and retail trade, real estate, renting and business services, hotels and restaurants and other services.

Data used is at national, industry- and firm-level. In this section, I will present the data sources as well as the definition of the variables employed in the analysis.

4.3.1 Measures of innovation, competition, and other firms' characteristics

The primary data source is the Business Environment and Enterprise Performance Survey (BEEPS) which is a joint survey of firms in 27 transition countries by the European Bank for Reconstruction and Development (EBRD) and the World Bank Group (World Bank) and which has been designed to evaluate the environment for private enterprise and business development. BEEPS was collected in five rounds (1999-2000, 2002, 2005, 2008-2009 and 2011-2014) and it covers questions regarding firms' innovative behaviour such as, whether a firm developed a significantly new product or process. It also covers a wide range of related business environment topics, such as access to finance, infrastructure, corruption, crime, competition and performance measures. As such, BEEPS is a rich source of data for investigating the relationship between innovation and competition.

Many different innovation intensity measures at the firm level have been considered in the literature; for example: research and development spending, innovation counts, patents, total factor productivity and indicators of whether a firm has developed any products or processes or not. In this study, I rely on BEEPS data which provides information about firms' innovation activity through data regarding firms introducing new or significantly improved products or processes in the last three years. This allows me to distinguish between two types of innovation: product and process innovation. As for product innovation, I construct a dummy variable which takes the value of 1 if the firm reports that it has introduced a new or significantly improved product in the last three years. Similarly, for process innovation, I construct a dummy variable which takes the value of 1 if the firm reports the introduction of a new or significantly improved process in the last three years. Another measure of innovation is Research and Development (R&D). This measure focusses on innovation input rather the output of the innovation process. I construct a dummy variable that is equal to one if a firm reports positive R&D spending in the last three years and zero otherwise. Also, I use the total amount of R&D spending in the last fiscal year as a measure of innovation. This measure is skewed, as a large number of firms report zero expenditure. Since few firms answer the question regarding R&D expenditure, the sample size shrinks considerably.

As a measure of competition intensity, I use two different measures. First, I use self-reported price-cost margins to gain an insight into the firms' competitive behaviour as well as the level of competition they believe they face. Moreover, firms are asked to answer the survey question: how many competitors did the establishment's main product line face? I include the number of competitors as an alternative measure of competition intensity.

BEEPS also contains information on several characteristics of the firm, such as size, sales, exports and type of ownership. I introduce the lagged values of these measures as explanatory variables to account for their potential endogeneity in these measures. The lags refer to a 3-year period which is the interval between the single BEEPS waves.

To measure the firm's size, BEEPS provides data on the number of full-time employees in the 36 months then classifies firms as: small if the number of employees is less than 50, as medium if the number of employees is between 50 and 249, and as large firms if the number of employees is greater or equal to 250. The argument for controlling for size is that it can affect the ability to invest in R&D because of easier access to funds and resources as well as spread R&D costs. Furthermore, I control for firms' exports. This variable is constructed as the percentage of exports in sales in the last fiscal year. I add two variables that capture the firms' ownership:

private or public. I also control for corruption by constructing a dummy that takes a value of one if a firm reports that corruption constitutes an obstacle.

In addition to the main firm-level variables, I include a small set of country-level data. Since this analysis involves 27 countries, the set of control variables is small due to comparability issues. I control for the natural logarithm of the GDP per capita in US dollars. GDP per capita is taken from the World Bank, and it is measured in US dollars currency. Moreover, I control for the EU East enlargement by adding a dummy variable for the new member states. This dummy takes a value of one after the year in which a country has joined the EU. Information of EU membership is obtained from the European Commission presented in Table 1. As for the instrumental variable, I construct a dummy variable that takes a value of one if the year postdates the implementation of a leniency programme in a country and zero otherwise. To reduce the heterogeneity in leniency programmes, as in Klein (2010), I only consider the date in which full amnesty is granted by the programme for the first confessor. Data is collected from the homepages of the national authorities for each country. Table 4.1 shows the dates at which countries in the sample adopted a leniency programme.

4.3.2 Descriptive statistics

Table 4.4 provides descriptive statistics for the main variables discussed above. It compares means and standard deviations for the key variables used in the empirical analysis. 1457 firms are surveyed in two years 2002 and 2005. On average, 36.46 percent of firms report product innovation in the last fiscal year while 51.45 percent of firms report process innovation. Unfortunately, only a small fraction of firms respond to the question about the amount of R&D expenditures in the sample period. Thus, the sample size with non-missing responses is reduced to 1,066 for real R&D expenditures. The average amount spent on R&D investment is about 14.96 US Dollars. On average, 42 percent of firms reported positive spending on R&D activities.

Table 4.2 shows the distribution of firms across industries. BEEPS covers firms operating in the majority of manufacturing sectors (excluding extraction), retail and a residual stratum that includes most services sectors (wholesale, hotels, restaurants, transport, storage, communications, IT) and construction. Thus, the survey provides a representative sample of an economy's private sector. Table 4.3 shows that 25.07 percent of firms are operating in a wholesale and retail trade industry followed by manufacturing industries. Table 4.4 lists the countries used in the analysis and show the distribution of firms across these countries. The highest fraction of firms is located in Turkey followed by Russia, Albania and Poland.

Table 4.5 presents data on the number of firms innovating in the two rounds, innovating in one round only and firms which report no innovation. 206 firms report product innovation in both 2002 and 2005 while 352 firms report process innovation. There are 484 firms which report no product innovation and 323 firms that do not report any process innovation. 353 firms conduct product innovation while 350 firms conduct process innovation once in the two rounds.

4.4 Empirical Strategy

To assess whether more competition induces more innovation, I start by estimating simple probit and linear probability models to account for the binary nature of the innovation variables. More specifically, the central relationship I want to estimate is captured in the following model:

$$Innovation_{f,t} = \Phi\{\delta_1 Competition\ _{f,t} + \beta_1 X_{f,t} + \ \beta_2 Z_{c,t-1} + \alpha_{i,c} + \alpha_t + \epsilon_{f,t}\} \qquad (1)$$

where $Innovation_{f,t}$ is a dummy variable that takes a value of one if firm f at time t reports an innovation-related activity and zero otherwise, Φ is the c.d.f of standard normal random variable, $Competition\ _{f,t}$ is measured by price-cost margin or number of competitors, $X_{f,t}$ is a set of firm-level control variables such as firms' size as measured by the number of employees, exports and ownership, $Z_{c,t-1}$ is a set of country-level controls such as GDP growth and EU membership, $\alpha_{i,c}$ are industry and country fixed effects, α_t are time dummies, δ_1, β_1 and β_2 are the parameters and $\epsilon_{f,t}$ is the error term. I include time, industry and country fixed effects. I estimate equation (1) separately taking product innovation, process innovation and R&D dummies as the dependent variable.

One of the main concerns is that price-cost margin might be endogenous to the innovation-decision due to reverse causality. In other words, it is not only market structure that affects innovation; highly innovative firms might dominate the market. Another potential source of endogeneity bias is omitted variables that affect both innovation and competition. As a first attempt to address this problem, I allow for industry effects to remove the bias that results from the correlation between the permanent level of innovation activity and competition level. I introduce a set of firm- and country-level variables that affect the innovative activity. I introduce a time lag for all control variables to reduce potential bias due to two-way causality.

Although I control for firm-level and industry-level characteristics, omitted-variable bias may still be a concern as firm and industry dummies might not remove all spurious correlation between the competition intensity measure and innovation. In particular, unobserved characteristics that are, at the same time, correlated with innovation and the price-cost margin index may cause a correlation between price-cost margin and innovation and therefore, result in biased estimators. That is, industries may differ according to their institutional features (Griffith et al., 2005). In particular, industries may differ by the technological opportunities and the appropriability conditions. Therefore, I employ an instrumental variable approach, using leniency programme as an instrument for the degree of competition that firm faces in a market (as measured by price-cost margin). Leniency programmes are tools which aim to destabilise, detect and deter cartels. Successful leniency programmes should ultimately deter *ex-ante* or *ex-post* collusive behaviour. If cartels are deterred, a non-cooperative competitive market outcome is achieved. As the ultimate goal of leniency programmes is to increase industries' competition intensity, leniency programmes may be valid instruments as they are arguably uncorrelated with a firm's innovativeness, but positively correlated with industry's competition intensity. Klein (2010) uses industry level data for 23 countries over a period of 20 years to show that the impact of leniency programmes on competition intensity is to increase the competition intensity (bring down the price-cost margin). According to his estimates, price-cost margin came down by around 3 to 5 percent.

Thus, to account for the endogenous relationship between competition and innovation, I estimate a linear probability and IV probit models using leniency programmes as instrumental variables, controlling for the firm- and industry-level characteristics. Thus, the first-stage equation is given by:

$$Competition_{f,t} = \beta_l \, Leniency\ programmes_{c,t} + \beta_1 X_{f,t} + \beta_2 Z_{c,t-1} + \alpha_{i,c} + \alpha_t + \epsilon_{f,t}\,, \quad (2)$$

where $Competition_{f,t}$ is measured only by the price-cost margins in the Instrumental Variable approach.

I also provide an alternative approach to tackle reverse-causality using lagged values of the competition intensity measures. As a drawback of this approach, the price-cost margin is only observed in two waves, namely the 2002 and 2005 wave. Thus, I would lose many observations.

4.5 The Effect of Competition on Innovation

My main interest is to assess the effect of competitive pressure on the likelihood of product and process innovation and R&D expenditures econometrically. Since the dependent variables are binary variables, the natural starting point is to estimate probit and linear probability models with both types of innovation as dependent variables. Then I move to address the endogeneity bias using 2SLS and IV probit models.[47]

4.5.1 The Effect of competition on product innovation

In Table 4.6, I start with the baseline specification in columns (1) and (2) by running linear probability and probit models with product innovation as the dependent variable. I take these two models as baseline estimations although they arguably ignore potential endogeneities of the competition variable. For the probit model, marginal effects at the sample mean are reported. I report marginal effects rather than the coefficients as they are of more direct economic relevance and they are directly comparable across specifications. Results fail to reveal a significant impact of price-cost margins on product innovation. In columns (3) and (4), I control for potential endogeneity using IV specifications. Competition intensity is positive and significant throughout both IV specifications.[48] Including industry-country-specific fixed effects attempt to control for unobserved heterogeneity among industries and countries. Column (3) shows the first-stage estimate in which I use leniency programmes implementation as an instrument. The results of the first-stage reveal a negative and significant impact of leniency programmes on the price-cost margin. Indeed, the F-statistics of the excluded instrument in the first-stage of 12.6022 (p-value 0.0004) suggests, according to Stock and Yogo (2002), that there may not be a weak instrument problem. This could be interpreted, as, in countries where leniency programmes are imposed, firms are more likely to face a higher degree of competition. The first-stage fitted values are then plugged into the second-stage regression to obtain the causal effect of competition on innovation. Column (4) reveals a negative impact of price-cost margins on product innovation. That is, an increase in the price-cost margin by one percentage point decreases the probability of product innovation by 0.0458 percentage points. Consistent with the endogeneity concern, a Hausman

[47] Angrist and Pischke (2009) suggest using a linear two-stage least square identification when having an endogenous binary regressor even if the dependent variable is of a binary nature.
[48] Running the regressions in Table 4.5 including country-time specific effect provides positive, but insignificant marginal effects of competition on innovation.

test rejects the null hypothesis that OLS and IV coefficients do not differ (p-value 0.0000).

In columns (5) and (6), I provide the results of an IV probit model, where competition intensity is instrumented by the presence of leniency programmes. IV probit linearises the first-stage regression while estimating a probit model in the second stage. Column 6 shows the marginal effect of the second-stage IV-probit estimates. Again, the positive coefficient suggests that firms that face less competitive pressure are, indeed, more likely to introduce new products. Specifically, the estimate of the marginal effect, estimated at the sample means, is 0.0593 and it is significant at the one-percent significance level. A Wald test rejects the null hypothesis of exogeneity (p-value 0.0002) which suggests again the necessity to use IV to address the causal relationship between competition intensity and product innovation. As a side finding, the estimates in the second-stage show the propensity of both product and process innovation is positively associated with firm size.

4.5.2 The effect of competition on process innovation

Table 4.7 presents the impact of competition intensity on process innovation. In column (1), I present the results of a linear probability model. Results suggest that the probability of innovating increases by 0.0279 percentage points. The results of the probit model in column (2) also suggest that facing less competition increases the propensity of process innovating by 0.0725 percentage points.

Moving to the 2SLS estimation results in column (4) suggest that higher price-cost margin increases the probability of process innovation by 0.0365 percentage points. In comparison with the results of the estimation of the linear probability model, the coefficient of competition has increased from 0.0279 to 0.0365. This increase in the magnitude after employing IV suggests that endogeneity is probably an issue in the estimate. Indeed, running a Hausman test, which compares OLS with IV, confirms an endogenous relationship between price-cost margin and innovation and favours the use of IV techniques (p-value 0.0067). In particular, the null hypothesis of an exogenous regressor is rejected which reinforces that the IV estimates differ statistically from OLS estimates. The results highlight the importance of controlling for the endogeneity of competition intensity when identifying its effect on process innovation. In columns (5) and (6), I present the results of the IV probit model. The results are consistent with the 2SLS. Specifically, the estimates of the marginal effect, estimated at the sample means, is 0.0551 which is significant at the one-percent significance level. Controlling for potential endogeneity problem, using IV probit specifications shows a significant increase of the magnitude of the price-cost margins from 0.0725 to 0.0551. Wald test rejects the null hypothesis of exogeneity (p-value 0.0103).

Overall, the positive marginal effects/coefficients of Table 4.7 suggest that firms which report facing greater competitive pressure are less likely to develop new processes.

4.5.3 The effect of competition on R&D expenditures

As a robustness check, I provide alternative measures for innovation, namely, a dummy for R&D positive spending as well as the real R&D expenditures. By using these measures, I focus on innovation efforts (or input), rather than on the outcome of the innovation process (output).

Table 4.8 presents results of R&D using a binary variable of whether a firm has made a positive R&D spending as the dependent variables. In column (1), linear probability and probit models reveal a significant and positive relationship. In column (4) and (5), I use an IV setting to control for the potential endogenous relationship between competition intensity and the R&D dummy. The second-stage IV results suggest that an increase in the price-cost margin increases the probability to invest in R&D by 0.0653. Results are significant at the 5 percent level. A Hausman test of endogeneity suggests that the relationship is of endogenous nature and thus IV is preferable to OLS. Similarly, when applying the IV-probit model, the results show an increase in the probability to invest in R&D by 0.0624 as price-cost margin increases by one percentage point.

I compliment the analysis by studying the impact of competition intensity on the log of real R&D expenditures. However, the downside when analysing innovation, using log of real R&D expenditures as the dependent variable, is that I will drop 84.67 percent of firms with zero R&D expenditures. Therefore, following Card and DellaVigna (2013), I instead use an alternative functional form, namely log (real R&D +1). Table 4.9 presents the results using log (real R&D +1) as the dependent variable. Running an OLS model reveals that, on average, a one percentage point increase in price-cost margins increases R&D expenditures by 0.20 percent. Second stage IV specifications also suggest that, on average, a one percentage point increase in price-cost margins is associated with a 3.05 increase in R&D spending. However, in both previous specifications, no significant impact is captured. Despite the endogeneity concern, running a Hausman test which compares OLS and IV estimates, cannot reject the null hypothesis of the exogeneity of competition intensity (p-value 0.73). That is, the results obtained with OLS are in line with the ones obtained using IV specifications. Overall results suggest that an increase in the price-cost margin provides an incentive to invest in innovative R&D activities.

4.6 Discussion and Additional Robustness Checks

This section provides some robustness checks. First, as a robustness check, I address the reverse-causality between competition and innovation by using earlier values of competition intensity measures (year 2002) and later values of the innovation measures (year 2005). While competition intensity is likely to affect innovation, it is also the case that successful innovation affects the competitive situation in the market. In other words, successfully innovating firms will have lower costs and will be able to sell at a lower price or they will produce a superior quality good. Thus, by using the lagged values of the competition intensity measure, I can get a sense of the magnitude of the endogeneity bias (given that three years' lag is enough to minimise the reverse causality). Table 4.10 uses price-cost margins in 2002 as a measure of competition intensity. The impact of an increase in price-cost margins on the probability of innovation is positive. However, no significant impact is obtained. This might be attributed to a significant drop in the sample size.

Second, I use an alternative measure of competition which is the number of competitors that the firm is facing. In Table 4.11, I use the number of competitors as competition intensity index. Linear probability model shows that the probability of product and process innovation decreases by 0.00362, 0.00315 percentage points respectively as the number of competitors increases by one firm. Also, as the number of competitors increases by one firm, the probability of investing in R&D activities drops by 0. 00683 percentage points.

One concern regarding the analysis is that the quality of the survey data relies heavily on the knowledge and judgement of the respondent. As discussed by Mairesse and Mohnen (2010), self-reported measures may be subjective as it reflects the respondent's judgment to the survey questionnaire. For instance, it may not be clear to the respondent what exactly defines a new or improved product or process. Furthermore, the accuracy of the self-reported measures relies heavily on the respondent's knowledge of his market. For example, respondent's knowledge is what determines his ability to distinguish between "new to the market" and "new to the firm". Another concern regarding the use of the survey data is that, even with accounting and financial variables, the respondent might report a wrong value. This is because firms normally do not keep this information in a form that enables them to give precise answers. I check the validity of the self-reported competition measures, namely PCM and the number of competitors. Figure 3.1 shows that firms which report facing zero competitors have the highest PCM, and this PCM decreases with the number of competitors.

Another concern in the data is regarding the quantitative measure of innovation, namely

R&D expenditures. The sample size decreases significantly when using the R&D expenditures, as many firms did not report R&D expenditures. The results also show no significance when using R&D expenditures as the dependent variable. However, this issue is not unusual in innovation surveys. Mairesse and Mohnen (2010) point that R&D variable is often of a low quality and even is left not answered. Therefore, in the next chapter, I address this issue by analysing an industry-level panel with R&D spending as the main innovation measure. Nevertheless, with these limitations in mind, this chapter provides an insight of the role that competition intensity plays in developing countries.

And finally, the Instrumental variable approach only estimates a local average treatment effect (LATE): the effect of leniency programmes on the compliers[49], i.e. the firms who were eligible and actually applied for leniency. According to the LATE theorem, the population is divided with the instrument into four possible groups: the compliers, the never-takers, the always-takers and the deifiers. The compliers are the firms that their treatment status is affected by the instrument in the right direction (decrease in price-cost margins). The always-takers are firms that always take the treatment (apply for leniency) independent of the instrument. The never-takers are the firms that never take the treatment (never apply for leniency) independently of the existence of the programme. And the defiers are the firms that their treatment status is affected by the instrument in the “wrong” direction. The Instrumental Variable approach cannot estimate the effect for firms which do not comply. First, it assumes that defiers do not exist because if they do this could cancel/partially cancel the effects on compliers by the opposite effects on the defiers. Second, the Instrumental Variable is not informative about the effect on always-takers and never-takers because the implementation of leniency programmes does not change their treatment status. Whereas the always-takers is less of a concern in my analysis, one may be interested in estimating the average treatment effect on the whole population (ATE) and

[49] For details about the LATE theorem see Imbens and Angrist (1994)

which is not possible with the instrumental variable approach.

4.7 Conclusion

Earlier empirical work has shown ambiguous effects of competition intensity on innovation. Some authors point to a positive relationship, others to a negative one, and even to a U-shaped relationship. These conflicting conclusions could be attributed to endogeneity problems when analysing this relationship empirically. In particular, there may be a reverse causality bias in the relationship: market structure may affect innovation as high market shares boost the innovation activity. At the same time, highly innovative firms might control the market. Moreover, it is necessary to control for other observable and unobservable firm characteristics to eliminate the omitted variable bias. The panel structure of my data allows me to control for firm characteristics that are correlated with competition intensity and constant over time using firm fixed effects. In addition, lagged values of competition intensity measures allow for reducing the reverse causality bias, assuming that the competitive situation for firms in an earlier year might give rise to future innovation, but not vice versa.

In this chapter, I test the effect of competition intensity, as measured by the price-cost margin on developing new products, processes and investing in R&D activities, using a comprehensive sample of firms in low and middle-income economies in Eastern Europe and Central Asia.

To tackle the endogeneity problem, I employ a novel instrumental variable that affects competition intensity but does not affect innovation directly, namely, leniency programmes implementation. Leniency programmes are tools used to detect and destabilise cartels, ultimately increasing product market competition. I use only the variation in competition that is induced by the existence exogenous variation in the implementation of leniency programmes. In other words, I identify the causal effect of competition on innovation under the presence of leniency policies.

Results are in line with the Schumpeterian hypothesis and tell a consistent story: firms which face less competitive pressure are more likely to innovate. OLS results suggest that the probability of innovation increases when firms face less competition. An instrumental variable approach reveals a positive and significant causal effect of price-cost margins on the probability of innovation. Results are robust to different measures of innovation and competition. As a measure of innovation, I employ both input (R&D expenditures) and output measures (process and product innovation).

In the next chapter, I complement my analysis by analysing a panel of OECD countries at the industry level. I aim to verify whether innovation can be maintained under a low level of competition in more developed countries.

4.8 Appendix

Table 4. 1: Leniency Implementation and EU Membership

Country	National Leniency Programme	EU Members
Albania	2003	-
Armenia	2000	-
Azerbaijan	-	-
Belarus	-	-
Bosnia	2006	-
Bulgaria	2003	2007
Croatia	2010	2013
Czech Republic	2001	2004
Estonia	2010	2004
Macedonia	2010	-
Georgia	-	-
Hungary	2003	2004
Kazakhstan	2008	-
Kyrgyz	-	-
Latvia	2004	2004
Lithuania	2008	2004
Moldova	2012	-
Montenegro	2012	-
Poland	2004	2004
Romania	2004	2007
Russia	2006	-
Serbia	2009	-
Slovakia	2001	2004
Slovenia	2008	2004
Tajikistan	-	-
Turkey	2013	-
Ukraine	2012	-
Uzbekistan	2012	-

Table 4. 2: Distribution of Firms Across Industries

Industry	Freq.	Percent
Mining and quarrying	13	1.27
Construction	110	10.73
Manufacturing	247	24.10
Transport storage and communication	75	7.32
Wholesale and retail trade	257	25.07
Real estate, renting and business services	170	16.59
Hotels and restaurants	56	5.46
Other services	97	9.46
Total	1025	100

Table 4. 3: Distribution of Firms Across Countries

Country	Freq.	Percent
Bulgaria	51	4.98
Albania	60	5.85
Croatia	47	4.59
Belarus	33	3.22
Georgia	38	3.71
Tajikistan	10	0.98
Turkey	111	10.83
Ukraine	16	1.56
Uzbekistan	35	3.41
Russia	69	6.73
Poland	57	5.56
Romania	45	4.39
Kazakhstan	16	1.56
Moldova	45	4.39
Azerbaijan	16	1.56
FYR Macedonia	30	2.93
Armenia	28	2.73
Kyrgyz Republic	51	4.98
Estonia	32	3.12
Czech Republic	44	4.29
Hungary	43	4.2
Latvia	45	4.39
Lithuania	24	2.34
Slovak Republic	53	5.17
Slovenia	26	2.54
Serbia	51	4.98
Total	1025	100

Table 4. 4: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.
Innovation Variables			
Product innovation dummy	2049	0.364568	0.481426
Process innovation dummy	2048	0.514648	0.499907
R&D expenditures, in US dollars	1396	14.96132	84.54369
R&D dummy	2050	.4234146	.4942204
Competition Variables			
PCM	1748	0.226201	0.155222
Number of Competitors	840	10.77381	16.03464
Firm-level Controls			
Ownership Dummy (private public)	2050	0.842927	0.363959
Exports Dummy	2046	0.087859	0.228633
Corruption Dummy	2050	0.611707	0.487481
Firm Size Dummy (small)	2050	0.703415	0.456864
Firm Size Dummy (medium)	2050	0.190244	0.392589
Firm Size Dummy (large)	2050	0.106342	0.308349
Country-level Controls			
EU Member Dummy	2050	0.176098	0.380996
GDP Growth	2050	6.676905	2.939844
Instrumental variable			
National Leniency	2032	0.240158	0.427284

Table 4. 5: Firms and Innovation

	Product innovation	Process Innovation
Number of firms reported no innovation	484	323
Number of firms innovated once	335	350
Number of firms innovated twice	206	352

Table 4. 6: Product Innovation

			IV-2SLS		IV- PROBIT	
	LPM	PROBIT	First-Stage	Second-Stage	First-Stage	Second-Stage
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.00225	0.00806		0.0458**		0.0593***
	(0.0186)	(0.0527)		(0.0216)		(0.00618)
Private	-0.0331	-0.0981	1.770	-0.125	1.770	-0.160*
	(0.0378)	(0.103)	(1.174)	(0.0767)	(1.174)	(0.0830)
Exports Percentage of Sales	0.178***	0.489***	-1.184	0.245**	-1.184	0.298**
	(0.0634)	(0.172)	(1.554)	(0.103)	(1.554)	(0.147)
Medium (50-249)	0.0611*	0.0760	-2.651***	0.185**	-2.651***	0.0202
	(0.0312)	(0.0653)	(0.886)	(0.0765)	(0.886)	(0.0681)
Large (250-9999)	0.215***	0.163*	-1.445	0.286***	-1.445	0.227***
	(0.0436)	(0.0847)	(1.166)	(0.0752)	(1.166)	(0.0638)
EU Member	-0.0756**	0.582***	0.398	-0.0865	0.398	0.343***
	(0.0315)	(0.118)	(1.139)	(0.0542)	(1.139)	(0.125)
GDP Growth (in logs, 1lag)	-0.00419	-0.218**	-0.0769	-0.00429	-0.0769	-0.109
	(0.00459)	(0.0901)	(0.120)	(0.00776)	(0.120)	(0.0773)
Corruption	0.0271	-0.0115	1.249	0.0175	1.249	-0.00516
	(0.0233)	(0.0127)	(0.762)	(0.0501)	(0.762)	(0.00989)
Leniency			-2.060**		-2.060**	
			(0.847)		(0.847)	
Constant	0.588***	0.258	21.20***	-0.370	21.24***	-1.100***
	(0.137)	(0.366)	(2.590)	(0.456)	(2.578)	(0.239)
Observations	1,735	1,735	1,730	1,730	1,730	1,730
R-squared	0.080		0.036		0.036	
Year Dummy	x	x	x	x	x	x
Firm FE	x	x	x	x	x	x
Hausman p-value			(0.0000)			
Wald test of exogeneity						
Chi2					13.60	
p-value					(0.0002)	

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*
Marginal effects at the sample mean are reported in the probit model, and the coefficients are reported in the LPM. The instrument used is national leniency programmes implementation.

Table 4. 7: Process Innovation

			IV-2SLS		IV- PROBIT	
	LPM	PROBIT	First-Stage	Second-Stage	First-Stage	Second-Stage
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.0279	0.0725		0.0365*		0.0551***
	(0.0198)	(0.0521)		(0.0197)		(0.00955)
Private	0.0740**	0.198**	1.770	0.0149	1.770	0.0236
	(0.0371)	(0.100)	(1.174)	(0.0679)	(1.174)	(0.108)
Exports	0.125**	0.362**	-1.184	0.168*	-1.184	0.269*
	(0.0606)	(0.175)	(1.554)	(0.0874)	(1.554)	(0.150)
Medium (50-249)	0.0214	0.333***	-2.651***	0.218***	-2.651***	0.327***
	(0.0240)	(0.0849)	(0.886)	(0.0697)	(0.886)	(0.0794)
Large (250-9999)	0.127***	0.515***	-1.445	0.247***	-1.445	0.380***
	(0.0315)	(0.121)	(1.166)	(0.0657)	(1.166)	(0.137)
EU Member	0.190***	0.515***	0.398	-0.0985*	0.398	-0.149
	(0.0430)	(0.121)	(1.139)	(0.0538)	(1.139)	(0.101)
GDP Growth (in logs, 1lag)	-0.104***	-0.276***	-0.0769	-0.00388	-0.0769	-0.00555
	(0.0322)	(0.0860)	(0.120)	(0.00776)	(0.120)	(0.00943)
Corruption	0.0214	0.0533	1.249	0.0175	1.249	0.0292
	(0.0240)	(0.0637)	(0.762)	(0.0501)	(0.762)	(0.0744)
Leniency			-2.060**		-2.060**	
			(0.847)		(0.847)	
Constant	0.419***	-0.216	21.20***	-0.289	21.20***	-1.193***
	(0.133)	(0.349)	(2.590)	(0.415)	(2.590)	(0.259)
Observations	1,734	1,734	1,730	1,730	1,730	1,728
R-squared	0.073		0.036		0.036	
Year Dummy	x	x	x	x	x	x
Firm FE	x	x	x	x	x	x
Hausman p-value			(0.0067)			
Wald test of exogeneity						
Chi2					6.59	
P-value					(0.0103)	

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*
Marginal effects at the sample mean are reported in the probit model, and the coefficients are reported in the LPM.
The instrument used is national leniency programmes implementation.

Table 4. 8: R&D Positive Spending Dummy

	LPM	PROBIT	IV-2SLS First-Stage	IV-2SLS Second-Stage	IV- PROBIT First-Stage	IV- PROBIT Second-Stage
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.0360**	0.103**		0.0653**		0.0624***
	(0.0183)	(0.0520)		(0.0287)		(0.00399)
Private	0.0625	0.165	1.770	-0.0656	1.770	-0.0672
	(0.0390)	(0.107)	(1.174)	(0.100)	(1.174)	(0.0850)
Exports	-0.0410	-0.117	-1.184	0.0325	-1.184	0.0316
	(0.0581)	(0.163)	(1.554)	(0.115)	(1.554)	(0.107)
Medium (50-249)	0.192***	0.519***	-2.651***	0.372***	-2.651***	0.341***
	(0.0313)	(0.0841)	(0.886)	(0.0999)	(0.886)	(0.0847)
Large (250-9999)	0.295***	0.798***	-1.445	0.381***	-1.445	0.344***
	(0.0416)	(0.116)	(1.166)	(0.0963)	(1.166)	(0.123)
EU Member	0.0199	0.0619	0.398	-0.0985*	0.398	0.00213
	(0.0295)	(0.0864)	(1.139)	(0.0538)	(1.139)	(0.0765)
GDP Growth (in logs, 1lag)	0.0192***	0.0560***	-0.0769	0.00340	-0.0769	0.0181*
	(0.00452)	(0.0131)	(0.120)	(0.0804)	(0.120)	(0.0103)
Corruption	-0.0728***	0.0533	1.249	0.0192**	1.249	-0.130**
	(0.0234)	(0.0637)	(0.762)	(0.00840)	(0.762)	(0.0537)
Leniency			-2.060**		-2.060**	
			(0.847)		(0.847)	
Constant	0.279**	-0.634*	21.20***	-0.885	21.20***	-1.322***
	(0.126)	(0.350)	(2.590)	(0.596)	(2.590)	(0.195)
Observations	1,736	1,736	1,730	1,730	1,730	1,730
R-squared	0.101		0.036		0.036	
Year Dummy	x	x	x	x	x	x
Firm FE	x	x	x	x	x	x
Hausman p-value			(0.0000)			
Wald test of exogeneity						
Chi2						18.54
P-value						(0.0000)

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*
Marginal effects at the sample mean are reported in the probit model, and the coefficients are reported in the LPM.
The instrument used is national leniency programmes implementation.

Table 4. 9: Logs of R&D Spending

	LPM	IV-2SLS	
		First-Stage	Second-Stage
	(1)	(2)	(3)
PCM	0.00197		0.0305
	(0.00577)		(0.0828)
Private	0.342	1.996	0.232
	(0.306)	(1.508)	(0.430)
Exports	1.171**	-0.734	1.204*
	(0.490)	(1.933)	(0.623)
Medium (50-249)	2.444***	-2.525**	2.502***
	(0.260)	(1.156)	(0.400)
Large (250-9999)	4.139***	-2.861*	4.129***
	(0.360)	(1.516)	(0.585)
Corruption	0.00271	0.930	-0.0555
	(0.202)	(0.988)	(0.220)
EU Member	0.501*	1.572	0.434
	(0.301)	(1.411)	(0.322)
GDP Growth (in logs, 1lag)	-0.0492	-0.0734	-0.0492
	(0.0351)	(0.145)	(0.0327)
Leniency		-2.565***	
		(0.985)	
Constant	3.353***	21.07***	2.844
	(0.961)	(3.140)	(2.058)
Observations	1,238	1,224	1,224
R-squared	0.264		0.247
Year Dummy	x	x	x
Firm FE	x	x	x
Hausman p-value	0.73		

Robust standard errors in parentheses.
Significant at *** p<0.01, ** p<0.05, * p<0.1
Marginal effects at the sample mean are reported in the probit model, and the coefficients are reported in the LPM.
The instrument used is national leniency programmes implementation.

Table 4. 10: Lagged Values of PCM

	Product Innovation		Process Innovation		R&D Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	Probit	LPM	Probit	LPM	Probit
PCM (2002)	0.0140	0.0413	0.0331	0.0874	0.0299	0.0861
	(0.0267)	(0.0746)	(0.0283)	(0.0739)	(0.0260)	(0.0744)
Private	-0.0516	-0.150	-0.00669	-0.0208	0.102*	0.290*
	(0.0546)	(0.148)	(0.0540)	(0.144)	(0.0555)	(0.155)
Exports Percentage of Sales	0.166*	0.443*	0.159*	0.449*	-0.0708	-0.212
	(0.0923)	(0.251)	(0.0869)	(0.252)	(0.0834)	(0.240)
Corruption	-0.00954	-0.0315	0.0172	0.0412	-0.0818**	-0.239**
	(0.0339)	(0.0938)	(0.0351)	(0.0918)	(0.0335)	(0.0946)
Medium (50-249)	0.0754*	0.202*	0.104**	0.274**	0.191***	0.527***
	(0.0447)	(0.121)	(0.0455)	(0.122)	(0.0443)	(0.121)
Large (250-9999)	0.159**	0.434**	0.0974	0.264	0.320***	0.896***
	(0.0632)	(0.171)	(0.0632)	(0.170)	(0.0579)	(0.169)
EU Member	-0.0285	-0.0739	-0.0795	-0.209	0.0729*	0.230*
	(0.0465)	(0.140)	(0.0490)	(0.127)	(0.0434)	(0.132)
GDP growth (in logs, 1lag)	0.0248	0.0712	-0.0499	-0.127	0.186***	0.569***
	(0.0369)	(0.107)	(0.0410)	(0.107)	(0.0367)	(0.115)
Constant	0.512**	0.0619	0.667***	0.436	0.0547	-1.310**
	(0.200)	(0.570)	(0.203)	(0.536)	(0.190)	(0.525)
Observations	845	844	846		846	846
R-squared	0.090		0.064		0.114	
Year Dummy	x		x		x	
Firm FE	x	x	x	x	x	x

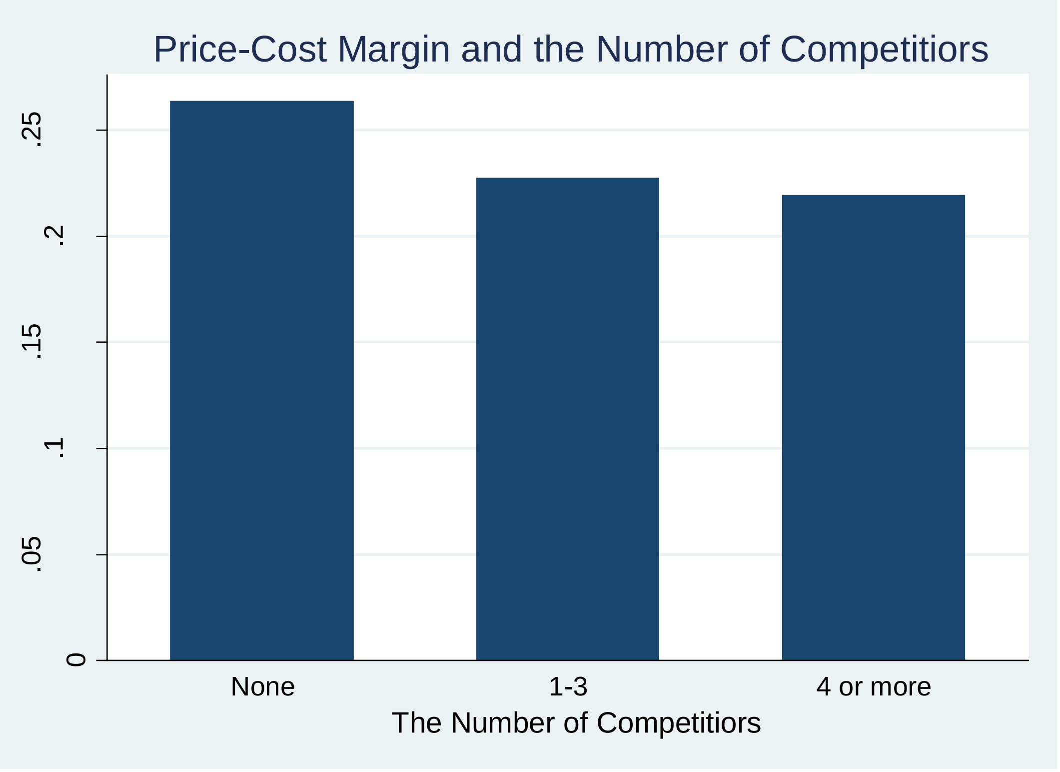
Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*

Table 4. 11: Number of Competitors as a Measure of Competition

	Product Innovation		Process Innovation		R&D Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	Probit	LPM	Probit	LPM	Probit
Competitors Number	-0.00362***	-0.0112***	-0.00315***	-0.00834***	-0.00249**	-0.00683**
	(0.000922)	(0.00326)	(0.00108)	(0.00288)	(0.00110)	(0.00308)
Private	-0.0666	-0.191	-0.0194	-0.0561	0.0255	0.0849
	(0.0527)	(0.145)	(0.0515)	(0.143)	(0.0547)	(0.145)
Exports Percentage of Sales	0.0329	0.0869	0.0271	0.0859	-0.126*	-0.351*
	(0.0739)	(0.204)	(0.0685)	(0.202)	(0.0702)	(0.195)
Corruption	0.00350	0.00800	-0.00777	-0.0265	-0.0663*	-0.182*
	(0.0348)	(0.0942)	(0.0346)	(0.0942)	(0.0353)	(0.0945)
Medium (50-249)	0.0472	0.122	0.0583	0.160	0.146***	0.391***
	(0.0424)	(0.115)	(0.0414)	(0.117)	(0.0425)	(0.113)
Large (250-9999)	0.144***	0.387***	0.0762	0.215	0.246***	0.673***
	(0.0505)	(0.139)	(0.0500)	(0.141)	(0.0490)	(0.138)
EU Member	-0.0141	-0.0370	-0.0592	-0.162	0.0818*	0.226*
	(0.0446)	(0.122)	(0.0442)	(0.121)	(0.0451)	(0.121)
GDP growth (in logs, 1lag)	0.00418	0.0110	-0.00459	-0.0125	0.0112	0.0318
	(0.00701)	(0.0191)	(0.00695)	(0.0197)	(0.00733)	(0.0197)
Constant	0.671***	0.488	0.736***	0.628	0.350**	-0.423
	(0.167)	(0.433)	(0.157)	(0.427)	(0.160)	(0.422)
Observations	840	840	838	838	840	840
R-squared	0.103		0.057		0.100	
Year Dummy	x		x		x	
Firm FE	x	x	x	x	x	x

Robust standard errors in parentheses.
*Significant at *** p<0.01, ** p<0.05, * p<0.1*

Figure 4. 1: Average PCM and Competitors



Chapter 5 The Effect of Product Market Competition on R&D: Industry-Level Analysis

Abstract

This chapter empirically analyses the impact of competition intensity on innovation behaviour in OECD countries. I analyse a panel of sixteen industries in eighteen countries over 1990 to 2009. I measure innovation by both industries' R&D intensity and R&D expenditures. Competition intensity is measured by industries' price-cost margins. My identification strategy accounts for the potential endogeneity bias in the measure of competition intensity. I exploit an exogenous variation in the competition intensity by of leniency programmes implementation. Both national leniency programmes implementation and EU supranational leniency programmes are used as instruments. Results suggest a positive and significant effect of competition intensity on R&D intensity. More specifically, one percentage point fall in PCM increases, on average, R&D intensity by 0.03 percentage points.

Keywords: Innovation, Leniency Programmes, Competition

JEL Classification: O31, K21, L4, D41

5.1 Introduction

Theoretical work and empirical evidence on competition and innovation show diverse and even conflicting results. A number of authors suggest that less competition is associated with greater innovation level, while other authors suggest that a more competitive market is more conducive to innovation. Some recent literature suggests the existence of an inverted U-shaped relation between competition and innovation.

In Chapter 4, I analysed the impact of competition intensity on innovation at the firm level in developing countries. Results confirm the Schumpeterian hypothesis that a lower degree of product market competition is associated with a greater innovative activity. However, given the segmented and often contradictory literature, in this chapter, I compliment the work of Chapter 4 using a different dataset. The main differences between Chapter 4 and Chapter 5 are the following. Firstly, in this chapter, the data is aggregated at the industry-level while in Chapter 4, I analyse firm-level dataset. Secondly, the analysis in Chapter 4 is based on a sample of developing countries, whereas in this chapter it consists mainly of developed countries. Lastly, the measure of innovation I use in this chapter is R&D expenditures, whereas in Chapter 4 I consider product and process innovation.

As discussed earlier in Chapter 4, the major challenge researchers face when analysing the relationship between innovation and competition intensity is the endogeneity problem due to reverse causality of innovation and competition and omitted variable bias. In this analysis, I resolve these issues exploiting exogenous variation in the expected impact of leniency programmes implementation across OECD countries to identify the effects of these programmes on competition intensity, and then the effects of competition intensity on innovation.

Following the literature, I draw on price-cost margins (PCM) as a measure of competition intensity. Moreover, I use R&D intensity as an indicator of industries' innovation activity. I propose two instruments to deal with the problem mentioned above, namely national and supranational leniency programme implementation. Countries started implementing these programmes since the early 1990s as tools to enhance product market competition by detecting and destabilising cartels. The US Department of Justice (DoJ) was the first to introduce leniency programme in 1978 which was subsequently revised in 1993. The EU introduced a similar programme in 1996 and revised it in 2002. Thus, I expect their implementation to be associated with a reduction in price-cost margins. In all specifications of the model, I control for industry-level and country-level characteristics which are likely determinants of innovative activity.

Findings suggest a robust and positive significant link between increased competition and innovation, as measured by R&D intensity and the logarithm of R&D expenditures. This result is consistent with the strand of the literature where more intense competition leads to more innovative activities, known as the escape competition effect. That is, more intense competition might increase the incentives for firms to innovate to maintain or improve their market position (Gilbert and Newbery, 1982; Aghion, 2001; Aghion, 2005; Aghion et al., 2009). Moreover, leniency programmes appear to be associated with a fall in price-cost margins, which suggests the effectiveness of leniency programmes in promoting product market competition.

The previous theoretical literature on the relationship between competition and innovation exhibits conflicting results. On the one hand, Schumpeter (1942) suggest that innovation is driven by the expected monopoly rents of a successful innovator and those rents decline with competition. On the other hand, Arrow (1962) argues that the incentives to innovate are greater in competitive conditions in comparison to monopolistic settings. As a compromise, Aghion et al. (2005) reconcile the two opposing effects of competition, suggesting a non-linear relationship between competition and innovation. Similarly, the empirical literature also captures these contradictory results. In line with the Schumpeterian hypothesis, authors such as Kraft (1989), Crepon et al. (1998), Gayle (2001) and Carlin et al. (2004) find that product market competition affects the innovative activity negatively. Conversely, others, such as Nickell (1996), Blundell et al. (1995), Blundell et al. (1999), Geroski (1990, 1995), Aces and Audretsch (1998a, 1988b) and Benito et al. (2015) find that product market competition spurs the innovative activity. However, there are authors that find an inverted-U relationship between competition and innovation, such as Aghion et al. (2005), Tingvall and Poldahl (2006), Friesenbichler (2007), Askenazy et al. (2008), Tingvall and Karpty (2011), Polder and Veldhuizen (2012), and Bos et al. (2013). In Chapter 4, I provide more details on the theoretical and empirical literature on the relationship between competition and innovation. This chapter provides evidence in support of the hypothesis that product market competition is associated with greater innovative activity.

The main contribution of this chapter is to shed light on whether product market competition is likely to raise innovative activity using industry-level data across countries and to employ a novel instrument. Previous work, such as Nickell (1996), Blundell et al. (1999), Aghion (2005), and Aghion et al. (2009) address the association between competition and innovation using firm-level data within a single country. However, industry-level across countries studies are still limited. In this chapter, I provide empirical evidence using a panel of sixteen industries across nineteen countries between 1990 and 2009.

The results of this chapter contradict those obtained in Chapter 4. This could be attributed to different reasons. One potential explanation could be attributed to the measure of innovation employed in the analysis. While Chapter 4 analysed the impact of competition on the innovation outcome, measured by product and process innovation, this chapter considers the innovation inputs, as measured by R&D expenditures. Competition might spur exerting innovation efforts by investing in R&D activities, but it does not necessarily lead to a successful innovation output. Another possible reason lies behind the level of aggregation used in the dataset. In Chapter 4, I have analysed a firm-level dataset while here I analyse an industry-level dataset. Moreover, lastly, Chapter 4 focused on developing countries whereas here analyses mainly developed countries. That is, as discussed by Aghion and Griffith (2008), an additional product market competition in technological frontier economies increases innovation. And vice versa, an additional degree of competition in laggard economies reduces innovation. This might hint to a U-shaped relationship between competition and innovation.

The rest of the chapter is structured as follows. In Section 2, I present the data, variables and descriptive statistics. Section 3 describes the econometric model and the identification strategy. Section 4 discusses the results. In section 6, I provide some explanations of obtaining conflicting results in Chapters 4 and 5. Section 5 provides some concluding remarks.

5.2 Data

I assemble a panel of sixteen industries in eighteen countries over the period 1990-2009. The countries included in the study are Austria, Belgium, Canada, Czech Republic, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, United Kingdom and the United States. The main source of data is the OECD STAN and the OECD Analytical Business Expenditure on Research and Development (ANBERD) databases which provide disaggregated data at the industry level. This data was integrated with several sources as described below.

5.2.1 Measures of innovation, competition intensity, and other control variables

I obtain Innovation measures from the OECD Analytical Business Expenditure on Research and Development (ANBERD), which is available at industry-country level. To capture innovation, I employ R&D intensity which is given by the nominal R&D expenditures divided by nominal value added in industry i, country j, at time t. I use R&D intensity as a measure of innovation to gauge the relative importance of R&D activities across industries. Given that R&D activities might be more intensive in larger industries, using this relative measure eliminates the size effect of the industry. As a robustness check, I use the natural logarithm of R&D expenditures, which is given in national currency.

The main regressor in the empirical specifications is competition intensity. It is measured by the price-cost margin, which is calculated as an industry's value added, divided by the sum of labour costs and capital costs at the industry-country level. Boone (2000) shows that this competition measure is theoretically more robust than other competitions measures that are based on market shares and market concentration. Griffith et al. (2010) point out that PCM is the only commonly used measure that allows for international comparison at the industry-country level. Specifically,

$$PCM_{i,j,t} = \frac{Value\ Added_{i,j,t}}{Labour\ Cost_{i,j,t} + \ Capital\ Cost_{i,j,t}},$$

where all variables are in nominal prices. Information on industry's value-added, industry's labour cost and capital cost is collected from the OECD STAN database. The subscripts i, j, t refer to industry, country and time respectively.

Identifying the causal impact of competition on innovation relies crucially on the ability to account for the potential endogeneity of competition. Thus, I instrument for competition drawing on the exogenous variations in the national leniency programmes. Information on leniency programmes is obtained from the homepages of national competition authorities. I also use information on these programmes from the European Competition Networks definition to prevent confusion with the frequently revised and very heterogeneous leniency programmes. In the estimation, I consider the programmes in which the first confessor receives full immunity from fines. To capture the existence of such a leniency programme, I construct a dummy variable that takes a value of one from the year in which the programme is adopted onward. I also use the information on the first European Union leniency programme by including an additional dummy to capture whether an industry is affected by the European supranational leniency programme in 1996. Using the EU leniency programmes rather than national programmes may be more preferable as it is more exogenous than the national one. However, they may not be relevant to all cartel cases as it targets cross-boarders cartels. The EU leniency programme 1996 is employed as an instrument on estimation based on a subsample of European countries.

I control for industry-level factors such as, trade openness which is measured by import penetration in each industry. Furthermore, I control for deflated industries' level of production. Data is obtained from the OECD STAN database. All industry level variables are in nominal prices and measured in units of national currency. Obviously, competition is an important determinant of innovation. However, it is not the only one since institutional factors play an important role. Hence, I control for country's specific institutional factors as measured by the Worldwide Governance Indicators (WGIs) (Kaufman et al., 2010). Data is available for over 200 countries over the period 1996-2016 and for six dimensions of governance. I employ the control-of-corruption index as it considers the extent to which public power is used for private gain. Another measure used is the rule-of-law index which captures the degree to which agents have confidence in and abide by the rules of society, such as, quality of contract enforcement, property rights, the police, and the courts, and the likelihood of crime and violence. These institutional quality indices are measured on a normalised scale from -2.5 to +2.5, where the highest value reflects a better governance outcome.

5.2.2 Descriptive statistics

Table 5.1 describes data availability by country. Table 5.2 contains information on industries used in the estimation. Given data availability, most industries are in the manufacturing sector. Table 5.3 provides the preliminary statistics for the variables used in the regression equation. Information on leniency variables is presented in Chapter 2, Table 5.1. That table presents information on the year in which each country implemented the leniency programmes. It also shows whether a country is affected by supranational leniency programmes. More specifically, it shows whether a country was affected by the first European Union leniency programme in 1996 and its revision in 2002.

5.3 Empirical Strategy

The objective of leniency programmes is to deter behaviours that reduce competition. Thus, the causal link between leniency programmes and innovation goes through the impact of the former on product market competition. A higher level of competition may incentivise firms to undertake innovative activities to protect or improve their market position (i.e., to escape competition). However, increased competition may also discourage innovative activities due to lower innovation rewards associated with higher number of competitors in a market (i.e., the Schumpeterian effect).

The identification of the causal impact of competition on innovation implies controlling for potential endogeneity of competition that arises from two-way causality and omitted variable bias. Omitted variable bias is a significant concern as many factors can potentially affect both competition intensity and innovation. To reduce the potential bias resulting from two-way causality, I use lagged values of the competition intensity index and the other control variables. Furthermore, using a panel data reduces the omitted variable bias by controlling for time-invariant unobserved heterogeneity using industry, country, and time fixed effects. However, there might be time-varying unobserved heterogeneity resulting from factors correlated with competition intensity that might affect innovative activity. To tackle this issue, I introduce relevant control variables, as discussed in Section 2. Nonetheless, I propose employing an instrumental variable approach to test explicitly whether endogeneity problem is a feature of the equation instrumenting competition intensity by the introduction of national leniency programmes. I also estimate a subsample of European countries using the implementation of the EU leniency programme in 1996 as an instrument.[50]

The work of this chapter is closely related to the work of Griffith et al. (2006) and Griffith et al. (2010) who analyse the effect of the EU single market programme on product market competition and the following impacts on innovation and productivity growth. Their results suggest that the reforms that were conducted under the single market programme increase the competition intensity and which on its turn increases both innovation and productivity growth.

The main empirical approach takes the form of a two-stage instrumental variables estimation. In the first stage, I estimate the relationship between leniency programmes and product market competition, as measured by price-cost margin (PCM). More precisely, I estimate:

$$PCM_{i,j,t} = \beta_L LeniencyProgrammes_{j,t} + \beta_x X_{i,j,t-1} + \alpha_{i,j} + \alpha_t + \epsilon_{i,j,t} \ , \qquad (1)$$

where $PCM_{i,j,t}$ is the measure of product market competition in industry i, country j, and year t. $LeniencyProgrammes_{j,t}$ is an indicator whether a national or EU supranational leniency programme is in place, $X_{i,j,t-1}$ is a vector of control variables that influence these relationships, $\alpha_{i,j}$ are industry-country fixed effects, α_t are time dummies, β_L and β_x are the parameters and $\epsilon_{i,j,t}$ is the error term. I expect a direct effect of leniency programmes on competition intensity, $PCM_{i,j,t}$, which is the main channel through which leniency programmes affect innovation

[50] I also use the implementation of the EU leniency programme in 2002 as an instrument. However, the F-statistics suggest that there is a potential weak instrument problem and therefore, I only report the results when employing the EU-1996 programme as an instrument.

activities.

The second-stage equation characterises the relationship between innovation and competition intensity:

$$Innovation_{i,j,t} = \beta_{pcm} PCM_{i,j,t-1} + \beta_x X_{i,j,t-1} + \alpha_{i,j} + \alpha_t + \varepsilon_{i,j,t} \;, \qquad (2)$$

where $Innovation_{i,j,t}$ is measured by the R&D intensity and the natural logarithm of R&D spending. I cluster standard errors at the country-level to deal with concerns about serial correlation.

5.4 The Effect of Price-Cost Margins on Innovation

I analyse the impact of competition intensity on both R&D intensity and the natural logarithm of R&D expenditures. This allows me to rule out that results are not driven by the relationship between competition and value added (the denominator of R&D intensity). Table 5.4 provides the estimates of the impact of product market competition on innovation where the dependent variable is R&D intensity. Column (1) presents OLS estimation as a baseline. I find a small negative and significant effect of PCM (lower competition) on R&D intensity. That is, a one percentage point increase in PCM is associated with on average about a 0.00980 percentage point decrease in R&D intensity. Column (2) adds further factors that might have an impact on innovation to reduce possibly omitted variable bias. The PCM coefficient shows a greater magnitude of -0.0108 when controlling for institutional factors. Better institutional quality, as measured by the rule-of-law index, has a positive impact on R&D intensity, with a magnitude of 0.0351. The coefficient of corruption control is not statistically significant. To test whether the previously observed and persistent impact of PCM is of a causal nature, I use instrumental variable approach (2SLS). I use national leniency programme implementation as an instrument to verify whether the previously found impact of increased PCM on R&D intensity or, in other words, the positive impact of increased competition. Column (3) and (4) report results of the IV (2SLS) estimation using national leniency programmes implementation as an instrument. Column (3) shows the second stage estimate and suggests that a one percentage point increase in PCM (lower competition) is, on average, associated with a decrease in R&D intensity of about 0.0108 percentage point. The first stage F-statistic is equal to 98.935 and is by far exceeding the rule of thumb value of 10 indicated by Stock and Yogo (2002). The Hausman t-statistics which compares OLS and 2SLS finds no evidence of endogeneity (the p-value is equal to 0.66). In column (4), I control for institutional factors. The magnitude of the effect of PCM on R&D intensity increases to 0.0308. Again, the first stage F-statistic is above the critical values for weak instruments test provided by Stock and Yogo (2002), which suggests that the instrument has explanatory power. The Hausman t-statistics show no evidence of endogeneity again. The rule-of-law index has a positive and significant impact on R&D intensity, with a magnitude of 0.0495. The results from the first-stage are shown in Table 4.5. As expected, in both specifications, national leniency programme implementation appears to be associated with lower PCM. In column (1) national leniency implementation appears to affect PCM negatively, suggesting a positive impact of leniency programmes on competition intensity, with a decrease of the PCM by 0.184 percentage point. Similarly, column (2) shows a positive impact of national leniency implementation on PCM, with a slight increase in the magnitude of the effect to 0.195 when controlling for institutional factors. The strong significance of leniency programmes indicator adds to the evidence that it is a viable instrument. Overall, estimates suggest that the results obtained by 2SLS are in line with those of the OLS. Specifically, the coefficient of interest, PCM, has a negative and significant impact on R&D intensity.

5.5 Robustness Checks

Table 5.6 checks that the results are robust using the logarithm of R&D expenditures rather than R&D intensity as a dependent variable. In column (1) and (2) I present the OLS specification.

The coefficients of PCM in both specifications are not statistically significant. Column (3) and (4) present the results of the IV (2SLS) estimation using national leniency programmes implementation as an instrument. As before, the estimated coefficient of PCM is negative and significant with an increase in the magnitude when controlling for institutional factors. F-tests in both specifications ensure the explanatory power of the instrument. The Hausman test suggests that PCM is endogenous which indicates the necessity to use an instrumental variable approach. Compared to the OLS results in column (1) and (2), coefficients indicate a much larger effect of PCM on R&D expenditures. This suggests an upward bias in the OLS results that might be attributed to reverse causality or omitted variables bias.

In Table 5.7, I test the robustness of the relationship estimated above using a sample of countries that were affected by the European Union supranational leniency programme in 1996. Using the EU leniency programmes implementation as an instrument may be preferable to the national leniency programmes implementation as it is more exogenous. Coefficients seem to be roughly consistent with the results obtained before; there is a negative relationship between PCM and innovation. Column (1) presents the OLS estimates. A one percentage point increase in the PCM decreases R&D intensity by 0.0109 percentage points. Column (2) and (3) show IV (2SLS) estimates. The first stage estimate in column (2) indicates that EU leniency programmes was associated with lower PCM. In particular, EU leniency implementation seems to reduce PCM by 0.421 percentage points. Column (3) shows the second-stage estimates. These suggest that a one percentage point fall in PCM increases R&D intensity, on average, by 0.0139 percentage points. The impact is greater than in the OLS estimates which is potentially due to endogeneity problem. The first stage F-statistics is 25 is above the rule-of-thumb values for weak instruments. The Hausman test of endogeneity points out that PCM is endogenous and thus it is favourable to use IV specifications. Importantly, the impact on R&D intensity remains negative and significant among both specifications. In Table 5.8, I repeat the previous OLS and IV specifications presented in Table 5.7, using the logarithm of R&D expenditures as my dependent variable. In column (1), the OLS specification shows no significant impact of PCM on the logarithm of R&D expenditures. The IV estimation of the model shows that competition, measured by a reduction in PCM, affects R&D expenditures positively.

Overall, findings suggest that the coefficient estimate for PCM is negative and statistically significant across all specifications, which provide additional support for the argument that competition boosts innovative activity.

5.6 Discussion

Looking back at Chapter 4, results capture the opposite effect. That is, lower level competition (a higher price-cost margin) is more conducive to innovation. One possible explanation for getting an opposite effect of competition on innovation in two different datasets might be attributed to the fact that growth has several engines which do not necessarily require the same institutions or policies (Gerschenkron, 1962; Acemoglu et al., 2006). Aghion and Griffith (2008), Acemoglu et al. (2006), Hausmann and Rodrik (2003) argue that, in developing countries, growth relies on factor accumulation and imitating or adapting technologies that have been developed elsewhere. Factor accumulation and imitation can prosper under low level of competition. Conversely, frontier innovation is the primary engine of growth in developed countries as the potential growth from factor accumulation and imitation has been already exhausted. Thus, in developed economies, moving to more competitive institutions might favour innovation. Another potential explanation lies in the choice of innovation measure. Competition appears to be associated with more innovative effort, measured by R&D expenditures, but does not necessarily lead to a successful innovation output, as measured by the introduction of new products and processes.

5.7 Conclusion

Since innovation plays a key role in the growth and the nation wealth, it is crucial to understand the determinants to innovate at the industry level. This study analyses the effect of one of the determinants of innovation, namely competition intensity, measured by PCM.

As identification strategy in investigating the extent to which the level of competition is associated with the innovative activity, I employ an Instrumental Variable approach, and I lag the variables by one year to account for the potential endogeneity bias. Thus, I claim that the link between competition and innovation obtained in this study is of a causal nature. National and supranational leniency programmes implementation are used as instruments for PCM since they aim to deter anticompetitive behaviour that reduces social welfare. I provide two different measures of innovation: R&D intensity and real R&D expenditures. Also, I estimate a subsample of European countries in which they were the European Union leniency programme was relevant. The estimated Instrumental Variable results of the impact of product market competition on innovation are LATE. That is, The Instrumental Variable approach only captures the effect of leniency programmes on the compliers, i.e. the firms that were eligible and actually applied for leniency. This may beg the question that the innovative firms might be the "never-takers". In other words, innovative firms may be the ones that never apply for leniency, regardless of whether it exsists or not. The Instrumental Variable approach is not informative about those types of firms.

The reported results support the argument that increased product market competition increases the innovative activities. Leniency programmes reduce price-cost margins which lead to a tougher level of competition, which in turn, increase industries' R&D activities. In comparison to Chapter 4, I find interesting differences, particularly in the direction of the impact of product market competition on innovation. In countries where growth relies on imitating and adapting technologies from the knowledge-based economies, a higher degree of product market competition does not appear to be conducive to innovation. Whereas, in economies that are close to the technological frontier, competition appears to boost innovation.

5.8 Appendix

Table 5. 1: Countries and Observations

Country	Freq.	Percent	Cum.
Austria	120	4.16	4.16
Belgium	179	6.21	10.37
Canada	105	3.64	14.02
Czech Republic	142	4.93	18.95
Finland	201	6.97	25.92
France	165	5.73	31.64
Germany	244	8.47	40.11
Greece	146	5.07	45.18
Hungary	144	5	50.17
Ireland	158	5.48	55.66
Italy	222	7.7	63.36
Netherlands	247	8.57	71.93
Norway	185	6.42	78.35
Poland	82	2.85	81.2
Portugal	31	1.07	82.27
Spain	210	7.29	89.56
United Kingdom	139	4.82	94.38
Sweden	162	5.62	100
Total	2,882	100	

Table 5. 2: Industry and Observations

Industry	Freq.	Percent	Cum.
Food products and beverages	95	3.3	3.3
Tobacco product	95	3.3	6.59
Wearing apparel	170	5.9	12.49
Leather, leather products, and footwear	196	6.8	19.29
Wood and products of wood and cork	232	8.05	27.34
Printing and publishing	198	6.87	34.21
Coke, refined petroleum products and nuclear fuel	199	6.9	41.12
Chemical and chemical products	187	6.49	47.61
Rubber and plastics products	245	8.5	56.11
Fabricated metal products, except machinery and equipment	225	7.81	63.91
Radio, television and communication equipment	202	7.01	70.92
Medical, precision and optical instruments	201	6.97	77.9
Other transport equipment	229	7.95	85.84
Manufacturing n.e.c.	151	5.24	91.08
Research and development	126	4.37	95.45
Other business activities	131	4.55	100
Total	2,882	100	

Table 5. 3: Summary Statistics

Variable	Observations	Mean	Std. Dev.
R&D intensity	2,882	0.0661074	0.1348356
R&D expenditures	2,882	1.09E+09	4.35E+09
PCM	2,672	0.209508	0.185432
Import penetration	2,605	2.410562	3.833457
GDP growth	2,720	2.806756	2.30475
Production	2,874	7.47E+10	2.61E+11
Control of corruption	1,906	1.481767	0.5222455
Rule of law	1,906	1.352325	0.4504664
National leniency	2,882	0.3785566	0.4851115
EU leniency	2,882	0.5839695	0.4929842

Table 5. 4: R&D Intensity

Dep. Var.: R&D Intensity	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
PCM (in logs, 1 lag)	-0.00980***	-0.0108***	-0.0174**	-0.0308*
	(0.00284)	(0.00277)	(0.00837)	(0.0180)
Import penetration (in logs, 1 lag)	0.0243***	0.0295***	0.0331***	0.0305***
	(0.00768)	(0.00679)	(0.00260)	(0.00420)
GDP growth (in logs, 1 lag)	0.000179	0.00106	-0.00652***	-0.00510**
	(0.00239)	(0.00365)	(0.00216)	(0.00257)
Production (in logs, 1 lag)	0.00161	0.00523**	0.00597***	0.00332
	(0.00214)	(0.00243)	(0.00189)	(0.00402)
Control of corruption (in logs, 1 lag)		-0.00843		-0.0151
		(0.0150)		(0.0181)
Rule of law (in logs, 1 lag)		0.0351*		0.0495***
		(0.0198)		(0.0178)
Industry dummies	x	x	x	x
Country dummies	x	x	x	x
Time dummies	x	x	x	x
Constant	-0.105	-0.215***	-0.248***	-0.223***
	(0.0702)	(0.0773)	(0.0325)	(0.0644)
First stage F-statistics			98.9351	16.3463
Hausman p-value			0.6662	0.7717
Observations	2,152	1,432	2,152	1,432
R-squared	0.27	0.29	0.28	0.31

*Cluster-robust standard errors on the country-level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. The Two-Stage Least Square (2SLS) approach uses national leniency programmes implementation as an instrument for PCM.*

Table 5. 5: First Stage Estimates

	(1) ln(PCM)	(2) ln(PCM)
National Leniency	-0.184***	-0.195***
	(0.0562)	(0.0582)
Import penetration (in logs, 1 lag)	-0.0360	-0.0533
	(0.0304)	(0.0413)
GDP growth (in logs, 1 lag)	0.0111	-0.0793**
	(0.0363)	(0.0398)
Production (in logs, 1 lag)	0.0171	0.0327
	(0.0255)	(0.0421)
Control of corruption (in logs, 1 lag)		0.417***
		(0.161)
Rule of law (in logs, 1 lag)		-0.173
		(0.215)
Industry dummies	x	x
Country dummies	x	x
Time dummies	x	x
Constant	-3.903***	-3.609***
	(0.682)	(0.998)
Observations	2,152	1,432
R-squared	0.677	0.737

*Cluster robust standard errors on the country-level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1*

Table 5. 6: Logarithm of Real R&D Expenditures

Dep. Var.: ln (R&D)	(1) OLS	(2) OLS	(3) IV	(4) IV
PCM (in logs, 1 lag)	-0.000962	0.0293	-0.252*	-1.017***
	(0.0425)	(0.0330)	(0.137)	(0.355)
Import penetration (in logs, 1 lag)	-0.0866	0.267***	0.665***	0.540***
	(0.0771)	(0.0624)	(0.0295)	(0.0605)
GDP growth (in logs, 1 lag)	-0.0253	-0.00375	-0.0702	-0.0786
	(0.0415)	(0.0310)	(0.0464)	(0.0609)
Production (in logs, 1 lag)	0.442***	0.524***	0.924***	0.819***
	(0.0414)	(0.0608)	(0.0324)	(0.0795)
Control of corruption (in logs, 1 lag)		-0.550***		-0.773**
		(0.149)		(0.390)
Rule of law (in logs, 1 lag)		0.486*		2.029***
		(0.253)		(0.372)
Industry dummies	x	x	x	x
Country dummies	x	x	x	x
Time dummies	x	x	x	x
Constant	9.033***	3.642***	-7.465***	-6.806***
	(0.868)	(1.412)	(0.588)	(1.175)
First stage F-statistics			91.16	15.28
Hausman p-value			0.02	0.07
Observations	2,104	1,398	2,104	1,398
R-squared	0.75	0.53	0.63	0.58

*Cluster-robust standard errors on the country-level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. The Two-Stage Least Square (2SLS) approach uses national leniency programmes implementation as an instrument for PCM.*

Table 5. 7: R&D Intensity, EU Countries Only

Dep. Var.: R&D Intensity	(1)	(2)	(3)
	OLS	IV	
		First Stage	Second Stage
PCM (in logs, 1 lag)	-0.0109***		-0.139***
	(0.00292)		(0.0284)
Import penetration (in logs, 1 lag)	0.0301***	-0.145***	0.0178***
	(0.00711)	(0.0224)	(0.00450)
GDP growth (in logs, 1 lag)	0.00108	-0.0217	-0.00264
	(0.00367)	(0.0411)	(0.00578)
Production (in logs, 1 lag)	0.00520**	-0.237***	-0.0176***
	(0.00248)	(0.0235)	(0.00595)
Control of corruption (in logs, 1 lag)	-0.00836	-0.772***	-0.106***
	(0.0151)	(0.197)	(0.0358)
Rule of law (in logs, 1 lag)	0.0349*	0.722***	0.126***
	(0.0197)	(0.207)	(0.0355)
EU leniency programme		-0.421***	
		(0.0826)	
Industry dummies	x	x	x
Country dummies	x	x	x
Time dummies	x	x	x
Constant	-0.217***	3.777***	0.0282
	(0.0799)	(0.609)	(0.0884)
First stage F-statistics		25.90	
Hausman p-value		0.0000	
Observations	1,373	1,373	1,373
R-squared	0.297	0.165	

*Cluster-robust standard errors on the country-level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. The Two-Stage Least Square (2SLS) approach uses EU leniency programme implementation as an instrument for PCM.*

Table 5. 8: Log R&D, EU Countries Only

Dep. Var.: ln(R&D)	(1)	(2)	(3)
	OLS	IV	
		First Stage	Second Stage
PCM (in logs, 1 lag)	0.0223		-2.237***
	(0.0338)		(0.485)
Import penetration (in logs, 1 lag)	0.261***	-0.145***	0.402***
	(0.0647)	(0.0224)	(0.0770)
GDP growth (in logs, 1 lag)	-0.00546	-0.0217	-0.0720
	(0.0314)	(0.0411)	(0.0966)
Production (in logs, 1 lag)	0.504***	-0.237***	0.566***
	(0.0614)	(0.0235)	(0.108)
Control of corruption (in logs, 1 lag)	-0.558***	-0.772***	-1.780***
	(0.149)	(0.197)	(0.564)
Rule of law (in logs, 1 lag)	0.453*	0.722***	2.857***
	(0.254)	(0.207)	(0.564)
EU Leniency		-0.421***	
		(0.0826)	
Industry dummies	x	x	x
Country dummies	x	x	x
Time dummies	x	x	x
Constant	4.005***	3.777***	-3.691**
	(1.419)	(0.609)	(1.625)
First stage F-statistics		22.68	
Hausman p-value		0.0000	
Observations	1,339	1,373	1,339
R-squared	0.528	0.165	

*Cluster-robust standard errors on the country-level are in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1. The Two-Stage Least Square (2SLS) approach uses EU leniency programmes implementation as an instrument for PCM.*

Chapter 6 Conclusion

The thesis has addressed two different topics in industrial organisation: the effectiveness of leniency programmes and the relationship between competition and innovation.

In the first pair of chapters, I analysed the efficiency of leniency programmes in detecting and destabilising cartels by evaluating their effect on their final aim, which is to increase industries' competition intensity. The empirical literature on the effectiveness of leniency is largely based on a population of discovered cartel cases, and so ignores potentially colluding firms. I proposed several approaches to address this gap in the literature. I first implemented Klein's methodology as a prelude to my proposed methodology, where I conducted a difference-in-differences analysis. I analysed a panel of OECD countries at the industry-level from 1990 to 2007. The results showed an increase in the industries' competition intensity after adopting the leniency programmes at both the national and the EU level, which suggests that these programmes are effective. As this result is only revealed after I delved into the differences-in-differences approach, it suggests that my methodological contribution could advance the literature by settling a currently unsettled issue.

In the other pair of chapters, I turned into a different topic, where I analysed the causal effect of competition intensity on innovation. Again, this is an unsettled question in the literature. I provided two separate contributions to the debate based on developing and OECD countries. I use both firm- and industry-level data. As a measure of innovation, I employed both inputs (R&D expenditures) as well as outputs (product and process innovation). To obtain a causal inference, I proposed a novel instrument, namely leniency programmes implementation. The choice of this instrument was driven by my results obtained in Chapter 2 and 3 where I found that leniency programmes were associated with a drop in price-cost margin. As well as from the analysis that shows that leniency programmes could be interpreted as exogenous. My instrumental variable results showed two conflicting results based on the set of countries included in the analysis as well as the level of aggregation. In particular, in developing countries (at the firm-level), competition intensity affects innovation outcome negatively, whereas in developed economies (at the industry-level) competition intensity increases the investment in R&D.

References

Abreu, D., Pearce, D., and Stacchetti, E. (1986). Optimal Cartel Equilibria with Imperfect Monitoring. *Journal of Economic Theory*, *39*(1), 251-269.

Acemoglu, D., Aghion, P., and Zilibotti, F. (2006). Distance to Frontier, Selection, and Economic Growth. *Journal of the European Economic Association*, *4*(1), 37-74.

Acs, Z. J., and Audretsch, D. B. (1988a). Innovation in Large and Small Firms: An Empirical Analysis. *The American Economic Review*, 678-690.

Acs, Z. J., and Audretsch, D. B. (1988b). Testing the Schumpeterian Hypothesis. *Eastern Economic Journal*, *14*(2), 129-140.

Aghion, P., Bechtold, S., Cassar, L., and Herz, H. (2014). The Causal Effects of Competition on Innovation: Experimental Evidence (No. w19987). *National Bureau of Economic Research.*

Aghion, P., Blundell, R., Griffith, R., Howitt, P., and Prantl, S. (2009). The Effects of Entry on Incumbent Innovation and Productivity. *The Review of Economics and Statistics*, *91*(1), 20-32.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics*, *120*(2), 701-728.

Aghion, P., and Griffith, R. (2008). Competition and Growth: Reconciling Theory and Evidence. MIT Press.

Aghion, P., and Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, *60*(2), 323-351.

Aghion, P., Harris, C., and Vickers, J. (1997). Competition and Growth with Step-by-Step Innovation: An Example. *European Economic Review*, *41*(3), 771-782.

Aghion, P., Harris, C., Howitt, P., and Vickers, J. (2001). Competition, Imitation and Growth with Step-by-Step Innovation. *The Review of Economic Studies*, *68*(3), 467-492.

Amir, R. (2003). Market Structure, Scale Economies and Industry Performance. Mimeo

Angrist, J. D., and Pischke, J. S. (2008). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Arrow, K. (1962). Economic Welfare and the Allocation of Resources for Invention. In the Rate and Direction of Inventive Activity: Economic and Social Factors (pp. 609-626). Princeton University Press.

Askenazy, P., Cahn, C., and Irac, D. (2013). Competition, R&D, and the Cost of Innovation: Evidence for France. *Oxford Economic Papers*, 65(2), 293-311.

Aubert, C., Rey, P., and Kovacic, W. E. (2006). The Impact of Leniency and Whistle-Blowing Programs on Cartels. *International Journal of Industrial Organization*, 24(6), 1241-1266.

Autor, D. H. (2003). Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics*, 21(1), 1-42.

Baily, M. N., Gersbach, H., Scherer, F. M., and Lichtenberg, F. R. (1995). Efficiency in Manufacturing and the Need for Global Competition. *Brookings Papers on Economic Activity. Microeconomics*, *1995*, 307-358.

Beneito, P., Coscollá-Girona, P., Rochina-Barrachina, M. E., and Sanchis, A. (2015). Competitive Pressure and Innovation at the Firm Level. *The Journal of Industrial Economics*, *63*(3), 422-457.

Besley, T., and Burgess, R. (2004). Can labor Regulation Hinder Economic Performance? Evidence from India. *The Quarterly Journal of Economics*, *119*(1), 91-134.

Besley, T., and Case, A. (2000). Unnatural Experiments? Estimating the Incidence of Endogenous Policies. *The Economic Journal*, *110*(467), 672-694

Blundell, R., Griffith, R., and Van Reenen, J. (1995). Dynamic Count Data Models of Technological Innovation. *The Economic Journal*, 333-344.

Blundell, R., Griffith, R., and Van Reenen, J. (1999). Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *The Review of Economic Studies*, *66*(3), 529-554.

Boone, J. (2000). Competitive Pressure: The Effects on Investments in Product and Process Innovation. *The RAND Journal of Economics*, 549-569.

Boone, J. (2008). A New Way to Measure competition. *The Economic Journal*, *118*(531), 1245-1261.

Bos, J. W., Kolari, J. W., and Van Lamoen, R. C. (2013). Competition and Innovation: Evidence from Financial Services. *Journal of Banking and Finance, 37*(5), 1590-1601.

Brenner, S. (2009). An Empirical Study of the European Corporate Leniency Program. *International Journal of Industrial Organization*, *27*(6), 639-645.

Buccirossi, P., Ciari, L., Duso, T., Spagnolo, G., and Vitale, C. (2013). Competition Policy and Productivity Growth: An Empirical Assessment. *Review of Economics and Statistics*, *95*(4), 1324-1336.

Bulow, J., and Klemperer, P. (2002). Prices and the Winner's Curse. *RAND Journal of Economics*, 1-21.

Card, D., and DellaVigna, S. (2013). Nine Facts about Top Journals in Economics. *Journal of Economic Literature*, 51(1), 144-161.

Carlin, W., Schaffer, M., and Seabright, P. (2004). A Minimum of Rivalry: Evidence from Transition Economies on the Importance of Competition for Innovation and Growth. *Contributions in Economic Analysis and Policy*, *3*(1).

Chen, J., and Harrington, J. E. (2007). The Impact of the Corporate Leniency Program on Cartel Formation and the Cartel Price Path. *Contributions to Economic Analysis*, *282*, 59-80.

Correa, J. A. (2012). Innovation and Competition: An Unstable Relationship. *Journal of Applied Econometrics*, *27*(1), 160-166.

Crepon, B., Duguet, E., and Kabla, I. (1996). Schumpeterian Conjectures: A Moderate Support from Various Innovation Measures. In Determinants of Innovation (pp. 63-98). Palgrave Macmillan UK.

Dasgupta, P., and Stiglitz, J. (1980). Industrial Structure and the Nature of Innovative Activity. *The Economic Journal*, *90*(358), 266-293.

Djankov, S., and Hoekman, B. (2000). Market Discipline and Corporate Efficiency: Evidence from Bulgaria. *Canadian Journal of Economics*, 190-212.

Duso, T., and Seldeslachts, J. (2010). The Political Economy of Mobile Telecommunications Liberalization: Evidence from the OECD Countries. *Journal of Comparative Economics*, *38*(2), 199-216.

Duso, T., and Röller, L. H. (2003). Endogenous Deregulation: Evidence from OECD Countries. *Economics Letters*, *81*(1), 67-71.

European Commission, (2002). Commission Notice on Immunity from Fines and Reduction of Fines in Cartel Cases. Official Journal of the European Commission C 45, 3–5.

Evenett, S. J., Levenstein, M. C., and Suslow, V. Y. (2001). International Cartel Enforcement: Lessons from the 1990s. *The World Economy*, *24*(9), 1221-1245.

Fridolfsson, S. O., Bigoni, M., Le Coq, C., and Spagnolo, G. (2009). Fines, Leniency and Rewards in Antitrust: An Experiment. Available at SSRN 1744864.

Friesenbichler, K. S. (2007). Innovation and Market Concentration in Europe's Mobile Phone Industries. Evidence from the Transition from 2G to 3G (No. 306). WIFO Working Papers.

Galdon-Sanchez, J. E., and Schmitz, J. A. (2002). Competitive Pressure and Labor Productivity: World Iron-Ore Markets in the 1980's. *The American Economic Review*, *92*(4), 1222-1235.

Gali, J., Gertler, M., and Lopez-Salido, J. D. (2007). Markups, Gaps, and the Welfare Costs of Business Fluctuations. *The Review of Economics and Statistics*, *89*(1), 44-59.

Gayle, P. G. (2001). Market Concentration and Innovation: New Empirical Evidence on the Schumpeterian Hypothesis. *University of Colorado at Boulder: unpublished paper*.

Gerschenkron, A. (1962). Economic Backwardness in Historical Perspective: A Book of Essays (No. 330.947 G381). Cambridge, MA: Belknap Press of Harvard University Press.

Geroski, P. A. (1990). Innovation, Technological Opportunity, and Market Structure. *Oxford Economic Papers*, *42*(3), 586-602.

Geroski, P. A. (1995). Market Structure, Corporate Performance, and Innovative Activity. *OUP Catalogue*.

Gilbert, R. J., and Newbery, D. M. (1982). Preemptive Patenting and the Persistence of Monopoly. *The American Economic Review*, 514-526.

Green, E. J., and Porter, R. H. (1984). Noncooperative collusion under imperfect price information. *Econometrica: Journal of the Econometric Society*, 87-100.

Grether, J. M. (1996). Mexico, 1985-90: Trade Liberalization, Market Structure, and Manufacturing Performance. *Industrial Evolution in Developing Countries*, 260-83.

Griffith, R., Harrison, R., and Macartney, G. (2007). Product Market Reforms, Labour Market Institutions and Unemployment. *The Economic Journal*, 117(519).

Griffith, R., Harrison, R., and Simpson, H. (2006). The link between product market reform, innovation and EU macroeconomic performance (No. 243). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Griffith, R., Harrison, R., and Simpson, H. (2010). Product Market Reform and Innovation in the EU. *The Scandinavian Journal of Economics*, 112(2), 389-415.

Grout, P. A., and Sonderegger, S. (2005). Predicting Cartels, Office of Fair Trading Discussion Paper (OFT 773). UK Office of Fair Trading, London.

Grossman, G. M., and Helpman, E. (1993). Innovation and Growth in the Global Economy. MIT press.

Häckner, J. (1994). Collusive Pricing in Markets for Vertically Differentiated Products. *International Journal of Industrial Organization*, *12*(2), 155-177.

Haltiwanger, J., and Harrington Jr, J. E. (1991). The Impact of Cyclical Demand Movements on Collusive Behavior. *The RAND Journal of Economics*, 89-106.

Hamaguchi, Y., Kawagoe, T., and Shibata, A. (2009). Group Size Effects on Cartel Formation and the Enforcement Power of Leniency Programs. *International Journal of Industrial Organization*, 27(2), 145-165.

Hausmann, R., and Rodrik, D. (2003). Economic Development as Self-Discovery. *Journal of Development Economics*, *72*(2), 603-633.

Harrington, J. E. (2008). Optimal Corporate Leniency Programs. *The Journal of Industrial Economics*, *56*(2), 215-246.

Harrison, A. E. (1994). Productivity, Imperfect Competition and Trade Reform: Theory and Evidence. *Journal of International Economics*, *36*(1-2), 53-73.

Hart, O. D. (1983). The Market Mechanism as an Incentive Scheme. *The Bell Journal of Economics*, 366-382.

Hinloopen, J., and Soetevent, A. R. (2008). Laboratory Evidence on the Effectiveness of Corporate Leniency Programs. *The RAND Journal of Economics*, 39(2), 607-616.

Imbens, G. W., and Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica, 62(2),* 467-475.

Ivaldi, M., Jullien, B., Rey, P., Seabright, P., and Tirole, J. (2007). The Economics of Tacit Collusion: Implications for Merger Control. In *The Political Economy of Antitrust* (pp. 217-239). Emerald Group Publishing Limited.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The Worldwide Governance Indicators: Methodology and Analytical Issues. *Hague Journal on the Rule of Law*, *3*(2), 220-246.

Klein, G. J. (2010). Cartel Destabilization and Leniency Programs: Empirical Evidence (No. 10-107). *ZEW-Zentrum für Europäische Wirtschaftsforschung/Center for European Economic Research*.

Klingemann, H. D. (2006). Mapping Policy Preferences II: Estimates for Parties, Electors, and Governments in Eastern Europe, European Union, and OECD 1990-2003 (Vol. 2). Oxford University Press on Demand.

Kraft, K. (1989). Market Structure, Firm Characteristics and Innovative Activity. *The Journal of Industrial Economics*, 329-336

La Porta, R., Lopez-de-Silanes, F., and Shleifer, A. (2008). The Economic Consequences of Legal Origins. *Journal of Economic Literature*, *46*(2), 285-332.

Levin, R. C., Cohen, W. M., and Mowery, D. C. (1985). R&D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses. *The American Economic Review*, *75*(2), 20-24.

Levinsohn, J. (1993). Testing the Imports-as-Market-Discipline Hypothesis. *Journal of International Economics*, *35*(1-2), 1-22.

Mairesse, J., and Mohnen, P. (2010). Using Innovation Surveys for Econometric Analysis. *Handbook of the Economics of Innovation*, *2*, 1129-1155.

Martins, J. O., Scarpetta, S., and Pilat, D. (1996). Mark-Up Pricing, Market Structure and the Business Cycle. *OECD Economic Studies*, (27), 71-106.

Miller, N. H. (2009). Strategic Leniency and Cartel Enforcement. *The American Economic Review*, *99*(3), 750-768.

Motta, M., and Polo, M. (2003). Leniency Programs and Cartel Prosecution. *International Journal of Industrial Organization*, *21*(3), 347-379.

Nekarda, C. J., and Ramey, V. A. (2013). *The Cyclical Behavior of the Price-Cost Markup* (No. w19099). National Bureau of Economic Research.

Nickell, S. J. (1996). Competition and Corporate Performance. *Journal of Political Economy*, *104*(4), 724-746.

Okada, Y. (2005). Competition and Productivity in Japanese Manufacturing Industries. *Journal of the Japanese and International Economies*, *19*(4), 586-616.

Polder, M., and Veldhuizen, E. (2012). Innovation and Competition in the Netherlands: Testing the Inverted-U for Industries and Firms. *Journal of Industry, Competition and Trade*, *12*(1), 67-91.

Porter, M. E. (1990). The Competitive Advantage of Nations. *Harvard Business Review*, *68*(2), 73-93

Raith, M. A. (1996). Product Differentiation, Uncertainty and the Stability of Collusion. London School of Economics and Political Science, LSE Library.

Roeger, W. (1995). Can Imperfect Competition Explain the Difference Between Primal and Dual Productivity Measures? Estimates for US Manufacturing. *Journal of Political Economy,* 103(2), 316-330.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, *94*(5), 1002-1037.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, *98*(5, Part 2), S71-S102.

Rosenthal, R. W. (1980). A Model in which an Increase in the Number of Sellers Leads to a Higher Price. *Econometrica: Journal of the Econometric Society*, 1575-1579.

Rotemberg, J. J., and Saloner, G. (1986). A Supergame-Theoretic Model of Price Wars during Booms. *The American Economic Review*, *76*(3), 390-407.

Rotemberg, J. J., and Woodford, M. (1999). The Cyclical Behavior of Prices and Costs. *Handbook of Macroeconomics*, *1*, 1051-1135.

Salop, S. (1977). The Noisy Monopolist: Imperfect Information, Price Dispersion and Price Discrimination. *The Review of Economic Studies*, 393-406.

Scharfstein, D. (1988). Product-Market Competition and Managerial Slack. *The RAND Journal of Economics*, 147-155.

Scherer, F. M. (1965a). Corporate Inventive Output, Profits, and Growth. *Journal of Political Economy*, *73*(3), 290-297.

Scherer, F. M. (1965b). Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. *The American Economic Review*, *55*(5), 1097-1125.

Schmidt, K. M. (1997). Managerial Incentives and Product Market Competition. *The Review of Economic Studies*, *64*(2), 191-213.

Schumpeter, J. A. (1943). Capitalism, Socialism and Democracy. London: Allen Unwin.

Scott, J. (1984). Firm versus Industry Variability in R&D Intensity. In *R&D, Patents, and Productivity* (pp. 233-248). University of Chicago Press.

Spagnolo, G. (2004). Divide et Impera: Optimal Leniency Programs. CEPR Discussion Papers, 4840.

Spagnolo, G. (2006). Leniency and Whistleblowers in Antitrust.

Spagnolo, G. (2008). Leniency and Whistleblowers in Antitrust, in Handbook of Antitrust Economics, Paolo Buccirossi, ed., Cambridge, Mass.: The MIT Press.

Stephan, A. (2005). An Empirical Assessment of the 1996 Leniency Notice. Centre for Competition Policy.

Stigler, G. J. (1964). A Theory of Oligopoly. *Journal of Political Economy*, *72*(1), 44-61.

Stiglitz, J. E. (1989). Imperfect Information in the Product Market. *Handbook of Industrial Organization*, *1*, 769-847.

Stock, J.H., Yogo, M., (2002). Testing for Weak Instruments in Linear IV Regression. Technical Report. National Bureau of Economic Research.

Symeonidis, G. (1996). Innovation, Firm Size and Market Structure: Schumpeterian Hypotheses and Some New Themes. OECD Economics Department Working Paper 161.

Symeonidis, G. (2002a). Cartel Stability with Multiproduct Firms. *International Journal of Industrial Organization*, *20*(3), 339-352.

Symeonidis, G. (2002b). The Effects of Competition: Cartel Policy and the Evolution of Strategy and Structure in British Industry. MIT Press.

Symeonidis, G. (2008). The Effect of Competition on Wages and Productivity: Evidence from the United Kingdom. *The Review of Economics and Statistics*, *90*(1), 134-146.

Tingvall, P. G., and Karpaty, P. (2011). Service-Sector Competition, Innovation and R&D. *Economics of Innovation and New Technology*, *20*(1), 63-88.

Tingvall, P. G., and Poldahl, A. (2006). Is There Really an Inverted U-Shaped Relation between Competition and R&D?. *Economics of Innovation and New Technology*, *15*(2), 101-118.

Vives, X. (2008). Innovation and Competitive Pressure. *The Journal of Industrial Economics*, *56*(3), 419-469.