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Abstract

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JEL Classification: K21, L40

Keywords: Merger Policy, EU Commission, Dominance, Concentration, Entry Barriers, foreclosure, causal forests

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25 Years of European Merger Control[*]

Pauline Affeldt[†], Tomaso Duso[‡] and Florian Szücs[§]

March 30, 2020

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1 Introduction

Competition policy, that is, the design and enforcement of competition rules, is a cornerstone of the European Union (EU)'s program to enhance the European single market and foster growth.[1] The European Commission's (EC) Directorate General for Competition (DG Comp) has jurisdiction over community-wide competition matters, making it the most important antitrust agency in Europe. Competition policy covers several areas ranging from the monitoring and blocking of anticompetitive agreements – such as cartels – to abuses by dominant firms, to mergers and acquisitions as well as state aid. Among these areas of antitrust enforcement, merger control plays a peculiar role. First, it is the only area with *ex-ante* enforcement. Second, it has important implications for other areas of antitrust: if anticompetitive mergers reduce competition and strengthen the dominant position of the merging firms, the *ex-post* control of anticompetitive behaviour becomes more difficult. Finally, mergers are the area of antitrust where the largest consensus on best practices exists. Therefore, among competition policy tools, it is the area that attracted most policy interest and economic research.

The European Communities Merger Regulation (ECMR), the legal basis for common European merger control, came into force in 1990. Over the course of the next 25 years, European merger control saw significant changes. While in the early 1990s there were approximately 50 notified cases per year, the annual workload increased significantly in the late 1990s and has averaged around 280 cases in the 2000s. DG Comp's enforcement activity reflects these changes. Procedurally, many novelties were implemented in the 2004 amendment to the ECMR: not only were new horizontal merger guidelines and the office of the chief economist introduced, but also, more importantly, a new substantive test, the "significant impediment of effective competition" (SIEC) test and an efficiency defense clause were introduced. These amendments marked a substantial change in the legal basis for merger control enforcement in Europe. Yet, the pressure for these changes began much earlier with the increasing belief that a mere form-based assessment of mergers could often result in wrong decisions. The three overturned prohibitions by the Court of First Instance at the beginning of the 2000s marked the peak of this process.

In this paper, we employ a new dataset containing all merger cases with an official decision by DG Comp (more than 5000 individual decisions) to evaluate the time dynamics of the EC's decision procedures (see Affeldt, Duso, and Szücs (2018)). Specifically, we assess how consistently different arguments related to structural market parameters – market shares, concentration, likelihood of entry, and foreclosure – were put forward to motivate a particular decision. In order to obtain a more fine-grained picture of the decision determinants, we extend our analysis to the specific relevant product and geographic markets concerned by a merger. Thus, instead of only looking at the determinants of a merger decision in the aggregate as commonly done in the literature, we also investigate the factors that caused competitive concerns in specific sub-markets and how they have changed over time. This step is particularly important because large mergers typically affect many different product markets in many different geographic regions. For example, the mergers in our data affect an average of six markets. Therefore, by analyzing individual markets we better model the process that lead to a specific decision. Thus, the scope and depth of our data allow us to go beyond the existing literature by i) not relying on a sample of decisions but instead reporting patterns for the whole population

[1]Gutiérrez and Philippon (2018) claim that since the 1990s, European markets have become more competitive than their US counterparts because of the increased economic integration and the enactment of the European single market. They attribute a key role in this process to the tough enforcement of competition policy rules.

of merger cases examined by DG Comp; and ii) allowing for heterogeneity within merger cases by analyzing the individual product and geographic markets concerned.

In a first step, and in line with the existing literature (e.g., Bergman, Jakobsson, and Razo, 2005; Bergman, Coate, Jakobsson, and Ulrick, 2010; Mai, 2016), we start by estimating the probability of intervention as a function of merger characteristics at the merger level. We find that the existence of barriers to entry, the increase of concentration measures and, in particular, the share of product markets with competitive concerns are positively associated with the likelihood of an intervention. This approach naturally extends to the level of the individual markets: instead of estimating the overall probability of an intervention, we estimate the likelihood that competitive concerns are found in a specific product/geographical market. We find that, again, barriers to entry, but also the risk of foreclosure play a role. While tightly defined (national) markets increase the probability of concerns, the number of active competitors decreases it. Structural indicators of market shares and concentration show the expected positive and significant correlation with the likelihood of competitive concerns.

In a second step, we introduce non-parametric supervised machine learning (ML) techniques to analyse competition policy outcomes. In particular, we implement the causal forest algorithm proposed by Athey and Imbens (2016). This allows a more flexible approach to model the heterogeneity in merger control decisions. Specifically, the association between structural indicators and the Commission's decisions is made a function of all other covariates. The estimated conditional average effects confirm the qualitative findings of the simple linear model, although the OLS estimates seem to be plagued by a significant upward bias. We then discuss several dimensions of heterogeneity. First, we look at how the role of the structural indicators to motivate competitive concerns has changed over time. Especially after the reform of 2004, a so-called effects-based approach, centered around a clearly stated theory of harm, was made a cornerstone of EU merger control. In such an approach, the reliance on structural parameters was expected to decrease. We find that the importance of the merging parties' market shares – our proxy for dominance – and, to a lesser extent, concentration have declined over time while the importance of barriers to entry and the risk of foreclosure has not changed in DG Comp's decision making. Yet, the impact of structural indicators appears to be much less volatile than in the simple linear probability model. Thus, the arguments put forward by the EC to substantiate its decisions appear to be more consistently applied once the process underlying these decisions is modelled in a flexible way.

Second, in the effects-based approach the interactions of various merger-specific characteristics, in particular the structural indicators, might play a crucial role to substantiate the theory of harm. Indeed, we observe that dominance plays a particularly important role when concentration is high, whereas concentration has a larger positive correlation with the likelihood of concerns when entry barriers and the risk of foreclosure are high. Third, we show that the geographic market definition does not seem to affect the way theories of harm are put forward to motivate the competitive concerns. Finally, we observe that the role of dominance is more important the more complex the merger under scrutiny.

The remainder of the study is structured as follows. In section 2, we discuss the institutional details of European merger control and review recent studies that empirically investigate the determinants of merger intervention. In section 3, we describe the dataset used in estimation. We present the parametric model as well as estimation results for the determinants of EC merger interventions in section 4, while section 5 presents the model and results for non-parametric estimation of heterogeneous correlations between merger characteristics and intervention by the EC. We conclude in section 6.

2 Literature & Institutional Details

2.1 Institutional Details

The European Communities Merger Regulation (ECMR) was passed in 1989 and came into force in September 1990.[2] It specifies the scope of intervention and juridical competence of the European Commission in merger cases with a "community dimension." In article 1.2 of regulation 4064/89, a combination is defined to have community dimension by meeting the following conditions:

(a) the aggregate worldwide turnover of all the undertakings concerned is more than ECU[3] 5 000 million, and

(b) the aggregate Community-wide turnover of each of at least two of the undertakings concerned is more than ECU 250 million, unless each of the undertakings concerned achieves more than two-thirds of its aggregate Community-wide turnover within one and the same Member State.

That means that from 1990 onwards, all major combinations affecting EU markets have been scrutinized by the EC, whereas national competition authorities have been focusing on mergers affecting a single Member State. In 1997, the above definition was significantly widened by the passing of regulation 1310/97, which made the definition of a community dimension less stringent.[4]

Notice that these definitions also include companies that are located, produce, and sell outside of Europe, as long as their sales to European markets are sufficiently high. Thus, a merger can be subject to the jurisdiction of more than one competition authority. This resulted in diplomatic strife, for instance, when a merger of two US companies *General Electric* and *Honeywell* was ratified by American authorities, but prohibited by the European Commission.

Once it is established that a combination is subject to EC jurisdiction, the merging parties are required to notify the Commission prior to the implementation of the concentration. On receipt of the notification, the Commission publishes a note in the Official Journal of the European Communities, where third parties can comment on the proposed transaction.

After the notification of the Commission, phase-1 proceedings are initiated. The EC then has 25 working days (which can be extended to a maximum of 35) for an initial assessment of the merger. Based on this investigation the EC can clear the proposed merger (phase-1 clearance), clear it subject to remedies proposed by the merging parties (phase-1 remedy), or initiate a more in-depth investigation (phase-2 investigation)

[2] Council Regulation (EEC) No 4064/89 of 21 December 1989 on the control of concentrations between undertakings [Official Journal L 395 of 30 December 1989].

[3] ECU was replaced by Euro in 1998.

[4] Council Regulation (EC) No 1310/97 of 30 June 1997 [Official Journal L 180 of 9 July 1997] defines a community dimension when i) the combined aggregate worldwide turnover of all the undertakings concerned is more than EUR 2 500 million; ii) in each of at least three Member States, the combined aggregate turnover of all the undertakings concerned is more than EUR 100 million; iii) in each of at least three Member States included for the purpose of point (b), the aggregate turnover of each of at least two of the undertakings concerned is more than EUR 25 million; and iv) the aggregate Community-wide turnover of each of at least two of the undertakings concerned is more than EUR 100 million, unless each of the undertakings concerned achieves more than two-thirds of its aggregate Community-wide turnover within one and the same Member State.

depending on whether the proposed transaction raises competitive concerns and depending on whether these can be addressed by initial remedies or not. Furthermore, the merging parties can also withdraw the proposed merger during phase-1 (phase-1 withdrawal).

If the EC initiates an in-depth investigation, the phase-2 investigation may take up to 90 working days. Following this second investigation phase, the EC can unconditionally clear the merger (phase-2 clearance), clear the merger subject to commitments (phase-2 remedy) or prohibit the merger (phase-2 prohibition). Again, the merging parties can also withdraw the proposed merger in phase-2 (phase-2 withdrawal). It is argued that withdrawing a merger in phase-2 of the investigation process is virtually equivalent to a prohibition as parties often withdraw a merger before an actual prohibition by the EC can take place (Bergman, Jakobsson, and Razo, 2005). Hence, both a prohibition as well as a phase-2 withdrawal suggest that the EC and the notifying parties were unable to find suitable remedies to address the anti-competitive concerns of the proposed transaction. Thus, we consider prohibitions, phase-2 remedies, phase-2 withdrawals, and phase-1 remedies as an intervention in our empirical analysis.

Significant changes to European merger control were introduced in 2004 through an amendment to ECMR with the aim of bringing merger control closer to economic principles: the concept of an efficiency defense was introduced, a chief economist was appointed, the timetable for remedies was improved and horizontal merger guidelines were issued. The reception of the new merger regulation was generally favorable (Lyons, 2004). One of the most significant changes was the change from a "dominance test" for market power to a "significant impediment of effective competition test" (SIEC).

The pre-2004 dominance test required the creation or strengthening of a dominant position as a necessary condition for the prohibition of a merger. It has been argued that the dominance test is deficient in cases of collective dominance and tacit collusion, and that the "substantial lessening of competition" test employed by the United States' Federal Trade Commission (FTC) would be preferable. The SIEC test used by the European Commission after the 2004 reform is more closely aligned with US practice (Bergman, Coate, Jakobsson, and Ulrick, 2007; Szücs, 2012).

2.2 Previous Literature

This paper most closely relates to the literature that empirically studies the determinants of merger policy intervention decisions by competition authorities. Most of the related literature – with the prominent exception of Bradford, Jackson, and Zytnick (2018) and Mini (2018) – investigate the determinants of merger intervention decisions *at the merger level* and for a *sample of merger cases* only. The scope and depth of our data (see section 3) allow us to go beyond the existing literature by, firstly, not relying on a sample of decisions but instead reporting patterns for the entire population of merger cases examined by DG Comp and, secondly, allowing for heterogeneity within merger cases by examining the individual product and geographic markets concerned. Furthermore, all of the existing literature uses parametric models to empirically study the determinants of merger intervention decisions. We instead go one step further by using flexible, non-parametric machine learning techniques to study the heterogeneity in the association between structural market parameters and the intervention decision.

Bergman, Jakobsson, and Razo (2005) are the first to study the determinants of EU merger control. They employ a logit model and a sample of 96 EU merger cases to estimate the likelihood of going to phase-2 or prohibition decisions as a function of market and political variables. They find that decisions of the European Commission are only influenced by variables that directly affect welfare. In both estimated models (likelihood of phase-2 and likelihood of prohibition), the probability of intervention increases with the market share of the companies involved in the merger. Dummy variables indicating the possibility of post-merger joint dominance and the existence of entry barriers are also relevant determinants of the intervention decision while political/institutional variables are not significant. Bergman, Coate, Jakobsson, and Ulrick (2010) examine instead similarities between EU and US merger decisions using a sample of horizontal phase-2 mergers between 1990-2004 for both the EU (109 cases) and the US (166 cases). They estimate a probit model for each regime, where the dependent variable is an indicator for intervention. They find that market shares, the Herfindahl-Hirschman-Index (HHI),[5] and entry barriers matter for the intervention decision. In a second step, they apply the model of the EU authority to the US case sample and vice versa to predict the challenge probabilities if the other competition authority had decided the case. For dominance mergers, the study finds that the EU is tougher than the US on average, in particular for mergers where the market shares of the notifying parties are modest. The US, on the other hand, seem to be more aggressive for coordinated interaction and non-dominance, unilateral effects cases. In a recent study, Bergman, Coate, Mai, and Ulrick (2019) update the dataset of Bergman, Coate, Jakobsson, and Ulrick (2010) by adding observations to both the EU as well as the US dataset for the time period after the 2004 EU merger policy reform. The final dataset used in the analysis contains a sample of 151 EU phase-2 cases (covering 1991-2014) and 260 US cases (covering 1993-2013). Separate logit models for intervention indicators are estimated for the EU (distinguishing pre- and post-reform) and US cases. Market shares and entry barriers are found to have a significant positive effect on the probability of intervention. Predictions of interventions using the model of respectively the other jurisdiction (and distinguishing pre- and post-reform cases) show evidence of convergence between US and EU case decisions in unilateral effects mergers, where EU policy seems to be less aggressive post-reform.[6]

Duso, Gugler, and Szücs (2013) differentiate form the previous literature and evaluate European merger policy effectiveness along three dimensions: predictability, correctness, and deterrence. Regarding predictability of European merger policy, Duso, Gugler, and Szücs (2013) estimate pre- and post-reform models for a sample of 368 EU merger cases where the intervention decision of DG Comp is a function of *ex ante* observable merger characteristics. Unlike the existing literature, they do not use characteristics derived from the decision itself but constructed by matching the merger data to firm-level data from Datastream and Compustat. Prior to the 2004 merger policy reform full mergers, conglomerate mergers, and mergers, where the parties have high market value, increase the probability of intervention while mergers involving US firms are less likely to be challenged. Post-reform, mergers between US firms, full mergers, and cross-border mergers, decrease the probability of intervention while conglomerate mergers are more likely to be challenged.

[5]The HHI is defined as the sum of squared market shares of all firms active in the market.

[6]Similar to this study, Szücs (2012) investigates the convergence between US and EU merger policy following the 2004 EU merger policy reform. In particular, he uses a sample of 309 EU and 286 US merger cases scrutinized by DG Comp and the FTC, respectively, between 1991 and 2008. Using pre-reform EU, post-reform EU and US merger samples, he estimates a logit model on the decision to intervene and then uses the estimated models to predict the probability of intervention for each merger case from the point of view of both competition authorities. Based on the decreasing differences in the predicted intervention probabilities between the EU and the US authorities over time, he concludes that EU and US merger policy are converging in the era following the 2004 EU merger policy reform. Both pre- and post-reform, barriers to entry as well as the existence of a dominant player in the market increase the likelihood of intervention. Post-reform, also the HHI has a positive and significant effect on intervention.

Mai (2016) studies the effect of the EU merger policy reform on the probability of a merger being challenged by DG Comp based on a sample of 341 phase-1 and phase-2 horizontal mergers between 1990 and 2012. The probability of a challenge in a probit model pooling pre- and post-reform cases is driven by the market shares of the merging parties, entry barriers, and some other factors. Political factors, measured as the country of the merging firms, are found to be insignificant. The merger reform reduces the probability of challenge by between 8 and 16 percentage points. Mai (2016) also estimates separate pre- and post-reform models and applies the methodology used by Bergman, Coate, Jakobsson, and Ulrick (2010), Szücs (2012), and Bergman, Coate, Mai, and Ulrick (2019) by predicting the probability of challenge for pre-reform mergers using the post-reform model and vice versa. The author finds that the EU merger policy seems to have slightly softened post-reform and that market shares and entry barriers are important predictors of challenge both pre- and post-reform. However, the importance of market shares is lower post-reform.

Two recent papers differ from the previous literature by significantly expanding the sample of mergers analyzed. Bradford, Jackson, and Zytnick (2018) empirically investigate whether European merger control is used for protectionism. Similar to our data, they collect information on all merger cases scrutinized by DG Comp between 1990 and 2014. However, their analysis is conducted at the level of the merger rather than the concerned product and geographic market. Furthermore, they do not collect information on the structural parameters of market shares, concentration, likelihood of entry, and foreclosure from the case documents.[7] The authors find that DG Comp did not intervene more frequently or extensively in transactions involving non-EU or US-based firms. While transaction value, HHI, hostile takeovers, and whether the merger is horizontal increase the likelihood of intervention, mergers involving a financial sponsor, taking place in large markets, and being stock acquisitions are less likely to be challenged.

The paper that is most closely related to this study in terms of data is Mini (2018). Mini (2018) also collected information on the universe of EU merger decisions from the publicly available case documents between 1990 and 2013, recording each market concerned by the transaction as a separate observation. Thus, his data are very similar to ours. He then estimates probit models at the market level for horizontal overlap markets, interacting all explanatory variables with a post-reform indicator variable. In the first model, the main variables of interest are the merging parties' market shares and the change in market shares, while in the second he focuses on post-merger HHI as well as the change in HHI due to the merger. Similarly to Bergman, Coate, Jakobsson, and Ulrick (2010), Szücs (2012), Bergman, Coate, Mai, and Ulrick (2019) and Mai (2016), he uses the models to predict how the estimated pre-reform model would have handled post-reform cases, decomposing observed differences into policy and case mix effects. He concludes that while the EC changed neither its stance towards mergers to quasi-monopoly or monopoly nor towards mergers in unconcentrated markets, it has challenged fewer mergers due to unilateral concerns for mid ranges of market shares and HHI post-reform.

Thus, Mini (2018) is the only paper that studies the determinants of merger policy interventions at the relevant product and geographic market level based on the population of European merger decisions as we do. However, we focus on a different aspect in our analysis by studying the heterogeneity in the association between structural market parameters and other merger and market characteristics and the intervention

[7] The HHI and market size variables are constructed based on European-wide sales at the two-digit NACE code industry level from the Amadeus data base. Clearly, these measures are quite different from those calculated by the Commission itself in well-defined product and geographic markets.

decision by DG Comp. To this end, we use flexible, non-parametric machine learning techniques and, in particular, show how the association between structural market parameters and the intervention decision has evolved over time as well as other dimensions of heterogeneity. Unlike the existing literature, we let the data determine these patterns rather than imposing specific parametric models.

3 Data and Descriptives

The data contain almost the entire population of DG Comp's merger decisions, both in the dimension of time and with regard to the scope of the decisions encompassed. The data were obtained from the publicly accessible cases published by DG Comp on the EC's webpage.[8] We started data collection with the very first year of common European merger control, 1990, and included all years up to 2014. This amounts to data on the first 25 years of European merger control.

Rather than taking a particular merger case as the level of observation, we collected data at a more fine-grained level and defined an observation as a particular product and geographic market combination concerned by a merger.

For the analysis in this study, we dropped cases that were referred back to member states as well as phase-1 withdrawals.[9] The final dataset used in the estimation contains 5,109 DG Comp merger decisions, where each decision includes a number of observations equal to the number of product/geographic markets affected in the specific transaction. The dataset contains a total of 30,995 market level observations. For further details on the merger database as well as the data collection procedure, we refer the reader to the data documentation (Affeldt, Duso, and Szücs, 2018).

The data set contains information on the name and country of the merging parties (acquirer and target), the date of the notification, the date of the decision[10] and the type of decision eventually taken by DG Comp (clearance, remedy, and prohibition) or whether the proposing parties withdrew the notification. The data also allow us to distinguish between a policy action taking place in the initial (phase-1) or second phase (phase-2) of the merger review process.

Figure 1 shows the number of yearly merger notifications, phase-1 merger cases, mergers cleared subject to remedies (phase-1 and phase-2) and prohibitions between 1990 and 2014. Overall, merger notifications show an increasing trend with a big drop around 2002. Most of the notified mergers are decided in phase-1: Phase-1 mergers track the number of notifications very closely. The number of mergers cleared subject to remedies increased dramatically after 1996 and oscillates between 10 and 25 per year in more recent years. The number of prohibitions varies between zero and three prohibitions per year.

The dataset further contains information on the nature of mergers. Variables for full mergers and joint ventures indicate whether DG Comp considered the case to be a full merger (55% of the notified mergers) and/or a joint venture (37% of the mergers); these are reported in table 1.

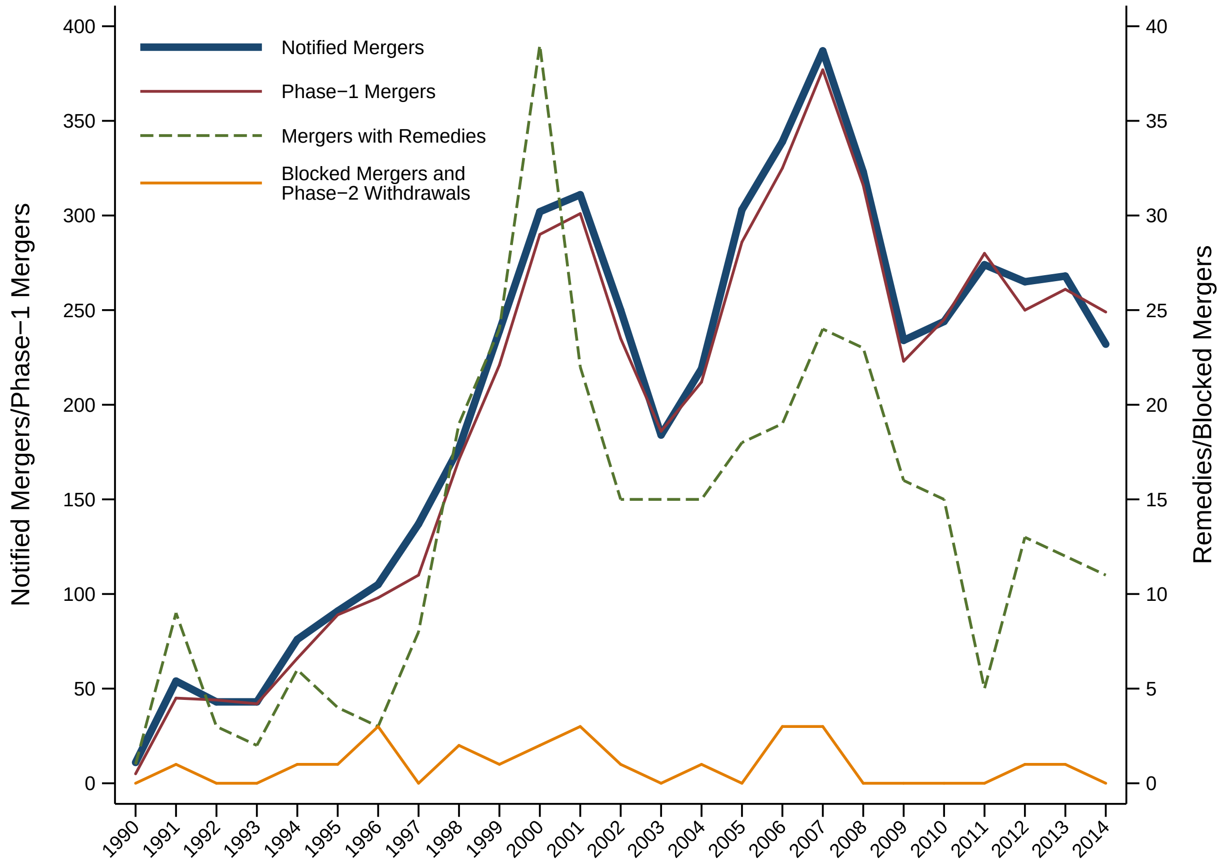
Further indicator variables for vertical and conglomerate transactions indicate whether a product/geographic

[8] The types of notified mergers, decisions taken and reports for each of the EC's decisions can be downloaded from: `http://ec.europa.eu/competition/mergers/cases/` and `http://ec.europa.eu/competition/mergers/legislation/simplified_procedure.html`.

[9] We only have information on two phase-1 withdrawals in the data.

[10] Note that the notification of a merger and the decision do not necessarily take place in the same year. We calculate the number of notifications based on the notification year and the number of decisions of a certain type based on the decision year.

Figure 1: Enforcement History of DG Comp Merger Cases, 1990-2014



We report notified cases per notification year and phase-1 cases per decision year (left axis) as well as remedies (phase-1 and phase-2) and prohibitions per decision year (right axis). We exclude phase-1 withdrawals from the count of phase-1 mergers and include phase-2 withdrawals in the count of prohibitions. We exclude all cases where the decision type is "other."

market is vertically affected by the merger (26% of the concerned markets) and whether the merger is conglomerate in nature in the particular concerned market (2% of the concerned markets), see table 2.

Furthermore, the dataset contains information on the geographic market definition adopted in each market by DG Comp. In about 58% of the concerned markets the geographic market is defined as national, in about 20% it is considered to be EU wide, in 10% it is defined as a worldwide market while in about 12% of the cases the geographic market definition is left open (see table 2).

We also observe which markets DG Comp considered to be problematic. The variable *concern* indicates the geographic and product markets affected by the merger, in which competitive concerns arose. This is the case in about 11% of markets. Further indicator variables record whether DG Comp considered barriers to entry to exist and whether DG Comp raised concerns that the merger would foreclose other firms in a particular market. As table 2 shows, DG Comp considered entry barriers to exist in about 12% of the concerned markets, while risk of foreclosure was present in about 3% of markets.

The database also contains a count of the number of competitors in the concerned market and an indi-

Table 1: Summary Statistics Indicator Variables at Merger Level, 1990-2014

	0	1	mean	sd
Intervention	4,742	367	0.07	0.258
Full merger	2,293	2,816	0.55	0.497
Joint Venture	3,228	1,881	0.37	0.482

Table 2: Summary Statistics Indicator Variables at Market Level, 1990-2014

	0	1	mean	sd
Concerns	27,675	3,320	0.11	0.309
Vertical merger	22,802	8,193	0.26	0.441
Conglomerate merger	30,472	523	0.02	0.129
National market	12,990	18,005	0.58	0.493
EU wide market	24,741	6,254	0.20	0.401
Worldwide market	28,037	2,958	0.10	0.294
Left open market	27,218	3,777	0.12	0.327
Entry barriers	27,423	3,572	0.12	0.319
Risk of foreclosure	30,184	811	0.03	0.160
No competitor information	13,733	17,262	0.56	0.497

cator variable equal to one if no information on competitors is available. Merging parties face, on average, 1.6 competitors, with the number of competitors varying between 0 and 34. However, information on competitors is missing in about 56% of the markets - these are mainly mergers that were cleared in phase-1. We also include a variable indicating the complexity of a particular merger case, measured as the count of product/geographic markets concerned by the merger. A merger affects on average 6 geographic/product markets, ranging between one and 245 concerned markets.

Where available, data on the market shares of the merging parties were collected from DG Comp's competitive assessment in the decision document. Data availability is thus constrained by the extent of DG Comp's analysis. Market share information is collected at the level of the relevant product/geographic market combination. This information allows the calculation of the merging parties' combined market shares, the HHI and the change in HHI.[11]

Table 3 shows summary statistics for the market share related variables. The merging parties' average joint market share is 33%, with average post-merger HHI between 2,148 and 5,639 depending on the calculation method.[12] The mean change in HHI due to the merger is about 445, ranging from 0 to 8,450.

[11] DG Comp generally reports only a range of market shares in the publicly available documents. We defined the market shares to be equal to the central value of the reported interval. If for example the market share range indicated is [0-10] percent, we record a value of 5 percent. If however the interval given in the decision is only 5 percentage points wide, we report the conservative lower market share bound. If for example the market share interval is [15-20] percent, we record a 15 percent market share, leading to some degree of measurement error. However, this is an issue that this study shares with the existing literature. To our knowledge, Mini (2018) is the only study that, rather than using the midpoints of the market share ranges reported in the case documents, constructs the expected market shares and expected HHI from the reported market share ranges. Thus, he highlights the issue of measurement error in market shares and HHI, explicitly accounting for it in estimation. As market shares in our data are likely to be underestimated, our results might be biased towards zero.

[12] We calculate two different HHI measures. The variable *Post-merger HHI (low)* is a lower bound of the post-merger HHI: it is calculated

As table 3 shows, market share information is not available for all observations: while joint market share and HHI information is available for about 23,000 out of the 31,000 observations, the change in HHI due to the merger can be calculated for only about 13,000 observations.

Table 3: Summary Statistics Continuous Variables at Market Level

	mean	sd	min	max	observations
Joint market share	32.5	23.6	0	100	22,812
Post-merger HHI (low)	2,147.7	2,368.3	0	10,000	22,812
Post-merger HHI (high)	5,639.0	2,251.1	650	10,000	22,812
Delta HHI	444.7	779.1	0	8,450	12,875
Number of competitors	1.6	2.3	0	34	30,995

Lastly, the data include information on the main industry in which a merger took place. The industry is identified by NACE codes, which is the industry classification system used by the European Union to classify different economic activities. For the empirical analysis, we group the industries into 25 groups, as shown in table 4, where some NACE codes are grouped together but, primarily, the manufacturing industry has been further divided into smaller subgroups. In 150 merger cases, the industry code was missing. For these cases, we went back to the decision documents and manually classified the mergers into the 25 industry groups according to our best judgement.

Note that all of these merger and market characteristics are *as stated in DG Comp's decision documents*. As such, they reflect, to some extent, the assessment, subjective views, and potential mistakes of DG Comp. However, this issue is present in all papers in the empirical literature on the determinants of merger decisions.

The final merger sample contains information on 5,109 merger cases concerning 30,995 markets. For the analysis at the merger level, we take the mean value across concerned markets for those variables that vary at the market level.

4 Linear Probability Model

In this section, we explore the association between merger characteristics and the intervention decision by DG Comp within a parametric approach. We first replicate the results of the existing literature, which explain a competition authority's decision as a function of merger characteristics *at the merger level*. In contrast to previous studies, we explicitly estimate different models in various sub-samples to assess the issue of sample selection, which could arise because some important indicators – prominently market share and concentration measures – are only observable for about 60% of the mergers. Second, as a merger often affects many different markets, while its characteristics and effects on competition can be heterogeneous across

as the square of the merging parties' joint market share plus the sum of squared market shares of competitors, whenever information on competitors' market shares is available. This assumes that competitors are very small whenever market share information of competitors is not available but market shares do not add up to 100%. The variable *Post-merger HHI (high)*, on the other hand, is an upper bound for the post-merger HHI: it adds the square of all missing market shares (100% minus all available market share information) to *Post-merger HHI (low)*. This hence treats all missing market share information as one missing competitor. While in our empirical analysis we use *Post-merger HHI (high)*, results based on *Post-merger HHI (low)* are largely equivalent.

Table 4: Industry Groups, 1990-2014

Industry group	obs	cases
Accomodation and food service	192	64
Agriculture, forestry, fishing, mining	1,106	173
Arts, other services, households as employers	392	55
Electricity, gas, steam	1,381	280
Financial service activities	960	249
Information and communication	1,304	259
Insurance and pensions	925	237
Manufacturing (coke, petroleum, chemicals)	3,827	401
Manufacturing (computer, electronics, optical products)	1,702	247
Manufacturing (food, beverages, tobacco)	1,845	230
Manufacturing (furnitures , other manufacturing)	669	52
Manufacturing (machinery and equipment)	865	173
Manufacturing (metals and metallic products)	1,113	219
Manufacturing (motor vehicles, trailers, transport equipment)	1,539	302
Manufacturing (pharmaceuticals)	2,068	106
Manufacturing (rubber, plastic, non-metallic)	1,086	165
Manufacturing (textiles, clothes, leather)	169	31
Manufacturing (wood, paper, printing)	1,031	152
Public administration, education, human health, social work	169	47
Real estate, professional activities, administrative service activities	1,162	254
Repair, installation of machinery and equipment	1,046	200
Telecommuications	1,090	224
Transporting and storage	2,729	329
Water supply, waste management, construction	520	152
Wholesale and retail trade	2,105	508
Total	30,995	5,109

these affected markets, we investigate in a second step the correlation between merger characteristics and DG Comp's intervention decision *at the market level*.

4.1 Methodology

We employ a linear probability model to estimate the relationship between merger characteristics and the intervention decisions of DG Comp.[13]

The dependent variable is an indicator variable for whether DG Comp intervened following a merger notification. We define the indicator variable *intervention* to be equal to one if DG Comp prohibited the merger, cleared the merger subject to remedies in phase-1, cleared the merger subject to remedies in phase-2, or the merging parties withdrew the merger proposal in phase-2. As table 1 shows, DG Comp intervened in 367 out of the 5,109 merger cases in the estimation dataset (i.e. 7% of mergers).

The estimation equation for the probability of intervention at the merger level is:

$$P_j(Y_j = 1|X_j, \overline{X}_{ij}, \eta_{m_j}, \eta_{t_j}) = \beta_0 + \beta_1 X_j + \beta_2 \overline{X}_{ij} + \eta_{m_j} + \eta_{t_j} + \epsilon_j \tag{1}$$

where i refers to a particular concerned product and/or geographic market, j refers to a merger, m_j refers to an industry group, and t_j refers to the year when merger j took place. The merger characteristics X_j vary at the merger level, while X_{ij} are market-specific characteristics within merger j. In the merger-level regressions, we use the average of market-level variables ($\overline{X}_{ij}$).

This approach naturally extends to the level of individual markets. Thus, in a second step, we estimate the correlation between market and merger characteristics and DG Comp's assessment at the level of the concerned product/geographic market. The dependent variable is *concern*, a dummy variable indicating that a specific product/geographic market i affected by merger j raised competitive concerns according to DG Comp. As table 2 shows, DG Comp raised competitive concerns in about 11% of the concerned markets.

The estimation equation for the probability of competitive concerns at the market level is:

$$P_{ij}(Y_{ij} = 1|X_j, X_{ij}, \eta_{m_j}, \eta_{t_j}) = \beta_0 + \beta_1 X_j + \beta_2 X_{ij} + \eta_{m_j} + \eta_{t_j} + \epsilon_{ij} \tag{2}$$

where the unit of observation is now the concerned market i in merger j rather than the merger j itself, X_j are the characteristics varying at the merger level, while X_{ij} are the characteristics varying at the market level.

Lastly, we explore the heterogeneity in the correlation between merger characteristics and competitive concerns by DG Comp over time. We run separate OLS regressions at the market level dividing the dataset into sub-samples based on the notification year.[14]

The explanatory variables of primary interest are four determinants of competitive concerns that are expected to drive DG Comp's intervention decision. The so called structural market parameters - market shares, concentration, the likelihood of entry, and the likelihood of foreclosure - are measured as follows:

[13]We decided to use a linear probability model rather than a probit or logit specification for easy interpretability of the estimated coefficients.

[14]The results are reported in appendix A.1.

- Indicator variable for *high post-merger concentration*: equal to one if post-merger HHI is above 2000 and the change in HHI is larger than 150.[15]

- Indicator variable for *joint market share*: equal to one if the merging firms' joint market share is above 50% in the concerned market.[16]

- Indicator variable *barriers to entry*: equal to one if DG Comp considered barriers to entry to exist in the concerned market.

- Indicator variable *risk of foreclosure*: equal to one if DG Comp raised concerns that the merger would foreclose other firms in a particular market.

In addition to these four determinants of competitive concerns of a merger, we control for further merger characteristics. We include the market definition indicator variables for national, EU wide, and worldwide geographic markets as well as information on the type of merger. Specifically, we use indicator variables for vertical mergers, conglomerate mergers, full mergers, and joint ventures; the count of the number of competitors in concerned markets; an indicator variable for whether information on competitors is missing in the data as well as a measure of the complexity of the merger measured by a count of the concerned markets.

Lastly, we include different industry and year fixed effects, depending on the specification. Industry dummy variables are defined for the 25 different industry groups as presented in table 4. For the OLS regressions at the merger and market level, we include a set of industry-year fixed effects, controlling for unobserved time-varying industry specific factors.[17] For the regressions that explore time dynamics we pooled the years 1990-1994, as there are relatively few merger cases in these early years of European merger control. In each of the year-specific OLS regressions, we include industry fixed effects. We corrected the error term by clustering standard errors at the industry group level.

4.2 Estimation Results

4.2.1 Determinants of Intervention at the Merger Level

We present four specifications at both the merger and market levels. Specification 1 is estimated on the full dataset without including market share variables. Hence, this specification includes essentially all mergers decided by DG Comp. If we include market share variables in the regression, sample size decreases significantly. However, as market share information is frequently missing for phase-1 clearances, changes in the estimated coefficients could be driven by selection effects. To address this concern, specifications 2 and 3 estimate the baseline model (column (1)) for the sub-samples of cases without (column (2)) and with market share information (column (3)). Finally, specification 4 adds the indicator variables for joint market share above 50% and high concentration to specification 3.

[15]We used the variable *Post-merger HHI (high)* for the construction of the indicator variable. Results obtained with *Post-merger HHI (low)* are qualitatively similar.

[16]We also run models where we use the level of the market shares rather than the dummy variable for high market shares. Results are similar. We decided to use the dummy for comparability with the approach based on machine learning discussed in section 5.

[17]As a robustness check, we use industry and year fixed effects separately and include a set of time-varying control variables at the industry based on Worldscope data (e.g., mean size, mean total assets, mean Tobit's q, mean R&D...) as suggested by Clougherty and Seldeslachts (2013) and Clougherty, Duso, Lee, and Seldeslachts (2016). However, this does not qualitatively change the results.

Table 5 report the results. Reassuringly, we find that the EC's decision determinants are similar across all four sub-samples considered: the share of markets where entry barriers exist, the number of markets raising concerns, as well as the total number of markets affected by the merger are positively correlated with the probability of a challenge. While the size of the effects is relatively constant for the number of markets affected, the impact of barriers to entry is almost 50% larger in cases where no market share information was gathered.

Neither merger characteristics (full mergers and joint ventures) nor the variables indicating alternative theories of harm (foreclosure concerns, vertical mergers, conglomerate mergers) significantly affect the Commission's decisions. Interestingly, the extent of concerned markets (national, EU wide or worldwide) also has no effect. In the full sample (column 1), we find some evidence for more challenges after the 2004 reform, but the coefficient is not precisely estimated in the other samples. Finally, in the sample including market share information (column 4), the indicator for a joint market share above 50% has no effect whereas the indicator pertaining to HHIs strongly and significantly increases the probability of challenge. Mergers in markets with HHIs above 2000 that entail an HHI increase of at least 150 are almost 9% more likely to be remedied or blocked.

4.2.2 Determinants of Concern at the Market Level

Table 6 contains the same sets of regressions estimated at the level of concerned markets. In general, more covariates appear to be significantly associated with competitive concerns at the market level than what is observed at the merger level. While this might be due to the larger number of observations in these regressions, it is likely that the aggregation to the merger level hides some of the EC's more fine-grained considerations concerning specific markets.

In line with the merger level regressions, we find that barriers to entry are positively correlated with the likelihood of competitive concerns at the market level as well. In addition, the risk of foreclosure also shows a positive and significant correlation. Joint ventures appear to be treated more leniently. Market size now plays a more decisive role, with national markets being positively correlated with the probability of concerns in all specifications except (2). While the total number of competitors (across all markets) was insignificant at the merger level, the number of competitors in a specific market is negatively correlated with the probability of competitive concerns in all four specifications. When the EC does not collect data on competitors, i.e. when not too much effort is spent on gathering market information, the likelihood of concerns is expectedly lower.

Finally, in the sub-sample with market share information, both market power indicators are now significantly positively correlated with the likelihood of concerns: a joint market share in excess of 50% increases it by almost a quarter, while the HHI indicator increases it by 10%.

5 Machine Learning / Causal Forests

In section 4, we explore the association between concentration, market shares, entry barriers, and the risk of foreclosure with the intervention decision by DG Comp parametrically. However, the correlation between

Table 5: Linear Probability Model for Intervention (Merger Level)

	(1) Full sample	(2) Selected sample no market share info	(3) Selected sample market share info	(4) Selected sample market share info
mean barriers to entry	0.2673***	0.3793***	0.2278**	0.2127**
	(0.0560)	(0.0786)	(0.0899)	(0.0857)
mean risk of foreclosure	0.0145	-0.0289	0.0016	0.0040
	(0.0691)	(0.0878)	(0.1115)	(0.1087)
fullmerger	-0.0019	0.0170	-0.0079	-0.0044
	(0.0194)	(0.0116)	(0.0483)	(0.0472)
joint venture	-0.0150	0.0147	-0.0321	-0.0283
	(0.0159)	(0.0105)	(0.0464)	(0.0449)
mean conglomerate merger	-0.0051	0.0404	-0.0222	-0.0238
	(0.0471)	(0.0770)	(0.0735)	(0.0740)
mean vertical merger	-0.0024	0.0155	-0.0269	-0.0067
	(0.0107)	(0.0145)	(0.0240)	(0.0241)
mean market definition national	0.0103	-0.0059	0.0171	0.0143
	(0.0075)	(0.0047)	(0.0646)	(0.0621)
mean market definition EU wide	0.0202	0.0079	0.0068	0.0066
	(0.0137)	(0.0111)	(0.0589)	(0.0578)
mean market definition worldwide	-0.0158	-0.0069	-0.0343	-0.0382
	(0.0120)	(0.0113)	(0.0781)	(0.0767)
number of concerned markets	0.0036***	0.0030***	0.0030***	0.0031***
	(0.0005)	(0.0011)	(0.0009)	(0.0008)
percentage of markets with concerns	0.9375***	0.7312***	0.9681***	0.9340***
	(0.0623)	(0.1094)	(0.1107)	(0.1117)
total number of competitors in all product markets	0.0004	0.0003	0.0008	0.0006
	(0.0004)	(0.0008)	(0.0005)	(0.0005)
post reform indicator	0.0333**	0.0042	0.1169	0.1384*
	(0.0147)	(0.0069)	(0.0824)	(0.0768)
joint market share above 50%				-0.0009
				(0.0481)
HHI $\geq$ 2000 & delta HHI $\geq$ 150				0.0881***
				(0.0169)
Constant	-0.0541***	-0.0211**	-0.1110	-0.2210**
	(0.0177)	(0.0090)	(0.0913)	(0.0924)
Industry Group Year FE	Yes	Yes	Yes	Yes
R2	0.609	0.557	0.682	0.689
Observations	5,109	3,665	1,444	1,444

We report heteroskedasticity robust standard errors clustered at the industry group level.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

Table 6: Linear Probability Model for Concern (Market Level)

	(1) Full sample	(2) Selected sample no market share info	(3) Selected sample market share info	(4) Selected sample market share info
barriers to entry in submarket	0.3856***	0.3408***	0.4067***	0.3160***
	(0.0558)	(0.0856)	(0.0485)	(0.0406)
risk of foreclosure in submarket	0.2066**	0.2958**	0.1849*	0.1777*
	(0.0956)	(0.1248)	(0.0921)	(0.0951)
fullmerger	-0.0375	-0.0071	-0.0615	-0.0586
	(0.0250)	(0.0263)	(0.0373)	(0.0347)
joint venture	-0.0656**	-0.0218	-0.1192***	-0.1061***
	(0.0244)	(0.0285)	(0.0323)	(0.0301)
conglomerate merger in submarket	0.0201	0.0302	0.0259	0.0140
	(0.0372)	(0.0469)	(0.0355)	(0.0353)
vertical merger in submarket	-0.0024	0.0240	-0.0410***	-0.0135
	(0.0100)	(0.0180)	(0.0128)	(0.0125)
market definition national	0.0182***	0.0042	0.0690***	0.0634***
	(0.0049)	(0.0076)	(0.0239)	(0.0213)
market definition EU wide	-0.0108	0.0007	0.0039	0.0264
	(0.0087)	(0.0129)	(0.0246)	(0.0248)
market definition worldwide	0.0076	0.0176	0.0245	0.0496**
	(0.0163)	(0.0224)	(0.0252)	(0.0224)
number of concerned markets	0.0001	-0.0001	0.0002	0.0000
	(0.0003)	(0.0005)	(0.0004)	(0.0003)
number of competitors	-0.0099***	-0.0066***	-0.0116***	-0.0080**
	(0.0030)	(0.0020)	(0.0040)	(0.0036)
indicator no info on competitors	-0.0652***	-0.0358***	-0.0792***	-0.0502**
	(0.0152)	(0.0124)	(0.0230)	(0.0202)
post reform indicator	-0.1916	-0.0332	-0.3779	-0.3113
	(0.1300)	(0.0305)	(0.2222)	(0.2339)
joint market share above 50%				0.2313***
				(0.0226)
HHI $\geq$ 2000 & delta HHI $\geq$ 150				0.1043***
				(0.0134)
Constant	0.2355*	0.0640**	0.4508*	0.2658
	(0.1360)	(0.0279)	(0.2417)	(0.2557)
Industry Group Year FE	Yes	Yes	Yes	Yes
R2	0.377	0.410	0.401	0.473
Observations	30,995	18,185	12,810	12,810

We report heteroskedasticity robust standard errors clustered at the industry group level.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

these variables might differ for different types of mergers.[18] In this section, we explore this potential heterogeneity by employing machine learning techniques. Specifically, we use the causal forest algorithm developed by Athey and Imbens (2016), Wager and Athey (2018), and Athey, Wager, and Tibshirani (2019) to investigate these correlations non-parametrically. Causal forests are a flexible tool to uncover heterogeneous effects, in particular when there are many covariates and potentially complex interactions between them. They allow getting the richest possible specification supported by the data. This has three main advantages.

First, this approach allows a better modelling of the process that leads to a particular decision by taking into account the specificities of each merger. As an example, consider that we want to measure the impact of high market shares on the likelihood that a market is considered problematic. In a facts-based approach, the Commission would surely consider that high market shares might have a different impact if the market is narrowly defined than if it is global in nature. Further, it is likely that industry-specific information also plays a role: in national telecom markets, the role of high market shares is likely to be different than in a global manufacturing market. The strength of machine learning tools is that they allow to determine the relevant interactions among covariates based on the observed data.

Second, by generating a more saturated model through numerous variable interactions, omitted variable bias is less of a concern than in the standard linear probability model discussed in the previous sections and used in the literature. While we still need to be careful in attributing causality, any potential bias in the coefficient estimates should be reduced. This, in turn, increases the confidence that the estimated correlations are not spurious.

Third, this approach makes the exact definition of regression covariates less relevant. In some cases (e.g. measuring the HHI or market shares), we face a trade-off between simple, dichotomous measures and more sophisticated metrics. For reasons of data availability, we have opted for the more simple measures. Such trade-off is less of a constraint in a causal forest model, where the covariates become complex interactions among all indicator variables.

5.1 Methodology

5.1.1 Heterogeneous Effects

The main goal of the analysis is to understand how the effect of an explanatory variable (i.e. concentration, market shares, entry barriers, and risk of foreclosure) on an outcome (i.e. the competitive concerns raised by DG Comp) varies with merger and market characteristics. This question relates to the literature on heterogeneous treatment effects, where a major concern is that researchers might search for subgroups with high treatment effects and report results for these sub-groups. The causal tree and causal forest algorithms address this problem as they non-parametrically identify subgroups that have different treatment effects. The methodology lets the data discover the relevant subgroups without invalidating the confidence intervals constructed on the treatment effects within the subgroups (Athey and Imbens, 2016).

In the context of heterogeneous treatment effect estimation, the model to be estimated is:

$$Y_{ij} = \tau(X_{ij})W_{ij} + \mu(X_{ij}) + \epsilon_{ij} \tag{3}$$

[18]In a first attempt to assess heterogeneity, we run separate regressions over time and industries. Results are reported in appendix A.1 and appendix A.2 respectively.

where Y_{ij} is the outcome variable for market i in merger j, W_{ij} is a binary treatment variable (i.e. the structural indicators), $\tau(X_{ij})$ is the effect of W_{ij} on Y_{ij} at point X_{ij} in covariate space, and ϵ_{ij} is an error term that may be correlated with W_{ij}. Using the notation of the potential outcomes framework by Rubin (1974), the treatment effect can be written as:

$$\tau(x) = \mathbf{E}\left[Y_{ij}^1 - Y_{ij}^0 | X_{ij} = x\right] \tag{4}$$

where Y_{ij}^1 is the potential outcome for unit ij under treatment – i.e. whether the EC identifies a concern when market shares are high – and Y_{ij}^0 is the potential outcome for unit ij absent treatment – i.e. whether the EC identifies a concern when market shares are low – where one of the two is not observed. The aim is to estimate how the function $\tau(x)$ varies with the covariates X. This is different from estimating a single parameter such as an average treatment effect while controlling for a large set of covariates, X.

The so-called unconfoundedness assumption implies that the treatment assignment W_{ij} is independent of potential outcomes Y_{ij} conditional on X_{ij}. This means that observations that are similar in X-space can be treated as having come from a randomized experiment. Untreated observations that are close to the treated observations can then be used to predict the outcome Y_{ij}^0 absent the treatment. In such a case, local matching methods allow for consistent estimation of $\tau(x)$.

Notice that the identification assumption is essentially identical to the OLS model discussed above. Thus, we need to be cautious in attributing a causal interpretation to $\tau(x)$, even though the causal forest model is likely to fare better than the simple OLS model since it allows for complex interactions between covariates. Nonetheless, we cannot claim that we estimate any causal effect of these variables on DG Comp's intervention decision.

5.1.2 Estimation using Causal Forests

We use the causal forest algorithm by Athey, Wager, and Tibshirani (2019) implemented in the generalized random forest (grf) package in R[19] to investigate how the correlation between treatment variables and DG Comp's competitive concerns varies with market as well as merger characteristics. Causal forests are based on the random forest methodology (Breiman, 2001). They extend the regression tree and random forest algorithms so as to estimate average treatment effects for different subgroups, rather than predicting outcomes as is the case for regression trees and random forests (Athey and Imbens, 2016; Wager and Athey, 2018; Athey, Wager, and Tibshirani, 2019).

In case of a causal forest, we are not interested in predicting individual outcomes Y_{ij} as in a standard regression tree, but individual treatment effects $Y_{ij}^1 - Y_{ij}^0$ to study how treatment effects vary by subgroup.[20] This implies that standard goodness-of-fit measures used in regression trees and random forests, such as the mean squared error, are not available since one of the potential outcomes and hence the actual treatment

[19] We use version 0.10.2 of the grf package.

[20] In a standard regression tree, the aim is to predict individual outcomes Y_{ij} using the mean outcome Y of observations that are close in X-space. To determine which observations are close, the algorithm starts to recursively split the covariate space (binary splits) until it is partitioned into a set of so-called leaves L that contain only a few observations. The algorithm automatically decides on the splitting variables and split points based on an in-sample goodness-of-fit criterion such as a mean squared error. The outcome Y_{ij} for observation ij is then predicted by identifying the leaf containing observation ij based on its characteristics X_{ij} and setting the prediction to the mean outcome within that leaf. A random forest is essentially an ensemble of trees, where the predictions of outcomes Y_{ij} are averaged across all trees in the forest to reduce variance and produce more robust predictions.

effect is never observed. However, the causal forest methodology builds on regression tree methods in that it also applies a goodness-of-fit criterion in treatment effects to decide on splits. Athey and Imbens (2016) show that the mean squared error function of a causal tree can be estimated and is a function of the variance of the estimated treatment effect. Basically, the goodness-of-fit measure to be minimized rewards a partition of the data for finding strong heterogeneity in treatment effects and penalizes a partition for high variance in leaf estimates. Minimizing the expected mean squared error of predicted treatment effects is shown to be equivalent to maximizing the variance of predicted treatment effects across leaves with a penalty for within-leaf variance.

Within a causal tree, the conditional average treatment effects are then simply estimated as the difference of mean outcomes between treated and control observations within a leaf. Thus, causal trees are similar to nearest-neighbor methods as they also rely on the unconfoundedness assumption and use close observations to predict treatment effects. However, rather than defining closeness based on some pre-specified distance measure (such as Euclidean distance in k-nearest-neighbor matching), closeness is defined with respect to a decision tree and the closest control observations to ij are those that are in the same leaf.

A causal forest is an ensemble of causal trees, which only uses a random subset of the full dataset to grow each individual causal tree. The causal forest algorithm weights nearby control observations according to the fraction of trees in which a control observation appears in the same leaf as the treated observation ij (Athey, Wager, and Tibshirani, 2019). This implies that for each observation an individual treatment effect τ_{ij} can be estimated while in a causal tree all units assigned to a given leaf have the same estimated treatment effect (Wager and Athey, 2018).

Athey and Imbens (2016) further introduce so-called "honesty" in causal trees to ensure correct inference: the data is divided in half, where one-half of the data is used to build the tree (i.e. determine the splits in covariate space) and the other half is used to predict treatment effects. Wager and Athey (2018) extend this idea to causal forests and develop theory for inference in causal forests. Thus, the causal forest algorithm by Athey, Wager, and Tibshirani (2019) does not only allow for predicting treatment effects but also for constructing confidence intervals.

The big advantage of causal trees and forests is that they allow the data to determine the relevant subgroups in a flexible, data-driven way without invalidating confidence intervals. This is particularly important in applications with many covariates and potentially complex interactions between these covariates that matter for measuring the effects, as in our case. Wager and Athey (2018) also highlight the advantage that leaves can be narrower along some dimensions and wider along others, depending on how fast the signal is changing.[21]

We estimate causal forests at the market (ij) rather than the merger level (j). The outcome is therefore the *concern* dummy variable that indicates which specific product/geographic markets affected by the merger raised competitive concerns. We estimate different causal forests for the four determinants of competitive concerns. These are the same four indicator variables as before: *high post-merger concentration*, *joint market share above 50%*, *barriers to entry*, and *risk of foreclosure*.

In addition to the treatment variable, each of the causal forests includes a set of covariates X across which treatment effects are allowed to vary. These are essentially the same as in the regression analyses of section 4 and also include the other three structural indicators. For example, in the causal forest for the market share

[21] For further technical background on the causal forest methodology and the implementation using the grf package, see appendix A.3.

indicator, the concentration, barriers to entry and foreclosure dummies are included in the set of covariates X, allowing the effect of market share to vary in conjunction with these structural indicators. In contrast to the regression analyses, we include the notification year as a continuous variable from 1990 to 2014 rather than fixed effects. This allows the algorithm to determine the relevant binary splits over time. We include market definition indicators for national, EU wide, and worldwide geographic markets as well as all information on the type of merger available in the data – vertical mergers, conglomerate mergers, full mergers, joint ventures, a count of the number of competitors in the concerned market as well as an indicator variable for whether information on competitors is missing in the data, and the complexity of the merger measured by a count of the concerned markets. Lastly, we include a set of industry fixed effects for the 25 different industry groups defined as presented in table 4.

Training the causal forests at the market (ij) rather than the merger level (j) has an important implication: It is unlikely that the observations of the different markets affected by a given merger are independent. We adress this concern by using the clustering option of the grf package, which allows to draw the random subsets of the data used to grow individual trees within the forest at the cluster level rather than the market level, where clusters are mergers. Hence, either all markets affected by a merger are included in the random subsample or none.[22] This way we ensure correct treatment effect prediction and inference. See Athey and Wager (2019) for a discussion of clustering in causal forests.

Each of the causal forests is grown with a minimum node size of 10 and consists of 12,000 trees, the other tuning parameters are chosen by cross-validation implemented in the grf package.[23] Lastly, note that all causal forests are trained based on the dataset containing market share information, so that the market share and concentration indicators can be defined. For a discussion of the potential selection bias, see section 4.2.1.

5.2 Estimation Results

While a causal forest allows for predicting conditional average treatment effects, we are not primarily interested in the average correlation between a variable of interest and the outcome variable, rather, we want to explore and visualize how this correlation varies over the covariate space X. In particular, we look at how the correlation between high concentration, market shares, entry barriers, risk of foreclosure, and concerns identified by DG Comp varies over time and industry as well as the complexity of the merger and the geographic market definition.[24]

In order to explore how the correlation between the treatment variable and the outcome varies with one of the dimensions included in the covariates X, we need to hold all other variables included in X constant

[22]Given that each merger affects a different number or markets, the clustersize varies. By default, the grf package sets the number of observations sampled from each cluster equal to the number of observations in the smallest cluster. In our dataset the smallest clustersize is one, as some mergers only affect one market. However, we firstly do not want to lose too many observations as subsamples need to be large enough for the tree growing algorithm to be stable and secondly, we also want to give more weight to larger and more complex merger cases. Therefore, we set the number of observations to be sampled from each cluster to 30. This implies that for mergers with less than 30 affected markets, all markets will be sampled if the cluster is drawn, while for large mergers a maximum of 30 affected markets are sampled each time the cluster is drawn.

[23]The term "minimum node size" is a bit misleading. The minimum node size in a causal forest is the minimum number of observations that must be part of a node in order for a split to be attempted. We ran causal forests for the entry barrier treatment using minimum node sizes of 5, 10, 15, 20, 30, and 40. The estimated conditional average treatment effect did not change much using these different node sizes.

[24]Predicted correlations across industries are shown in appendix A.5 as variation across industries is small.

and vary only the covariate of interest.[25]

Thus, the prediction plots discussed in the next sections are obtained as follows: We generate a prediction dataset that contains the range of one X variable of interest (here notification year), for which we want to explore heterogeneous treatment effects. We set all the other covariates included in X to their mean respectively median sample value.[26] We then predict treatment effects using the causal forest and plot the coefficients along with 95% confidence intervals. In short, we take the mean/median merger in terms of all covariates, and look at how the treatment effect varies if that merger had been notified in different years.[27]

5.2.1 The Impact of Structural Indicators over Time

Joint Market Share above 50%. We start our discussion by looking at the role played by high joint market shares of the merging parties, which is a good proxy for their dominance in the market.[28] Since dominance was the substantive test in European merger control until the reform in 2004, it is key to understand how the importance of this structural indicator to determine competitive concerns changed over time.

The upper part of figure 2 shows the predicted correlation between the indicator variable for merging parties' market shares above 50% and competitive concerns of DG Comp over time, setting all other covariates to their mean (dark blue) or median (light blue) value, respectively. In the lower part of the figure, instead, we report the same graphs by switching on and off the other structural indicators. This allows us to better understand how different structural indicators and the connected theories of harm interact with each other. In the different graphs, we also report the estimate of the average treatment effect obtained with the linear probability model as well as the in-sample conditional average treatment effect obtained with the causal forest.

First off, the figure shows that the simple linear probability model significantly overestimates the average effect of high market shares on concerns. The correlation estimated by OLS is 0.22 (specification 4 in table 6) while the conditional average effect of the causal forest is as low as 0.125. Yet, allowing for heterogeneity in this correlation is also very important. Indeed, the predicted effect for the average or median merger lies always above the conditional ATE and their confidence intervals do not overlap. Moreover, we find considerable heterogeneity in the predicted correlation between the market share indicator and concerns over time. While the treatment effect is positive and significant during the entire sample period, market shares seem to be very important up to the early 2000's (correlation around 0.3) and lose relevance afterwards. Using median rather than mean values, the predicted correlation is even lower in the first part of the sample period.

If we compare the discussed results with a simpler linear probability model where the effect of concentration is allowed to vary with time (see appendix A.1 that reports the results), the estimated effect of high market shares based on the causal forest is much smoother over time. This indicates that, once we use a

[25]As an example see Athey, Wager, and Tibshirani (2019), who study the effect of child rearing on labor-force participation, where the mother's age at first birth and the father's income are varied while all other covariates are set to their median values.

[26]Employing means or medians sometimes leads to sizeable differences in predictions. This is mostly due to the fact that many of our regressors are dummy variables. Indeed, the mean of a dummy variable varies continuously between zero and one, while its median is either zero or one.

[27]Rather than taking the mean merger over the entire sample, we also created a prediction dataset based on the mean merger for which we have information on the market shares and concentration variables. We then used this prediction dataset to create alternative predictions based on the causal forests for high concentration and joint market share. As the predicted treatment effects did not change by much, we only report the predictions based on the mean merger over the entire sample.

[28]According to the old ECMR, joint market shares of the merging parties above 45%-50% usually give rise to serious concerns and may represent a sufficient reason for the prohibition of a merger.

richer model that better describes the process behind DG Comp's decision practices, the impact of this structural indicator is less volatile and more consistent over time. The estimated time dynamics of the effect of high market shares on concerns is thus much more consistent with the shift away from evaluating mergers based on the concept of dominance and more conform to the new substantive test – the so-called SIEC test – introduced by the reform in 2004. This confirms the preliminary findings by Röller and De La Mano (2006), who suggested a gradual impact of the new merger regime on the Commission's decisional practices. Moreover, we confirm that dominance continues to play an important role in determining competitive concerns, although there has been an increasing process towards an effects-based approach to merger control.

In the bottom part of figure 2, we visualize additional dimensions of heterogeneity by looking at the interaction between the impact of the different structural indicators over the years. The most important driver of heterogeneity among the various structural indicators is the dummy capturing high concentration. Dominance plays a significantly more important role in markets that are highly concentrated. In these markets, the correlation between high market shares and competitive concern is over 30% higher than for mergers in markets where concentration was low, independently of whether the Commission was concerned about the existence of entry barriers or high risk of foreclosure. Indeed, in the concentrated markets the correlation starts at 0.31 at the beginning of the sample and drops to 0.2 at the end of the sample while the respective values obtained for markets where concentration is lower are around 0.2 in 1990 and 0.1 in 2014.

The bottom line of this analysis is that dominance is an important determinant of competitive concerns. Yet, its role is significantly more important in concentrated markets and it significantly decreases over time and, especially, after the introduction of the new ECMR in 2004.

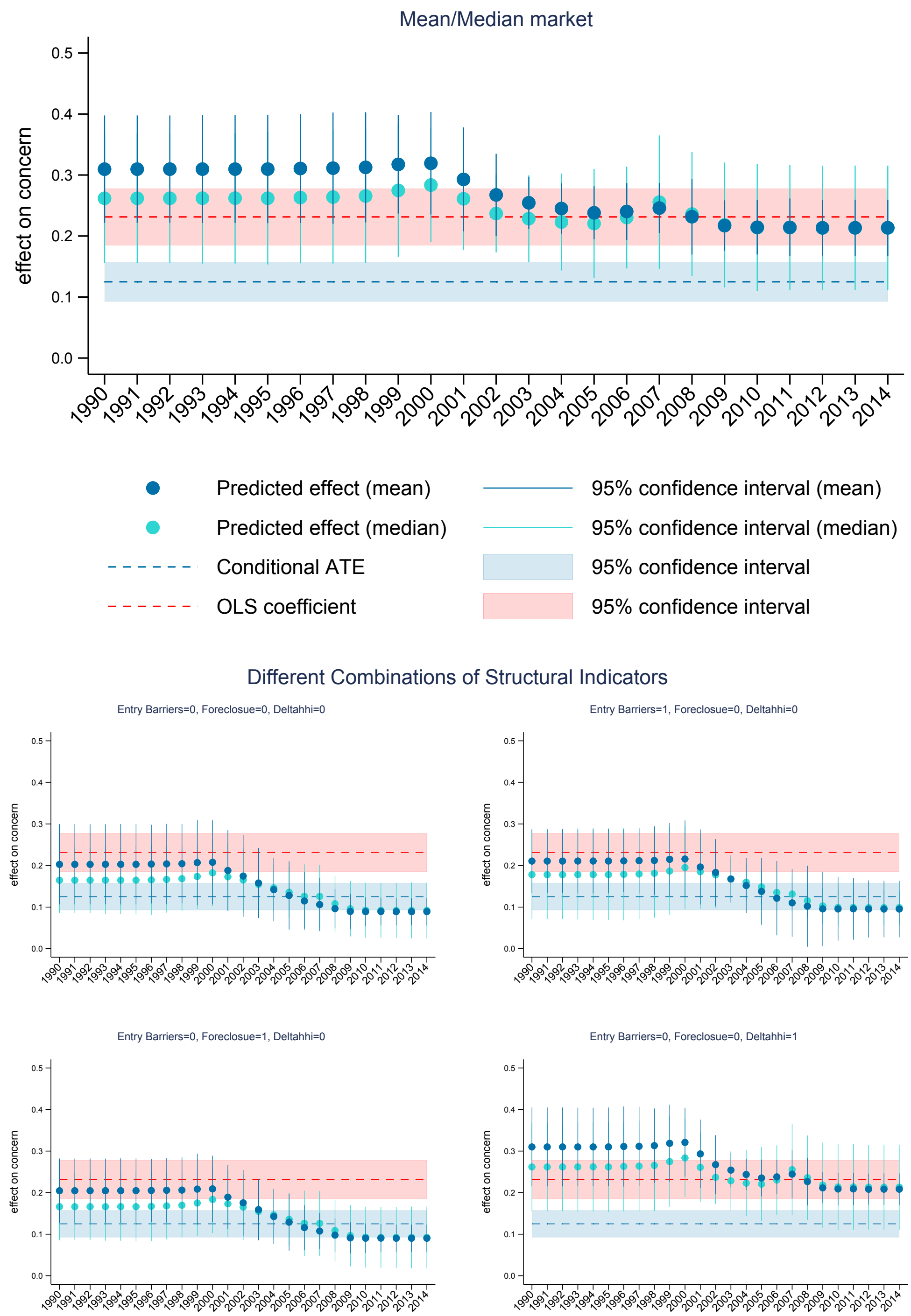
High Concentration. The second structural indicator we look at is the dummy measuring highly concentrated markets. The results are presented in a very similar fashion as for high market shares. The upper part of figure 3 shows the predicted correlation between high concentration and DG Comp's competitive concerns over time setting all other covariates to their mean (dark blue) or median (light blue) value, respectively. In the lower part, instead, we report the same graphs by additionally switching on and off the other structural indicators. Again, in the different graphs, we also report the average treatment effect obtained by OLS as well as the in-sample average conditional treatment effect obtained with the causal forest.

Also for high concentration we observe that the average correlation estimated through the linear probability model (0.1043, from specification 4 of table 6) significantly overestimates the in-sample conditional average treatment effect (0.056). In this case, however, we observe a much larger impact of heterogeneity. The predicted effect of high concentration for the mean merger is almost three times larger than the conditional ATE. There appears to be little variation over time with a bump between 2006 and 2009.[29] The confidence intervals of these predictions are however very large. We obtain a fundamentally different picture by looking at the median merger. In this case, the predicted effect of high concentration is much closer to the OLS and conditional ATE effects, starting from a value around 0.1 with relatively large confidence intervals and significantly decreasing over time after the early 2000s. While the predicted effect for the median merger is not different from the OLS estimate until 2005, it becomes significantly smaller for the last 7 years of our sample.

To better appreciate where the differences between the mean and the median merger come from, the second part of the panel is particularly useful. Indeed, the strong shift upwards in the predicted effects is driven

[29] Also in this case, results obtained by using a linear probablility model based on yearly subsamples appear to be much more volatile. See appendix A.1.

Figure 2: Effect of Joint Market Share on Concerns over Time



Predicted effect of indicator variable for joint market share above 50% on concerns over time, setting all other included explanatory variables equal to the sample mean/median.

by markets characterized by high entry barrier and large market shares of the merging parties. Conditional on these two indicators, the effect predicted for mean and median mergers is almost identical and much higher than for mergers with low entry barriers and market shares. This suggests that the presence of entry barriers and dominance in a market, makes high concentration even more problematic for the Commission. As there is little change over time, the use of this structural indicator as a determinant of competitive concern is quite consistent over the first 25 years of EU merger control.

Barriers to Entry and Risk of Foreclosure. The final piece of evidence we provide in this section relates to the importance of the indicators for barriers to entry and risk of foreclosure. We represent the results in figure 4. The figures are built is a similar fashions as above: they show the predicted correlation between the structural indicator and competitive concerns over time, setting all other covariates to their mean (dark blue) or median (light blue) value. The OLS and conditional average treatment effect predicted by the causal forest are also reported.

Strikingly, we do not observe any heterogeneity in the estimated effects, neither over time nor between mean and median mergers. The correlations are positive (around 0.3 for high entry barrier and 0.2 for the risk of foreclosure), not very precisely estimated (especially for the risk of foreclosure), and very stable over time.[30] While for high entry barriers, the OLS linear probability model slightly overestimates the conditional average treatment effect and for the risk of foreclosure it slightly underestimates it, these differences are not significant. Nor are the differences between the average effects and the predicted effects significant for both indicators and mean and median merger.

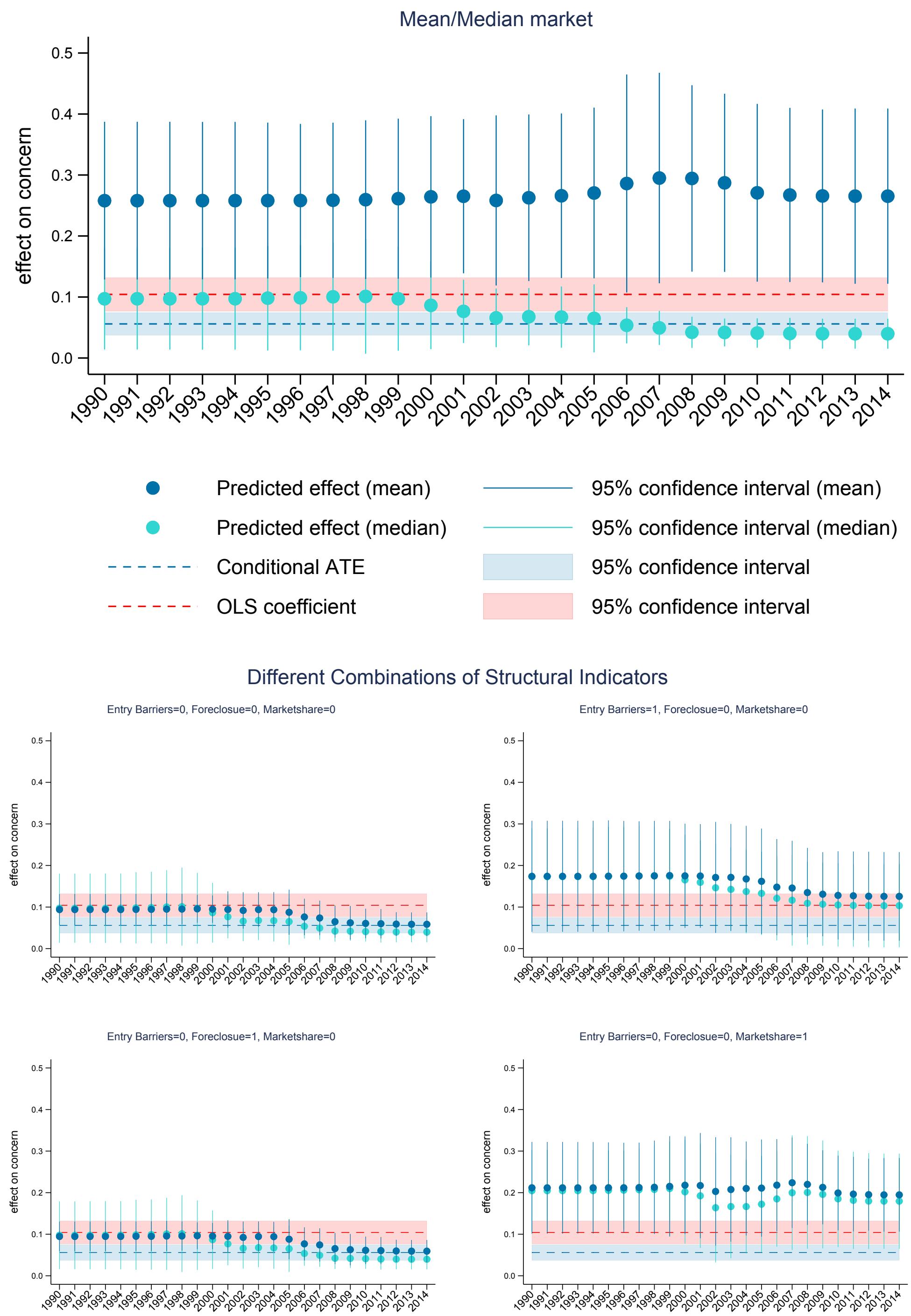
From a policy point of view, these results suggests that high entry barriers and the risk of foreclosure are consistently used by DG Comp as driver of potential concerns in their merger analysis. From a methodological point of view, these findings suggests that a simple model such as the linear probability model is perfectly able to capture the importance of these two indicators on the competitive concerns, while this is not the case for the most important drivers of the Commission decisions such as the dominance of the merging firms as well as the concentration of the market.

5.2.2 The Impact of Geographic Market Definition and Complexity

As we discussed above, the difficulty of representing results based on the causal forest is that each individual treatment effect is a function of all covariates included in the model. In the previous section we focused on the role of time and the interactions between the four key structural indicators. In this section, we instead look at two further dimensions that appear to be important: the geographic market definition and the complexity of the merger. We do this for two reasons. First, these two dimensions appear to be important for the implementation of our machine learning algorithm. Indeed, they are consistently among the most important variables determining the split among the different leaves of the trees populating the causal forest (see appendix A.4 for a discussion). Second, from a more substantive viewpoint, the geographic market definition is a key element of any merger decision and the complexity of a merger may play a crucial role in the definition of the theory of harm. In this additional analysis, we only focus on the role of high joint market shares of the merging firms, as this appear to be the indicator whose role has changed the most over time.

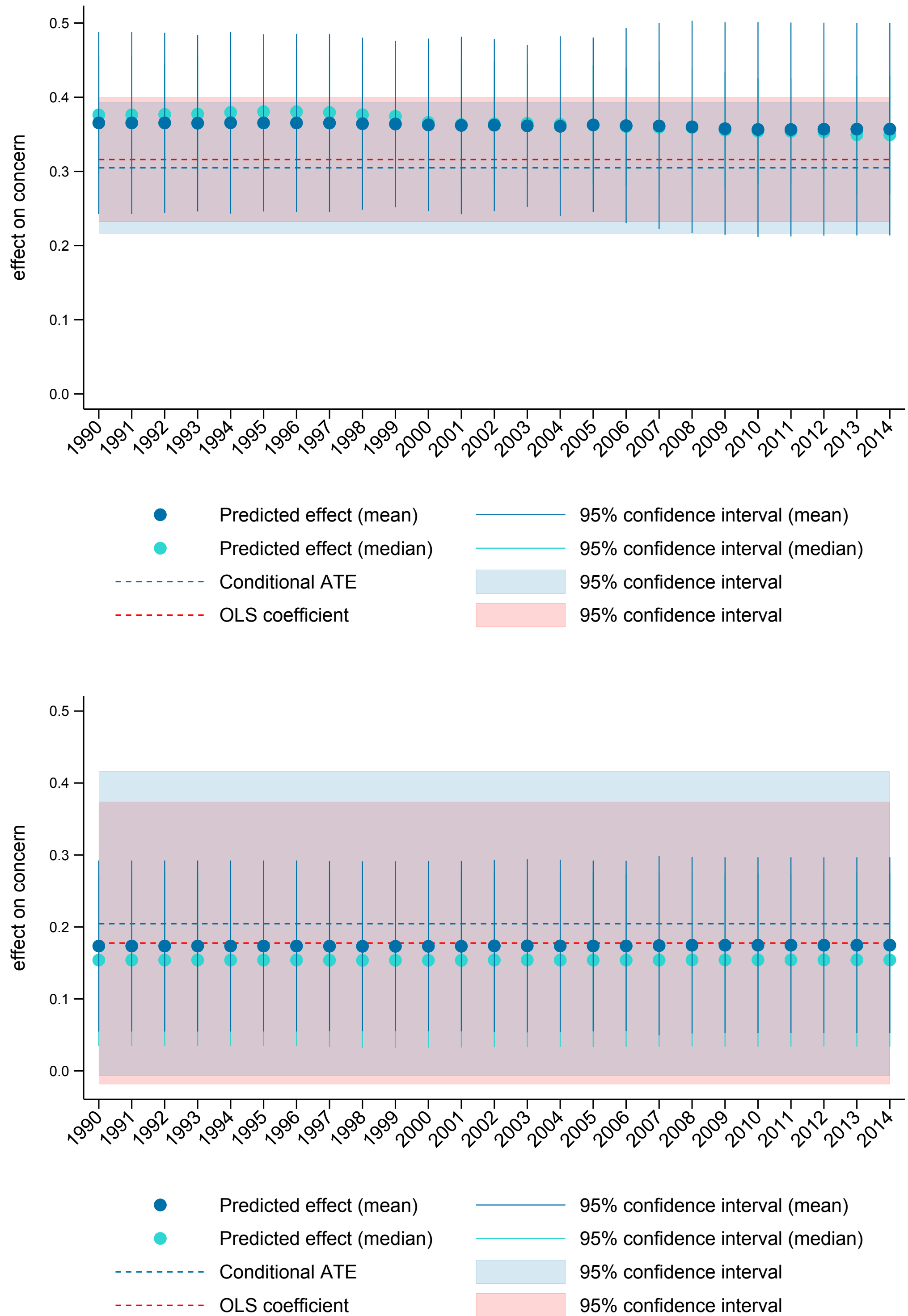
[30] As shown in table 2, DG Comp considered risk of foreclosure to exist in only about 3% of the concerned markets. Consequently, the confidence intervals are very wide.

Figure 3: Effect of High Concentration on Concerns over Time



Predicted effect of indicator variable for post-merger HHI above 2000 and change in HHI larger than 150 on concerns over time, setting all other included explanatory variables equal to the sample mean/median.

Figure 4: Effect of Barriers to Entry (upper panel) and Foreclosure (lower panel) on Concerns over Time



Predicted effect of barriers to entry and foreclosure on concerns over time, setting all other included explanatory variables equal to the sample mean/median.

Market Definition. Figure 5 reports the same kind of information discussed in the previous section but distinguishing between markets that have been defined to be national, EU wide, or world wide. Again we report the predicted correlations between high market shares and concerns for mean and median mergers, as well as the OLS estimates and conditional ATE. Strikingly, we do not observe any substantial difference in the correlation patterns across the different market definitions, suggesting that DG Comp applied the dominance substantive criterium in a very consistent way independently of the geographic nature of the market. This is an important finding in light of the fact that, over the years, the Commission's geographic market definition practice have been criticized, often for being to narrow.

As pointed out by Fletcher and Lyons (2016), the geographic market definition should not necessarily affect the final decision. Indeed, the competitive assessment that generally comes after the markets have been defined, should take all competitive constrains into account, including the market shares of the merging parties but also the competitive constraints from outside the market. As our machine learning algorithm exactly aims at taking other conditions of competition and their interactions into account, it is somewhat reassuring in terms of legal certainty that market shares are given the same weight independently of the geographic extent of the market.

Complexity. As discussed in section 3, mergers notified to DG Comp have different levels of complexity. While the average merger affects 6 geographic/product markets, some of them affect as much as 245 markets. We try to account for the potential correlation in the decision process among different markets affected by the same merger in our machine learning algorithm. However, it seems important to understand whether the role of dominance in determining the concerns in one particular market is influenced by how many other markets the merger is affecting.

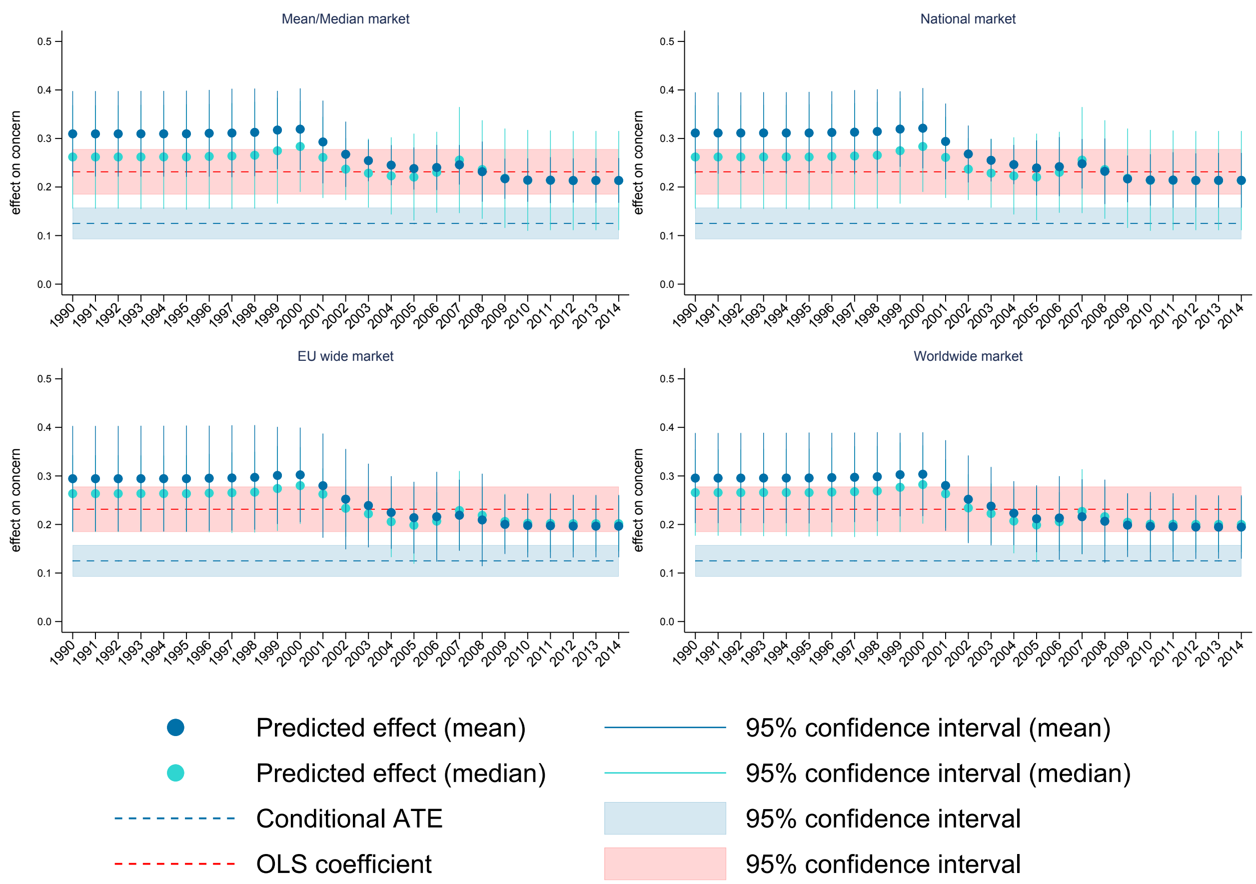
Figure 6 investigates this. The upper panel reports predicted correlations between high market shares and concerns for mean and median mergers as a function of the deciles of complexity. The bottom panel, instead, reports the evolution of the correlation over time for the (2) mergers in the 1st complexity decile and the (107) mergers in the 9th complexity decile respectively. All other characteristics are set to the mean. Both figures show that complexity constitutes a shifter for the role of dominance in determining concerns. In mergers that affect many markets, the likelihood that DG Comp expresses competitive concerns in any of these markets is more than 10 p.p. higher than for mergers that affect only few markets.

6 Conclusion

In this paper, we study the dynamics of the EC's merger decision procedure over the first 25 years of European merger control using a new dataset containing all merger cases with an official decision documented by DG Comp (more than 5000 individual decisions). Specifically, we evaluate how consistently different arguments related to the structural market parameters – market shares, concentration, likelihood of entry, and foreclosure – are put forward to motivate a particular decision over time and along other dimensions such as the geographic market definition and the complexity of the merger.

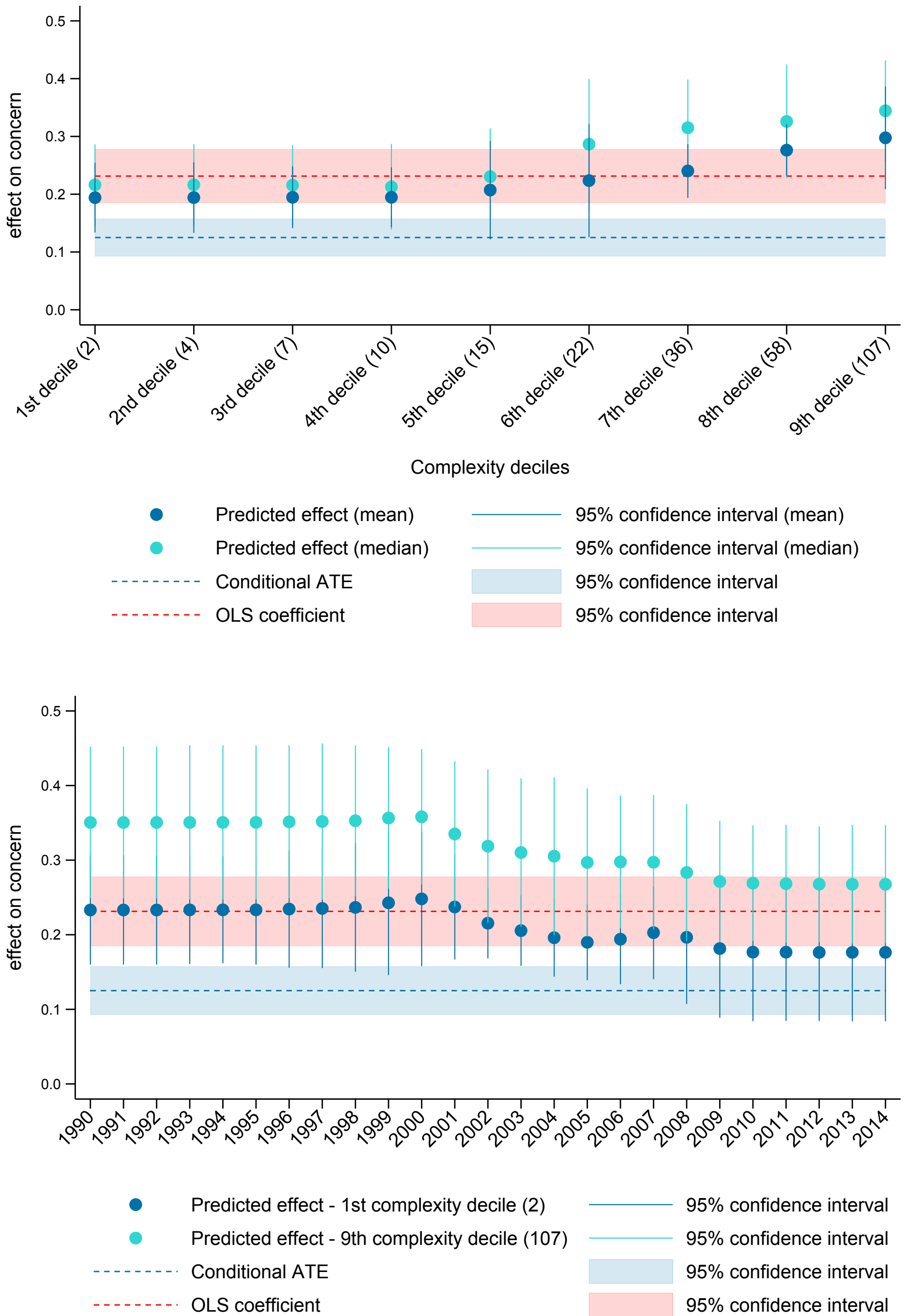
In a first step, we estimate the probability of intervention as a function of merger characteristics at the merger level. We find that the existence of barriers to entry, the increase of concentration measures and, in particular, the share of product markets with competitive concerns increase the likelihood of an interven-

Figure 5: Effect of High Market Shares on Concerns by Geographic Market Definition



Predicted effect of high market shares of the merging parties on concerns over time and by geographic market definition, setting all other included explanatory variables equal to the sample mean/median.

Figure 6: Effect of High Market Shares on Concerns by Merger's Complexity



Predicted effect of high market shares of the merging parties on concerns over time and by deciles of complexity, setting all other included explanatory variables equal to the sample mean/median.

tion. In order to obtain a more fine-grained picture of the decision determinants, we extend our analysis to the specific product and geographic markets concerned by a merger. Instead of estimating the overall probability of an intervention, we estimate the likelihood that competitive concerns are found in a specific product/geographical market (our data contain more than 30,000 affected markets). This step is important because larger mergers typically affect different product markets in different geographic regions. Therefore, by analyzing individual markets we not only get more statistical power but we are also able to conduct a more disaggregate analysis. We find that, barriers to entry, but also the risk of foreclosure play an important role for the competitive analysis. Moreover, while tightly defined (national) markets increase the probability of concerns, the number of active competitors decreases it. Finally, structural indicators of market shares and concentration have the expected effects and are more relevant than in the merger-level analysis. Thus, it appears that conducting the analysis at the merger level – as commonly done in the literature – rather than at the relevant market level obscures some of the EC's more fine-grained considerations concerning specific markets.

In the second, more substantial, step, we use non-parametric machine learning methods, in particular the causal forest algorithm, to explore how the correlation between the Commission's concerns and the potential determinants of such concerns vary with other merger and market characteristics. Using trained causal forests to predict the relationship between a structural market parameter and competitive concerns allows us to set up a more flexible model that better captures the decision process of the Commission. Specifically, we explore and discuss four main dimensions of heterogeneity: interactions among structural indicators, time, geographic market definition, and merger complexity. These dimensions should capture important aspects of the process behind the Commission's decisions. First, it seems quite natural to consider that these structural indicators – dominance, concentration, barrier to entry, foreclosure – and the related theories of harm might interact. Second, there were several reforms over time that affected EU merger regulation. Third, geographic market definition is a key element of any merger decision and the structural indicators might have been adapted accordingly. Fourth, whether few or many product/geographic markets are affected by a single merger is also potentially a key aspect in the Commission decision process and how the theories of harm are applied. These dimensions are also chosen for statistical reasons, as they appear to be key elements in the functioning of our machine learning algorithm to determine the splits in the forests.

We find that dominance plays a particularly relevant role until the early 2000's and especially in concentrated markets. Over time, however, this pattern changes substantially and dominance, while still important, shows a much lower correlation with the Commission's competitive concerns. Furthermore, we also show that dominance seems to play a more important role in complex mergers that affect several antitrust markets simultaneously. The role of concentration, instead, does not seem to have substantially changed over time. Yet, the correlation between this structural indicator and the Commission's competitive concerns is particularly strong in markets facing high entry barriers and where the merging parties have large market shares. The relevance of both dominance and concentration in determining competitive concerns is, instead, not affected by the geographic market definition. This is a relevant finding in light of the controversial discussion on the role of geographic market definition and the mounting critique against a too narrow interpretation of markets' geographic boundaries. The role of entry barriers and foreclosure seems to be much less heterogenous, especially over time, although both indicators seem to play a more crucial role when markets are highly concentrated.

The overall picture that we portrait seems to be quite in line with the goals of the 2004 merger policy reform, which aimed at adopting a more economics based approach of merger assessment and, consequently, putting less weight on simple structural indicators and more on the role of the merger in affecting effective competition. From a methodological point of view, we contend that simple linear models as they have been used in the existing literature, might miss important dimensions of heterogeneity that help to better understand the process behind the Commission's merger policy enforcement.

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A Online Appendix

A.1 Determinants of Concern - Market Level - Split Sample over Time

We explore heterogeneities over time by running separate OLS regressions, splitting the market-level dataset by notification year, pooling the early years 1990-1994. For each of the yearly sub-samples, we estimate the regression including high concentration and joint market share indicators (specification 4). Note that we have relatively few observations from 2014 that include market share information. For this sub-sample, the barriers to entry indicator perfectly predicts the outcome variable of competitive concerns. We therefore show coefficient plots only up to and including the year 2013.

Table A1: Linear Probability Model for Concern by Notification Year

	1990-1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
barriers to	0.253**	0.730***	0.788***	-0.211***	0.499***	0.365***	0.395***	0.241***	0.299**	0.328***
entry in submarket	(0.107)	(0.063)	(0.212)	(0.051)	(0.112)	(0.078)	(0.111)	(0.085)	(0.134)	(0.086)
risk of			-0.017	0.693***		0.300***	0.613***	-0.043	0.060	-0.037
foreclosure in submarket			(0.111)	(0.091)		(0.083)	(0.098)	(0.085)	(0.147)	(0.062)
joint market	0.015	0.137	0.383***	0.262**	0.155**	0.341***	0.411***	0.176***	0.181***	0.210**
share above 50%	(0.075)	(0.091)	(0.099)	(0.093)	(0.072)	(0.051)	(0.077)	(0.038)	(0.058)	(0.084)
HHI $\geq$ 2000	0.076	0.079	-0.196**	0.081*	0.208	0.183***	0.149**	0.111**	-0.015	0.205***
& delta HHI $\geq$ 150	(0.066)	(0.048)	(0.068)	(0.039)	(0.155)	(0.038)	(0.066)	(0.044)	(0.042)	(0.069)
fullmerger	-0.062	0.070	0.261	-0.176**	0.004	-0.067	-0.062	0.118*	-0.006	-0.181
	(0.122)	(0.074)	(0.185)	(0.066)	(0.147)	(0.129)	(0.111)	(0.063)	(0.044)	(0.115)
joint venture	-0.201***	0.046	0.096	-0.268***	0.042	-0.088	-0.152*	0.083	0.027	-0.151
	(0.067)	(0.067)	(0.119)	(0.055)	(0.160)	(0.130)	(0.088)	(0.055)	(0.046)	(0.156)
conglomerate	0.074	0.066	1.098	0.057	-0.310*	-0.027	0.093***	-0.085*	-0.195	-0.001
merger in submarket	(0.116)	(0.038)	(0.810)	(0.045)	(0.157)	(0.050)	(0.024)	(0.048)	(0.131)	(0.060)
vertical merger	-0.196**	0.012	-0.376*	0.237	0.067	0.010	-0.027	0.078	-0.015	-0.009
in submarket	(0.082)	(0.020)	(0.208)	(0.165)	(0.083)	(0.047)	(0.045)	(0.055)	(0.058)	(0.055)
market	0.100*	0.516*	0.160	0.019	0.261*	0.065	0.050	0.208**	-0.188*	0.270
definition national	(0.049)	(0.270)	(0.196)	(0.065)	(0.139)	(0.040)	(0.188)	(0.082)	(0.092)	(0.246)
market	0.026	0.501*	0.233	0.188**	0.217	0.074**	-0.015	0.129**	-0.280***	0.226
definition EU wide	(0.067)	(0.272)	(0.190)	(0.063)	(0.153)	(0.030)	(0.195)	(0.049)	(0.094)	(0.241)
market	0.391	0.367*	0.160	0.138	0.430**	0.060	0.075	0.299**	-0.201*	0.321
definition worldwide	(0.250)	(0.201)	(0.196)	(0.126)	(0.171)	(0.068)	(0.191)	(0.133)	(0.116)	(0.220)
number of	-0.012**	-0.004	-0.009	0.002	-0.001	0.001	-0.001	0.001	-0.001	0.000
concerned markets	(0.005)	(0.003)	(0.010)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
number of	-0.003	-0.002	0.020**	-0.019	-0.004	-0.005	0.022	0.001	0.006	-0.002
competitors	(0.010)	(0.018)	(0.007)	(0.015)	(0.016)	(0.011)	(0.017)	(0.017)	(0.011)	(0.021)
indicator no	-0.040	-0.069	0.141***	0.014	0.070	-0.045	0.076*	-0.049	-0.036	0.000
info on competitors	(0.047)	(0.073)	(0.026)	(0.069)	(0.132)	(0.046)	(0.044)	(0.061)	(0.113)	(0.085)
Constant	0.495***	-0.482	-0.017	-0.080	-0.354	0.239	0.126	-0.316***	0.260	-0.058
	(0.097)	(0.292)	(0.094)	(0.083)	(0.312)	(0.161)	(0.157)	(0.108)	(0.170)	(0.353)
Industry Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.515	0.687	0.591	0.632	0.636	0.592	0.612	0.698	0.403	0.508
Observations	205	137	155	242	204	520	887	774	569	494

We report heteroskedasticity robust standard errors clustered at the industry group level.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

Table A2: Linear Probability Model for Concern by Notification Year (Continued)

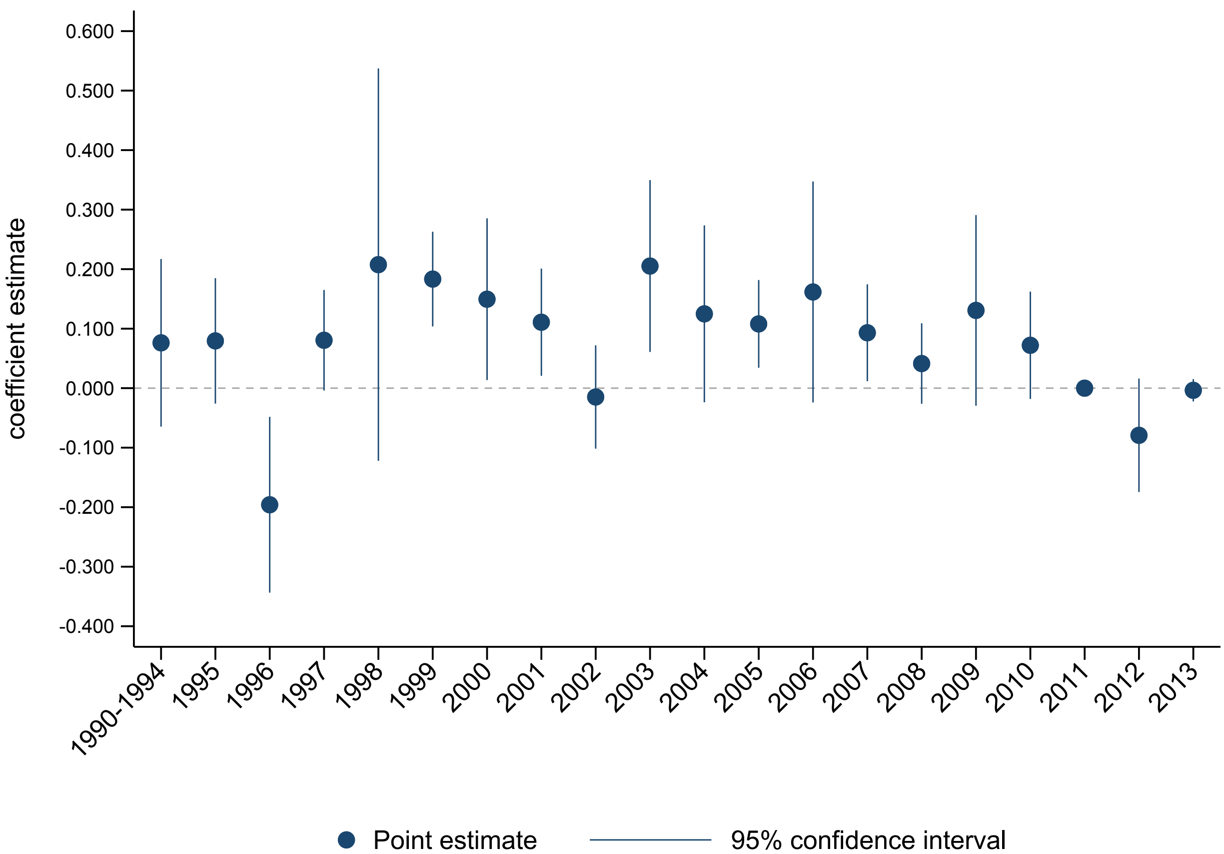
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
barriers to	0.226**	0.326**	0.392***	0.366*	0.397***	0.435***	-0.083*	0.000	0.058***	0.113***	1.000***
entry in submarket	(0.103)	(0.126)	(0.072)	(0.197)	(0.110)	(0.081)	(0.042)	(.)	(0.016)	(0.007)	(0.000)
risk of	0.234	0.406***	0.131	0.241	0.046	0.419*	0.930***			0.065	
foreclosure in submarket	(0.264)	(0.116)	(0.224)	(0.301)	(0.335)	(0.239)	(0.108)			(0.048)	
joint market	0.246***	0.191***	0.143	0.356***	0.281***	0.142***	0.049*	0.000	0.109*	0.080***	0.000
share above 50%	(0.049)	(0.058)	(0.086)	(0.084)	(0.063)	(0.041)	(0.026)	(.)	(0.059)	(0.021)	(0.000)
HHI $\geq$ 2000	0.125*	0.108***	0.162*	0.093**	0.041	0.131	0.072	0.000	-0.079*	-0.004	0.000
& delta HHI $\geq$ 150	(0.070)	(0.036)	(0.090)	(0.039)	(0.032)	(0.076)	(0.043)	(.)	(0.045)	(0.009)	(0.000)
fullmerger	0.190**	-0.173**	-0.141**	-0.105	0.041	0.014	0.050***	0.000	0.044	-0.039	0.000
	(0.089)	(0.069)	(0.054)	(0.064)	(0.101)	(0.031)	(0.014)	(.)	(0.038)	(0.036)	(0.000)
joint venture	0.445*	-0.208**	-0.231**	-0.127**	-0.038	0.024	-0.025	0.000	0.088*	0.004	
	(0.219)	(0.075)	(0.104)	(0.050)	(0.110)	(0.051)	(0.034)	(.)	(0.048)	(0.005)	
conglomerate	-0.393***		-0.001	-0.119	0.052	-0.453*					
merger in submarket	(0.072)		(0.098)	(0.079)	(0.130)	(0.225)					
vertical merger	-0.226***	-0.075*	0.227**	-0.020	-0.009	-0.026	-0.115	0.000	0.060	-0.008	-0.000
in submarket	(0.074)	(0.039)	(0.086)	(0.053)	(0.031)	(0.096)	(0.071)	(.)	(0.060)	(0.007)	(0.000)
market	0.032	-0.043	0.024	-0.007	0.154***	0.042	0.331***	0.000	0.001	-0.010	0.000
definition national	(0.069)	(0.091)	(0.112)	(0.104)	(0.046)	(0.049)	(0.038)	(.)	(0.006)	(0.009)	(0.000)
market	-0.090	0.049	-0.066	0.011	0.014	0.115**	0.250***	0.000	-0.201	0.003	0.000
definition EU wide	(0.065)	(0.078)	(0.118)	(0.100)	(0.046)	(0.041)	(0.084)	(.)	(0.117)	(0.013)	(0.000)
market		0.093	-0.003	-0.051	-0.045	0.092*	0.196**	0.000	-0.088		
definition worldwide		(0.089)	(0.115)	(0.088)	(0.032)	(0.050)	(0.072)	(.)	(0.064)		
number of	-0.004	0.002	0.000	-0.000	-0.001	0.001	0.001	0.000	0.002***	0.000	-0.000
concerned markets	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(.)	(0.000)	(0.000)	(0.000)
number of	-0.052**	-0.012	-0.009	-0.009	-0.008	-0.004	0.003	0.000	-0.013	0.003	0.000
competitors	(0.021)	(0.010)	(0.014)	(0.006)	(0.007)	(0.010)	(0.003)	(.)	(0.012)	(0.002)	(0.000)
indicator no	-0.363***	0.020	-0.131*	0.013	-0.003	-0.091*	0.027	0.000	-0.099	0.002	-0.000
info on competitors	(0.093)	(0.047)	(0.064)	(0.045)	(0.038)	(0.047)	(0.026)	(.)	(0.083)	(0.006)	(0.000)
Constant	0.308*	0.039	0.051	0.040	0.274**	0.014	0.044	0.000	0.011	-0.010	-0.000
	(0.152)	(0.121)	(0.150)	(0.120)	(0.103)	(0.099)	(0.079)	(.)	(0.063)	(0.014)	(0.000)
Industry Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.483	0.446	0.547	0.445	0.496	0.415	0.542	.	0.468	0.122	1.000
Observations	546	1,209	1,408	1,423	1,534	761	411	179	519	595	38

We report heteroskedasticity robust standard errors clustered at the industry group level.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

In the following figures, we present regression coefficient plots for our four main explanatory variables of interest. Figure 7 shows the impact of the HHI indicator. With few exceptions, coefficient estimates are positive but only significantly during the years 1999-2001, as well as in 2003, 2005, and 2007. Thus, in the last six years of the data, 2008 - 2013, high concentration was not a significant determinant of competitive concerns.

In figure 8, we repeat the exercise focusing on the time dynamics of the joint market share of the merging parties. The impact of market share on competitive concerns was - with the exception of 2006 - consistently significant and positive from 1996 to 2009. The coefficient estimates are roughly twice the size of those associated with the concentration indicator presented above, suggesting that a high market share of the merging parties carries more weight in DG Comp's assessment than overall high concentration. However,

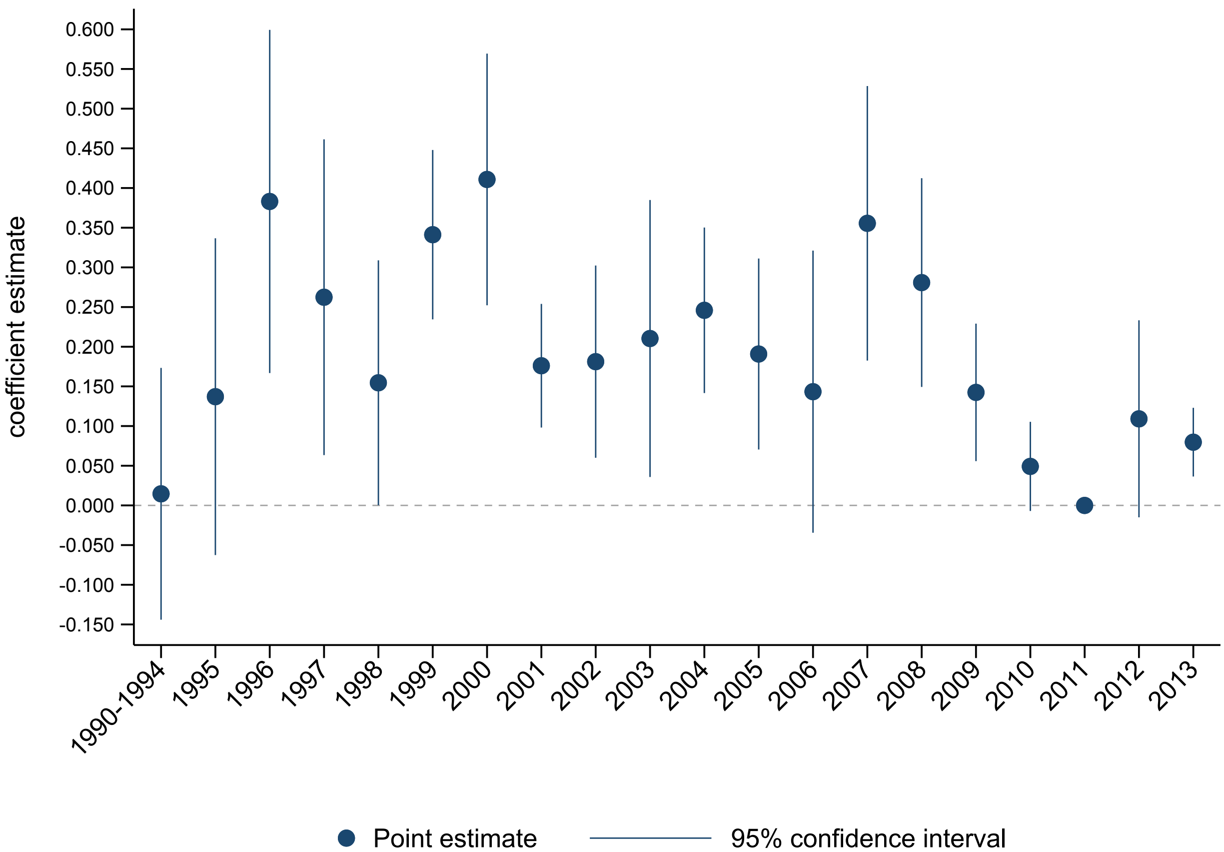
Figure 7: OLS Regression Coefficient on High Concentration over Time



Regression coefficient on indicator variable for post-merger HHI above 2000 and change in HHI due to the merger larger than 150 in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective time period. Confidence intervals are based on heteroskedasticity robust standard errors clustered at the industry group level.

similarly to the concentration measure, the importance of market shares seems to have declined after 2009.

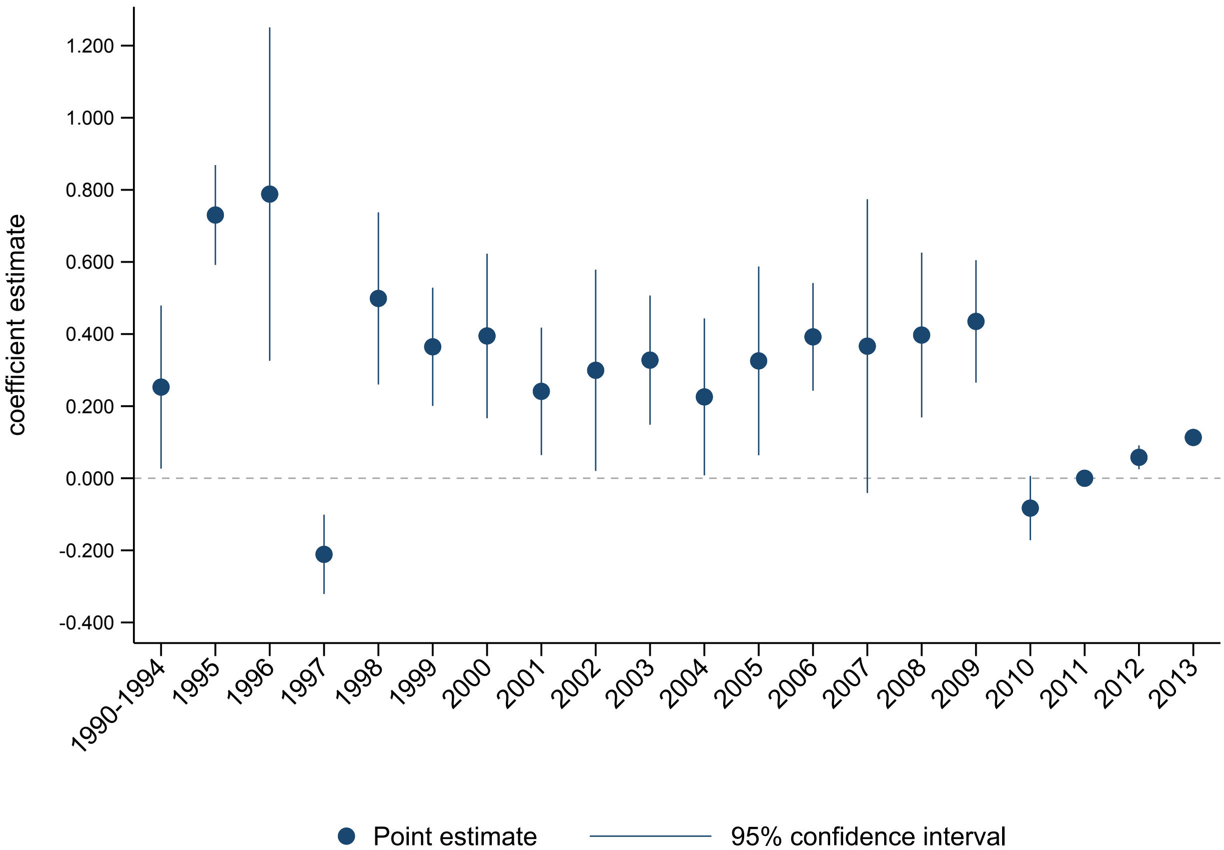
Figure 8: OLS Regression Coefficient on Joint Market Share over Time



Regression coefficient on indicator variable for joint market share above 50% in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective time period. Confidence intervals are based on heteroskedasticity robust standard errors clustered at the industry group level.

Figure 9 reports the coefficient estimates for barriers to entry in different time periods. Similar to market shares, barriers to entry were consistently associated with a higher probability of intervention for a long period of time (1990 to 2009, with the exception of 1997 and 2007). The size of the effect is, on average, even larger than that of market shares. Yet similarly to market shares and high concentration, its importance seems to have declined in the last years of the data.

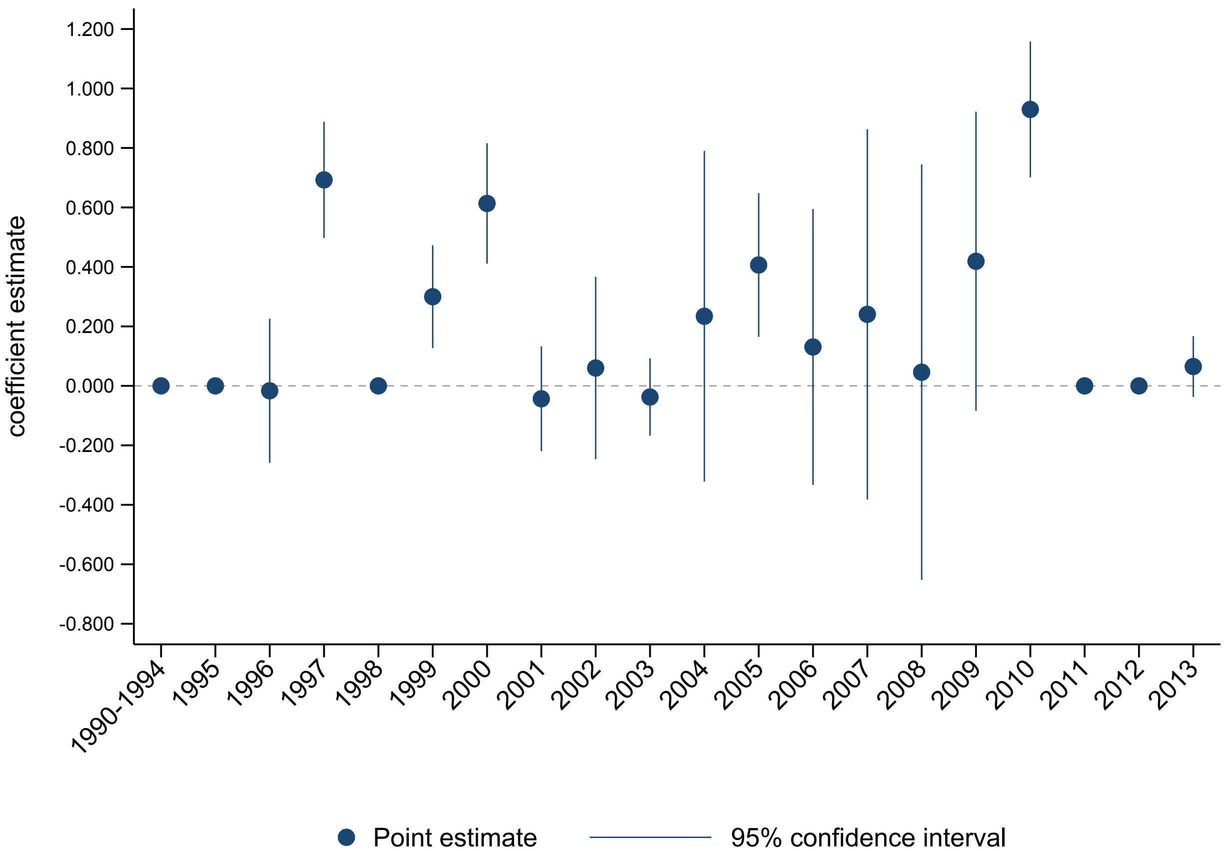
Figure 9: OLS Regression Coefficient on Barriers to Entry over Time



Regression coefficient on barriers to entry in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective time period. Confidence intervals are based on heteroskedasticity robust standard errors clustered at the industry group level.

Finally, in figure 10 we report the period-specific coefficients associated with foreclosure concerns. While the coefficients are positive and, in a few periods, significant, no clear pattern seems to emerge. Note that the coefficients reported as zero without confidence intervals indicate years, in which no cases with foreclosure concerns were handled.

Figure 10: OLS Regression Coefficient on Risk of Foreclosure over Time



Regression coefficient on risk of foreclosure in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective time period. Confidence intervals are based on heteroskedasticity robust standard errors clustered at the industry group level.

A.2 Determinants of Concern - Market Level - Split Sample over Industries

We explore heterogeneities across industries by running separate OLS regressions, splitting the market-level dataset over industries. For each of the industry sub-samples, we estimate the regression including high concentration and joint market share indicators (specification 4).

Table A3: Linear Probability Model for Concern by Industry

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Group 9
barriers to	0.412***	0.071	1.000***	0.637***	0.241***	0.487***	0.403***	0.066	0.467***
entry in submarket	(0.070)	(0.067)	(0.000)	(0.054)	(0.032)	(0.038)	(0.095)	(0.157)	(0.057)
risk of	0.326***	0.659***			0.469***		-0.364	0.213*	0.502***
foreclosure in submarket	(0.113)	(0.147)			(0.055)		(0.260)	(0.118)	(0.103)
joint market	0.415***	0.329***		0.217***	0.265***	0.301***	0.302***	0.215***	0.155***
share above 50%	(0.047)	(0.029)		(0.046)	(0.022)	(0.028)	(0.061)	(0.061)	(0.036)
HHI $\geq$ 2000	0.135***	0.079***	-0.000	0.066*	0.076***	0.177***	0.072**	0.057**	0.081***
& delta HHI $\geq$ 150	(0.029)	(0.020)	(0.000)	(0.034)	(0.017)	(0.029)	(0.031)	(0.027)	(0.019)
fullmerger	0.068	0.153***	0.000	-0.223***	-0.067***	0.121***	-0.228***	0.058	-0.200***
	(0.053)	(0.026)	(0.000)	(0.051)	(0.025)	(0.043)	(0.073)	(0.055)	(0.044)
joint venture	-0.006	0.060**		0.089	-0.150***	-0.093*	-0.280***	0.002	-0.218***
	(0.054)	(0.030)		(0.101)	(0.034)	(0.056)	(0.079)	(0.060)	(0.056)
conglomerate		-0.087*			-0.185***	0.355***		0.265*	-0.156***
merger in submarket		(0.048)			(0.069)	(0.075)		(0.143)	(0.057)
vertical merger	0.021	-0.042	-0.000	-0.009	-0.010	0.022	0.042	-0.080***	0.005
in submarket	(0.040)	(0.026)	(0.000)	(0.055)	(0.021)	(0.046)	(0.040)	(0.028)	(0.019)
market	0.201**	0.043	0.000	0.148**	0.011	-0.244***	0.444**	0.178*	0.025
definition national	(0.091)	(0.062)	(0.000)	(0.073)	(0.059)	(0.057)	(0.178)	(0.094)	(0.105)
market	0.157*	0.045		0.106	-0.047	-0.171**	0.431**	0.201**	0.087
definition EU wide	(0.089)	(0.066)		(0.068)	(0.057)	(0.069)	(0.173)	(0.096)	(0.104)
market	0.157*	0.033		0.219	-0.002	-0.198***	0.348*	0.242**	0.062
definition worldwide	(0.081)	(0.100)		(0.207)	(0.060)	(0.072)	(0.196)	(0.095)	(0.103)
number of	-0.000	0.000	-0.000	0.002*	-0.001***	-0.001	-0.000	-0.003***	0.005***
concerned markets	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
number of	-0.004	0.007	-0.000	0.003	-0.006	-0.021***	0.024*	0.002	-0.019**
competitors	(0.006)	(0.008)	(0.000)	(0.011)	(0.006)	(0.005)	(0.013)	(0.006)	(0.008)
indicator no	-0.061	-0.026		-0.123*	-0.089***	-0.061**	0.114*	0.042	-0.145***
info on competitors	(0.037)	(0.033)		(0.066)	(0.025)	(0.027)	(0.058)	(0.038)	(0.037)
post reform	0.093	0.052	0.000	-0.715***	-0.865***	-0.103	-0.067**	0.101	-0.109**
indicator	(0.085)	(0.052)	(0.000)	(0.179)	(0.037)	(0.108)	(0.033)	(0.091)	(0.055)
Constant	-0.213*	-0.227***	0.000	0.485**	1.010***	0.218*	-0.294	-0.331***	0.079
	(0.123)	(0.087)	(0.000)	(0.198)	(0.070)	(0.129)	(0.205)	(0.124)	(0.119)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.671	0.409	1.000	0.586	0.507	0.483	0.577	0.392	0.644
Observations	455	1,022	39	435	1,919	1,035	339	369	621

We report heteroskedasticity robust standard errors.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

Table A4: Linear Probability Model for Concern by Industry (Continued)

	Group 10	Group 11	Group 12	Group 13	Group 14	Group 15	Group 16	Group 17	Group 18
barriers to	0.681***	0.268***	0.407***	0.328***	0.406***	0.000	0.346***	0.199***	
entry in submarket	(0.072)	(0.078)	(0.055)	(0.077)	(0.069)	(.)	(0.054)	(0.028)	
risk of	-0.322**	0.510***	-0.047	0.408***	0.046		0.269***	-0.027	
foreclosure in submarket	(0.125)	(0.088)	(0.044)	(0.117)	(0.066)		(0.104)	(0.040)	
joint market	0.146**	0.132***	0.171***	0.187***	0.253***	0.000	0.071	0.113***	0.000
share above 50%	(0.057)	(0.031)	(0.036)	(0.050)	(0.048)	(.)	(0.045)	(0.020)	(.)
HHI $\geq$ 2000	-0.016	0.106***	-0.037	0.028	0.205***	0.000	0.134***	0.197***	0.000
& delta HHI $\geq$ 150	(0.020)	(0.020)	(0.035)	(0.018)	(0.036)	(.)	(0.020)	(0.028)	(.)
fullmerger	-0.158***	-0.219***	-0.114**	0.061*	-0.297***	0.000	-0.120***	-0.029	0.000
	(0.052)	(0.036)	(0.045)	(0.032)	(0.064)	(.)	(0.036)	(0.087)	(.)
joint venture	-0.126**	-0.213***		0.019	-0.372***	0.000	-0.084**	0.003	0.000
	(0.057)	(0.035)		(0.037)	(0.064)	(.)	(0.036)	(0.093)	(.)
conglomerate	0.022	-0.131	-0.016	-0.059*		0.000	-0.025	0.130**	
merger in submarket	(0.032)	(0.096)	(0.040)	(0.036)		(.)	(0.037)	(0.063)	
vertical merger	0.031	-0.039**	-0.030	-0.050	0.047	0.000	0.006	0.037	0.000
in submarket	(0.029)	(0.016)	(0.033)	(0.031)	(0.038)	(.)	(0.015)	(0.028)	(.)
market	0.294***	0.078	0.182**	0.075*	0.004	0.000	-0.026	0.092*	
definition national	(0.095)	(0.075)	(0.074)	(0.043)	(0.061)	(.)	(0.023)	(0.048)	
market	0.132*	0.072	0.091	0.039	-0.166**	0.000	0.014	0.062	
definition EU wide	(0.074)	(0.073)	(0.066)	(0.028)	(0.078)	(.)	(0.024)	(0.059)	
market	0.079	0.149*		0.068		0.000	0.070*	0.052	
definition worldwide	(0.081)	(0.076)		(0.051)		(.)	(0.036)	(0.055)	
number of	-0.003***	0.001	-0.001***	0.001	-0.000	0.000	-0.001	0.000	0.000
concerned markets	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(.)	(0.001)	(0.000)	(.)
number of	-0.005	0.003	-0.009	-0.004	0.002	0.000	0.006*	-0.028***	0.000
competitors	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)	(.)	(0.004)	(0.006)	(.)
indicator no	-0.109***	0.052*	-0.007	-0.046	0.009	0.000	0.088***	-0.108***	0.000
info on competitors	(0.040)	(0.028)	(0.055)	(0.039)	(0.035)	(.)	(0.022)	(0.034)	(.)
post reform	-0.351***	-0.021	0.632***	-0.028	0.106*	0.000	0.038***	-0.121	0.000
indicator	(0.110)	(0.026)	(0.087)	(0.023)	(0.057)	(.)	(0.012)	(0.078)	(.)
Constant	0.240*	-0.109	0.053	-0.141*	0.212**	0.000	-0.034	0.128	0.000
	(0.129)	(0.082)	(0.042)	(0.079)	(0.097)	(.)	(0.048)	(0.127)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.793	0.522	0.385	0.453	0.657	.	0.548	0.326	.
Observations	339	632	443	435	547	85	680	1,398	60

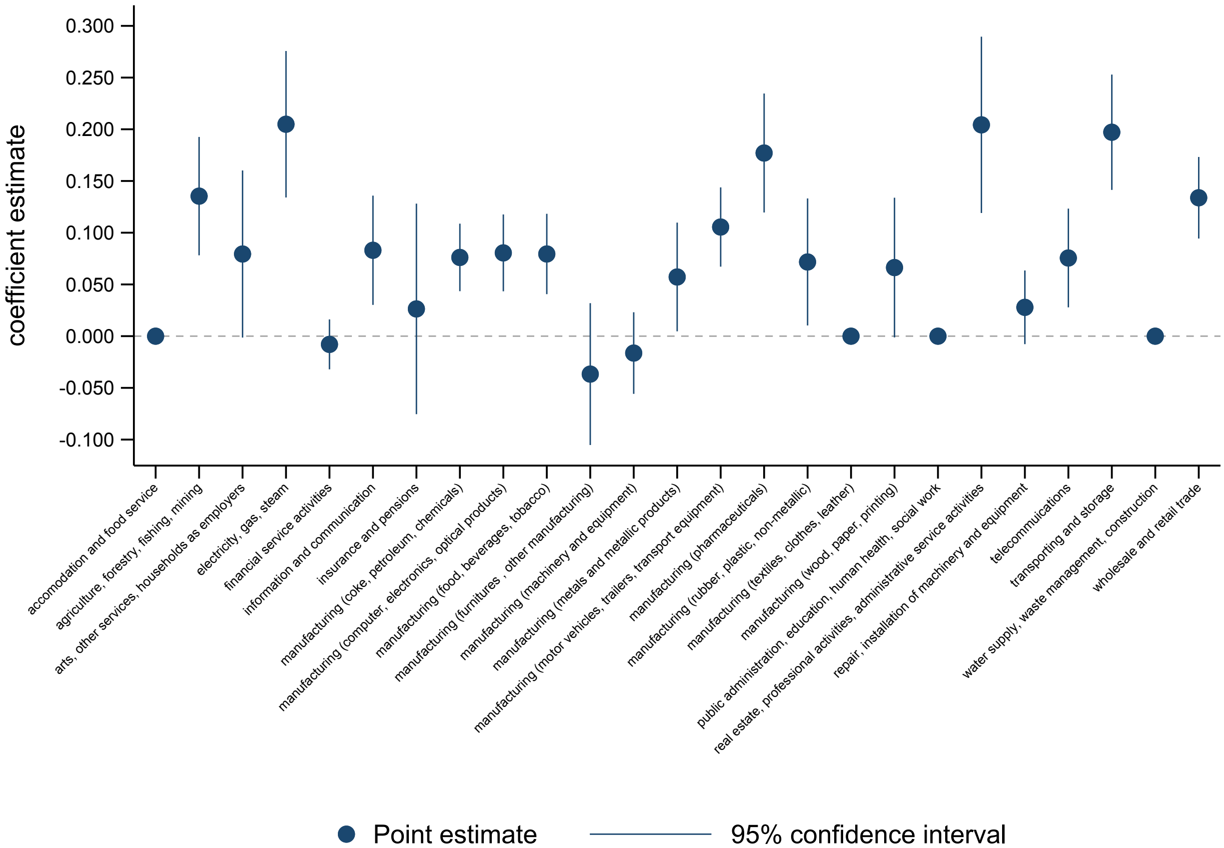
We report heteroskedasticity robust standard errors.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

Table A5: Linear Probability Model for Concern by Industry (Continued)

	Group 19	Group 20	Group 21	Group 22	Group 23	Group 24	Group 25
barriers to	0.581^{***}	0.362^{***}	0.974^{***}	0.215	0.178^{**}		0.751^{***}
entry in submarket	(0.119)	(0.062)	(0.042)	(0.147)	(0.082)		(0.194)
risk of	0.131	-0.283^{***}	0.957^{***}		-0.274^{**}		0.980^{***}
foreclosure in submarket	(0.174)	(0.085)	(0.044)		(0.123)		(0.044)
joint market	0.221^{***}	0.025	0.191	0.233^{***}	0.268^{***}	0.000	-0.021
share above 50%	(0.052)	(0.022)	(0.124)	(0.078)	(0.078)	(0.000)	(0.038)
HHI $\geq$ 2000	0.083^{***}	0.076^{***}	-0.008	0.026	0.204^{***}	0.000	0.079^{*}
& delta HHI $\geq$ 150	(0.027)	(0.024)	(0.012)	(0.052)	(0.043)	(0.000)	(0.041)
fullmerger	0.171	0.082^{***}	-0.002	0.057	0.267	-1.000^{***}	0.124
	(0.115)	(0.027)	(0.014)	(0.052)	(0.168)	(0.000)	(0.140)
joint venture	0.155^{**}	-0.083	-0.031	-0.022	0.302^{*}	-1.000^{***}	
	(0.066)	(0.063)	(0.025)	(0.067)	(0.178)	(0.000)	
conglomerate	0.018	0.145		-0.001	-0.141		
merger in submarket	(0.086)	(0.134)		(0.067)	(0.132)		
vertical merger	0.003	0.062	0.015	-0.097	0.103^{*}	0.000	0.039
in submarket	(0.032)	(0.038)	(0.022)	(0.114)	(0.062)	(0.000)	(0.047)
market	-0.004	-0.033	-0.042	-0.214^{***}	-0.227^{***}	-0.000	-0.158
definition national	(0.177)	(0.079)	(0.032)	(0.072)	(0.047)	(0.000)	(0.124)
market	0.003	-0.022	-0.033	-0.075	-0.281^{***}	-0.000	-0.054
definition EU wide	(0.175)	(0.088)	(0.027)	(0.112)	(0.075)	(0.000)	(0.073)
market	-0.045	-0.032	-0.027	-0.224^{***}	-0.187	-0.000	-0.169
definition worldwide	(0.166)	(0.088)	(0.023)	(0.083)	(0.121)	(0.000)	(0.134)
number of	-0.001	-0.003^{*}	0.000	0.013^{***}	-0.001	0.000	0.001
concerned markets	(0.001)	(0.002)	(0.000)	(0.004)	(0.001)	(0.000)	(0.001)
number of	0.025^{***}	-0.004	-0.006	-0.026^{*}	-0.011	0.000^{**}	-0.089
competitors	(0.009)	(0.003)	(0.009)	(0.014)	(0.011)	(0.000)	(0.057)
indicator no	0.076^{*}	-0.002	-0.021	-0.275^{***}	0.093	0.000^{**}	-0.356^{*}
info on competitors	(0.039)	(0.024)	(0.045)	(0.082)	(0.073)	(0.000)	(0.203)
post reform	-0.185	-0.044	-0.027	-0.135	0.137	-0.000	-0.099
indicator	(0.166)	(0.090)	(0.024)	(0.143)	(0.181)	(0.000)	(0.094)
Constant	-0.319	0.055	0.091	0.389^{**}	0.020	1.000^{***}	0.355^{*}
	(0.207)	(0.181)	(0.083)	(0.171)	(0.184)	(0.000)	(0.203)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.640	0.479	0.889	0.427	0.282	1.000	0.724
Observations	420	442	251	244	434	50	116

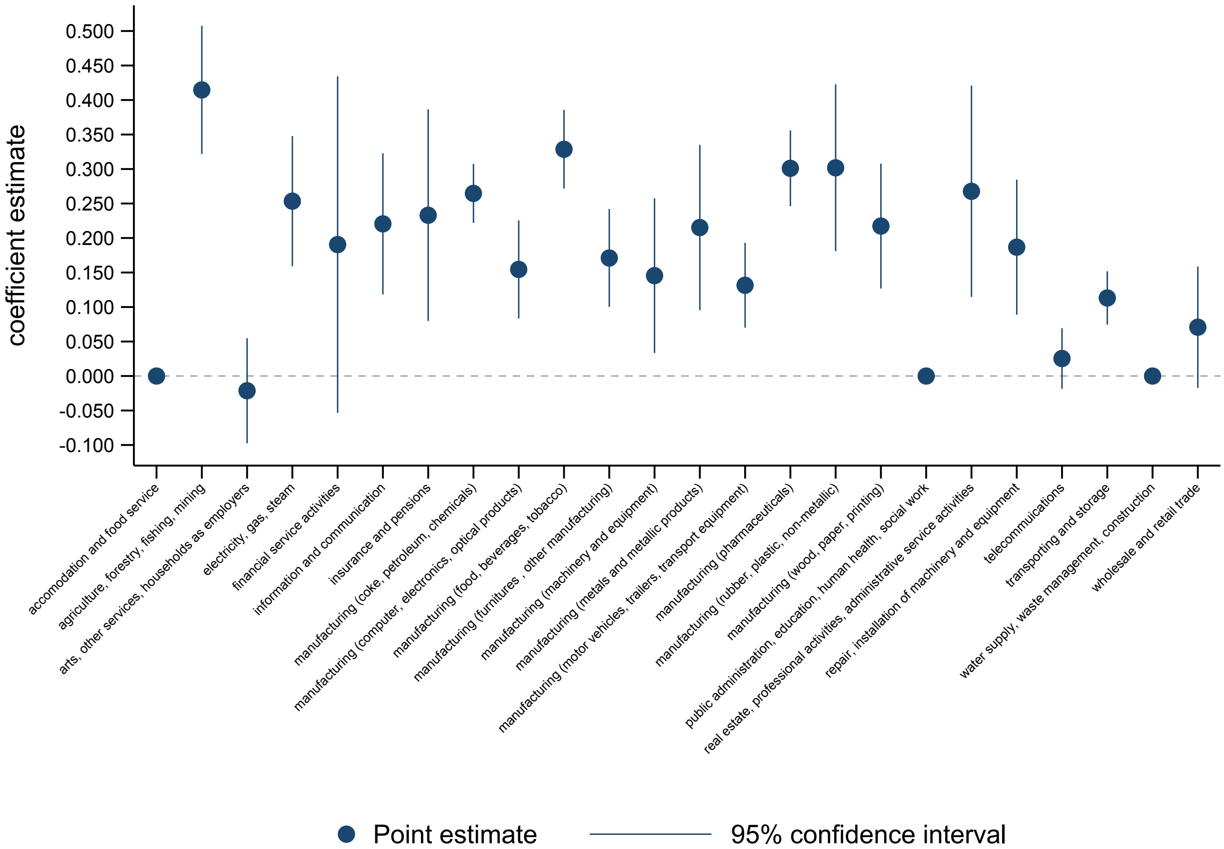
We report heteroskedasticity robust standard errors.
Significance at the 1%, 5%, and 10% levels is represented by ***,** and * respectively.

Figure 11: OLS Regression Coefficient on High Concentration over Industry



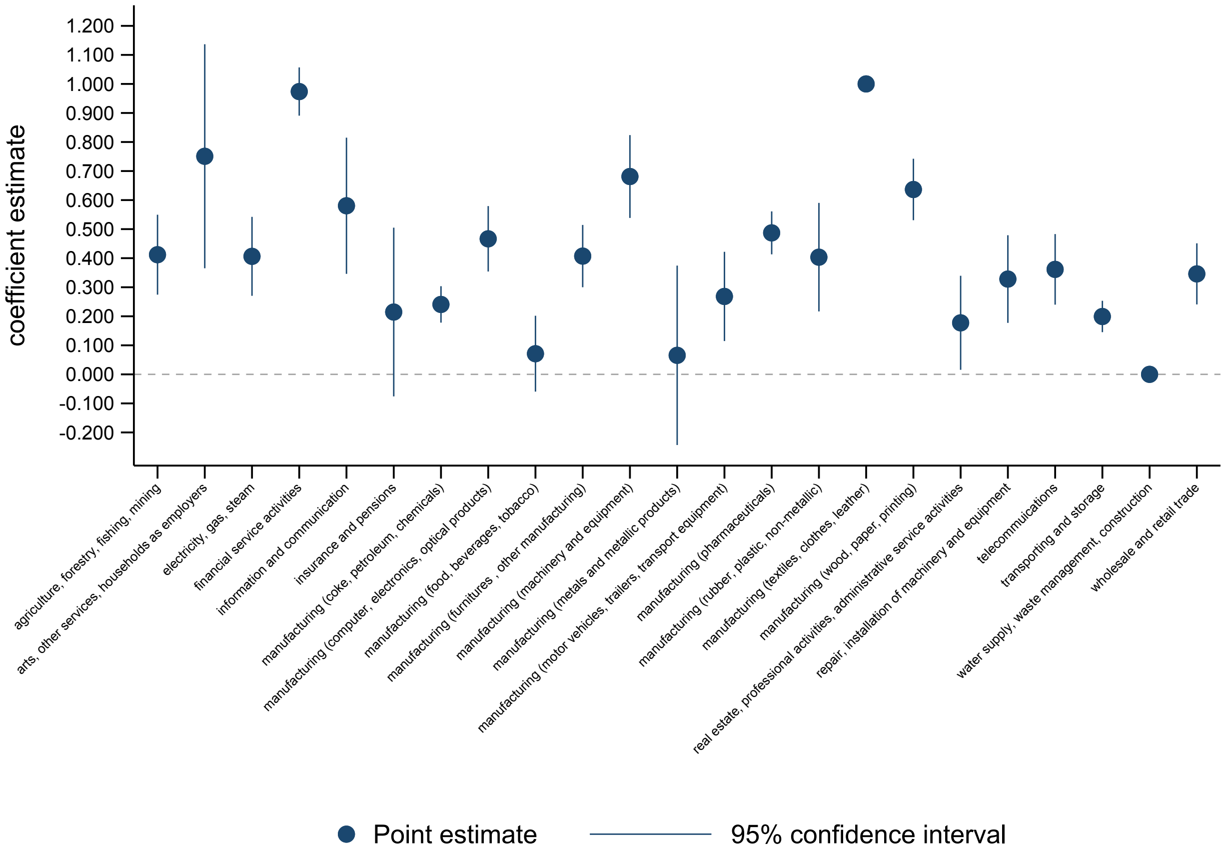
Regression coefficient on indicator variable for post-merger HHI above 2000 and change in HHI due to the merger larger than 150 in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust standard errors.

Figure 12: OLS Regression Coefficient on Joint Market Share over Industry



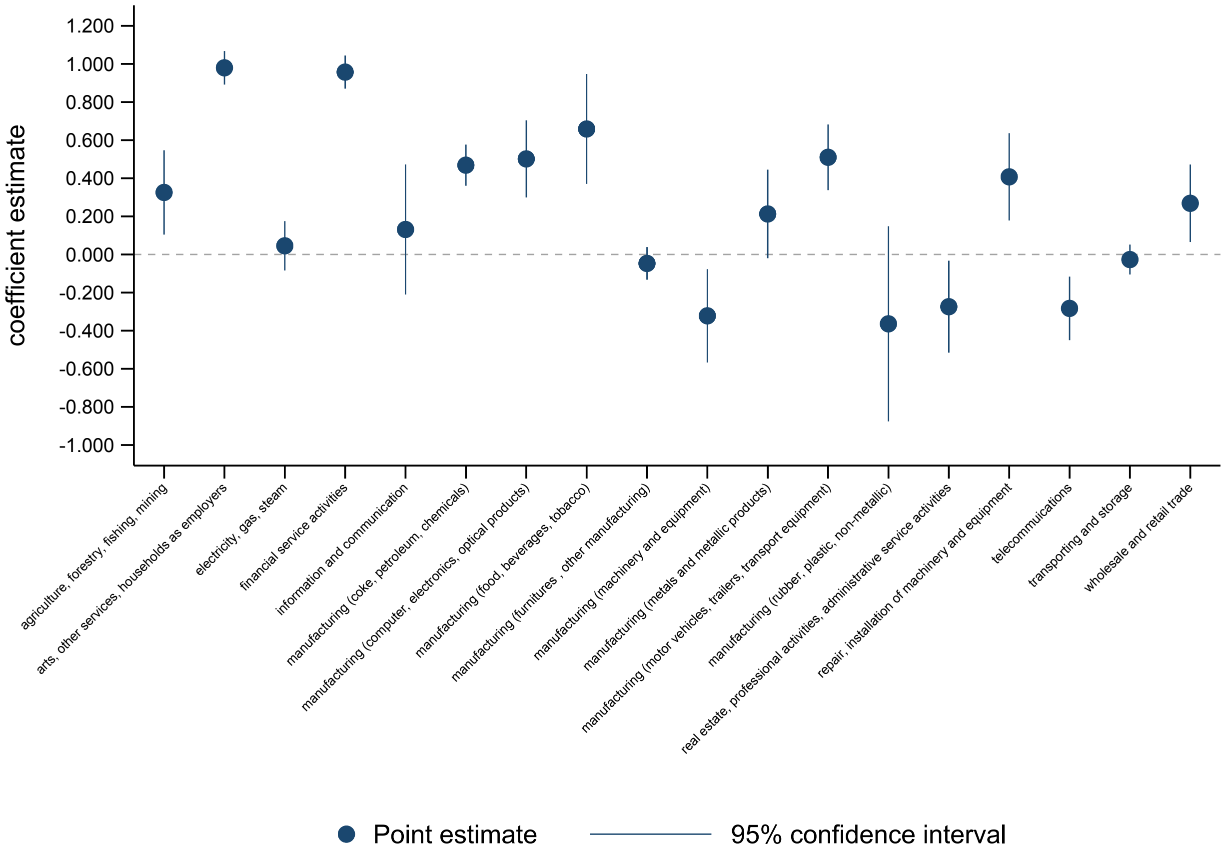
Regression coefficient on indicator variable for joint market share above 50% in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust standard errors.

Figure 13: OLS Regression Coefficient on Barriers to Entry over Industry



Regression coefficient on barriers to entry in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust standard errors.

Figure 14: OLS Regression Coefficient on Risk of Foreclosure over Industry



Regression coefficient on risk of foreclosure in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust standard errors.

A.3 Technical Background on Causal Forests

A.3.1 Background on Causal Forests

Causal forests are based on the random forest methodology by Breiman (2001). They have been developed by Athey and co-authors in a series of papers (see Athey and Imbens (2016), Wager and Athey (2018) and Athey, Wager, and Tibshirani (2019)), extending the regression tree and random forest algorithms so as to estimate average treatment effects for different subgroups, rather than predicting outcomes as is the case for regression trees and random forests.

In a standard CART tree (Classification and Regression Tree), the goal is to predict individual outcomes Y_i using the mean outcome Y of observations that are "close" in X-space. To determine which observations are "close", the algorithm starts to recursively split the covariate space (binary splits) until it is partitioned into a set of so-called leaves L that contain only a few training samples. The outcome Y_i for observation i is then predicted by identifying the leaf containing observation i based on its characteristics X_i and setting the prediction to the mean outcome within that leaf:

$$\hat{\mu}(x) = \frac{1}{|\{i : X_i \in L(x)\}|} \sum_{\{i:X_i \in L(x)\}} Y_i \tag{5}$$

The algorithm automatically decides on the splitting variables and split points. This is done based on an in sample goodness-of-fit criterion (so essentially how close the predicted outcomes are to the actual outcomes). For regression trees (continuous outcome variable Y) the goodness-of-fit criterion used is the mean squared error, for classification trees (categorical outcome variable Y) the goodness-of-fit criterion is a measure of classification error based on the empirical classification probabilities in the leaves. The algorithm then splits on the covariate at the cut-off value that leads to the greatest improvement in the goodness-of-fit criterion. Once the best split at a given point in the tree is found, the splitting process is repeated in each of the resulting two regions. For CART trees, the splitting process is usually stopped when a specified minimum node size is reached - by default this is a node size of 5 for regression and 1 for classification trees. The tree is then pruned based on some cost-complexity trade-off measure in order to avoid over-fitting (See Hastie, Tibshirani, and Friedman (2008, chapter 9) for further details).

A random forest is then an ensemble of regression or classification trees, where the predictions are averaged across trees (for classification problems, the random forest obtains a class vote from each tree and then classifies based on majority vote). Each individual tree in the forest is grown using a random sample with replacement from the training set. One third of the data is not used for training and can be used for testing (out-of-bag error). Differently from growing a single tree, splitting for each node in a tree in the forest is done based on only a subset of the covariates X and each tree is grown to the largest extent possible without pruning. The idea behind random forests is to reduce variance and produce more robust predictions compared to a single tree. The splitting on only a subset of variables at each node reduces the correlation between the trees in the forest and the variance of the predictions further (See Breiman (2001) and Hastie, Tibshirani, and Friedman (2008, chapter 15) for further details).

In case of a causal forest, we are not interested in predicting individual outcomes Y_i but individual treatment effects $Y_i^1 - Y_i^0$ to study how treatment effects vary by subgroup. This implies that standard goodness-of-fit measures used in regression trees and random forests, such as the mean squared error, are not available since one of the potential outcomes and hence the actual treatment effect is never observed. However, the causal forest methodology builds on regression tree methods in that it also applies a "goodness-of-fit" criterion in treatment effects to decide on splits. Athey and Imbens (2016) show that the mean squared error function of a causal tree can be estimated and is a function of the variance of the estimated treatment effect. Basically, the goodness-of-fit measure to be minimized rewards a partition of the data for finding strong heterogeneity in treatment effects and penalizes a partition for high variance in leaf estimates. Minimizing the expected mean squared error of predicted treatment effects (rather than the infeasible mean squared error), is shown to be equivalent to maximizing the variance of the predicted treatment effects across leaves with a penalty for within-leaf variance (variance of means of treatment and control group outcomes within leaves).

Causal trees are similar to nearest-neighbour methods as they also rely on the unconfoundedness assumption and use "close" observations to predict treatment effects. However, rather than defining closeness based on some pre-specified distance measure (such as Euclidean distance in k-nearest-neighbour matching), closeness is defined with respect to a decision tree and the closest control observations to i are those that fall in the same leaf. Analogously to CART regression trees, the leaves in causal trees should be small enough so that the (Y_i, W_i) pairs in a given leaf act as though they had come from a randomized experiment (Wager and Athey, 2018). The treatment effect for observation i with covariates $X_i = x$ falling into leaf L is then simply estimated as the difference of mean outcomes between treated and control observations within that leaf:

$$\begin{aligned}\hat{\tau}(x) = & \frac{1}{|\{i : W_i = 1, X_i \in L\}|} \sum_{\{i:W_i=1,X_i\in L\}} Y_i \\ & - \frac{1}{|\{i : W_i = 0, X_i \in L\}|} \sum_{\{i:W_i=0,X_i\in L\}} Y_i\end{aligned}$$

Given the procedure for generating a single causal tree, a causal forest then generates B such trees, each of which delivers an estimate $\hat{\tau}_b(x)$. The causal forest as developed by Wager and Athey (2018) then aggregates the predictions of the single trees by averaging:

$$\hat{\tau}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{\tau}_b(x) \tag{6}$$

The causal forest algorithm by Athey, Wager, and Tibshirani (2019) (the one we use here), predicts treatment effects slightly differently. For each observation i, the algorithm weights the nearby control observations according to the fraction of trees in which a control observation appears in the same leaf as the treated observation i. The treatment effect is then calculated as the difference between observation i's actual outcome and the weighted average outcome of its control observations. This implies that for each observation an individual treatment effect τ_i can be estimated.

As for CART trees and random forests, the advantage of a causal forest over a causal tree is that it is not always clear what the "best" causal tree is. The aggregation across trees helps to reduce variance, the estimates of the causal effects change more smoothly with covariates and individual treatment effects τ_i can be estimated while in a causal tree all individuals assigned to a given terminal leaf have the same estimated treatment effect (Wager and Athey, 2018).

Athey and Imbens (2016) further introduce so-called "honesty" in causal trees to ensure correct inference: the data is divided in half, where one half of the data is used to build the tree (so determine the splits in covariate space) and the other half is used to predict treatment effects. Wager and Athey (2018) extend this idea to causal forests and develop asymptotic theory for inference in causal forests. Thus, the causal forest algorithm by Athey, Wager, and Tibshirani (2019) does not only allow to predict heterogeneous treatment effects in a very flexible way but also provides confidence intervals for these estimates.

A.3.2 Background on grf package

We use the generalized random forest (grf) R package of Athey, Wager, and Tibshirani (2019).[31] The package allows, among others, to train a causal forest, obtain the conditional average treatment effect and predict treatment effects, either in-sample using out-of-bag training samples or out-of-sample using prediction datasets as we do in our application. As the package also predicts the variance of treatment effects, it is possible to compute point-wise confidence intervals for predicted treatment effects.

To build the trees in the forest, the package uses by default 50% of the data to grow each tree. When honesty is used, these sub-samples are further cut in half, where one half is used to place the splits within

[31] We use version 0.10.2 of the grf package.

the tree and the other half is used to estimate treatment effects within the leaves.

While the causal forest algorithm is based on the regression tree methodology, it can still be applied to a binary outcome variable Y as is the case in our application. Athey, Wager, and Tibshirani (2019) apply the causal forest methodology themselves in the example of the effect of child rearing on female labor-force participation where the outcome variable is an indicator variable for whether the mother did not work in the year preceding the census.

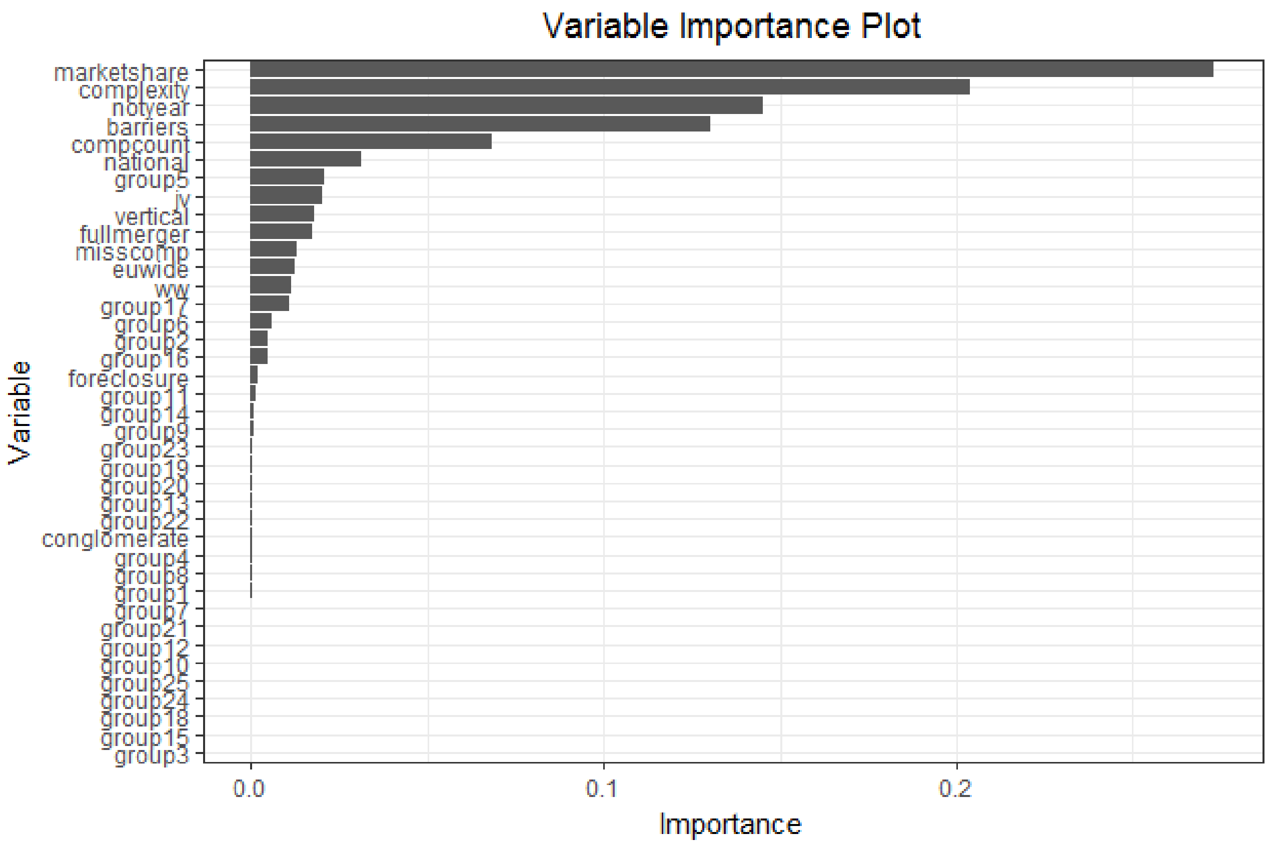
In case of a binary outcome variable, the causal forest function gives estimates of $\tau(x) = \mathbf{E}\left[Y(1) - Y(0)|X = x\right]$ and according to a forum discussion on the grf package by the authors, the provided confidence intervals are also formally justified for binary Y as long as $Y(w)$ is not a deterministic function of X (i.e. there is still some randomness in the outcome Y given X and W). For binary outcome Y, the prediction function for causal forests then returns the estimated change in the probability of Y associated with the treatment W, which should be between -1 and 1.

A.4 Variable Importance Plots of Causal Forests

The variable importance measures the frequency with which the causal forest splits over a given covariate. It is based on the split frequencies function provided in the grf R package by Athey, Wager, and Tibshirani (2019) that shows how often the forest chose to split on each covariate at different split depths. For the plots shown here, we take into account splits within trees up to a split depth of 4. The variable importance function first counts the fraction of times the forest splits on each covariate at split levels 1, 2, 3 and 4. To calculate the overall variable importance measure, splits on a given covariate are weighted differently depending on the split depth. In the variable importance plots below, we use a decay exponent of 2, implying weights for splits at depth 1,2,3 and 4 of 1, 0.25, 0.1111 and 0.0625 respectively.

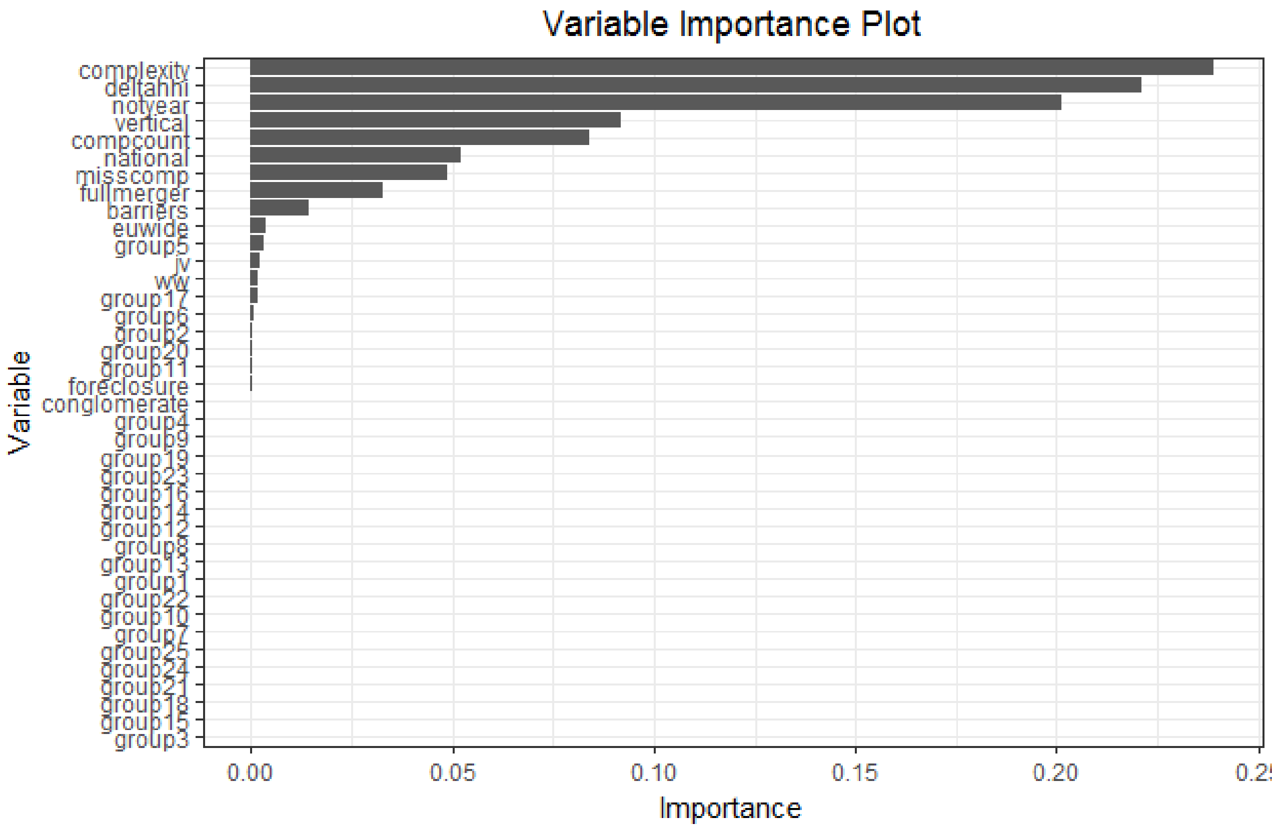
A.4.1 Treatment - High Concentration

Figure 15: Variable Importance Plot for Correlation between High Concentration and Concerns



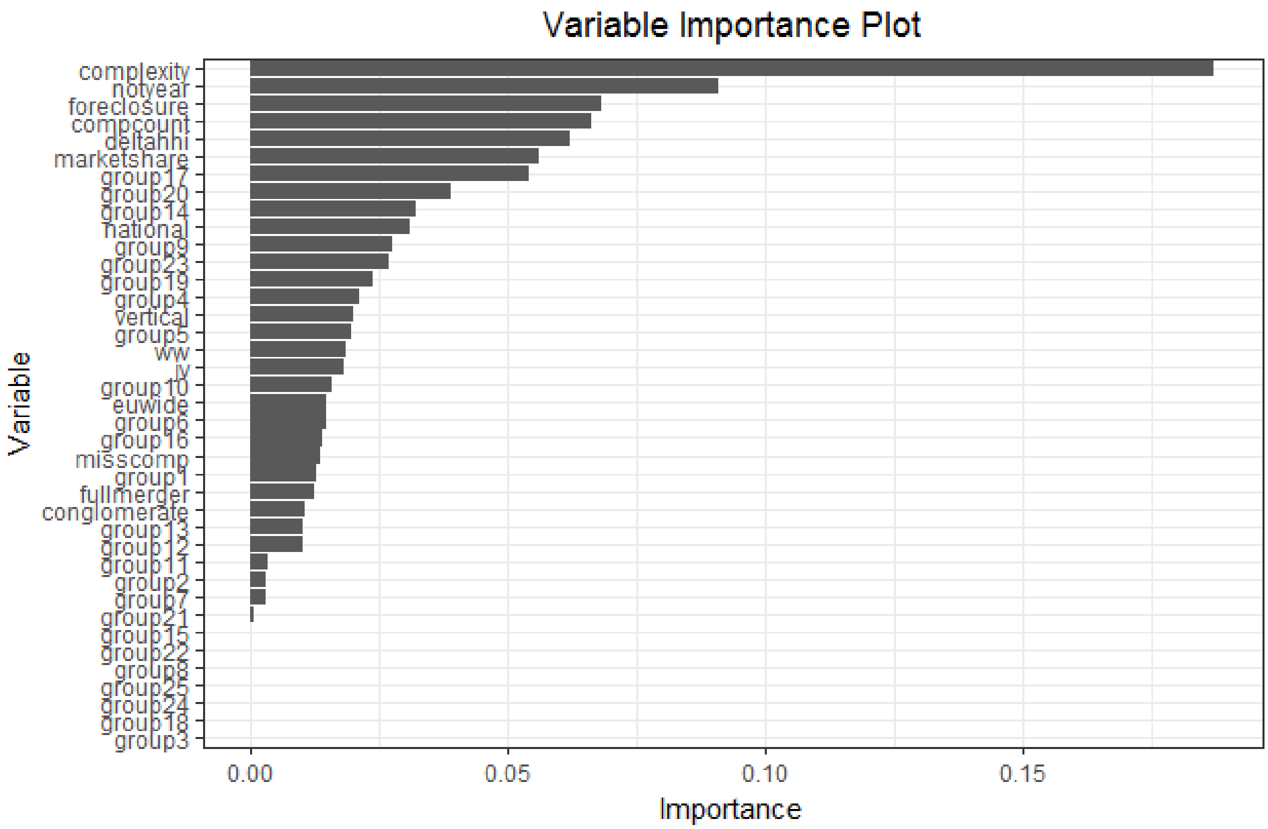
A.4.2 Treatment - Joint Market Share above 50%

Figure 16: Variable Importance Plot for Correlation between Joint Market Share and Concerns



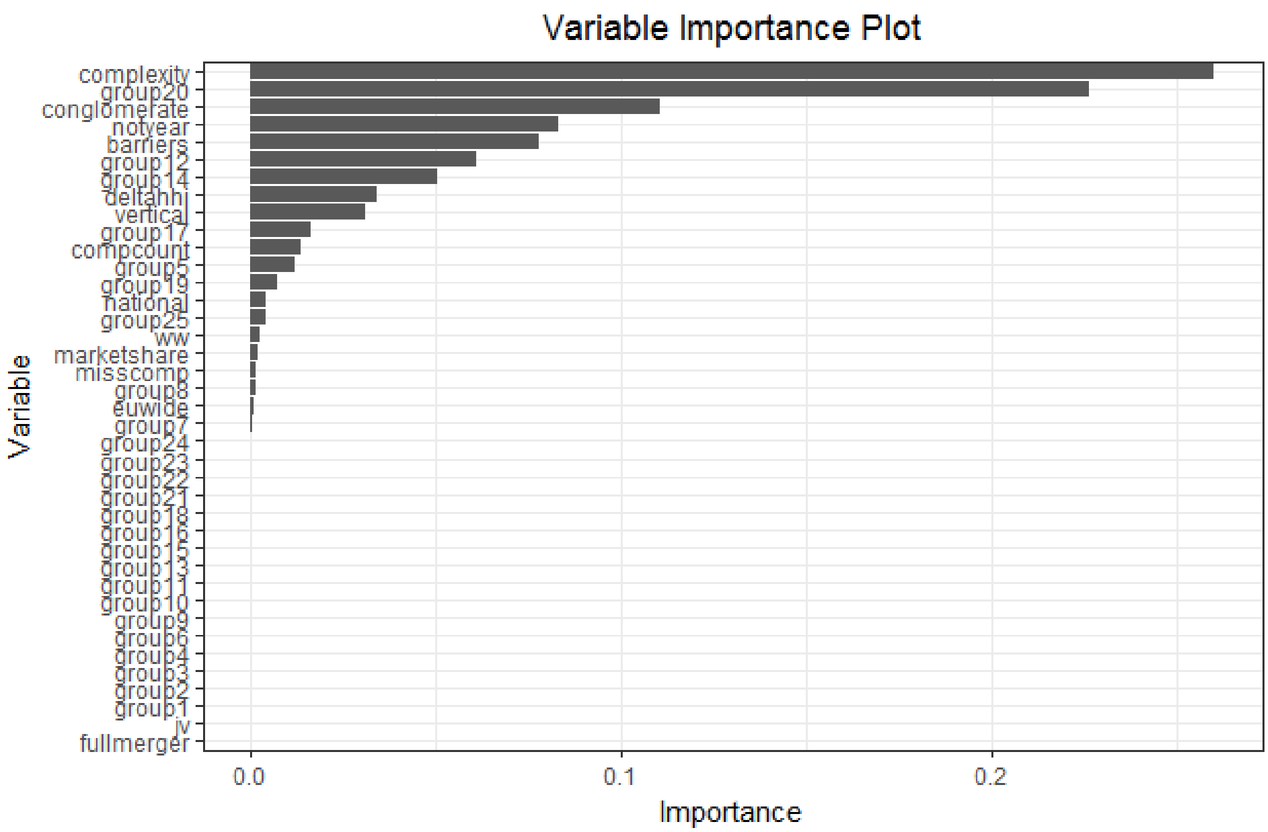
A.4.3 Treatment - Barriers to Entry

Figure 17: Variable Importance Plot for Correlation between Barriers to Entry and Concerns



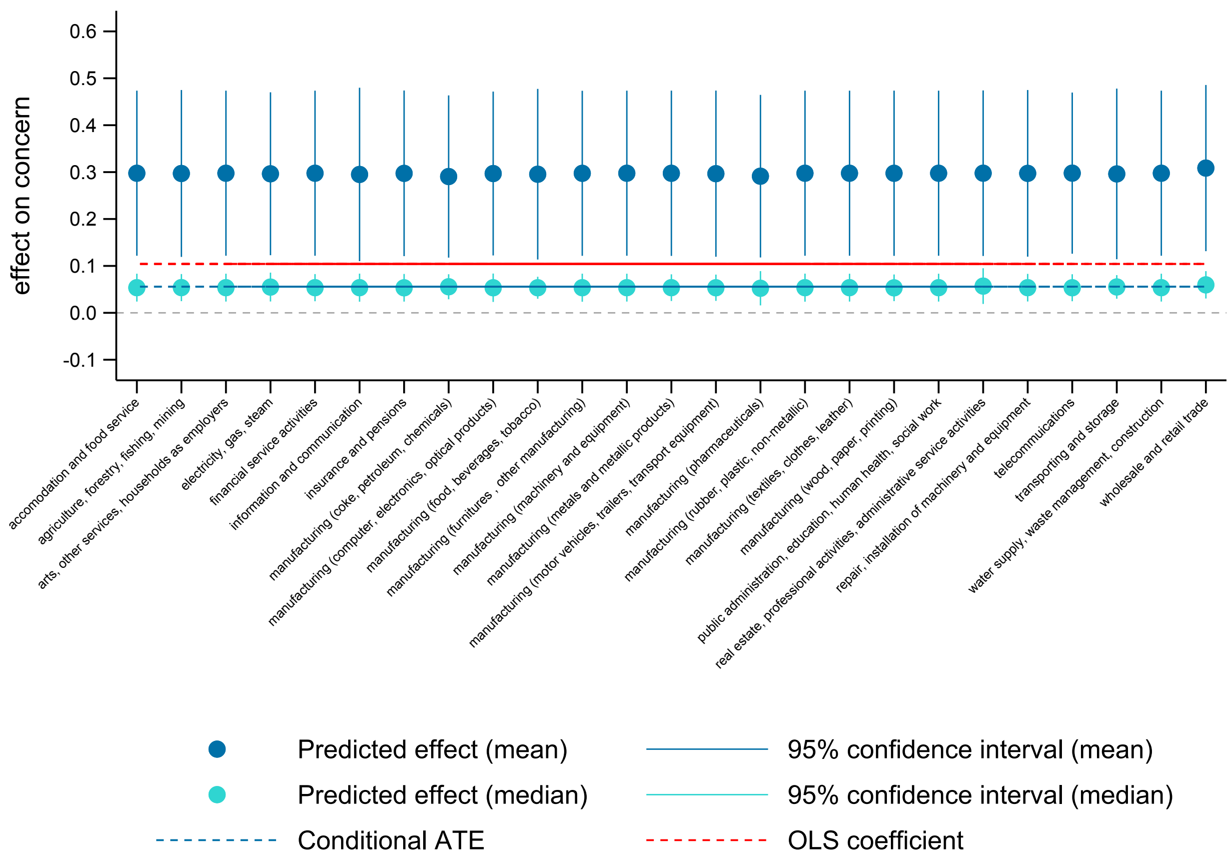
A.4.4 Treatment - Risk of Foreclosure

Figure 18: Variable Importance Plot for Correlation between Risk of Foreclosure and Concerns



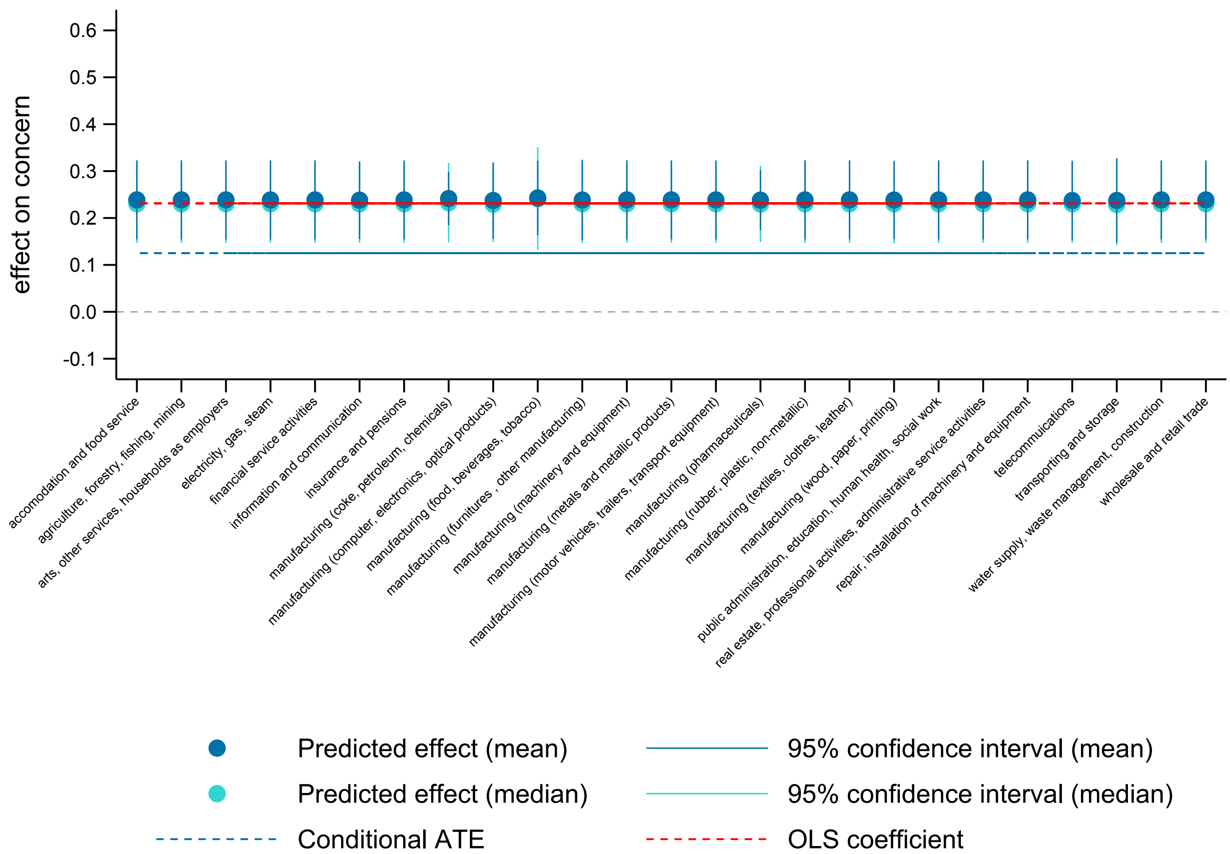
A.5 Determinants of Concern - Causal Forest Predictions over Industries

Figure 19: Effect of High Concentration on Concerns over Industries



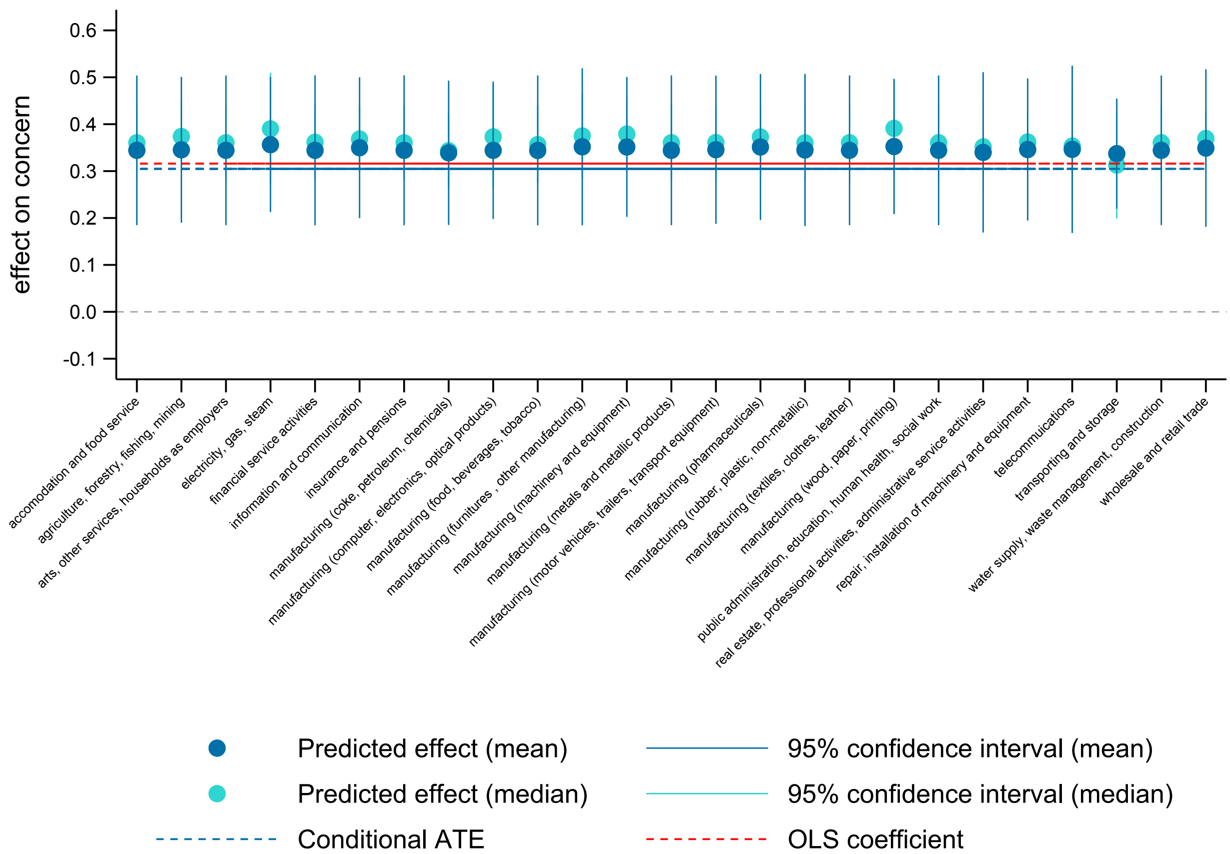
Predicted effect of indicator variable for post-merger HHI above 2000 and change in HHI larger than 150 on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.

Figure 20: Effect of Joint Market Share on Concerns over Industries



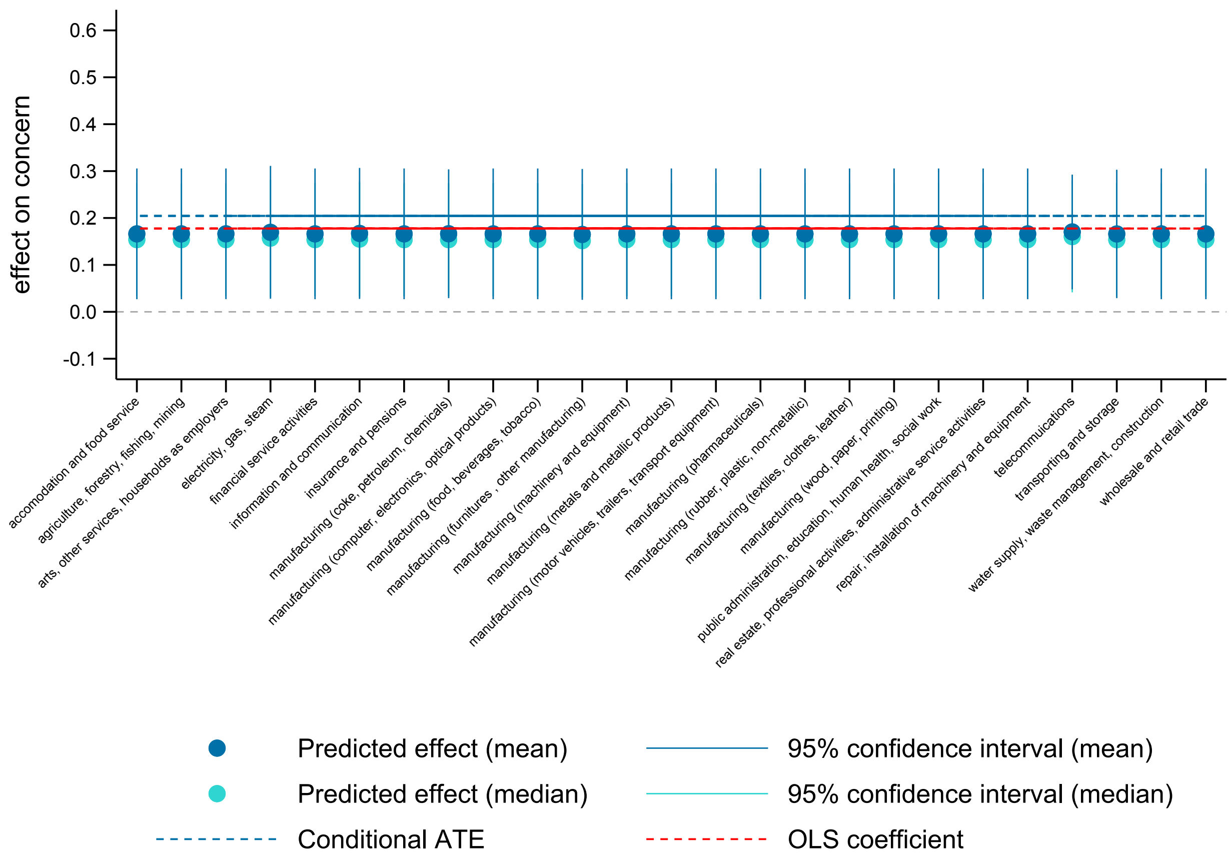
Predicted effect of indicator variable for joint market share above 50% on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.

Figure 21: Effect of Barriers to Entry on Concerns over Industries



Predicted effect of barriers to entry on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.

Figure 22: Effect of Risk of Foreclosure on Concerns over Industries



Predicted effect of risk of foreclosure on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.