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25 Years of European Merger Control*

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Abstract We study the determinants of common European merger policy over its first 25 years, from 1990 to 2014. Using a novel dataset at the level of the relevant antitrust markets and containing all relevant merger cases notified to the European Commission, we evaluate how consistently arguments related to structural market parameters – dominance, rising concentration, barriers to entry, and foreclosure – were applied over time and across different geographic market definitions. On average, linear probability models overestimate the effects of structural indicators. Using non-parametric machine learning techniques, we find that dominance is positively correlated with competitive concerns, especially in markets with a substantial increase in post-merger concentration and in complex mergers. Yet, its importance decreased following the 2004 merger policy reform. Competitive concerns are also correlated with rising concentration, especially if entry barriers and foreclosure are of concern. The impact of these structural indicators in explaining competitive concerns is independent of the geographic market definition and does not change over time.

JEL Classification: K21; L40

Keywords: Merger policy; EU Commission; dominance; concentration; entry barriers; foreclosure; causal forests

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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 policy 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 behavior becomes more difficult. Finally, mergers are the area of antitrust where the largest consensus on best practices exists. Therefore, of all competition policy tools, it is the one that attracts the 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. In the early 1990s there were approximately 50 notified cases per year; this workload increased significantly in the late 1990s, reaching in the 2000s an average of about 280 cases annually. 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. In this so-called effects-based approach, centered around a clearly stated theory of harm, the reliance on structural indicators of competition, such as market shares and measures of concentration was expected to decrease.

In this paper, we employ a new dataset containing all merger cases with an official decision by DG Comp (more than 5,000 individual decisions) to evaluate the time dynamics of the EC's decision procedures. Moreover, 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 (more than 30,000 individual markets). Thus, instead of only looking at the determinants of a merger decision in the aggregate, as commonly done in the literature, we also investigate those factors that cause 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. 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 of merger cases examined by DG Comp; and ii) allowing for heterogeneity within merger cases by analyzing the individual product and geographic markets concerned.² This is one of the main contributions of our paper.

To make our findings comparable to the existing literature, we start by estimating the probability of

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

²For detailed information on the data collection procedure, we refer to section 3, as well as the data documentation Affeldt, Duso, and Szücs (2018).

intervention as a function of merger characteristics at the merger level. In particular, we focus on the role of four "structural indicators": (1) dominance when the joint market shares of the merging parties are above 50%; (2) a substantial increase in concentration, if the post-merger HHI is above 2,000 and the change in HHI is larger than 150; (3) entry barriers; and (4) the risk of foreclosure. We find that barriers to entry as well as a substantial increase of concentration are positively associated with the likelihood of an intervention, while our measures of dominance and the risk of foreclosure are not statistically significantly related to intervention. Moreover, the share of product markets with competitive concerns affected by the merger is also significantly related to an intervention decision. This approach naturally extends to the level of the individual markets, which represents the second main contribution of this paper: instead of estimating the overall probability of an intervention, we estimate the likelihood that competitive concerns are found in each specific product/geographical market affected by a merger. In this more fine-grained model, we find that both barriers to entry and the risk of foreclosure play a role. Structural indicators measuring joint market shares above 50% and a substantial increase in concentration show the expected positive and significant correlation with the likelihood of competitive concerns. While tightly defined (national) markets are positively correlated with the probability of concerns, the number of active competitors show a negative correlation with concerns.

The final contribution of this study is to assess the heterogeneity of the relation between the likelihood of competitive concerns and the four main structural indicators. Indeed, when and how these structural arguments are used might depend on the specificities of the observed market. To model this heterogeneity in the most flexible way, we employ non-parametric supervised machine learning (ML) techniques. Specifically, we implement a causal forest algorithm (Athey and Imbens, 2016), which allows us to model the heterogeneity in merger control decisions by making the association between structural indicators and the Commission's decisions a function of *all* other covariates. In reporting our results, we focus on how the role of structural indicators has changed over time and along other relevant dimensions such as geographic market definition and the merger's complexity. Moreover, we also study how the different structural indicators interact to explain the Commission's competitive concerns.

First, we find that the importance of the merging parties' market shares – our proxy for dominance – and, to a lesser extent, the role of a substantial increase in concentration due to the mergers 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 less volatile than in the simple linear probability model. Thus, the arguments put forward by the EC to substantiate its decisions appear to be consistently applied over time once the process underlying these decisions is modelled in a flexible and rich way. Second, we observe that dominance plays a particularly important role in markets where the merger would substantially increase concentration, whereas rising concentration is more important when entry barriers and the risk of foreclosure are high. This is consistent with an effects-based approach where the interactions of various merger-specific characteristics play a key role to substantiate the theory of harm. 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 this paper is structured as follows. In section 2, we discuss the institutional details of European merger control and review related studies. In section 3, we describe the dataset used in estimation. We present the parametric model of EC merger interventions in section 4, while section 5 presents the non-

parametric estimations. We conclude in section 6.

2 Literature & Institutional Details

2.1 Institutional Details

The ECMR was passed in 1989 and came into force in September 1990.³ 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 conditions related to aggregate and community-wide turnover, which are not too stringent. This means that from 1990 onwards, all major combinations affecting EU markets have been scrutinized by the EC. In 1997, the stringency of the notification criteria was further relaxed (Council Regulation (EC) No 1310/97).

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. The Commission then 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). 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 notifying parties and the EC were unable to agree on 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 were made 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 developments 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, as well as that the "substantial

³Council Regulation (EEC) No 4064/89 of 21 December 1989 on the control of concentrations between undertakings [Official Journal L 395 of 30 December 1989].

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 is closely related to the literature that empirically studies the determinants of merger policy intervention decisions by competition authorities. Most of this literature – with the prominent exceptions of Bradford, Jackson, and Zytnick (2018) and Mini (2018) – investigates 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, first, 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. Instead, we use 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. They find that the decisions of the EC are influenced by variables that affect welfare, but not by political motives. While the probability of intervention increases with increasing market shares, variables indicating the possibility of post-merger joint dominance and entry barriers, political, and institutional variables do not play a role. Instead, Bergman, Coate, Jakobsson, and Ulrick (2010) examine 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) 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, especially for mergers where the market shares of the notifying parties are modest. The US, on the other hand, seem to be more aggressive in non-dominance, unilateral effects cases.

In a more recent study, Bergman, Coate, Mai, and Ulrick (2019) update the dataset of Bergman, Coate, Jakobsson, and Ulrick (2010) to contain 151 EU phase-2 cases (covering 1991-2014) and 260 US cases (covering 1993-2013). Logit models for interventions 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 show evidence of convergence between US and EU case decisions in unilateral effects mergers, where EU policy seems to be less aggressive post-reform.⁴

Duso, Gugler, and Szücs (2013) depart from the previous literature by evaluating European merger policy

⁴Szücs (2012) also investigates the convergence between US and EU merger policy following the 2004 EU merger policy reform. In particular, he uses samples of 309 EU and 286 US merger cases between 1991 and 2008 and estimates logit models on the decision to intervene. Based on the decreasing differences in the predicted intervention probabilities between the EU and the US authorities over time, the paper concludes that EU and US merger policy are converging in the era following the 2004 EU merger policy reform.

effectiveness along three dimensions: predictability, correctness, and deterrence. Regarding predictability, they 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* observables and merger characteristics are not derived from the decision itself but constructed from firm-level data. 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

Two papers differ from the previous literature by significantly expanding the sample of mergers analyzed. Bradford, Jackson, and Zytneck (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.⁶ The authors find that DG Comp did not intervene more frequently or extensively in transactions involving non-EU or US-based firms. While transaction values, HHI, hostile takeovers, and horizontal mergers increase the likelihood of intervention, transactions involving a financial sponsor, taking place in large markets, and stock acquisitions are less likely to be challenged.

The paper most closely related to this study in terms of data is Mini (2018). Mini (2018) also collect 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 his first model, the main variables of interest are the merging parties' market shares and the change in market shares; the second focuses on post-merger HHI as well as the change in HHI due to the merger. Like other studies, 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 toward mergers to quasi-monopoly or monopoly nor toward 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 antitrust market level based on the population of European merger decisions as we do. However, we focus on a different aspect by studying the heterogeneity in the association between structural market parameters and other characteristics with the intervention decision by DG Comp. To this end, we use flexible, non-parametric machine learning techniques and show how this association has evolved over time as well as other dimensions of heterogeneity.

⁵Mai (2016) also studies the effect of the EU merger policy reform using a sample of 341 phase-1 and phase-2 horizontal mergers between 1990 and 2012. The probability of a challenge is driven by the market shares of the merging parties, entry barriers, and some other factors. Political aspects, 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.

⁶The HHI and market size variables are constructed based on European-wide sales at the two-digit NACE code industry level from the Amadeus database. Clearly, these measures are quite different from those calculated by the Commission itself in well-defined product and geographic markets. See Affeldt, Duso, Gugler, and Piechucka (2021) for a discussion of this issue.

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 case files published by DG Comp.⁷ 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. Specifically, we downloaded all available merger decision documents for merger cases notified to the EC between 1990 and the end of 2014. The database was then manually coded by research assistants by scanning the case documents for the relevant information. Instead of taking a particular merger case as the level of observation, we collected the data at the level of the concerned antitrust markets.

For the analysis in this study, we dropped cases that were referred back to member states (a few dozen cases) as well as phase-1 withdrawals (2 cases). The final dataset 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).⁸

The data set contains, first, information on the name and country of the merging parties (acquirer and target), the date of the notification, the date of the decision⁹ 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, phase-2 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 notified mergers are decided in phase-1: Phase-1 mergers track the number of notifications very closely, while only around 5 to 15 mergers per year enter a phase-2 investigation. 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.

Table 1 describes the main variables used in the analysis. Some of these are recorded at the merger-level (panel A) others are recorded at the market level (panel B). Note, however, that all market level variables are also used in the merger-level analysis in that we take the average of the values across all markets affected by the merger. The variable *Intervention*, which is our dependent variable in the merger-level regressions, is a dummy that indicates whether DG Comp intervened in a particular merger case. We define this variable 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-2.¹⁰ DG Comp intervened in 7% of the 5,109 mergers. The corresponding dependent variable at the

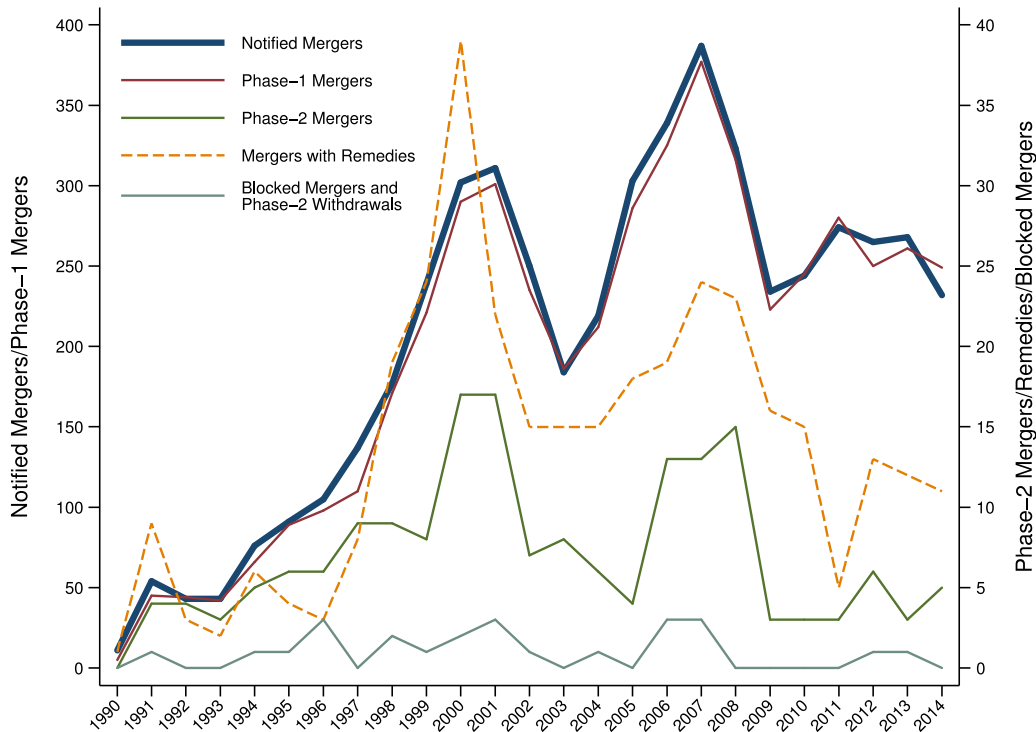
⁷The types of notified mergers, decisions taken and reports for each of the EC’s decisions can be downloaded from: <http://ec.europa.eu/competition/mergers/cases/> and http://ec.europa.eu/competition/mergers/legislation/simplified_procedure.html.

⁸The data (Affeldt, Duso, and Szücs, 2021) can be freely downloaded under: https://doi.org/10.25652/diw_data_S0019_1.

⁹Note 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.

¹⁰We decided to aggregate prohibitions/withdrawals and remedies into one intervention indicator since the number of observations

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 phase-2 cases, 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."

product/geographic market level (panel B) is *Concern*, an indicator variable equal to one if the Commission explicitly mentions in its competitive assessment that the merger raised competitive concerns in a specific product/geographic market. This is the case in about 11% of the 30,995 markets.

The other variables contained in Table 1 are used as covariates in the empirical analyses and describe the merger as well as the concerned markets. About 55% of the notified mergers are full mergers and 37% are joint ventures (panel A). About 26% of the concerned markets were affected vertically by the merger, while mergers had conglomerate effects in 2% of the concerned markets (panel B). 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. We also record the number of competitors in concerned markets and an indicator 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

does not allow for focusing only on prohibitions/withdrawals. Secondly, as the corresponding variable at the market level (concern) does not distinguish between different levels of competitive concerns, we prefer to use the aggregate intervention indicator in the merger-level analysis so that the two outcome variables are more comparable.

Table 1: Description of Merger-Level & Market-Level Variables, 1990-2014

Variable	Description	Mean
Panel A: Merger-level Variables		
<i>Dependent variable</i>		
<i>Intervention</i>	<i>Indicator equal to one if DG Comp intervened in merger case. Prohibitions, phase-1 remedies, phase-2 remedies, and phase-2 withdrawals are considered as interventions.</i>	0.07 (0.26)
<i>Other characteristics</i>		
Full merger	Indicator equal to one for full merger (rather than acquisition of shares).	0.55 (0.50)
Joint Venture	Indicator equal to one if merger is a joint venture.	0.37 (0.48)
Complexity	Number of product/geographic markets affected by the merger.	6.07 (13.43)
Panel B: Market-level Variables		
<i>Dependent variable</i>		
<i>Concern</i>	<i>Indicator equal to one if DG Comp found competitive concerns likely to arise from the merger in the concerned market.</i>	0.11 (0.31)
<i>Structural indicators</i>		
Substantial increase in post-merger concentration	Indicator equal to one if post-merger HHI is above 2,000 and the change in HHI is larger than 150 in the concerned market.	0.54 (0.50)
Joint market share > 50%	Indicator equal to one if the merging firms' joint market share is above 50% in the concerned market.	0.21 (0.41)
Barriers to entry	Indicator equal to one if DG Comp considered entry barriers to exist in the concerned market.	0.12 (0.32)
Risk of foreclosure	Indicator equal to one if DG Comp raised concerns that merger would foreclose other firms in the concerned market.	0.03 (0.16)
<i>Other characteristics</i>		
Vertical merger	Indicator equal to one if the concerned market is vertically affected by the merger.	0.26 (0.44)
Conglomerate merger	Indicator equal to one if merger is conglomerate in nature in the concerned market.	0.02 (0.13)
National market	Indicator equal to one if geographic market is defined as national.	0.58 (0.49)
EU wide market	Indicator equal to one if geographic market is defined as EU-wide.	0.20 (0.40)
Worldwide market	Indicator equal to one if geographic market is defined as worldwide.	0.10 (0.29)
Left open market	Indicator equal to one if exact geographic market is left open.	0.12 (0.33)
Number of competitors	Number of competitors in the concerned market.	1.58 (2.33)
No competitor information	Indicator equal to one if no information on competitors is contained in the decision documents. This can arise either if no competitors exist in the concerned market or if DG Comp did not report on competitors.	0.56 (0.50)

Standard deviation reported in parentheses. At the merger level, the dataset contains 5,109 merger cases. At the market level, the dataset contains 30,995 concerned markets. Due to missing values, the number of observations differs depending on the variables. The indicator variable for joint market share > 50% is based on 22,812 observations for which information on joint market share is available, while the indicator for a substantial increase in post-merger concentration is based on 12,810 observations for which HHI and Δ HHI can be calculated.

56% of the markets - these are mostly mergers that were cleared in phase-1 without competitive concerns.¹¹ 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. On average, a merger affects 6 geographic/product markets, ranging between one and 245 concerned markets.

The main explanatory variables in our regressions are the four structural indicators. We are able to record whether DG Comp explicitly mentions the existence of barriers to entry and whether foreclosure was a concern in each relevant market. As panel B of Table 1 shows, entry barriers were identified in about 12% of the concerned markets, while risk of foreclosure was present in about 3% of markets.

Instead, our measure of dominance – joint market shares of the merging parties above 50% – as well as the indicator of a substantial increase in concentration can be recorded only for sub-samples of our markets as data availability on merging firms’ and competitors’ market shares is constrained by the extent of DG Comp’s analysis as well as confidentiality clauses. Table A1 in Appendix A.1 reports the summary statistics for the market-shares related variables.¹² Based on the market share and concentration measures, we define two further indicator variables reported in panel B of Table 1. Our proxy for dominance is an indicator variable equal to one if the merging firms’ joint market share is above 50% in the concerned market. This is the case in 21% of the 22,812 affected markets for which we can construct this measure. The indicator for a substantial increase in post-merger concentration is equal to one if the post-merger HHI is above 2,000 and the change in HHI is larger than 150.¹³ This is the case in 54% of the 12,810 affected markets for which we can calculate this indicator.

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 A2 in Appendix A.1, 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.

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

¹¹We coded the variable counting the number of competitors as equal to zero whenever we have no information on competitors. In these cases, the indicator variable for no competitor information is equal to one. Both variables vary at the market level. Missing information on competitors can have two reasons, either the merging parties have 100% market share in a given market or there is just no information on competitors in the decision document. By adding the indicator variable for no competitor information, we avoid setting the number of competitors variable equal to missing for these 56% of markets.

¹²DG Comp generally reports 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 with the exception of Mini (2018). We calculate two different HHI measures. *Post-merger HHI (low)* is a lower bound of the post-merger HHI. It is calculated as the square of the merging parties’ joint market share plus the sum of squared market shares of competitors, assuming that competitors are very small whenever market share information of competitors is not available but market shares do not add up to 100%. *Post-merger HHI (high)* 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)*, treating 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.

¹³See Nocke and Whinston (2020) for a theoretical and an empirical discussion supporting the use of concentration-based screens for horizontal mergers based on the change in the HHI. See also Affeldt, Duso, Gugler, and Piechucka (2021) for a discussion of increasing concentration and its determinants based on the same data used in this paper.

at the market level. However, note that, because values for markets shares and HHI are missing for several observations as shown in Table A1, the regressions including indicators based on these variables as well as the causal forests are based on only 12,810 observations. We discuss possible issues of selection due to missing observations in section 4.

4 Linear Probability Model

In this section, we explore the association between merger characteristics and the intervention decision by DG Comp using a parametric approach that follows the existing literature. 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 potential issue of sample selection, which could arise because some important indicators – prominently market share above 50% and substantial increase in concentration measures – are only observable for about 60% of the mergers. Second, we investigate the correlation between merger characteristics and DG Comp’s intervention decision *at the market level*.

At this point, it is important to flag two further identification issues. Ideally, we would like to attach a causal interpretation to the relationship between the main variables of interest and the probability of intervention/competitive concerns. Yet, there are different potential sources of endogeneity that, we believe, do not allow us to do so. First, while our dataset is quite rich, there are surely some omitted variables that might be correlated with the four structural indicators. Second, all the merger and market characteristics we use on the right-hand side 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. This might lead to a reverse causality between the intervention/concern decision and the elements used to motivate it: DG Comp might assess entry barriers to be high *because* it wants to remedy or block a merger. While we think that the former issue can be, at least partially, addressed through the use of machine learning, as discussed in section 5, there is nothing we can do about the second issue. Therefore, we cautiously interpret our results as correlations.

4.1 Methodology

We employ a linear probability model to estimate the relationship between merger characteristics and the intervention decisions of DG Comp.¹⁴ The estimation equation for the probability of intervention at the merger level is:

$$Y_j = \beta_0 + \beta_1 X_j + \beta_2 \bar{X}_{ij} + \eta_{m_j} + \eta_{t_j} + \epsilon_j \quad (1)$$

where i refers to product and/or geographic markets, j refers to mergers, m_j refers to an industry group, and t_j refers to the year when merger j took place. The dependent variable Y_j is a dummy equal to one if the EC intervened in the merger. The merger characteristics X_j vary at the merger level, while \bar{X}_{ij} are market-specific characteristics within merger j . In the merger-level regressions, we use the average of market-level

¹⁴Alternatively, one could use a probit or logit specification as the outcome variable is binary. We decided to use a linear probability model for ease of interpretability. Further, the inclusion of fixed effects is problematic in a probit or logit specification. In particular, we cannot include industry-year fixed effects in the probit specification. However, we provide the estimation results of a probit specification both at the merger and the market level including industry and year fixed effects in Appendix A.2 and A.3 respectively.

variables (\bar{X}_{ij}) .

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

$$Y_{ij} = \beta_0 + \beta_1 X_j + \beta_2 X_{ij} + \eta_{m_j} + \eta_{t_j} + \epsilon_{ij} \quad (2)$$

where the unit of observation is now the concerned market i in merger j rather than the merger j itself, Y_{ij} is a dummy equal to 1 if the EC identifies competitive concerns in market i affected by merger j , X_j are the characteristics varying at the merger level, while X_{ij} are the characteristics varying at the market level.

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 above 50%, substantial increase in concentration, the likelihood of entry, and the likelihood of foreclosure – which are measured as discussed in Table 1. We also explore heterogeneities in the correlation between merger characteristics and competitive concerns by DG Comp over time by running separate OLS regressions dividing the dataset into sub-samples based on the notification year. We pool the years 1990-1994, as there are relatively few merger cases in these early years of European merger control.¹⁵

In addition, we control for further merger characteristics. We include the market definitions (national, EU wide, and worldwide geographic markets) as well as 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.

Finally, 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 A2 in Appendix A.1. 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.¹⁶ The error terms of the regressions are robust to clustering 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 without market share variables, thus including essentially the full population of mergers analyzed by DG Comp. As market share information is frequently missing for cases cleared in phase-1, changes in the estimated coefficients when these data are included 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

¹⁵The results are reported in Appendix A.6. Specifications interacting the four structural indicators with the notification year rather than splitting the sample lead to similar results and are not reported.

¹⁶As a robustness check, we use industry and year fixed effects separately and include a set of time-varying control variables at the industry level 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.

joint market share above 50% and substantial increase in concentration.

Table 2 reports 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 an intervention. 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) are significantly correlated with 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 interventions 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 mean market share above 50% does not display a significant correlation whereas the indicator for an increased in HHIs is strongly and significantly correlated with the probability of intervention. Mergers in markets with mean HHIs above 2000 that entail a mean 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 3 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 much effort is spent on gathering market information, the likelihood of concerns is lower.

Finally, in the sub-sample with market share information, both market power indicators are now significantly positively correlated with the likelihood of concerns: the probability of concerns is almost a quarter higher when the mean joint market share of the merging parties in the concerned markets exceed 50% and 10% higher in mergers where the mean concentration in the concerned markets would substantially increase.¹⁷

¹⁷We obtain similar results using continuous measures instead of dummy variables, as well as using individual market shares of the acquirer and target instead of their sum. Similarly, we obtain a comparable result if using the continuous version of the HHI instead of a dummy for substantial increase in concentration. See Appendix A.4 (merger level) and Appendix A.5 (market level).

Table 2: 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*** (0.0560)	0.3793*** (0.0786)	0.2278** (0.0899)	0.2127** (0.0857)
mean risk of foreclosure	0.0145 (0.0691)	-0.0289 (0.0878)	0.0016 (0.1115)	0.0040 (0.1087)
fullmerger	-0.0019 (0.0194)	0.0170 (0.0116)	-0.0079 (0.0483)	-0.0044 (0.0472)
joint venture	-0.0150 (0.0159)	0.0147 (0.0105)	-0.0321 (0.0464)	-0.0283 (0.0449)
mean conglomerate merger	-0.0051 (0.0471)	0.0404 (0.0770)	-0.0222 (0.0735)	-0.0238 (0.0740)
mean vertical merger	-0.0024 (0.0107)	0.0155 (0.0145)	-0.0269 (0.0240)	-0.0067 (0.0241)
mean market definition national	0.0103 (0.0075)	-0.0059 (0.0047)	0.0171 (0.0646)	0.0143 (0.0621)
mean market definition EU wide	0.0202 (0.0137)	0.0079 (0.0111)	0.0068 (0.0589)	0.0066 (0.0578)
mean market definition worldwide	-0.0158 (0.0120)	-0.0069 (0.0113)	-0.0343 (0.0781)	-0.0382 (0.0767)
number of concerned markets	0.0036*** (0.0005)	0.0030*** (0.0011)	0.0030*** (0.0009)	0.0031*** (0.0008)
percentage of markets with concerns	0.9375*** (0.0623)	0.7312*** (0.1094)	0.9681*** (0.1107)	0.9340*** (0.1117)
total number of competitors in all product markets	0.0004 (0.0004)	0.0003 (0.0008)	0.0008 (0.0005)	0.0006 (0.0005)
post reform indicator	0.0333** (0.0147)	0.0042 (0.0069)	0.1169 (0.0824)	0.1384* (0.0768)
mean joint market share above 50%				-0.0009 (0.0481)
mean HHI \geq 2000 & mean delta HHI \geq 150				0.0881*** (0.0169)
Constant	-0.0541*** (0.0177)	-0.0211** (0.0090)	-0.1110 (0.0913)	-0.2210** (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. We take the mean value across concerned markets for those variables that vary at the market level. The indicator variables for high market shares and substantial increase in concentration are equal to one for a merger if the mean joint market share is above 50% and if the mean HHI \geq 2000 & mean delta HHI \geq 150, respectively. Marginal effects of a probit estimation including industry and year fixed effects are similar (see Appendix A.2).

Table 3: 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*** (0.0558)	0.3408*** (0.0856)	0.4067*** (0.0485)	0.3160*** (0.0406)
risk of foreclosure in submarket	0.2066** (0.0956)	0.2958** (0.1248)	0.1849* (0.0921)	0.1777* (0.0951)
fullmerger	-0.0375 (0.0250)	-0.0071 (0.0263)	-0.0615 (0.0373)	-0.0586 (0.0347)
joint venture	-0.0656** (0.0244)	-0.0218 (0.0285)	-0.1192*** (0.0323)	-0.1061*** (0.0301)
conglomerate merger in submarket	0.0201 (0.0372)	0.0302 (0.0469)	0.0259 (0.0355)	0.0140 (0.0353)
vertical merger in submarket	-0.0024 (0.0100)	0.0240 (0.0180)	-0.0410*** (0.0128)	-0.0135 (0.0125)
market definition national	0.0182*** (0.0049)	0.0042 (0.0076)	0.0690*** (0.0239)	0.0634*** (0.0213)
market definition EU wide	-0.0108 (0.0087)	0.0007 (0.0129)	0.0039 (0.0246)	0.0264 (0.0248)
market definition worldwide	0.0076 (0.0163)	0.0176 (0.0224)	0.0245 (0.0252)	0.0496** (0.0224)
number of concerned markets	0.0001 (0.0003)	-0.0001 (0.0005)	0.0002 (0.0004)	0.0000 (0.0003)
number of competitors	-0.0099*** (0.0030)	-0.0066*** (0.0020)	-0.0116*** (0.0040)	-0.0080** (0.0036)
indicator no info on competitors	-0.0652*** (0.0152)	-0.0358*** (0.0124)	-0.0792*** (0.0230)	-0.0502** (0.0202)
post reform indicator	-0.1916 (0.1300)	-0.0332 (0.0305)	-0.3779 (0.2222)	-0.3113 (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* (0.1360)	0.0640** (0.0279)	0.4508* (0.2417)	0.2658 (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. Marginal effects of a probit estimation including industry and year fixed effects are similar (see Appendix A.3).

5 Machine Learning / Causal Forests

In section 4, we explore the association between a substantial increase in concentration, market shares above 50%, entry barriers, and the risk of foreclosure with the intervention decision by DG Comp parametrically. However, these correlations might differ for different merger types. In a first attempt to assess heterogeneity, we run separate regressions over time and industries. Results are reported in Appendix A.6 and Appendix A.7, respectively.¹⁸ In this section, we further explore these heterogeneities 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.¹⁹ They allow for obtaining 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, imagine 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 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. In particular, causal forests allow the effect of a variable of interest on the outcome to vary with all other controls included. The controls relevant for effect heterogeneity are determined by the algorithm and we do not need to specify *ex-ante* which interactions might matter.²⁰

Second, there are two reasons for why omitted variable bias might be less of a concern in a causal forest than in the standard linear probability model. Machine learning techniques provide models that are robust to irrelevant variables and potential multicollinearity among covariates. They perform variable selection by exploring potential nonlinearities and interaction across variables. Thus, for one, omitted variable bias might be reduced by allowing for flexible and higher order interactions between the variables, i.e. by "saturating" the model. Further, the estimates are based on many trees, each one different (i.e., they split on different covariates at different levels of the tree). Because we expect that, in every tree, the potential omitted variable bias is smaller than in a single estimated linear model, so should be the average of the bias over all trees. While we still need to be careful in attributing causality because of the potential issue of reverse causality discussed above, any potential bias in the coefficient estimates should at least be reduced. This, in turn,

¹⁸We also run a specification interacting the four structural indicators with the notification year rather than splitting the sample. Results are essentially the same and, therefore, not reported.

¹⁹Note that we cannot use random forests to achieve this goal, since they do not allow us to estimate heterogeneous coefficients. Random forests are about predictions, i.e. the left-hand side, while causal forest are about the heterogeneity of the impact of right-hand side variables. See Affeldt (2019) for a companion paper using the same data and a random forest algorithm to assess the predictability of merger decisions.

²⁰Of course, we could also include some interactions in the linear probability model (which we do by estimating separate models over time and industries). However, we would need to decide on the controls that matter for effect heterogeneity *ex-ante* rather than letting the model determine effect heterogeneity. Studying effect heterogeneity with a parametric model in a way as flexible as in a causal forest is essentially impossible. We would have to include not only all possible simple interactions between the variables of interest and the controls but also all possible higher order interaction terms.

increases the confidence that the estimated correlations are not spurious.

Third, this approach makes the exact definition of regression covariates less critical. 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 opt for the more simple measures. Such a 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. substantial increase in concentration, market shares above 50%, 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:

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

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, $\mu(X_{ij})$ is the effect of X_{ij} on Y_{ij} , 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:

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

where Y_{ij}^1 is the potential outcome for unit ij under treatment – e.g. whether the EC identifies a concern when market shares are high – and Y_{ij}^0 is the potential outcome for unit ij absent treatment – e.g. 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 set of covariates, X .

The 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) as implemented in the generalized random forest (grf) package in R²¹ to investigate how the correlation between treatment variables and DG Comp’s competitive concerns varies with market as well as merger characteristics. Causal forests 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 rather individual treatment effects $Y_{ij}^1 - Y_{ij}^0$ to study how treatment effects vary by subgroup.²² 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 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

²¹We use version 0.10.2 of the grf package. For further technical background on the causal forest methodology and the implementation using the grf package, see Appendix A.8.

²²In 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.

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 are divided in half, where one-half of the data are used to build the tree (i.e. determine the splits in covariate space) and the other half are 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 those 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. In the linear probability model, we would instead have to *ex-ante* decide on the relevant controls in order to include interaction terms. Yet, even higher order interaction terms are never as flexible as causal forests.

We estimate causal forests at the market level (ij). The outcome is therefore the *concern* dummy variable that indicates which specific product/geographic markets affected by the merger raised competitive concerns.²³ We estimate different causal forests for the four determinants of competitive concerns. These are the same four indicator variables as before: *substantial increase in 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 indicator of market shares above 50%, the substantial increase in 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 is a more flexible specification that 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, and joint ventures – a count of the number of competitors (as well as an indicator for whether information on competitors is missing), 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 A2.

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 different markets affected by a given merger are independent. We address 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

²³While 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).

subsample or none.²⁴ 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, consists of 12,000 trees, and uses half of the observations to determine the splits and half of the observations to predict the treatment effects. The other tuning parameters are chosen by cross-validation implemented in the `grf` package.²⁵ Lastly, note that all causal forests are trained based on the dataset containing market share information, so that indicators for market shares above 50% and substantial increase in concentration 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 a substantial increase in concentration, market shares above 50%, 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.²⁶ 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 and vary only the covariate of interest.²⁷

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.²⁸ 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.²⁹

²⁴Given that each merger affects a different number of markets, `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, first, we 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.

²⁵The minimum node size in a causal forest is the minimum number of observations that must be part of a node 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. For further details on tuning parameters see Appendix A.8.

²⁶Predicted correlations across industries are shown in Appendix A.10 as variation across industries is small.

²⁷As 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.

²⁸Employing 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.

²⁹Rather 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 substantial increase in concentration and joint market share above 50%. As the predicted treatment effects did not change by much, we only report the predictions based on the mean merger over the entire sample.

5.2.1 The Impact of Structural Indicators over Time

Joint market shares 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. Since dominance was the substantive test in European merger control until the 2004 reform, it is critical to understand how the importance of this structural indicator changed over time.

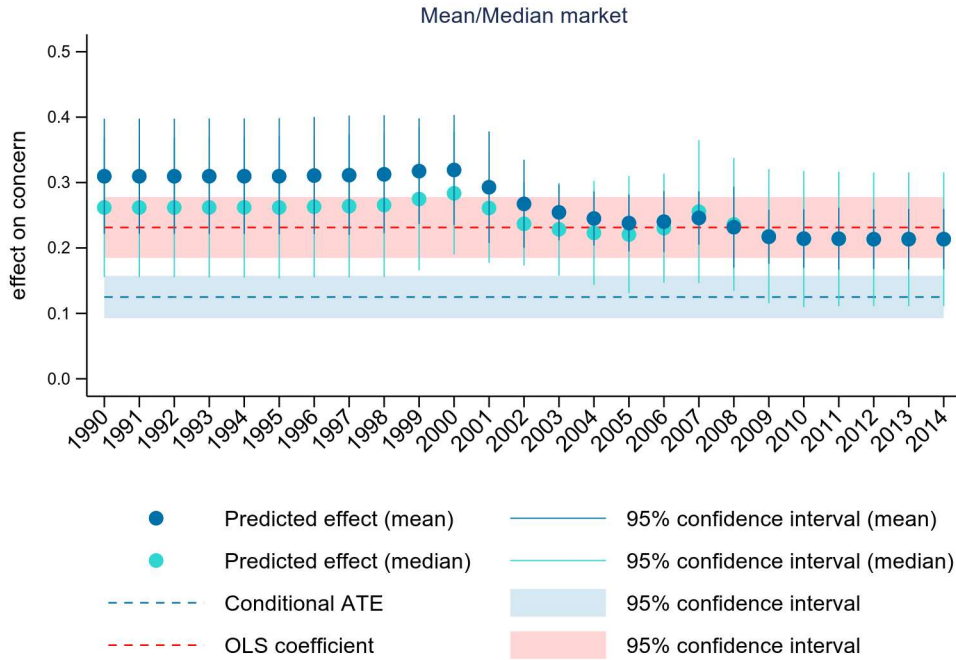
The upper part of Figure 2 shows the predicted correlation between the indicator variable for merging parties' market shares above 50% and competitive concerns of DG Comp over time, setting all other covariates to their mean (dark blue) or median (light blue) value, respectively. In the lower part of 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, the figure shows that the simple linear probability model significantly overestimates the average effect of high market shares on concerns (red, dotted line). The correlation estimated by OLS is 0.22 (specification 4 in Table 3) while the conditional average effect of the causal forest is as low as 0.125 (blue, dotted line). Yet, allowing for heterogeneity in this correlation is also very important. Indeed, the predicted effect for the average or median merger always lies 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 correlation is positive and significant throughout the entire sample period, market shares seem to be very important up to the early 2000s (correlation around 0.3) and lose relevance thereafter. Using median rather than mean values, the predicted correlation is even lower in the first part of the sample period.

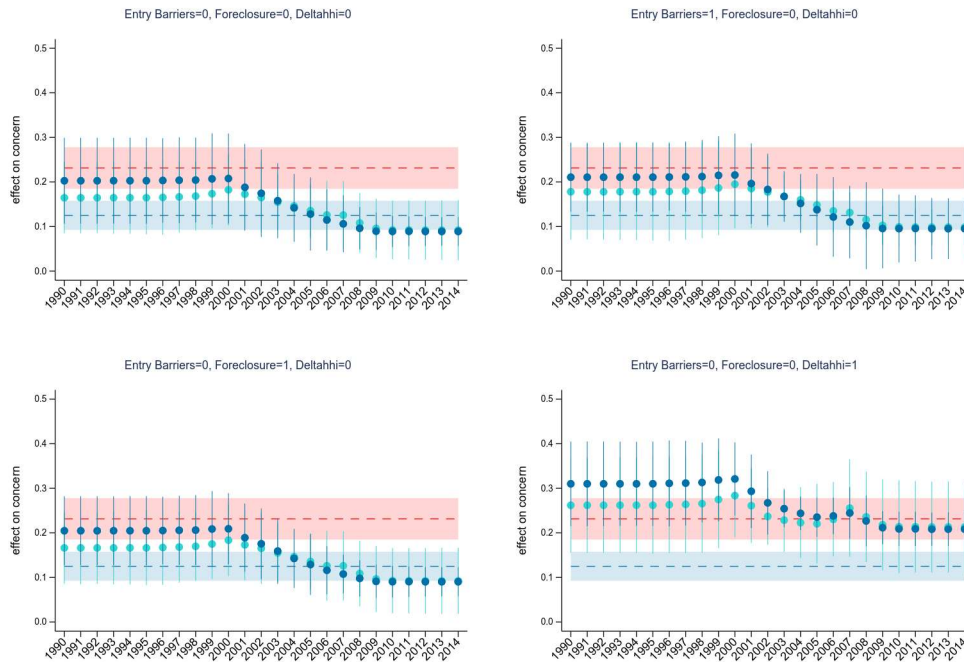
If we compare these results with the linear probability model where the effect of a substantial increase in concentration is allowed to vary with time (see Appendix A.6), the estimated effect of high market shares based on the causal forest is much smoother over time. This indicates that, once we use a richer model that better captures the process behind DG Comp's decision practices, the impact of this structural indicator is less volatile. Thus, the estimated time dynamics of the effect of high market shares on concerns are much more consistent with the shift away from evaluating mergers based on the concept of dominance and more aligned with the new substantive test introduced by the reform in 2004. This confirms the preliminary findings of Röller and De La Mano (2006), which suggest a gradual impact of the new merger regime on the Commission's decision practices. Yet we confirm that dominance continues to play an important role in determining competitive concerns.

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 a substantial increase in concentration. Dominance plays a significantly more important role in markets where concentration substantially increases following the merger. In these markets, the correlation between high market shares and competitive concern is over 30% higher than for mergers in markets where the rise of concentration was low, independently of whether the Commission was concerned about the existence of entry barriers or high risk of

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



Different Combinations of Structural Indicators



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.

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 the rise in 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 markets where the merger would substantially increase concentration and it significantly decreases over time, especially following the introduction of the new ECMR in 2004.

Substantial increase in concentration. The second structural indicator we look at is the dummy measuring markets where the mergers would substantially increase concentration. 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 a substantial increase in 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.

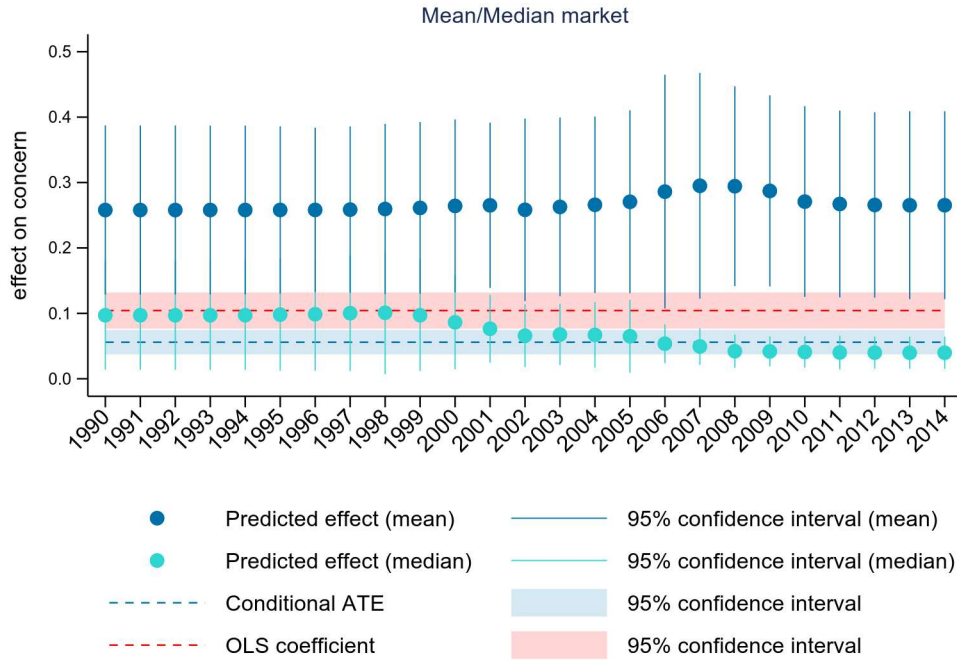
For this indicator, we also observe that the average correlation estimated through the linear probability model (0.1043, from specification 4 of Table 3) significantly overestimates the in-sample conditional average treatment effect (0.056). However, in this case, we observe a much larger impact of heterogeneity. The predicted effect of increased 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. 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 increasing 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 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 a substantial increase in 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.

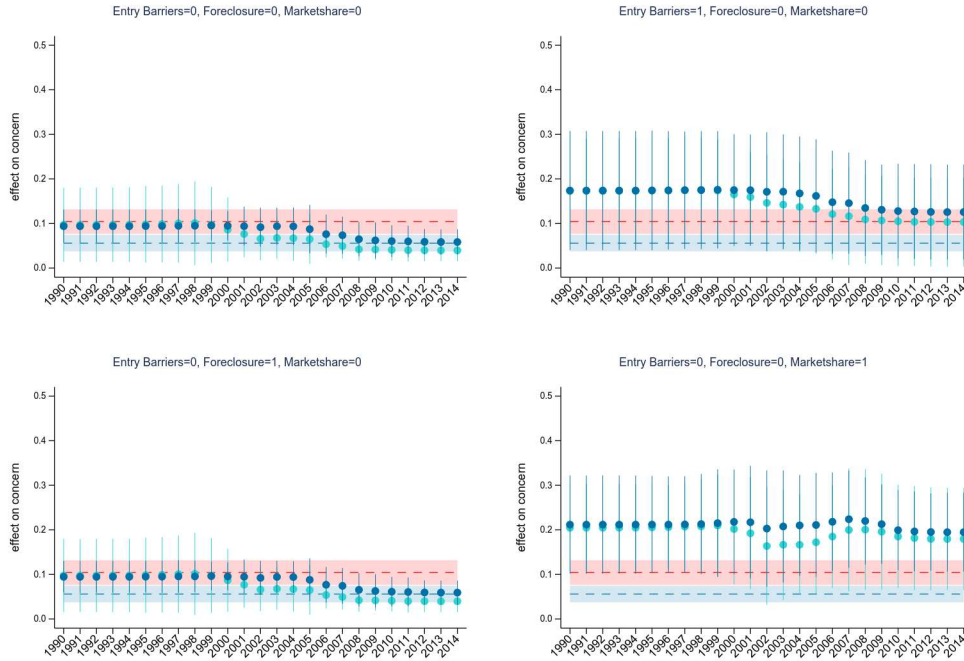
Barriers to entry and risk of foreclosure. The final piece of evidence we provide in this section relates to the importance of the indicators for barriers to entry and risk of foreclosure. We represent the results in Figure 4. The figures are built in a similar fashion to those above: they show the predicted 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

Figure 3: Effect of a Substantial increase in Concentration on Concerns over Time



Different Combinations of Structural Indicators



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.

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 perspective, these results suggest that high entry barriers and the risk of foreclosure are consistently used by DG Comp as a driver of potential concerns in their merger analysis. From a methodological perspective, these findings suggests that a simple model, such as the linear probability model, is well 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 a substantial increase in concentration in the relevant market.

5.2.2 The Impact of Geographic Market Definition and Complexity

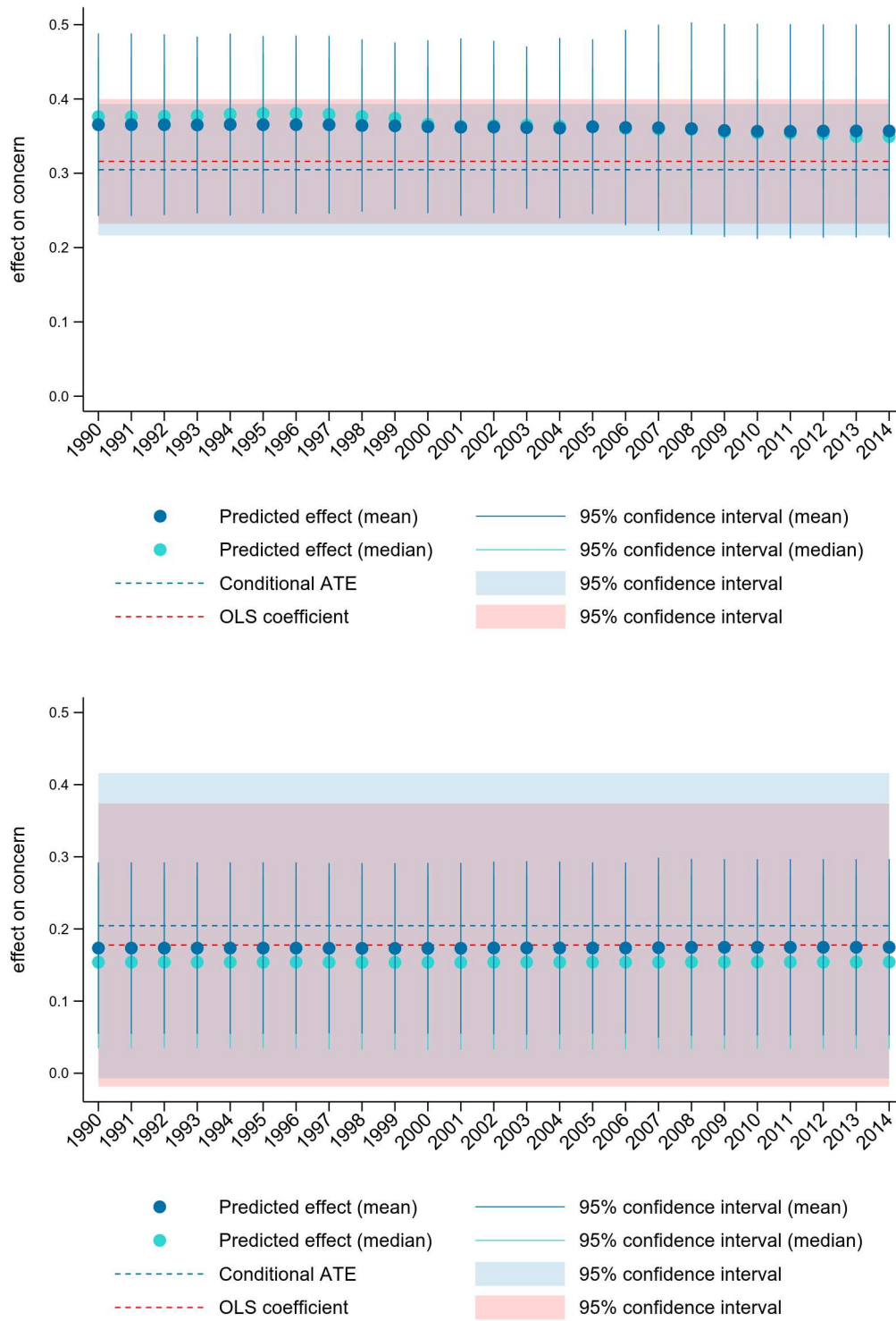
As we discuss above, the difficulty of representing results based on the causal forest is that each individual treatment effect is a function of all covariates included in the model. In the previous section, we focus on the role of time and the interactions between the four key structural indicators. 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.9 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 as, at the end, the Commission has to issue one common decision for all markets affected by the same merger. In this additional analysis, we only focus on the role of joint market shares of the merging firms above 50%, as this appears to be the indicator whose role has changed the most over time.

Market Definition. Figure 5 reports the same findings as previously, but distinguishes between national, EU wide, and world wide markets. 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 differences in the correlation patterns across the different market definitions, suggesting that DG Comp applied the dominance substantive criterium in a very consistent way and 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 has been criticized, often for being too 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 constraints into account, including the market shares of the merging parties but also the competitive constraints from outside the market. As our machine learning algorithm

³⁰As shown in Table 1, DG Comp considered risk of foreclosure to exist in only about 3% of the concerned markets. Consequently, the confidence intervals are very wide.

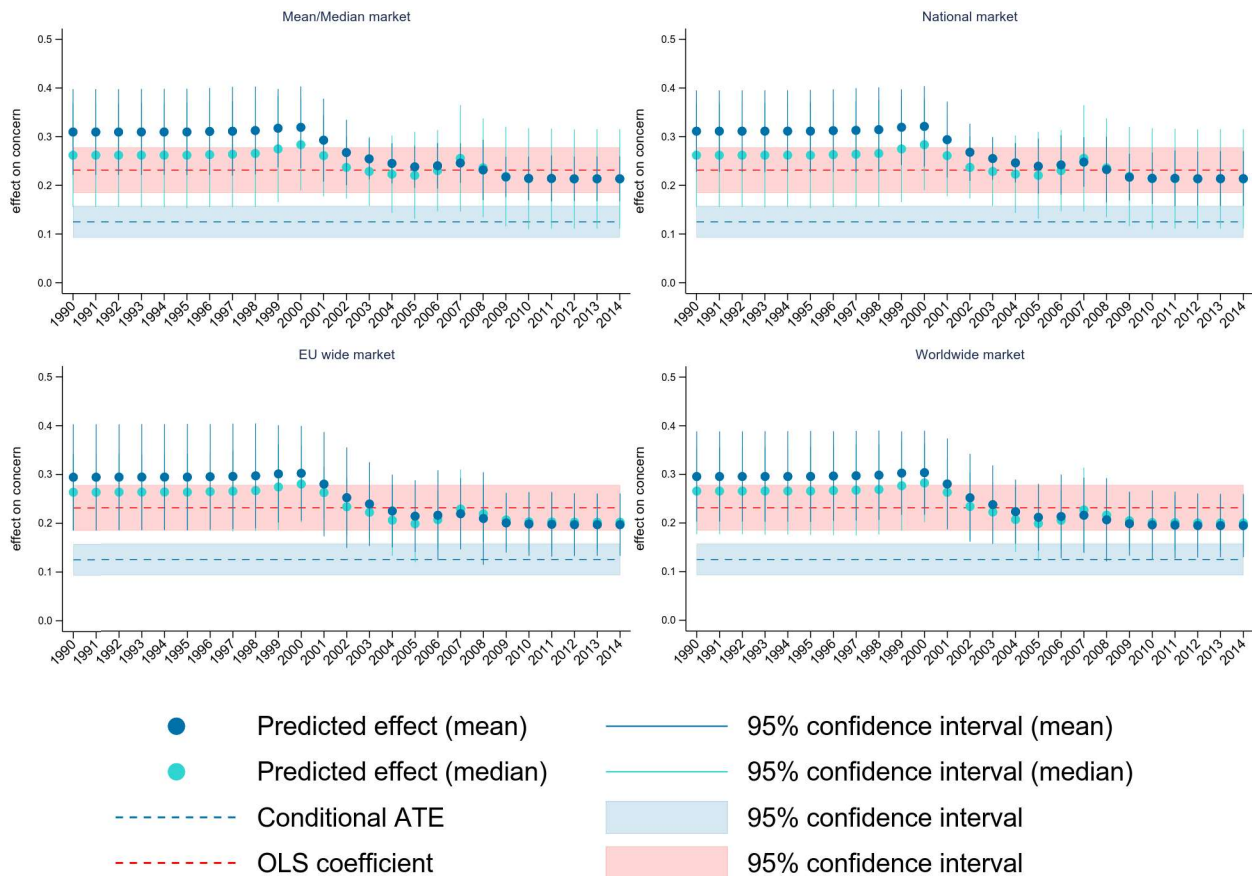
Figure 4: Effect of Barriers to Entry (upper panel) and Foreclosure (lower panel) on Concerns over Time



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

aims exactly at taking these conditions 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.

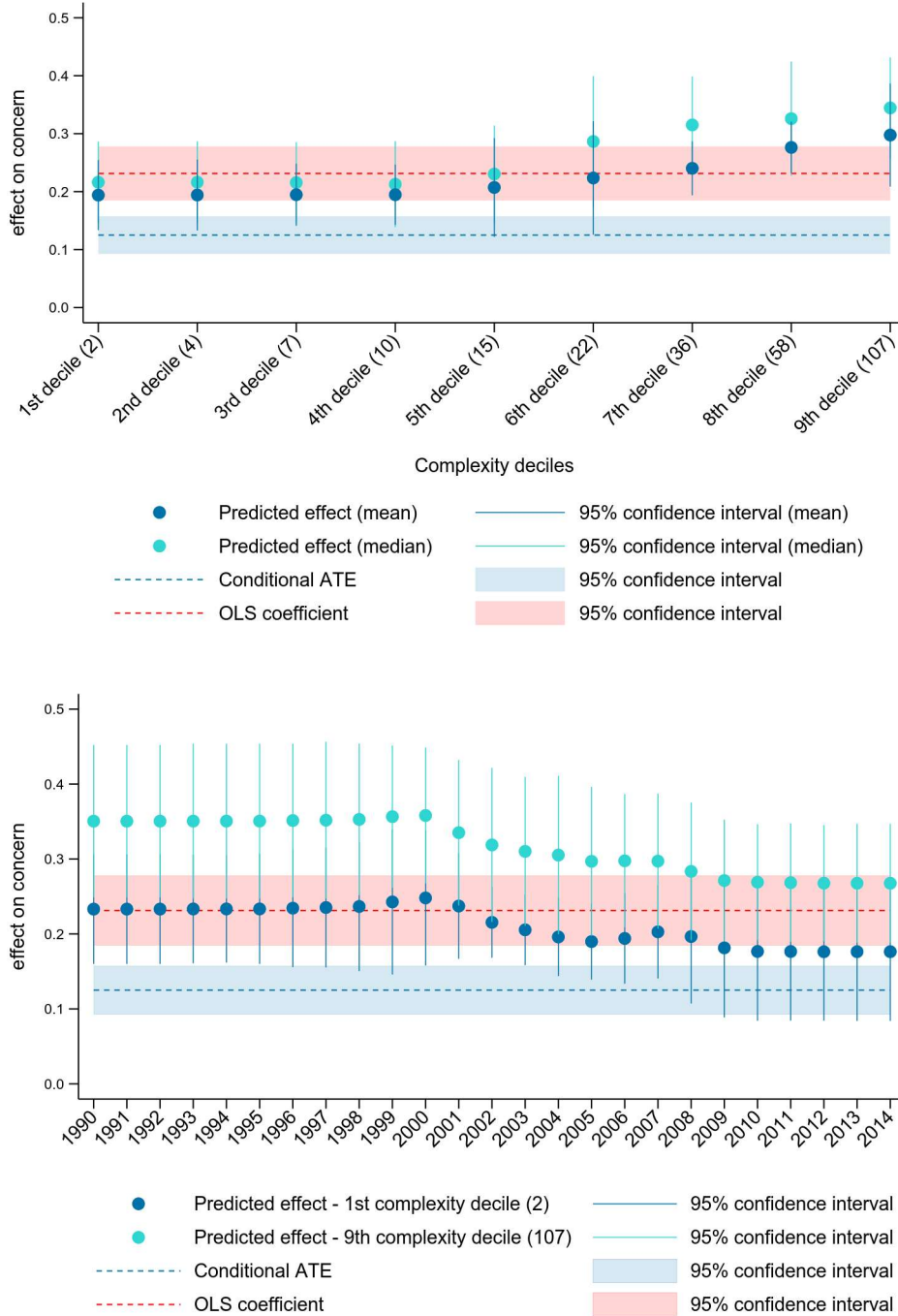
Figure 5: Effect of High Market Shares on Concerns by Geographic Market Definition



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.

Complexity. Mergers notified to DG Comp on average affect six geographic/product markets, while some affect up to 245 markets. In Figure 6 we investigate whether the role of dominance in determining the concerns in one particular market is influenced by how many other markets the merger is affecting. The upper panel reports predicted correlations between market shares of the merging parties above 50% and concerns for mean and median mergers as a function of the deciles of complexity, i.e. the number of markets affected by the merger. 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 percentage points higher than for mergers that affect only few markets.

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.

6 Conclusion

In this paper, we study the determinants of the EC's merger control enforcement 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 and information at the relevant market level (more than 5,000 individual decisions affecting more than 30,000 antitrust markets). Specifically, we evaluate how consistently different arguments related to structural market parameters – market shares above 50%, substantial increase in 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. Moreover, we study how these structural indicators interact leading to an intervention decision.

In a first step, to compare with the existing literature, 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, substantial increases of concentration measures, and, in particular, the share of product markets with competitive concerns raise the likelihood of an intervention. 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. This is a major contribution of this paper. By assessing individual markets, we not only gain statistical power but are also able to conduct a more disaggregate and precise analysis. We find that barriers to entry, as well as the risk of foreclosure, play an important role during 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 dominance – joint market shares of the merging parties above 50% – and substantial increase in concentration have the expected effects and appear to be more relevant than shown in the aggregated 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 a second step, we use non-parametric machine learning methods to explore how the correlation between the Commission's concerns and the determinants of such concerns varies with other characteristics. Using trained causal forests has several advantages. First, it allows us to set up a more flexible model that better captures the complex decision process of the Commission by taking into account the specificities of each merger. Second, by reducing the potential of omitted variable bias, it increases the confidence that the estimated correlations are not spurious. Finally, it makes the exact definition of regression covariates less relevant. With this approach, 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 the structural indicators – dominance, substantial increase in 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 is potentially a key aspect in deciding on the theory of harm. These dimensions are also chosen for statistical reasons, as they are key elements in determining the splits by the machine learning algorithm.

We find that dominance plays a particularly important role until the early 2000s and especially in markets

where concentration would have been substantially increased by the merger. In the latter half of the sample, the impact of dominance on the Commission's decisions is somewhat diminished. Furthermore, dominance seems to play a more important role in complex mergers that affect many antitrust markets simultaneously.

The impact of a significant increase in 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 with entry barriers and high market shares. The relevance of both dominance and concentration in determining competitive concerns is, instead, not affected by the geographic market definition. This is relevant 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 (Fletcher and Lyons, 2016). The role of entry barriers and foreclosure seems to be much less heterogeneous, especially over time, although both indicators play a more crucial role when markets get substantially more concentrated due to the merger.

The overall picture that we portray 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. Consequently, less weight is being put on simple structural indicators and more on the impact of the merger on effective competition. From a methodological point of view, we contend that simple linear models might miss important details that can help us to better understand the process behind the Commission's merger policy enforcement.

There are numerous avenues to extending the analysis presented in this paper. First, it would be interesting to delve deeper into the role of market characteristics, potentially by complementing the merger data with additional information from firm- or industry-level data sources. Particularly, our data do not contain a measure of the overall size or importance of the affected markets. Having additional and external data would, secondly, also make it possible to address issues of reverse causality in the Commission's decision process. We leave these questions for future research.

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A Online Appendix

A.1 Additional Descriptives

Table A1 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.³¹ The mean change in HHI due to the merger is about 445, ranging from 0 to 8,450. As shown in Table A1, 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. This is because in about 10,000 markets, DG Comp only reports the *joint* market share of the merging parties rather than separately outlining the market shares of acquirer and target. In these cases, we cannot compute the change in HHI due to the merger. In those markets, where market shares of acquirer and target are reported separately, the average market share of the acquirer is 20% while the average market share of the target is 17%.

Table A1: Summary Statistics Market Share Variables, 1990-2014

	mean	sd	min	max	observations
Joint market share (%)	32.46	23.60	0	100	22,812
Market share acquirer (%)	19.67	20.79	0	100	13,596
Market share target (%)	17.47	21.03	0	100	13,608
Post-merger HHI (low)	2,147.73	2,368.30	0	10,000	22,812
Post-merger HHI (high)	5,638.99	2,251.08	650	10,000	22,812
Delta HHI	444.74	779.13	0	8,450	12,875

The indicator for high post-merger concentration is equal to one if the post-merger HHI (high) is greater than or equal to 2,000 and the change in HHI due to the merger is greater than or equal to 150.

Table A2 contains 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, where some NACE codes are grouped together but, primarily, the manufacturing industry is 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.

³¹We calculate two different HHI measures. The variable *Post-merger HHI (low)* is a lower bound of the post-merger HHI: it is calculated 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)*. Hence, this 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 A2: Industry Groups, 1990-2014

Industry group	obs	cases
Accommodation 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
Telecommunications	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

A.2 Probit Merger Level

Table A3: Probit Model for Intervention (Merger Level) - Average Marginal Effects

	(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	0.0804*** (0.0152)	0.0402*** (0.0125)	0.1668*** (0.0423)	0.1375*** (0.0389)
mean risk of foreclosure	0.0113 (0.0228)	-0.0075 (0.0256)	0.0510 (0.0486)	0.0428 (0.0500)
fullmerger	-0.0039 (0.0084)	0.0078 (0.0119)	-0.0063 (0.0258)	0.0054 (0.0234)
joint venture	-0.0177** (0.0072)	0.0051 (0.0106)	-0.0259 (0.0234)	-0.0178 (0.0221)
mean conglomerate merger	-0.0058 (0.0308)	0.0223 (0.0152)	-0.0545 (0.0794)	-0.0450 (0.0783)
mean vertical merger	0.0101** (0.0051)	0.0098** (0.0046)	-0.0053 (0.0174)	0.0181 (0.0176)
mean market definition national	0.0243*** (0.0069)	0.0002 (0.0042)	-0.0032 (0.0396)	-0.0058 (0.0422)
mean market definition EU wide	0.0296*** (0.0065)	0.0156*** (0.0054)	-0.0125 (0.0272)	-0.0127 (0.0292)
mean market definition worldwide	-0.0082 (0.0172)	0.0047 (0.0102)	-0.1190** (0.0582)	-0.1175** (0.0597)
number of concerned markets	0.0012*** (0.0003)	0.0009*** (0.0002)	0.0025*** (0.0007)	0.0023*** (0.0006)
percentage of markets with concerns	0.2183*** (0.0111)	0.1392*** (0.0222)	0.5119*** (0.0377)	0.4519*** (0.0365)
total number of competitors in all product markets	0.0002 (0.0002)	0.0001 (0.0002)	0.0003 (0.0003)	0.0002 (0.0003)
post reform indicator	0.0991*** (0.0349)	0.1657*** (0.0438)	0.2013*** (0.0485)	0.2036*** (0.0448)
mean joint market share above 50%				0.0366 (0.0278)
mean HHI \geq 2000 & mean delta HHI \geq 150				0.0910*** (0.0110)
Industry Group FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Log likelihood	-535.09	-156.96	-313.49	-298.19
Pseudo R2	0.595	0.604	0.552	0.574
Observations	5,109	3,084	1,397	1,397

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. We take the mean value across concerned markets for those variables that vary at the market level. The indicator variables for high market shares and concentration are equal to one for a merger if the mean joint market share is above 50% and if the mean HHI \geq 2000 & mean delta HHI \geq 150 respectively.

A.3 Probit Market Level

Table A4: Probit Model for Concern (Market Level) - Average Marginal Effect

	(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	0.3396*** (0.0406)	0.3179*** (0.0603)	0.3856*** (0.0354)	0.2396*** (0.0292)
risk of foreclosure in submarket	0.1527*** (0.0563)	0.2183*** (0.0698)	0.1654*** (0.0581)	0.1596*** (0.0566)
fullmerger	-0.0213 (0.0202)	0.0063 (0.0190)	-0.0500 (0.0348)	-0.0472 (0.0294)
joint venture	-0.0483*** (0.0178)	-0.0069 (0.0254)	-0.0920*** (0.0273)	-0.0830*** (0.0270)
conglomerate merger in submarket	0.0006 (0.0210)	0.0102 (0.0349)	-0.0307 (0.0271)	-0.0241 (0.0265)
vertical merger in submarket	0.0081 (0.0136)	0.0215 (0.0146)	-0.0186 (0.0170)	0.0140 (0.0165)
market definition national	0.0471** (0.0206)	0.0159 (0.0135)	0.0867* (0.0475)	0.0509 (0.0430)
market definition EU wide	0.0355 (0.0237)	0.0152 (0.0229)	0.0647 (0.0593)	0.0483 (0.0562)
market definition worldwide	0.0411 (0.0373)	0.0272 (0.0342)	0.0720 (0.0572)	0.0516 (0.0526)
number of concerned markets	0.0004** (0.0001)	0.0001 (0.0002)	0.0007*** (0.0002)	0.0004*** (0.0001)
number of competitors	-0.0080*** (0.0023)	-0.0051** (0.0025)	-0.0120*** (0.0035)	-0.0073** (0.0032)
indicator no info on competitors	-0.0623*** (0.0122)	-0.0360*** (0.0136)	-0.0833*** (0.0178)	-0.0475*** (0.0174)
post reform indicator	-0.1596* (0.0876)	-0.0943 (0.0685)	-0.2311** (0.1103)	-0.1680 (0.1062)
joint market share above 50%				0.1988*** (0.0178)
HHI \geq 2000 & delta HHI \geq 150				0.1119*** (0.0108)
Industry Group FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Log likelihood	-7,076.57	-2,655.22	-3,993.74	-3,347.58
Pseudo R2	0.329	0.356	0.317	0.427
Observations	30,995	18,055	12,439	12,439

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.

A.4 LPM Merger Level - Continuous Share Variables

Table A5: Linear Probability Model for Intervention (Merger Level) - Continuous Share Variables

	(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*** (0.0560)	0.3793*** (0.0786)	0.2278** (0.0899)	0.1756* (0.0853)
mean risk of foreclosure	0.0145 (0.0691)	-0.0289 (0.0878)	0.0016 (0.1115)	0.0079 (0.1171)
fullmerger	-0.0019 (0.0194)	0.0170 (0.0116)	-0.0079 (0.0483)	0.0032 (0.0447)
joint venture	-0.0150 (0.0159)	0.0147 (0.0105)	-0.0321 (0.0464)	-0.0211 (0.0430)
mean conglomerate merger	-0.0051 (0.0471)	0.0404 (0.0770)	-0.0222 (0.0735)	-0.0073 (0.0683)
mean vertical merger	-0.0024 (0.0107)	0.0155 (0.0145)	-0.0269 (0.0240)	-0.0149 (0.0243)
mean market definition national	0.0103 (0.0075)	-0.0059 (0.0047)	0.0171 (0.0646)	0.0015 (0.0580)
mean market definition EU wide	0.0202 (0.0137)	0.0079 (0.0111)	0.0068 (0.0589)	-0.0089 (0.0518)
mean market definition worldwide	-0.0158 (0.0120)	-0.0069 (0.0113)	-0.0343 (0.0781)	-0.0437 (0.0705)
number of concerned markets	0.0036*** (0.0005)	0.0030*** (0.0011)	0.0030*** (0.0009)	0.0032*** (0.0008)
percentage of markets with concerns	0.9375*** (0.0623)	0.7312*** (0.1094)	0.9681*** (0.1107)	0.8748*** (0.1028)
total number of competitors in all product markets	0.0004 (0.0004)	0.0003 (0.0008)	0.0008 (0.0005)	0.0005 (0.0005)
post reform indicator	0.0333** (0.0147)	0.0042 (0.0069)	0.1169 (0.0824)	0.1357* (0.0726)
mean joint market share (%)				0.0013 (0.0010)
mean post-merger HHI (high)				-0.0000 (0.0000)
mean delta HHI				0.0001*** (0.0000)
Constant	-0.0541*** (0.0177)	-0.0211** (0.0090)	-0.1110 (0.0913)	-0.1440 (0.0999)
Industry Group Year FE	Yes	Yes	Yes	Yes
R2	0.609	0.557	0.682	0.691
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.

A.5 LPM Market Level - Continuous Share Variables

Table A6: Linear Probability Model for Concern (Market Level) - Continuous Share Variables

	(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*** (0.0558)	0.3408*** (0.0856)	0.4067*** (0.0485)	0.2678*** (0.0449)
risk of foreclosure in submarket	0.2066** (0.0956)	0.2958** (0.1248)	0.1849* (0.0921)	0.1918** (0.0864)
fullmerger	-0.0375 (0.0250)	-0.0071 (0.0263)	-0.0615 (0.0373)	-0.0573* (0.0309)
joint venture	-0.0656** (0.0244)	-0.0218 (0.0285)	-0.1192*** (0.0323)	-0.1008*** (0.0246)
conglomerate merger in submarket	0.0201 (0.0372)	0.0302 (0.0469)	0.0259 (0.0355)	0.0277 (0.0371)
vertical merger in submarket	-0.0024 (0.0100)	0.0240 (0.0180)	-0.0410*** (0.0128)	-0.0263** (0.0098)
market definition national	0.0182*** (0.0049)	0.0042 (0.0076)	0.0690*** (0.0239)	0.0517** (0.0207)
market definition EU wide	-0.0108 (0.0087)	0.0007 (0.0129)	0.0039 (0.0246)	0.0146 (0.0220)
market definition worldwide	0.0076 (0.0163)	0.0176 (0.0224)	0.0245 (0.0252)	0.0534* (0.0270)
number of concerned markets	0.0001 (0.0003)	-0.0001 (0.0005)	0.0002 (0.0004)	0.0001 (0.0002)
number of competitors	-0.0099*** (0.0030)	-0.0066*** (0.0020)	-0.0116*** (0.0040)	-0.0080** (0.0037)
indicator no info on competitors	-0.0652*** (0.0152)	-0.0358*** (0.0124)	-0.0792*** (0.0230)	-0.0653*** (0.0216)
post reform indicator	-0.1916 (0.1300)	-0.0332 (0.0305)	-0.3779 (0.2222)	-0.2881 (0.2226)
joint market share (%)				0.0023*** (0.0004)
post-merger HHI (high)				0.0000 (0.0000)
delta HHI				0.0001*** (0.0000)
Constant	0.2355* (0.1360)	0.0640** (0.0279)	0.4508* (0.2417)	0.2649 (0.2295)
Industry Group Year FE	Yes	Yes	Yes	Yes
R2	0.377	0.410	0.401	0.504
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.

A.6 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 the indicators for a substantial increase in concentration and joint market share above 50% (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. Therefore, we show coefficient plots only up to and including the year 2013.

Table A7: Linear Probability Model for Concern by Notification Year

	1990-1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
barriers to entry in submarket	0.253** (0.107)	0.730*** (0.063)	0.788*** (0.212)	-0.211*** (0.051)	0.499*** (0.112)	0.365*** (0.078)	0.395*** (0.111)	0.241*** (0.085)	0.299** (0.134)	0.328*** (0.086)
risk of foreclosure in submarket			-0.017 (0.111)	0.693*** (0.091)		0.300*** (0.083)	0.613*** (0.098)	-0.043 (0.085)	0.060 (0.147)	-0.037 (0.062)
joint market share above 50%	0.015 (0.075)	0.137 (0.091)	0.383*** (0.099)	0.262** (0.093)	0.155** (0.072)	0.341*** (0.051)	0.411*** (0.077)	0.176*** (0.038)	0.181*** (0.058)	0.210** (0.084)
HHI \geq 2000 & delta HHI \geq 150	0.076 (0.066)	0.079 (0.048)	-0.196** (0.068)	0.081* (0.039)	0.208 (0.155)	0.183*** (0.038)	0.149** (0.066)	0.111** (0.044)	-0.015 (0.042)	0.205*** (0.069)
fullmerger	-0.062 (0.122)	0.070 (0.074)	0.261 (0.185)	-0.176** (0.066)	0.004 (0.147)	-0.067 (0.129)	-0.062 (0.111)	0.118* (0.063)	-0.006 (0.044)	-0.181 (0.115)
joint venture	-0.201*** (0.067)	0.046 (0.067)	0.096 (0.119)	-0.268*** (0.055)	0.042 (0.160)	-0.088 (0.130)	-0.152* (0.088)	0.083 (0.055)	0.027 (0.046)	-0.151 (0.156)
conglomerate merger in submarket	0.074 (0.116)	0.066 (0.038)	1.098 (0.810)	0.057 (0.045)	-0.310* (0.157)	-0.027 (0.050)	0.093*** (0.024)	-0.085* (0.048)	-0.195 (0.131)	-0.001 (0.060)
vertical merger in submarket	-0.196** (0.082)	0.012 (0.020)	-0.376* (0.208)	0.237 (0.165)	0.067 (0.083)	0.010 (0.047)	-0.027 (0.045)	0.078 (0.055)	-0.015 (0.058)	-0.009 (0.055)
market definition national	0.100* (0.049)	0.516* (0.270)	0.160 (0.196)	0.019 (0.065)	0.261* (0.139)	0.065 (0.040)	0.050 (0.188)	0.208** (0.082)	-0.188* (0.092)	0.270 (0.246)
market definition EU wide	0.026 (0.067)	0.501* (0.272)	0.233 (0.190)	0.188** (0.063)	0.217 (0.153)	0.074** (0.030)	-0.015 (0.195)	0.129** (0.049)	-0.280*** (0.094)	0.226 (0.241)
market definition worldwide	0.391 (0.250)	0.367* (0.201)	0.160 (0.196)	0.138 (0.126)	0.430** (0.171)	0.060 (0.068)	0.075 (0.191)	0.299** (0.133)	-0.201* (0.116)	0.321 (0.220)
number of concerned markets	-0.012** (0.005)	-0.004 (0.003)	-0.009 (0.010)	0.002 (0.004)	-0.001 (0.004)	0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.001 (0.000)	0.000 (0.001)
number of competitors	-0.003 (0.010)	-0.002 (0.018)	0.020** (0.007)	-0.019 (0.015)	-0.004 (0.016)	-0.005 (0.011)	0.022 (0.017)	0.001 (0.017)	0.006 (0.011)	-0.002 (0.021)
indicator no info on competitors	-0.040 (0.047)	-0.069 (0.073)	0.141*** (0.026)	0.014 (0.069)	0.070 (0.132)	-0.045 (0.046)	0.076* (0.044)	-0.049 (0.061)	-0.036 (0.113)	0.000 (0.085)
Constant	0.495*** (0.097)	-0.482 (0.292)	-0.017 (0.094)	-0.080 (0.083)	-0.354 (0.312)	0.239 (0.161)	0.126 (0.157)	-0.316*** (0.108)	0.260 (0.170)	-0.058 (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 A9: Linear Probability Model for Concern by Notification Year (Continued)

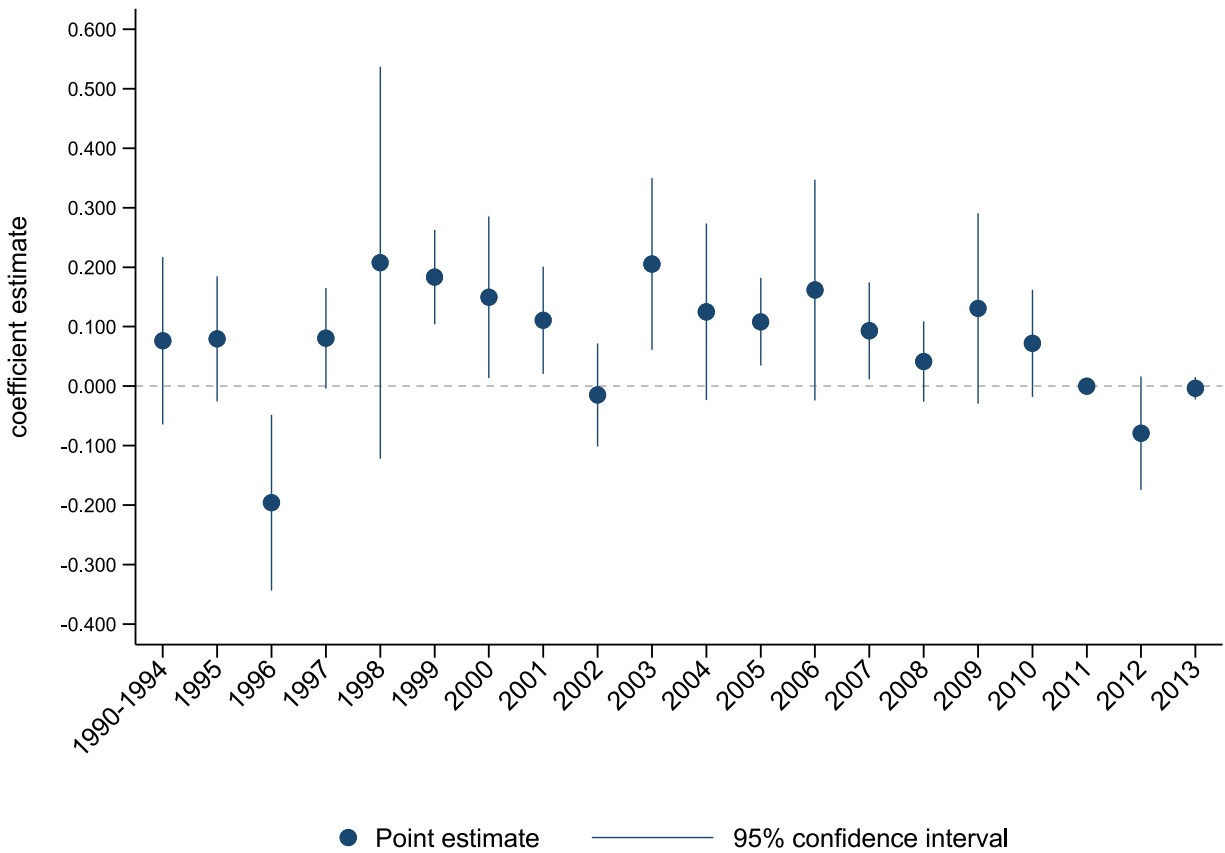
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
barriers to entry in submarket	0.226** (0.103)	0.326** (0.126)	0.392*** (0.072)	0.366* (0.197)	0.397*** (0.110)	0.435*** (0.081)	-0.083* (0.042)	0.000 (.)	0.058*** (0.016)	0.113*** (0.007)	1.000*** (0.000)
risk of foreclosure in submarket	0.234 (0.264)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

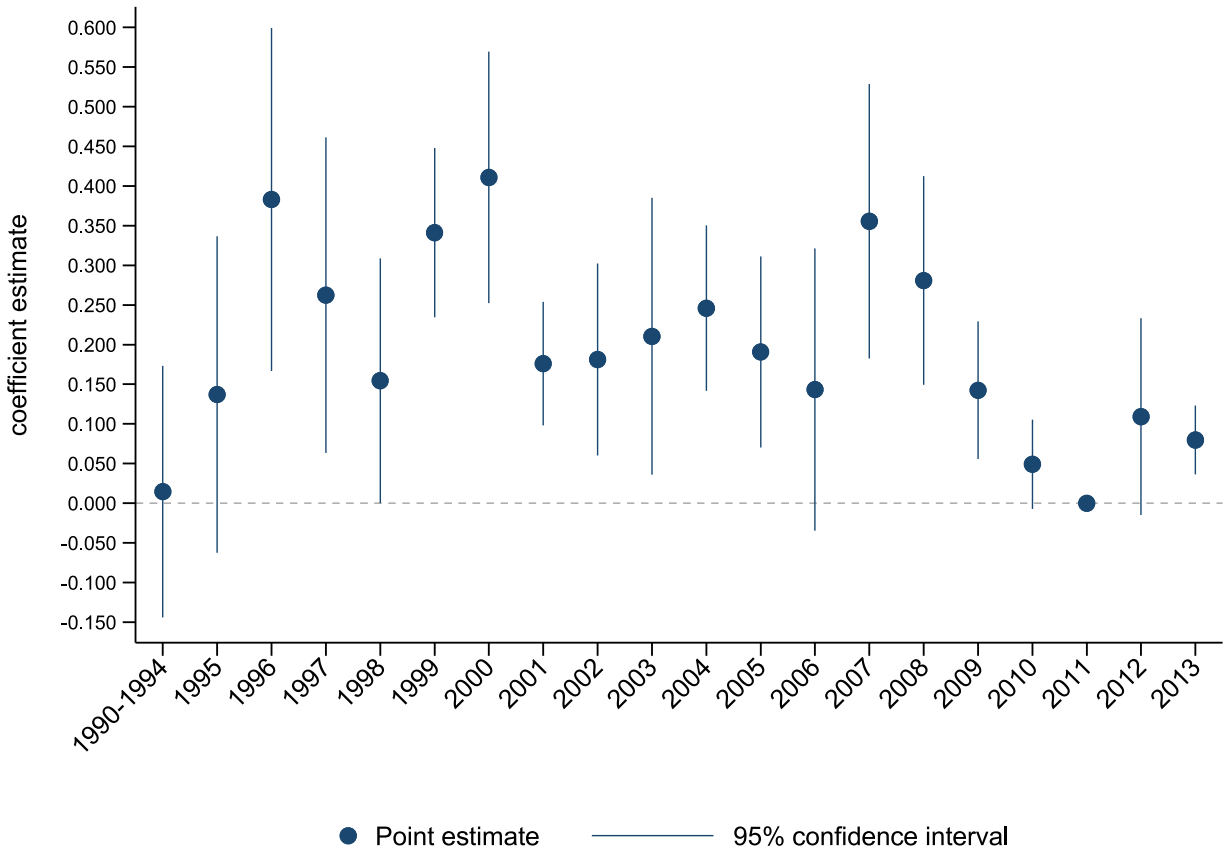
Figure 7: OLS Regression Coefficient on Substantial Increase in Concentration over Time



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.

post-merger. However, similar to the concentration measure, the importance of market shares above 50% seems to have declined after 2009.

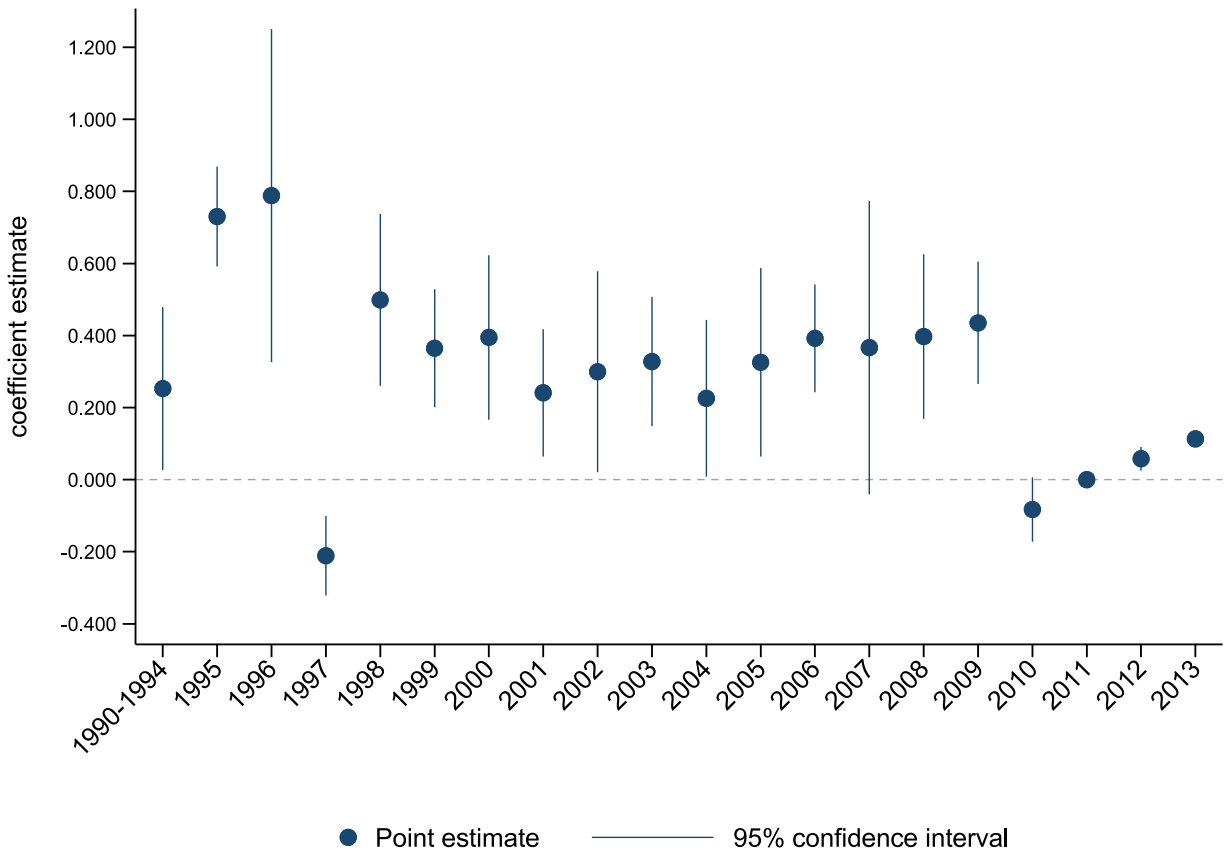
Figure 8: OLS Regression Coefficient on Joint Market Shares above 50% over Time



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 joint market shares above 50%, 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, like the indicators for dominance and substantial increase in concentration, its importance seems to have declined in the last years of the data.

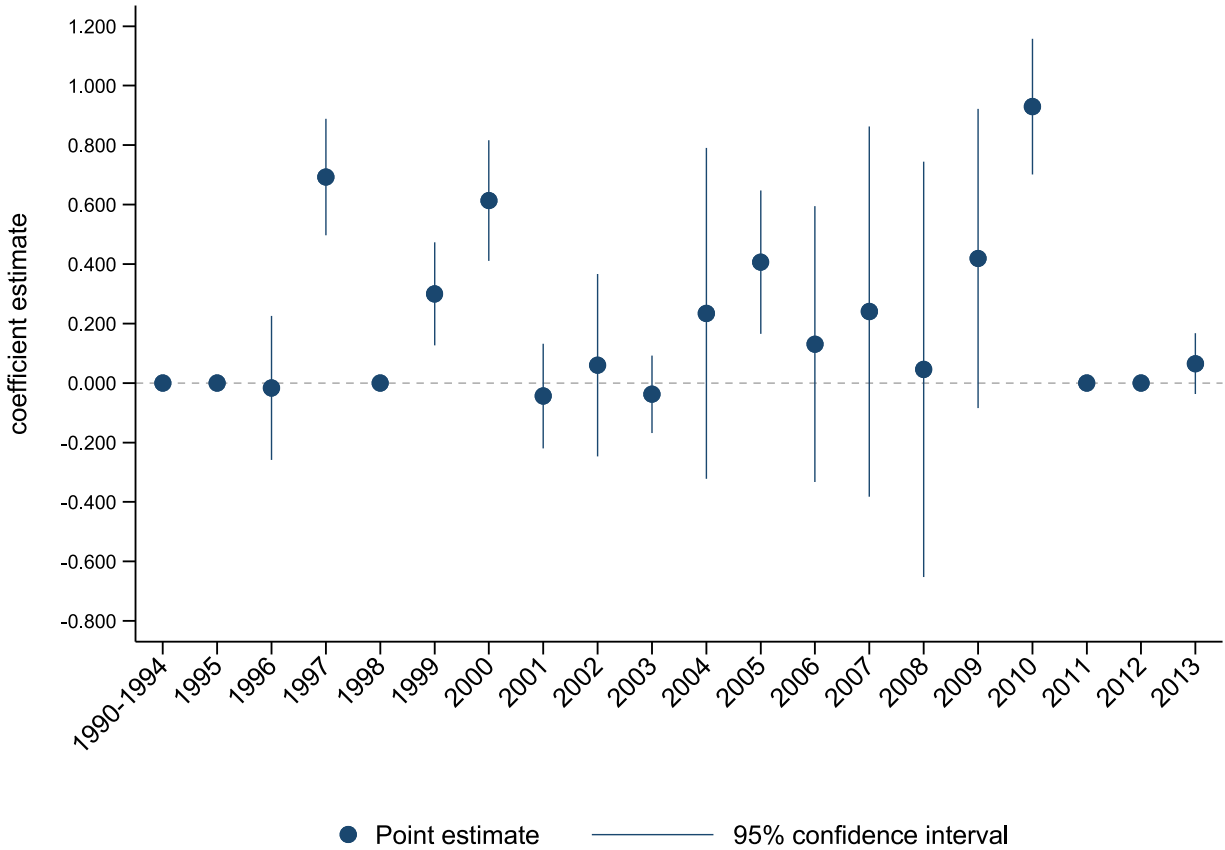
Figure 9: OLS Regression Coefficient on Barriers to Entry over Time



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.7 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 the indicators for a substantial increase in concentration post-merger and joint market shares of the merging parties above 50% (specification 4).

Table A11: 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 entry in submarket	0.412*** (0.070)	0.071 (0.067)	1.000*** (0.000)	0.637*** (0.054)	0.241*** (0.032)	0.487*** (0.038)	0.403*** (0.095)	0.066 (0.157)	0.467*** (0.057)
risk of foreclosure in submarket	0.326*** (0.113)	0.659*** (0.147)			0.469*** (0.055)		-0.364 (0.260)	0.213* (0.118)	0.502*** (0.103)
joint market share above 50%	0.415*** (0.047)	0.329*** (0.029)		0.217*** (0.046)	0.265*** (0.022)	0.301*** (0.028)	0.302*** (0.061)	0.215*** (0.061)	0.155*** (0.036)
HHI \geq 2000 & delta HHI \geq 150	0.135*** (0.029)	0.079*** (0.020)	-0.000 (0.000)	0.066* (0.034)	0.076*** (0.017)	0.177*** (0.029)	0.072** (0.031)	0.057** (0.027)	0.081*** (0.019)
fullmerger	0.068 (0.053)	0.153*** (0.026)	0.000 (0.000)	-0.223*** (0.051)	-0.067*** (0.025)	0.121*** (0.043)	-0.228*** (0.073)	0.058 (0.055)	-0.200*** (0.044)
joint venture	-0.006 (0.054)	0.060** (0.030)		0.089 (0.101)	-0.150*** (0.034)	-0.093* (0.056)	-0.280*** (0.079)	0.002 (0.060)	-0.218*** (0.056)
conglomerate merger in submarket		-0.087* (0.048)			-0.185*** (0.069)	0.355*** (0.075)		0.265* (0.143)	-0.156*** (0.057)
vertical merger in submarket	0.021 (0.040)	-0.042 (0.026)	-0.000 (0.000)	-0.009 (0.055)	-0.010 (0.021)	0.022 (0.046)	0.042 (0.040)	-0.080*** (0.028)	0.005 (0.019)
market definition national	0.201** (0.091)	0.043 (0.062)	0.000 (0.000)	0.148** (0.073)	0.011 (0.059)	-0.244*** (0.057)	0.444** (0.178)	0.178* (0.094)	0.025 (0.105)
market definition EU wide	0.157* (0.089)	0.045 (0.066)		0.106 (0.068)	-0.047 (0.057)	-0.171** (0.069)	0.431** (0.173)	0.201** (0.096)	0.087 (0.104)
market definition worldwide	0.157* (0.081)	0.033 (0.100)		0.219 (0.207)	-0.002 (0.060)	-0.198*** (0.072)	0.348* (0.196)	0.242** (0.095)	0.062 (0.103)
number of concerned markets	-0.000 (0.001)	0.000 (0.000)	-0.000 (0.000)	0.002* (0.001)	-0.001*** (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.003*** (0.001)	0.005*** (0.001)
number of competitors	-0.004 (0.006)	0.007 (0.008)	-0.000 (0.000)	0.003 (0.011)	-0.006 (0.006)	-0.021*** (0.005)	0.024* (0.013)	0.002 (0.006)	-0.019** (0.008)
indicator no info on competitors	-0.061 (0.037)	-0.026 (0.033)		-0.123* (0.066)	-0.089*** (0.025)	-0.061** (0.027)	0.114* (0.058)	0.042 (0.038)	-0.145*** (0.037)
post reform indicator	0.093 (0.085)	0.052 (0.052)	0.000 (0.000)	-0.715*** (0.179)	-0.865*** (0.037)	-0.103 (0.108)	-0.067** (0.033)	0.101 (0.091)	-0.109** (0.055)
Constant	-0.213* (0.123)	-0.227*** (0.087)	0.000 (0.000)	0.485** (0.198)	1.010*** (0.070)	0.218* (0.129)	-0.294 (0.205)	-0.331*** (0.124)	0.079 (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 A13: 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 entry in submarket	0.681*** (0.072)	0.268*** (0.078)	0.407*** (0.055)	0.328*** (0.077)	0.406*** (0.069)	0.000 (.)	0.346*** (0.054)	0.199*** (0.028)	
risk of foreclosure in submarket	-0.322** (0.125)	0.510*** (0.088)	-0.047 (0.044)	0.408*** (0.117)	0.046 (0.066)		0.269*** (0.104)	-0.027 (0.040)	
joint market share above 50%	0.146** (0.057)	0.132*** (0.031)	0.171*** (0.036)	0.187*** (0.050)	0.253*** (0.048)	0.000 (.)	0.071 (0.045)	0.113*** (0.020)	0.000 (.)
HHI \geq 2000 & delta HHI \geq 150	-0.016 (0.020)	0.106*** (0.020)	-0.037 (0.035)	0.028 (0.018)	0.205*** (0.036)	0.000 (.)	0.134*** (0.020)	0.197*** (0.028)	0.000 (.)
fullmerger	-0.158*** (0.052)	-0.219*** (0.036)	-0.114** (0.045)	0.061* (0.032)	-0.297*** (0.064)	0.000 (.)	-0.120*** (0.036)	-0.029 (0.087)	0.000 (.)
joint venture	-0.126** (0.057)	-0.213*** (0.035)		0.019 (0.037)	-0.372*** (0.064)	0.000 (.)	-0.084** (0.036)	0.003 (0.093)	0.000 (.)
conglomerate merger in submarket	0.022 (0.032)	-0.131 (0.096)	-0.016 (0.040)	-0.059* (0.036)		0.000 (.)	-0.025 (0.037)	0.130** (0.063)	
vertical merger in submarket	0.031 (0.029)	-0.039** (0.016)	-0.030 (0.033)	-0.050 (0.031)	0.047 (0.038)	0.000 (.)	0.006 (0.015)	0.037 (0.028)	0.000 (.)
market definition national	0.294*** (0.095)	0.078 (0.075)	0.182** (0.074)	0.075* (0.043)	0.004 (0.061)	0.000 (.)	-0.026 (0.023)	0.092* (0.048)	
market definition EU wide	0.132* (0.074)	0.072 (0.073)	0.091 (0.066)	0.039 (0.028)	-0.166** (0.078)	0.000 (.)	0.014 (0.024)	0.062 (0.059)	
market definition worldwide	0.079 (0.081)	0.149* (0.076)		0.068 (0.051)		0.000 (.)	0.070* (0.036)	0.052 (0.055)	
number of concerned markets	-0.003*** (0.001)	0.001 (0.001)	-0.001*** (0.000)	0.001 (0.001)	-0.000 (0.001)	0.000 (.)	-0.001 (0.001)	0.000 (0.000)	0.000 (.)
number of competitors	-0.005 (0.005)	0.003 (0.005)	-0.009 (0.006)	-0.004 (0.008)	0.002 (0.006)	0.000 (.)	0.006* (0.004)	-0.028*** (0.006)	0.000 (.)
indicator no info on competitors	-0.109*** (0.040)	0.052* (0.028)	-0.007 (0.055)	-0.046 (0.039)	0.009 (0.035)	0.000 (.)	0.088*** (0.022)	-0.108*** (0.034)	0.000 (.)
post reform indicator	-0.351*** (0.110)	-0.021 (0.026)	0.632*** (0.087)	-0.028 (0.023)	0.106* (0.057)	0.000 (.)	0.038*** (0.012)	-0.121 (0.078)	0.000 (.)
Constant	0.240* (0.129)	-0.109 (0.082)	0.053 (0.042)	-0.141* (0.079)	0.212** (0.097)	0.000 (.)	-0.034 (0.048)	0.128 (0.127)	0.000 (.)
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

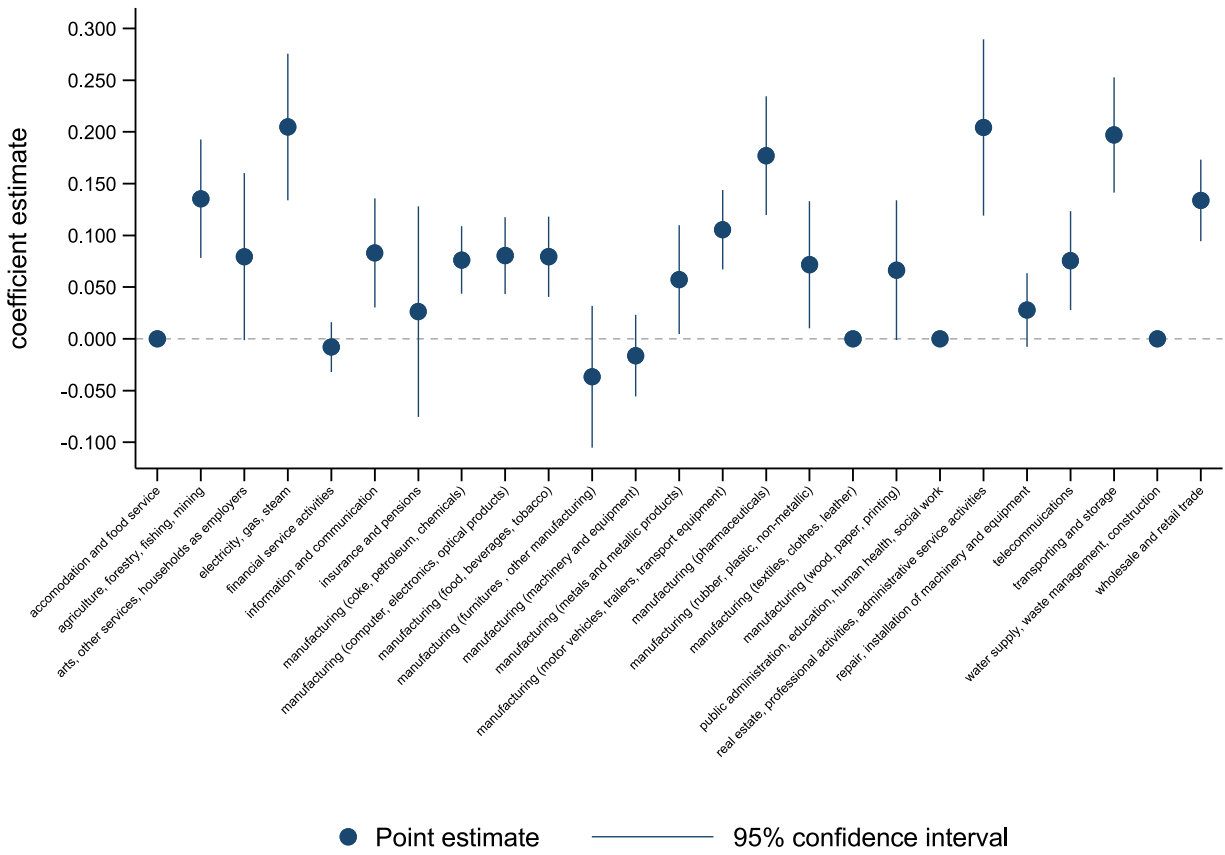
We report heteroskedasticity robust standard errors. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively.

Table A15: Linear Probability Model for Concern by Industry (Continued)

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

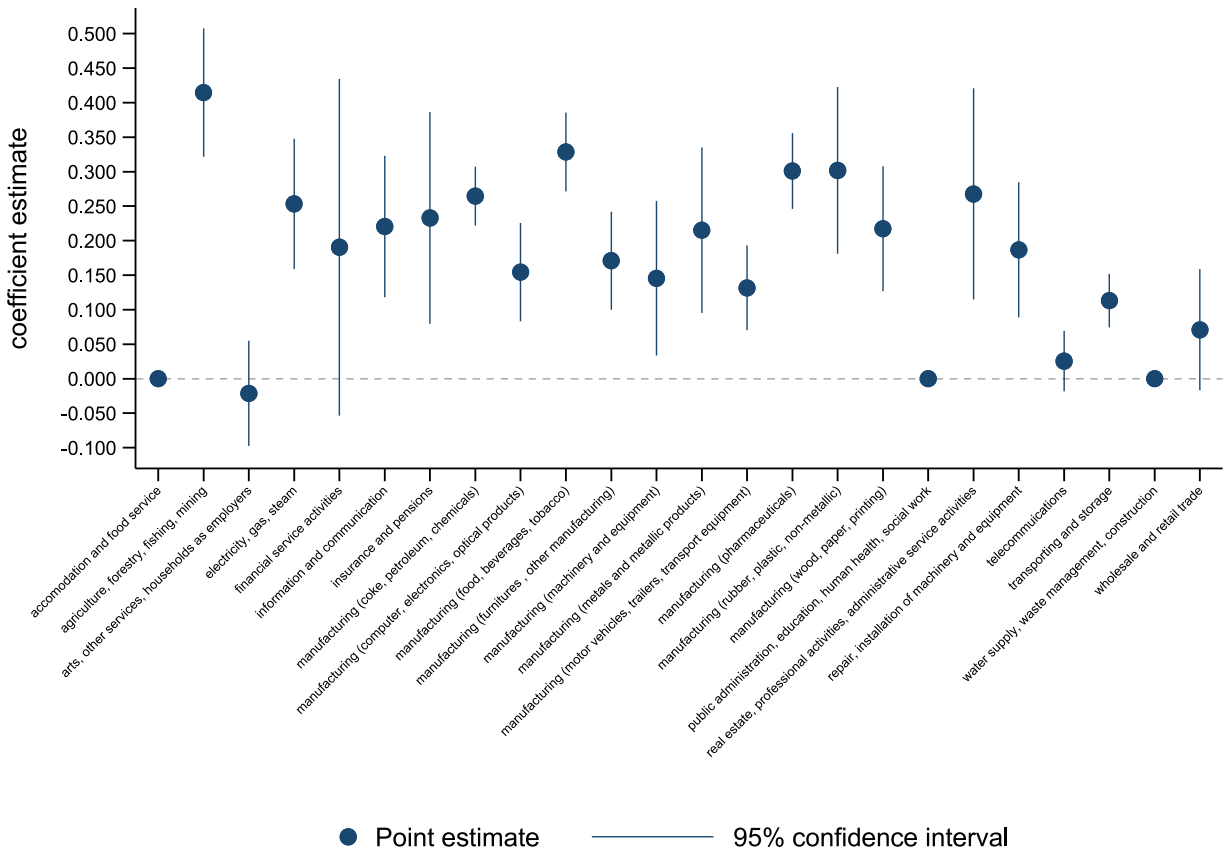
We report heteroskedasticity robust standard errors. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively.

Figure 11: OLS Regression Coefficient on Substantial Increase in Concentration over Industry



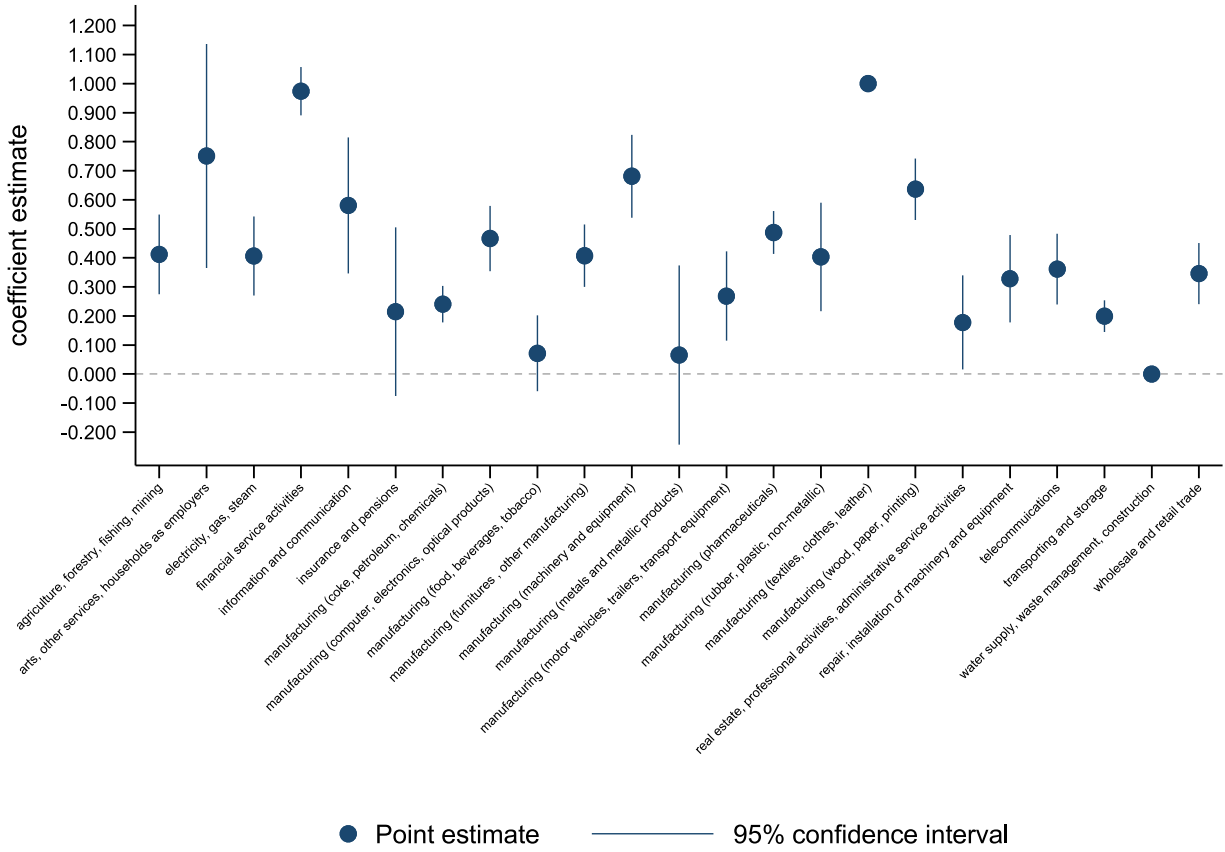
Regression coefficient on indicator variable for post-merger HHI above 2000 and change in HHI due to the merger larger than 150 in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust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

Figure 12: OLS Regression Coefficient on Joint Market Share above 50% over Industry



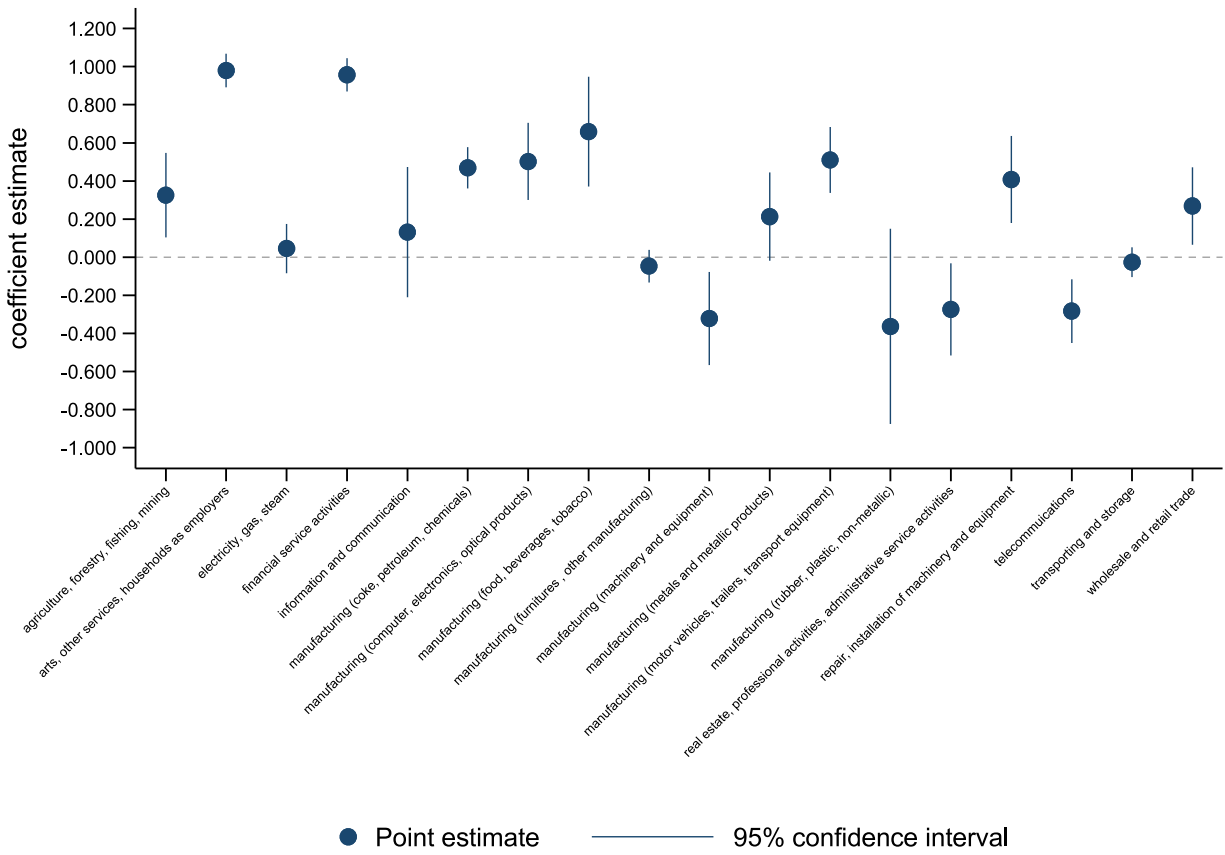
Regression coefficient on indicator variable for joint market share above 50% in OLS regression on concerns. Each reported coefficient stems from a separate regression for the respective industry. Confidence intervals are based on heteroskedasticity robust standard errors.

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.8 Technical Background on Causal Forests

A.8.1 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:

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

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-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 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:

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

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:

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

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 just allow for predicting heterogeneous treatment effects in a very flexible way but it also provides confidence intervals for these estimates.

A.8.2 Background on grf package

We use the generalized random forest (grf) R package of Athey, Wager, and Tibshirani (2019).³² 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, by default the package uses 50% of the data to grow each tree. Since honesty is used, these sub-samples are further cut in half, where one half is used to place the splits within

³²We 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 $\tau(x) = E[Y(1) - Y(0)|X = x]$ 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.

When training a causal forest, one must choose a set of tuning parameters. The grf package allows to choose tuning parameters via cross-validation. In general, the tuning is done over the parameters minimum node size, number of variables to be considered at each split within a tree (mtry), the fraction of the data used to build each tree (sample.fraction), alpha, which controls the maximum imbalance of each split, and the imbalance penalty controlling how harshly imbalanced splits are penalized. We tune over all of these parameters except nodesize. The default node size is 5 but tuning could well choose a minimum node size smaller than 5. However, such a small minimum node size seems implausible. Therefore, 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. Thus, we impose a minimal node size of 10 in all causal forests.

The procedure that the grf package uses to tune the parameters is essentially the following:³³

- Draw a number of random parameter values considered when using the model to select the optimal parameters (we use the default of 1,000 parameter values and 50 forests used to fit the tuning model but increase the number of trees within each mini forest from 200 to 500).
- For each set of parameter values, train a mini forest with these values and compute the out-of-bag-error. Now, however, the notion of error is not straightforward in the context of treatment effect estimation. This is of course different in a random forest, where the goal is the correct prediction of the outcome variable and the ground truth is known. For causal forests, the grf package uses instead a measure of error developed in Nie and Wager (2017). Furthermore, given that the mini forests are composed of few trees (here 500), the out-of-bag error is a biased estimate of the final forest error. The error is therefore debiased through variance decomposition.
- Given the debiased error estimates for each set of parameters, a smoothing function is applied to determine the optimal parameter values. The optimal parameters are the ones minimizing the predicted smoothed error on a new random draw of possible parameter values.
- The final causal forests are then estimated using the tuned parameter values and 12,000 trees within each forest.

We obtain the following tuning parameters based on cross-validation for each of the causal trees:

- Joint market share treatment: minimum node size (imposed): 10, sample.fraction: 0.5, mtry: 15, alpha: 0.2492382, imbalance.penalty: 0.00254824.
- High concentration treatment: minimum node size (imposed): 10, sample.fraction: 0.5, mtry: 20, alpha: 0.09136238, imbalance.penalty: 0.1426334.

³³See <https://grf-labs.github.io/grf/REFERENCE.html>.

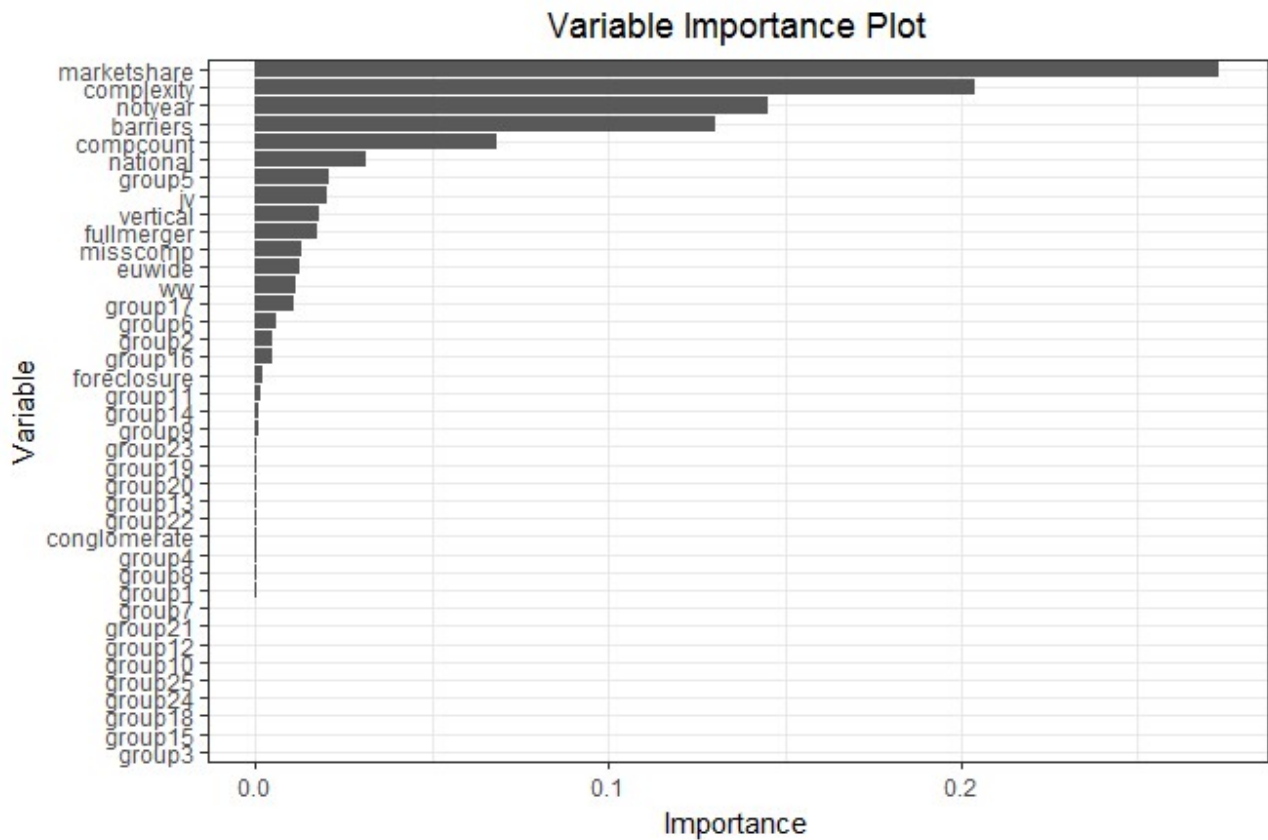
- Barriers to entry treatment: minimum node size (imposed): 10, sample.fraction: 0.5, mtry: 11, alpha: 0.03055952, imbalance.penalty: 0.1119597.
- Foreclosure treatment: minimum node size (imposed): 10, sample.fraction: 0.5, mtry: 19, alpha: 0.04946822, imbalance.penalty: 3.783623.

A.9 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), which 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.

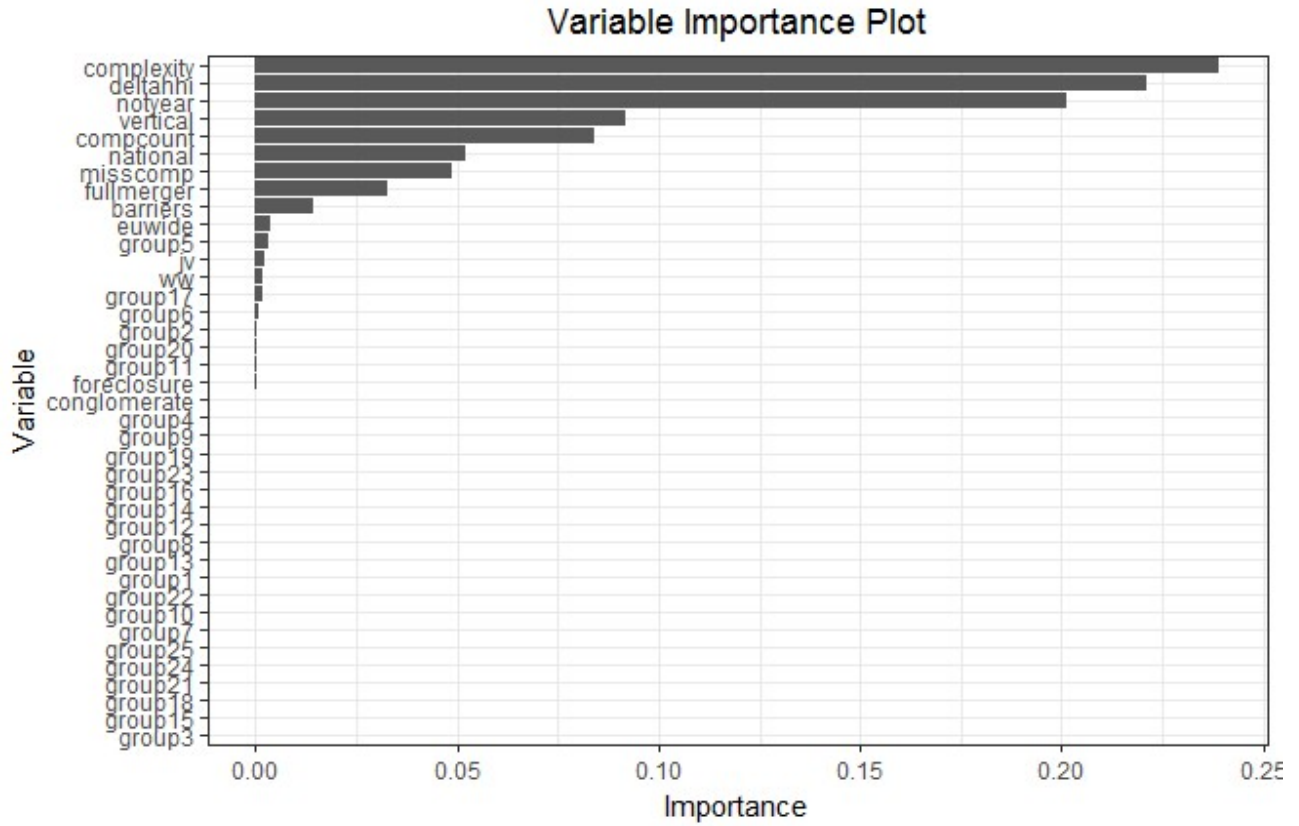
A.9.1 Treatment - Substantial Increase in Concentration

Figure 15: Variable Importance Plot for Correlation between Substantial Increase in Concentration and Concerns



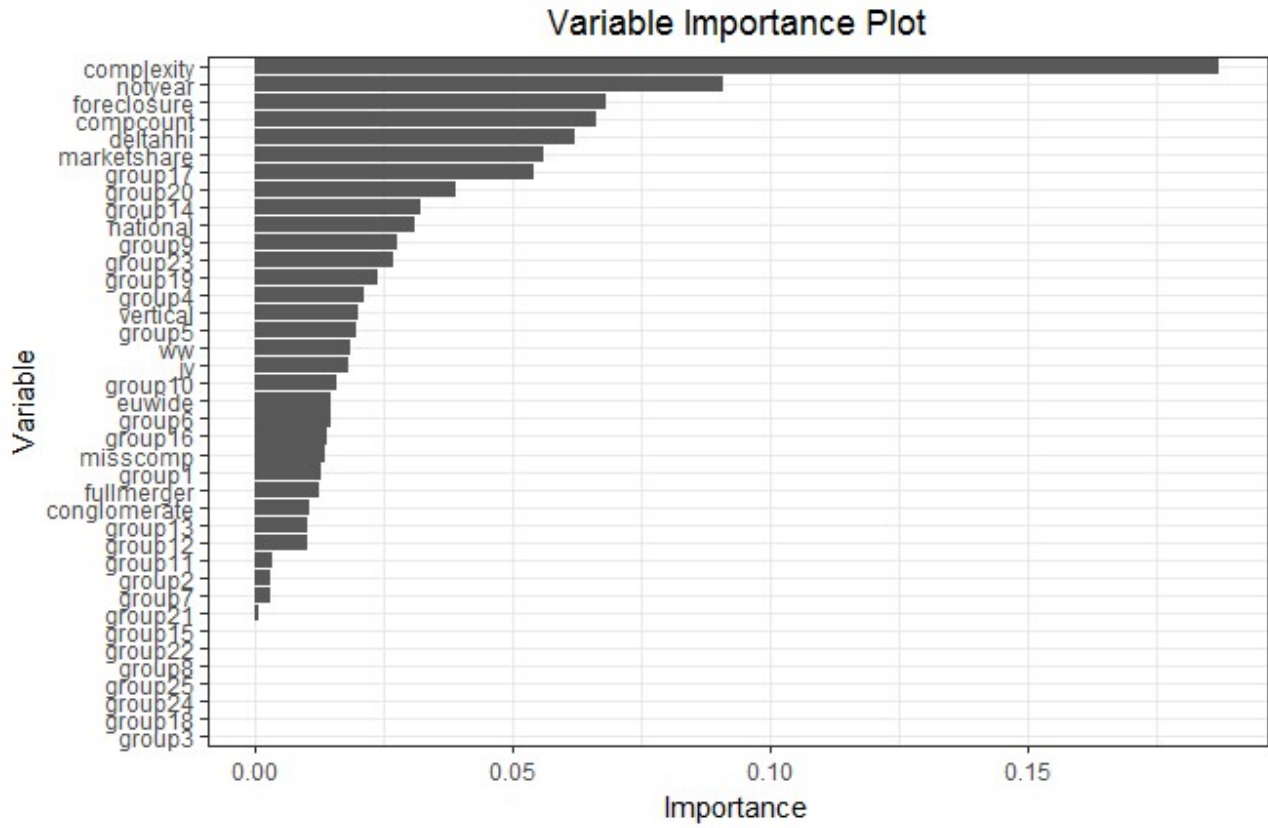
A.9.2 Treatment - Joint Market Share above 50%

Figure 16: Variable Importance Plot for Correlation between Joint Market Share above 50% and Concerns



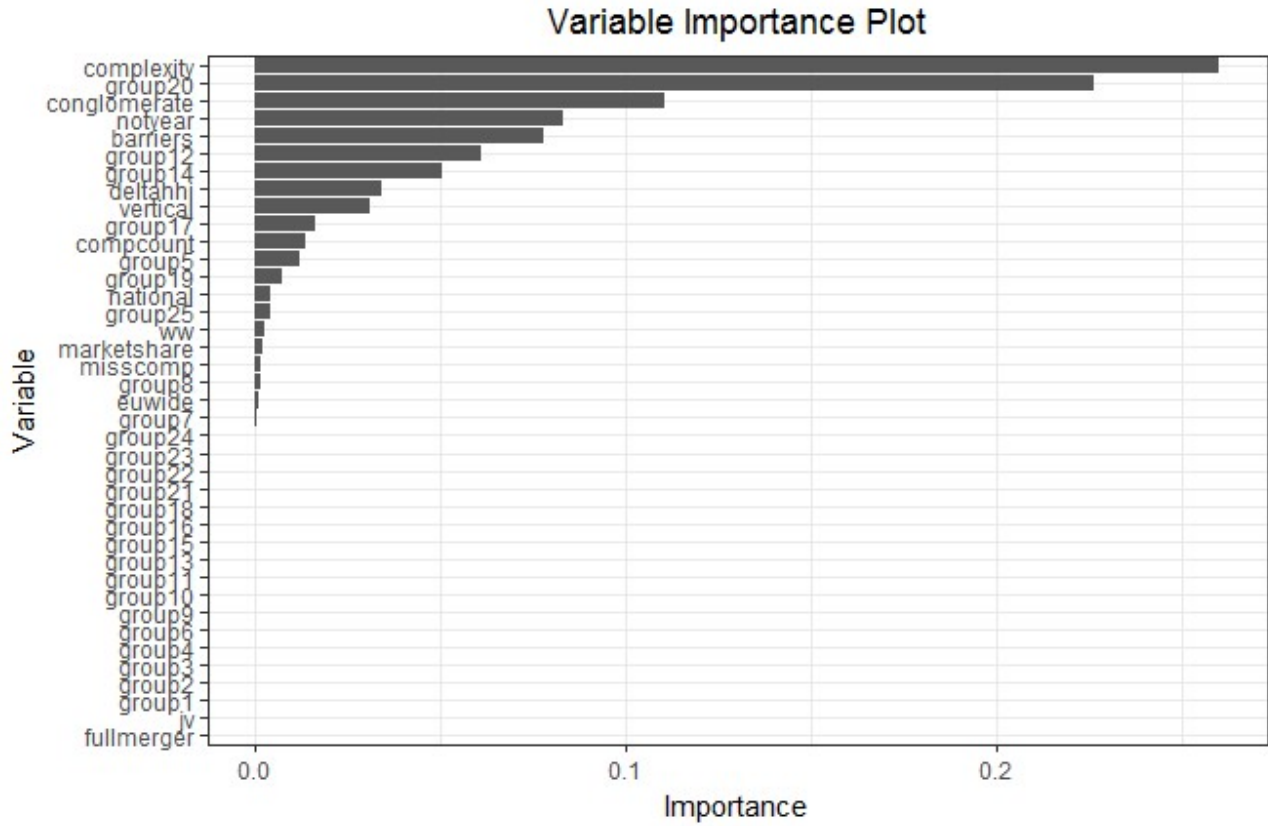
A.9.3 Treatment - Barriers to Entry

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



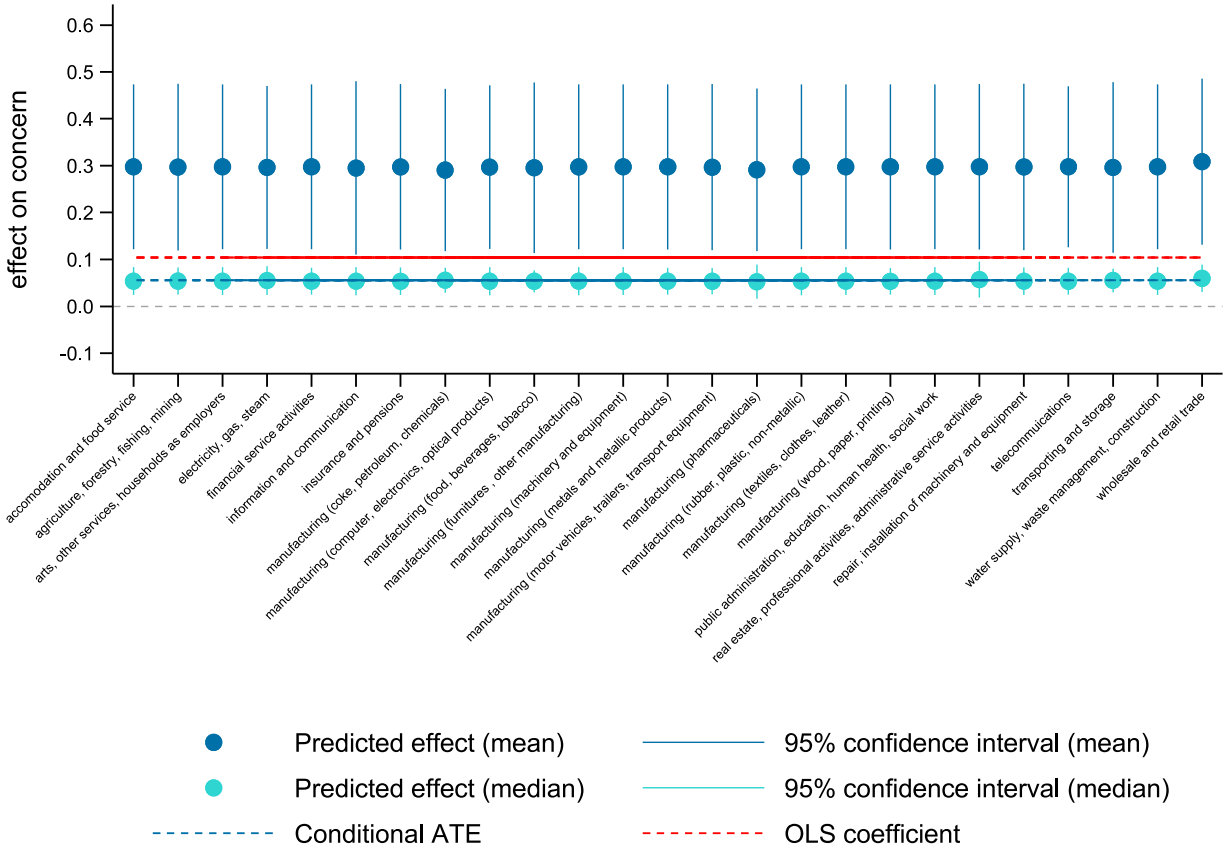
A.9.4 Treatment - Risk of Foreclosure

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



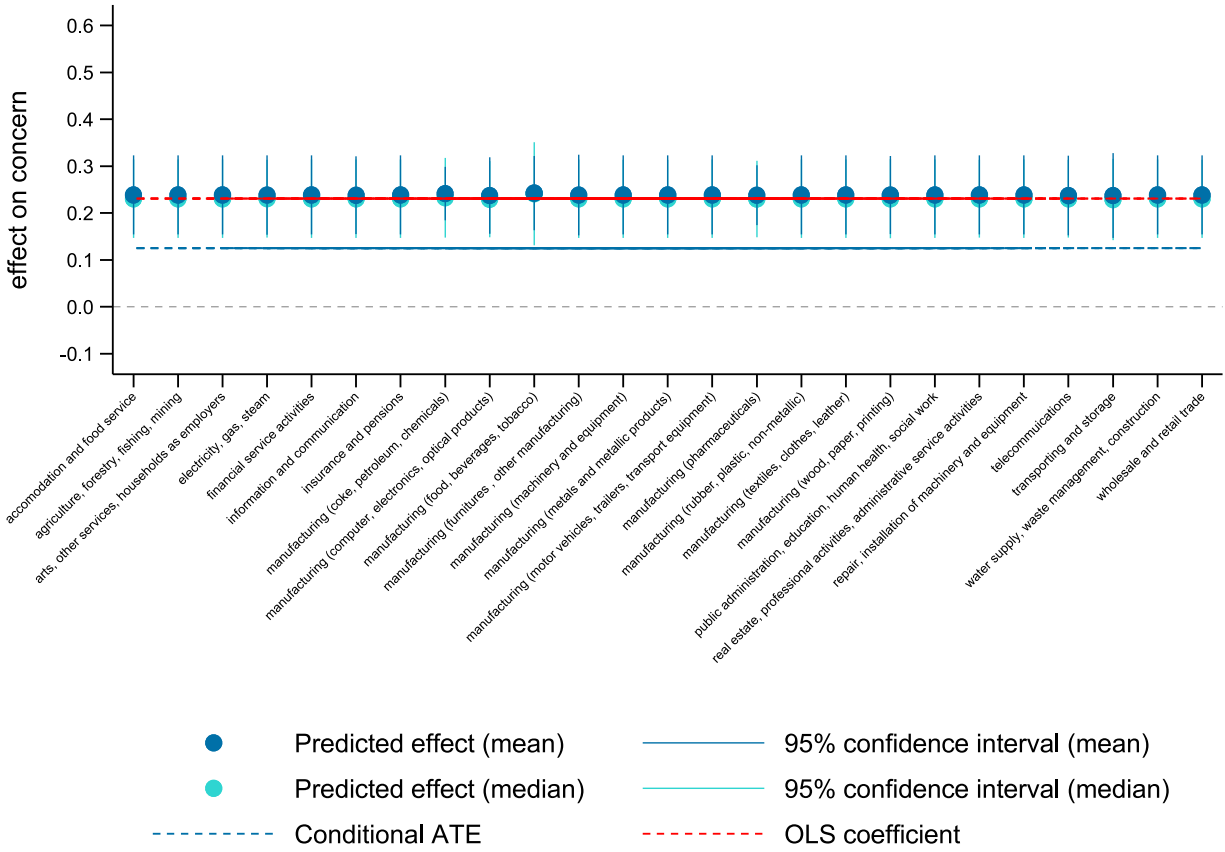
A.10 Determinants of Concern - Causal Forest Predictions over Industries

Figure 19: Effect of Substantial Increase in Concentration on Concerns over Industries



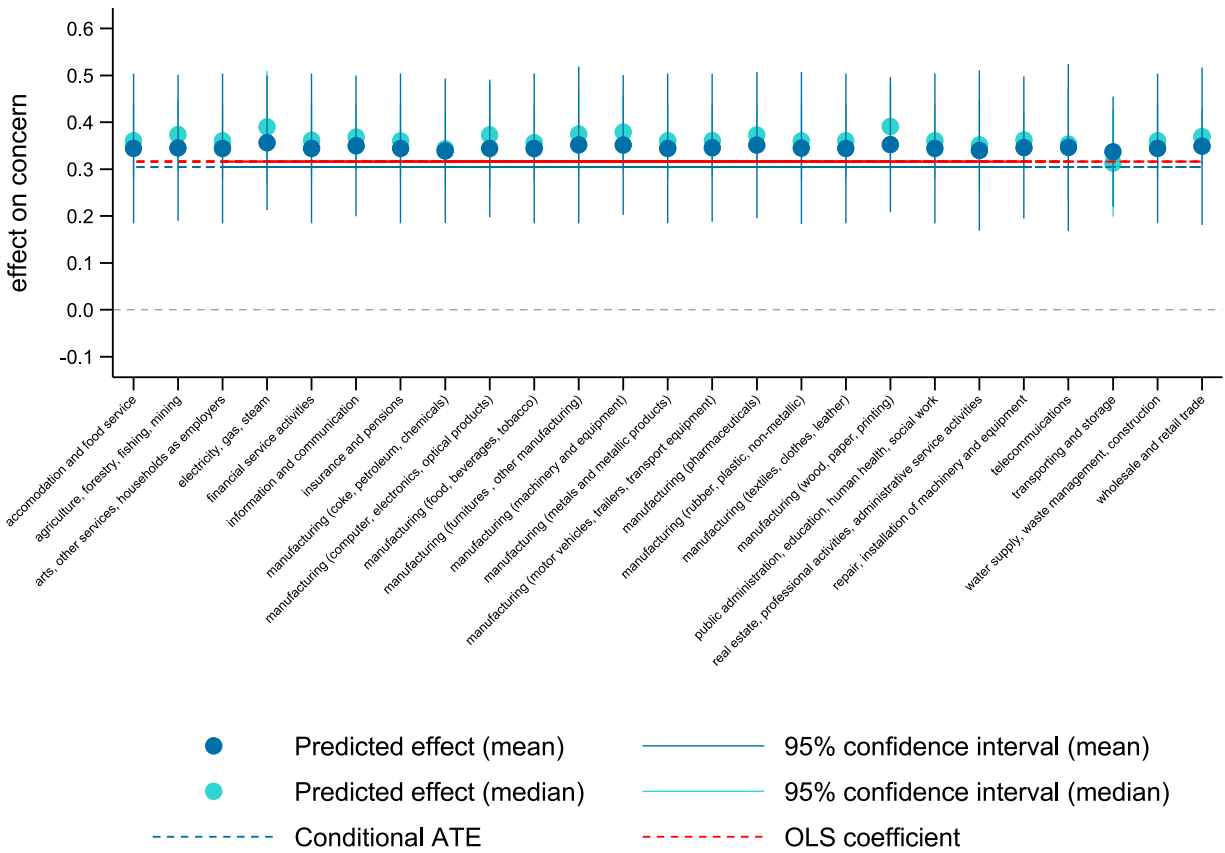
Predicted effect of indicator variable for post-merger HHI above 2000 and change in HHI larger than 150 on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.

Figure 20: Effect of Joint Market Share above 50% on Concerns over Industries



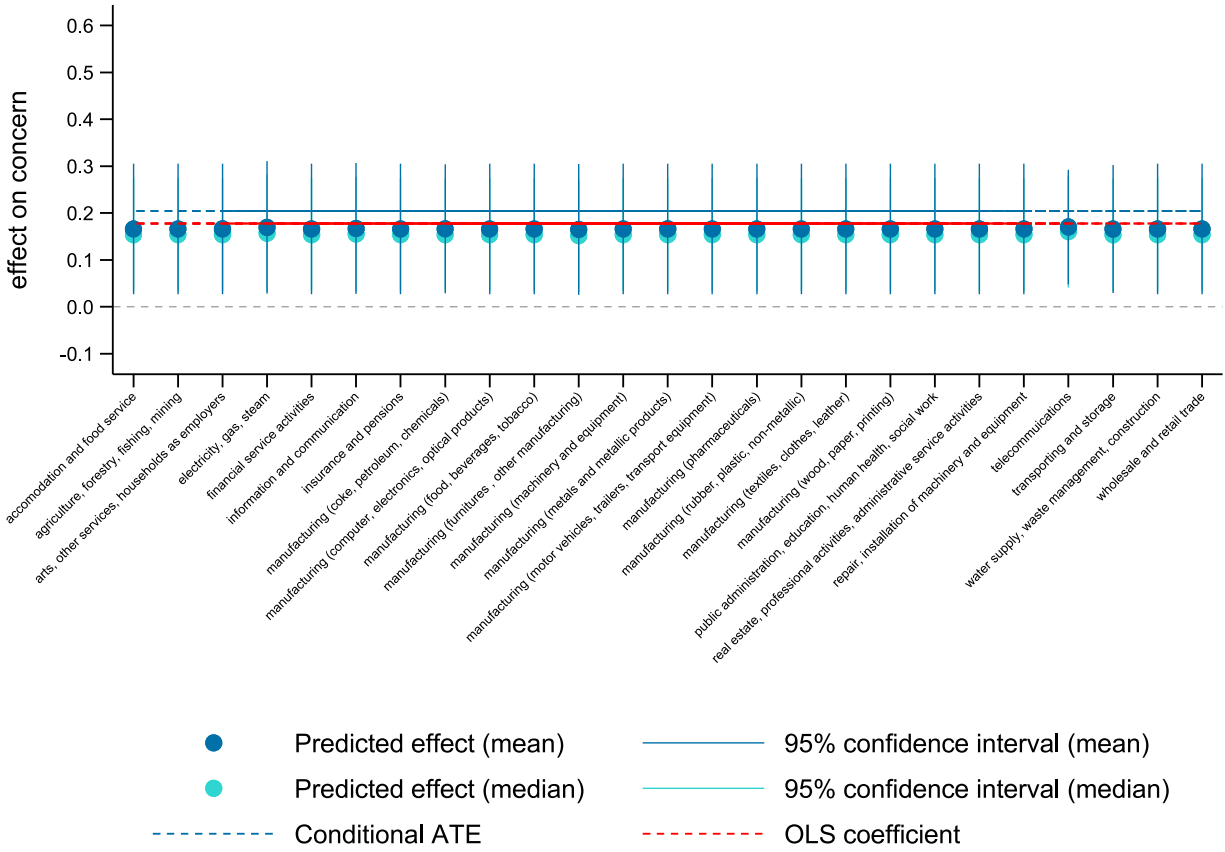
Predicted effect of indicator variable for joint market share above 50% on concerns over industries, setting all other included explanatory variables equal to the sample mean/median.

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.