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Is there a causal effect of concentration on persistent profitability differentials?

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Abstract

This article searches for a causal effect of industry concentration on estimates of persistent profitability differentials. I offer solutions to identification problems that plague related analyses by applying an IV and a natural experiment. This is the first study that explains estimates of persistent profit differentials using business segments data, allowing to match micro- and industry-level data more consistently. Testing linear relations, critical concentration levels, and interactions with mobility barriers, I find no evidence that concentration has any positive effect on long-run profitability differences. Results rather tend to point to a statistically and economically significant negative causal effect.

JEL classification: L10, D40

Dynamic theories of competition following Schumpeter (1934, 1942) describe how not just external shocks, but healthy competition itself can produce disruptive impulses that naturally produce profitability differentials between firms at any given point of time. If economists attach any value to this idea, the analysis of single *annual* profit rates, Lerner indexes, or their short-term averages becomes unsuited for assessing market power (Brozen, 1970, 1971). However, competition has also equilibrating influences on profitability over time through flows of capital and the imitation of innovations. Mueller (1977, 1986) developed measures of extra normal profitability that model this adjustment process and "correct" snapshot point of time differentials for it. This gives his estimates of long-run profit differentials much potential for the empirical analysis of market power. Several studies attempt to explain these proxies from industry structure and firm-level information. However, not only is the evidence ambiguous, none of them manages to identify a causal relationship. I attempt to accomplish precisely this. First, I match industry structural variables to the microunit correctly for the first time through the use of business segments instead of company data, and address several other measurement and omitted variable problems. Second, I offer two main solutions to the problem that industry concentration is endogeneous. One is the use of the share of industry sales originating from publicly listed companies as an instrumental variable in a setting that also controls for a rich set of industry and segment variables and where the explanatory variables of interest are measured at the beginning of the period during which profit differentials are observed (to further reduce endogeneity concerns). The other is a natural experiment where mergers that were unsuccessfully challenged by the US antitrust authority are used as shocks to industry structure.

There is a currently very active line of research in the tradition of the persistence of profit literature that can also be found in recent issues of this journal (Capasso *et al.*, 2014). Most studies compute the speed of adjustment of excess profits to the norm (or short-run persistence) as well as the persistent profit rate differential (or long-run excess profits) and focus on stationarity tests and the interpretation the magnitude of these estimated variables (Goddard and Wilson, 1999; Glen *et al.*, 2003; Crespo-Cuaresma and Gschwandtner, 2008, and others). Commonly detected high degrees of persistence and large positive long-run differentials are interpreted as indicators for monopoly power. However, resource-based theories of the firm argue that profit rate differentials may also prevail because of persistent competitive advantages that are unrelated to any form of market power abuse (Barney, 1986; Hill and Deeds, 1996). Accordingly, the observation of persistency and long-run profit rate differentials is only a necessary, not sufficient, condition to attest market power.

A small number of researchers go another path and attempt to explain these estimates from industry structural variables for which economic theory predicts a competition impeding effect, with industry concentration being the most obvious one (Bain, 1951, 1956b; Porter, 1980). Results are mixed but point toward a weak positive impact of concentration on persistent profit rate differentials. Mueller (1986) analyzes 551 manufacturing companies between 1950 and 1972 and finds that a proxy for concentration is weakly related to long-run profit differentials in a nonlinear way, where concentration decreases profitability at lower levels of concentration and increases it at higher ones. Using Compustat data for US manufacturing industries, Gschwandtner (2012) detects negative and positive coefficients for a concentration ratio in regressions on short- and long-run persistence. Coefficients are insignificant when explaining long-run persistent, while few are significant and negative in the case of short-run persistence.[1] Yurtoglu (2004) focuses on 172 of the largest manufacturing firms in Turkey. In explaining the speed of adjustment and the persistent differential, he reports positive coefficients for the four-firm concentration ratio (CR4) and the Herfindahl–Hirschman index (HHI) in all regressions. Coefficients are significant when the long-run differential is explained. Hirsch and Hartmann (2014) detect an insignificant positive effect of the HHI on persistent differentials for 590 European dairy companies. With Compustat company-level data, Acquaah (2003) reports an insignificant positive impact of the CR4 on short-run persistence. Goddard *et al.* (2011) find that in their study of 65 banking industries (in different countries) that industry averages of the short-run persistence of profit differentials are significantly and positively related to concentration and barrier variables. Kambhampati (1995) produces similar (weakly significant) findings for Indian manufacturing industries with the same methodology.

There are several concerns with respect to the identification strategies in all these articles. These shortcomings may explain why results are anything but conclusive. First, no study analyzes more than one single sector, making it hard to generalize any obtained result to the entire economy. Differences in outcomes may be due to heterogeneity between sectors.

Second, some studies like Acquaah (2003) rely on Compustat or other incomplete data samples to proxy concentration measures. This is known to be inappropriate as such proxies are virtually uncorrelated with the more comprehensive official concentration measures (Ali *et al.*, 2009; Keil, 2017b) published by national statistics offices (the Economic Census in case of the United States).

Third, other existing related work does not account for imports, potentially making the computation of concentration indicators and any industry structural variable numerically incorrect. The domestic market may actually be significantly larger and characterized by a different sample of producers that also includes additional foreign suppliers. Specific to explanations of competition is that imports can increase competitive pressure and limit the ability of incumbents to exercise market power (Landes and Posner, 1981; Helpman and Krugman, 1989; Levinsohn, 1993; Ghosal, 2002). Exports can likewise produce measurement errors when domestic producers cater to markets abroad.

Fourth, company data are most widely used, although economists argued long ago that the segment level is a more suitable unit of analysis (Scherer, 1980). Any industry-level variable can become entirely unrelated to the company unit whenever the latter is active internationally or in multiple industries. This problem is especially severe when large publicly listed companies are analyzed. Over one-third of all Compustat companies are active in multiple industries, while almost half operate business segments located outside of the United States. Unsurprisingly, numerous studies have shown that the segment level explains a larger fractions of profit variance than the corporate, industry, and time dimensions (Schmalensee, 1985; McGahan and Porter, 1997).

Fifth, the use of industry aggregates in some studies does not allow to control for market share. Since the formulation of the efficiency hypothesis it is accepted that productivity may drive profitability and concentration (Demsetz, 1973, 1974). Productivity is reflected by market share which must be included as a control variable to have any chance of isolating a causal effect of concentration (Scherer, 1980).

1 She reports insignificant negative coefficients for some of her regressions in an earlier paper (Gschwandtner, 2005).

Sixth, no author attempts to address the most obvious forms of endogeneity of concentration indicators that are likely to result even if market share is included as a control. For example, above-average profitability represents an entry signal that directly lowers concentration if industry outsiders respond to it (Siegfried and Evans, 1994; Driffield, 1999; Dunne *et al*., 2013). This could produce an insignificant or negative concentration–profit relationship (for less competitive incumbents). Labor unions are known to place greater efforts into organizing more concentrated industries (Hirsch, 1997; Kaufman and Hotchkiss, 2006: 637–638). Using the data sample here, unionization and the CR4 have a highly significantly pairwise correlation coefficient of 0.17. Since unions also affect profits negatively and capture parts of possible monopoly rents (Salinger, 1984; Doucouliagos and Laroche, 2009), this may again mask a potential positive effect of concentration on profit. Similarly, if concentration really implies market power, then concentration of supplier and customer industries matters too by affecting their relative bargaining power (Porter, 1980). Insignificant concentration indicator coefficients could then result, since concentrated industries also tend to interact more with concentrated upstream and downstream industries (the pairwise correlation coefficient with the CR4 is 0.2). There is also a reverse causality problem where high profits ease financial constraints (Greenwald *et al*., 1984; Myers, 1984; Myers and Majluf, 1984) and allow firms to invest, increase barriers, and in turn elevate concentration levels. This causal chain may result in a spurious positive concentration–profitability relationship.

To sum up, biases are likely, but their overall effect is unclear. Without any attempts to solve underlying endogeneity problems, previous studies could not establish any causal relation between persistent profitability estimates and industry concentration. The goal of this article is to attempt exactly this by addressing all mentioned problems. To lessen data quality issues I use Compustat business segments; exclude industries whose imports account for more than 10% or whose exports add up to over 20% of sales (the average values in my sample are less than 2% and 4%, respectively); and rely on comprehensive US Census concentration measures from a large file compiled by the author—with manufacturing and nonmanufacturing industries.

I offer two alternative answers to the endogeneity problem of concentration. The first relies on IV regressions. Equations include control variables that address the most obvious endogeneity problems identified above (market share, two different entry barriers, unionization, the average concentration ratio of supplier and customer industries, and CAPX). To further elude concerns about endogeneity, only concentration (and mobility barrier) data are used that come from the first year of the period from which long-run profit differentials are computed. The second solution is based on a natural experiment where I interpret mergers that were unsuccessfully challenged by US antitrust authorities as shocks to industry structure which are increasing concentration in the presence of obstacles to entry. The average treatment effect (ATE) on the treated is estimated via difference-in-differences from a matching estimator.

Three long-run profit differential estimates are used as dependent variables and different versions of the concentration–profit relationship are modeled in the IV and OLS regressions: a simple linear one, a concentration–barrier interaction and a critical concentration level that acts as a threshold.

I find no evidence that concentration has a statistically or economically significant positive impact on persistent profit rate differentials. This is a highly robust result throughout all regressions. Instead, there is some evidence for a statistically and economically significant *negative* causal effect of concentration on profitability—especially when higher concentration is associated with higher mobility barriers. A small number of researchers (Shepherd, 1972; Ravenscraft, 1983; Mueller, 1986; Gschwandtner, 2012) find significant negative coefficients of concentration and of barrier variables separately. However, they all are only able to describe partial correlations.

The article proceeds as follows. Section 1 describes the data and the regressions used to compute long-run differentials; Section 2 presents the results from IV regressions that explain these differentials; Section 3 discusses the natural experiment; Section 4 concludes.

1. Data and estimation results of long-run differentials

The analysis covers business segments located in the United States between 1976 and 2015. Segment-level profit rates and segment controls come from Compustat Segments. Additional firm-level controls originate from the same file and from Compustat North American and Global Fundamentals. All regulated utilities, space and military products, education, and medical and social services are excluded. Data on industry concentration, establishments, and sales used in the computation of some controls are obtained from the US Economic Census of the Department of

Commerce in electronic form.[2] Current Population Survey unionization data are collected from the NBER for years before 1983 and from Hirsch's and Macpherson's Unionstats Web page for thereafter. Non-merger antitrust cases are collected from the websites of the Federal Trade Commission and the Department of Justice.[3] All nonproprietary data are available on request. Where necessary, the Appendix further describes variables in technical detail.

For the baseline model, I follow standard methodology to obtain persistence of profit estimates by modeling the AR(1) process:

$$\delta_{it} = \alpha_i + \lambda_i \delta_{it-1} + \mu_{it}, \tag{1}$$

and computing its unconditional mean as $\hat{p}_i = \frac{\hat{\alpha}_i}{1-\hat{\lambda}_i}$. δ_{it} is the differential of the profit rate of segment i in period t versus the economy-wide average of that period.[4] It includes a permanent and a short-run rent. μ_{it} is a random error. The AR parameter $\hat{\lambda}_i$ measures the speed of adjustment to the equilibrium value, the persistent or long-run profitability differential $\hat{p}_i$. The latter is calculated for all segments with at least 5 consecutive years.

One reason to consider an alternative estimation of $\hat{p}_i$ is that the adjustment of the individual excess profit toward the mean of the economy may be non-monotonic, such that a differential converges quickly with relatively large adjustment steps when its initial magnitude is large and slower when it is close to the average. I allow for this by computing $\hat{p}_i = \frac{\hat{\alpha}_i}{1-\hat{\lambda}_{1i}-\hat{\lambda}_{2i}}$ from the AR(2) process (as in Glen *et al.*, 2003):

$$\delta_{it} = \alpha_i + \lambda_{1i} \delta_{it-1} + \lambda_{2i} \delta_{it-2} + \mu_{it}, \tag{2}$$

for all segments with at least 10 consecutive observations.[5] It is also possible that adjustment speeds differ between positive and negative deviations form the average. Industry exits associated with below average profits should depend to some degree on sunk costs, which are again a function of the depreciation rate of fixed assets. Entries of competitors, imitations of innovations, or augmentations of capacities by incumbents on the other hand are associated with above-average profits and may be limited by the availability of capital goods and time it takes to develop equivalent innovations or to install new plants and equipment. Accordingly, I follow McMillan and Wohar (2011), allow for different parameters (depending on above or below average profit rates), and compute the asymmetric AR model:

$$\delta_{it} = \alpha_i + \lambda_{1i} \delta_{it-1} I_{t-1} + \lambda_{2i} \delta_{it-1}(1 - I_{t-1}) + \mu_{it}. \tag{3}$$

$I_{t-1} = 1$ if $\delta_{it} > 0$ and $I_{t-1} = 0$ if $\delta_{it} \leq 0$. The long-run profit differential is $\hat{p}_i = \frac{\hat{\alpha}_i}{1-\hat{\lambda}_{1i}}$ where $\hat{\alpha}_i > 0$ and $\hat{\lambda}_{1i} > 0$; $\hat{p}_i = \frac{\hat{\alpha}_i}{1-\hat{\lambda}_{2i}}$ when $\hat{\alpha}_i \leq 0$ and $\hat{\lambda}_{2i} > 0$; $\hat{p}_i = \frac{\hat{\alpha}_i}{1-\hat{\lambda}_{1i}-\hat{\lambda}_{2i}}$ in in all other instances.[6] The summary statistics for up to 11,487 profit persistence estimations are displayed in Table 1.[7] Parameter values are in line with those of previous studies and similar to when the models are estimated with Compustat company data.[8] The AR(2) and threshold AR models both increase the average explanatory power of the regressions with the AR(2) explaining the largest fraction of the variation of profit rate differentials. The adjustment is faster for below- than above-average differentials. The AR(2) suggests an initial adjustment speed to a shock similar as the AR(1) model, but a slower convergence later on when the rate of return is close to the average of the economy. The table shows that 80–92% of all segment time series are stationary.

2 The file is assembled by the author and available at online, including technical descriptions.

3 See https://www.justice.gov/atr/antitrust-case-filings, https://www.ftc.gov/site-information/open-government/data-sets and https://www.ftc.gov/policy/reports/policy-reports/annual-competition-reports.

4 Using the deviation from the average allows to remove variation due to cyclical factors or secular trends.

5 A longer minimum time period is chosen due to a loss of a degree of freedom.

6 Whichever parameter is used in the computation of $\hat{p}_i$, a minimum of five nonzero observations are required for the respective AR term ($\delta_{it-1}(1 - I_{t-1})$ or $\delta_{it-1} I_{t-1}$). A minimum of five consecutive observations are always required.

7 In all computations, observations with profit rates in excess of |500%| are excluded. Results are not dependent on the choice of this value.

8 See Table A8 in the Online Appendix. Interestingly, company-level differentials persist longer than segment differentials.

Table 1. Summary statistics from parameter estimations

Parameters	Mean	Standard deviation	First quartile	Median	Third quartile
AR(1)					
λ	0.387	1.081	0.014	0.379	0.697
p	2.1	336.4	−0.9	12.1	22.1
α	0.3	36.7	−1.1	5.1	12.2
Mean observation: 7.5		Mean R^2: 0.32		Regressions: 11,487	Stationary: 87.6%
AR(2)					
$\lambda_1(\lambda_2)$	0.6 (−0.176)	0.785 (0.499)	0.286 (−0.427)	0.59 (−0.197)	0.91 (0.047)
p	4.5	332.8	5.8	16.9	23.5
α	3.3	33.2	2.2	6.3	12.6
Mean Obs.: 12		Mean R^2: 0.45		Regressions: 3188	Stationary: 92.5%
Asymmetric AR					
$\lambda_1(\lambda_2)$	0.454 (0.307)	0.842 (0.793)	0.096 (−0.068)	0.441 (0.233)	0.743 (0.582)
p	4.9	411.0	0	16.1	23.9
α	3.0	23.3	1.3	6.0	11.7
Mean obsevations: 8.4		Mean R^2: 0.42		Regressions: 8056	Stationary: 80.7%

Notes: The table summarizes persistence of profit estimations for the United States from 1976 to 2015 using Compustat Segments. "Stationary" describes the percentage of all segments with characteristic roots $< |0.95|$. Regressions in Section 2 are based on subsamples with fewer observations due to missing values of explanatory variables and winsorization at the 1st and 99th percentiles (reducing standard deviations).

2. Instrumenting industry concentration

Researchers interested in the determinants of persistent profit rate differentials estimate $\hat{p}_i = \beta' \boldsymbol{x_i} + e_i$, where e_i is an error term, $\boldsymbol{x_i}$ the vector of explanatory variables, and β' the coefficient vector.[9] Some authors explain $\hat{\lambda}_i$ instead of $\hat{p}_i$. This is not followed here,[10] since large values of $\hat{\lambda}_i$ may describe a high degree of persistence of a differential that could be negative or very close to 0. Accordingly, finding a positive impact of concentration or barrier variables on this persistence variable provides no decisive evidence of market power. Irrespectively of which variable is chosen as the regressand, the inclusion of a concentration measure in $\boldsymbol{x_i}$ produces an OLS coefficient that does not describe a causal relation due to the numerous endogeneity problems described above. Identification requires an experiment or an IV.

It is not trivial to find an instrument for concentration. I propose the share of industry sales generated by publicly listed firms for the following reason. As companies grow they rely on different sources of financing. Small firms access private persons, venture capital companies, or banks, while larger ones source financial markets directly through share or bond emissions (Tirole, 2010). Due to this size–stock market link it is likely that an industry is more concentrated if more incumbents are stock market listed. The share of public companies in total industry has a highly significantly correlation of 0.31 with the persistence of profit measure from the AR(1) process. *F*-statistics exceed all critical levels with values above 300 when CR4 is regressed on this variable. This is also true for all critical values for the Cragg–Donald *F*-statistic (Stock and Yogo, 2005) in all first-stage regressions of the 2SLS estimations reported in Table 3, providing sufficient confidence to assume that the variable is a strong instrument.

2.1 Exclusion restriction

The exclusion restriction is naturally more challenging. For a problem to emerge, the competitiveness of an incumbent must be partially correlated with its status of being public (while controlling for other observable factors

9 This regression is usually added as a second-stage regression upon running. It is also possible that both equations are estimated simultaneously in the single equation $\delta_{it} = \alpha(x_i) + \lambda(z_i)\delta_{it-1} + \mu_{it}$ (Gschwandtner, 2012), where explanatory variables are included in vectors x_i and z_i. The latter is not possible here, since some variables are not available on an annual basis.

10 For the sake of comparability regressions explaining $\hat{\lambda}_i$ and $\hat{\alpha i}$ are nevertheless included in Table A9 of the Online Appendix.

identified in the regressions). This may result when the status affects its competitiveness through channels unrelated to concentration. It could also be explained by a selection bias where competitive firms are more likely to go and/or stay public (or private). Note that the proposed IV cannot impact the dependent variable directly, since all segments used belong to publicly listed companies. Only an indirect effect is possible where the public status of competitors affects their competitiveness, which in turn determines the long-run profitability of another entity. This means that the first link in the causal chain must be unambiguous and of significant magnitude. This is unlikely for several reasons.

The impact of publicly listed status on performance is unclear. It could be negative as firms face transaction costs of going public and of regularly disclosing financial information. Since their ownership concentration tends to be lower, monitoring incentives are weakened. On the other hand, it could be positive as managers are disciplined by takeover threats, can be incentivized positively with share price based compensation, and are able to access funds from the stock market directly. In any case the impact should be of limited magnitude. First, equity is at the bottom of the pecking-order hierarchy of finance (Myers and Majluf, 1984). Even if equity from an organized public exchange market has capital cost (dis)advantages relative to private sources of equity finance, its effect will be small. Second, literature suggests that family control (ownership or management) is the most important difference between public and private firms that may affect performance. But since this status has very ambiguous effects theoretically and empirically,[11] the true comparative differences between the average firms may actually not be that significant. Effects of family control (as well as of transaction and agency costs) are likely to have at least some mutually offsetting effect. Furthermore, the dimension "family control" does not coincide with a company's status being private or public. Many listed entities are dominated by founding families (like in the automotive sector), while numerous private ones are run and owned by parties unaffiliated with the founders.

With regard to the selection bias, IPO decisions may depend systematically and significantly on persistent profit differentials. However, it is theoretically not clear if highly profitable companies are more or less inclined to go public than unprofitable ones. Corporate finance suggests that the main determinants of this decision are of a different nature. An IPO is most importantly an exit mechanism of entrepreneurs (Zingales, 1995) and venture capitalists (Black and Gilson, 1998) at a certain company life cycle stage; it reflects a desire of pre-IPO investors to diversify (Chemmanur and Fulghieri, 1999); or is a function of market valuation cycles (Lucas and McDonald, 1990). All companies are exposed these factors similarly, while other determinants appear to play at best only minor roles. LBO activity is even less likely to produce an endogeneity problem. Decisions to go private account for less than 0.2% of the aggregate stock market volume in most years, with an exception being the brief LBO boom period in the late 80s (Holmstrom and Kaplan, 2001). In addition, stock market exit decisions seem to be, again, mainly driven by cyclical macroeconomic or other factors[12] that are unrelated to competitiveness or long-run profit rate differentials.

One way to increase confidence in the instrument is to test if it has any significant partial correlation with the observable variables used in the study. I estimate versions of equation (4), where I add the instrument as another regressor, take an individual variable out of the vector of controls, and use it as the dependent variable instead of $\hat{p}_i$. One of the six segment and company-level variables and one of the eight industry-level variables is significant at 5%, while the rest are clearly insignificant at 10%. This contrasts with a highly a significant (at 1%) positive coefficient for the instrument when the CR4 is used as the regressor. The findings (available upon request) suggest that the IV indeed seems to have little impact on firm-level and industry structural variables other than concentration, making the case for effects on persistent profit rate differentials through alternative channels less likely.

To sum up, possible endogeneity producing channels must be very weak and are likely to be even entirely absent, while there is a straightforward direct link between the share of public firms and industry concentration. Thus, I assume that this instrument is at least weakly exogenous.

11 Some find evidence for worse performance of family member managed companies (Perez-Gonzalez, 2006; Bennedsen *et al.*, 2007), while (Anderson & Reeb, 2003; Sraer & Thesmar, 2007) find family ownership and management to have positive effects. Villalonga and Amit (2006) find that family ownership enhances performance when the owner serves as CEO and destroys it when descendants lead.

12 See Kaplan and Stein (1993); Ivashina and Kovner (2011); Demiroglu and James (2010); Axelson *et al.* (2013).

2.2 Regression design

I use the share of industry sales publicly listed companies as an IV for the CR4 in a 2SLS estimation of equation:

$$\hat{p}_i = \beta CR4_i + \alpha_i^n + \alpha_i^t + \delta Controls_i + \epsilon_i, \tag{4}$$

where $\hat{p}_i$ is the persistent profit differential estimate for segment i. The years from which it is computed are different for every segment. Accordingly, control variables represent segment-specific time averages of all observations that are covered by the period over which $\hat{p}_i$ is computed. Exceptions are the main variables of interest, the $CR4_i$ (which is defined for five- and six-digit NAICS industries), the share of sales from public companies and the mobility barrier controls, minimum efficient scale, and strategic investments. To rule out that profitability directly and immediately impacts barrier variables and concentration I use for these variables only the value from the first year of the period from which $\hat{p}_i$ is computed. α^n is a vector of 14 2-digit NAICS fixed effects. α^t is a vector of six time fixed effects where each fixed effect is equal to 1 when $\hat{p}_i$ is computed from observations from this decade (and 0 otherwise). The $Controls_i$ consists of segment and company controls (market share, capital intensity, sales growth, standard deviation of the segment profit rate differential (during the period from which $\hat{p}_i$ is computed), and company diversification HHI (Berry, 1971: 62) and industry controls (minimum efficient scale, strategic investments, average CR4 of industries up and down the value chain, the percentage of industry workers unionized, the share of industry sales going to the final consumption sectors: government and households, and CAPX/total assets).[13] ϵ_i is an error term. Table 2 describes the distribution of all variables used and can be used to assess the economic magnitude of regression results.

One might expect a nonlinear relation between concentration and profitability where the effect is only significantly positive beyond a critical concentration level (Chamberlin, 1929). To account for this I test an alternative version of equation (4) where I add an interaction term between CR4 and a dummy that is equal to 1 when CR4 is above a threshold value (and 0 otherwise). While different thresholds yield equivalent results, I report outcomes for the 60% value used by researchers as a common border line (Scherer, 1980). It is the 90th percentile and corresponds in the distribution of the HHI to 0.15 (same percentile), the value that the DoJ and FTC define as the threshold to "moderate concentration."[14] It is also possible that a positive effect of concentration on profitability is contingent on existence of entry barriers (Bain, 1956a; Porter, 1980), while both of these variables may have no explanatory power individually.[15] Accordingly, the second alternative to equation (4) adds an interaction term of the CR4 and the total value of minimum efficient scale and strategic investments.[16]

2.3 Results

OLS and IV estimations are illustrated in Table 3. Regressions explain up to 35% of the variation of long-run differentials. The samples consist of up to 4270 spells of segment data. Endogeneity tests for all IV regressions are based on the difference of Sargan–Hansen statistics providing strong evidence at a 1% significance level (in a few cases at 5%) against the null that concentration can be treated as exogenous. More attention should accordingly be paid to the IV regressions. The explanatory power and significance of regressions explaining AR(2) estimates is the greatest (as this was also the case in the first-stage regressions), suggesting that the focus should be drawn to these equations.

There is no evidence in any equation for a statistically significant positive effect of concentration on profit differentials. In the linear OLS regressions in Panel A, two coefficients are insignificant and positive, while one is significantly negative. The positive ones become negative in the IV regressions. In all nonlinear IV equations in Panel B, CR4 is negative, while its interaction with the critical concentration dummy is positive (significant in one equation).

13 The implicit GDP price deflator from the Federal Bank of St. Louis is used to denominate all variables are in 2012 \$. All variables computed from Compustat data are winsorized at the 1st and 99th percentiles. This choice is not driving the findings (results when other cutoff points are used are available upon request). Variables only involving Census data are less noisy and not winsorized. See the Appendix for further technical details about the variables used.

14 Results are robust against alterations of the threshold. The reported threshold represents an upper bound of commonly applied values. I also applied 45% (and values within the range), which is the lower bound of what researchers use (Scherer, 1980; Abbasoglu *et al.*, 2007). Regressions with this lower threshold are included in the Online Appendix.

15 See Dunne *et al.* (2013) for some recent evidence that suggests a positive effect of entry barriers on profits.

16 See the Online Appendix for a combination of the critical concentration level and the concentration–barrier interaction.

Table 2. Descriptive statistics of explanatory and other variables

	Mean	Std. Deviation	1st Quartile	Median	3st Quartile
Industry variables					
CR4 (%)	26.43	16.905	12.2	25.9	36.06
HHI approximation	0.055	0.053	0.02	0.04	0.076
Barrier (M$)	55.92	100.92	7.17	22.22	51.94
Minimum efficient scale (M$)	30.52	68.41	2.19	7.0	22.02
Strategic investment (M$)	23.62	49.91	1.30	6.51	22.17
Unionization (%)	7.39	8.31	1.56	4.54	10.21
CAPX/assets	0.034	0.032	0.005	0.027	0.05
Final consumption (%)	45.02	32.23	17.71	36.88	78.86
CR4 upstream (%)	15.97	8.93	10.38	16.72	21.43
CR4 downstream (%)	25.6	19.64	11.95	22.29	34.52
Industry Imports (%)	1.9	2.8	0	0.5	2.5
Industry exports (%)	0.4	4.8	0.2	1.7	6.6
Public company share (%)	65.82	87.18	16.52	44.11	85.16
Segment and company variables					
Market share (%)	2.147	5.161	0.055	0.289	1.554
Sales growth (%)	18.22	33.24	1.32	9.01	23.83
Sales/assets	1.171	0.928	0.396	1.035	1.69
Profit standard deviation	15.54	22.77	4.62	7.97	15.15
Diversification	0.126	0.207	0	0	0.203

Notes: The table summarizes the explanatory variables. The sample covers the observations from the regressions of Column (1) in Table 3. Barrier is the sum of minimum efficient scale and strategic investments, final consumption is the share of industry sales sold to government and households, CR4 upstream and downstream are average CR4s of supplying and purchasing industries, and "diversification" is the diversification HHI (Berry, 1971: 62). The HHI approximation is the lower bound of the HHI given the available concentration ratios (Hall and Tideman, 1967). Public company share is the percentage of industry sales produced by publicly listed companies. Variables are described in the text and the Appendix.

However, coefficient magnitudes only imply a lower (roughly half) but nevertheless *still negative* effect of concentration on profitability above the threshold. The strongest and most robust result is the concentration–barrier interaction in Panel C, which turns out to be negative in 5 of 6 OLS and IV estimations and highly significant negative in all three IV regressions. As far as I am aware of, this is a novel and theoretically unexplained finding.

In the significant regression in Panel A [the IV estimation in Column (2)] the economic significance implied by the concentration coefficient is moderate. Moving from the first quartile of the distribution of CR4 in the regression's estimation sample to the third decreases the long-run profit rate differential by 2.5 percentage points (the median profit differential is between 12% and 17%, depending on the AR model). In the significant IV regression that incorporates the critical concentration threshold a rather extreme movement from the industry with the lowest concentration up to the threshold level of 60% CR4 decreases the profit rate by 28 points. A movement from the threshold level up to the industry with the highest degree of concentration reduces the profitability by another 13 percentage points. The economic significance implied by OLS estimates is in all cases much lower, implying a bias that makes the inverse relation between concentration and profitability appear to be weaker than it actually is.

With respect to the interpretation of the main results of interest in Table 3, insignificance of concentration can be explained well from X-inefficiency (Leibenstein, 1966; Stigler, 1976) or cost of maintaining market power arguments (Spence, 1977). Insignificant or small effects of barrier variables may be rationalized with contestable markets (Baumol, 1982). However, explanations of the negative effect of concentration and of its interaction with barriers are either nonexistent or not supported by the data. Versions of some of the dynamic models following Jovanovic (1982) and Ericson and Pakes (1995) describe how higher mobility barriers may reduce concentration, which in turn results in lower profitability (Amir and Lambson, 2007). But this cannot explain a negative effect of concentration when barriers are controlled for, while a negative effect of their interaction term is the opposite of what that intuition implies. The inverted-U relation between concentration and the degree of competition described by Mueller (1986) cannot be reproduced with any of the nonlinear specifications either. More promising are ideas formulated by

Table 3. IV regressions explaining long-run profitability differentials

	Persistent profit rate differential estimated from:					
	AR(1)		AR(2)		TAR	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Controls						
Segment and company	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Panel A: Baseline regression						
CR4	0.0068	−0.15	−0.095*	−0.53**	0.023	−0.2
	(0.03)	(0.17)	(0.05)	(0.23)	(0.04)	(0.19)
Observations	4286	4206	1325	1313	2982	2942
R^2	0.23	0.23	0.35	0.30	0.20	0.19
Panel B: Critical concentration level						
CR4	−0.0051	−0.14	−0.09	−0.52**	0.00058	−0.19
	(0.04)	(0.16)	(0.06)	(0.22)	(0.05)	(0.18)
CR4 × threshold	0.02	0.064	−0.0092	0.23*	0.039	0.12
	(0.04)	(0.09)	(0.05)	(0.12)	(0.05)	(0.10)
Observations	4286	4206	1325	1313	2982	2942
R^2	0.23	0.24	0.35	0.32	0.20	0.19
Panel C: Concentration–barrier interaction						
CR4	0.026	−0.074	−0.1*	−0.5**	0.046	−0.11
	(0.04)	(0.17)	(0.05)	(0.26)	(0.04)	(0.19)
CR4 × barriers	−0.00027	−0.0024***	0.00012	−0.0042***	−0.00034	−0.0028***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4270	4192	1321	1310	2972	2932
R^2	0.23	0.21	0.35	0.13	0.20	0.15

Notes: This table reports OLS and IV regressions explaining long-run profit differential estimates from an AR(1), AR(2) and a threshold AR(1) ("TAR") processes. The sample covers US business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for two-digit NAICS aggregates. CR4 is the four-firm concentration ratio. "Threshold" is a critical concentration level that is 1 when the CR4 is above 60% and 0 otherwise. "Barriers" are the sum of industry strategic investments and minimum efficient scale. All regressions include minimum efficient scale, strategic investments, and other industry and segment controls. Variables interacted with CR4 are included in the regressions, but not printed in the table. The IV is the share of industry sales produced by publicly listed companies. Standard errors (in parentheses) are robust for OLS regressions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Ravenscraft (1983) and Keil (2017a), which imply that larger incumbents within an industry represent more competitive direct intra-industrial rivals that put greater competitive pressure on the profit margins of any given firm.

2.4 Robustness

While the use of the CR4 is standard, results may still be sensitive to the choice of the concentration indicator. Unfortunately, the HHI cannot be used due to its limited availability (only for manufacturing and not the entire period). Instead, I approximate the HHI from the four available concentration ratios in the most simple possible way as the smallest HHI that is consistent with these ratios (see Hall and Tideman, 1967, and the Appendix for details). The resulting indicator has a correlation of over 0.9 with the Census HHI for manufacturing and yields results virtually identical to the ones based on the CR4 (see Table A5 in the Online Appendix). Results in Panels B and C could also be driven by the choice of the interacted barrier variable (e.g., using strategic investment *or* minimum efficient scale) or the critical concentration level (a lower threshold value). Furthermore, another nonlinear specification where a squared term is added may be more suited. All these results are included in Online Appendix Table A7.

The findings of no significant positive effect of concentration are stable and hold for these alternatives to the threshold specification. The use of other barriers still results in a significant negative effect of the concentration-barrier interaction.

Another source of concern may be a possible bias that may be produced by the short period from which long-run differentials are estimated. While the mean length is 12 for the AR(2) estimates (more than in some other studies), the minimum values of 5 and 10 may still be considered as too short. They were chosen for the sake of a greater observation count in the second-step estimations. Still, I ran all regressions for the AR(1) model, restricting the observations to those persistent profit rate differentials computed from at least 15 years. Except for an expected loss in estimate precision, previously obtained findings are not changed much (see Table A6 in the Online Appendix). Most importantly, coefficients do not become significantly positive (results for a minimum of 20 years are equivalent and available upon request).

It could also be that statistically unstable processes [a $\lambda_i > |0.95|$ in the case of long-run profit rate differentials obtained from the AR(1)] or very low, negative profit rate differentials that are not economically viable (e.g., $\hat{p}_i < -0.5$) are driving the results. To test this I exclude all such observations and estimate all regressions from Table 3 again. This reduces the estimation sample significantly, by almost 20%. Results are included in Table A1 of the Online Appendix and look very similar. They even yield less evidence in support of a positive relationship and point more than before toward a negative impact of concentration—the only significant positive coefficient in Table 3 (the concentration–threshold interaction variable in Column 4, Panel B) becomes insignificant, while the positive insignificant coefficient in Column 1, Panel B becomes negative and significant.

A further point of critique may be that heterogeneity of results due to differences of the nature of competition between industries should be expected. For example, one may expect differentiation between firms when advertising or R&D expenditures are high—industry structure may only matter for homogeneous industries (Mueller and Raunig, 1999). The equations with a barrier–concentration interaction term in Panel C in Table 3 account for heterogeneity along precisely this dimension. Regressions with an interaction term between strategic investment and concentration in Panel D (and between minimum efficient scale and concentration in Panel C) in Table A7 in the Online Appendix are even more explicit. None of the results suggests significant positive concentration coefficients for low values of strategic investment. However, advertising and R&D spendings do matter, and there really seems to be some heterogeneity with respect to these variables: in industries with more strategic investment an increase in the HHI implies lower persistent profit rates. This relation is clearly weaker or even absent when strategic investments are low. Unsurprisingly, the same results emerge from a sample split with respect to strategic investment percentiles (available upon request).

Potentially more important may be heterogeneity on the business segment, not the industry level.[17] Specifically, it could be that the negative effect of concentration on profitability is driven by small companies in the sample, while large ones may even be in a position to benefit when concentration increases due to easier coordination or (tacit) collusion. I explore such a differential impact with a sample split where I identify "relatively small" segments as those in the bottom tercile of the market share distribution of their respective sector. "Relatively large" ones are in the top tercile.[18] I then estimate all regressions from Table 3. Results for the small segment sample are in Table A2 and for the large sample in Table A3 in the Online Appendix. They show that there is indeed some heterogeneity. The negative effect of concentration is driven largely by small companies, which may be in a more exposed position when industry concentration increases because rivals become more competitive and able to exploit economies of scale (power is reduced due to a decrease in the observation count compared to the baseline table). However, large companies do not benefit from increases in industry concentration. Instead, they seem to be little effected, as all coefficients of interest are insignificant, except a single one (which is weakly significant and implies a negative relation). Larger units may on average be better at responding to competitive threats and catch up with strong rivals.

I addressed several data quality and endogeneity problems simultaneously. However, it may be of interest to determine which of these are responsible for how the findings here differ from those of other studies. I attempt to reproduce the results of others by reintroducing errors. Positive significant concentration coefficients in the simple linear OLS specification result when control variables are dropped (those which were included to lessen endogeneity

17 I thank an anonymous referee at Industrial and Corporate Change for pointing this out.

18 Results are equivalent when quartiles are used and when I use the distribution of entire sample, not the individual sectors.

problems); industries with high import and export volumes are included; time averages for CR4 are used (instead of the first observation of the period from which $\hat{p}_i$ is computed) and when segment is replaced by company data. Table A4 in the Online Appendix shows how coefficients turn positive and increase in significance when these problems are reintroduced consecutively. In the first step, dropping industry and market share controls takes away significance of the negative coefficient of the second OLS regression in Table 3, while a positive one becomes significant. Adding trade exposed industries results in all coefficients being positive and two significant. Using time averages instead of beginning-of-period concentration data produce throughout highly significant positive coefficients. One can see that this also holds for company-level data.

3. Mergers as a natural experiment

3.1 Unsuccessfully challenged mergers

The IV used in the previous section is not based on some physical process that is automatically exogeneous. Even with the arguments provided for weak exogeneity objections may still remain. Accordingly, I use mergers and acquisitions which were unsuccessfully challenged by the US DoJ or the FTC as a natural experiment. They are interpreted as treatment effects representing shocks to industry structure and increases in the degree of concentration in an environment of barriers to entry.[19]

This is the first analysis explaining accounting profit rates (or measures derived from them) in a difference-in-differences framework where mergers challenged by antitrust authorities in the US are utilized. However, there are two related recent studies. Egger and Hahn (2010) analyze merging banks in Austria, finding higher returns on equity, greater productivity, and lower costs. Gugler and Szücs (2016) examine main competitors of firms whose merger was challenged by the European Commission. They detect a positive effect of mergers on the annual return of assets. More distantly related, Ornaghi (2009) and Szücs (2014) use mergers as natural experiments to analyze R&D spendings, while Gugler and Siebert (2007) focus on efficiency gains in the semiconductor industry. Other studies focus either on single individual mergers or do not attempt to determine causality by estimating ATEs or average treatment effects on the treated (ATT).

The present application adopts ideas from previous work. Most importantly, Gugler and Szücs (2016) interpret the occurrence of an unsuccessfully challenged merger as a shock to the structure of the respective industry experiencing the merger. As in this study, merging entities are excluded from the file to rule out efficiency-related causalities. However, I use a different dependent variable, DoJ and FTC challenges, and a data sample for the United States.

3.2 A matching estimator

Since one cannot assume that the treatment is assigned randomly, the obvious problem with the use of mergers is a selection bias. As in Egger and Hahn (2010), the solution offered is to take first differences between persistent profit rate differentials from before and after the merger and apply a matching estimator that assigns matches using observable covariates of the pre-merger period, $X_{i,t-1}$. This estimates directly the difference-in-differences while circumventing the asymptotic biases from self-selection. Of course, the assumption must be that the treatment assignment is random, conditional on the characteristics observed.[20]

The persistent profit rate differentials are calculated from the baseline AR(1) process for the 5 years preceeding the merger and for the 5-year period starting with in merger year t.[21] The differential $\Delta\hat{p}_{it} = \hat{p}_{i\ post} - \hat{p}_{i\ pre}$ is used as the outcome variable of interest. If the industry in which a segment operates experienced a merger in the 5 years preceding year t, then this observation is excluded from the analysis and does not serve as treated or controlled observation. The covariates in X_{it-1} only include the pretreatment year's values of the industry- and segment-level variables used as controls in the previous section. To further migrate concerns about a bias due to omitted relevant covariates,

19 Antitrust authorities use industry concentration as the main source of concern in their legal complaint documents, alongside with an evaluation of barriers to entry into the specific industry.

20 The matching estimator described below offers a solution for an obvious violation of this condition in the present setting.

21 Using the AR(2) or TAR reduces the observation count dramatically, as only few segments have such long series of consecutive observations and experienced a "treatment."

Table 4. Nearest neighbor matching estimation of the ATT

	(1)	(2)
ATT	−3.987**	−3.980*
Standard error	1.945	2.383
P-value	0.04	0.095
Perfect 2-digit NAICS matches	Yes	Yes
Minimum # of control observations/treated observations	1	10
Treated observations	389	291
Observations	3880	2096

Notes: This table reports the ATT from a nearest neighbor matching estimator. The dependent variable is the difference between the long-run profit differential AR(1) estimate for the 5-year pre-merger period and the one for the 5-year post-merger period. The sample covers US business segments and a period from 1985 to 2014. Perfect matches are required for the variables year and the 2-digit NAICS classification. Other pre-merger industry and segment variables are used as covariates. Estimations are corrected for a large-sample bias due to the inclusion of multiple continuous covariates. Estimation (1) has at least 1 nontreated observation matched to one treated, while Estimation (10) requests a minimum of 10 control observations. Standard errors (in parentheses) are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

I add pre-treatment values of industry imports and exports in percent of total sales and the segment-level variables log of total assets, a conglomerate membership dummy (for when company sales in other industries account for at least 30%), and a dummy for the existence of a debt rating by a major agency (S&P, Fitch, Moodys, or Duffs & Phelps). The matching estimator is a nearest neighbor match that is corrected for the large-sample bias occurring when observations are matched on more than one continuous covariate. The ATT is the difference in the pre- or post-merger change of the long-run profit differential between the observed outcome of treated individuals, $\Delta\hat{p}^1_{it}|d_{it}=1$, and the unobserved potential outcome if the treated individuals were not treated, $\Delta\hat{p}^0_{it}|d_{it}=1$. Since the latter is counterfactual, it has to be estimated from the control group $\Delta\hat{p}^0_{it}|d_{it}=0$. Using $d_{i,t}$ as a dummy variable that is 1 when a merger occurred in industry i in year t and 0 otherwise, the ATT is then given by:

$$ATT = E(\Delta\hat{p}^1_{it}|d_{it}=1, X_{it-1}) - E(\Delta\hat{p}^0_{it}|d_{it}=1, X_{it-1}), \tag{5}$$

and the nearest neighbor matching estimator of the ATT by:

$$ATT_{match} = E_{(X_{it-1}|d_{it}=1)}[E(\Delta\hat{p}^1_{it}|d_{it}=1, X_{it-1}) - E(\Delta\hat{p}^0_{it}|d_{it}=0, X_{it-1})]. \tag{6}$$

In total, 419 segments are located in industries experiencing a merger but not being involved themselves while having non-missing values for all pretreatment covariates, a sufficient number of observations to estimate the pre- and post-merger long-run differentials, and no experience of another merger in the recent past. With the usable control variables this adds to a total of up to 9830 observations that can be used in the estimation. Table 4 lists the ATT computed from the matching estimation. Two different estimators are included. All require perfect matches by year and the two-digit NAICS level. Estimation (1) requests a minimum of 1 control observations for a treated 1, while Estimation (2) requires at least 10. However, the precision of the estimate decreases due to a reduction in the sample size.

Results are in line with OLS and IV regressions above. Mergers that are likely to increase concentration have a consistently *negative* effect on persistent profit rate differentials. In one it is statistically significant at 5%, while it is significant at 10% in the second. The economic magnitude of the point estimates is significant. A merger decreases the long-run profit rate differential by almost 4 percentage points, using the significant point estimate in equation.

3.3 Validity

Identifying the ATT requires that the assignment of firms to the treatment is random. The matching estimator is consistent if this is true, conditionally on the vector of observable covariates, X_{it-1} (unconfounded). Furthermore there must be comparable observations such that there are probabilities between 0 and 1 that subjects are in the treated and in the control group (overlap). Given the rich set of controls and the acceptable number of observations, I assume both conditions are fulfilled.

Validity of an estimation of the ATT also rests of the parallel trends assumption. I reran the entire model in an equivalent version as a difference-in-differences regression with pretreatment covariates, industry, year fixed effects, and lags and leads of the treatment indicator. The dependent variable is replaced by annual profit rate differentials. Figure A1 shows that there is no preexisting trend and a moderate, but statistically not significant decline of profit rates post-merger. This increases the confidence in the estimation results from the natural experiment.

4. Conclusion

Contrary to most related empirical research, I find no trace of any evidence that more industry concentration leads to greater profitability. Concentration neither raises long-run profit rates via a simple linear relation, nor when a critical concentration threshold or an interaction with barriers to entry are considered. Significant positive coefficients can only be reproduced by reintroducing measurement, heterogeneity, and endogeneity problems.

Estimations identifying causality rather point to the opposite—there is a statistically weak but significant *negative* effect of concentration on long-run profitability. This result is especially pronounced for interactions between profitability and barriers to mobility, which is a novel finding. It is robust for different estimates of long-run profit rate differentials. The negative effect of concentration is obtained from IV estimates where the share of stock market listed firms in an industry is used to instrumental concentration. It holds when mergers that were unsuccessfully challenged by an antitrust authority are used as treatments in a matching estimator of difference-in-differences.

Supplementary material

Supplementary material is available at *Industrial and Corporate Change* online.

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Appendix

Variable construction

Long-run differentials are estimated annual segment-level ratios of operating profit to identifiable total assets from S&P's Compustat Segments. The segment unit analyzed here includes all operations of a company which are located in the United States and taking place within the same five- or six-digit NAICS (or four-digit SIC) industry. Overhead and corporate assets and earnings are divided among operative segments in proportion to their shares in total company sales. All variables used in the second stage are means for each segment computed over the years from which the long-run differential is estimated. The market share is the ratio of Compustat segment sales (SALE) to total industry sales (from US Census data). "Diversification" is the company diversification HHI (Berry, 1971: 62):

$$\text{diversification}_c = 1 - \sum_{i=1}^{N} \left(\frac{\text{Segmenti's sales}}{\text{Company sales}} \right)^2 .$$

The subscript c indicates "company." The share of industry sales going to final consumption sectors (government and households) is computed from detailed input–output use tables, as do the data used to compute the average concentration of upstream and downstream industries along the value chain. These variables are computed as:

$$\text{CR4 upstream}_i = \sum_{j=1}^{N} \left(CR4_j \frac{I_{ij}}{I_i} \right), \qquad \text{CR4 downstream}_i = \sum_{k=1}^{M} \left(CR4_k \frac{X_{ik}}{X_i} \right).$$

I_{ij} is the value of inputs of intermediate goods that industry i obtains from industry j and I_i the sum of intermediate inputs into industry i. X_{ik} is the output industry i sells to industry k and X_i the total output of industry i. N industries supply inputs to and M industries buy output from industry i. Purchases by government and households are assigned a CR4 of 100 and 0, respectively. The sum of the share of total sales to household and government ("final consumption") is also computed from input–output data. Minimum efficient scale of industry i is computed from both Compustat and Census data as:

$$\text{Minimum efficient scale}_i = \left(\frac{\text{sales}_i}{\text{establishments}_i} \right)_{\text{Census}} \times \left(\frac{\text{total assets}_i}{\text{sales}_i} \right)_{\text{Compustat}},$$

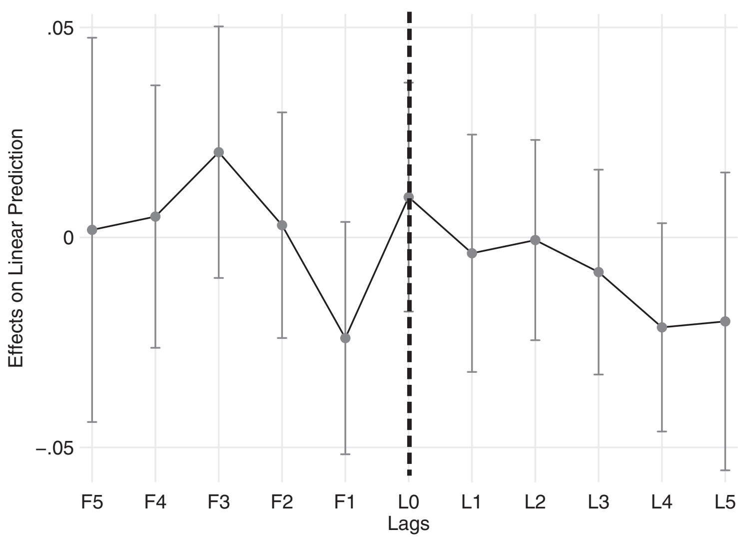

Figure A1. Exploring possible preexisting trends.

Notes: This figure plots the coefficient estimate of annual profit rate differential on the pretreatment covariates used above, excluding import- and export-intensive industries of the regression $Differential_j = \beta \sum_{t=-5}^{5} D_{st} + \gamma Covariates_{i,t-1} + \alpha_i + \alpha_t + \epsilon_j$, where $\sum_{t=-5}^{5} D_{st}$ refers to a set of dummy variables on the industry-treatment year level from 5 years before to 5 years after the merger. α_i and α_t are industry and year fixed effects. Confidence intervals show the 90% significance level with standard errors computed on the state-year level.

where the number of establishments is used from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages Data Files wherever Census data are missing. The second fraction is the industry-year median. Strategic investments are computed from Compustat advertising (XAD) and R&D (RDX) expenditures as a stock variable that accumulates and depreciates (linearly) over time:

$$\text{Strategic investment}_i = \sum_{t=0}^{4}(1 - 0.2 \times t)\text{ADX}_{-t,i} + \sum_{t=0}^{9}(1 - 0.1 \times t)\text{RDX}_{-t,i}.$$

$\text{ADX}_{-t,i}$ and $\text{RDX}_{-t,i}$ are the industry median advertising and R&D expenses from t years ago, respectively. Total 20% and 10% linear depreciation rates are suggested by empirical research (Bloch, 1974; Tang and Popp, 2016).

The minimum value that the HHI can have in an industry for which only the concentration ratios are known (Hall and Tideman, 1967) is the simplest way to combine the information of all available ratios into one single number. It has the interpretation of the lower bound of the Herfindahl–Hirschman). For US Census publications that include the 4-, 8-, 20-, and 50-firm concentration ratios (CR4, CR8, CR20 and CR50), the computation is given by:

$$\text{HHI lower bound} = 4\left[\frac{CR4}{4}\right]^2 + [8-4]\left[\frac{CR8 - CR4}{8-4}\right]^2 + [20-8]\left[\frac{CR20 - CR8}{20-8}\right]^2 + [50-20]\left[\frac{CR50 - CR20}{50-20}\right]^2.$$

Additional Regression Results

Online Appendix

Robustness Tables

Results from Alternative Regression Specifications