Is There a Causal Effect of Concentration on Persistent Profitability Differentials?

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This article searches for a causal effect of market share concentration on estimates of persistent profitability differentials developed by Müller (1977, 1986). I offer solutions to identification problems that plague all related analyses by applying IVs and a natural experiment, by taking advantage of the time structure of panels, new control variables and by addressing several data quality and measurement complications. This is the first study that explains estimates of persistent profit differentials using business segments data. 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* L10, D40)

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Dynamic theories of competition following Schumpeter (1942) describe how not just external shocks, but healthy competition itself can produce disruptive impulses that naturally dis-equalize 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. Müller (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 micro unit 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 market share concentration is endogeneous. One is the use of an instrumental

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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. The other is a natural experiment where mergers that were unsuccessfully challenged by the U.S. anti-trust authority are used as shocks to industry structure.

Most persistence of profit 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 & Wilson, 1999; Glen *et al.* , 2003; Crespo-Cuaresma & 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 & Deeds, 1996). Accordingly, the observation of persistency and of persistent differentials are only a necessary, not sufficient conditions 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 towards a weak positive impact of concentration on persistent profit rate differentials. Müller (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 non-linear way, where concentration decreases profitability at low levels of concentration and increases it at higher ones. Using Compustat data for U.S. manufacturing industries, Gschwandtner (2012) detects negative and positive coefficients for a concentration ratio in regressions on short- and long-run persistence. They 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 & 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

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

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, several studies (for example, Müller, 1986; 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, 2016) published by national statistics offices (the Economic Census in case of the U.S.).

Third, existing articles do not account for imports, can make 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 & Posner, 1981; Helpman & Krugman, 1989; Levinsohn, 1993; Ghosal, 2002). Exports can likewise produce measurement errors when domestic producers cater to markets abroad.

Fourth, company data is most widely used while 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 U.S. 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 & 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).

Sixth, no author attempts to address the most obvious forms of likely endogeneity of concentration indicators that results 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 & Evans, 1994; Driffield, 1999; Dunne *et al.* , 2013). This could explain a negative concentration-profit relationship. Labor unions are know to place greater effort into organizing more concentrated industries

(Kaufman & Hotchkiss, 2006, pp. 637-638, Hirsch, 1997). Here, unionization and the CR4 correlate highly significantly with a positive 0.17. Since unions also affect profits negatively and capture parts of possible monopoly rents (Salinger, 1984; Doucouliagos & 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 up- and down-stream industries (a highly significant positive correlation of 0.2 using the CR4). There is also a reverse causality problem where high profits ease financial constraints (Greenwald *et al.* , 1984; Myers, 1984; Myers & 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. It is safe to say that previous studies did not identify a causal relation between persistent profitability estimates and market share 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 U.S. Census concentration measures from a large file compiled by the author – with manufacturing and non-manufacturing 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 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.[2] The second solution is based on a natural experiment where I interpret mergers that were unsuccessfully challenged by U.S. anti-trust authorities as shocks to industry structure which are increasing concentration. The average treatment effect 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

[2] Concentration data is published in 5-year intervals and interpolated here. This implies in fact that the industry structural variables of concern are a weighted average of the first observation in the period of analysis and the latest *preceeding* observation before that period.

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. Very few researchers (Shepherd, 1972; Ravenscraft, 1983; Müller, 1986; Gschwandtner, 2012) find significant negative coefficients of concentration and of barrier variables *separately* (not interacted). None of the few existing theoretical explanations is supported by the data.

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

1 Data and Estimation Results of Long-run Differentials

The analysis covers business segments located in the U.S. 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, medical and social services are excluded. Data on industry concentration, establishments and sales used in the computation of some controls are obtained from a file containing all concentration data ever produced by the U.S. Economic Census of the Department of Commerce in electronic form.[3] 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.[4] All non-proprietary data are available on request. Where necessary, the online appendix further describes variables in technical detail.

I follow standard methodology to obtain persistence of profit estimates by modeling an 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.[5] 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

[3] It is assembled by the author and available at online, including technical descriptions.

[4] 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.

[5] Using the difference to the average allows to remove variation due to cyclical factors or secular trends.

consecutive years.

There are reasons to consider alternative estimations of $\hat{p}_i$. First, the adjustment of the individual excess profit towards 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.[6] 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 & Wohar (2011), allow for different parameters 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.[7] The summary statistics for up to 11,487 profit persistence estimations are displayed in table 1.[8] Parameter values are in line with those of previous studies and similar to when the models are estimated with Compustat company data.[9] 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. Most time series are stationary.

[6] A longer minimum time period is chosen due to a loss of a degree of freedom.

[7] Whichever parameter is used in the computation of $\hat{p}_i$, a minimum of 5 non-zero 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 5 consecutive observations is always required.

[8] In all computations, observations with profit rates in excess of |500%| are excluded.

[9] See table 8 in the online appendix. Interestingly, company level differentials persist longer than segment differentials.

Table 1: Summary Statistics from Parameter Estimations

	Mean	Std. Deviation	1st Quartile	Median	3st Quartile
AR(1)					
λ	.387	1.081	.014	.379	.697
p	2.1	336.4	-0.9	12.1	22.1
α	0.3	36.7	-1.1	5.1	12.2
Mean Obs.: 7.5	Mean R^2: .32		Regressions: 11,487		Stationary: 87.6%
AR(2)					
$\lambda_1(\lambda_2)$	.6 (-.176)	.785 (.499)	.286 (-.427)	.59 (-.197)	.91 (.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: .45		Regressions: 3,188		Stationary: 92.5 %
Asymmetric AR					
$\lambda_1(\lambda_2)$	.454 (.307)	.842 (.793)	.096 (-.068)	.441 (.233)	.743 (.582)
p	4.9	411.0	0	16.1	23.9
α	3.0	23.3	1.3	6.0	11.7
Mean Obs.: 8.4	Mean R^2: .42		Regressions: 8,056		Stationary: 80.7%

The table summarizes persistence of profit estimations for the U.S. from 1976 to 2015 using Compustat Segments. "Stationary" describes the percentage of all segments with characteristic roots < |0.95|. Regressions in sections 2 are based on subsamples with fewer observations due to missing values of explanatory variables, the exclusion of dynamically unstable series and winsorization (reducing standard deviations significantly).

2 Instrumenting Industry Concentration

Researchers interested in the determinants of persistent profit rate differentials estimate $\hat{p}_i = \boldsymbol{\beta}'\boldsymbol{x_i} + e_i$, where e_i is an error term, $\boldsymbol{x_i}$ the vector of explanatory variables and $\boldsymbol{\beta}'$ the coefficient vector.[10] Some authors explain $\hat{\lambda}_i$ instead of $\hat{p}_i$. This is not followed here,[11] 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 zero. Finding a positive impact of concentration or barrier variables on persistency of such a differential provides no evidence for 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 emmissions (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 & 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.

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 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 trans-

[10] 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.

[11] For the sake of comparability regressions explaining $\hat{\lambda}_i$ and $\hat{\alpha i}$ are nevertheless included in table 9 of the online appendix.

action 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 & 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,[12] 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 regards 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 suggest 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 & Gilson, 1998) at a certain company life cycle stage; it reflects a desire of pre-IPO investors to diversify (Chemmanur & Fulghieri, 1999); or is a function of market valuation cycles (Lucas & 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 & Kaplan, 2001). In addition, stock market exit decisions seem to be, again, mainly driven by cyclical macroeconomic or other factors[13] 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 $\hat{p}_i$. 1 of the 6 segment and company level variables and 1 out of the 8 indus-

[12] 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 & Amit (2006) find that family ownership enhances performance when the owner serves as CEO and destroys it when descendants lead.

[13] See Kaplan & Stein (1993); Ivashina & Kovner (2011); Demiroglu & James (2010); Axelson *et al.* (2013).

try 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 four-firm concentration ratio 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 straight forward direct link between the share of public firms and market share concentration. Thus, I assume at weak exogeneity for this instrument and use it as an IV for the CR4 in a 2SLS estimation of equation

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

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 5- and 6-digit NAICS industries), the share of sales from public companies and the mobility barrier controls minimum efficient scale and strategic investments. To lessen endogeneity concerns I use for these variables only the value from the first year of the period from which $\hat{p}_i$ is computed. $\boldsymbol{\alpha^n}$ is a vector of 14 2-digit NAICS fixed effects. $\boldsymbol{\alpha^t}$ is a vector of 6 time fixed effects where each fixed effect is equal to 1 when $\hat{p}_i$ is computed from observations from this decade (and zero otherwise). The remainder 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, p. 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, CAPX/total assets).[14] ε_i is an error term. Table 2 describes the distribution of all variables used.

One might expect a non-linear 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

[14] The implicit GDP price deflator from the Federal Bank of St. Louis is used to denominate all variables are in 2012 $. Every variable involving Compustat data is winsorized at the 1st and 99th percentile. See the online appendix for further technical details about the variables used.

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	.055	.053	.02	.04	.076
barrier (M$)	55.92	100.92	7.17	22.22	51.94
min. efficient scale (M$)	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	.034	.032	.005	.027	.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 & Company Variables					
market share (%)	2.147	5.161	.055	.289	1.554
sales growth (%)	18.22	33.24	1.32	9.01	23.83
sales/assets	1.171	.928	.396	1.035	1.69
profit std. deviation	15.54	22.77	4.62	7.97	15.15
diversification	.126	.207	0	0	.203

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, "diversification" is the diversification HHI (Berry, 1971, p. 62)). The HHI approximation is the lower bound of the HHI given the available concentration ratios (Hall & 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.

results, I report outcomes for the 60% value which is used by researchers as a common border line Scherer (1980) and which corresponds in the distribution of concentration indexes (90th percentile) to the 0.15 HHI that the DoJ and FTC define as the threshold to "moderate concentration".[15] 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.[16] 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.[17]

OLS and IV estimations are illustrated in table 3. They explain up to 35% of the variation of long-run differentials. The samples consist of up to 4,270 spells of segment data. Endogeneity tests for all IV regressions are based on the difference of Sargan-Hansen statistics provide 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, 2 coefficients are insignificant and positive while one is significantly negative. The positive ones become negative in the IV regressions. In all non-linear IV equations in panel B, CR4 is negative while its interaction with the critical concentration dummy is positive (significant in 1 equation). 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 out of 6 OLS and IV estimations and highly significant negative in all 3 IV regressions. As far as I am aware of, this is a novel 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 1st quartile of the distribution of CR4 in the regression's estimation sample to the 3rd decreases the long-run profit rate differential by 2.5 percentage points (the median profit differential is between 12 and 17 percent, 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

[15]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 (Abbasoglu *et al.* , 2007; Scherer, 1980). Regressions with this lower threshold are included in the appendix.

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

[17]See the online appendix for a combination of the critical concentration level and the concentration-barrier interaction.

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 & 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	.0068	-.15	-.095*	-.53**	.023	-.2
	(0.03)	(0.17)	(0.05)	(0.23)	(0.04)	(0.19)
Observations	4,286	4,206	1,325	1,313	2,982	2,942
R^2	0.23	0.23	0.35	0.30	0.20	0.19
	Panel B: Critical concentration level					
CR4	-.0051	-.14	-.09	-.52**	.00058	-.19
	(0.04)	(0.16)	(0.06)	(0.22)	(0.05)	(0.18)
CR4 × threshold	.02	.064	-.0092	.23*	.039	.12
	(0.04)	(0.09)	(0.05)	(0.12)	(0.05)	(0.10)
Observations	4,286	4,206	1,325	1,313	2,982	2,942
R^2	0.23	0.24	0.35	0.32	0.20	0.19
	Panel C: Concentration-barrier interaction					
CR4	.026	-.074	-.1*	-.5**	.046	-.11
	(0.04)	(0.17)	(0.05)	(0.26)	(0.04)	(0.19)
CR4 × barriers	-.00027	-.0024***	.00012	-.0042***	-.00034	-.0028***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4,270	4,192	1,321	1,310	2,972	2,932
R^2	0.23	0.21	0.35	0.13	0.20	0.15

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 U.S. business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for 2-digit NAICS aggregates. CR4 is the 4-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. 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.

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 relation between concentration and profitability appear to be weaker than it actually is.

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 & 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 appendix 5). Results in panels B and C could also be driven by the choice of the interacted barrier variable (for example using strategic investment *or* minimum efficient scale) or the critical concentration level (a lower threshold value). Furthermore, another non-linear specification where a squared term is added may be more suited. All these results are included in appendix table 6. 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.

I addressed several data quality and endogeneity problems simultaneously. However, it is interesting 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 re-introducing errors. Positive significant concentration coefficients in the simple linear OLS specification result when control variables are dropped (those which were included to lessen endogeneity 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 7 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 produces throughout highly significant positive coefficients. One can see that this also holds for company level data.

With respect to the interpretation of the main results of interest in table 3, insignificance of concentration can be explained well from X-inefficiency (Stigler, 1976; Leibenstein, 1966) 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 non-existent or not supported by the data. Versions of some of the dynamic models following Jovanovic (1982) and Ericson & Pakes (1995) describe how higher mobility barriers may reduce concentration, which in turn results in lower profitability (Amir & 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 Müller (1986) cannot be reproduced with any of the non-linear specifications either. More promising are ideas formulated by Ravenscraft (1983) and Keil (2017), 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.

3 Mergers as a Natural Experiment

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 U.S. 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.[18]

This idea has been implemented in two closely related recent studies. Egger & Hahn (2010) analyze merging banks in Austria, finding higher returns on equity, greater productivity and lower costs. Examining main competitors of firms whose merger was challenged by the European Commission, Gugler & Szücs (2016) detect a positive effect of mergers on the return of assets. More distantly related, Ornaghi (2009) and Szücs (2014) use mergers as natural experiments to analyze R&D spendings, while Gugler & Siebert (2007) focus on efficiency gains in the semiconductor industry. Most other studies focus either on single individual mergers or do not attempt to determine causality by estimating average treatment effects (ATE) or average treatment effects on the treated (ATT).

The present application adopts elements from the related investigations. As in Gugler & Szücs (2016), the occurrence of an unsuccessfully challenged merger is interpreted as a shock to the structure of the respective industry experiencing the merger. Merging entities are excluded from the file to rule out efficiency related causalities. 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 & 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-

[18] Anti-trust authorities uses market share concentration as the main source of concern in their legal complaint documents, alongside with an evaluation of barriers to entry into the specific industry.

selection. Of course, the assumption must be that the treatment assignment is random, conditional on the characteristics observed.

The persistent profit rate differentials are calculated from an AR(1) process for the 5 years preceeding the merger and for the 5-year period starting with in merger year t. The differential $\Delta\hat{p}_{it} = \hat{p}_{i\ post} - \hat{p}_{i\ pre}$ is used as the outcome variable of interest. If a segment's industry 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 pre-treatment 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 I add lagged 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. Using $d_{i,t}$ as a dummy variable that is 1 when a merger occurred in industry i in year t and zero otherwise, the ATT is then given by

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

and the nearest neighbor matching estimator of the ATT by

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

The ATT is the difference in the pre-/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 $\Delta\hat{p}^{0}_{it}|d_{it} = 0$. 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.

419 segments are located in industries experiencing a merger but not being involved themselves while having non-missing values for all pre-treatment 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 9,830 observations that can be used in the estimation. Table 4 lists the ATT computed from the matching estimation. Three different estimators are included. (1) only requires perfect matches by year while observations in (2) must additionally match perfectly on the 2-digit NAICS level. Estimation (3) restricts the sample to industries whose imports and exports account for less than 10% and 20% respectively.

Table 4: Nearest Neighbor Matching Estimation of the ATT

	(1)	(2)	(3)
ATT	-1.053	-3.987**	-5.493
Standard Error	1.728	1.945	3.678
P-value	.542	.04	.135
Perfect 2-digit NAICS matches	no	yes	yes
Only domestic industries	no	no	yes
Treated observations	419	389	135
Observations	9,830	3,880	796

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 U.S. business segments and a period from 1985 to 2014. Perfect matches are required for the variables year (all estimations) and the 2-digit NAICS classification (columns 2 and 3). 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 (3) restricts industries to such whose industry level imports (exports) account for less than 10% (20%). Standard errors (in parentheses) are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

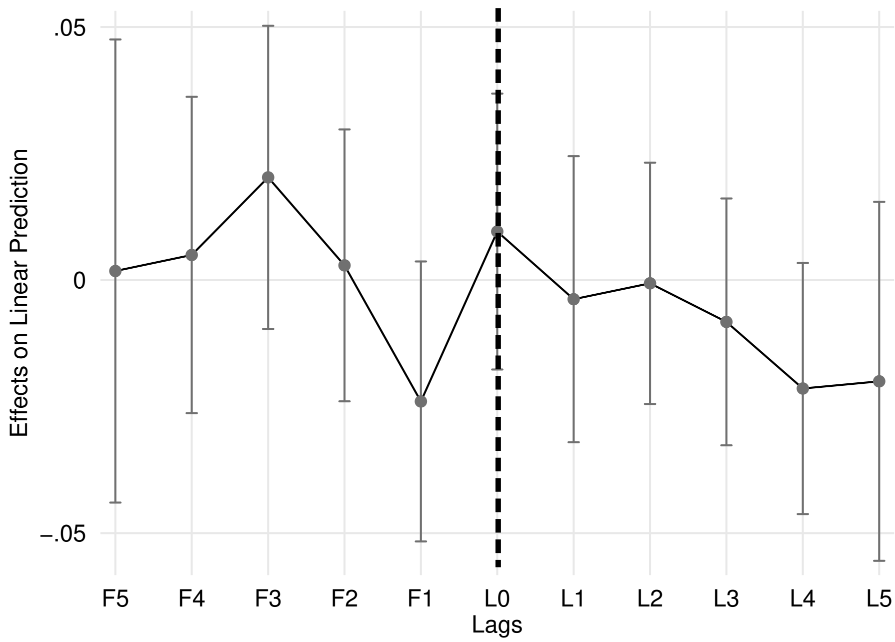
Results are in line with OLS and IV regressions above. Mergers that are likely to increase concentration have a consistently *negative* effect on persistent profit rate differentials in all regressions. In one it is statistically significant at 5%, while it is insignificant in the other two (but almost significant at 10% in one of them). The economic magnitude is significant as a merger decreases the long run profit rate differential by 1-5.5 percentage points, depending on the estimate.

The validity of an estimation of the ATT rests of the parallel trends assumption. I re-ran the entire model in an equivalent version as a diff-in-diff regression with pre-treatment covariates, industry, year fixed effects and lags and leads of the treatment indicator. The dependent variable is replaced by annual profit rate differentials. Figure 1 shows that there is no pre-existing 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 market share concentration leads to greater profitability. Neither for a simple linear relation, nor for a critical concentration

Figure 1: Exploring Possible Pre-existing Trends



This figure plots the coefficient estimate of annual profit rate differential on the pre-treatment covariates used above, excluding import and export intensive industries. of the regression $Differential_j = \beta \sum_{t=-5}^{5} D_{st} + \gamma Covariates_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_j$, 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.

threshold or an interaction with barriers to entry. Significant positive coefficients can only be reproduced by re-introducing 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 are used as treatments in a matching estimator of difference-in-differences.

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Appendix

Variable Construction

Long-run differentials are estimated annual segment level ratios of operating profit (OPS) to identifiable total assets (AT) from S&P's Compustat Segments. The segment unit analyzed here includes all operations of a company which are located in the U.S. and taking place within the same 5- or 6-digit NAICS (or 4-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 U.S. Census data). "Diversification" is the company diversification HHI (Berry, 1971, p. 62),

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

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 up- and downstream industries along the value chain. These variables are computed as

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

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") are also computed from input-output data. Minimum efficient scale of industry i is computed from both Compustat and Census data as

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

where the number of establishments is used from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages Data Files wherever Census data is 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. 20% and 10% linear depreciation rates are suggested by empirical research (Bloch, 1974; Tang & Popp, 2016).

The minimum value that the HHI can have in an industry for which only the concentration ratios are known (Hall & 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

Table 5: IV Regressions based on a HHI Approximation

	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 & 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					
HHI	5	-97	-43*	-371**	19	-132
	(17.85)	(112.44)	(24.93)	(166.96)	(21.48)	(127.17)
Observations	4,286	4,206	1,325	1,313	2,982	2,942
R^2	0.23	0.23	0.35	0.24	0.20	0.18
	Panel B: Critical concentration level					
HHI	7.9	-91	-2.2	-5509	16	-263
	(23.89)	(270.69)	(40.17)	(42,001.53)	(27.84)	(386.96)
HHI × threshold	12	73	-1.7	3784	35	177
	(24.37)	(181.71)	(35.87)	(28,907.18)	(29.35)	(261.80)
Observations	1,310	1,282	385	383	917	902
R^2	0.36	0.35	0.42	-32.26	0.26	0.18
	Panel C: Concentration-barrier interaction					
HHI	18	-35	-51*	-313*	30	-54
	(20.48)	(111.41)	(29.52)	(188.66)	(24.06)	(126.67)
HHI × barriers	-.12	-1.3***	.079	-2.1***	-.11	-1.5***
	(0.11)	(0.29)	(0.11)	(0.68)	(0.12)	(0.32)
Observations	4,270	4,192	1,321	1,310	2,972	2,932
R^2	0.23	0.19	0.35	-0.04	0.20	0.12

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 U.S. business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for 2-digit NAICS aggregates. The HHI approximation is the minimum value that the Herfindahl index can have given the concentration ratios of the industry (see (Hall & Tideman, 1967) and the appendix). "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. 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.

Table 6: Alternative Specifications

	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 & 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: Lower critical concentration level (CR4=45%)					
CR4	.0062	-.16	-.16***	-.55**	.011	-.23
	(0.05)	(0.19)	(0.06)	(0.23)	(0.06)	(0.23)
CR4 × threshold	.00051	.038	.065	.16	.012	.063
	(0.04)	(0.09)	(0.05)	(0.11)	(0.04)	(0.10)
Observations	4,286	4,206	1,325	1,313	2,982	2,942
R^2	0.23	0.24	0.36	0.33	0.20	0.19
	Panel B: Non-linear specification adding squared CR4					
CR4	-.0076	1.8	-.12	.71	-.085	.15
	(0.09)	(2.47)	(0.12)	(4.07)	(0.12)	(1.75)
CR4^2	.0002	-.04	.00027	-.027	.0015	-.0072
	(0.00)	(0.05)	(0.00)	(0.08)	(0.00)	(0.03)
Observations	4,286	4,206	1,325	1,313	2,982	2,942
R^2	0.23	-0.16	0.35	-0.18	0.20	0.16
	Panel C: Concentration-minimum efficient scale interaction					
CR4	.031	.042	-.054	-.21	.045	.027
	(0.03)	(0.14)	(0.05)	(0.20)	(0.04)	(0.17)
CR4 × MES	-.00042	-.0045***	-.00044	-.0061***	-.00016	-.0053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4,539	4,421	1,365	1,350	3,163	3,105
R^2	0.23	0.21	0.35	0.29	0.19	0.15
	Panel D: Concentration-strategic investment interaction					
CR4	-.0079	-.22	-.12**	-.56**	.011	-.21
	(0.04)	(0.15)	(0.05)	(0.23)	(0.05)	(0.18)
CR4 × stra. invest.	-.00072**	-.0048***	.00012	-.0026	-.0005	-.0064***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4,332	4,238	1,330	1,317	3,008	2,961
R^2	0.22	0.18	0.34	0.24	0.18	0.09

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 U.S. business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for 2-digit NAICS aggregates. CR4 is the 4-firm concentration ratio. "Barriers" are the sum of industry strategic investments and minimum efficient scale. 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.

Table 7: Introducing Endogeneity & Measurement Problems to Reproduce the Literature

	AR(1)	AR(2)	TAR	AR(1)	AR(2)	TAR	AR(1)	AR(2)	TAR	AR(1)	AR(2)	TAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Controls												
Segment / Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & market share controls	-	-	-	-	-	-	-	-	-	-	-	-
Trade intensive industries excluded	Yes	Yes	Yes	-	-	-	-	-	-	-	-	-
First year CR4, not time average	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-
Segment, not company data	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-
CR4	.042	-.03	.066**	.06**	.027	.11***	.088***	.083**	.13***	.041**	.036*	.044**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
Observations	6,080	1,617	3,966	4,534	1,480	3,050	5,366	1,699	3,519	8,572	4,958	6,550
R^2	0.20	0.29	0.17	0.36	0.35	0.33	0.34	0.33	0.31	0.44	0.40	0.43

This table reports OLS regressions explaining long-run profit differential estimates from an AR(1), AR(2) and a threshold AR(1) ("TAR") processes. Results compare to equations (1), (3), (5) in panel A of table 3. The sample covers U.S. business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for 2-digit NAICS aggregates. CR4 is the 4-firm concentration ratio. "Trade intensive industries" have imports amounting to at least 10% or exports amounting to 20% of industry output. The CR4 is either taken from the first observation of the sequence of consecutive data from which the long run differential was computed, or computed as the (potentially endogenous) time average. Standard errors (in parentheses) are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Online Appendix

Results from Alternative Regression Specifications

Table 8: Summary Statistics from Parameter Estimations, Company-level Data

	Mean	Std. Deviation	1st Quartile	Median	3st Quartile
			AR(1)		
λ	.432	.716	.152	.475	.72
p	3.3	283.8	-1.7	12.1	18.4
α	-3.2	35.8	-1.7	4.	8.8
Mean Obs.: 12.1		Mean R^2: .34		Regressions: 11,573	Stationary: 91.0 %
			AR(2)		
$\lambda_1(\lambda_2)$	.619 (-.157)	.444 (.346)	.352 (-.355)	.637 (-.166)	.897 (.031)
p	8.4	100.2	3.7	13.1	18.7
α	1.0	23.5	0.7	4.6	9.0
Mean Obs.: 16.8		Mean R^2: .44		Regressions: 6,200	Stationary: 93.6 %
			Asymmetric AR		
$\lambda_1(\lambda_2)$	.497 (.382)	.64 (.858)	.236 (.033)	.54 (.356)	.764 (.677)
p	5.6	290.2	1.7	13.7	19.4
α	0.4	22.0	0.6	4.6	8.7
Mean Obs.: 13.48		Mean R^2: .43		Regressions: 9,500	Stationary: 86.3%

The table summarizes persistence of profit estimations for the U.S. from 1976 to 2015 using Compustat North American Fundamentals. "Stationary" describes the percentage of all segments with characteristic roots < $|0.95|$. Regressions in sections 2 are based on subsamples with fewer observations due to missing values of explanatory variables, the exclusion of dynamically unstable series and winsorization (reducing standard deviations significantly).

Table 9: Explaining λ and α from the AR(1) Estimations

	λ			α		
	(1)	(2)	(3)	(4)	(5)	(6)
Controls						
Segment & 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
CR4	.032	.032	.052	-.00015	.0003	.00051
	(0.05)	(0.05)	(0.05)	(0.00)	(0.00)	(0.00)
CR4 × barriers		.000053			-7.3e-06**	
		(0.00)			(0.00)	
CR4 × threshold			-.034			-.0011**
			(0.05)			(0.00)
Observations	4,393	4,377	4,393	3,772	3,757	3,772
R^2	0.21	0.21	0.21	0.08	0.08	0.08

This table reports OLS regressions explaining the short run speed of adjustment λ and the regression constant α that are obtained from an AR(1) processes in annual profit rate differentials. The sample covers U.S. business segments and a period from 1976 to 2015. Time fixed effects are for decades and sector fixed effects for 2-digit NAICS aggregates. CR4 is the 4-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. Standard errors (in parentheses) are robust for OLS regressions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.