Common Ownership in America: 1980–2017*

Matthew Backus[†] Christopher Conlon[‡] Michael Sinkinson[§]

May 16, 2019

Abstract

This paper measures the implications of the common ownership hypothesis for S&P 500 firms between 1980 and 2017. In the time series, the growth of common ownership is driven by the broad rise of diversified investment strategies, rather than well–known investment managers. In the cross section, there is substantial variation that can be traced, both in the theory and the data, to observable firm characteristics — particularly retail investor share. Finally, we show that the theory predicts incentives for expropriation of undiversified shareholders via tunneling, even in the Berle and Means (1932) world of the widely held firm.

JEL Codes: L0, L21, L13, G34

*Thanks to seminar and conference participants at CEPR IO, Cornell, Harvard-MIT, IIOC, MACCI - Mergers and Antitrust, Microsoft, Penn State, Purdue, Rice, SITE, University of Chicago Booth, University of Pennsylvania, University of California at Santa Cruz, University of Virginia, WBEC, Wisconsin and Yale, and conversations with Steve Berry, Wouter Dessein, Wei Jiang, Charles Jones, Amit Khandelwal, Bruce Kogut, Nathan Miller, Fiona Scott Morton, Nancy Rose, Martin Schmalz, and Glen Weyl. All remaining errors are our own.

[†]Columbia University and NBER, matthew.backus@columbia.edu

[‡]New York University, cconlon@stern.nyu.edu

[§]Yale SOM and NBER, michael.sinkinson@yale.edu

1 Introduction

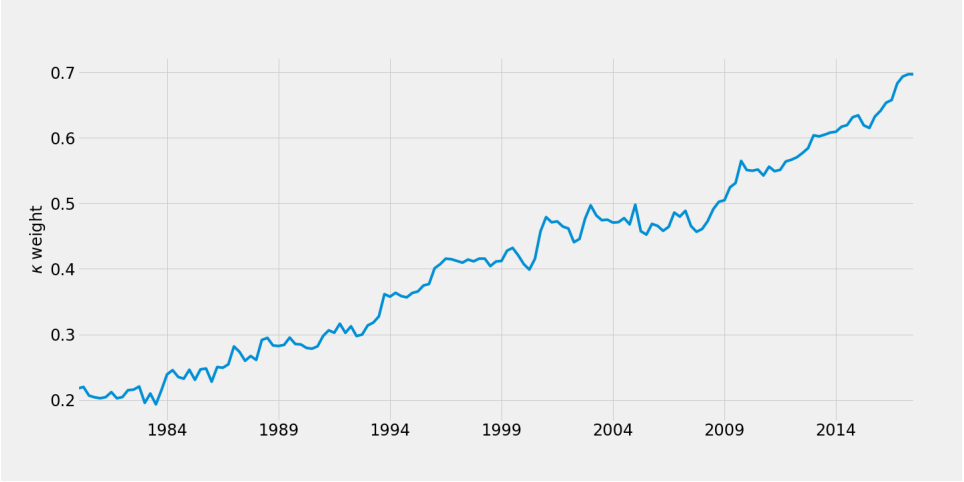
Economists usually assume that firms maximize profits. Motivating the assumption, Friedman (1953) contends that investors will discipline firms that do not at least mimic profit-maximizing behavior. Investor's interests, however, may be complicated by holdings in competing firms, which happens naturally when they seek the benefits of diversification. If firm decision–making is an expression of investor interests, and powerful investors have stakes in competing firms, then one might not expect the firm to simply maximize their own profits, yielding competitive outcomes, but instead to also value the profit of their competitors when making strategic decisions. The idea that large diversified owners imply nonzero "profit weights" among ostensibly competing firms, is known as the *common ownership hypothesis*.

The theoretical framework of the common ownership hypothesis was first articulated in Rotemberg (1984), but it has recently become the subject of a lively public policy debate thanks to empirical work suggesting that the growth of large, diversified common owners may have caused prices to increase among banks and airlines (Azar et al., 2016, 2018). Contemporaneously, Eekhout et al. (2018) argue that markups, economy-wide, have sharply increased since 1980. Combining these lines of work (see Shambaugh et al. (2018)) could go so far as to implicate common ownership in macro-level phenomena such as declining labor share and investment, the productivity slowdown, and diminished "dynamism" (Gutiérrez and Philippon, 2016).

However appealing the explanation may initially be, there are myriad unanswered questions to address before we connect common ownership to the rise of market power in general.[1] From a historical perspective, how should we understand the rise of common ownership and measure its economic significance? If common ownership has increased over time, what has led to this increase and how should we measure it? Is there clear econometric evidence mapping these incentives to market outcomes such as prices? And, what are the objectives of the institutions that manage portfolios for others, and what are the mechanisms by which they might communicate incentives to the firms they hold? This paper focuses on the first two questions by documenting these profit weights, decomposing them into economically meaningful parts, and contributing a novel dataset of institutional holdings that exhibits better coverage than existing commercial datasets.

[1]The popular press has seized on this story and run articles with titles such as "Are Index Funds Evil?" (The Atlantic), "Stealth Socialism" (The Economist), and "Should Mutual Funds Be Illegal" (Bloomberg).

Figure 1: Common Ownership Profit Weights Over Time



Notes: This figure depicts the mean implied profit weight across all pairs of firms in the S&P 500 index by year, excluding own profit weights, which are normalized to 1. See Section 2 for an explicit formula for common ownership weights and derivation.

We compute the implied common ownership profit weights for the full set of S&P 500 Index constituents, pairwise, from 1980 through the end of 2017. Revisiting the math of common ownership, we offer some simple insights on how the implied profit weights depend on investor concentration, growing adoption of diversified investment strategies, as well as some very particular assumptions on the nature of corporate governance. Guided by this, we are able to show how each factor contributed to a staggering increase in implied common ownership profit weights over the period, depicted on the vertical axis in Figure 1. For comparison: a weight of 0 corresponds to what we expect in a world of profit-maximizing firms, and a weight of 1 corresponds to the weight that a merged firm places on an acquired subsidiary business (or, equivalently, full collusion). We find that the average pairwise profit weights implied by the common ownership hypothesis more than tripled among S&P 500 firms, from just over 0.2 in 1980 to almost 0.7 in 2017.

This paper explores the empirical implications of taking the common ownership hypothesis seriously; we take a bird's–eye view of the economy at large to the end of measuring the economic significance and patterns of common ownership.[2] We focus directly on the firm's objective function rather than imposing market definitions or specific forms of competition that are sure to vary across industries. An interpretation of our findings is that if firms behave as the theory predicts, the macro-level effects are potentially very large, a claim we explore in Section 4 in a quantification exercise using a differentiated Bertrand pricing model and the

[2]Of course, one might take the plausibility or implausibility of the macro-level implications discussed here as an implicit test of the common ownership hypothesis.

rise in profit weights depicted in Figure 1. Of course, this raises more questions for additional research. In particular, how should we go about testing whether these patterns of common ownership do in fact translate into firm behavior, e.g. higher prices? In related research we take this question up in the context of a specific market — the ready-to-eat cereal industry — and revisit prior work on conduct testing in industrial organization (Backus et al., 2018a). The focus of this paper is not testing. However, we do show that while the markups implied by our calibrated example are comparable in magnitude to the rise in markups depicted by Eekhout et al. (2018), it is clear that the timing is inconsistent. Where that paper finds a substantial increase in markups in the 1980s, the rise of markups predicted by common ownership is largely in the period following 2010.

Prior work on aggregate measurement of common ownership has focused on the modified Herfindal–Hirschman Index (MHHI), measured at the four-digit SIC code level (Gutiérrez and Philippon, 2016; Anton et al., 2016). The use of the MHHI index has been a source of controversy in the common ownership literature for two reasons, and both are related to the fact that it conflates common ownership incentives with market shares. The first is its relationship to the now–defunct structure–conduct–performance (SCP) literature in industrial organization, and the econometric problems associated with treating functions of market share as independent variables. We discuss and explore this concern in a companion piece (Backus et al., 2018b). But second, the computation of market shares introduces a market definition problem, as well as a number of other measurement problems that are likely to bias any measure of time trends. For instance, foreign firms are unobserved in the Securities and Exchange Commission (SEC) and Compustat data used to construct such indices, but are growing in U.S. market share during this period of rising trade flows. Likewise, the number of public firms has decreased by half since 1996 as firms have gone or remained privately held. We show in Section 4 that the presence of a single privately held firm can dramatically affect the predictions of the common ownership hypothesis. Our profit weight measure is a key input into the MHHI; indeed the only input which comes from overlapping ownership. The MHHI interacts our profit weights with the market shares of each firm and sums them up over all pairs of firms. Economically meaningful interpretation of MHHI requires the researcher to believe not only in everything that we require, but also the restrictive framework of symmetric Cournot competition. Therefore we advocate a focus on the primitive of the common ownership hypothesis: the implied profit weights that arise in the firm's optimization problem.

Our focus on the profit weights affords us an opportunity to look more closely into the

sources of the growth of common ownership incentives. In the time series, we show that this is driven not only by the rise of the largest players (Blackrock, Vanguard, and State Street), which have earned outsized mention in the literature, but instead an older trend of increasing diversification among institutional portfolios that we trace back as far as 1980. In other words, these firms are simply the most recent torchbearers of a trend that predates them. In the cross section, however, the story is rather different. Both in the theory and the empirics, we show that the common ownership profit weights are strongly positively correlated with the proportion of shares held by non-institutional (i.e. retail) investors, which has been declining since 1980.

Moreover, we observe that for a number of cases, the profit weights implied by common ownership can exceed one. This would imply that the firm values a dollar of profits at another firm *more* than a dollar of its own. This is important because a profit weight greater than one is the condition under which we might expect to see "tunneling," a phenomenon typically thought to arise only when control rights are explicitly divorced from cash flow rights, e.g. when there are multiple classes of stock or a pyramid structure (Porta et al., 1999; Johnson et al., 2000). This is not often thought to happen in the world of the Berle and Means (1932) "widely-held firm," the United States. However, under the math of common ownership, the potential for the phenomenon arises because low investor concentration effectively dilutes control rights, leaving the remaining few investors with disproportionately high influence. In particular, this is driven by holdings of retail investors, who do not exert the same influence in corporate governance as institutional investors, and consistent with this we show that firms with high retail shares (and, relatedly, large market capitalization) tend to place larger profit weights on other firms.

This paper complements work on related questions that also bear on the common ownership hypothesis. Do institutional investors, as managers rather than ultimate owners, have an incentive to grow portfolio value? For instance, if profits in the market for institutional investment management are competed away, it may be that they have little incentive to invest in corporate governance initiatives that grow their portfolio value. This seems empirically implausible given the degree of corporate governance involvement, the statements of investment managers themselves Fink (2018), as well as a line of research showing the positive corporate governance effects of having large institutional shareholders (Boone and White, 2015; Appel et al., 2016). Closer to the common ownership question, in an example we discuss in Section 4.2, Matvos and Ostrovsky (2008) show that merger activity is a concrete example where institutional investors internalize the incentives implied by their

cross holdings. We add to this by using our calibrated pricing game to compute the implied increase in portfolio value if common owners were able to implement an objective function that represented their cross-holdings consistent with the theory. In our stylized example, by 2017 common ownership would increase the value of their portfolio by a factor of three. We show that there are many reasons to think that this is an overstatement, but the number is an order of magnitude larger than what we would call "large," and we show how the exercise suggests potential sources of variation that could be used to test the hypothesis.

All of this is moot, of course, if institutional managers are unable to implement their incentives within the firm. Here there is a true paucity of evidence. In particular cases, e.g, that of Matvos and Ostrovsky (2008), there is a clear mechanism through the exercise of voting rights, but how would an institutional manager manipulate lower-level choices such as prices? Anton et al. (2016) offer some evidence on this point, showing that executives compensation is less performance sensitive when large shareholders own large stakes in competing firms. Our analysis offers no support for the existence of a mechanism, but our work suggests a different framing of the question: if there is no "common ownership" effect on pricing, what are the organizational frictions that allow institutional investors to affect mergers but not pricing? And, given the large effects on portfolio value, should we expect institutional managers to figure it out? So, while we intend for the analysis here to inform the burgeoning literature hunting for evidence of common ownership price effects in particular industries, we also believe that understanding the implications of common ownership is of deeper economic interest.

A final contribution of this paper is a new dataset of institutional holdings of United States publicly traded firms. While most research to date in this area has used a commercial dataset of these holdings (Thomson Reuters), it has been frequently noted that this dataset has gaps in coverage and errors relative to the source documents. As a result, we collected all 13(f) filings from the SEC since electronic filing was made mandatory in 1999 through 2017 and extracted holdings of S&P 500 firms.[3] We are making the code for this parsing exercise available to other researchers as our alternative dataset appears to provide more complete coverage, particularly during 2010-2014, as further discussed in Section 3.1. If one were to complete our exercise using only the commercial dataset, one would reach different qualitative and quantitative conclusions, as shown in Appendix Figure 21, which contrasts Figure 1 using the commercial dataset vs our novel dataset.

[3]A total of 318,038 quarterly filings by institutional investors, including amendments. The total size of the corpus is approximately 25GB.

The structure of the paper is as follows: In Section 2 we outline the theory of common ownership, the derivation of the common ownership profit weights, and finally highlight some yet-unexplored mathematical features of those weights. In Section 3 we offer our descriptive evidence on profit weights from the S&P 500, in addition to particular industries. Section 4 discusses the economic implications of the implied common ownership profit weights through the lens of tunneling and through simulation. Robustness considerations to various assumptions are addressed in Section 5, and Section 6 concludes.

2 Common Ownership: Theoretical Preliminaries

We begin with a generic setup: a firm f makes a strategic choice x_f and earns profits given by $\pi_f(x_f, x_{-f})$, which depend on their rivals' choices x_{-f} as well. Under the maintained hypothesis of firm profit maximization, the profit function constitutes the objective function of the firm, and it is in this framework that economists have traditionally modeled behavior ranging from pricing to entry to R&D. This is occasionally motivated by the claim that the firm answers to its investors, who should be unwilling to provide capital should the firm fail to at least mimic profit maximization (Friedman, 1953). Shareholders hold different portfolios, and thus receive different payoffs from the profits of those investments.

Consider the payoffs of an investor — for our purposes, a shareholder of a publicly traded company. We assume that shareholder s has cash–flow rights denoted β_{fs}, equal to the fraction of each firm f that they own. The profit of the shareholder, $\tilde{\pi}_s$, is given by the sum of profits over their portfolio of investments weighted by cash-flow rights,

$$\tilde{\pi}_s = \sum_{\forall g} \beta_{gs} \pi_g. \tag{1}$$

In the framework of Rotemberg (1984), a firm acts to maximize the profits of shareholders. However, because their portfolios differ, investors will disagree about the optimal strategy. Firm f resolves this problem, as one might resolve a social choice problem, by placing Pareto weights γ_{fs} on the profits of investor s and maximizing the Pareto-weighted sum of their investors' profits. Letting Q_f denote the proposed objective function of the firm, we can

derive the weight, κ_{fg}, that firm f places on its competitors g's profits, π_g, as follows:[4]

$$\begin{aligned} Q_f(x_f, x_{-f}) &= \sum_{\forall s} \gamma_{fs} \cdot \tilde{\pi}_s(x_f, x_{-f}) \\ &= \sum_{\forall s} \gamma_{fs} \cdot \left(\sum_{\forall g} \beta_{gs} \cdot \pi_g(x_f, x_{-f}) \right) \\ &= \sum_{\forall s} \gamma_{fs} \beta_{fs} \pi_f + \sum_{\forall s} \gamma_{fs} \sum_{\forall f \neq g} \beta_{gs} \pi_g \\ &\propto \pi_f + \sum_{g \neq f} \underbrace{\left(\frac{\sum_{\forall s} \gamma_{fs} \beta_{gs}}{\sum_{\forall s} \gamma_{fs} \beta_{fs}} \right)}_{\equiv \kappa_{fg}(\gamma_f, \beta)} \pi_g. \end{aligned} \tag{2}$$

In the second to last line we show that one can rewrite the maximization of shareholder profits into a maximization problem over own- and competing firms' profits. Therefore, it is useful to normalize by $\sum_{\forall s} \gamma_{fs} \beta_{fs}$, as we do in the last line. Then, κ_{ff} is always normalized to one, so that κ_{fg} can be interpreted as the value of a dollar of profits accruing to firm g, relative to a dollar of profits for firm f, in firm f's maximization problem. These are the profit weights that are the object of interest in this paper. These profit weights follow directly from the objective function proposed by Rotemberg (1984), but we use the notation and formulation in O'Brien and Salop (2000).

In most competitive models (Cournot, Bertrand, etc.), one assumes that firms ignore their rivals' profits, i.e. $\kappa_{fg} = 0$. A large literature in Industrial Organization treats mergers as changing $k_{fg} = k_{gf} = 0 \to 1$ (see, e.g., Bresnahan (1987); Nevo (2001)). Common ownership concerns can, in principle, rationalize any $\kappa \geq 0$, but the interesting case is when $\kappa_{fg} > 0$ so the firm puts positive weight on its rivals' profits. This occurs when $(\gamma_{fs}, \beta_{fs}, \beta_{gs}) > 0$, in other words, when at least one investor which f pays attention to ($\gamma_{fs} > 0$) has cash-flow rights in both the firm f and the rival g.[5]

We refer to these κ terms as *profit weights* and they are the primary focus of our paper. The next question is: Where do we obtain the information on γ_{fs} and β_{fs} that allows us to calculate κ? For most publicly traded firms in the US, the cash flow rights of shareholder s in firm f are given by the fraction they own of total shares outstanding. These quantities are observed for large institutional investors from mandatory 13(f) filings made every quarter

[4]Our setup is meant to mirror that of Bresnahan and Salop (1986) or O'Brien and Salop (2000).

[5]It is difficult to rationalize the conventional model of own-profit maximization in this framework, in the presence of diversified investors. Implicitly, one needs to motivate the assumption that $\gamma_{fs} = 0$ for diversified investors, and $\gamma_{fs} > 0$ for undiversified investors.

to the SEC, discussed further in Section 3.1, and calculating β_{fs} using this information is straightforward.

The second element, the Pareto weight a firm places on each of its shareholders, sometimes called the *control weight*, is less transparent. Any formulation of γ is implicitly a model of corporate governance, and one where theory offers precious little guidance. Absent an obvious alternative, much of the literature assumes $\gamma_{fs} = \beta_{fs}$. This assumption is sometimes motivated by intuitive appeals to *proportional control*—the "one share one vote" rule which characterizes most publicly traded firms in the US. We caution that there is no formal link between this parameterization and any micro-founded voting game that we are aware of.

We will at times relax the proportional control assumption and allow for $\gamma_{fs} = f(\beta_{fs})$. There are two desirable properties that we would like to retain: first, that $f(\cdot)$ be monotonically increasing and continuous in holdings, and second, that $f(0) = 0$.[6] A convenient choice is $f(\beta_{fs}) \propto (\beta_{fs})^{\alpha}$, which satisfies both.[7] By varying α we can modify the convexity of the control weights, with a larger value of α leading to more weight on the largest investors. We will show that most of our results are qualitatively insensitive to the choice of α.

2.1 Additional Properties of κ

Here we highlight some additional mathematical properties of κ to set the stage for our empirical exercise. Starting from the definition of κ_{fg} in (2), and letting β_f and γ_f be vectors over s, then κ_{fg} can be expressed as a ratio of inner (dot) products $\frac{\langle \gamma_f, \beta_g \rangle}{\langle \gamma_f, \beta_f \rangle}$. And, from the geometric definition of an inner product, $\langle x, y \rangle = \cos(x, y) \, \|x\| \, \|y\|$, with $\cos(x, y)$ the cosine distance (i.e. the cosine of the angle between vectors x and y) and $\|x\|$ the L_2 norm $\sqrt{\sum_i x_i^2}$. Substituting, we obtain a useful decomposition of κ_{fg}:

$$\kappa_{fg} = \frac{\cos(\gamma_f, \beta_g)}{\cos(\gamma_f, \beta_f)} \sqrt{\frac{IHHI_g}{IHHI_f}}. \tag{3}$$

[6] As an example where these features may fail, consider κ in the case where $\gamma = 1$ for all shareholders of firm f, i.e. the firm maximizes their shareholders' portfolio value. This model introduces a potentially large discontinuity when a new investor with a large portfolio purchases a single share of a firm.

[7] We write $\propto$ rather than $=$ because we can always scale the $S \times 1$ vector $\gamma_{\cdot s}$ by a scalar, and this is because it appears in both numerator and denominator of $\kappa_{fg} = \frac{\langle \gamma_f, \beta_g \rangle}{\langle \gamma_f, \beta_f \rangle} = \frac{\langle a\gamma_f, \beta_g \rangle}{\langle a\gamma_f, \beta_f \rangle}$.

Here, $IHHI_f \equiv \|\beta_f\|^2$. Because β_{fs} represents the fraction of firm f owned by s, then $\|\beta_f\|^2 = \sum_{s=1}^{S} \beta_{fs}^2$ is the Herfindahl–Hirschman Index (HHI) for the *investors* in firm f, which we label the $IHHI_f$. Under the proportional control assumption of Rotemberg (1984) $\gamma_{fs} = \beta_{fs}$, we can further simplify the expression, because $\cos(\beta_f, \beta_f) = 1$:

$$\kappa_{fg}(\gamma_f, \beta) = \cos(\beta_f, \beta_g)\sqrt{\frac{IHHI_g}{IHHI_f}}. \tag{3'}$$

What is helpful about this expression in (3) or (3') is that it decomposes profit weights into two economically meaningful components. First, it draws a clear link between investor concentration and common ownership profit weights. They are determined in part by relative concentration of investors. If firm g has a large (undiversified) investor then $IHHI_g$ will be large; if firm f has many small investors then $IHHI_f$ will be small. All other things being equal, firms with concentrated investors will place more weight on their own profits and less weight on competitor profits. However, if a diversified investor increases its positions in several firms at once, this may not change the ratio $\frac{IHHI_g}{IHHI_f}$.

It is entirely possible for $\sqrt{\frac{IHHI_g}{IHHI_f}}$ to be greater than one, or even greater than two or three, which makes it possible that $\kappa_{fg} > 1$ (a firm places more weight on its competitors' profits than their own), despite the fact that the cosine similarity is never greater than one. Also, because it is a quadratic measure, $IHHI$ shows that small retail investors have a negligible contribution towards $IHHI$ and thus κ. This is a result of proportional control rather than an additional assumption, and will hold for any model of control such that $\gamma \to 0$ as $\beta \to 0$.

The second important term in (3') is the cosine of the angle between the positions which investors hold in f and those which investors hold in g.[8] So long as all investors hold long positions in both (f, g) we have that $\cos(\beta_f, \beta_g) \in [0, 1]$. As the investor positions become more similar, the angle between those portfolios shrinks and $\cos(\beta_f, \beta_g) \to 1$. This suggests a link between indexing strategies, e.g. investing in the "market portfolio," and common ownership profit weights. We explore this relationship further in our empirical results.

Finally, a brief word on the term that appears in (3) but not (3'): $\cos(\beta_f, \gamma_f)$. This corresponds to the alignment of cash-flow rights and control rights within firm f. The proportional control assumption aligns them perfectly, so it is equal to 1. All else held equal, a weaker relationship between the two will, since this term sits in the denominator, inflate common

[8] There is a similar expression in 3, except it measures the angle between control and ownership.

ownership profit weights.

The relationship between control rights and cash-flow rights is central to the common ownership hypothesis. Typically, the discussion of these two hinges on institutional structures that divorce them, e.g. "golden shares" in the hands of founders, or business groups that centralize control (Porta et al., 1999). In the objective function defined by (2), the mechanisms are different. On the intensive margin, the issue is that it is the product γ and β that enters into the firm's objective function. If γ_{fs} is increasing in β_{fs}, then this means that even if my cash flow rights are proportional to my control rights, the marginal effect on κ_{fg} of additional investment by shareholder s is increasing in their existing holdings. Therefore, larger investors can have an outsized effect in determining strategies of the firm. Moreover, if $\gamma_{fs} \to 0$ as $\beta_{fs} \to 0$, then retail investors, who are assumed to be atomistic, drop out of the objective function of the firm altogether. This is the extensive margin. Since retail investors have no influence, it implies that the influence of institutional investors is magnified whenever the retail share is large, in proportion to the inverse of the institutional share. This will tend to magnify the responsiveness of firms to common ownership among even a relatively small set of institutional investors, as we see in the examples that follow.

2.2 Examples of the Math of Common Ownership

The following examples maintain the proportional control assumption of $\gamma_{fs} = \beta_{fs}$.

Example 1: Consider a market with three firms. Firm 1 is privately held, in its entirety, by an undiversified investor. Firms 2 and 3 have the following identical ownership structure: 60 percent of each is held by small, undiversified retail investors. 20 percent of each are held, respectively, by two large, undiversified investors. The final 20 percent of each is held by a single, diversified investor. This ownership pattern is summarized in Table 1.

This yields the following set of profit weights:

$$\kappa = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1/2 \\ 0 & 1/2 & 1 \end{bmatrix}.$$

Table 1: Example 1 Ownership Structure

	Firm 1	Firm 2	Firm 3
Investor 1	100%	-	-
Investor 2	-	20%	-
Investor 3	-	-	20%
Investor 4	-	20%	20%
Retail Share	-	60%	60%

Notes: This table presents investor holdings in three firms for Example 1.

Table 2: Example 2 Ownership Structure

	Firm 1	Firm 2
Investor 1	1%	x%
Investor 2	1%	x%
⋮	⋮	⋮
Investor N	1%	x%
Retail Share	$(100 - N)$ %	$(100 - N \cdot x)$%

Notes: This table presents investor holdings in two firms for Example 2. Note that $N \cdot x < 100$.

To see how this calculation is done, denote column j of Table 1 as β_j (excluding the bottom row, the retail share which is assumed to have no control weight). Then, the profit weight firm f has on firm g's profit is $\kappa_{fg} = (\beta_f{}' \cdot \beta_g)/(\beta_f{}' \cdot \beta_f)$. This example highlights that the profit weights can be quite large with a modest amount of common ownership. An important factor here is the large retail share, which at 60% corresponds to the average retail share (i.e. non-institutional share) among S&P 500 firms in the early 1980s (see Figure 4 below).

Example 2 Now consider an alternative market with just two firms. The vast majority of both firms are held by a large set of undiversified retail investors. A boundedly small fraction of both firms is held by a finite set of N symmetric, diversified investors who each hold 1 percent of firm one and x percent of firm two, and we assume $N \cdot x < 100$. This ownership pattern is summarized in Table 2.

Then, we would have the following κ matrix of profit weights:

$$\kappa = \begin{bmatrix} 1 & x \\ 1/x & 1 \end{bmatrix}.$$

The calculation follows in the same manner as Example 1. This example highlights a few points about profit weights. Notice that the profit weights do not depend directly on N. Letting $x = 1$, we have that an arbitrarily small share of ownership has led to monopoly pricing. If x is 2%, then the first firm will value \$1 of the competitor's profit as \$2 of their own. Therefore firm 1 would, if it could, divert profits directly to firm 2. This raises concerns around tunneling (Johnson et al., 2000), which we discuss in Section 4.2.

We can also re-interpret this problem by working backwards from the retail share. Suppose we know that all investors are symmetric (holding a "market portfolio") and we observe the retail shares (r_1, r_2). Then $\kappa_{12} = \frac{1-r_2}{1-r_1}$ and $\kappa_{21} = \frac{1-r_1}{1-r_2}$. This suggests that as a firm's retail share grows, it puts a higher weight on competitor profits. Holding all else equal, this suggests that the growth of institutional investors may dampen (rather than grow) common ownership profit weights.[9]

2.3 Profit Weights and Market Outcomes

Do common ownership incentives affect economic outcomes and welfare? In the context of pricing, our profit weights κ_{fg} relate to other measures of common ownership that have been used in the literature, in particular the Modified Herfindal–Hirschman Index and the Pricing Pressure Index, which have been used to understand effects on consumer welfare. We briefly review this here, and also provide a detailed (not original) derivation of each in Appendix A.1 for reference.

If we solve (2) where firms choose quantity in a homogeneous, symmetric Cournot game, we find a monotone relationship between the Lerner Index and the MHHI measure of Bresnahan and Salop (1986) which is used in empirical work on airlines (Azar et al., 2018) and banks (Azar et al., 2016):

$$MHHI_m = \underbrace{\sum_f s_{ft}^2}_{HHI_m} + \underbrace{\sum_f \sum_{g \neq f} \kappa_{fg} s_{fm} s_{gm}}_{MHHI\text{–}Delta_m}. \tag{4}$$

Observe that κ_{fg} appears inside the MHHI computation. In this sense the MHHI index it is not an alternative to κ weights; rather, it requires strictly stronger assumptions. Alterna-

[9] This is because that while the numerator changes at rate $-r_1$ the denominator changes at rate $\frac{-r_2}{(1-r_2)^2}$ when $r \in [0, 1]$.

tively, if we solve (2) where firms choose price in a differentiated Bertrand game, we get the less well-known Δ PPI measure of O'Brien and Salop (2000), which measures the effect of new ownership terms in the first-order conditions in terms of diversion ratios:[10]

$$\Delta PPI_{jm} = \sum_{g} \kappa_{fg} \cdot \left(\sum_{k \in \mathcal{J}_g} (p_{km} - mc_{km}) D_{jkm} \right). \tag{5}$$

For both of these games, common ownership implies higher prices, lower output, and welfare loss. However, in other games, e.g. complementary products, vertical relations or R&D, the welfare effects may be very different, and even positive (Levy, 2018; López and Vives, 2018).

We choose to make κ, the profit weight, our object of interest because it is the primitive which captures how common ownership affects MHHI or PPI. Both MHHI and PPI require additional assumptions on firm conduct and the nature of competition as well as additional data, which make them difficult to measure using aggregate data across multiple industries.

Our approach represents an important departure not just from industry-specific studies of common ownership: (Azar et al., 2018, 2016), but also broader cross-industry studies of common ownership: (Anton et al., 2016; Gutiérrez and Philippon, 2016) which rely on MHHI. In order to compute MHHI, we need to define a relevant market and compute appropriate market shares. Defining the relevant market is often the most contentious aspect of antitrust practice. Prior studies often use 4-digit SIC codes as reported in Compustat. These may not represent appropriate product markets either in terms of geography or the nature of the products themselves. If privately-held and foreign firms are present and unmeasured, then our market shares will be incorrect.[11] If the unmeasured share of privately-held and foreign firms is rising over time, this will cause us to overstate the growth of MHHI, as the residual share of publicly traded domestic firms appears more concentrated.

We provide a more detailed (and critical) discussion of MHHI and its relationship to the structure-conduct-performance (SCP) literature in Backus et al. (2018b), and propose a structural conduct testing approach in Backus et al. (2018a).

[10] We show the derivation in Appendix A.1. D_{jkm} is the diversion ratio from product j to k in market m.

[11] For example, in chocolate confections the four largest firms are: Mondelez (formerly Kraft foods, owner of Cadbury), a member of both the NASDAQ-100 and S&P 500 Indices; Hershey an S&P 500 component; Mars, one of the largest privately held firms in the world; and Nestle, which is traded on the Swiss stock exchange.

3 Trends and Patterns in Common Ownership

While there is broad agreement that common ownership is on the rise — under the premise that there is growing concentration among highly diversified institutional investors — little is known about the magnitude of the trend or patterns therein. Which types of firms seem most exposed to common ownership? And, what is it that drives the heterogeneity?

We compute common ownership profit weights (κ values) among all firms in the S&P 500 for the period 1980–2017, excluding a relatively small set of firms that use dual-class shares to separate control rights from cash-flow rights.[12] We use the S&P 500 as it is designed to reflect the broader US economy; it consists of widely held firms, and many investment funds offer products tied to the constituent firms in one way or another.

3.1 Data on Common Ownership

Our first data source for investor holdings is Thomson Reuters (TR) S34 database, which consolidates the "13(f)" filings required by the SEC for all investment managers with over $100 million in holdings among a list of "13(f) securities."[13] The filings are quarterly and mandatory. These data are available to researchers through Wharton Research Data Services (WRDS) and span the period from 1980 to 2017. There are some documented data issues in the S34 database, particularly in later years.[14] We augment this ownership data by scraping the data ourselves from the SEC filings. These data are available from 1999 onwards (when the SEC started requiring electronic filing), though they are much more reliable beginning in mid-2013 when the filings were required to be in XML format.[15] We also gather data on prices and shares outstanding from the Center for Research in Security Prices (CRSP).

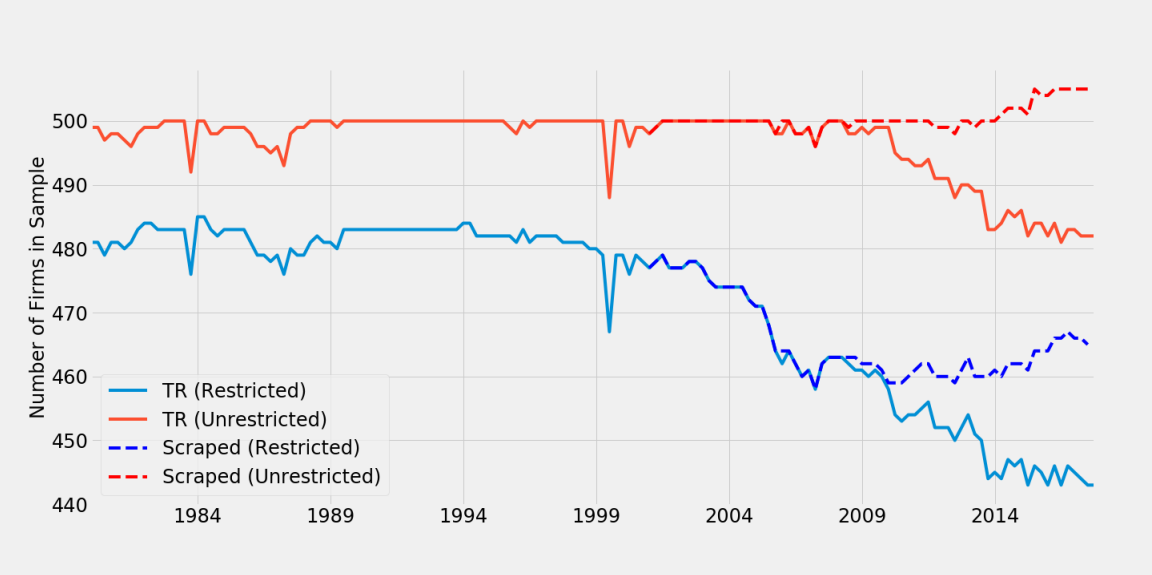
[12] We exclude a total of 49 firms for using dual-class shares throughout our sample. These tend to be relatively recent entrants, which in our sample falls somewhat more steeply below 500 constituents in later years, as seen in Figure 2.

[13] The SEC publishes a quarterly list of 13(f) securities whose holdings must be reported.

[14] Recently, WRDS and some researchers (Ben-David et al. (2018)) noticed data quality issues regarding the TR dataset, and they have worked to resolve these issues. We use the July 2018 update provided by WRDS below. We consolidate all BlackRock entities. Data quality issues are discussed in more depth in Backus et al. (2018b) and in Appendix B.

[15] A highly critical report from the SEC's Inspector General in 2010 noted a number of shortcomings in how 13(f) filings were treated, prompting a number of changes to 13(f) reporting. See Securities and of Inspector General (2010).

Figure 2: Number of Firms in The S&P 500 Sample



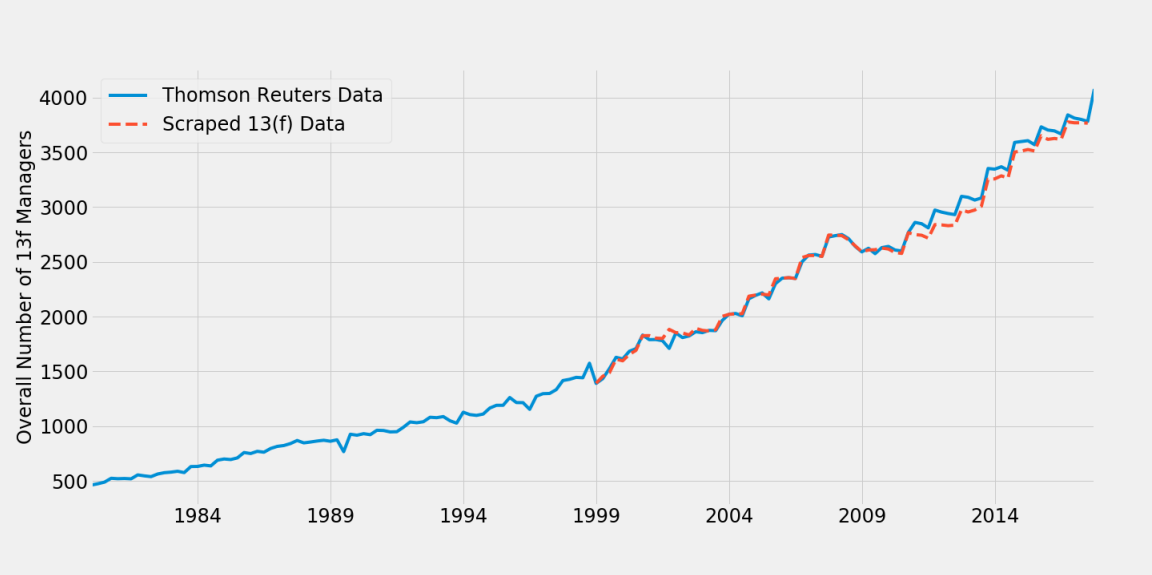
Notes: We report the Thomson Reuters in solid lines and our scraped sample in dashed lines. We report two sets of firms for each sample: (Red) an unrestricted sample consisting of all firms in the dataset (Blue) a restricted sample which drops firms with multiple share classes unlikely to satisfy control assumptions. The S&P 500 Index can contain fewer than 500 securities on a particular date (if the end of a quarter occurs on a weekend), and more recently has included over 500 securities as multiple classes of shares for the same company are included and deemed to count as one constituent (ie: BRKA and BRKB).

We use our scraped data on 13(f) holdings from 2000 onwards, and the S34 database for filings from 1980-1999. We provide additional details on dataset construction and comparisons of the two databases in Appendix B. We show that our scraped data seem to have better coverage than the Thomson Reuters database from 1999-2017 in Figure 2. Our sample of S&P 500 firms does not always include all 500 firms in each period. Because of our focus on profit weights that arise from overlapping investors, it is inappropriate to calculate these from financial holdings when there are controlling shareholders or multiple share classes. Therefore we exclude companies with controlling shareholders or special share classes with enhanced (or no) voting rights, such as Alphabet (Google) or Facebook.[16] We also exclude firms where the US listing is an ADR of a stock primarily traded on a foreign exchange.

We also document the number of 13(f) Managers holding S&P 500 constituents in Figure 3. The number of managers rises from around 500 in 1980 to around 4000 by 2017. In part,

[16]Occasionally, these controlling shareholders are inside or retail investors, e.g. the Walton family, in violation of our theoretical assumption that retail investors are atomistic. We have excluded known examples here, however it is possible to use data from SEC Forms 4,5, 6, and 144, available from the Thomson Reuters Insider holdings database through WRDS, in order to construct industry holdings where available. These data are impractical to clean for analysis at the aggregate level, however it is feasible and important to do so for case studies of particular industries as, e.g., Azar et al. (2018) do when they compute the profit weights for airlines.

Figure 3: Number of 13(f) Managers holding S&P 500 Constituents



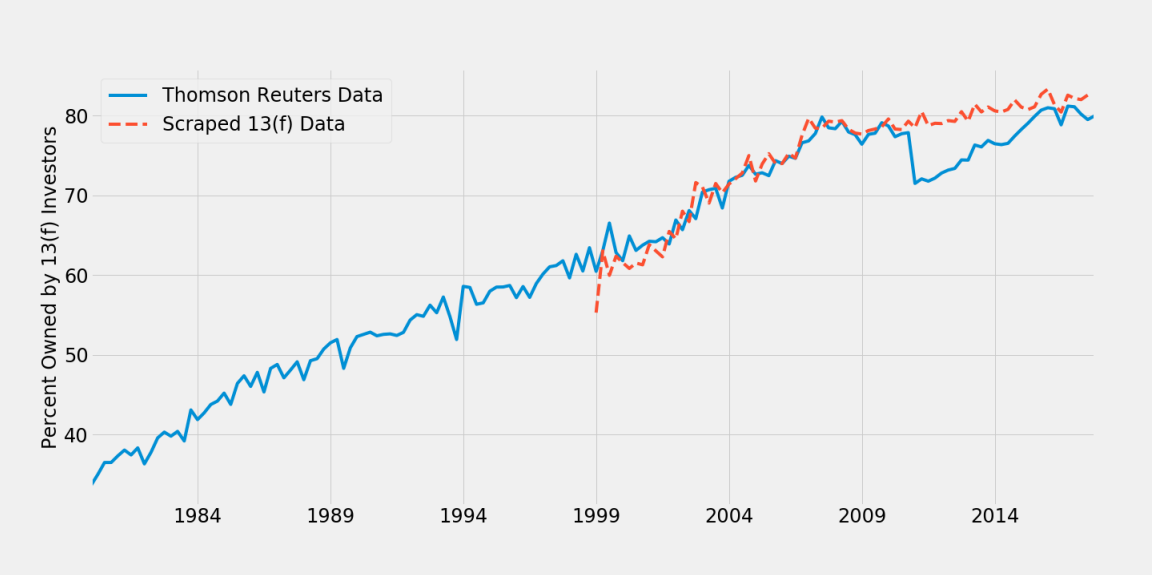
Notes: This figure depicts the number of managers filing 13(f) reports by year. For the scraped dataset, a manager is a Central Index Key (CIK). In the Thomson Reuters data, a manager is identified by a "mgrno".

this rise is driven by the fact that the reporting threshold of $100 million in 13(f) securities is nominal rather than indexed to inflation. Both the Thomson Reuters and our scraped data indicate similar numbers of 13(f) managers. We also compute the share of each firm owned by 13(f) managers and report the straight average over index constituents in Figure 4. This share has been rising from below 40% in 1980 to more than 80% by 2017, in part driven by the increasing number of 13(f) filers from Figure 3. Around 2010, the Thomson Reuters data indicates a sharp decline in the 13(f) share, while we observe no such decline in our scraped data.[17]

We document a number of additional discrepancies between our scraped dataset and the Thomson Reuters S34 dataset in Appendix B. In particular, Appendix Figure 19 shows the distribution of the number of owners reported for S&P 500 constituents over time in the TR dataset, as well as our scraped and parsed sample. In TR, up to 10% of firms have fewer than 50 reported shareholders in some periods, while in our data, the numbers are more consistent over time. To further highlight this coverage issue, Appendix Figure 20 shows how much of the ownership of three particular, large firms is reported in the TR dataset versus what we find in our dataset. There is an inexplicable drop in reported ownership in the TR data, while our dataset produces a smooth series for each firm. Finally, Appendix

[17]This is one of the documented issues with the S34 database see Ben-David et al. (2018).

Figure 4: Share of S&P 500 Owned by 13(f) Managers



Notes: This figure depicts the average total share of a firm that is owned by managers filing form 13(f). This corresponds to the institutional ownership share of the firm, and one hundred minus this number corresponds to what we are calling the retail share. We report the straight average across index constituents rather than a weighted average.

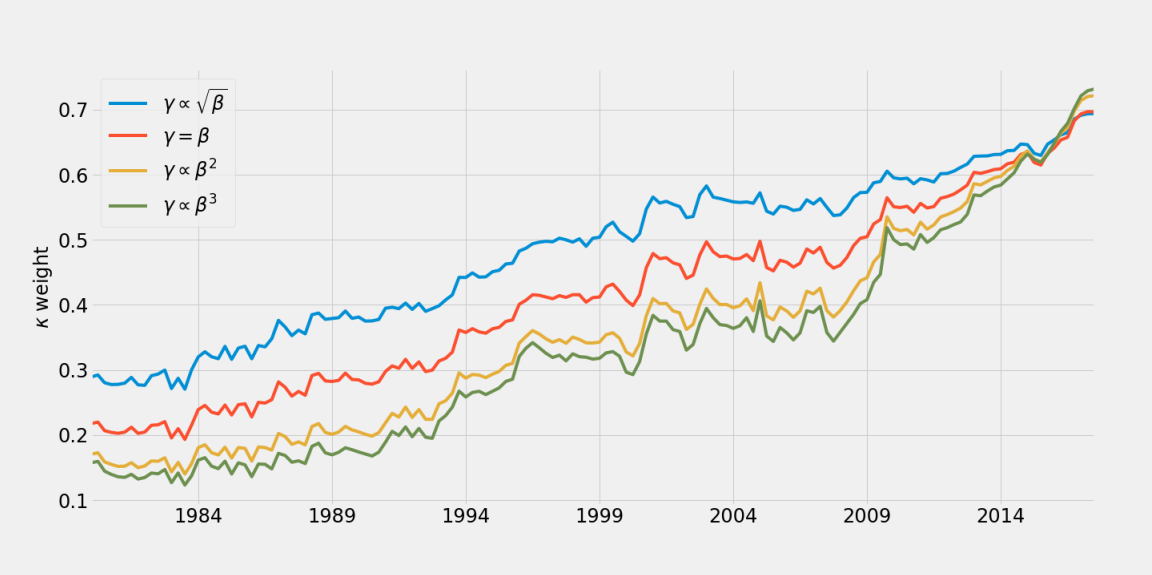
Figure 21 shows that if one were to create Figure 1 using only the TR dataset, one would get a very different time-series, with average profit weights doubling in some time periods.

3.2 Profit Weights and Control

In Figure 1, we saw that under the assumption of proportional control, $\gamma = \beta$, there is a stark positive trend in common ownership incentives (κ) among S&P 500 firms, growing from an average of 0.2 to 0.7 between 1980 and 2018. Figure 5 plots the average κ for every pair of S&P 500 firms by quarter for different control assumptions. We set $\gamma_{fs} \propto \beta^{\alpha}$ and vary the α parameter. As we increase the exponent α, we concentrate more control among the largest investors in firm f. We see that the increasing trend is relatively robust to assumptions about corporate control, and that toward the end of the sample (2012-2017), the average κ profit weight does not appear to depend on our choice of γ.

Perhaps contrary to expectations, as we increase α, the average weight κ that a firm places on its competitors' profits *decreases*. Toward the very end of the sample this relationship inverts, though differences among average profit weights become negligible.

Figure 5: Profit Weight κ Under Different Control Assumptions γ



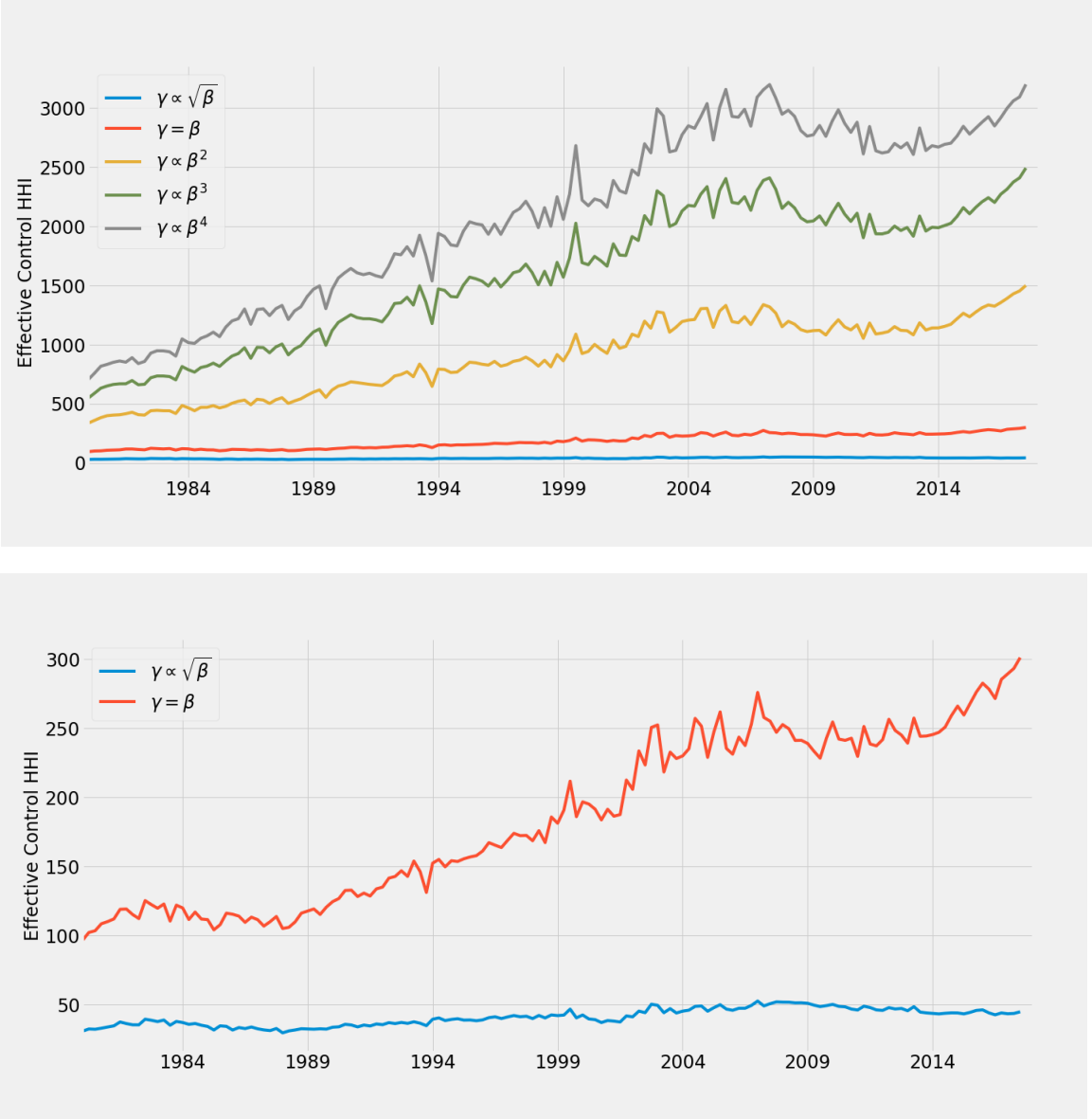
Notes: This figure reports $\overline{\kappa} = \frac{1}{F(F-1)} \sum_f \sum_{g \neq f} \kappa_{f,g}$ under different maintained assumptions of control weights, with $\gamma \propto \beta^{\alpha}$.

These results challenge some previously held assumptions regarding common ownership. If common ownership effects were driven entirely by the rise of the largest institutional investors, we would expect the profit weights to be more sensitive to different assumptions about effective control γ. Instead, we find that for most of the sample, more weight on large investors acts to reduce rather than increase κ. The second is that, while we know very little about how ownership translates into control, in recent years average profit weights are relatively insensitive to a wide range of control assumptions.

While our $\gamma_{fs} \propto \beta_{fs}^{\alpha}$ parameterization is convenient, our choice of $\alpha \in \{\frac{1}{2}, 1, 2, 3\}$ is not obviously interpretable, other than that larger values of α place more weight on the largest shareholders. In order to quantify the effects of α on effective control, we calculate a concentration measure for effective control for a particular firm f. We define $CHHI_f = \sum_s \gamma_{fs}^2$ and plot average $CHHI_f$ under different choices of α where $\gamma_{fs} \propto \beta_{fs}^{\alpha}$. Because this measure resembles an HHI, we can compute the equivalent number of symmetric controllers as $\frac{1}{CHHI_f}$.[18]

[18] Unlike in our calculation of κ where we can multiply $\gamma_{\cdot s}$ by a scalar a without loss of generality, because $CHHI_f = \sum_s \gamma_{fs}^2$ the normalization of $a_f \cdot \beta_{fs}^{\alpha}$ matters. We choose our normalization $a_f = \left(\frac{\sum_s \beta_{fs}}{\sum_s \gamma_{fs}}\right)^2$ so that $\sum_s \beta_{fs} = \sum_s \gamma_{fs}$. This keeps the overall institutional investor share the same as we change the convexity α.

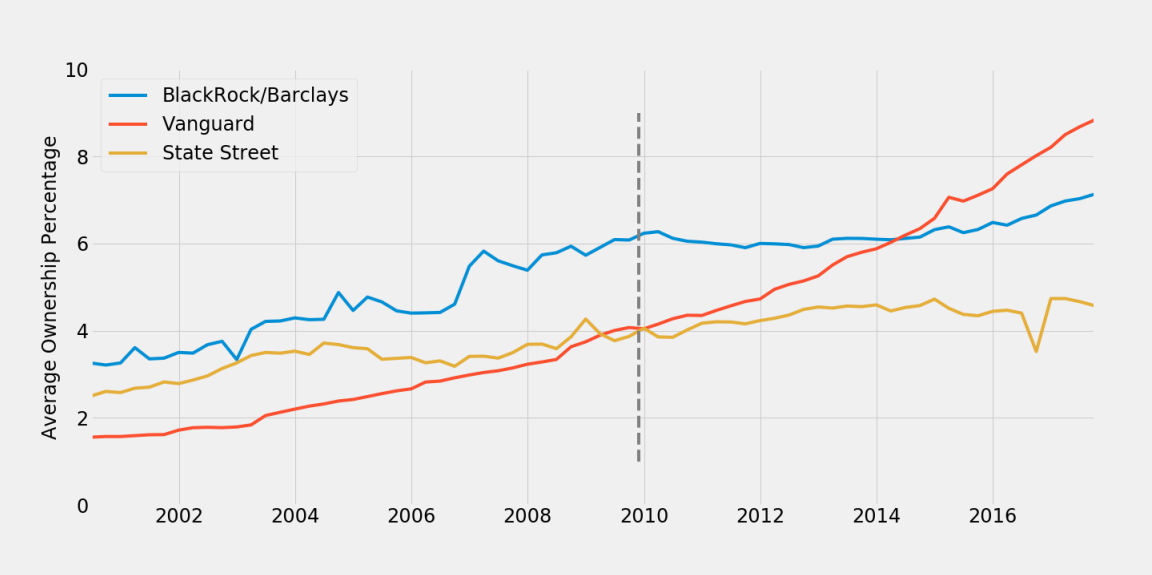
Figure 6: Control Weights γ Concentration (CHHI)



Notes: These figures average CHHI under different maintained assumptions of control weights, with $\gamma \propto \beta^{\alpha}$. The second zooms in on $\gamma \propto \sqrt{\beta}$ and $\gamma = \beta$.

In Figure 6, we report our concentration measures for effective control which we multiply by $10,000$ as is common in the antitrust literature. Under proportional control, $\alpha = 1$, $CHHI = IHHI$, so that a typical firm had the equivalent of 65 symmetric "controllers" ($CHHI \approx 150$) in 1980 and around 33 symmetric "controllers" ($CHHI \approx 300$) by 2018. As we increase α, we place more weight on a small number of larger investors. For example, when $\alpha = 3$, in 2018 we find that $CHHI \approx 2500$, or that firms effectively pay attention to the four largest investors. We can also see that this measure has grown substantially over

Figure 7: Share of Typical Firm Owned by Big Three Institutional Owners



Notes: This figure depicts the holdings of the three large asset managers over time, combining BlackRock and Barclays. The vertical line denotes the acquisition of the Barclay's Global Investors iShares business by BlackRock. The source data are the authors' own scraped 13(f) dataset.

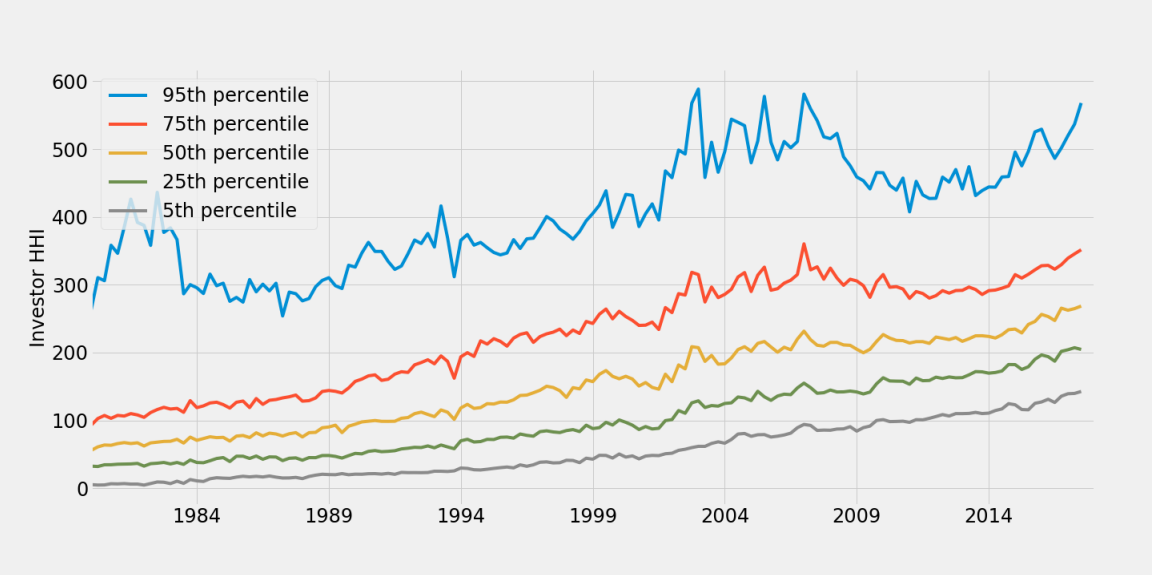
time, as it was only $CHHI \approx 600$ in 1980 (or around 17 symmetric "controllers"). This suggests we have considered the range of relevant values for α.

3.3 Trends in Profit Weights: Investor Concentration

Discussions of common ownership are often linked to the rise in concentration among a firm's investors, and the "Big Three" (BlackRock, Vanguard, and State Street) in particular. These three institutional investors collectively manage over $13 Trillion at present.[19] Figure 7 highlights holdings by these "Big Three" managers. The plot shows that these firms holdings in an average S&P 500 constituent has increased substantially over time, to between 4% and 9% of a typical S&P 500 firm in 2017. Most of that rise happened after the year 2000; combined, the "Big Three" owned approximately 6% of the average firm in 2000, and 21% percent of the average S&P 500 firm by the end of 2017. While this rise is staggering, Figure 1 indicates that much of the rise in common ownership incentives predates it; indeed $\overline{\kappa}$ rose from 0.2 to 0.5 from 1980-1999, and 0.5 to 0.7 from 1999-2017.

[19]Fichtner et al. (2017) maps the historic rise of the "Big Three" and raises concerns for their role in corporate governance.

Figure 8: Investor β Concentration (IHHI)



Notes: This figure plots quantiles of the firm distribution of IHHI, which is given by $\sum_s \beta_{fs}^2$. As is common in antitrust we report $10,000 \times IHHI_f$.

More broadly, we can ask: How concentrated are the set of investors in a typical S&P 500 constituent? We can calculate the investor HHI: $IHHI_f = \sum_s \beta_{fs}^2$ and interpret this measure in terms of equivalent symmetric investors as $\frac{1}{IHHI_f}$. We report the quantiles of investor concentration (multiplied by $10,000$ as is common practice) in Figure 8. What we see is that investor concentration has grown dramatically since 1980. In 1980, the median firm's investor concentration was around 50 points (or approximately 200 symmetric investors), and today it has an $IHHI \approx 250$, or around 40 symmetric investors. For the most concentrated firms (95th percentile of investor concentration), the $IHHI \approx 500$, which would represent around 20 equally-sized investors.[20]

We might ask, what has driven the rise in $IHHI$ over time? As we showed in Section 2.2, the $IHHI_f$ is related to $\frac{1}{1-r_f}$ where r_f is the "retail share" of firm f (ie: the fraction of shares held by investors who do not file a 13(f) form). Also recall that the typical retail share (Figure 4) has fallen from around 60% in 1980 to around 20% today. Thus part of this trend is about 13(f) filers taking larger positions, such as the rise of the "Big Three", while part is driven by the rise in 13(f) filers overall.

[20]Note that by antitrust standards, investors are not very concentrated at all. For example, the DOJ and FTC consider product markets to be highly concentrated only when $HHI > 2500$, and consider markets to be moderately concentrated when $HHI \in [1500, 2500]$. We caution that there is no reason to think antitrust guidelines for product markets are appropriate to apply to investors.

The theoretical relationship between investor concentration and profit weights is not straightforward. Recall equation (3) which showed that $\kappa_{fg} = \frac{\cos(\gamma_f,\beta_g)}{\cos(\gamma_f,\beta_f)}\sqrt{\frac{IHHI_g}{IHHI_f}}$, or that profit weights depend on relative investor concentration. Holding all else equal, as firm f's own investors become more concentrated we expect them to put *less* weight on other firms' profits.[21] Though $IHHI$ has been rising since 1980, relative investor concentration cannot be rising for all pairs of firms simultaneously, and so this cannot fully explain the rise in κ.

3.4 Trends in Profit Weights: Investor Similarity and Indexing

In addition to relative investor concentration, the other element determining profit weights in (3).[22] Cosine similarity is an L_2 measure, and measures how similar the investors' positions in firm f are to those in in firm g. For long-only portfolios it ranges from $[0, 1]$ and is maximized when the vector of investor shares in firm f can be expressed as a scalar multiple of the investor positions in firm g. This can arise if all of the investors agree on all of the portfolio weights for their investments but have differently sized portfolios.[23] To be explicit we can write:

$$L_2(\beta_f, \beta_g) = \cos(\beta_f, \beta_g) = \frac{\sum_s \beta_{fs}\beta_{gs}}{\|\beta_f\| \, \|\beta_g\|}.$$

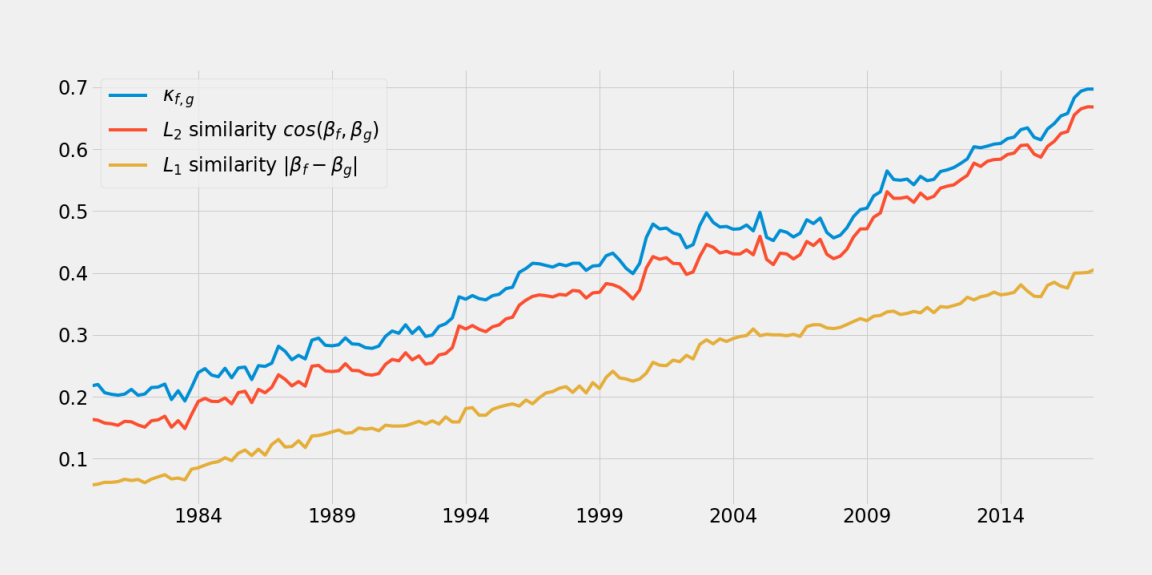
One potential criticism of L_2 measures of similarity is that they put additional weight on the largest investors, and may therefore conflate investor similarity and investor concentration. To better get at investor similarity directly, we can construct an L_1 measure. The core of this measure is $\sum_s |\beta_{fs} - \beta_{gs}|$. It is smallest when all investors hold the same fraction of both firms (f, g) so that $\beta_{fs} = \beta_{gs}$. Assuming no short positions are allowed, it is largest when investors hold either a position in firm f or in firm g, and thus are not common owners. We

[21] Conversely as g's investors become more concentrated we expect that all firms f' will increase the weight on g's profits.

[22] This is under the simplifying assumption of proportional control so that $\gamma_{fs} = \beta_{fs}$.

[23] As an example: assume that all investors have different sizes to their overall portfolio but allocate a portfolio share of β_{fs} to firm f and β_{gs} to firm g. If we can write $\frac{\beta_{fs}}{\beta_{gs}} = a$ for all investors s then $\cos(\beta_f, \beta_g) = 1$

Figure 9: Cosine Similarity Among Investors



Notes: We report average similarity measures across all pairs of firms in each period. Note that similarity here is across firms (the vector β_f) rather than investors (the vector β_s), where the latter appears in Figure 10 below.

construct a L_1 measure of similarity which varies from $[0, 1]$:[24]

$$L_1(\beta_f, \beta_g) = \frac{1}{2} \sum_s \left(\beta_{fs} + \beta_{gs} - |\beta_{fs} - \beta_{gs}| \right). \tag{6}$$

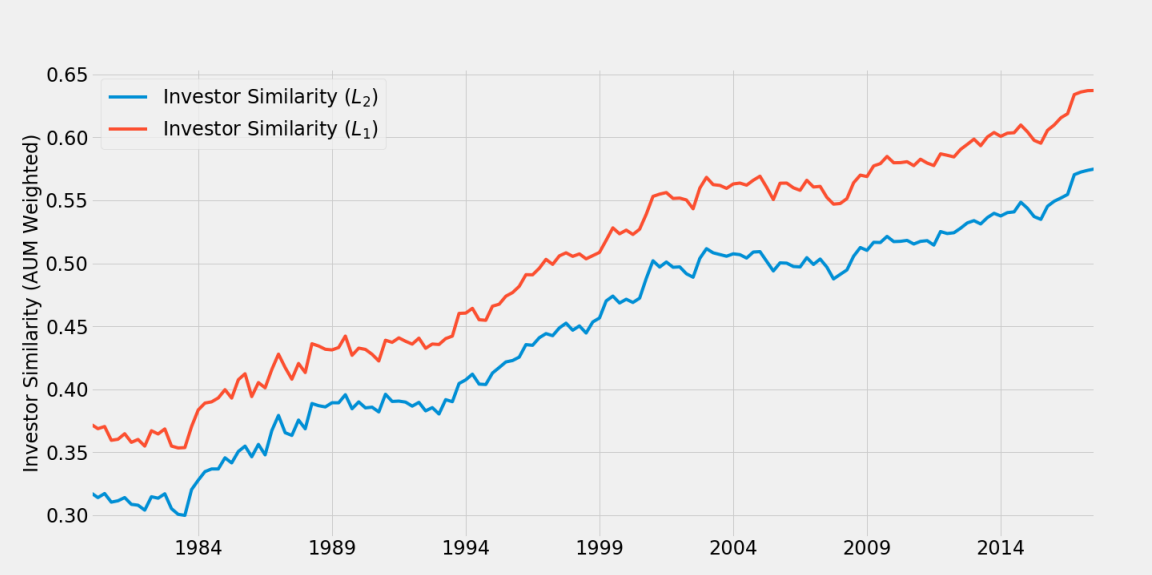
This is not our preferred measure, as it does not correspond to a profit weight of an objective function, but it may help us quantify the extent to which firms (f, g) have owners in common. In Figure 9 we depict this relationship; we find that the average (across pairs of firms) cosine similarity almost perfectly tracks the average profit weight κ. We also see that the L_1 measure of overlapping investors is also increasing though it doesn't line up as directly with the profit weights.

Both of our L_1 and L_2 measures focus on pairs of firms, and tell us that positions held in firm f look more similar to those in firm g over time. Perhaps the most important phenomenon from 1980–2017 is the rise of index investors. Instead of looking at pairs of firms, we might want to focus the extent to which investors pursue indexed strategies. For each period we can construct a set of $\overline{w}_f = \frac{\sum_s \beta_{fs}}{\sum_{f,s} \beta_{f,s}}$'s which represent the market portfolio.[25] We can

[24] Absent retail investors $\sum_{\forall s} \beta_{fs} = 1$. In practice, $\sum_{\forall s} \beta_{fs} < 1$, because the set of investors contains only large institutional investors who provide 13(f) filings to the SEC. We can think about $\sum_{\forall s} \beta_{fs} = 1 - r_f$ where r_f represents the retail investor share in firm f. As r_f grows, the L_1 measure declines, which may (or may not) be the desired behavior.

[25] Our measure of the "market portfolio" is based on cashflow shares rather than market-cap weights.

Figure 10: Similarity Between Investor Portfolios and S&P 500 Index



Notes: This figure depicts L1 and L2 similarity measures comparing investor portfolios weighted by investor AUM within our sample of S&P 500 assets.

then compare the normalized portfolio weights $w_{fs} = \frac{\beta_{fs}}{\sum_f \beta_{fs}}$ and measure the distance each investor's portfolio is to the market portfolio: $L_1(w_s, \overline{w})$ and $L_2(w_s, \overline{w})$. This is consistent with the literature in that the *active share* measure of Cremers and Petajisto (2009) is given by $1 - L_1(w_s, \overline{w})$.[26]

Our goal is to quantify how indexed each investor is on a scale of $[0, 1]$, with 1 being perfectly indexed. We compute the similarity between an investor's portfolio w_s and our constructed "market portfolio" $\overline{w}$. In Figure 10, we report the weighted average of these similarity measures, where we weight each investor by assets under management (AUM).[27] As one might expect, at least on an asset weighted basis, investor portfolios become much more similar to the "market portfolio".

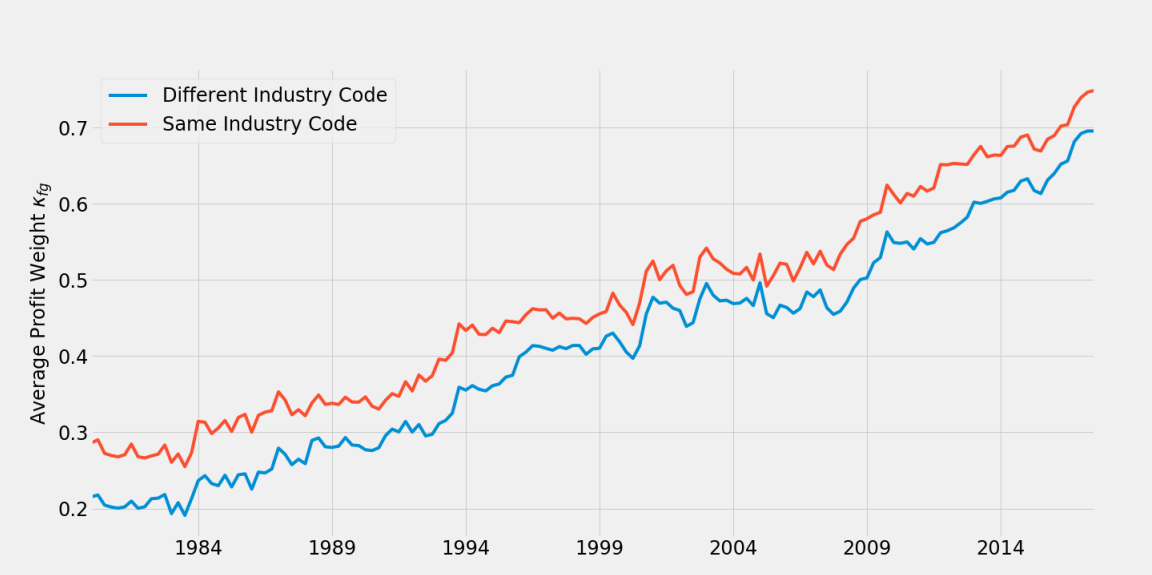
Taken together, these facts are meant to highlight what we think are the two main trends driving long run changes in common ownership profit weights: (1) the positions of investors in firms (f, g) become more similar to each other over time and (2) the similarity is largely

But for the "retail share" of non 13(f) filers, these two measures would coincide. One interpretation of our measure is as the "market portfolio" weights among large institutional investors only. We obtained S&P weights for the most recent period and our "market portfolio" weights were highly similar. Note: we ignore all non S&P 500 securities from our calculation of portfolio weights.

[26] We should point out that our analysis is at the investor/manager level from 13(f) filings not at the level of an individual fund.

[27] Again restricted to the set of S&P 500 securities.

Figure 11: Within & Between Industry Profit Weights



Note: This figure presents average pairwise profit weights separately between and within industry codes. Industry codes are from Compustat data as reported at the 4 digit SIC code level. Profit weight κ_{fg} computed under proportional control $\gamma_{fs} = \beta_{fs}$.

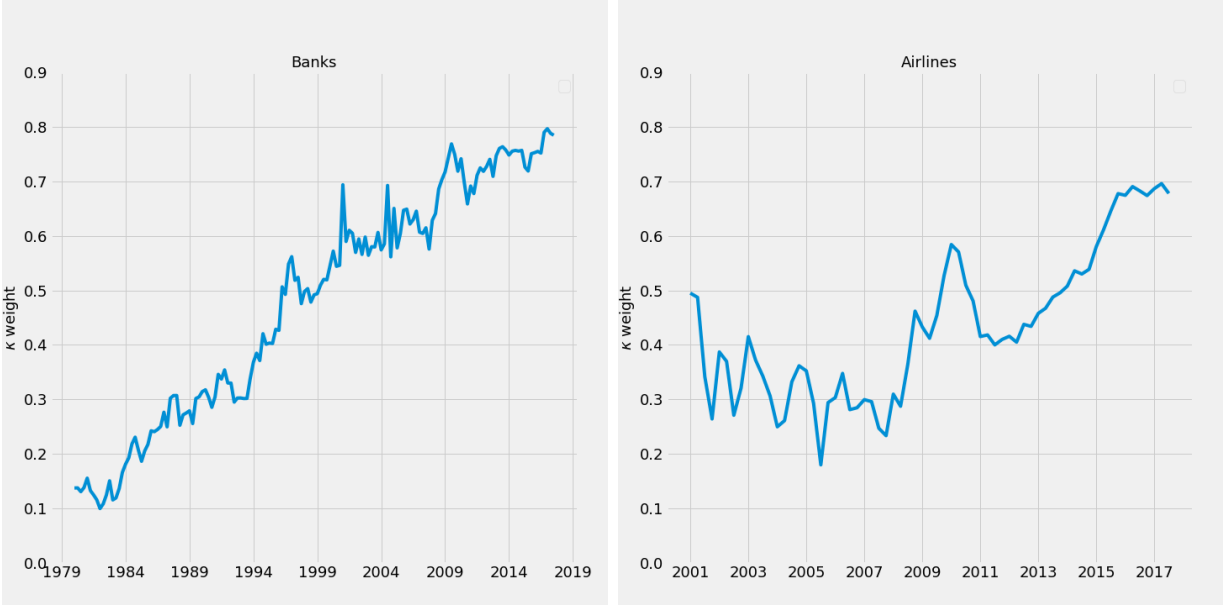
driven by a broad trend towards indexing among asset managers. This contrasts what appears to be the developing narrative that common ownership is largely a function of rising investor concentration particularly among the "Big Three" (as discussed in the previous section).

3.5 Within–Industry and Case Studies

An obvious criticism of the above economy–wide analysis is that a pharmaceutical firm's decisions hardly affect the profits of an airline, so why do these profit weights tell us anything? What are profit weights within relevant product markets? Answering this question requires us to make assumptions about market definition, which we have eschewed so far.

Here we follow the literature and adopt, perhaps unsatisfyingly, four-digit SIC codes as "markets." We show average profit weights κ_{fg} over time where both firms f and g are in the same four-digit SIC code according to Compustat. While these industry classifications are often criticized, it would be problematic if the overall trends we document did not hold under this restriction. Figure 11 shows the results: the overall trend is the same, and the level is, if anything, slightly higher.

Figure 12: Profit Weights Among Commercial Banks and Airlines



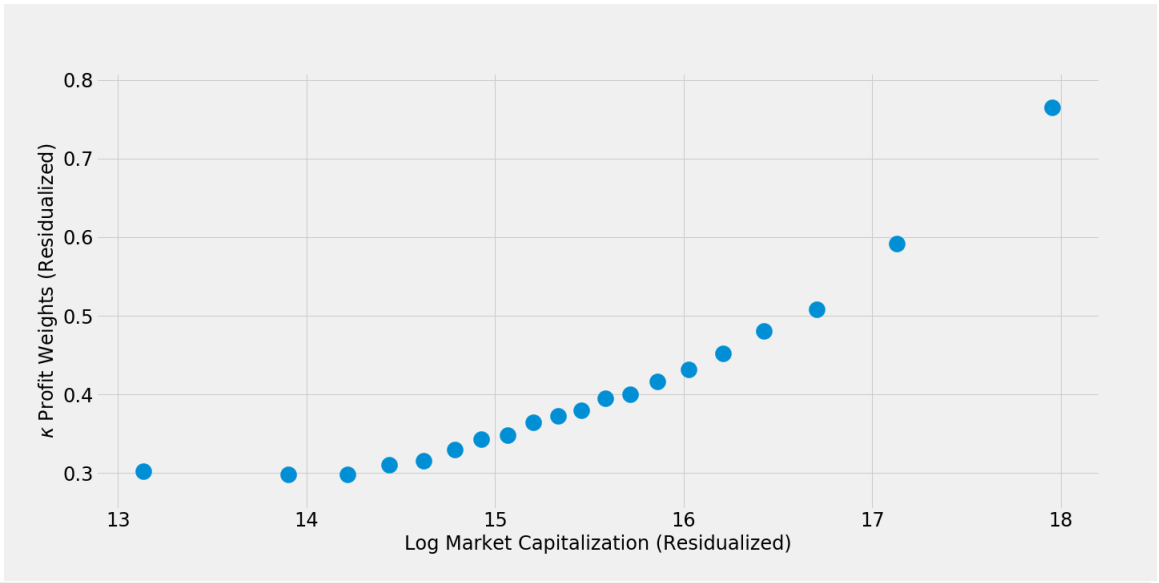
Note: This figure presents average pairwise profit weights separately for banks and airlines. Banks are for SIC code 6121 from S&P 500 sample only. Airlines are separately scraped from 13(f) filings and are available only for 2000-2017. Profit weight κ_{fg} computed under proportional control $\gamma_{fs} = \beta_{fs}$.

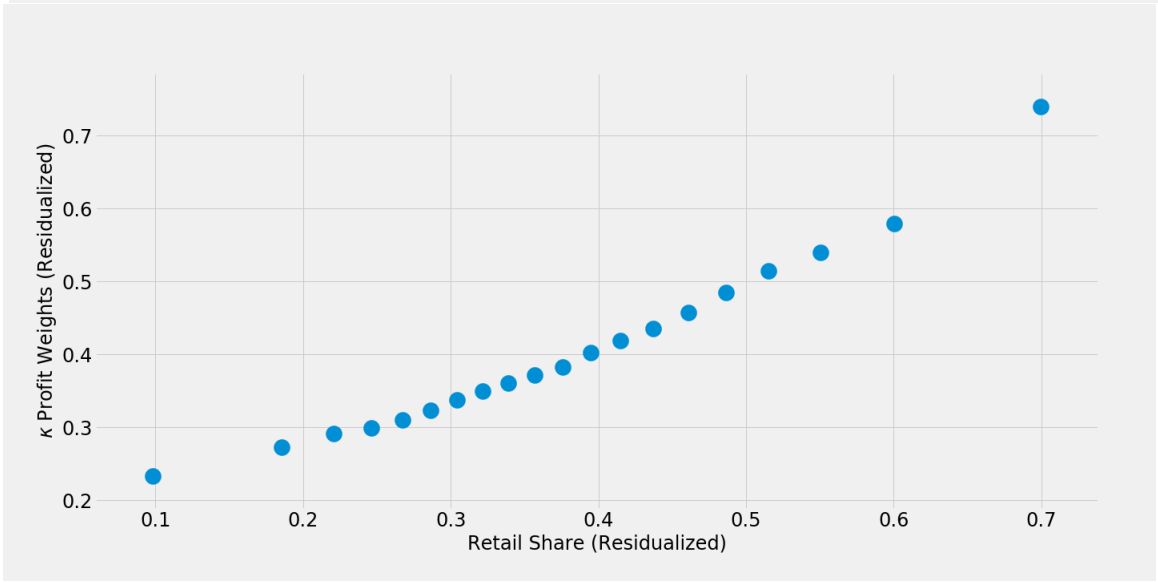
Next, we present the average profit weight for a pair of specific industries: commercial banks, as defined by SIC code 6021 (National Commercial Banks) in Compustat that are also S&P 500 constituents, and airlines, using a hand-collected sample of 27 nationwide airline securities. The airline sample required extensive data cleaning due to the many bankruptcies and mergers over the timeframe. Details are in Appendix B.2.5. Results are depicted in Figure 12. We see that the qualitative and quantitative patterns are similar to those in the S&P 500 as a whole: a large increase in profit weights for competing firms over the past few decades.

3.6 The Cross-Section: Correlations with Profit Weights

Next we turn to understanding the cross-sectional heterogeneity in common ownership weights among our sample of S&P 500 firms. In Figure 13 we plot the profit weights against log market capitalization as well as the retail share of investors for 20 equal-sized bins. The market capitalization and retail share are constructed at the firm-quarter level. The market capitalization comes from CRSP while the retail share is simply $r_{ft} = 1 - \sum_s \beta_{f,s,t}$ (the fraction shares owned by non 13(f) investors). All plots absorb year fixed effects to account

Figure 13: Heterogeneity in Common Ownership





Note: Binscatter plots are residualized using quarter fixed effects. Grand means are added back in to give sense of scale.

for levels of average nominal capitalization or retail share of aggregate investment. Our goal is to focus on cross-sectional variation in profit weights within a time period.

We find a stark relationship: Large market cap firms tend to have substantially higher common ownership weights for other firms. We hypothesize that this is related to retail share. In the common ownership framework, retail investors are infinitesimally small and therefore do not exercise any control over the firm. Large aggregate retail share then tends to inflate the control rights associated with institutional ownership. As we showed in Section 2.2, with symmetric investor holdings we expect $\kappa_{fg} \propto \frac{1}{1-r_f}$, where r_f is the retail share of firm f. Indeed, as we see in the second panel of Figure 13, retail share is strongly positively correlated with common ownership weights and appears proportional to $\frac{1}{1-r_f}$.

We can now put together both the time series evidence from sections 3.3 and 3.4 with the cross-sectional evidence from Figure 13 above in a regression framework. Here we include fixed effects at the firm level and either a time trend or quarter dummies.

Two additional key variables we include are the market-level and firm-level measures of investor indexing behavior. For the market-level variable, in each quarter we compute our L_2 (cosine similarity) measure between each investor's portfolio and the "market portfolio" and then take an AUM weighted average as we do in Section 3.4 and Figure 10. We also construct a firm-level measure of how "indexed" a particular firm's investors are by taking a weighted average of the same L_2 measure but using β_{fs} (the shares of firm f owned by investor s) as the weights. Finally, we also consider the number of (self-reported) Compustat business segments and dummies for being a *diversified* or *highly diversified* firm following the definition of Lang and Stulz (1994).

In Table 3 we present these results in regression form. Results are consistent with Figures 1 and 13; κ is robustly positively correlated with the time trend, market cap, and retail share. In Appendix C we replace the firm fixed effects with SIC division fixed effects. There is little heterogeneity across sectors — differences are small (less than 0.02) and not strongly significant.

It is important to stress that the relationship between retail share and common ownership incentives does not explain the trend we observed in Figure 1. In fact, as we saw in Figure 4, retail share is sharply declining between 1980 and 2017, from an average of approximately 65% to 20%. Here we have identified this relationship off of the cross section alone, and if

Table 3: Correlations with $\kappa_{f,g,t}$

	(1)	(2)	(3)	(4)	(5)
Quarter	0.0046*	0.0034*			
	(0.0002)	(0.0002)			
Aggregate Indexing$_t$	0.5383*				
	(0.1092)				
Indexing$_{f,t}$		0.9688*	1.0390*	1.0424*	1.0408*
		(0.0480)	(0.0509)	(0.0508)	(0.0508)
log(Market Cap)$_{f,t}$	0.0386*	0.0359*	0.0395*	0.0395*	0.0395*
	(0.0033)	(0.0031)	(0.0034)	(0.0033)	(0.0033)
Retail Share$_{f,t}$	0.7647*	0.6593*	0.6456*	0.6460*	0.6450*
	(0.0327)	(0.0312)	(0.0321)	(0.0319)	(0.0319)
no. Segments				-0.0016	
				(0.0008)	
Diversified Firm (2+)					-0.0164
					(0.0084)
Highly Diversified Firm (5+)					-0.0092
					(0.0063)
Firm FE	✓	✓	✓	✓	✓
Quarter FE			✓	✓	✓
R^2	0.5363	0.5510	0.5547	0.5549	0.5549
N	36355363	36355363	36355363	36353863	36355363

Notes: This table reports correlates of the common ownership profit weights. An observation is a pair of S&P 500 constituent firms in a given quarter. Robust standard errors are clustered at the firm level and reported in parentheses. * indicates significance at the 5% level.

anything, in the time series it has worked to dampen common ownership incentives.

We also find a strong relationship between our firm-level measure of "indexing" behavior and our $\kappa_{f,g,t}$ profit weights. For each percentage point that each of a firm's 13(f) investors become more similar to the index, we expect an equivalent rise in the profit weights that firm f places on all other firms g. The 10th percentile of our firm-level investor L_2 similarity measure is ≈ 0.373 and the 90th percentile is ≈ 0.625. Thus an increase from the "least indexed" firms in the sample to the "most indexed" would increase the average weight f places on other firms by ≈ 0.26 units. Much of the difference in our "indexing" measures has taken place over time, looking just at the last quarter of 2017, the range between the top and bottom deciles of "indexing" is between 0.56 and 0.70.[28]

There appears to be no relationship between the profit weights and the number of business segments or whether the firm is diversified, however those correlations are identified only off of within-firm changes. We provide additional regression specifications and robustness (including SIC-code fixed effects and firm pair fixed effects) in Appendix C.

4 Economic Implications of the Theory

4.1 Quantifying the Common Ownership Channel

Eekhout et al. (2018) document that average markups rise from 21% in 1980 to 61% in 2017 across a broad range of publicly traded firms. We conduct a simple calibration exercise in order to compare both the magnitude and the timing of the price effects implied by the common ownership hypothesis.

We start with J symmetric firms, with marginal costs c, selling differentiated products and competing in Nash-in-prices. We assume that each firm faces a logit demand such that its

[28] In Appendix Table 5 we extend this exercise to include the holdings of the "big three" investment managers. Conditional on our measures of indexing, the holdings of one of these large investors is negatively, rather than positively correlated with κ_{fg}, supporting our conclusion that indexing at large, rather than any particular investment managers, is what drives the common ownership hypothesis.

market share is given by:

$$s_j(p_j, p_{-j}) = \frac{e^{a-bp_j}}{1 + \sum_{k=1}^{J} e^{a-bp_k}}.$$

Each firm chooses its p_j simultaneously in order to maximize:

$$\widetilde{\pi}(p_j, p_{-j}, \kappa) = (p_j - c)s_j(p_j, p_{-j}) + \sum_{k=1}^{J} \kappa_{jk} \cdot (p_k - c)s_{k'}(p_j, p_{-j}).$$

Given the parameters of the problem (a, b, c, J, κ) it is possible to solve the $J \times J$ system of equations for the equilibrium prices $\widehat{p}(\kappa)$. Our goal is to hold fixed the (a, b, c, J) aspect of the problem, and to re-solve the problem with all κ_{fg} set equal to the average value reported in Figure 1 period by period. We then plot $\mu = p/c$ as Eekhout et al. (2018) does over time from 1980 to 2017.

We calibrate parameters as follows. First we set $c = 1$ without loss of generality. This means that prices and markups are one in the same: $\hat{p}(\kappa) = \mu$. Next we choose the number of firms $J = 8$ so that our $HHI \approx 1250$ to match Grullon et al. (2018).[29] Finally, we calibrate a and b for 1980. We construct a markup of $\mu = 1.21$ to match Eekhout et al. (2018) and an average own-elasticity of -7.21 in line with the range of elasticities reported in Eaton and Kortum (2002).[30] This all but eliminates the outside good share.[31][32]

Results for this calibration exercise are presented in Figure 14. The scale of the increase in markups predicted by the rise in common ownership is substantial: from 1.21 to 1.56. This is very similar in magnitude to the rise in markups found by Eekhout et al. (2018) for the same period. Moreover, a Granger test rejects the null that the lagged simulated common

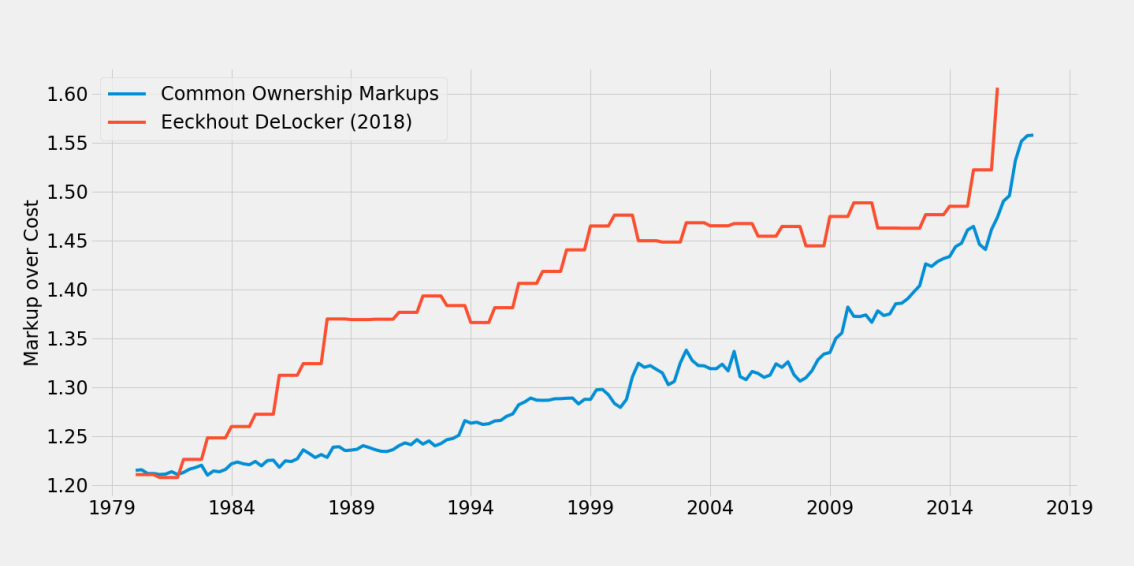
[29] We can obtain nearly identical results varying the number of firms from 5-15.

[30] Simonovska and Waugh (2014) obtain elasticities about half as large ≈ -4.0 which suggests that demand is too inelastic to get markups as small as $\mu = 1.21$ in 1980.

[31] Alternatively, one could eliminate the parameter a as well as the outside good, but the existence of even a very small outside good option substantially improves convergence of the simulated prices when computing equilibrium. This computation is done with the freely available `pyblp` python package (Conlon and Gortmaker, 2018).

[32] An important aspect of the Eekhout et al. (2018) results that this exercise misses is the reallocation from low– to high–markup firms, since in our exercise all firms are symmetric. Alternatively one could match κ_{fg}s to firm-level markups, but making sense of that relationship would require a pricing game (which firms compete with which and how, a particularly difficult question at this bird's-eye level), a problem we elude with our logit pricing example.

Figure 14: Simulated Markups: 1980–2017



Notes: This figure presents predicted markups for the calibration exercise. See the text for exact specification.

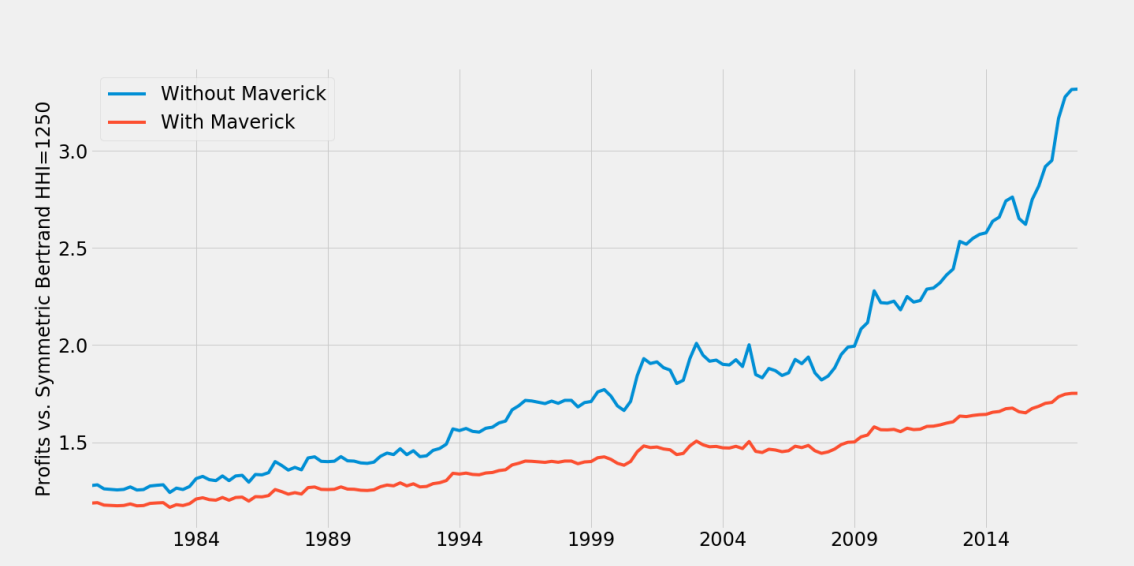
ownership markups are not predictive of the Eekhout et al. (2018) markups.[33] Despite this, we take the time series in Figure 14 as clear evidence that the bulk of the rise in markups described in Eekhout et al. (2018) is inconsistent with the predicted price effects of the common ownership hypothesis in our toy example. In particular, we note the timing, which is largely insensitive to the specification of the example: the former observe a substantial increase in markups in the 1980s, whereas the increase in markups predicted by common ownership follows largely after 2010. However, we do observe some coincidence in the two time series, particularly in 2009 and following 2015.

Whether or not one believes that common ownership price effects are manifested, we are also interested to know by how much profits would be greater if they were. This speaks directly to the incentives of institutional managers, who tax portfolio value linearly, or the incentives of the ultimate owners to delegate control to institutional managers who will exercise their corporate governance rights in a fashion consistent with the common ownership hypothesis. Therefore we depict profits associated with the pricing equilibrium in the blue line in Figure 15.

We find a dramatic, more than threefold increase in profits associated with the rise in simu-

[33]The test (Granger, 1969) is based on a VAR in first differences with two lags and a time trend, and rejects with a critical p value of 0.05.

Figure 15: Simulated Markups: 1980–2017



Notes: This figure presents predicted profits for the calibration exercise. The blue line represents the baseline model. The red line, i.e. With Maverick, depicts a modification of the model in which the eighth firm is held by an entirely undiversified owner.

lated markups for our calibrated example. However, this result is sensitive to the symmetry of the profit weights. If even one firm in the market prices aggressively, then the resulting markups (and profits) are much lower. To demonstrate this, the red line in Figure 15 depicts profits under a modification of the example in which the eighth firm is a "Maverick," i.e. they price as if held by an entirely undiversified owner. The change in profits is now substantially lower, an approximately 70% increase instead of a more than threefold increase. Nonetheless, the magnitude of these numbers emphasizes the fact that if owners could successfully incentivize institutional managers and firms to behave in a manner consistent with common ownership pricing incentives, they may stand to gain substantially.

We learn two more things from the Maverick exercise, however, which we believe are important for the literature on testing common ownership moving forward. First, that within-market dispersion in common ownership profit weights can generate dramatic variation in the predictions of the model. That dispersion can even appear between pairs of firms: from (3'), $\kappa_{fg} \simeq \kappa_{gf}$ only when $IHHI_f$ and $IHHI_g$ are close. These latter expressions, however, are sensitive to variation in retail share. Within-market dispersion and between-firm asymmetries are obscured when the econometrician aggregates common ownership profit weights up to the market level using measures such as MHHI. In doing so, we believe they throw away some of the most interesting variation and its testable implications. This is a discus-

sion we continue in Backus et al. (2018a). Second, however, it suggests that the presence of privately-held firms is not merely a data nuisance, but has testable and useful implications for the manifestation of common ownership price effects.

4.2 Relationship to Tunneling

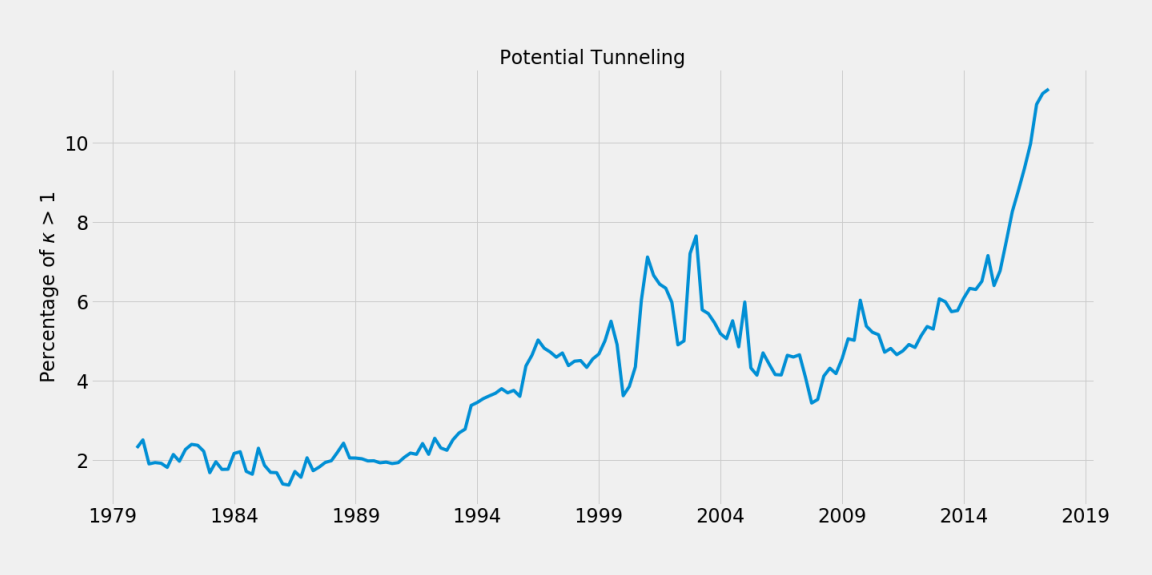
Following the language of Johnson et al. (2000), *tunneling* is the practice of transferring profits, whether via acquisition, mispriced purchase orders, or direct transfer, from one company to another in order to benefit the interests of a controlling stakeholder in both. This defrauds both creditors and minority shareholders in the former firm. The above-referenced paper offers anecdotal evidence of tunneling even in developed countries, particularly civil law countries, and other work has found evidence in the developing world (Bertrand et al., 2002). However, tunneling is not typically believed to occur in the US for two reasons: strong investor protections that facilitate healthy financial markets (Porta et al., 1999) and the near-universal absence of a controlling interest in publicly-traded firms, as the US is the land of the "widely-held" firm (Berle and Means, 1932).

The connection between common ownership and tunneling hinges on this second point. If as the common ownership hypothesis maintains: (1) owners are sufficiently diversified and (2) firms care about the effects of their decisions the entirety of their shareholders portfolios; then firms may have an incentive to engage in tunneling even in the absence of a controlling interest. On this point we can be precise: if $\kappa_{fg} > 1$ then firm f would, if it could, transfer profits directly to firm g.

In Figure 16, we report the share of firm pairs for which $\kappa_{fg} > 1$ under the proportional control assumption. Recall that, from equation (3'), since $cos(\beta_f, \beta_g)$ is bounded above by 1, $\kappa_{fg} > 1$ implies that $\kappa_{gf} < 1$ — i.e. that tunneling is in the interest of both firms. Because tunneling is necessarily unidirectional, the maximum amount of tunneling relationships would be 50%. Therefore, twice the number described in the figure yields the fraction of pairwise relationships among S&P 500 firms in which parties have an incentive to engage in tunneling. We find a striking rise in this frequency between 1993 and 2002, and again in the period following 2015.

There is a meaningful difference between the patterns of tunneling predicted by common ownership and the prior literature. In the latter, tunneling tended to be isolated within

Figure 16: Potential Tunneling Incentives $\kappa > 1$



Note: This reports the fraction of pairwise profit weights $\kappa_{f,g} > 1$ in each period under the assumption of proportional control.

small groups of firms that had a common controlling interest. For example, Bertrand et al. (2002) offers econometric evidence of tunneling about documented business groups in India. Therefore, the pattern of tunneling interest is *sparse*—firms possess few tunneling "targets". In contrast, tunneling arising from common ownership is driven by patterns of retail share via $IHHI_f$. When retail share is large, $\sqrt{\frac{IHHI_g}{IHHI_f}}$ grows for *all* potential tunneling "targets." This suggests that the resulting patterns of tunneling will tend to be dense rather than sparse—firms which have incentives to engage in tunneling may want to tunnel funds to many partners.

Taken at face value, this finding implies that in the world of the widely-held firm, i.e. in the absence of a controlling interest, the incentives for tunneling may be pervasive if firm incentives reflect common ownership concerns. It is worth emphasizing that, unlike our results in Section 3, in the later periods, the result depends heavily on our assumptions about control rights. We document this in Appendix Section C.3. Moreover, in the presence of strong minority shareholder protections, these incentives may not translate into behavior.

Empirical testing for tunneling is quite difficult. However, even before the recent controversy over common ownership arose, an example of tunneling based on cross-holdings of institutional investors was documented by Matvos and Ostrovsky (2008). That paper endeavors to solve the puzzle of why shareholders for an acquiring party do not block mergers, despite the

fact that acquirers stock prices typically fall, while stock prices of the acquired firm typically rise. They resolve the puzzle by documenting the existence of shareholders with large stakes in both firms, i.e. common owners. Moreover, in this example they can also document a mechanism — that common owners are systematically more likely to vote in favor of the merger than undiversified shareholders. We believe this is important because it is a concrete example in which the incentives implied by common ownership are internalized by institutional mangers. Combined with our evidence that the potential incentives for tunneling are on the rise, we believe this points to a useful direction for new empirical work.

4.3 The "Big Three": Mergers and Breakups

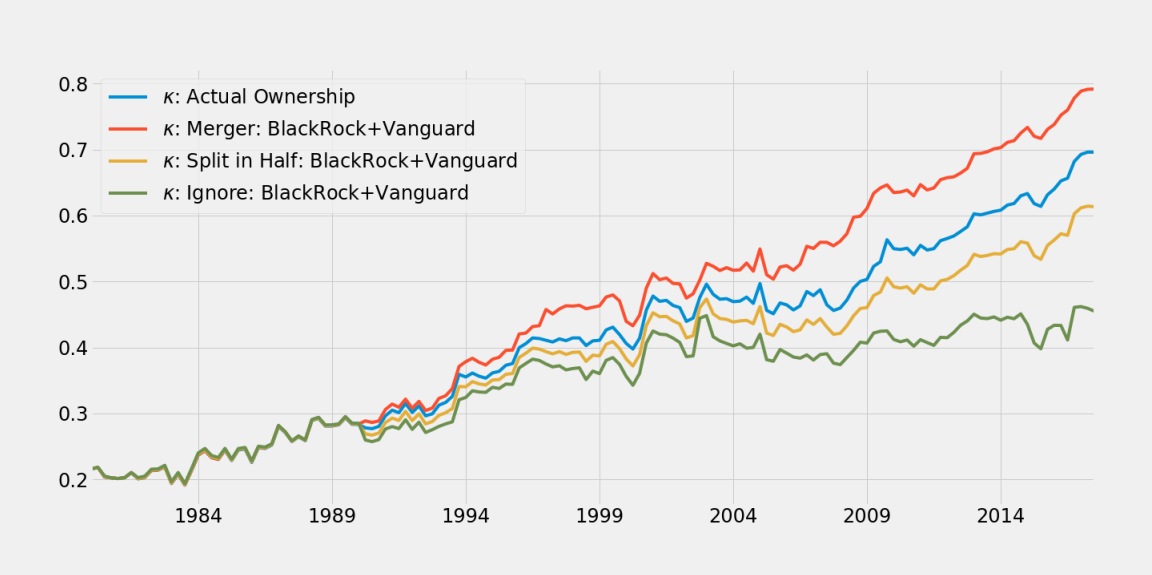
There has been much discussion of the role played by the "Big Three" investment management firms (BlackRock, Vanguard, and State Street) with respect to common ownership incentives, including various proposals to restrict the size of large institutional investors in different ways Posner et al. (2017). Here we consider a simple exercise where we either: (a) allow BlackRock and Vanguard to merge; (b) we take BlackRock and Vanguard and split them each into two firms (BlackRock A/B, Vanguard A/B) with identical holdings that are half as large as the current firm;[34] or (c) we tell firms to "ignore" BlackRock and Vanguard by setting $\gamma_{f,s} = 0$, which implicitly treats them as "retail" investors.

We report our findings in Figure 17. Up through 2004 there are limited effects on κ values of either allowing BlackRock and Vanguard to merge, or breaking them up into identically sized smaller firms. By the end of the sample, there begin to be more substantial differences. Under our baseline scenario of proportional control and the observed ownership structure $\overline{\kappa} \approx 0.7$, the merger would increase this to $\overline{\kappa} \approx 0.8$, while breaking them up would decrease this to $\overline{\kappa} \approx 0.62$. Qualitatively, the trend over time is similar to our baseline case. The most drastic difference comes when we "ignore" BlackRock and Vanguard by setting $\gamma_{f,s} = 0$. This gives $\overline{\kappa} \approx 0.46$ in 2017, and is implies that average profit weights are essentially unchanged since 2000.

First, we change the ownership structure of the two largest firms without changing the degree to which investors are "indexed" because we either merge them or split them into smaller

[34] We do not split holdings based on overlapping industries (one of the suggestions in Posner et al. (2017)) but rather simply increase or decrease the overall size of BlackRock and Vanguard. This shouldn't matter because we are reporting the average profit weight $\overline{\kappa}$ for the entire S&P 500 index.

Figure 17: Alternative Ownership Structures for BlackRock and Vanguard



Note: Actual ownership uses proportional control assumption from Figure 1. Splitting firms in half preserves portfolio weights but constructs two identical firms each half as large as the original. Merger combines BlackRock and Vanguard into single firm with combined holdings. Ignoring BlackRock and Vanguard sets $\gamma_{f,s} = 0$ for those investors and implicitly includes them in retail share.

firms with identical holdings. This tells us two things. While large firms like BlackRock and Vanguard play a role in the rise in common ownership incentives, they play a smaller role (controlling for "indexing") than one might think, because splitting them in half reduces $\overline{\kappa}$ by only ≈ 0.08 units. Likewise the combined BlackRock and Vanguard firm would be enormous (owning more than 15% of most S&P constituents). Under proportional control this increases the average profit weights, albeit not dramatically. Taken together, this highlights that indexing behavior, rather than the growth of the largest investment managers, seems to be driving the long-run trends in profit weights.

When we "ignore" BlackRock and Vanguard by setting $\gamma_{f,s} = 0$ for those two investors, we are implicitly treating them as if they are retail investors. This both drastically reduces the degree of "indexing" in the market by concentrating control in the remaining institutional investors who tend to be less "indexed" than BlackRock and Vanguard. We explore this in Appendix C.4, where Appendix Figure 25 shows the impact of removing those two firms from our measures of indexing developed in Section 3.4. More disagreement among the remaining investors tends to lead to lower profit weights overall. We can think of this scenario as similar to the "put the shares in a drawer" proposal of Posner et al. (2017), where institutional investors above a certain size would agree not to participate in corporate governance activities. As several have pointed out, while this remedy may be effective at

curbing common ownership incentives, this proposal might have unintended consequences in reducing the effectiveness of other corporate governance actions.

5 Robustness and Alternative Overlap Measures

5.1 Alternative κ Weights

An alternative specification is offered in Crawford et al. (2018), who develop profit weights in the different context of vertical incentives.[35] There each investor constructs their ideal weight $\tilde{\beta}_{fs} = \frac{\beta_{fs}}{\sum_g \beta_{gs}}$, and firms form a γ weighted average of their investors' desired weights. In the construction of κ_{fg} we find it more transparent to normalize $\tilde{\gamma}_{fs} = \frac{\gamma_{fs}}{\sum_g \beta_{gs}}$ so that:[36]

$$\kappa_{fg}^{CLWY} = \frac{\langle \gamma_f, \tilde{\beta}_g \rangle}{\langle \gamma_f, \tilde{\beta}_f \rangle} = \frac{\langle \tilde{\gamma}_f, \beta_g \rangle}{\langle \tilde{\gamma}_f, \beta_f \rangle} = \frac{\beta_f' \cdot g_f(\beta) \cdot \beta_g}{\beta_f' \cdot g_f(\beta) \cdot \beta_f}. \tag{7}$$

The CLWY weights are just the common ownership weights, but with a different assumption on control (γ). Investors with large diversified portfolios (such as index funds), have larger values for $\sum_g \beta_{gs}$ and receive a smaller weight $\tilde{\gamma}_{fs}$.[37] One justification for this re-weighting might be that investors with large portfolios may become *inattentive* (Van Nieuwerburgh and Veldkamp (2010), Gilje et al. (2018a)).

An alternative measure which more explicitly addresses investor inattention is proposed by Gilje et al. (2018b). Inattention is related to the *portfolio share* of firm f rather than the *normalized cash flow*. With a bit of work, one can show that their measure:

$$GGL_{fg} = \beta_f' \cdot g_f(\beta_s) \cdot \beta_g. \tag{8}$$

where $g_f(\beta_s)$ is a $S \times S$ diagonal matrix with entries which are a function of the *portfolio share* which f comprises in s's portfolio: $\alpha_{fs}(\beta_s) = \frac{\beta_{fs} v_f}{Y + \sum_g \beta_{gs} v_g}$, where v_f represents the

[35] It is important to note that Crawford et al. (2018) are not considering the common ownership hypothesis directly but rather examining incentives for vertical integration and bargaining among MVPDs and content providers where the former often have a partial ownership stake in the later.

[36] $g_f(\beta)$ represents a diagonal $S \times S$ weighting matrix with entries $\frac{1}{\sum_g \beta_{gs}}$

[37] The Crawford et al. (2018) paper only considers firms within the same industry in $\sum_g \beta_{gs}$ (albeit in a very different context). It is hard to understand what an equivalent assumption would be for the entire S&P 500 Index.

market capitalization of firm f. The authors consider a number of functional form choices for $g_f(\alpha_{fs})$,[38] which has the interpretation as the probability that investor s pays attention to the actions of firm f. It is important to note that while this overlap measure is a quadratic form like (3') it is not normalized by $\gamma_f' \cdot \beta_f$ and thus does not directly represent a change in the *profit weights* but rather some other difference in f's objective function.[39]

Because both the CLWY and GGL measures have the effect of putting less weight γ_{fs} on investors who are more diversified, we don't apply them to our study of the entire S&P 500 index. These measures seem more appropriate when examining a single industry at a time (such as the cable television industry).

5.2 Voting Authority

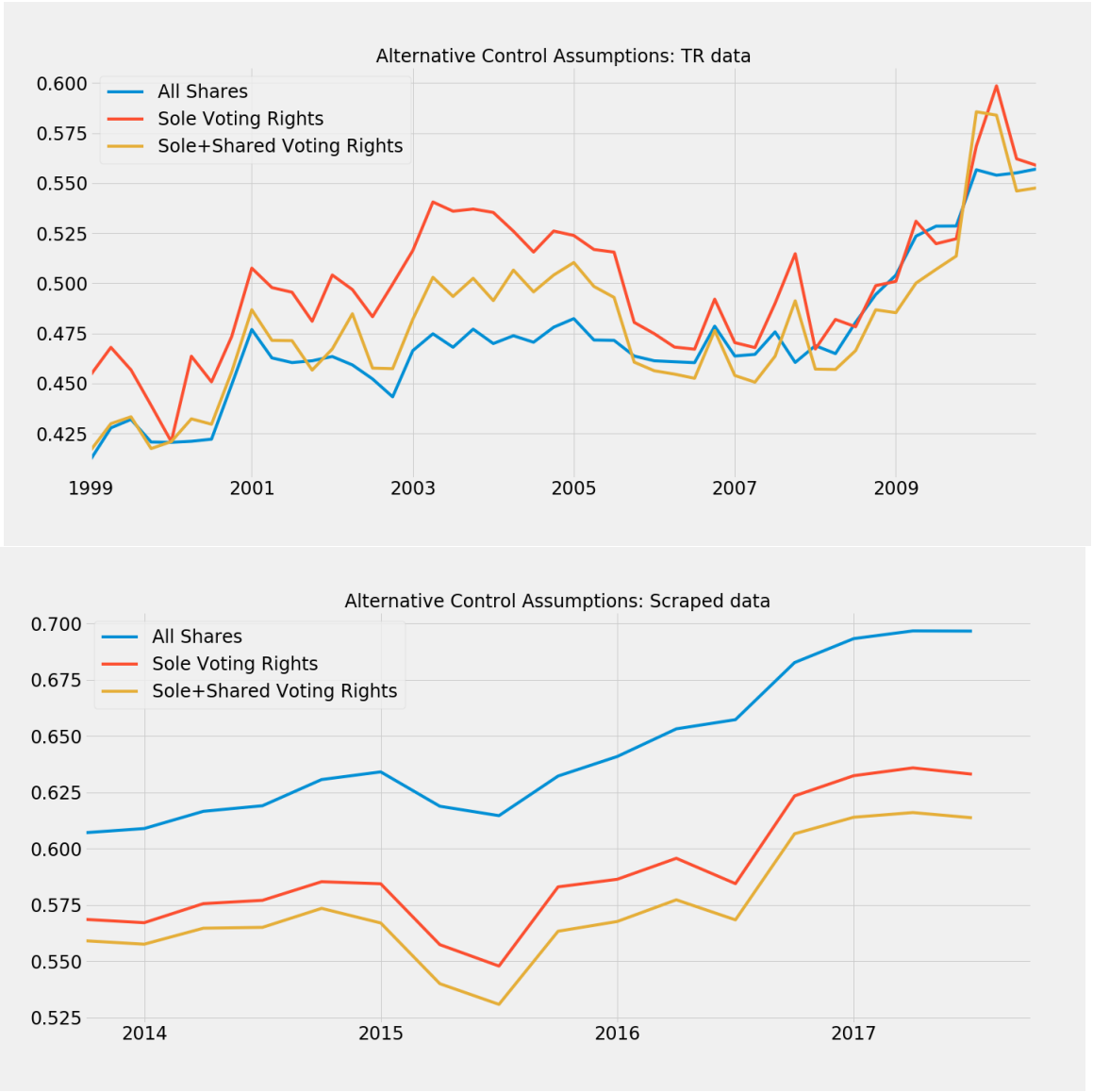
An objection that has been raised to the literature on common ownership is that many large institutional owners do not have full discretion in voting the shares that they control. To the extent that the Pareto weights γ_f represent control rights that derive from a voting game, this would cause us to potentially over-represent common ownership concerns.

Fortunately, the 13(f) filings require investors to report not only total share holdings, but to divide these among "sole," "shared," and "no" voting authority shares. Therefore, to show the sensitivity of our results to alternative assumptions, we next recompute profit weights under the assumption of proportional control ($\gamma_{fs} = \beta_{fs}$) where we limit attention to either "sole" and "shared" voting authority shares, or only "sole" voting authority shares. We restrict our attention to the period beginning in 2013 when we can reliably scrape this information from XML 13(f) filings. We display the results in Figure 18 where we observe that on average κ profit weights appear to be slightly higher when we exclude nonvoting shares or shares with shared voting rights. In general, the differences between the average κ measures appear to be miniscule.

[38] For example: linear, convex, etc.

[39] We also caution against normalizing the GGL_{fg} measure and interpreting it as a *profit weight* under any circumstances. Consider the case of the breakfast cereal industry: Kellogg's has a market cap of $21 Billion and derives most of its revenue from its breakfast cereal business. Pepsi has a market cap of $165 Billion, and derives only a small fraction of its revenue from its breakfast cereal business (Quaker Oats). An investor holding the S&P 500 index would then value $1 of profits 8 times as much for Pepsi as it would for Kellogg's even though they own the same fraction of each firm.

Figure 18: Alternative κ by Voting Authority



Note: This reports robustness checks where we compare the measure we report in our main results *All Shares* (blue-line) to cases where we exclude shares marked as *No Voting Rights* or *Shared Voting Rights* from the investment manager's portfolio. These data are available in our Scraped data only for the period where we have XML filing (post 2013) and for the TR data only after 1999.

6 Conclusion

This paper has endeavored to take the common ownership hypothesis seriously and work through the economic implications at an aggregate level, taking the universe of firms in the S&P 500 from 1980 to 2017. This began with a data challenge, and so in addition to the sources already exploited by the literature, we manually recompiled investor holdings from

13(f) reports downloaded from the SEC. We are making the source code for this compilation available for future researchers. From the exercise can draw a number of conclusions.

First, the implied common ownership incentives have risen substantially over the period, more than tripling from an average of 0.2 in 1980 to almost 0.7 in 2017. This rise is economically significant. A simple calibration exercise suggests that much of the rise in markups observed in Eekhout et al. (2018) is similar in magitude to that predicted by the common ownership hypothesis over the period in our stylized example, however a closer look at the timing (which is less sensitive to the specification of the example) suggests that this relationship cannot explain much of the purported rise in markups.

Moreover, merger analysis would look substantially different in a world where firms placed a weight of 0.7 on one another's profits before merging. This would suggest (perhaps contrary to evidence (Kwoka et al., 2015)) that we should systematically overpredict the price effects of mergers among public firms. Likewise, it suggests that purely financial transactions which eliminate or reduce common owners such as "taking firms private", de–listing from indices, and tax inversions might promote competition (in some cases substantially).

Second, even though the big three index funds have dominated the public debate on common ownership, much of the historic rise in common ownership incentives predates them, and is driven not by concentration in asset management but rather by a broader increase in diversification of investor portfolios. Indeed, the growth of these firms has an ambiguous relationship to common ownership incentives, as investor concentration appears both in the numerator and the denominator of the profit weight.

Third, we find a strong relationship between common ownership and retail share. We see this both in the theory, by decomposing the common ownership profit weights, as well as in the cross-sectional variation of common ownership weights between firms. Taken at face value, this implies that large firms popular with individual investors (e.g., PepsiCo, which owns Quaker Oats) should be among the least aggressive competitors towards other public firms (e.g., Kellogg's, General Mills, and Post).

Under the common ownership theory, a large retail share tends to inflate common ownership incentives by giving outsized control rights to a small set of large, diversified institutional investors. In extreme cases, which are becoming more common, this can even yield profit weights that exceed one. This is a necessary condition for "tunneling," and overturns the

traditional defense of the "widely held firm," that in the absence of a controlling interest, investors are safe from expropriation. Again, taken at face value, our calculations imply that 10% of all pairs of S&P 500 firms would have incentives to tunnel assets from one to the other. However, unlike our main results, this finding is sensitive to the specification of control weights. Also, unlike price effects of common ownership, tunneling benefits common owners at the expense of undiversified shareholders, and so legal protections for minority shareholders may bind the expression of these incentives.

It is important to emphasize that the goal here has not been to explicitly test the common ownership hypothesis, but rather to articulate its implications in order to better form the policy debate and research efforts that are already underway. There is much more work to be done and we believe that there are two important areas for future research in particular. The first is a forensic question of understanding the mechanisms of corporate governance and the means by which common ownership incentives are, or are not, manifested. The second is to develop tests to detect effects of common ownership on market outcomes. The literature so far, including our companion piece (Backus et al., 2018a), has focused on pricing. We hope that we have contributed to this effort in part by highlighting the theoretically-motivated and empirically salient variation and asymmetries in common ownership profit weights driven by, e.g., retail share, market capitalization, and the growth of indexing. This variation is entirely lost when researchers use dated, market-level indices such as MHHI. Above and beyond pricing, however, we hope that this will be useful as researches go on to examine other strategic interactions, from entry and location decisions to advertising and product development, as well as mergers and tunneling, to test the implications of common ownership more fully.

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Appendices

A Main Appendix

A.1 Common Ownership and Oligopoly Models

Relationship to Cournot

Much attention in the common ownership literature has been paid to the Modified Herfindahl–Hirschman Index (MHHI) concentration measure, which is derived from a Cournot oligoopoly model of competition in O'Brien and Salop (2000).[40] MHHI extends the traditional concept of HHI to incorporate common ownership, and is defined from the following firm objective function:

$$\max_{q_f} \pi_f(q_f, q_{-f}) + \sum_g \kappa_{fg} \pi_g(q_f, q_{-f}).$$

After taking the FOC (where η represents the elasticity of demand) we get:

$$\frac{P_f - MC_f}{P_f} = \frac{1}{\eta} \sum_g \kappa_{fg} s_g.$$

Which gives the share weighted average markup of:

$$\begin{aligned} \sum_f s_f \frac{P_f - MC_f}{P_f} &= \frac{1}{\eta} \underbrace{\sum_f \sum_g \kappa_{fg} s_g s_f}_{MHHI} \\ \text{— where } MHHI &= \underbrace{\sum_f s_f^2}_{HHI} + \underbrace{\sum_f \sum_{g \neq f} \kappa_{fg} s_f s_g}_{\Delta MHHI}. \end{aligned}$$

Note that many of the papers that regress price on measures of ownership separately include HHI and $\Delta MHHI$ as independent variables. It is important to point out that both measures vary only at the *across markets* while the incentive terms κ_{fg} vary *across firms* within a market.

[40] Originally the MHHI was derived by Bresnahan and Salop (1986) in the context of a joint-venture.

Relationship to Bertrand

The Price Pressure Index (PPI) is similarly defined for differentiated Bertrand competition. We consider the objective function for firm f when setting the price p_j holding fixed the prices of all other products p_{-j}. As firm f raises the price p_j some consumers substitute to other brands owned by f: $k \in \mathcal{J}_f$ on which it receives full revenue, and substitute brands owned by competing firms g: $k' \in \mathcal{J}_g$ for which it acts as if it receives a fraction of the variable profit κ_{fg}:

$$(p_j - mc_j)q_j(p_j, p_{-j}) + \sum_{k \in \mathcal{J}_f} (p_k - mc_k)q_k(p_j, p_{-j}) + \sum_g \kappa_{fg} \cdot \left(\sum_{k' \in \mathcal{J}_g} (p_{k'} - mc_{k'})q_{k'}(p_j, p_{-j})) \right).$$

When solving the FOC it is helpful to do two things: (1) divide through by $-\frac{\partial q_j}{\partial p_j}$; (2) define the diversion ratio $D_{jk} = -\frac{\frac{\partial q_k}{\partial p_j}}{\frac{\partial q_j}{\partial p_j}}$, this gives:

$$p_j - mc_j \;=\; -q_j / \frac{\partial q_j}{\partial p_j} + \sum_{k \in \mathcal{J}_f} (p_k - mc_k)D_{jk} + \sum_g \kappa_{fg} \cdot \left(\sum_{k' \in \mathcal{J}_g} (p_{k'} - mc_{k'})D_{jk'} \right). \quad (9)$$

This clarifies what common ownership does under differentiated Bertrand competition. It raises the effective opportunity cost of selling product j. Now as p_j rises, some customers are *recaptured* by other products controlled by the same firm $k \in \mathcal{J}_f$ (this is the usual multiproduct oligopoly effect), also by products controlled by competing (but commonly owned firms) $k' \in \mathcal{J}_g$ with $\kappa_{fg} > 0$.

A.2 Alternative Similarity Measures

Our primary interest is how overlapping ownership relates to *profit weights* or *cooperation incentives* among firms in the product market. The measure in Rotemberg (1984) or O'Brien and Salop (2000) is shown in (3') to be an L_2 measure. We could construct alternative measures of investor overlap, such as an L_1 measure.

For example:

$$L_1(\beta_f, \beta_g) = \frac{1}{2} \left(\sum_s \beta_{fs} + \sum_s \beta_{gs} - \sum_s |\beta_{fs} - \beta_{gs}| \right).$$

It is important to point out that $\sum_s \beta_{fs} < 1$. This is because the set of investors $s \in S$ contains only large institutional investors who provide a 13(f) form to the SEC. We can think about $\sum_s \beta_{fs} = 1 - r_f$ where r_f represents the retail investor share in firm f. The L_1 measure varies from $[0, 1]$. It is highest if we don't have any retail investors, yet all investors hold the same portfolio so that $\beta_{fs} = \beta_{gs}$. Likewise the L_1 measure declines as portfolios become more dissimilar $|\beta_{fs} - \beta_{gs}|$ becomes large.

B Data Appendix

B.1 Data Sources

Our main data source is the universe of 13(f) filings from 1980–2017. The 13(f) form is a mandatory SEC filing for institutional investors with over 100M USD in assets. We compile 13(f) filings from two sources: for the period 1980–1999, we use the Thompson Reuters s34 database. For 2000-2017, we use our own proprietary dataset, for which we are making the code publibly available, based on scraped and parsed source documents from the SEC. The latter dataset is discussed below in Appendix B.2.

For many filings there are multiple filing dates (fdate) for the same report date (rdate). This happens when filings are amended, often because of an error in the original submission or in the case of a stock split. For an ordinary revision, e.g. in case of error, we would like to take the last fdate for each rdate. However, revisions following a stock split are often retroactively applied to report dates prior to the split event itself, and in these cases we want to use the first filing date. This is a frequent issue in the data.

In order to resolve the problem, we identify the universe of stock splits for all S&P 500 firms in our sample using the CRSP data CFACSHR multiplier, and from that identify a set of quarter-firm pairs at which we use the *first*, rather than the last fdate for duplicate rdate reports.

In addition, there is a notable exception: in several instances BlackRock holdings appear to conflate the two dates, and so for BlackRock we use the filing date exclusively. This resolves the otherwise inexplicable disappearance of BlackRock Inc. from the s34 in 2010q2 and 2010q3.

13(f) filings use investor-reported values and tallies of shares outstanding and these frequently contain errors, so we use the CRSP monthly database, merged on contemporaneous CUSIP codes (nCUSIP), to compute these figures.

From CRSP we also obtain historical data on membership in the S&P 500.

From Compustat we obtain additional fields: Aggregate short interest for each member firm by quarter, and the number of business segments, as reported in the Compustat (North America) Database. There are two limitations of this data. First, coverage is imperfect. Of the 1,587 firms that ever appear in the S&P 500 between 1980 and 2017, we lack data on business segments for 209 of them. Second, the data are self-reported. What constitutes a "business segment" is an ill-defined notion, and may vary from firm to firm. Moreover, as suggested by [where's that citation again], there may be incentives for strategic misreporting here.

B.2 Alternative Dataset

Given our concerns with the Thomson Reuters dataset, as well as the concerns voiced by others such as WRDS and Ben-David et al. (2018), we also recreated a dataset of 13(f) holdings directly from the source filings. This involved gathering approximately 25GB of 13(f) filings from the SEC, for the time period 1999-2017. Mandatory electronic filing of 13(f) forms began in 1999; for earlier years, coverage is poor. These files are then parsed to extract holdings of S&P 500 firms. The parsing is handled slightly differently for filings made before the third quarter of 2013, as starting then, the SEC mandated an XML filing format. The code is written in Perl and uses regular expressions to match text patterns corresponding to holdings. The code is freely available from the authors. Note that we do not claim that every single one of the nearly 19M observations in our scraped and parsed sample are correct; we have a number of examples of filings that are so irregular as to be un-parsable. However, we believe this alternative dataset does capture many filings missing from Thomson Reuters, and is more consistent over time in a number of measures.

B.2.1 Pre-XML Parsing

In these filings (covering January 31, 1999 through June 30, 2013), most reports are fixed-width tables of holding name, holding CUSIP, value, number of shares, and then a possible breakout of shares by voting rights. For each file, our code first extracts the reporting date, filing date, CIK of the filing firm, and form type from the filing header. The code then looks for any line of text that contains an S&P 500 CUSIP for that form's reporting period. As firms on occasion report derivative holdings for a CUSIP, we drop any records that match any of the following words (case insensitive, with word boundaries on both sides): put, call, conv bd, conv bond, opt. The code then attempts to match a pattern that is consistent with most filings: a CUSIP, followed by a value, followed by a number of shares. As filings are far from uniform, the code also attempts to correct a number of common problems: for example, in some cases there is no space in between the value and the number of shares; the code attempts to discern the correct breakdown based on the price and shares outstanding for that holding in that quarter, as reported by CRSP. The code then outputs a list of share holdings at the CIK-CUSIP-reporting date level.

B.2.2 XML Parsing

For filings beginning in the third quarter of 2013, our code exploits the XML structure when parsing for filings. As before, we first extract the reporting date, filing date, CIK of the filing firm, and form type from the filing header. We then separate the file into "infotable" XML objects. We keep all such objects that have a CUSIP element that contains an S&P 500 CUSIP for that form's reporting date. We further drop any records that have a "put" or "call" element, or a "principal amount" element. We finally drop any where the title of class contains "put" or "call" surrounded by word boundaries, or that begins with "opt" or "war" (all case insensitive). The code also extracts the reported value from the value element of the information table, and compares that to the extracted number of shares times the CRSP-reported price at the reporting date. If the two values differ by less than 10%, we also include a flag in the output that the data appear valid (we use this when there are multiple filings per reporting date for a CIK-CUSIP).

B.2.3 Final Cleaning

We take the output of the parsing steps above and obtain a dataset of institutional holdings. In the case of restated filings, we keep the initial filing unless the reported value and number of shares appears impossible, in which case we keep the first rational report filed within 90 days of the mandatory reporting date. We consolidate all BlackRock entities into the same entity and collapse their holdings (while the argument could be made for collapsing other investment management firms' sub-entities, we solely do this for BlackRock given the practice in the literature). Finally, we drop 331 observations where the reported shareholdings are greater than 50% of shares outstanding. Some of these observations are correct: for example, Loews Corporation, an S&P 500 component, controlled more than 50% of common stock of Diamond Offshore Drilling, another S&P 500 component, from 2009-2016. Other records among these 331 observations appear to be either parsing errors or raw data errors. For example, in 2014, Guardian Life (CIK: 901849) reported holdings in Noble Corp (CUSIP: G6543110) of over 144 billion shares valued at $144 billion dollars, while Noble Corp had a just over 250M shares outstanding and a market capitalization of $5.6B.[41] The result is a dataset of 18,968,596 observations of unique CIK-CUSIP-record date holdings across 75 reporting quarters.

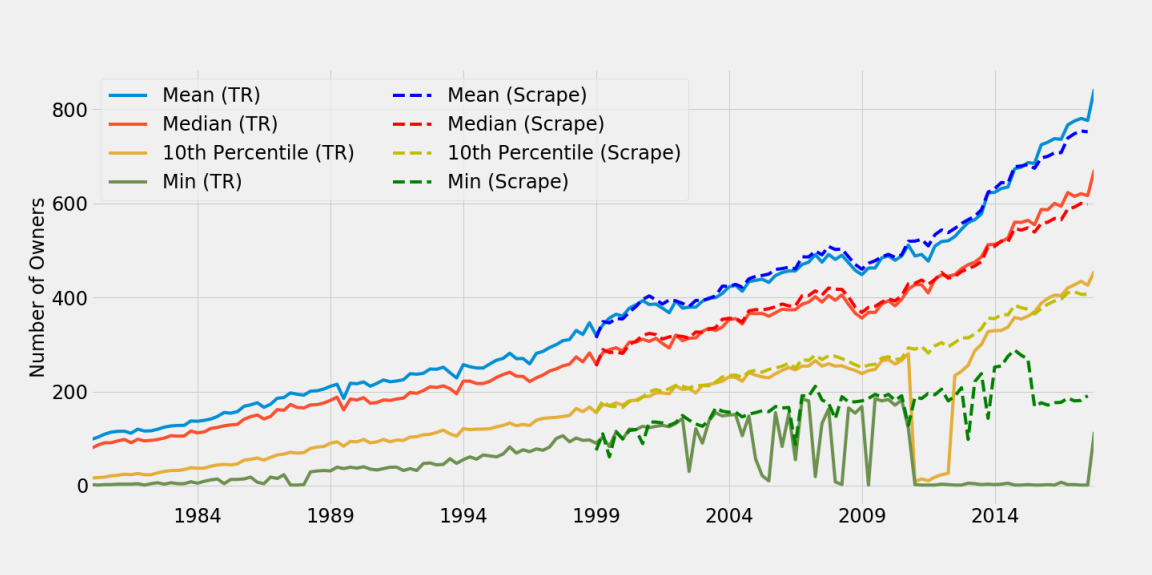
B.2.4 Comparison to Thomson Reuters

We do two primary comparisons against the Thomson Reuters (TR) dataset, followed by a deep-dive on some particular holdings where the TR dataset seems deficient. First, we consider the number of 13(f) owners per S&P 500 firm. Second, we consider the number of S&P 500 single-class of share firm that has over 100 owners in the dataset. In both cases we indicate the TR data with solid lines and our scraped data with dashed lines.

Appendix Figure 19 plots the mean, median, 10th percentile, and minimum of the number of owners of S&P 500 firms over time. Solid lines are the TR data, dashed are the scraped data. As is clear, there appears to be an issue in the TR data where some firms show few owners, as evidenced by the "min" line. In addition, the "10th percentile" line shows that there is a series of quarters beginning in 2011 where over 10% of S&P 500 firms have very few reported owners. In contrast, the dashed lines show more consistent patterns in the scraped

[41] Guardian's XML filing is available at:
https://www.sec.gov/Archives/edgar/data/901849/000072857214000014/xslForm13F_X01/SepGLIC.xml

Figure 19: Owners Per Firm



Notes: This figure depicts statistics of the number of investment managers per issue in the S&P 500 over time. The TR data uses "mgrno," manager number, as a manager while the scraped data uses the SEC's CIK number for a manager.

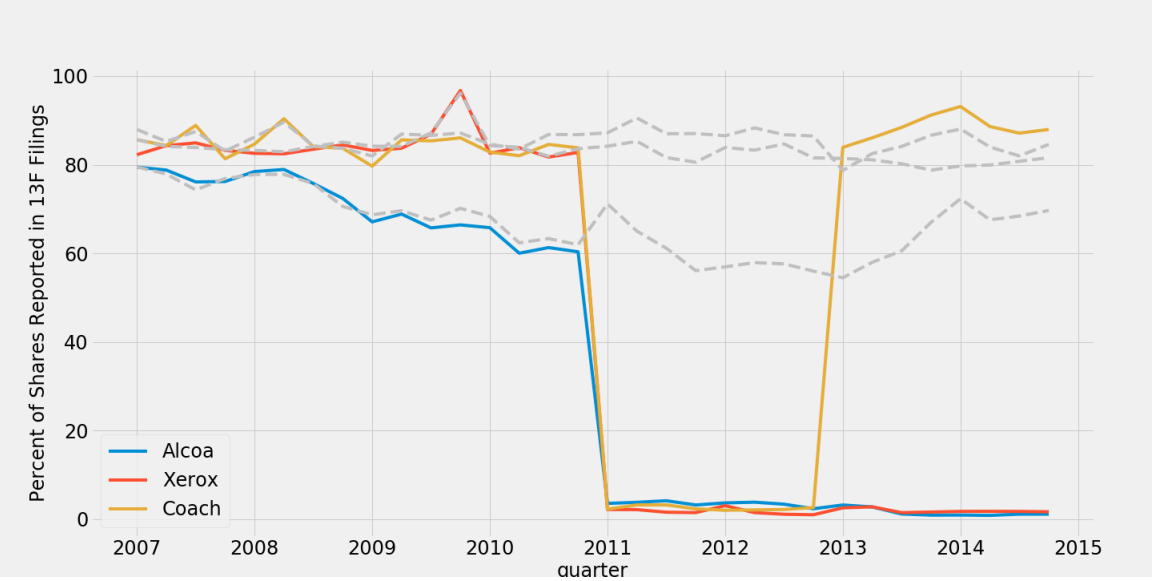
data.

Appendix Figure 2 presents these data in a different way: for each quarter, it plots the number of single-class of share firms held by 13(f) managers in the respective datasets, limited to issuances held by at least 100 investment managers. Note that this should be below 500 as we omit firms with multiple classes of shares. As is immediately clear, there is an issue with the TR dataset beginning in 2011. If a firm appears to have very few owners, this directly impacts κ through the $IHHI$, as shown in equation 3.

Finally, Appendix Figure 20 does a "deep dive" for three S&P 500 securities around the 2011 window where the TR dataset appears to have deficiencies. The plot shows, in solid color lines, the percent of shares outstanding reported to be held by 13(f) managers for three major firms: Alcoa, Xerox, and Coach in the TR dataset. The solid lines show that prior 2011, 13(f) investment firms held between 60% and 90% of these firms. However, in 2011, that falls dramatically to under 10%, before reverting back in 2013 for one of the three firms. In dashed lines are the percent of shares outstanding found in our scraped and parsed dataset. The TR data seem unreliable while the scraped data present a reasonable time series for institutional ownership.

To summarize the issue with the Thomson Reuters dataset, Appendix Figure 21 shows what

Figure 20: Examples of TR Coverage Issues



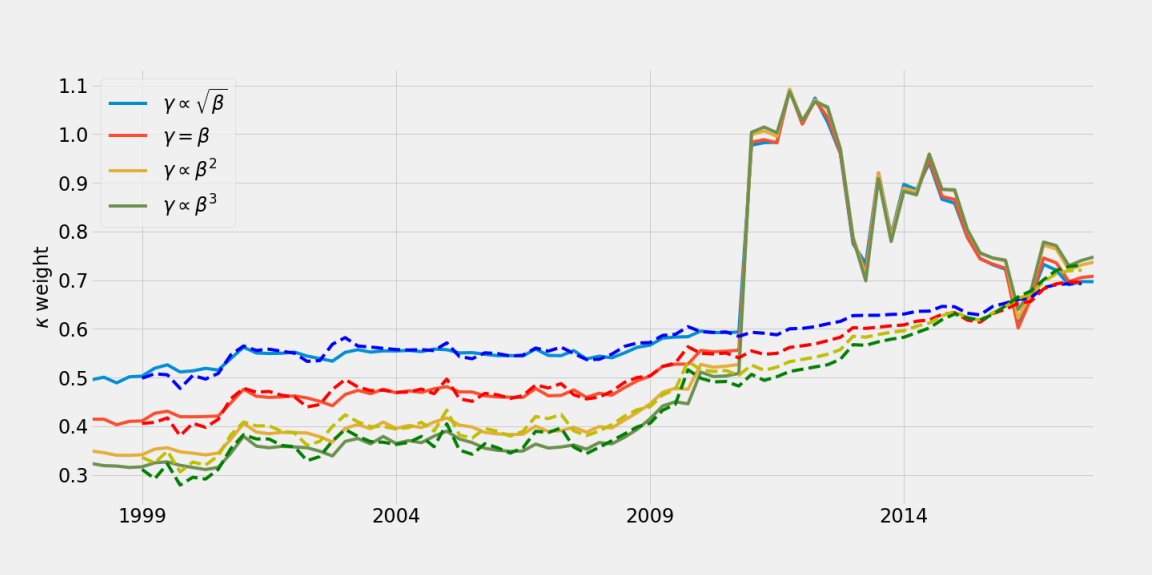
Notes: This figure sums the holdings of all 13(f) managers for three firms: Alcoa (permno: 24643, CUSIP: 03965L10), Xerox (permno: 27983, CUSIP: 98412110), and Coach (permno: 88661, CUSIP: 87603010). TR data series are plotted solid lines, the authors' scraped and parsed data in dashed lines.

the average computed profit weights (the κ values) would be using the raw Thomson Reuters data in solid lines, and our new dataset in dashed lines. As is clear, the Thomson Reuters dataset has coverage deficiencies in several years that result in large swings of the average κ, even reaching improbably high values starting in 2010.

B.2.5 Airline Sample

Most airlines are not S&P 500 constituents during this time period (one notable exception is Southwest Airlines). Therefore, we began by assembling a set of CUSIPs for airlines from CRSP and arrived at a set that consisted of major airlines (excluding foreign and regional). We were careful to drop any reported holdings after any bankruptcy declaration: there are many cases of institutional investors continuing to report holdings of non-existent securities. We also gather CUSIPs for entities that emerge from bankruptcy, or from mergers. The final set of airlines consists of: AirTran, Alaska, American, Continental, Delta, Eastern, Hawaiian, JetBlue, Northwest, Pan Am, Southwest, Spirit, Trans World, United, US Airways, and Virgin America. Several of these have multiple CUSIPs over this time period. We do not adjust for insider holdings in this exercise, although in practice this may be a good thing to do if insider holdings are significant.

Figure 21: Profit Weight Comparison, TR vs Scraped Data



Notes: This figure presents average profit weights for both the TR and scraped datasets by control assumption. Solid lines denote Thomson-Reuters dataset and dashed line denotes scraped and parsed 13(f) dataset.

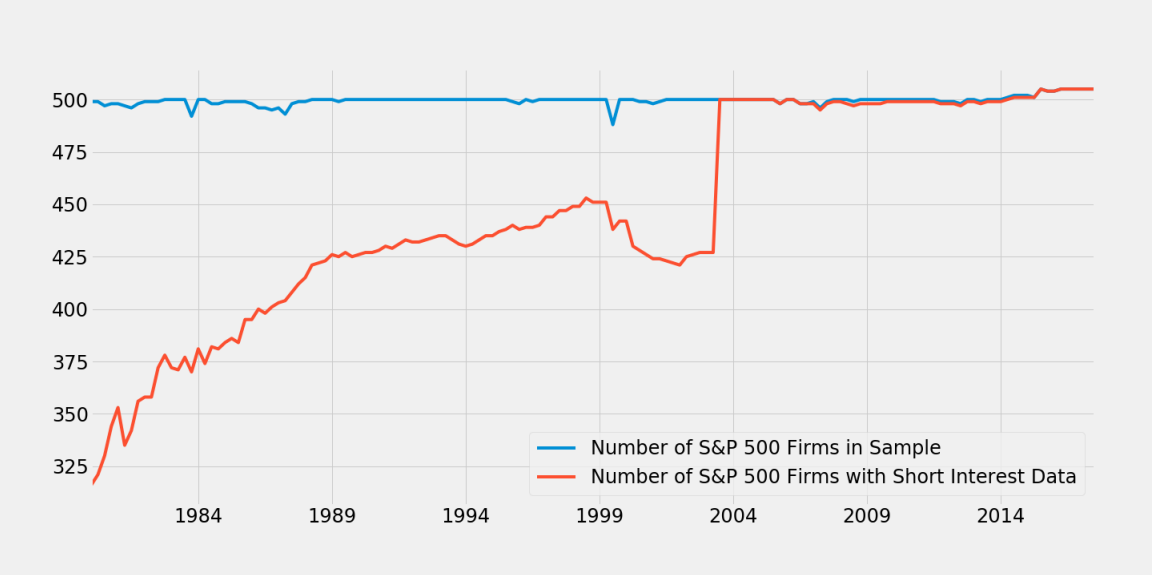
B.3 Short Interest

A known limitation of the 13(f) data for calculating institutional ownership is that short interest is double-counted. When an investor takes a short position they borrow shares from another investor and sell them, with a promise to repay the shares at a later date. These shares are then double-counted, reported on form 13(f) by both the initial investor as well as the investor to whom they are sold. It is for this reason that one can often observe "institutional ownership," as reported in online sources, in excess of 100%.

Data on short interest are obtained from the Compustat short interest supplemental dataset. These data are available at the firm level, not the investor level. Moreover, evidence suggests that even if we had data at the investor level, it is not clear how we should think about control rights. While it seems intuitive that only the actual holder of the stock should cast votes in corporate governance activities, in practice it seems that *both* the initial investor as well as the current holder may end up voting the same shares, see Kahan and Rock (2008).

Appendix Figure 22 characterizes the coverage of the short interest data in our sample, which improves dramatically after 2004. Appendix Figure 23 documents the degree of short interest. We see that while short interest in excess of 2% is quite common, short interest in

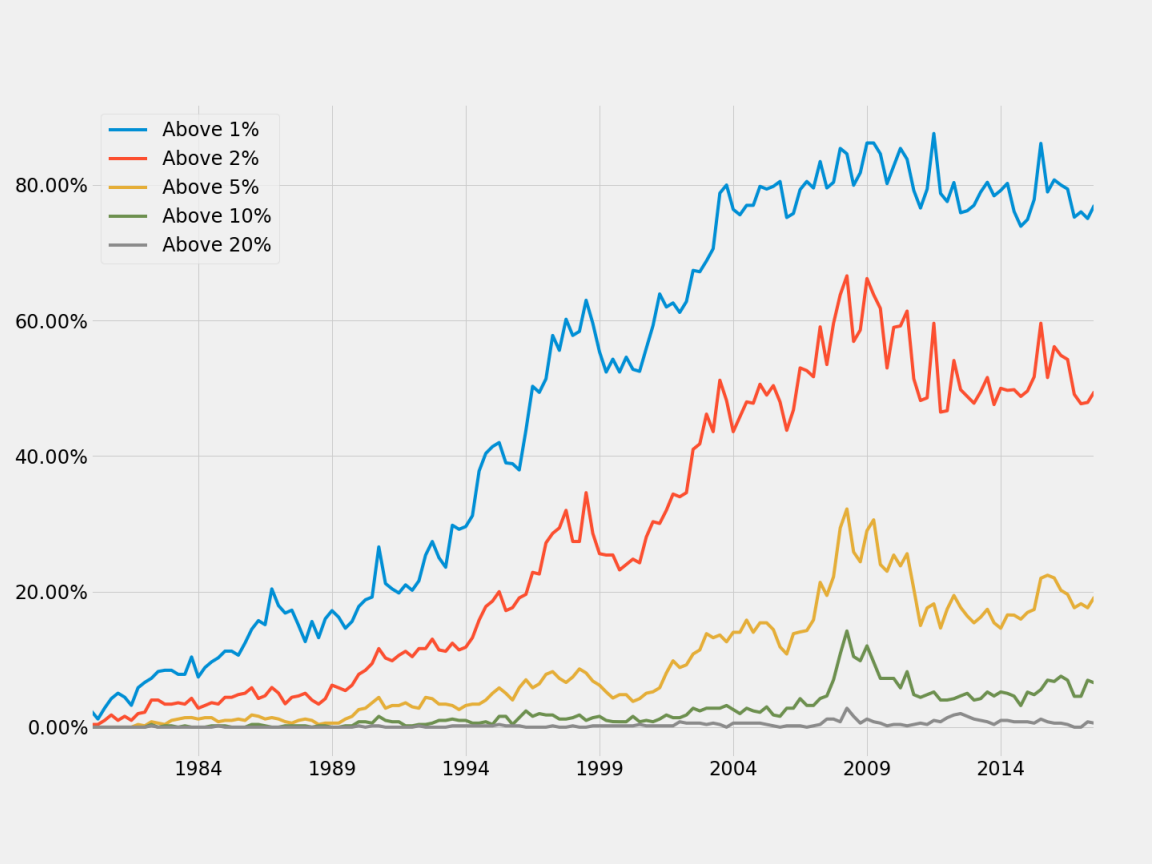
Figure 22: Coverage of Short Interest Data



Notes: This figure compares the number of firms in the sample against the number of firms for which we observe the level of short interest in Compustat.

excess of 20% is quite rare.

Figure 23: Short Interest Levels



Notes: This figure shows the distribution of short interest levels over time reported for our sample firms in Compustat.

C Additional Tables and Figures

C.1 Correlations with Two-Digit SIC Divisions

Here we re-consider Table 3 without firm-level fixed effects, instead including fixed effects for two-digit SIC divisions. Results are presented in Table 4.

The results concerning investor similarity, market cap, and retail share are similar to our findings with firm fixed effects. What is new here is the inclusion of SIC division fixed effects. Though there are statistically distinguishable differences in the mean profit weight in different industries, they are small (on the order of 0.02 to 0.05) relative to the much larger changes we observe in the time series and in the variation induced by differences investor similarity, market cap, and retail share. We also note that, different from Table 3, now

Table 4: Correlations with κ, SIC FE

	(1)	(2)	(3)	(4)	(5)
Quarter	0.0046*	0.0031*			
	(0.0002)	(0.0002)			
Aggregate Investor Similarity	0.6339*				
	(0.1101)				
β-weighted Investor Similarity		1.2232*	1.2981*	1.2974*	1.2972*
		(0.0537)	(0.0575)	(0.0575)	(0.0574)
log(Market Cap)	0.0587*	0.0560*	0.0588*	0.0587*	0.0588*
	(0.0041)	(0.0037)	(0.0039)	(0.0039)	(0.0039)
Retail Share	0.7060*	0.5677*	0.5525*	0.5526*	0.5510*
	(0.0339)	(0.0297)	(0.0301)	(0.0300)	(0.0301)
Agriculture, Forestry, and Fishing	0.0215	-0.0069	-0.0150	-0.0160	-0.0168
	(0.0309)	(0.0294)	(0.0277)	(0.0279)	(0.0276)
Mining	0.0443*	0.0462*	0.0449*	0.0449*	0.0464*
	(0.0200)	(0.0199)	(0.0199)	(0.0199)	(0.0198)
Construction	0.0315	0.0246	0.0238	0.0232	0.0242
	(0.0182)	(0.0220)	(0.0220)	(0.0220)	(0.0217)
Manufacturing	0.0272	0.0274	0.0259	0.0257	0.0266
	(0.0148)	(0.0159)	(0.0159)	(0.0159)	(0.0157)
Transportation and Utilities	0.0486*	0.0292	0.0267	0.0265	0.0269
	(0.0172)	(0.0177)	(0.0177)	(0.0178)	(0.0176)
Retail Trade	0.0452*	0.0420	0.0415	0.0419	0.0420
	(0.0227)	(0.0228)	(0.0227)	(0.0226)	(0.0226)
Finance, Insurance, and Real Estate	0.0340*	0.0300	0.0295	0.0293	0.0299
	(0.0162)	(0.0169)	(0.0169)	(0.0169)	(0.0168)
Services	0.0331	0.0442*	0.0450*	0.0450*	0.0453*
	(0.0183)	(0.0188)	(0.0187)	(0.0187)	(0.0186)
Nonclassifiable	-0.0309	0.0387	0.0301	0.0375	0.0305
	(0.0618)	(0.0484)	(0.0481)	(0.0482)	(0.0481)
no. Segments				0.0002	
				(0.0009)	
Diversified Firm (2+)					-0.0094
					(0.0079)
Highly Diversified Firm (5+)					0.0076
					(0.0069)
Firm FE					
Quarter FE			✓	✓	✓
R^2	0.3890	0.4286	0.4334	0.4335	0.4336
N	36355363	36355363	36355363	36353863	36355363

Notes: This table reports correlates of the common ownership profit weights. An observation is a pair of S&P 500 constituent firms in a given quarter. The excluded industry is Wholesale Trade. Robust standard errors are clustered at the firm level and reported in parentheses. * indicates significance at the 5% level.

the correlations with the number of business segments and dummies for being diversified or highly diversified are identified using the within-division cross-sectional variation. However, we still find no statistically significant relationship.

C.2 Pair-level Fixed Effects

Here we provide additional robustness for the regressions reported in Table 3. We include $\lambda_{f,g}$ fixed effects for each pair of firms (up to $250,000$ pairs in each period) as well as λ_t quarterly fixed effects. These fixed effects are directional in that $\lambda_{f,g} \neq \lambda_{g,f}$. This enables us to look within the pair of firms $\kappa_{f,g,t}$. We examine only the periods from 2000-2017 so that we can include data on the "Big Three" institutional investors. As a robustness check, we include the $\beta_{f,s}$-weighted measure of how "indexed" a firm's investors are in polynomial form.

We report our results in Table 5. As before, we find that retail share and market cap are positively correlated with $\kappa_{f,g,t}$. Once we control for investor concentration the correlation with retail share changes sign. This makes sense as we expected the primary mechanism by which retail share was associated with κ was through $IHHI_f$ measure. As one might expect from (3'), there is a strong positive correlation between $\kappa_{f,g}$ and $\frac{1}{IHHI_{f,t}}$ (by construction). Also, as investors in f become more "indexed" $\kappa_{f,g}$ is increasing though at a decreasing rate. Finally, in-so-far as there is a direct relationship with the "Big Three" institutional investors and $\kappa_{f,g}$ that relationship appears to be negative (though the "Big Three" investors are also very indexed). This is at least suggestive of the possibility that the increase in size of the "Big Three" may not be driving the rise in common ownership incentive terms alone.

C.3 Tunneling and Specifications of Control

Here we re-create figure 16 under alternative specifications of γ The results are depicted in Figure 24. While the proportion of pairwise profit weights greater than one is insensitive to specification from 1980 to the late aughts, it becomes very sensitive in the period following. This coincides with the rise of the "Big Three" from Figure 7. If we place more weight on the holdings of these large firms in constructing control rights, we find substantially greater incentives for firms to engage in tunneling.

Table 5: Correlations with κ 2000-2017: Large Institutional Investors

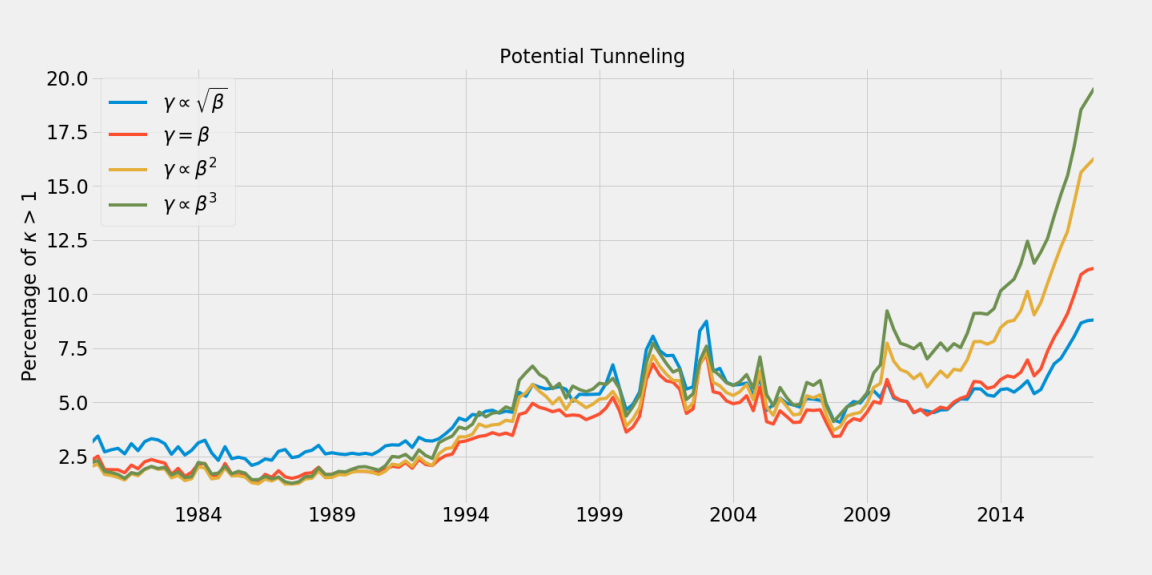
	(1)	(2)	(3)	(4)	(5)
$\frac{1}{1-r_{f,t}}$	0.314*	0.301*	0.304*	0.305*	−0.172*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\frac{1}{IHHI_{f,t}}$					45.505*
					(0.083)
$\log(\text{market cap})_{f,t}$	0.081*	0.078*	0.077*	0.077*	0.029*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\text{Indexing}_{f,t}$	0.964*	1.079*	237.411*	237.069*	1.253*
	(0.004)	(0.004)	(1.065)	(1.069)	(0.004)
$\text{Indexing}^2_{f,t}$			−68.704*	−70.900*	
			(0.656)	(0.636)	
$\text{Indexing}^3_{f,t}$				−19.064*	
				(0.520)	
$\beta_{f,s,t}$ BlackRock		−0.406*	−0.333*	−0.344*	−0.288*
		(0.007)	(0.007)	(0.007)	(0.006)
$\beta_{f,s,t}$ Vanguard		−0.311*	−0.234*	−0.229*	−1.226*
		(0.016)	(0.016)	(0.016)	(0.014)
$\beta_{f,s,t}$ StateStreet		−0.509*	−0.420*	−0.414*	−0.275*
		(0.014)	(0.014)	(0.014)	(0.012)
N	17,397,247	17,397,247	17,397,247	17,397,247	17,397,247
R^2	0.735	0.735	0.737	0.737	0.797

Notes: * denotes significant at the 1 percent level. All standard errors are clustered at the firm pair (f, g) level.

C.4 Rise of Indexing

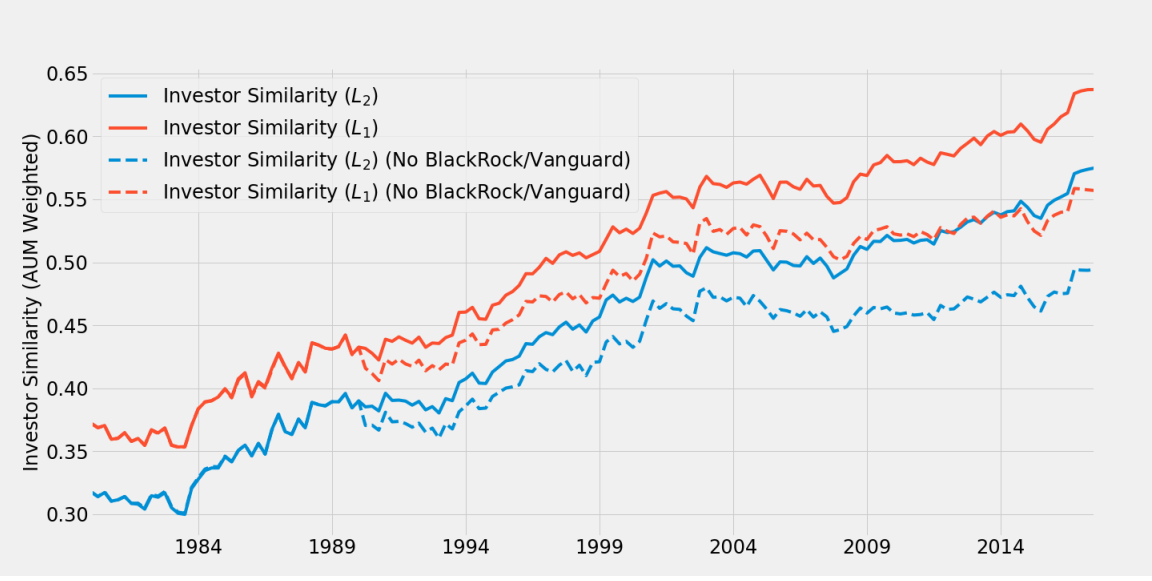
To understand the role that large institutional investment firms BlackRock and Vanguard have had on the rise of indexing, we now revisit Figure 10, which plotted the similarity of investor portfolios to the "market" portfolio of the S&P 500. The figure computes the average in each time period weighted by assets under management. We now re-compute these figures removing BlackRock and Vanguard entirely. This allows us to see the contribution to the rise in indexing attributable to those firms. Appendix Figure 25 shows the results. From this, we see that while those particular firms are indeed large, they are large and particularly indexed, and as a result they have had a sizable effect on the increase in indexing.

Figure 24: Potential Tunneling Incentives $\kappa > 1$, Alternative Control Specifications



Note: This figure reports the fraction of pairwise profit weights $\kappa_{f,g} > 1$ in each period under different control assumptions.

Figure 25: Similarity Between Investor Portfolios and S&P 500 Index



Notes: This figure depicts L1 and L2 similarity measures comparing investor portfolios weighted by investor AUM within our sample of S&P 500 assets. Dashed lines show the result if we exclude BlackRock and Vanguard.