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OWNERSHIP DIVERSIFICATION AND PRODUCT MARKET PRICING INCENTIVES

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Ownership Diversification and Product Market Pricing Incentives*

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November 11, 2022

Abstract

We link investor ownership to profit loads on rival firms by the managers of a firm. We propose a theory model in which we distinguish between passive and active investors' holdings, where passive investors are relatively more diversified. We find that if passive investors become relatively bigger, then common ownership incentives increase. We show that these higher incentives, in turn, are linked to higher firm markups. We empirically confirm these relationships for public US firms in the years 2004-2012, where the financial crisis coincides with passive investors' rise. The found effects are small but non-negligible.

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1 Introduction

Common ownership, whereby large (institutional) investors hold ownership stakes in several firms, has been shown to be an increasingly pervasive pattern in several sectors, such as airlines, banking and pharma (Azar et al., 2018a; Azar et al., 2022; Newham et al., 2018), as well as more generally across the S&P 500 firms (Azar and Vives, 2021; Backus et al., 2019), particularly since the 2007-2008 great financial crisis (Banal-Estanol et al., 2022; Clap, 2019; Lewellen and Lowry, 2021). In the presence of common ownership, and provided that firm decision–making depends on investors' interests, the profits of other firms in the same industry should be taken into account when making strategic decisions (O'Brien and Salop, 2000). Common ownership should thus give rise to "common ownership incentives," i.e., the firms' conceptual objective function should place positive loads on the profits of the other firms in the same industry. As we show later, for the period 2004-2012, the standard measure of common ownership incentives, the average "lambda," has been increasing over time across the US publicly-listed firms, especially since the 2007-2008 "great financial crisis."[1]

To understand the evolution of the common ownership incentives around the great financial crisis, as well as their relationship with the evolution of product market outcomes, our paper takes a step back. It analyzes, for the first time we believe, the characteristics of the ownership holdings of active and passive investors, respectively, and their relationship with common ownership incentives. We argue that, as a consequence of their distinct holding patterns, active and passive investors differ in how their holdings are split within and across firms. By nature of their investments, passive investors hold more diversified portfolios of stocks, as passive investors spread their holdings relatively evenly across firms, because they seek to track the return of benchmark indices (such as the S&P 500 and the Russell 1000). As a consequence, their holdings tend to provide a broad and relatively even coverage of the market. Active investors, instead, hold portfolios with particular stocks overweighted, while others are underweighted. As a result, the holdings of passive investors are, on average, more diversified across the firms of the industry than those of active investors.

We argue that the increasing levels of common ownership incentives can be explained by the increase in the money holdings of passive investors relative to those of active investors.

[1]As defined formally later, lambda is the weight that a firm should place on the other firms' profits, relative to the weight it places on its own profits, in its objective function, if one assumes that the firm's decision-makers maximize a weighted sum of the interests of their investors, some of which may be common.

These relative assets under management of passive investors have increased steadily over time after the 2007-2008 financial crisis (Anadu et al., 2020; Wigglesworth, 2018). We show, at the firm level, both theoretically and empirically, that as the holdings of a more diversified group of investors become relatively larger (the passive investors in our sample), the firm's common ownership incentives increase. We find, in particular, that a 1% change in the relative holdings of the more diversified passive investors is positively and significantly related to a change in lambda by 0.13%. Thus, we find a clear link between investor holding patterns and the firms' common ownership incentives.

We further show that this change in common ownership incentives can be associated with a change in product market markups, which averages increased since the 2007-2008 financial crisis (De Loecker et al., 2020). In terms of magnitudes, a 1% change in the common ownership incentives is positively and significantly related to a change in structurally estimated markups by $0.16\% - 0.29\%$, depending on the exact specification. In other words, we find empirical evidence that common ownership pricing incentives and markups are meaningfully linked. Combining both pieces of evidence, we tentatively show that firms' markups can be linked to the relative holdings of its passive investors, and this through the firm's common ownership incentives. Our estimations show that a 1% change of the relative holdings of the diversified-passive investors is positively and significantly related, through lambda, to a change in markups by about $0.02\% - 0.04\%$. In other words, we find robust evidence that product market outcomes can ultimately be linked to investor ownership patterns, whereby the magnitude of the effect is small but non-negligible.

Our paper, thus, has essentially two steps. In the first step, we make use of a set of investor variables that characterize the ownership holdings of the sets of passive and active investors of the firms: relative holdings, diversification and concentration. We argue that, for a given level of concentration and diversification of each type of investor, the common ownership incentives increase in the relative holdings of the most diversified type of investors, which are in practice the passive ones. We first prove this argument formally, within a particular model of corporate ownership. Subsequently, we corroborate it empirically with data of all publicly listed firms in US industries between 2004 and 2012.

In a second step, we argue that changes in common ownership incentives can in turn be linked to changes in firms' markups. Intuitively, as the levels of common ownership between a given firm and its competitors increase, price increases in the firm's products are less harmful for its investors, as part of the diverted sales and profits are lost to other commonly-owned firms. Further, common ownership structures may help firms to reduce their costs through e.g., a better informational flow between connected firms (Lopez and Vives, 2019). Both mechanisms, i.e., higher prices or lower costs, lead to a positive relationship between common ownership incentives and markups. We first illustrate this argument formally, within the context of a simple model of product market competition. We illustrate the same argument empirically through OLS and 2SLS regressions. The 2SLS estimation results reflect the two successive steps of our setup, where first we investigate how investor variables connect to lambda, and then how lambda in turn connect to markups.

We show several extensions and robustness checks, with alternative sets of fixed effects and standard errors, alternative functional form assumptions, alternative assumptions on the levels of control, and alternative industry definitions. The main conclusion of these alternative specifications is that our results are robust to different assumptions.

We believe the contribution of our paper to prior literature is two-fold. First, it analyzes, for the first time the distinctive role of active and passive investors in the determination of the common ownership incentives. As Anadu et al. (2020, p1) write, "the shift toward passive investing stands out as one of the key developments in asset management in recent years."[2] Backus et al. (2021) further show that much of the rise in common ownership among the S&P 500 firms in recent decades is driven by a general increase in diversification of the investors' portfolios. Lewellen and Lewellen (2022) find that a firm's investors gain relatively more from other firms within the same industry doing well, when these investors are more diversified. Our paper identifies a channel through which common ownership incentives at the firm level can be affected through diversification; namely the shift of money holdings from active to passive investors. Note that this shift from active to passive investors accelerated around the 2007-2008 financial crisis.[3] Lewellen and Lowry (2021) show that jumps in common

[2]Note that the shift to passive investing has not only occurred in the US but also in other countries (Bhattacharya and Galpin, 2011; Sushko and Turner, 2018).

[3]Several factors appear to be contributing to this active-to-passive shift. The development of the efficient market hypothesis called into question the ability of active selection of securities to "beat the market" and indicated that investors should instead hold the market portfolio itself (Bhattacharya and Galpin 2011). Particularly since the great financial crisis, it has become increasingly more common to prioritize ETFs and index funds as investment vehicles, mainly due to a higher demand for lower fee passive investment strategies (Sushko and Turner, 2018), and the continuous underperformance of active management of invested money (Malkiel, 2005). A greater regulatory focus on the fees of investment products may have further encouraged the financial industry to offer low-cost, passive products to individual investors (Sushko and Turner, 2018b).

ownership incentives are often due to mergers of institutional investors around the same time window. Our paper, thus, offers an explanation that complements their findings.

The second part of the paper contributes to the recent literature on the effects of common ownership on product market outcomes, by relating investors to product markets: we link investors' holdings to structurally-estimated product market markups, through lambda weights. Common ownership has been shown to have effects on prices, profits and firm value in several markets (see Schmalz, 2018 and 2021, for recent reviews). Azar et al. (2018a, 2016), for example, link common ownership to prices in the US airline and banking industries. Newham et al. (2018) further show that stronger common ownership links between incumbent brand firms and potential generic entrants in pharmaceutical markets reduce generics' incentives to enter. Gutierrez and Philippon (2017, 2018) show that "quasi-indexer" ownership (and, thus, higher common owneship) leads to lower investment. He and Huang (2017) find that common ownership improves innovation productivity and operating profitability.[4] Boller and Scott Morton's (2019) results are consistent with the hypothesis that common ownership raises profits. Kang et al. (2018) report that the number of blocks that a firm's large institutional investors hold is associated with firm value. On the other hand, Koch et al. (2021) examine the correlation between common ownership and industry-level accounting markups and industry profitability and find no relationship between these market outcomes and common ownership. Similarly, Lewellen and Lowry (2021) find little robust evidence that common ownership affects firm behavior over longer time horizons, and argue that the use of mergers between investors as a source of identifying variation may not be suitable outside the years of the great financial crisis.[5]

The rest of the paper is organised as follows. Section 2 provides the general framework, introduces the investor variables and the standard common ownership incentive measure, lambda, together with a novel decomposition of this measure. Section 3 derives formal propositions on the effects of the investor variables on the common ownership incentives within a simple model of corporate ownership. Section 4 explains the data and shows that our empirical analysis for US public companies in the period 2004-2012, which includes

[4]Bindal and Nordlund (2022) discover that an increase in common ownership leads to a stronger decrease in R&D and a stronger increase in prices and profitability when a firm has similar products.

[5]Dennis et al. (2022) also question the conclusions of Azar et al. (2018a) that common ownership within the airline industry resulted in anti-competitive practices; but see also Azar et al. (2018b) for a general defense of their results.

the financial crisis, are in line with the theory model's propositions. Section 5 decomposes the changes in the average common ownership incentive measure using our new decomposition. Section 6 analyzes the impact of the common ownership incentives on product market markups, both theoretically and empirically. Section 7 provides extensions and robustness checks. Section 8 concludes. As appendices, we include more details on the data, derivations of the lambdas in matrix algebra and the markup estimates.

2 General Framework

This section introduces first our classification of investor types into active and passive investors. It then provides an informal introduction and formal definition of a set of "investor variables" that allow us to characterize firms' ownership holdings of active and passive investors, respectively. Subsequently, we introduce the standard measure of common ownership incentives, λ, and show that it can be decomposed due to the separation of the investors into active and passive types.

Throughout most of the paper, we focus on the investors and firms within a particular product market, or "industry." We thus concentrate on "horizontal shareholdings," whereby shareholders own partial financial rights in several firms operating within the same industry (Elhauge, 2016, and Scott Morton and Hovenkamp, 2017). We therefore disregard the common ownership links between vertically-related firms (or industries), or between unrelated firms. Thus, to simplify, we assume industries to be independent of each other, and thus the interests of an investor in firms outside the industry do not affect firm decision-making; but see footnote 35 where we discuss alternative assumptions and results.

2.1 Active versus passive investors

In this subsection, we give a general overview of how we classify investors, and how these investor groups differ in some key dimensions. This serves as an introduction towards formally defining key investor and common ownership variables.

Decision-makers within firms need to weigh the interests of different investors. The most-used classification of investors is according to their investment orientation. Some investors can be considered mostly "active" while others are considered mostly "passive".[6] In general terms, active investors use a hands-on approach and select stocks on the basis of company analysis. Passive investors, instead, seek to track the return of benchmark indices, such as the S&P 500 or the Russell 1000, and construct their portfolios to reflect the characteristics of the chosen benchmarks. In other words, while active investors focus on outperforming benchmarks or return levels, passive investors mimic the investment holdings of a specific benchmark in order to achieve similar results.[7]

As a consequence of their distinct investment strategies, active and passive investors might differ in how they split their holdings across firms. Passive investors should have more diversified portfolios of stocks than active investors. Indeed, passive investors might spread their holdings relatively more evenly across firms because benchmark indices tend to provide a broad and relatively even coverage of the market.[8] Active investors, instead, perhaps overweight particular stocks. As a result, active investors should be less diversified than passive investors. While this assumption will be verified in the empirical section, diversification is a key variable in our analysis and will be formally defined in the next subsection.

A second key element is the level of overall holdings of investors. Passive investors, and particularly the "Big Three index fund managers" –BlackRock, Vanguard, and State Street Global Advisors– have enjoyed a large, steady, and continuing growth over the last decades, and even more so after the financial crisis (Bebchuk and Hirst, 2019). The growing demand for passive investment, and the resulting increase in assets under management and overall

[6]To be sure, the distinction between active and passive investing is not always clear-cut; for example, some nominally active investment funds behave passively by following so-called closet indexing strategies (Cremers and Petajisto, 2009). Some papers make a more fine-grained classifications, often using on Brian Bushee's institutional investor classification data, which assigns : https://accounting-faculty.wharton.upenn.edu/bushee/. However, for the purposes of this paper, it is more useful to have two large and as distinct as possible investor groups.

[7]The same investor may follow an active investment strategy with some funds and a passive investment strategy with other funds. To simplify, though, our theoretical analysis assumes a one-to-one relationship between investor and type of investment strategy, while our empirical analysis classifies the investors according to their most important investment strategy. In other words, we assume that an investor can only be passive or active, but not both; see e.g., Schmalz (2021) for details on this reasoning.

[8]Indices differ by their index weight methodology, and on rules on how stocks are allocated in the index. For example, the S&P 500 and the S&P 500 Equal Weight both cover the 500 largest stocks from the S&P Total Market Index, but the S&P 500 is weighted by market capitalization and the S&P 500 Equal Weight gives each company equal weight. Many indices also impose constraints, such as concentration limits, on the inclusion rules.

level of ownership holdings in the hands of passive relative to active investors, is often attributed to lower costs, superior returns after fees, and tax advantages, as compared to active investment. The empirical section will confirm the growing importance of passive investors in our sample, where one can tentatively link the 2008 financial crisis to an acceleration of this growing importance.

Finally, the concentration of ownership of the active investors within a given firm could be larger than the concentration of the passive investors within the same firm. Indeed, a passive investor should have similar holdings in any firm than any other passive investor with the same level of overall holdings, as long as they benchmark against the same index. As the investments of active investors are more asymmetric, their concentration level could be larger. Still, the within-firm level of concentration of each type of investor also depends on the overall number of investors in the firm, as well as the distribution of overall holdings of each type of investor across individual investors. In the empirical section, we will verify which type of investor is more concentrated within the firms in our sample.

2.2 The investor variables

This subsection provides a formal definition of the three firm-level measures that characterize the level and distribution of holdings of each type of investor in the firm: (i) the degree of portfolio diversification, as a measure of how diversified the investors of that type are, on average, **across** the firms of the industry, (ii) the relative level of holdings, as a measure of how large the investors of each type are, on aggregate, **within** the firm, and (iii) the ownership concentration, as a measure of how concentrated the holdings of each type of investor are **within** the firm.

We denote the set of firms in the industry by S, their set of active and passive investors by A and P, respectively, the monetary ownership holdings of an investor $i \in A \cup P$ in a firm $j \in S$ by h_{ij}, and her fraction of the shares in the firm by $\beta_{ij}(= h_{ij}/\sum_{l \in A \cup P} h_{lj})$. A given investor i may have holdings in several firms of the same industry, thus generating common ownership within that industry.

We first define the firm investors' weighted average **degree of portfolio diversification** of holdings across the firms of the industry of each type of investor $\tau(\in A, P)$ as

$$DIV_j^\tau \equiv \sum_{i\in\tau}(\frac{h_{ij}}{\sum_{i\in\tau} h_{ij}})DIV_{i,S} \quad \text{where} \quad DIV_{i,S} \equiv 1 - \sum_{k\in S}(\frac{h_{ik}}{\sum_{l\in S} h_{il}})^2. \tag{1}$$

The individual investor diversification $DIV_{i,S}$ (right-hand side in (1)) is defined, following standard practice (see e.g., Berger et al., 2010), as one minus the concentration of the investor's ownership holdings across firms.[9] An investor with holdings in only one firm of the industry would have $DIV_{i,S} = 0$ whereas an investor that spreads evenly her holdings in the firms of the industry would have $DIV_{i,S} = (|S|-1)/|S|$. We aggregate the diversification levels of the investors of the same type, and define the firm-level measures DIV_j^τ (left-hand side in (1)). We use, as weights, the fraction of holdings within the investors of the same type, so as to give more weight to the larger investors of that type in the firm-level average.

Second, we define the **relative level of holdings** of passive investors in firm j as

$$RLH_j^{P/A} \equiv \frac{\sum_{i\in P} h_{ij}}{\sum_{i\in A\cup P} h_{ij}}, \tag{2}$$

i.e., the total percentage holdings of the passive investors, $RLH_j^{P/A} = \sum_{i\in P}\beta_{ij}$. This reflects the overall size of the passive investors in the firm relative to the size of the active ones.

Finally, we define the degree of **ownership concentration** of holdings of each type of investor $\tau(\in A, P)$ within firm j as

$$CON_j^\tau \equiv \sum_{i\in\tau}(\frac{h_{ij}}{\sum_{i\in\tau} h_{ij}})^2. \tag{3}$$

A firm with only one investor of type τ, for instance, would have $CON_j = 1$ whereas a firm with m identical investors of type τ would have $CON_j = 1/m$.

[9] Where concentration is defined using the sum of the squares of the percentage holdings across firms, i.e. the Herfindahl-Hirschman Index (HHI).

2.3 The common ownership measure lambda, and a decomposition

We introduce now our measure of common ownership incentives, λ, and show that it can be decomposed due to the separation of the investors into active and passive types. Our measure is a standard measure of common ownership, starting from O'Brien and Salop (2000), and is based on the idea that a firm's decision-makers maximize a weighted sum of the interests of their investors, where (i) the interests of each investor depend on her portfolio of ownership holdings in the firms of the industry, and (ii) the weights attributed by the firm to the interests of each of its investors of the firm depend on her degree of control of the firm.[10]

To derive the measure formally, note that the payoff of investor i's portfolio of ownership holdings in the industry is given by $\sum_k \beta_{ik}\pi_k$, where β_{ik} is the investor i's fraction of ownership in firm k and π_k the firm k's profit. Denoting the weight attributed by firm j to the interests of investor i by γ_{ij}, the firm j's objective function to maximize is:

$$\sum\nolimits_i \gamma_{ij} \sum\nolimits_k \beta_{ik}\pi_k. \tag{4}$$

Rearranging, this is equivalent to maximize:

$$\pi_j + \sum_{k \neq j} \lambda_{jk}\pi_k, \text{ where } \lambda_{jk} \equiv \frac{\sum_i \gamma_{ij}\beta_{ik}}{\sum_i \gamma_{ij}\beta_{ij}}. \tag{5}$$

The variable λ_{jk} is the weight that firm j should place on firm k's profits, relative to the weight it places on the profits of the firm j itself, in its objective function. The weight that firm j should place on the profits of any firm k (be it $k = j$ or $k \neq j$) is given by the scalar product of the levels of control in firm j and ownership in firm k of all investors, that is, of their abilities and incentives to steer decision-making of firm j towards the profits of firm k.

To better understand the relationship between the investor variables and the common ownership incentives, as well as the dynamics of the common ownership incentives, we propose a novel decomposition of λ_{jk} based on the distinction of the two types of investors.

[10] See Schmalz (2021) for a review of the theoretically plausible governance mechanisms by which common ownership can affect behavior. Anton et al. (2002) present a mechanism based on managerial incentives through which common ownership affects product market outcomes. Shekita (2022) documents 30 actual cases of intervention, showing that common owners can have the ability and incentive to alter the behavior of portfolio firms.

Indeed, we can rewrite lambda as a linear combination of the type-specific lambdas, i.e.,

$$\lambda_{jk} = (1 - \nu_j^{P/A})\lambda_{jk}^A + \nu_j^{P/A}\lambda_{jk}^P, \tag{6}$$

where λ_{jk}^τ captures the relative weight of firm j in firm k because of investors of type τ only,

$$\lambda_{jk}^\tau \equiv \frac{\sum_{i\in\tau}\gamma_{ij}\beta_{ik}}{\sum_{i\in\tau}\gamma_{ij}\beta_{ij}} \text{ for } \tau = A, P, \tag{7}$$

and $\nu_j^{P/A}$ is the weight that firm j should place on the weight of passive relative to all the investors in firm j,

$$\nu_j^{P/A} \equiv \frac{\sum_{i\in P}\gamma_{ij}\beta_{ij}}{\sum_{i\in A\cup P}\gamma_{ij}\beta_{ij}}. \tag{8}$$

This decomposition shows that the common ownership links between firms (λ_{jk}) may change if the common ownership links through active or passive investors (λ_j^A or λ_j^P) change, or if the weight the firm places on each type of investor $\nu_j^{P/A}$ changes.

As we focus on firm level outcomes (also in the empirical part), we aggregate the measures of common ownership of a given firm with respect to all the other $|k-1|$ firms in the industry by taking simple averages:

$$\lambda_j \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{jk} \quad \text{and} \quad \lambda_j^\tau \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{jk}^\tau, \tag{9}$$

and thus, analogously, $\lambda_j = (1 - \nu_j^{P/A})\lambda_j^A + \nu_j^{P/A}\lambda_j^P$.

3 Impact of Investor Variables on Lambda - Theory

This section analyzes, from a theoretical point of view, the effects of the investor variables (DIV_j^τ, $RLH_j^{P/A}$ and CON_j^τ) on the common ownership incentive measure (λ_j). To understand these effects, we consider a particular model of corporate ownership, parameterised by a limited number of parameters, which allows active and passive investors to differ in terms of diversification, relative holdings, and ownership concentration, while retaining symmetry in terms of firms and investors of each type. This simple model allows us to derive formal comparative static results that will be carried through to the empirical section.[11]

3.1 A simple model

Assume that the n firms of an industry are symmetric in terms of value and ownership. In particular, suppose that each firm has a distinct set of m_A identical active "major" shareholders and a distinct set of m_P identical passive "major" shareholders. Each of these major shareholders is also a "minority" shareholder in all the other $n-1$ firms in the industry.[12] Thus, each firm has m_A active major shareholders and $(n-1)m_A$ active minor shareholders and, similarly, m_P passive major shareholders and $(n-1)m_P$ passive minor shareholders. The total number of investors in each firm, as well as in the industry as a whole, is $n * m_A + n * m_P$.

Active and passive investors are assumed to be symmetric within their investor type but they differ across types, and this in several dimensions. First, active and passive investors may own, in total, different fractions of the firms. We will denote the overall fraction of the shares owned by each type of investor by $\sigma_\tau \in (0,1)$, where $\sigma_A + \sigma_P = 1$. Second, active and passive investors may split their majority and minority shareholdings across firms differently. We will denote by $1-(n-1)\alpha_\tau$ and $(n-1)\alpha_\tau$ the split of shares between type-τ majority and minority shareholders, respectively.[13] Third, we also allow for the possibility that passive shareholders have different levels of control than active ones. We denote the control of each type of investor per unit of ownership by κ_τ so that $\gamma_{ij} = \kappa_\tau \beta_{ij}$ for each investor i of type τ

[11] In a more general setup, the investor variables, as well as the measures of common ownership, would depend on the holdings h_{ij} of each investor i in each firm j.

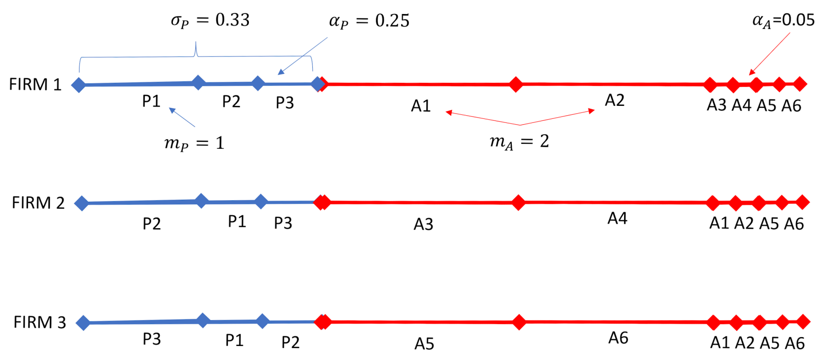
[12] One way of thinking about the set of major shareholders is taking, as a starting point, a set of investors who fully own a firm. These investors then subsequently sell, to other investors (who are themselves major investors in other firms), some shares (but they remain the most important shareholders).

[13] We should restrict $\alpha_\tau \in [0, 1/n]$ to ensure that major shareholders indeed have larger stakes than minority shareholders. In the extreme case in which $\alpha_\tau = 0$ investors of type τ only own shares in one firm. In the other extreme, $\alpha_\tau = 1/n$, they have their holdings equally split across all firms. In the case of perfect diversification, the stake is the same in all firms. For notational purposes, we will still be calling to some shareholders, major shareholders, and to the others, minority shareholders.

in firm j.[14] As the levels of control need to add up to 1 then $\sigma_A\kappa_A + \sigma_P\kappa_P = 1$.[15]

Figure 1 plots an example of the simple model with $n = 3$ firms, $m_P = 1$ major passive investors in each firm, $m_A = 2$ major active investors in each firm, a fraction $\sigma_P = 0.33$ owned by passive investors and $\alpha_P = 0.25$ the split of ownership between major and minor passive shareholders and $\alpha_A = 0.05$ for the active shareholders.

Figure 1. Example of ownership in simple model.



This figure plots an example of ownership of the simple model with $n = 3$ firms, $m_P = 1$ major passive investors in each firm, $m_A = 2$ major active investors in each firm, a fraction $\sigma_P = 0.33$ owned by passive investors and $\alpha_P = 0.25$ the split of ownership between major and minor passive shareholders and $\alpha_A = 0.05$ for the active shareholders.

The resulting fractions of ownership and control for each investor i of type τ ($\tau = A, P$), and for the firm j for which she is a major shareholder, are

$$\beta_{ij} = \sigma_\tau[1 - (n-1)\alpha_\tau]/m_\tau \text{ and } \gamma_{ij} = \kappa_\tau\sigma_\tau[1 - (n-1)\alpha_\tau]/m_\tau, \tag{10}$$

[14] Two leading cases to consider are the case in which all investors have "proportional control" to the shares they own ($\kappa_\tau = 1$ for $\tau = A, P$), in which case $\gamma_{ij} = \beta_{ij}$ for each investor, be it active or passive, and the case in which passive investors have "silent financial interests" in the firms they own ($\kappa_P = 0$), in which case $\gamma_{ij} = \frac{1}{\sigma_A}\beta_{ij}$ for each active investor and $\gamma_{ij} = 0$ for each passive investor. Notice that if one type of investors, say the active, has more control than the others, say the passive, then $\kappa_A > 1$ and $\kappa_P < 1$ and $\gamma_{ij} \geq \beta_{ij}$ for active investors and $\gamma_{ij} \leq \beta_{ij}$ for passive investors. Indeed, since $\sigma_A\kappa_A + \sigma_P\kappa_P = 1$ and $\sigma_A + \sigma_P = 1$, as long as $\kappa_P < 1$ then we have that $\kappa_A = (1 - \sigma_P\kappa_P)/\sigma_A > (1 - \sigma_P)/\sigma_A = 1$. Furthermore, as κ_A increases κ_P decreases, and viceversa.

[15] Notice also that it cannot be that investors of one type have zero ownership and some control. That is if $\sigma_\tau = 1$ (no ownership) then $\kappa_P = 0$ (no control).

whereas, for all the other firms k for which she is a minority shareholder, they are

$$\beta_{ik} = \sigma_\tau \alpha_\tau / m_\tau \text{ and } \gamma_{ik} = \kappa_\tau \sigma_\tau \alpha_\tau / m_\tau. \tag{11}$$

Intuitively, the fraction of ownership and control of each investor in each firm increases in the fraction of overall wealth of the investors of her type (σ_τ) and decreases in the number of investors of her type (m_τ). By increasing α, the fraction of ownership in the firm in which she is a major shareholder gets reduced, whereas that of the firms in which she is a minority shareholder is increased. As $\sigma_A + \sigma_P = 1$, we from now focus on σ_P.[16]

3.2 Investor variables in the simple model

We now link the investor variables to the parameters of the simple model. Substituting β_{ij} in (10) and (11) onto (1), (2) and (3), and simplifying,

$$DIV_j^\tau = (n-1)\alpha_\tau(2 - n\alpha_\tau) \tag{12}$$

$$RLH_j^{P/A} = \sigma_P \text{ and} \tag{13}$$

$$CON_j^\tau = \frac{(1-(n-1)\alpha_\tau)^2 + (n-1)\alpha_\tau^2}{m_\tau}. \tag{14}$$

Note that the level of overall holdings of passive relative to active investors ($RLH_j^{P/A}$) can be parametrized by σ_P, whereas the degree of portfolio diversification of passive investors is greater than those of active investors ($DIV_j^P > DIV_j^A$) if and only if the passive investors spread their holdings more evenly between the firms than the active investors ($\alpha_P > \alpha_A$ for a given number of firms n). Notice though that the spread of holdings across firms (α_τ) affects both the portfolio diversification and degree of ownership concentration of each type of investor: DIV_j^τ increases in α_τ and CON_j^τ decreases in α_τ.[17] Finally, the degree of ownership concentration CON_j^τ is decreasing in the number of investors of type τ, m_τ.

[16] Below, while doing comparative statics on σ_P, we will keep κ_A/κ_P constant, and thus both κ_P and κ_A will need to adjust so as to keep $\sigma_A\kappa_A + \sigma_P\kappa_P = 1$.

[17] In the extreme case in which $\alpha_\tau = 0$, investors of type τ are completely undiversified and only own shares in one firm, and $CON_j^\tau = 1/m_\tau$ and $DIV_j^\tau = 0$. In the other extreme case in which $\alpha_\tau = 1/n$, they have perfectly diversified portfolios, and $CON_j^\tau = 1/(nm_\tau)$ and $DIV_j^\tau = (n-1)/n$.

3.3 The common ownership incentives in the simple model

We now link the common ownership incentive variables to the parameters of the simple model. Substituting β_{ij} and γ_{ij} in (10) and (11) into (7), (8) and (9), and simplifying, we can express $\lambda_j = (1-\nu_j^{P/A})\lambda_j^A + \nu_j^{P/A}\lambda_j^P$ as

$$\lambda_j^\tau = \frac{g(\alpha_\tau)}{h(\alpha_\tau)} \text{ and } \nu_j^{P/A} = \frac{1}{1+\frac{h(\alpha_A)}{h(\alpha_P)}\frac{1-\sigma_P}{\sigma_P}\frac{\kappa_A}{\kappa_P}\frac{m_P}{m_A}}$$

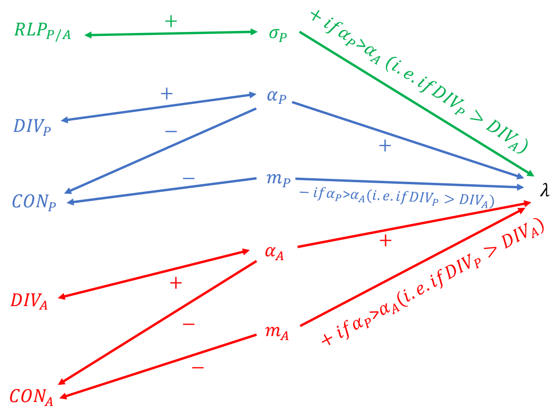
where $g(\alpha_\tau)$ is an increasing function of α_τ, $g(\alpha_\tau) \equiv 2[1-(n-1)\alpha_\tau]\alpha_\tau + (n-2)\alpha_\tau^2$, whereas $h(\alpha_\tau)$ is decreasing in α_τ, $h(\alpha_\tau) \equiv [1-(n-1)\alpha_\tau]^2 + (n-1)\alpha_\tau^2$.

We explain the two channels of influence. First, as $g(\alpha_\tau)$ and $h(\alpha_\tau)$ are increasing and decreasing, respectively, in α_τ, the relative weight that firm j has to put on the other firms because of the passive investors is greater than the weight it has to put because of the active investors ($\lambda_j^P > \lambda_j^A$), as long as the passive investors spread their holdings more evenly across firms ($\alpha_P > \alpha_A$). Second, as the holdings of the passive investors σ_P increase (while keeping α_τ as well as the ratios of κ_A/κ_P and m_A/m_P constant), the weight of the passive investors in the common ownership measure, $\nu_j^{P/A}$, increases. Provided that the passive investors have their holdings more spread out, and thus, $\lambda_j^P > \lambda_j^A$, an increase in the weight of the passive investors $\nu_j^{P/A}$ increases the overall level of common ownership incentives λ_j.

As for the case of the holdings of passive investors σ_P, the common ownership incentives λ_j increase, provided that the passive investors spread their holdings more evenly across firms ($\alpha_P > \alpha_A$), if the ratio of control of active investors (κ_A/κ_P) decreases, the number of passive investors (m_P) decreases or the number of the number of active investors (m_A) increases. That is, if the passive investors spread their holdings more evenly across firms and become relatively more powerful than the active investors, then λ_j increases.

In the case of the spread of holdings (α_A and α_A), simple algebra shows that they not only increase the relative weight that firm j has to put in the other firms because of the passive and active investors (λ_j^P, λ_j^A), respectively, but they also increase the overall weight the firm has to put on other firms, i.e., λ_j increases as well.

Figure 2. Relationships between the variables in the simple model.



This figure displays the relationships between the variables in the simple model, where + denotes positively related and − denotes negatively related. If there is a condition it is indicated.

3.4 Investor variables and common ownership incentives

We now use the results of the previous two subsections to link the investor variables with the common ownership incentives, via the parameters of the simple model. A summary of the relationships shown in the previous two subsections are depicted in Figure 2.
We link first the holdings of passive relative to active investors with the level of common ownership incentives, which is our key theoretical result.

Proposition 1. *For any given degree of diversification and concentration of passive and active investors (DIV_j^P, DIV_j^A, CON_j^P, CON_j^A), an increase in the level of overall holdings of passive relative to active investors ($RLH_j^{P/A}$) increases the common ownership incentives of the firm (λ_j) if passive investors are more diversified ($DIV_j^P > DIV_j^A$).*

Notice further that the level of diversification of each type of investor, which can be parametrised by the spread of holdings between firms, can also unambiguously linked to the level of common ownership incentives.

Remark 2. *The degrees of diversification of both passive and active investors (DIV_j^P and DIV_j^A) increase the common ownership incentives of the firm (λ_j).*

Finally, as shown in Figure 2, the effect of the concentration of holdings of passive investors is less clear. On the one hand, the common ownership incentives λ_j increase CON_j^P, provided that they spread their holdings more evenly across firms ($\alpha_P > \alpha_A$), as both λ_j and CON_j^P decrease with the number of passive investors (m_P). On the other hand, CON_j^P can be negatively related to λ_j as the more diversified investors across firms might have a tendency to have their holdings concentrated within a given firm. As an example, in an industry with two firms and two symmetric investors (of the same type), (i) if each investor owns a firm, the common ownership incentives are zero whereas (ii) if each owns half of each firm, the common ownership incentives are one. Investor concentration has decreased and the common ownership incentives have increased. In this case there is a negative relationship between diversification and ownership concentration.

Remark 3. *The relationship between the level of concentration of passive or active investors (CON_j^P or CON_j^A) and the level of common ownership incentives of the firm (λ_j) is ambiguous.*

4 Impact of Investor Variables on Lambda - Empirics

We now describe the data, set up the empirical specification and discuss the results on how the investors' characteristics have empirically an impact on the common ownership incentives in US industries for the years 2004 - 2012, where we highlight the role of the increasing holdings of passive investors relative to those of active investors around the financial crisis.

4.1 Data and descriptive statistics

We first present the ownership and firm-level data, and provide descriptive statistics of the main variables of interest.[18]

4.1.1 Investors

Money managers For the investors, we make use of the Thomson Reuters Global One Ownership Database for the period 2004-2012, which includes ownership data of publicly-listed US firms as well as information about the investment orientation of the investors (passive versus active). The data originate from a financial research database from Thomson

[18] We refer also to Banal-Estanol et al. (2020) and the corresponding data repository for further details on the construction of the dataset.

Reuters (TR) called Thomson Global One Ownership Database. This database replaces and upgrades the older Thomson ONE Banker platform and its successor, ThomsonONE.com Investment Banking. Like its predecessors, it integrates data and sources documents from multiple sources including Worldscope, Datastream, Thomson Financial, and SDC Platinum.[19] The US data, which we use for this paper, are drawn from 13F, 13D, 13G filings and forms 3, 4, and 5.

Our investor dataset offers advantages with regards to other often-used datasets on US ownership, we believe.[20] Most published papers on US common ownership (e.g., Azar et al., 2018a; He and Huang, 2017) use Thomson's CDA/Spectrum database, offered by the WRDS database management system. This database only includes 13F filings, and this only large institutional investors, whereas ours further includes 13D, 13G filings and forms 3, 4, and 5.[21]

Most importantly, the WRDS database shows holdings assigned to the owner that filed the 13F. This is what is commonly referred to as an "as-filed view." Our database utilizes a "money-manager view." With this view, the database combines together one or more filings to link the holdings to the actual firm that manages the investments. In other instances, it might break apart a single filing in order to accomplish the same thing. The holdings would then be assigned to one or more of the managers listed on the file. Thus, our database attempts to assign the *decision maker*, which is often not the same as the filer.[22]

Ultimate owners and aggregation of subsidiaries While our database does not suffer from the reported data problems of the WRDS Thomson Reuters data, we modify it to

[19] It includes quarterly global ownership data and investor profiles that can be screened to identify holdings of specific investor groups, which then can be combined with filters such as period, position, and investment style.

[20] A major limitation of this data at the time of extraction was that only up to 50 securities and 12 quarters could be included in a search, thereby making it cumbersome for users dealing with a large set of companies as the extraction of data in this way is extremely time consuming. However, the advantages of the data made us decide to do the effort.

[21] Furthermore, as pointed out by Backus et al. (2021), WRDS and Thomson Reuters began to notice data irregularities in that database. However, these were mostly addressed in an update in July 2018. For an interesting recent paper on ownership data in US firms that also includes not only 13F filings, but other owners as well, see Amel-Zadeh et al., (2022). Including all types of investors leads to a lower lambda overall (as compared to only including 13F filers).

[22] See also Backus et al. (2021), for a discussion on the mistakes that databases generate when using as-filed based ownership data, including short positions.

account for (i) name changes that occur, mainly through investors' (partial) M&As during the sample period and to (ii) identify ultimate decision makers (based on their names and via data from the National Information Center (NIC)). These modifications are carried out as follows. First, we consider the top500 investors in our dataset according to "The World's 500 Largest Asset Managers Year end 2011," prepared using joint research by Pensions and Investments and Towers Watson. We consider these top investors as initial ultimate owners, and verify, by means of online search and by using the NIC database for each investor in the list: (i) whether this ultimate owner is involved in M&A's within the time span of our sample, and (ii) identify the subsidiaries associated to this ultimate owner. We then construct a database containing the timing and investors involved in the detected M&As, as well as a dynamic mapping of subsidiaries into ultimate owners. Finally, we assign, for each investor/year in the Thomsom Reuters Global One Ownership database, an ultimate owner taking decisions for all their subsidiaries. Appendix A and Banal-Estanol et al. (2020) provide more details.

Active and passive investors To separate investors into our two main categories, active and passive, we use TR's classification of investment orientation, which reflects how the institution manages its portfolio. TR assigns the active vs. passive flag based on the following:

- *Active: the investment company manages its portfolio using a "hands-on" approach to allocate firm assets and determine stock selection; i.e., it makes decisions based on company/sector analysis and fundamental research.*
- *Passive: the investment company benchmarks its assets against indices, such as the S&P 500 or Russell 1000, and allows external factors to determine which sectors and regions they make investments in.*

While this is admittedly a crude categorisation, the use of these labels is for the purpose of the paper convenient, as the classification of active versus passive is given to us by TR, and not based on any of the variables we use in our analysis. This is for our analysis a major advantage, as investors being categorised into active or passive investors is exogenous to our empirical analysis.

Schmalz (2018), and references therein, makes the point that governance and voting are usually conducted at the ultimate owner level, also for the larger fund families. Failing to aggregate all holdings at the ultimate owner level and failing to assign the same label can lead to an underestimation of the power of a large owner's votes, and can thus lead to an underestimation of the respective control share of one class of owners. We, therefore, assign the same category to all subsidiaries of the same ultimate owner. In other words, an ultimate owner obtains only one label. In particular, we assign the label 'active' to an investor whenever its overall active money holdings are larger than its passive money holdings, and vice versa.

Finally, we assume for the main analysis of the empirics that both types of investors have the same levels of control per unit of money (proportional control), but we relax this assumption in a robustness check.

4.1.2 Firms and product markets

For the firms' presence and sales in US industries, and for the estimation of markups therein, we use the WRDS Compustat North America data files that record accountancy data for US publicly listed firms. We, thus, include all publicly traded firms covering all sectors of the US economy over the period 2004-2012 (excluding finance). Because there is no official filing requirement for the privately held firms, our data do not include non-listed companies. While publicly traded firms are relatively few relative to the total number of firms, these public firms tend to be the largest firms in the economy; they account for one third of total US employment and about 41% of sales (De Loecker and Eeckhout, 2017).

Matching and aggregation We use Capital IQ files to link the Compustat data, where firms are identified by the GVKEY variable, with the TR dataset of security holdings identified with (predominantly) ISIN numbers and CUSIP codes. If left unmatched, we use string-type matching technologies on the company names.

We further keep only common shares, i.e., where financial holdings equal voting rights, and further exclude ADR-type securities.[23] We then sum holdings at the "investor name"-

[23]TR also includes some other share types, such as preferred or dual-class shares, which have enhanced (or no) voting rights. But data on these are of low quality (missing, inconsistent, etc.). We, therefore, decided against using these in our analysis.

"investor type" firm-year level, and aggregate the security holdings of investors to the level of the ultimate owner by summing all the investments of its subsidiaries.

4.1.3 Sample, variables and descriptive statistics

Sample To find the right balance between having a high enough number of firms in each industry and having these firms selling similar enough products, we define industries at the NAICS4 level. Predictions about common ownership hinge on the assumption that the commonly owned firms interact, where interacting may not be equivalent to sharing the same NAICS4 code. However, we confirm in a robustness check our results for a much narrower industry definition (NAICS6). In terms of time period, we include four years before and four years after the great financial crisis of 2008 (2004 - 2012).

Our final sample consists of a panel of 24,210 individual firms spread over 177 industries during nine years (2004 - 2012). We allocate these firms into industries, and consider each of these industries independent from each other in terms of common ownership.[24]

Investor variables and common ownership measures We construct the investor variables as well as the common ownership incentive measures, as defined in (1), (2), (3) and (9), for each firm j in each industry S and for each year $t = 2004, ..., 2012$, using as input the value held of each investor in each firm in each industry in each point in time. We keep in the analysis the firms that are present in all years in the sample (balanced panel).[25]

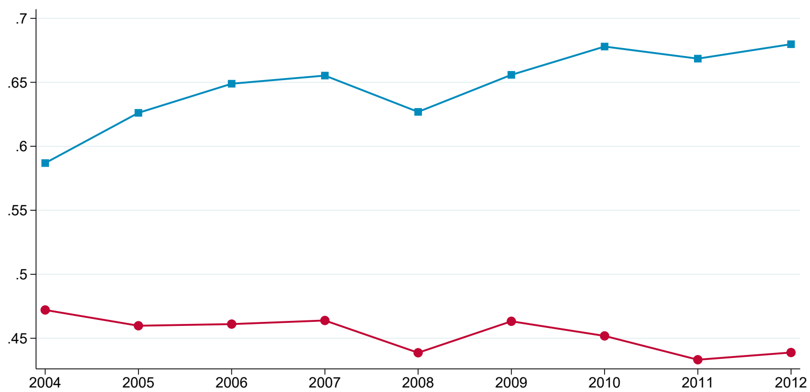
The evolution of the investor variables over time is depicted in Figures 3, 4 and 5. As shown by Figure 3, the median yearly diversification of passive investors across firms is consistently higher than the median diversification of active investors. These patterns are confirmed when we do a year-by-year firm-level t-test on differences between: $DIV^P_{j,t} > DIV^A_{j,t}$ in every year (Table 1). Furthermore, while there is a small bump around 2008, the trend is slightly upwards for passive investors and slightly downwards for active investors.

Figure 4 shows the yearly relative holdings of passive versus active owners per firm.

[24]However, we also perform an analysis where we include not only the common ownership links within the industry, but also the common ownership links of the firm with all companies that are located outside that industry; see footnote 35.

[25]In Appendix B we describe how we make use of matrices to stack and manipulate the ownership data, and construct our common ownership variables. This process is also helpful to view the lambdas as network measures of inter-connectedness of firms via their common investors.

Figure 3. Investor diversification levels (DIV$^\tau$) in US publicly-listed companies.



This figure displays the median of the investor diversification levels across firms in the same industry for each type of investor in each firm for the period 2004 - 2012 **(passive investors (τ = P) in blue squares and active investors (τ = A) in red dots)**. The median in each year is taken across all publicly-listed firms in the US. Investor diversification levels for each firm j are defined as $DIV_j^\tau \equiv \sum_{i\in\tau}(\frac{h_{ij}}{\sum_{i\in\tau} h_{ij}})DIV_{i,S}$ where $DIV_{i,S} \equiv 1 - \sum_{k\in S}(\frac{h_{ik}}{\sum_{l\in S} h_{il}})^2$ where $h_{i,j}$ denotes the monetary ownership holdings of investor i of type τ in firm j of industry S.

The trend is clearly upwards, especially since 2007. In other words, passive investors have increased their holdings in companies, relative to active investors, and have thus become relatively larger within in each firm, especially since the great financial crisis.

Figure 5 shows the yearly firm-level concentrations of active and passive investors. Active concentrations are (much) lower than passive concentrations (and relatively stable over time). As argued in the theoretical section, the level of concentration of a given type of investor is determined by two forces: (i) it is negatively related to the level of diversification of a type of investor, and (ii) decreasing in the number of investors of that type. Passive investors are more diversified than active investors but they are also fewer in number. Indeed, Table 2 shows that the median number of active investors per firm is 52 whereas the median number of passive investors per firm is only 12. On average, the second effect dominates in our concentration variables, and thus passive investors are more concentrated than active investors.

Figure 6 documents the evolution of the lambdas. The average lambdas have clearly

Table 1. Yearly diversification levels of active and passive investors

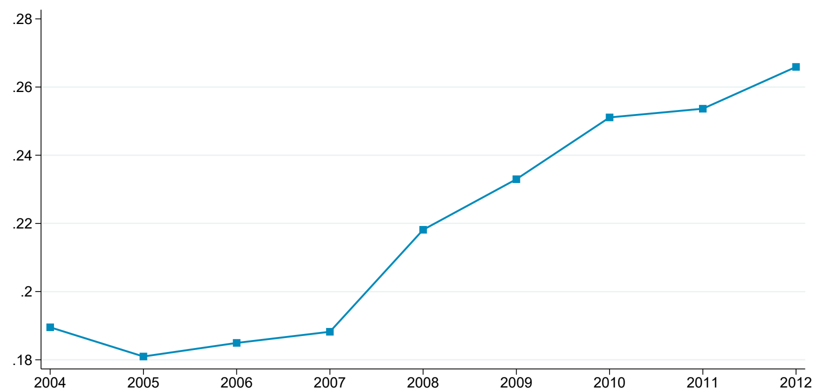
This table reports the mean diversification levels active and passive investors per year, as well as the mean difference, together with the p-value of the t-stats of mean differences. Diversification refers to the investor diversification levels across firms in the same industry for each type of investor in each firm. Investor diversification levels of each type of investor τ for each firm j are defined as $DIV_j^{\tau} \equiv \sum_{i \in \tau}(\frac{h_{ij}}{\sum_{i \in \tau} h_{ij}})DIV_{i,S}$ where $DIV_{i,S} \equiv 1 - \sum_{k \in S}(\frac{h_{ik}}{\sum_{l \in S} h_{il}})^2$ where $h_{i,j}$ denotes the monetary ownership holdings of investor i of type τ in firm j of industry S.

	DIV^A	DIV^P	Difference	P-value
2004	0.447	0.491	-0.0437	0.000
2005	0.446	0.518	-0.0719	0.000
2006	0.445	0.535	-0.0898	0.000
2007	0.450	0.535	-0.0854	0.000
2008	0.428	0.525	-0.0965	0.000
2009	0.444	0.551	-0.107	0.000
2010	0.437	0.559	-0.122	0.000
2011	0.430	0.549	-0.119	0.000
2012	0.430	0.553	-0.123	0.000

been increasing over time, especially since the 2007-08 great financial crisis.

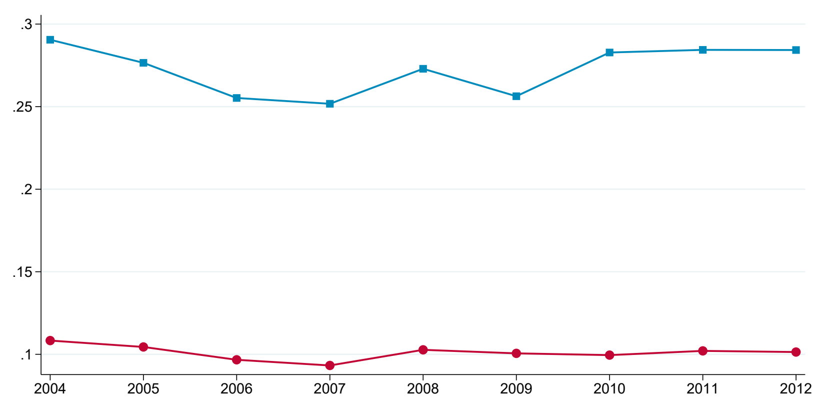
Table 2 presents summary statistics for all the variables used in the analysis. Passive investors hold 22% of firms' equity at the median. Their level of diversification is 0.65 versus 0.45 for active investors, thereby indeed indicating that passive investors are more diversified than active investors overall. Per confirmation of the above figure, the median level of concentration of passive investors within a firm is higher, 0.27 versus 0.10 for active investors, thus reflecting the smaller number of passive investors overall despite being more diversified across firms. Finally, in terms of common ownership incentives (lambdas), the median value is 0.065 (where we leave discussion of the remaining variables and their values for below).

Figure 4. Relative level of holdings (RLH$^{P/A}$) in US publicly-listed companies.



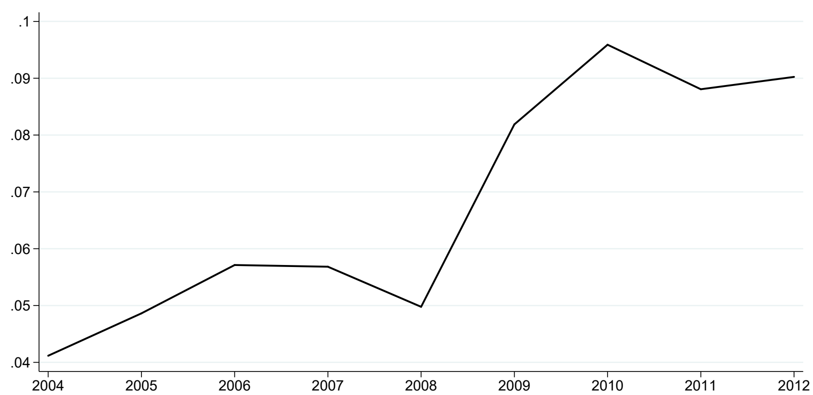
Relative level of holdings (RLH$^{P/A}$) in US publicly-listed companies. This figure displays the median of the relative levels of holdings of passive investors across all publicly-listed firms in the US for the period 2004 - 2012. The relative level of holdings of passive investors for each firm j are defined as $RLH_j^{P/A} \equiv \frac{\sum_{i \in P} h_{ij}}{\sum_{i \in A \cup P} h_{ij}}$ where $h_{i,j}$ denotes the monetary ownership holdings of investor i of type τ in firm j.

Figure 5. Investor concentration levels (CON$^{\tau}$) in US publicly-listed companies.



This figure displays the median of the investor concentration levels within firms for each type of investor in each firm **(passive investors ($\tau = P$) in blue squares and active investors ($\tau = A$) in red dots)** for the period 2004 - 2012. The median in each year is taken across all publicly-listed firms in the US. Investor concentration levels for each firm j are defined as $CON_j^{\tau} \equiv \sum_{i \in \tau} (\frac{h_{ij}}{\sum_{i \in \tau} h_{ij}})^2$ where $h_{i,j}$ denotes the monetary ownership holdings of investor i of type τ in firm j of industry S.

Figure 6. Lambdas (λ) of US publicly-listed companies.



This figure displays the median of the firm-level lambdas of each year across all publicly-listed firms in the US for the period 2004 - 2012. Firm-level lambdas for each firm j are defined as $\lambda_j \equiv \frac{1}{|k-1|}\sum_{k \neq j} \lambda_{j,k}$ where $\lambda_{j,k}$ is the load the manager of firm j should place on the profits of the other firms of the same industry, k, because of the presence of common investors. These loads are defined as $\lambda_{j,k} \equiv \frac{\sum_i \beta_{ij}\beta_{ik}}{\sum_i \beta_{ij}^2}$ where β_{ik} is the investor i's fraction of ownership in firm k (we are thus assuming here proportional control.)

Table 2. Descriptive statistics

This table reports the descriptive statistics for all the variables used in the regression analysis.

	RLH$^{P/A}$	DIV^{A}	DIV^{P}	CON^{A}	CON^{P}	INV^{A}	INV^{P}	COGS	PPENT
Obs.	24183	23823	23823	24183	24183	24183	24183	24183	24183
Mean	0.28	0.44	0.53	0.21	0.39	40.7	10.7	3573.4	2436.8
Std. Dev.	0.25	0.26	0.34	0.25	0.28	23.9	6.50	14849.9	9380.3
Min.	0	0	0	0	0	0	0	0.0010	0.0010
Median	0.22	0.45	0.65	0.10	0.27	52	12	324.2	117.3
Max.	1	0.96	0.97	1	1	92	40	408296.0	256834
	λ	λ^{A}	λ^{P}	ν^{A}	ν^{P}	μ	μ_{CO}		
Obs.	24183	23262	22497	24183	24183	24183	21626		
Mean	0.094	0.11	0.61	0.48	0.23	1.56	1.60		
Std. Dev.	0.098	0.36	1.90	0.32	0.28	0.87	0.92		
Min.	0	0	0	0	0	0.25	0.34		
Median	0.065	0.063	0.37	0.52	0.13	1.41	1.42		
Max.	0.82	29.4	108.0	1	1	40.7	40.2		

We further show correlations between the variables used in the analysis (Table 3). While we leave the relationships between most investor variables for the regression analysis, we report some patterns between other variables to justify the inclusion of extra control variables. First, INV^A and CON^A have a high negative correlation of -0.68, where INV^A is the number of active investors per firm. The same holds to some extent for the relation between INV^P and CON^P: the correlation amounts to -0.46, where INV^P is the number of passive investors per firm. As discussed in the theoretical analysis, the more investors per firm, the lower the per-firm concentration. These high correlations induce us to include number of active and passive investors as control variables in our regression analysis.

Table 3. Correlation matrix

This table reports the correlation between the main variables of our analysis (including the investor variables and two relevant controls, the number of active and passive investors per firm.)

	λ	RLH$^{P/A}$	DIV^{A}	DIV^{P}	CON^{A}	CON^{P}	INV^{A}
RLH$^{P/A}$	-0.11***						
DIV^{A}	0.35***	-0.08***					
DIV^{P}	0.50***	-0.40***	0.52***				
CON^{A}	-0.47***	0.08***	-0.27***	-0.42***			
CON^{P}	-0.42***	0.48***	-0.19***	-0.38***	0.31***		
INV^{A}	0.59***	-0.15***	0.34***	0.48***	-0.68***	-0.42***	
INV^{P}	0.57***	0.01	0.30***	0.44***	-0.56***	-0.46***	0.74***
	μ_{CO}	λ	λ^{A}	λ^{P}	ν^{A}	ν^{P}	
λ	-0.06***						
λ^{A}	-0.02**	0.08***					
λ^{P}	0.00	-0.05***	0.02**				
ν^{A}	0.01	0.31***	-0.12***	0.04***			
ν^{P}	-0.03***	0.06***	0.11***	-0.20***	-0.43***		
μ	0.90***	-0.07***	-0.02**	-0.00	-0.00	-0.04***	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Empirical specification

From our theoretical setup, we take that a firm's common ownership incentives depend on active and passive investors' relative holdings, diversification, and concentration. Proposition 1's hypothesis is that passive investors holdings have a positive impact on lambda whenever the passive investors are more diversified than the active investors. We, therefore, include a categorical variable, which is set to one whenever the firm has a set of passive investors that has a higher diversification than that of the firm's active set of investors, $DIV^{P}_{j,t} > DIV^{A}_{j,t}$, and interact this variable with $RLH^{P/A}_{j,t}$. In particular, the interaction term is hypothesised to be positive: whenever passive investors' diversification is higher than active investors' diversification, then an increase in relative holdings of passive investors leads to an increase in common ownership incentives. Furthermore, the theory's assumptions and comparative statics are taking the number of investors as given; we control for these in the regressions. We therefore estimate the following equation:

$$\begin{aligned}\lambda_{j,t} = \quad & \alpha_0 + \alpha_1 RLH_{j,t}^{P/A} + \alpha_2 RLH_{j,t}^{P/A} \times \mathbb{1}\{DIV_{j,t}^P > DIV_{j,t}^A\} + \alpha_3 DIV_{j,t}^A + \alpha_4 DIV_{j,t}^P \\ & + \alpha_5 CON_{j,t}^A + \alpha_6 CON_{j,t}^P + \alpha_7 INV_{j,t}^A + \alpha_8 INV_{j,t}^P + \beta_X X_{j,t} + \gamma_{S,t} + u_{j,t}, \end{aligned} \tag{15}$$

where j is a firm in industry S, t the year, $RLH_{j,t}^{P/A}$ the relative holdings of passive versus active investors, $DIV_{j,t}^{\tau}$ and $CON_{j,t}^{\tau}$ the diversifcation and concentration, respectively, $INV_{j,t}^{\tau}$ the number of investors of type τ, all in in firm j in year t, $X_{j,t}$ firm-level controls (in particular, COGS and PPENT, defined and explained in the next section), $\gamma_{S,t}$ a set of industry(x)year fixed effects, thereby controlling for time-varying industry effects, and $u_{j,t}$ the error term.

We estimate the above equation as the 1st stage of a 2SLS estimation (where the 2nd stage is explained in the next section). We estimate a log-log model (where in one of the robustness checks, we estimate a linear model). For each specification, we show two different treatments of the error term: robust standard errors, in order to account for potential heteroscedasticities across all firms, and standard errors clustered at the industry(x)year level, which permits firms' standard errors within an industry in a given year to be correlated, in line with defining investors' ownership networks among firms within an industry(x)year.

4.3 Results

The results of the investor variables on lambdas are shown in Table 4.[26] First, both estimations are well specified in terms of joint significance of variables: the F-statistics are high such that their corresponding p-values are near zero. Furthermore, the investor variables do a good job in explaining lambdas, where virtually each individual variable is significant. Second, in terms of control variables, active investors per firm have a negative impact on lambdas while passive investors' impact is positive (and less significant).

Focusing on our key variable, as per Proposition 1, whenever passive investors are more

[26]For presentation purposes, we scale all the explanatory variables by dividing them by 100.

Table 4. Regression results of lambdas on investor variables (log-log)

This table reports the coefficients for the first stage of the two-stage least squares (2SLS) log-log regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls. For presentation purposes of the coefficients, we scale all the explanatory variables by dividing them by 100.

	(1) $\log\lambda$	(2) $\log\lambda$
$\log \mathrm{RLH}^{P/A}$	3.162***	3.162***
	(0.354)	(0.378)
$\log \mathrm{RLH}^{P/A} \times \mathbb{1}\{\mathrm{DIV}^P > \mathrm{DIV}^A\}$	9.395***	9.395***
	(0.409)	(0.585)
$\log \mathrm{DIV}^A$	9.730***	9.730***
	(0.304)	(0.482)
$\log \mathrm{DIV}^P$	6.515***	6.515***
	(0.269)	(0.310)
$\log \mathrm{CON}^A$	-8.950***	-8.950***
	(0.295)	(0.315)
$\log \mathrm{CON}^P$	-9.671***	-9.671***
	(0.220)	(0.298)
$\log \mathrm{INV}^A$	-0.156*	-0.156
	(0.0830)	(0.109)
$\log \mathrm{INV}^P$	0.212**	0.212*
	(0.0966)	(0.114)
N	21151	21151
Fixed Effects	Ind. Yr.	Ind. Yr.
Std. Errors	Robust	Ind. Yr.
# of Groups	1392	1392
R^2	0.548	0.548
F-stat	2229.2	424.2
p-value F-stat	0.00	0.00

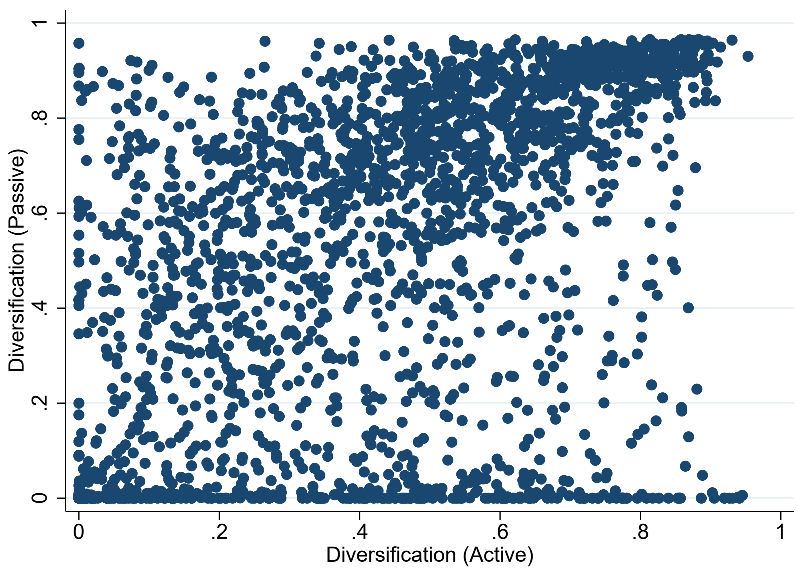
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

diversified than active investors, an increase in their holdings leads to higher lambdas, as the interaction terms in line two show with a coefficient of 7.6 (significant at the 1% level). Quantifying the total effect, i.e., summing up the interaction and main effect, whenever $DIV^P > DIV^P$, a 1% increase in $RLH^{P/A}$ leads to a total increase in lambda of 0.13% (remember that the variables are scaled by a factor 1/100).

Note that the main effect of $RLH^{P/A}$ is also positive. In other words, the impact of *any* shift of money holdings from active to passive investors leads to a higher lambda overall. This effect, while not present in our theory, can be empirically explained by the fact that DIV^A and DIV^P are positively correlated across firms: see Figure 7, where this is illustrated graphically, and Table 3, where the correlation between DIV^A and DIV^P is shown to be 0.52. In other words, both variables are not independent in our sample, which thus explains that the main effect is positive. However, the key proposition of the theory finds here its empirical equivalence: whenever $DIV^A > DIV^P$, then an increase in $RLH^{P/A}$ yields an (additional) large and positive impact on λ.

Figure 7. Investor diversification levels ($\mathbf{DIV}^\tau$) of US publicly-listed companies.



This figure displays the investor diversification levels across firms in the same industry for each type of investor in each firm. Investor diversification levels of each type of investor τ for each firm j are defined as $DIV_j^\tau \equiv \sum_{i\in\tau}(\frac{h_{ij}}{\sum_{i\in\tau} h_{ij}})DIV_{i,S}$ where $DIV_{i,S} \equiv 1 - \sum_{k\in S}(\frac{h_{ik}}{\sum_{l\in S} h_{il}})^2$ where $h_{i,j}$ denotes the monetary ownership holdings of investor i of type τ in firm j of industry S.

Our results are also consistent with the statement in Remark 2 of the theory. The impact of both active and passive investors' diversification levels on lambdas is positive. In particular, an increase of 1% in active investors' diversification leads to an increase in lambda by 0.09%, and similarly to an increase of 0.08% for passive investors' diversification. Finally, recall that the effect of the degree of concentration is ambiguous in the theory, as per Remark 3. The regressions show that the impact of both active and passive investors' concentration levels on lambdas is negative.

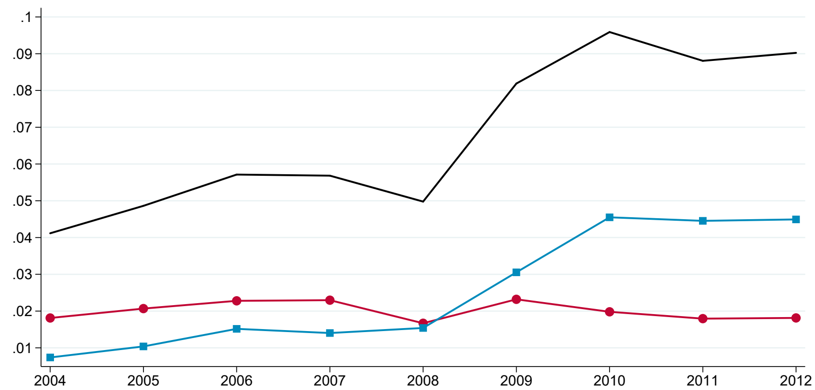
5 Decomposing into Lambda Active and Passive

The previous section showed that the increase in the average lambda, particularly since the financial crisis, can be linked to the increase in the relative holdings of passive versus active owners. This section analyzes if these changes in the average common ownership incentive measure are due to change in the common ownership links through active or passive investors change, "lambda active" or "lambda passive," respectively, or through the loads that firms should place on either of these because of the investors they have in common. To that purpose, we apply our data to the novel decomposition of lambda introduced in Section 2.3, $\lambda_j = (1 - \nu_j^{P/A})\lambda_j^A + \nu_j^{P/A}\lambda_j^P$. Considering the two terms of this sum separately, we can also measure the overall contribution of the active and passive investors, respectively, in the common ownership incentives measure, lambda.

Figure 8, shows that the increase in the (overall) lambda between 2004 and 2012, especially since the financial crisis, can be entirely explained by the increased contribution of the passive investors ($\nu^{P/A}\lambda^P$) towards lambda, whereas the contribution of the active investors stays constant ($(1-\nu^{P/A})\lambda^A$). Actually, the former overtook the latter in 2008. This further highlights the role played by the passive investors on the increasing levels of lambda over time.

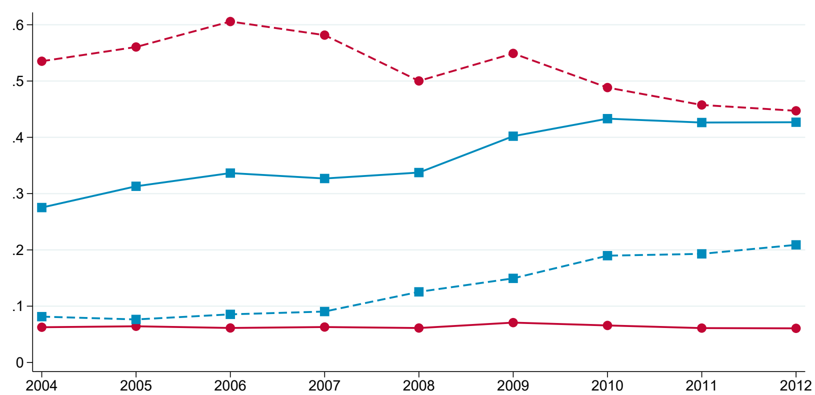
Figure 9 decomposes these contributions. It shows first that the median λ^P is higher than the median λ^A throughout the sample every year. This pattern is confirmed by the year-by-year firm-level t-test on differences displayed in Table 5: λ^P is significantly higher than λ^A in *every year*. This reflects the higher levels of diversification of passive investors. This highlights that the firms' links through passive investors are stronger than those running through active investors.

Figure 8. Lambdas (λ) and decomposition ($\lambda^{\tau} \times \nu^{\tau}$) in US publicly-listed firms.



This figure displays the median lambdas (black line) and the product of the type-specific lambdas and the weights firms should place on each type of investor, reflecting the weight the decision-maker should put on other firms because of the presence of investors of each type **(passive investors ($\tau = P$) in blue squares and active investors ($\tau = A$) in red dots)**. The median in each year is taken across all publicly-listed firms in the US. Firm-level lambdas for each firm j are defined as $\lambda_j \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{j,k}$ where $\lambda_{j,k} \equiv \frac{\sum_i \beta_{ij}\beta_{ik}}{\sum_i \beta_{ij}^2}$ where β_{ik} is the investor i's fraction of ownership in firm k. Type-specific lambdas and weights for each firm j are defined as $\lambda_j^{\tau} \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{jk}^{\tau}$ where $\lambda_{jk}^{\tau} \equiv \frac{\sum_{i\in\tau}\beta_{ij}\beta_{ik}}{\sum_{i\in\tau}\beta_{ij}^2}$ and $\nu_j^{\tau} \equiv \frac{\sum_{i\in\tau}\beta_{ij}^2}{\sum_{i\in A\cup P}\beta_{ij}^2}$. Recall that $\lambda_j = nu_j^A \times \lambda_j^A + \nu_j^P \times \lambda_j^P$. We are assuming proportional control.

Figure 9. Type-specific lambdas (λ^{τ}) and weights (ν^{τ}) in US publicly-listed firms.



This figure displays the median of the type-specific lambdas (dashed lines), reflecting the common ownership links due to this type of investors, and the weights firms should place on each type of investor (dotted lines) **(passive investors ($\tau = P$) in blue squares and active investors ($\tau = A$) in red dots)** for the period 2004 - 2012. The median in each year is taken across all publicly-listed firms in the US. Type-specific lambdas and weights for each firm j are defined as $\lambda_j^{\tau} \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{jk}^{\tau}$ where $\lambda_{jk}^{\tau} \equiv \frac{\sum_{i\in\tau}\beta_{ij}\beta_{ik}}{\sum_{i\in\tau}\beta_{ij}^2}$ and $\nu_j^{\tau} \equiv \frac{\sum_{i\in\tau}\beta_{ij}^2}{\sum_{i\in A\cup P}\beta_{ij}^2}$ where β_{ik} is the investor i's fraction of ownership in firm k (assuming proportional control.)

Table 5. Yearly type-specific lambdas of active and passive investors

This table reports the mean type-specific lambdas of active and passive investors per year, as well as the mean difference, together with the p-value of the t-stats of mean differences. Type-specific lambdas for each firm j are defined as $\lambda_j^\tau \equiv \frac{1}{|k-1|}\sum_{k\neq j}\lambda_{jk}^\tau$ where $\lambda_{jk}^\tau \equiv \frac{\sum_{i\in\tau}\beta_{ij}\beta_{ik}}{\sum_{i\in\tau}\beta_{ij}^2}$. We are assuming proportional control.

	λ^A	λ^P	Difference	P-value
2004	0.111	0.455	-0.344	0.000
2005	0.109	0.545	-0.436	0.000
2006	0.108	0.498	-0.390	0.000
2007	0.0929	0.568	-0.475	0.000
2008	0.103	0.653	-0.550	0.000
2009	0.104	0.665	-0.561	0.000
2010	0.111	0.703	-0.591	0.000
2011	0.105	0.738	-0.633	0.000
2012	0.104	0.699	-0.595	0.000

At the same time, the same Figure 9 shows that the weight of the passive investors $\nu^{P/A}$ steadily increases, whereas that of active investors decreases, reflecting the increase in the holdings of passive relative to active investors.

In sum, in accordance with our theory, λ^P being higher than λ^A in every year of our sample reflects DIV^P being higher than DIV^P across our sample, whereas the increase in $\nu^{P/A}$ over time is due to the passive investors becoming relatively larger, i.e., because of the increase in $RLH^{P/A}$.

6 The Impact of Lambdas on Markups

In this section, we investigate, both theoretically and empirically, the impact of firms' common ownership incentives on their markups. First we show that the common ownership incentives should positively affect firm markups within the context of a simple model of product market competition. We then describe the derivation of the markup data and set up the empirical model. We show both OLS and 2SLS estimation results. We interpret the 2nd stage results of the 2SLS estimation as the second part of our setup, where first we investigate how investor variables drive lambda, and then how lambda in turn impacts markups.

6.1 Theory

Starting from the objective function of our general framework, we can obtain closed-form solutions of the equilibrium relationship between firm common ownership incentives and firm markups within a simple symmetric model of Bertrand competition between the firms of the market (Lopez and Vives, 2019).[27] Assume for the rest of the subsection (i) symmetric levels of common ownership across firms, $\lambda_{jk} \equiv \lambda$ for all j and k, (ii) each of the n firms in the market produces one differentiated product at constant marginal costs c, possibly depending on λ, and (iii) the demand for each good j, is given by $q_j = D_j(p)$, where p is the vector of prices of all the firms, and the demand exhibits constant elasticity.

Taking into account these assumptions in (5), firm j's objective function is given by

$$\pi_j + \sum_{k \neq j} \lambda \pi_k = (p_j - c(\lambda))D_j(p) + \lambda \sum_{k \neq j}(p_k - c(\lambda))D_k(p).$$

Assuming that the level of common ownership and the marginal costs are taken as given, when firms compete in prices, the first order conditions for an interior equilibrium p_j^*, result in markups given by

$$\mu_j \equiv \frac{p_j^*}{c(\lambda)} = \frac{\eta_j - \lambda(n-1)\eta_{jk}}{\eta_j - \lambda(n-1)\eta_{jk} - 1}, \tag{16}$$

where the elasticities $\eta_j = -\frac{\partial D_j(p^*)}{\partial p_j}\frac{p^*}{D_j(p^*)}$ and $\eta_{jk} = \frac{\partial D_k(p^*)}{\partial p_j}\frac{p^*}{D_k(p^*)}$ for $k \neq j$ are constant.

We can now perform comparative statics in terms of λ, as a parameter of the model, which affects the markups through the costs as well as through the equilibrium prices (which in turn depend, not only on λ but also on the costs).[28] As the right-hand side in (16) is increasing in λ, we can state the following proposition.

Proposition 4. *In the context of the symmetric model of Bertrand competition, firm markups (μ_j) increase in the level of common ownership incentives (λ).*

Intuitively, as the levels of common ownership between a given firm and its competitors increase, price increases in the firm's products are less harmful for its investors, as part of the diverted sales and profits are lost to other commonly-owned firms. Common ownership thus

[27] There are other ways how common ownership might influence firm behaviour, as firms may act in concert with other firms in the industry through their common ownership links. We disregard them here.

[28] In this sense, the model is like a three stage model where λ is determined first, costs second and prices third. Stages one and two are not maximisation problems though, i.e., we only perform comparative statics.

affects the optimal pricing trade-off of lower sales on the margin versus higher prices on the infra-marginal sales. Further, common ownership structures may help firms to reduce their costs through e.g., a better informational flow between connected firms (Lopez and Vives, 2019). Both mechanisms, i.e., higher prices or lower costs, lead to a positive relationship between common ownership incentives and markups.

6.2 Estimation of the markups data

Our product market outcome of choice is a structurally estimated firm-level markup. As our aim is to reproduce these markups, we mimic closely the so-called production function method originally proposed by De Loecker and Warzynski (2012) and applied to the same Compustat firm-level data by De Loecker and Eeckhout (2017) and De Loecker at al. (2020).

We observe firm-level input and output data for all public firms in the US industries (in monetary terms). We use Compustat measures of sales, input expenditure, capital stock information, as well as detailed industry activity classifications. The item that we use to measure the variable input is "Cost of Goods Sold"(COGS). It bundles all expenses directly attributable to the production of the goods sold by the firm and includes intermediate inputs, labor cost, and energy. Furthermore, as a measure for capital we use "Net Capital"(PPENT), which is total fixed assets (property, plant, and equipment, adjusted for depreciation).

These data are sufficient to measure firm-level markups using several assumptions on producer behaviour, but without assumptions on the final product market competition.[29] A measure of the markup is obtained for each producer at a given point in time as the wedge between a variable input's expenditure share in revenue (directly observed in the data) and that input's output elasticity. The latter is obtained by estimating the associated production function. Mimicking De Loecker and Eeckhout (2017), we empirically derive markups for firm j at time t ($\mu_{j,t}$), which are the elasticity of output with respect to the variable input ($\theta_{j,t}$) over the revenue share of variable input ($\alpha_{j,t}$):

[29] See, however, Doraszelski and Jaumandreu (2019) and Flynn et al. (2019) for critiques (and solutions) on the identification of markups through these production function estimators; and Collard-Wexler and De Loecker (2016) on bias due to measurement problems.

$$\mu_{j,t} = \theta^V_{j,t} \left(\frac{P^V_{j,t} V_{j,t}}{P_{j,t} Q_{j,t}} \right)^{-1} = \frac{\theta_{j,t}}{\alpha_{j,t}}, \tag{17}$$

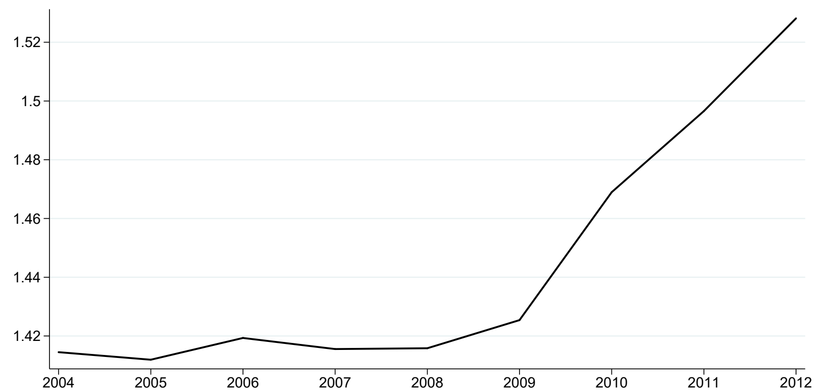
where $Q_{j,t}$ is firm-level output at time t, $V_{j,t}$ firm-level input, and $P_{j,t}$ and $P^V_{j,t}$ their corresponding prices. We refer to the cited papers for a theoretical derivation of the above equation, but the underlying idea is that the markup is equal to the input's output elasticity over the revenue share of its costs (where under perfect competition the output elasticity of a variable input equals its revenue share).

We refer to the markup Appendix C for the details of the empirical estimation, but we essentially estimate markups through two different specifications. In the first specification, we estimate markups using an industry-specific Cobb Douglas function and a law of motion that includes capital and (lagged) labor. In a second specification, we add lambda to the law of motion to allow lambda to have an impact on (future) productivity. Indeed, it has been shown that export (De Loecker and Warzysnki, 2012) and R&D (Doraszelski and Jaumandreu, 2013) have an influence on productivity; it could well be that common ownership structures might influence productivity too. For example, common ownership networks might lead to efficiency gains through spillovers within the network of connected firms (see Lopez and Vives, 2019, for a theoretical framework).

As can be seen from Figure 10, our estimated markups go on average from about 1.42 in 2004, reach their minimum in 2008 and afterwards climb to their sample maximum of about 1.58. Both levels and trends are very similar to markups shown on Figure 1 in De Loecker et al (2020).[30] Furthermore, as can be seen from Table 2, the markup with lambda in the law of motion, μ_{CO}, has slightly higher means and medians than the markup without lambda in the law of motion μ, thereby indicating that companies' production functions might be positively impacted by common ownership incentives, i.e., their markups are slightly higher through an increased productivity (equivalent to lower costs in our theoretical framework).

[30] Note that we work with consolidated data. However, De Loecker at al. (2019) indicate that there is little systematic difference between the markups based on the consolidated accounts and the markup based on the segment-based accounts.

Figure 10. Structurally estimated markups (μ) for US publicly-listed companies.



This figure displays the mean structurally-estimated markups across all publicly-listed firms in the US for the period 2004 - 2012. Markups for each firm j are estimated as $\mu_j = \frac{\theta_j}{\alpha_j}$ where θ_j is the (estimated) elasticity of output with respect to the variable input and α_j the revenue share of variable input.

6.3 Empirical setup and results

We estimate firm-level markups $\mu_{j,t}$ as a function of a one-period lagged lambdas $\lambda_{j,t-1}$. In particular, we regress

$$\mu_{j,t} = \delta_\lambda \lambda_{j,t-1} + \delta_X X_{j,t} + \gamma + \varepsilon_{j,t}, \tag{18}$$

where we use firm level controls (COGS and PPENT), and industry(x)year fixed effects, with $\varepsilon_{j,t}$ being the error term for this regression. Given potential endogeneity issues of lambdas (further discussed below), we lag lambdas one period to allow for temporal distance between lambda and markups. As estimation methods, we use both OLS and 2SLS, where the above equation represents either a simple OLS estimation or the 2nd stage regression of a 2SLS estimation (and equation 15 the first stage).[31]

For each specification, we show two different treatments of the error term: robust standard errors, to account for potential heteroscedasticities across firms, and standard errors

[31] Our OLS estimation is a similar specification as in De Loecker and Warzynski (2012), where they seek to relate firm-level exports to firm-level markups.

clustered at the industry(x)year level, to permit firms' standard errors within an industry in a given year to be correlated. While we prefer the clustered specification, we nevertheless include also here the results with robust standard errors. The main reason for this is that we are dealing with a dependent variable that is based on estimates, which means that the regression residual has an extra component due to some sampling error (the difference between the true value of the dependent variable and its estimated value). But the fact that the dependent variable is estimated does not necessarily present any difficulties for regression analysis when the sampling error is constant across observations (Lewis and Linzer, 2005). If, however, the sampling error in the dependent variable is not constant across observations, then the regression errors will be heteroscedastic. An easy fix to correct for this, is to apply heteroskedasticity-consistent standard errors or robust standard errors.

We, therefore, present the results of eight specifications. We first present the OLS and 2SLS estimation results, using robust and clustered standard errors, where markups are estimated using an industry-specific Cobb Douglas function and a law of motion that includes capital and (lagged) labor. We then repeat these four specifications where we allow common ownership to affect a firm's future productivity (i.e., the estimated markups include (lagged) λs in the law of motion). The underlying idea of this last set of regressions is to be to some extent in line with our theoretical setup, where we let marginal costs depend on lambda; while one needs to keep in mind that (future) productivity is not exactly the same as (current) marginal costs.

Our main set of regressions, using the log-log specification is shown in Table 6. The coefficient on lambda is mainly identified by the cross-sectional variation that arises from differences across individual companies. Specifically, as we use year fixed effects, interacted with the industry in which a firm operates, the coefficient is identified by the within variation in common ownership among firms that differs from the average common ownership level faced by firms in a certain industry and period. With this in mind, the empirical results are in line with our theoretical setup (Proposition 4): we find a positive and highly significant effect of lambdas on firm-level markups in all the specifications (significant at the 1% level).

Furthermore, the coefficient is larger for the 2SLS regressions as compared to the simple OLS regressions in each specification (see columns (3) and (4) with a coefficient of 0.293 as

Table 6. Regression results of markups on lambdas (log-log)

This table reports the coefficients for the OLS and second stage of the two-stage least squares (2SLS) log-log regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls.

	(1) $\log \mu$	(2) $\log \mu$	(3) $\log \mu$	(4) $\log \mu$	(5) $\log \mu_{CO}$	(6) $\log \mu_{CO}$	(7) $\log \mu_{CO}$	(8) $\log \mu_{CO}$
$\log \lambda$	0.175***	0.175***	0.293***	0.293***	0.159***	0.159***	0.213***	0.213***
	(0.0201)	(0.0265)	(0.0342)	(0.0567)	(0.0206)	(0.0261)	(0.0329)	(0.0451)
N	21464	21464	21151	21151	19229	19229	19210	19210
Regression	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Fixed Effects	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.
Std. Errors	Robust	Ind. Yr.	Robust	Ind. Yr.	Robust	Ind. Yr.	Robust	Ind. Yr.
# of Groups	1392	1392	1392	1392	1381	1381	1381	1381
R^2	0.475	0.475	0.480	0.480	0.488	0.488	0.488	0.488
F-stat	1543.4	330.0	1543.7	369.2	1437.2	334.6	1436.5	333.7
p-value F-stat	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
End. Stat.	-	-	17.8	10.1	-	-	5.8	5.7
p-value End.	-	-	0.00	0.00	-	-	0.02	0.02

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

compared to columns (1) and (2) with a coefficient of 0.175, and columns (7) and (8) with a coefficient of 0.213 as compared to columns (5) and (6) with a coefficient of 0.159). This indicates that when we allow lambda to be determined by investor variables, then its impact is higher. In other words, lambda's impact on markups is underestimated if we do not take into account the channel of investors $\Rightarrow$ lambdas $\Rightarrow$ markups.

One could further argue that lambdas are potentially endogenous, as firm performance outcomes (markups) and industry/market structure-related variables (lambdas) often mutually influence each other.[32] For example, firms' entry and exit within an industry might influence both a company's markup and its lambda, see for example Hopenhayn (1992) and Ericsson and Pakes (1995), for seminal works on the topic of industry dynamics. We there-

[32]Note, though, that by using unweighted averages of pairwise lambdas between firms, our measure does not suffer from the main methodological criticisms of Azar et al. (2018a) and other studies that use MHHI delta, which depends on the endogenously determined market shares of firms.

fore lag our lambdas one period in all our estimations. However, lagging one period does not (fully) solve for this endogeneity when variables are correlated over time, as is indeed the case with the lambdas in our sample.

Our investor variables tentatively correct for this endogeneity, as investor diversification, their money holdings and their concentration are unlikely to be directly influenced by firms' margins. We perform endogeneity tests, comparing the coefficients of OLS and corresponding 2SLS estimations, implemented through a test akin to a C statistic.[33] Table 6 shows these stats and corresponding p-values, where it is indeed confirmed that OLS and 2SLS yield significantly different coefficients. Hence, the OLS estimations might suffer from endogeneity bias, where our 2SLS estimates correct for this bias through investor variables' influence on lambda. Of course, (active) investment strategies might be partly driven by firms' markups, which in turn might influence some of our investor variables, such as diversification. Therefore, while this seems to be a less serious problem than the endogeneity of lambda, we cannot totally rule out that some of the investor variables are to some degree influenced by firms' markups.

However, we see our setup as a step forwards in correcting for lambda's potential endogeneity, as our set of investor variables is arguably less prone to potential endogeneity than lambda itself. Thus, although not the main focus of our study, money flows across different types of investors as we apply here in this study, could be used as an alternative identification mechanism to correct for the potential endogeneity of common ownership, where mergers between financial institutions (see e.g., Anton et al., 2022; Azar et al., 2018a; He and Huang, 2017) and index entry of companies (see e.g., Boller and Scott Morton, 2020; Schmidt and Fahlenbrach, 2017) are currently the most-often used identification strategies, but criticized by Lewellen and Lowry (2021).

Furthermore, if we take into account that common ownership may influence productivity (including lambda in the law of motion when estimating the markups, yielding μ_{CO}), we first see in Table 2 that mean and median of μ_{CO} are 1.60 and 1.42, respectively, and thus

[33]The test is performed like the "C statistic," defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments (zero in our case), where the suspect regressor is treated as endogenous, and one for the equation with the larger set of instruments (the investor variables in our case), where the suspect regressor is treated as exogenous. Under conditional homoskedasticity, this endogeneity test statistic is numerically equal to a Hausman test statistic. Unlike the classic Durbin-Wu-Hausman, however, this test can report test statistics that are robust to violations of conditional homoskedasticity (Hayasi, 2000).

slightly higher than the mean and median of our original μ (1.56 and 1.41, respectively). Therefore, common ownership incentives have an upward effect on markups through an increased efficiency, although their impact is small. When we then in turn look at the estimations of μ_{CO} on lambda, we see in Table 6 that the impact of lambda on markups is slightly smaller (lowering from 0.175 to 0.159 from columns (1)-(2) to columns (5)-(6), and lowering from 0.293 to 0.213 from columns (3)-(4) to columns (7)-(8)). These findings indicate that it makes a difference to allow common ownership to influence firms' production decisions. While our empirical setup is in essence not suited to (structurally) disentangle markups into market power and productivity/efficiencies, one can still tentatively do the thought exercise: when allowing lambdas to influence production decisions, the (remaining) impact of λ on μ_{CO} might be linked to common ownership incentives' connection to market power in the range of 0.159 - 0.213. Overall, in terms of magnitudes, a 1% increase in λ leads to an increase in μ of $0.175\% - 0.293\%$ and, with lambda in the law of motion, to an increase in μ_{CO} of $0.159\% - 0.213\%$. Thus, the 'pass through' from common ownership incentives to product market outcomes lies in between 15.9% and 29.3%.

One can further quantitatively link changes in $RLH^{P/A}$ to changes in μ and μ_{CO} in our 2SLS estimations (connecting the 1st and 2nd stages): whenever $DIV^P > DIV^A$, then a 1% increase in $RLH^{P/A}$ leads to an increase in μ of $0.0227\% - 0.0380\%$ and, with lambda in the law of motion, to an increase in μ_{CO} of $0.0207\% - 0.0277\%$.

In sum, our results indicate that our empirical model indeed captures the idea that investor variables influence common ownership incentives in product markets around the financial crisis, which in turn relate to markups. In other words, we empirically find evidence that investors (via money flows and ownership diversification) and product markets are connected. We further argue that, while common ownership incentives might be suspect of being endogenous, our key investor variables are less likely to be driven by individual firms' markups and hence, the investor channel's impact on lambdas offers an improvement in estimating the impact of common ownership incentives on firm markups.

A recent study by Lewellen and Lowry (2021) argues that studies on common ownership find effects mainly due to events around the financial crisis. That is exactly our focus: the financial crisis coincided with a shift of money holdings from active to passive investors, which has had an influence on common ownership incentives; note that we control for confounding industry-time related factors due to the inclusion of time(x)industry fixed effects.

7 Extensions and Robustness Checks

In this section, we show estimations with additional firm fixed effects, alternative functional form assumptions, alternative levels of control (non-proportional instead of proportional levels of control), and alternative levels of interconnections (narrower industry definitions). The main conclusion of these alternative specifications is that the significance of our results is robust to different assumptions on functional form, different levels of control and on the level of aggregation on which one defines investor variables and common ownership incentives.

7.1 Including firm fixed effects

We include in all our estimations industry(x)year fixed effects to control for confounding industry-time related factors. While we believe that in our context –with a focus on industry-level common ownership networks– this is the most important dimension to control for, one might further argue that controlling for firm-level confounding factors is important as well.[34] Although we include in all regressions two firm-specific factors (COGS and PPENT), we run regressions with additional firm-fixed effects to control for additional firm-specific non-time varying factors, and where we allow errors to be clustered at the firm level. Results in Tables 7 and 8 show that results stay highly significant and quantitatively in line with our main regressions.

7.2 Linear specification

Results are statistically similar if we use, instead of the log-log specification, a linear model, as shown in Tables 9 and 10. The coefficients are highly significant and the relative comparison of the key coefficient levels as well (where 2SLS produces larger estimates than OLS, as can be seen in Table 10).

Furthermore, where the log-log specification is our preferred specification, a linear specification is better suited to compare outcomes in absolute numbers. In particular, one can simulate how a change from "low" money flows to "high" money flows impacts lambdas, and how this change in lambdas in turn affects markups. In particular, Table 2 shows that the

[34]For example, see Colombo et al. (2022) and Lewellen and Lowry (2021) for a logic of why to include firm fixed effects in the context of common ownership.

Table 7. Regression results of lambdas on investor variables, firm and industry(x)year FEs (log-log)

This table reports the coefficients for the first stage of the two-stage least squares (2SLS) log-log regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls. For presentation purposes of the coefficients, we scale all the explanatory variables by dividing them by 100.

	(1) $\log\lambda$	(2) $\log\lambda$
$\log \mathrm{RLH}^{P/A}$	1.617***	1.617***
	(0.294)	(0.393)
$\log \mathrm{RLH}^{P/A} \times \mathbb{1}\{\mathrm{DIV}^P > \mathrm{DIV}^A\}$	5.127***	5.127***
	(0.286)	(0.380)
$\log \mathrm{DIV}^A$	5.956***	5.956***
	(0.251)	(0.359)
$\log \mathrm{DIV}^P$	3.235***	3.235***
	(0.228)	(0.315)
$\log \mathrm{CON}^A$	-4.178***	-4.178***
	(0.226)	(0.312)
$\log \mathrm{CON}^P$	-2.028***	-2.028***
	(0.198)	(0.265)
$\log \mathrm{INV}^A$	0.912***	0.912***
	(0.0814)	(0.112)
$\log \mathrm{INV}^P$	-0.663***	-0.663***
	(0.0898)	(0.120)
N	21180	21180
Fixed Effects	Firm Ind.Yr.	Firm Ind.Yr.
Std. Errors	Robust	Firm
# of Groups	2678	2678
R^2	0.117	0.117
F-stat	170.7	72.7
p-value F-stat	0.00	0.00

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Regression results of markups on lambdas, firm and industry(x)year FEs (log-log)

This table reports the coefficients for the OLS and second stage of the two-stage least squares (2SLS) log-log regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls.

	(1) $\log \mu$	(2) $\log \mu$	(3) $\log \mu$	(4) $\log \mu$	(5) $\log \mu_{CO}$	(6) $\log \mu_{CO}$	(7) $\log \mu_{CO}$	(8) $\log \mu_{CO}$
$\log \lambda$	0.116***	0.116***	0.421***	0.421***	0.105***	0.105***	0.323***	0.323***
	(0.0243)	(0.0322)	(0.0988)	(0.112)	(0.0247)	(0.0326)	(0.0906)	(0.104)
N	21496	21496	21180	21180	19221	19221	19204	19204
Regression	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
	Ind.Yr.	Ind.Yr.	Ind.Yr.	Ind.Yr.	Ind.Yr.	Ind.Yr.	Ind.Yr.	Ind.Yr.
Std. Errors	Robust	Firm	Robust	Firm	Robust	Firm	Robust	Firm
# of Groups	2687	2687	2678	2678	2503	2503	2501	2501
R^2	0.136	0.136	0.131	0.131	0.137	0.137	0.134	0.134
F-stat	99.9	51.2	94.7	51.2	73.7	41.3	71.8	41.1
p-value F-stat	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
End. Stat.	-	-	9.0	7.5	-	-	5.4	4.2
p-value End.	-	-	0.00	0.01	-	-	0.02	0.04

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

minimum and maximum of values of $RLH^{P/A}$ are 0 and 1, respectively. Therefore, while using means for the values of all other variables, when going from the minimum to the maximum of $RLH^{P/A}$, we would predict λ to go from 0.74 to 1.53. This would represent more than a doubling of lambda.

Connecting then these changes in $RLH^{P/A}$ with changes in μ through lambdas, when going from the minimum to the maximum of $RLH^{P/A}$, μ would go from 1.54 to 1.60, which represents an increase of about 4.6%. Doing the same for μ_{CO}, when going from the minimum to the maximum of $RLH^{P/A}$, μ_{CO} would go from 1.58 to 1.63, which represents an increase of about 3.5%. While this is in essence just a simulation exercise, we think it is still interesting to observe that going from lowest to highest money holdings in our sample, corresponding lambdas increase by more than 100% and markups increase by 3.5% – 4.6%.

Table 9. Regression results of lambdas on the investor variables (linear)

This table reports the coefficients for the first stage of the two-stage least squares (2SLS) linear regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls. For presentation purposes of the coefficients, we scale all the explanatory variables by dividing them by 100.

	(1) λ	(2) λ
$\text{RLH}^{P/A}$	2.119***	2.119***
	(0.223)	(0.240)
$\text{RLH}^{P/A} \times \mathbb{1}\{\text{DIV}^P > \text{DIV}^A\}$	8.425***	8.425***
	(0.348)	(0.518)
DIV^A	7.539***	7.539***
	(0.243)	(0.414)
DIV^P	4.558***	4.558***
	(0.186)	(0.238)
CON^A	-2.134***	-2.134***
	(0.226)	(0.224)
CON^P	-5.430***	-5.430***
	(0.180)	(0.223)
INV^A	0.0920***	0.0920***
	(0.00355)	(0.00458)
INV^P	0.0327***	0.0327**
	(0.0109)	(0.0133)
N	21151	21151
Fixed Effects	Ind. Yr.	Ind. Yr.
Std. Errors	Robust	Ind. Yr.
# of Groups	1392	1392
R^2	0.528	0.528
F-stat	2384.5	415.0
p-value F-stat	0.00	0.00

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Regression results of markups on lambdas (linear)

This table reports the coefficients for the OLS and second stage of the two-stage least squares (2SLS) linear regressions of (i) lambdas on the investor variables and (ii) markups on lambdas. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	μ	μ	μ	μ	μ_{CO}	μ_{CO}	μ_{CO}	μ_{CO}
λ	0.424***	0.424***	0.787***	0.787***	0.478***	0.478***	0.583***	0.583***
	(0.0590)	(0.0727)	(0.105)	(0.144)	(0.0724)	(0.0838)	(0.116)	(0.128)
N	21464	21464	21151	21151	19229	19229	19210	19210
Regression	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Fixed Effects	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.
Std. Errors	Robust	Ind. Yr.	Robust	Ind. Yr.	Robust	Ind. Yr.	Robust	Ind. Yr.
# of Groups	1392	1392	1392	1392	1381	1381	1381	1381
R^2	0.263	0.263	0.267	0.267	0.247	0.247	0.247	0.247
F-stat	376.8	99.9	358.4	150.8	341.1	120.3	317.6	105.2
p-value F-stat	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
End. Stat.	-	-	32.7	21.6	-	-	5.6	10.7
p-value End.	-	-	0.00	0.00	-	-	0.02	0.00

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.3 Non-proportional levels of control

In our main empirical specification, we give the same level of control to active and passive investors, i.e, we assume proportional control. Table 11 shows the empirical results of giving relatively more control to the active investors (vis-a-vis the passive investors). We use the specification that we deem to be our "best specification"(2SLS, log-log, common ownership in the law of motion and clustered standard errors). We allow for active investors to have a relatively higher level of control than passive investors in several steps: $\kappa_A/\kappa_P = 1$ (our baseline specification, i.e., proportional control), $\kappa_A/\kappa_P = 1.5$ and $\kappa_A/\kappa_P = 2$, where we use the same notation as in the simple model of Section 3. We, thus, redefine lambda variable in each specification.

Table 11. Regression results with alternative levels of control

This table reports the coefficients for the first and second stage of the two-stage least squares (2SLS) log-log regressions of (i) lambdas on investor variables and (ii) markups on lambdas, where lambdas are defined giving different levels of control to the active investors, relative to the passive ones. In particular, columns 1 and 2 report the results using $\kappa_A/\kappa_P = 1$ (our baseline specification, i.e., proportional control), columns 3 and 4 use $\kappa_A/\kappa_P = 1.5$ and columns 5 and 6 use $\kappa_A/\kappa_P = 2$, where we use the same definition and notation of κ_A/κ_P as in the simple model (Section 3). Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls. For presentation purposes of the coefficients, we scale all the first-stage explanatory variables by dividing them by 100.

	(1) $\log\lambda_{\kappa=1}$	(2) $\log\mu_{CO}$	(3) $\log\lambda_{\kappa=1.5}$	(4) $\log\mu_{CO}$	(5) $\log\lambda_{\kappa=2}$	(6) $\log\mu_{CO}$
$\log\lambda_{\kappa=1}$		0.213***				
		(0.0451)				
$\log\lambda_{\kappa=1.5}$				0.233***		
				(0.0495)		
$\log\lambda_{\kappa=2}$						0.246***
						(0.0526)
$\log \text{RLH}^{P/A}$	3.162***		3.062***		3.025***	
	(0.378)		(0.354)		(0.341)	
$\log \text{RLH}^{P/A} \times \mathbb{1}\{\text{DIV}^P > \text{DIV}^A\}$	9.395***		8.555***		7.952***	
	(0.585)		(0.558)		(0.538)	
$\log \text{DIV}^A$	9.730***		9.834***		9.903***	
	(0.482)		(0.472)		(0.466)	
$\log \text{DIV}^P$	6.515***		5.478***		4.868***	
	(0.310)		(0.285)		(0.272)	
$\log \text{CON}^A$	-8.950***		-8.433***		-8.126***	
	(0.315)		(0.292)		(0.279)	
$\log \text{CON}^P$	-9.671***		-8.808***		-8.296***	
	(0.298)		(0.285)		(0.277)	
$\log \text{INV}^A$	-0.156		-0.181*		-0.186*	
	(0.109)		(0.103)		(0.0996)	
$\log \text{INV}^P$	0.212*		0.182*		0.173*	
	(0.114)		(0.108)		(0.104)	
N	21151	19210	21151	19210	21151	19210
Regression	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Fixed Effects	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.
Std. Errors	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.
# of Groups	1392	1381	1392	1381	1392	1381
R^2	0.548	0.488	0.528	0.488	0.514	0.488
F-stat	424.2	333.7	434.9	335.2	440.9	336.1
p-value F-stat	0.00	0.00	0.00	0.00	0.00	0.00
End. Stat.	-	5.7	-	6.3	-	6.8
p-value End.	-	0.02	-	0.01	-	0.01

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results are intuitive: the impact of passive investors' relative holdings ($RLH^{P/A}$) on lambda decreases monotonically with a higher relative level of control for active investors (see the sum of the two $RLH^{P/A}$ coefficients in columns (1), (3) and (5)). In particular, the impact is reduced from 0.126% to 0.116% when we change $\kappa_A/\kappa_P = 1$ to $\kappa_A/\kappa_P = 1.5$, and then to 0.11% for $\kappa_A/\kappa_P = 2$. Thus, as passive investors become relatively less powerful, their holdings have relatively less impact on lambdas.

These differences are not that large, as the changes in control do not have a big impact. Indeed, the majority of the holdings in the database belong to active investors (the median of $RLP^{P/A}$ is 0.22, as shown in Table 2). As a result, doubling the relative level of control of active investors ($\kappa_A/\kappa_P = 2$) increases their median level of control (κ) from 77% to 88%, on average, and thus a an increase of just 11 percentage points. The quantitative effect on lambda, in turn, is small (from 0.094 if $\kappa_A/\kappa_P = 1$ to 0.083 if $\kappa_A/\kappa_P = 2$, a reduction of 12 percentage points). As a consequence, the effect of $RLP^{P/A}$ on lambda is not that large either.

Second, whereas passive investor's holdings have less impact on lambdas, lambda itself has a slightly higher impact on markups for higher levels of control of active investors (from 0.213 towards 0.246; see columns (2), (4) and (6)). As a consequence of the above-explained small changes, the differential impact of lambda on markups when going from proportional to non-proportional levels of control is again not substantial. In sum, our results are robust to changing the assumption of proportional control, and changes are small, as active investors are (much) larger than passive investors in terms of money holdings.

7.4 Narrower industry definition

In the main specification, we define industries at the NAICS4 level. It is unclear, though, how exactly investors operate and impact companies across industries. Table 12 shows, therefore, the analysis using a narrower level of aggregation of lambdas and investor variables, i.e., NAICS6 with again our preferred specification (2SLS, log-log, common ownership in the law of motion and clustered standard errors).[35]

[35] One could further imagine that firms interact to some degree also across markets, similar in vein as explained in Azar and Vives (2021). We re-estimated the within-industry impact of lambda on markups, while adding a firm-level lambda that summarizes all connections of the focal firm *outside* the industry. While correlations between these two measures are quite high, unreported results show that the within-industry lambda has a positive effect on markups, whereas the inter-industry common ownership incentives

Table 12. Regression results on NAICS6 level

This table reports the coefficients the two-stage least squares (2SLS) regressions of (i) lambdas on the investor variables and (ii) markups on lambdas at the NAICS6 level. Standard errors are treated as robust or clustered at the industry(x)year level. COGS and PPENT are included in all regressions as controls. For presentation purposes of the coefficients, we scale all the first-stage explanatory variables by dividing them by 100.

	(1) $\log \lambda_{Naics6}$	(2) $\log \mu_{CO}$	(3) $\log \lambda_{Naics6}$	(4) $\log \mu_{CO}$
$\log \lambda_{Naics6}$		0.253***		0.253***
		(0.0381)		(0.0539)
$\log \mathrm{RLH}^{P/A}$	3.419***		3.419***	
	(0.391)		(0.409)	
$\log \mathrm{RLH}^{P/A} \times \mathbb{1}\{\mathrm{DIV}^P > \mathrm{DIV}^A\}$	8.299***		8.299***	
	(0.440)		(0.607)	
$\log \mathrm{DIV}^A_{Naics6}$	10.68***		10.68***	
	(0.389)		(0.632)	
$\log \mathrm{DIV}^P_{Naics6}$	8.161***		8.161***	
	(0.323)		(0.420)	
$\log \mathrm{CON}^A$	-8.954***		-8.954***	
	(0.335)		(0.357)	
$\log \mathrm{CON}^P$	-10.16***		-10.16***	
	(0.254)		(0.348)	
$\log \mathrm{INV}^A$	-0.202**		-0.202*	
	(0.0948)		(0.121)	
$\log \mathrm{INV}^P$	0.210*		0.210	
	(0.109)		(0.128)	
N	19861	17957	19861	17957
Regression	2SLS	2SLS	2SLS	2SLS
Fixed Effects	Ind. Yr.	Ind. Yr.	Ind. Yr.	Ind. Yr.
Std. Errors	Robust	Robust	Ind. Yr.	Ind. Yr.
# of Groups	2421	2292	2421	2292
R^2	0.505	0.493	0.505	0.493
F-stat	1561.1	1312.0	336.1	321.3
p-value F-stat	0.00	0.00	0.00	0.00
End. Stat.	-	12.6	-	12.5
p-value End.	-	0.00	-	0.00

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results in Table 12 show that all the coefficients are equally significant, and the model is equally well specified. Furthermore, as perhaps expected, the impact of lambda on markups is a bit stronger. Indeed, given that industries are more narrowly defined, one can expect strategic interactions between firms to be stronger. In particular, a 1% increase in lambda leads to a an by 0.253% in markups for NAICS6 industries (whereas the impact was 0.213% in NAICS4 industries). In sum, when defining a narrower industry definition, results stay qualitatively the same and are quantitatively slightly higher.

8 Conclusion

This paper investigates the marked increase in common ownership incentives of US publicly listed firms around the great financial crisis. We argue that this rise can be traced back to the increase in money flows towards more diversified passive investors, relative to active investors, particularly after the financial crisis. We find evidence for the period 2004-2012 that a 1% increase in the relative holdings of the passive investors is positively and significantly related to a change in the common ownership incentives by 0.13%.

We show that this increase in common ownership incentives can in turn be associated with the observed increase in product market markups. A 1% change in the common ownership incentives is positively and significantly related to a change in markups of $0.15\% - 0.29\%$. Linking the two steps, a 1% change of the relative holdings of the diversified-passive investors is positively and significantly related to a change in markups of about $0.02\% - 0.03\%$. Ownership diversification and money flows can thus ultimately be linked to product markets, whereby the magnitude of the overall effect is small but non-negligible.

Our results suggest that common ownership might be connected to firms' markups. Common ownership can influence markups through a reduction in costs, an increase in prices, or both. Our empirical setup cannot cleanly separate these two elements, and thus we cannot determine whether common ownership is anti- or pro-competitive. Distinguishing between these two can be an interesting avenue for further research.

have a negative effect. The overall effect of common ownership incentives on markups is positive and in order of magnitude of our main estimations.

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Appendix

Appendix A: Data

Ultimate owners: NIC data

The NIC data is publicly available and readily downloadable via the NIC website. We work with data extracted on June 30th 2017. The data provided on the website is in xml format. NIC defines control as:

- ownership, control, or power to vote 25 percent or more of the outstanding shares of any class of voting securities of the investor, directly or indirectly or acting through one or more other persons
- control in any manner over the election of a majority of the individuals, or general partners (or persons exercising similar function) of the bank or other company
- the power to exercise, directly or indirectly, a controlling influence over the management or policies of the bank or other company. See Regulation Y Section 225.2 (e)(1)(i)(ii)(iii) or 12 CFR Part 574 for savings and loan holding companies.

The available data is split in five separate files with the following attributes:

- Active: provides information describing the characteristics of open and active institutions.
- Closed: Provides the last instance of closed / failed institutions.
- Branches: Provides the last instance of branches whose head office is listed in either the Active or Closed.
- Relationships: Provides the history of ownership between two entities.
- Transformations: Provides information on mergers and failures.

The relationship data provides parent-subsidiary tuples and additional information on the length and other characteristics of the relationship. For each of the top investors we build (recursively) the holding structure database up to the 5th (sub-)child level, storing also the intermediary level companies. We then obtain the legal company names corresponding to the tuples, by merging the holding structures with the attributes files. Next, we match the company names available in Thomson with the legal company names in the holding structure. To gauge the match, we use a range of fuzzy string matching algorithms (from the fuzzywuzzy python package). We filter the resulting list for matches with scores over 90; where 0 is worst and 100 is best match. In a last step, we performed manual match quality checks to ensure the best possible results.

Matching

We use Capital IQ files to link the Compustat data, where firms are identified by the GVKEY variable, with the Thomson dataset of security holdings, which are identified with CUSIP or (predominantly) ISIN numbers. In particular, we construct a file that maps each GVKEY-year to all the CUSIP and ISIN values of securities that correspond to the firm-year. We next use the Thomson securities information file to filter out — for each of the security identifiers — the non-ordinary shares and non-primary issues. We then match, for each year, the investor end-of-year holdings to the Compustat firm identifiers by security ISIN or CUSIP. In the case where Thomson observations are left unmatched we use the implied CUSIPs for the US firms to link them to the Compustat/Capital IQ data, as CUSIP numbers can be retrieved through the ISIN identifiers for the US firms. Since in our dataset the investors are primarily identified by the string variables containing their names, we further clean our data by recasting the names to the lower case and eliminating dots, commas, apostrophes, and dashes.

Appendix B: Lambdas in matrix form

Let us start by viewing the m investors' holdings in the n_S firms in market S as a bipartite graph where (i) the nodes are the (two disjoint sets of) firms and investors, (ii) the nodes of the two sets can be connected (across, but not within, the two sets) and (iii) the weight of a connection between a node investor i and a node firm j is given by the ownership stake of investor i in firm j, β_{ij}.[36]

[36]Note that while the number of firms per market S, n_S, is market-specific, the number of investors m is the same across all industries (where it can be that $\beta_{ij} = 0$ for all firms in industry S.)

This bipartite graph can be represented by the $m \times n_S$ adjacency matrix Ω_S of the holdings of the m investors in the n_S firms. Investor holdings in each firm j are stacked into a column vector β_j of length m. The matrix Ω_S is formed by these n_S firm-specific vectors,

$$\Omega_S \equiv (\beta_j),\ j = 1, ..., n_S, \text{ with } \beta_j \equiv (\beta_{ij}),\ i = 1, ..., m.$$ [37]

Let us now consider the projection of this bipartite graph onto the set of firms, represented by the (symmetric) $n_S \times n_S$ bi-adjency matrix Δ_S,

$$\Delta_S \equiv \Omega_S' \Omega_S \text{ and thus with elements } \delta_{jk} = \textstyle\sum_{i=1}^{m} \beta_{ij}\beta_{ik}$$

The elements δ_{jk} show the degree of interconnectedness of each pair of firms j and k via their common investors. But this measure of interconnectedness depends on firms' level of ownership concentration, which is an undesirable property.[38] The diagonal of the bi-adjency matrix contains the ownership concentration of each firm j, $\delta_{jj} = \sum_{i=1}^{m} \beta_{ij}^2$.

Therefore, we can rescale Δ_S, such that the diagonal elements are equal to one:

$$\Lambda_S = D_S^{-1} \Delta_S \text{ and thus with elements } \lambda_{jk} = \frac{\sum_{i=1}^{m} \beta_{ij}\beta_{ik}}{\sum_{i=1}^{m} \beta_{ij}^2}$$

with $D_S := Diag(\Delta_S)$ where $Diag(\cdot)$ is a function that keeps the diagonal elements of the matrix intact and sets the non-diagonal elements to zero. Thus, λ_{jk} represents the degree of interconnectedness between firms, normalized such that the "self-connection"is one; as such, λ_{jk} can be seen as a rescaled version of δ_{jk}.[39]

To derive the matrix of type-specific lambdas, $\Lambda_{S\tau}$, we need to consider the bipartite graph linking investors and firms but using the investors of type τ only. Proceeding as before, let us denote by $\Omega_{S\tau}$ the adjacency matrix of this graph, which is the submatrix of Ω_S that includes the rows of investors of type $S\tau$ only. Thus, $\Omega_{S\tau}$ has as many rows as investors of type τ and n_S columns. We can again project this bipartite graph onto the set

[37] Notice that, as the shares of all investors in any firm add up to 1, $B'1_m = 1_{n_S}$ where 1_k is a vector of ones of size k.

[38] For instance, if two firms j and k are fully owned by a (common) investor then $\delta_{jk} = 1$ whereas if they are fully owned by two (common) investors, with each investor owning half of the shares of each firm, then $\delta_{jk} = 0.5$.

[39] Notice also that Λ_S is no longer symmetric.

of firms,

$$\Delta_{S\tau} \equiv \Omega'_{S\tau}\Omega_{S\tau} \text{ and thus with elements } \delta^{\tau}_{jk} = \sum_{i=1}^{m}\beta_{ij}\beta_{ik}$$

The matrix of the lambdas of type τ can be seen as a rescaled version of $\Delta_{S\tau}$

$$\Lambda_{S\tau} \equiv D^{-1}_{S_\tau}\Delta_{S\tau} \text{ and thus with elements } \lambda^{\tau}_{jk} = \frac{\sum_{i=1, i\in\tau}^{m}\beta_{ij}\beta_{ik}}{\sum_{i=1}^{m}\beta_{ij}^2},$$

where $D_{S_\tau} := Diag(\Delta_{S_\tau})$. Thus, λ^{A}_{jk} and λ^{P}_{jk} represent the degree of interconnectedness between firms through their type τ investors only.

Notice that as $\Delta_S = \Delta_{S_A} + \Delta_{S_P}$, we have that

$$\Lambda_S = D^{-1}_S(\Delta_{S_A} + \Delta_{S_P}) = D^{-1}_S(D_{S_A}D^{-1}_{S_A}\Delta_{S_A} + D_{S_P}D^{-1}_{S_P}\Delta_{S_P}) = N_{S_A}\Lambda_{S_A} + N_{S_P}\Lambda_{S_P},$$

where

$$N_{S\tau} \equiv D^{-1}_S D_{S_\tau} \text{ and thus with (diagonal) elements } \nu^{\tau}_{j} = \frac{\sum_{i=1, i\in\tau}^{m}\beta_{ij}^2}{\sum_{i=1}^{m}\beta_{ij}^2}.$$

Appendix C: Markups

This appendix very closely follows De Loecker and Warzinsky (2012) and De Loecker et al. (2018), and we refer to those papers for a more detailed exposition. We employ what have become fairly standard methods in production function estimation. In particular, we estimate production functions with sector-specific coefficients, for each of the 3 digit NAICS sectors, but keep output elasticities constant over that period. There are of course good reasons to believe that technologies varies across different industries. Technology might be time-varying too, but we thus assume that over the period of our sample, technology is likely to stay fairly the same.

We use a panel of firms for which we estimate Cobb-Douglas production functions by industry, with a variable input and fixed capital as production factors, similar to Ackerberg et al. (2015). For a given industry s we consider the production function:

$$y_{it} = \theta^V_s v_{it} + \theta^K_s k_{it} + \omega_{it} + \epsilon_{it}, \tag{19}$$

where y_{it} is firm-level output at time t, and v_{it} and k_{it} firm-level variable input and capital respectively; all three variables expressed in logs. The variable ω_{it} is the firm-level (unobserved) productivity and ϵ_{it} an unobserved shock to output (or equivalently, measurement error).

The first issue in estimating production functions is dealing with unobserved productivity (ω_{it}). We rely on a control function approach, paired with a law of motion, to estimate the output elasticity of our variable input. The control function of (unobserved) productivity term ω_{it} is given by a (non-linear) function of the firm's inputs and a set of instruments z_{it} (explained below), such that $\omega_{it} = h_{st}(v_{it}, k_{it}, z_{it})$. We model the law of motion of productivity as a first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it}. \tag{20}$$

The estimation consists of a two-stage approach. In the first stage, the unanticipated shocks to output are removed by projecting output on the inputs:

$$y_{it} = \phi_t(v_{it}, k_{it}, z_{it}) + \epsilon_{it}, \tag{21}$$

where $\phi_t = \theta_s^V v_{it} + \theta_s^K k_{it} + h_{st}(v_{it}, k_{it}, z_{it})$. This equation is estimated by OLS, with ϕ_t a polynomial, controlling for unobserved productivity. Productivity can then be written as a function of the production function:

$$\omega_{it} = \hat{\phi}_t - \theta_s^V v_{it} + \theta_s^K k_{it}, \tag{22}$$

In the second stage, ξ_{it} is obtained, by building moments around ξ_{it}, the i.i.d. shock of the law of motion of productivity, which is observed by firms in period t and uncorrelated with past productivity such that

$$E[\xi_{it}|Z] = 0 \tag{23}$$

In line with the timing assumptions, our baseline specification specifies the instrument set Z with current investment (because determined one period ahead) and lagged labor. The underlying idea is that last period's input decisions should be highly correlated, but independent of this period's input decisions. This approach identifies the output elasticity of a variable input under the assumption that the variable input use responds to productivity shocks, but that the lagged values do not, and more importantly, that lagged variable input use is correlated with current variable input use, and this is guaranteed through the persistence in productivity.

In our second specification, we allow for common ownership (incentives) to affect future productivity. For example, if a higher degree of common ownership makes firms more capital intensive, then the estimate of capital would be upwards biased (too much output variation is attributed to a variation in capital). Thus, we include a lagged term of lambda in the law of motion:

$$\omega_{it} = g(\omega_{it-1}, \lambda_{it-1}) + \xi_{it}. \tag{24}$$

Another issue in estimating production functions with Compustat data –and virtually any other dataset– is that output and inputs are not measured in units or quantities, but in monetary terms. Given that we are only interested in estimating the output elasticity of the variable input for a given industry and time period, under certain modeling restrictions we can obtain consistent estimates of the production function without relying on separate price and quantity data (see again De Loecker et al., 2019, for a discussion on working with monetary data instead of units). Still, it is good practice to deflate the variables then with the relevant industry-specific deflator, and we thus apply industry-level deflators for our three variables (sales, COGS and PPENT).

We obtain investor variables of all US-incorporated publicly listed companies active at any point during the period 1950-2012. We access the Compustat North America database (through WRDS), and download the annual accounts for all companies. We keep unique records for each firm, and assign a firm to a unique 3 digit NACE industry code, as reported. All investor variables are deflated with the appropriate deflators. We eliminate firms with reported cost-of-goods to sales larger than 5 and industries with less than 3 companies.