Blockholder Heterogeneity, Multiple Blocks, and the Dance Between Blockholders*

Charles J. Hadlock
Michigan State University
hadlockc@broad.msu.edu

Miriam Schwartz-Ziv
Michigan State University
schwartzziv@broad.msu.edu

This Draft: October 18, 2018

*We thank Damien Brooks for superb research assistance and Nicole Boyson, David Denis, Alex Edmans, Radha Gopalan, Doron Levit, Sebastien Michenaud, Marco Pagano, Lea Stern, Francisco Urzúa I., an anonymous referee, and seminar participants at Illinois, Northeastern, Tennessee, Texas, Washington University in St. Louis, the 2015 Drexel Conference on Corporate Governance, the 2016 International Risk Management Conference, the 2017 Midwest Finance Association meetings, the 2017 European Finance Association Meetings, and the 2017 FMA meetings for helpful comments. Schwartz-Ziv thanks Harvard University for data access as a visiting scholar and Hadlock acknowledges the research support of the University of Chicago as a visiting faculty member. All errors remain our own.

Blockholder Heterogeneity, Multiple Blocks, and the Dance Between Blockholders

ABSTRACT

We study blockholder presence in a large panel and document substantial heterogeneity in holding periods, position sizes, and positions taken across blockholder types. Nonfinancial blocks are more likely to be observed in smaller, riskier, younger, and less liquid firms. These patterns are either not evident, or are reversed, for financial blocks. For all but small financial blocks, we detect significant negative interdependence in blockholder investment decisions, with the presence of one blockholder crowding out others, behavior that appears causal. Small financial blocks often coexist in the same firm, an outcome that appears driven by correlated investment styles.

1. Introduction

An extensive empirical literature considers the role of blockholders in firm governance. While this research demonstrates that blockholders can influence firm behavior in substantive ways, it is largely silent on the important issue of the decision to establish or maintain a block position. In this paper, we directly consider this issue by providing a detailed empirical description of blockholder presence in U.S. firms in a sample of 113,908 blockholdings (5% ownership or above) distributed over 41,673 Compustat-listed firm-years from 2001 to 2014. Given the omnipresent concern regarding the endogeneity of ownership in studies of the role of block ownership on firms, a basic description of the elements of this underlying endogenous mechanism appears long overdue.

In our analysis, we follow the recommendations of Edmans and Holderness (2017) and consider issues related to blockholder heterogeneity and coexistence. In particular, we first examine the factors that predict blockholder presence for *different types* of blockholders. We interpret this evidence in light of existing theories of blockholder motivations, thus offering insights into the varying motivations and roles of the different flavors of blockholders that appear in public corporations. After establishing this initial picture of blockholder presence, we directly examine the relation *between different* blockholders' investment decisions. This evidence allows us to provide evidence on potential blockholder interactions, a theme that is emphasized in many recent discussions of multiple blocks coexisting at the same firm.

The data indicate that blockholders are a heterogeneous group, with systematic variation across blockholder types in holding periods, position sizes, number of positions taken, and types of firms selected for a position. A useful dichotomy is to compare nonfinancial blockholders (e.g., individuals, corporations, strategic investors) with generic financial blockholders (e.g., mutual funds). Both of these groups are quite common (frequencies of 58.9% and 73.6%

respectively). Comparing the two, nonfinancial blockholders tend to have larger and longer-lived block positions, and they are much less likely to invest in a large number of firms. When we model the factors that predict blockholder presence, we find that nonfinancial blocks are more likely to be observed in smaller, riskier, younger, and less liquid firms. These patterns are either not evident, or are opposite to what we observe, for financial blocks.

Holding constant these identified factors associated with blockolder presence, we focus our attention on the interdependence of blockholder investment decisions. This allows us to test theories that emphasize potential blockholder interactions that may lead to negative or positive externalities within a blockholder group and any consequent effect on blockholder coalition formation (e.g., Zwiebel (1995), Edmans and Manso (2011)). Given that many authors have reported that the median public U.S. firm has multiple blockholders, this would appear to be a particularly important issue to investigate. While prior empirical evidence suggests that the structure of a firm's set of blockholders may affect firm outcomes, little evidence exists regarding what situations give rise to multiple block formations in the first place.

When we investigate this issue in the context of models predicting blockholder presence, we detect compelling evidence of negative blockholder interdependence in the case of large (10% or greater) block positions of any type, and of nonfinancial blocks regardless of position size. Thus, except for small financial blocks, the data appears consistent with models of Zwiebel (1995) and others that predict a negative influence of the presence of an incumbent blockholder on the decision of others to establish or maintain a block position in a firm. The estimated magnitude of this relation is quite strong, with the presence of a blockholder in some cases decreasing the likelihood of observing another blockholder by a factor of more than one third. This evidence on negative interdependence, which we regard as our most important finding, is compelling, as any inadequately controlled for positive correlation in investing styles will tend to bias us against detecting this behavior. However, to further consider causality issues, we examine cases in which an individual blockholder departs from the firm for likely exogenous reasons associated with death, illness, or advanced age. We find that after these exit events, firms experience abnormally high net blockholder entry, consistent with a causal negative blockholder interdependence relation.

In contrast to nonfinancial blocks, we do detect some evidence of a positive correlation in the appearance of small financial block in firms. This could reflect a causal positive interdependence relation, or it may reflect small financial blockholders' common attractions to similar firms on unobserved dimensions. To investigate, we consider exogenous financial blockholder departures associated with the 2003 mutual fund trading scandal. After these exogenous events, we do not detect any abnormal net changes in the presence of other financial blockholders. This suggests that the positive correlation we observe in the appearance of small financial blocks likely reflects correlated investment styles rather than a causal relation.

Summarizing, our evidence suggests substantial heterogeneity in blockholder motivations for establishing positions. Many of the investment patterns we detect can be interpreted as consistent with a governance role primarily through monitoring/voice by nonfinancial blocks, and through trading/exit for financial blocks, although this interpretation is admittedly speculative. Holding constant factors that appear to govern blockholder presence viewed in isolation, we detect compelling evidence that blockholders do condition their participation decisions on the presence or absence of other blocks at a firm. In general, the presence of one blockholder appears to inhibit others from establishing block positions at the same firm. This negative interdependence is more pronounced for larger blocks and nonfinancial blocks, and collectively our evidence suggests that the negative relation is causal.

In addition to our main findings, we fill in some important empirical details regarding blockholder behavior. In particular, we document a substantive secular trend towards more blockholdings and more cases of multiple blockholders at the same firm. These trends reflect a sharp increase over time in the presence of financial and strategic investor blocks, a pattern that is only slightly offset by a moderate decline in other blocks. We detect substantial differences in the median size of block positions, with a high of 13.0% for corporate blockholders and a low of 7.1% for generic financial blockholders. We also report that blockholder positions are moderately durable, with implied expected durations of 4.29 years for nonfinancial blocks, 3.29 years for financial blocks, and richer variation when considered at a less aggregated level.

The rest of the paper is organized as follows. In section 2, we review the literature and motivate our empirical strategy, while in section 3 we describe the sample. In section 4, we consider the initial issue of factors associated with blockholder presence viewed in isolation. In section 5, we directly examine the interrelated nature of blockholder participation decisions. Section 6 concludes.

2. Blockholder Activity and Presence

2.1 Blockholders and Governance

A long literature surveyed by Holderness (2003), Edmans (2014), and Edmans Holderness (2017) considers the potential role of blockholders in firm governance. One commonly hypothesized benefit of outside blockholders is their potential to monitor managers and curb agency problems (e.g., Shleifer and Vishny (1986), Winton (1993)). For inside blocks, a significant ownership position may generate strong incentives to maximize firm value, a form of self-monitoring (e.g., Morck, Shleifer, and Vishny (1988)). As emphasized by Edmans

(2009), for these forms of monitoring/voice to be effective, the blockholder must have sufficient incentives to push the firm in a desired direction, rather than choosing to simply exit.

Blockholder monitoring will also entail costs, both private and social. These include direct monitoring costs, risk-bearing costs associated with holding a large stake, and deadweight costs incurred in raising funds for a block position. In addition, theorists have identified indirect costs including diluted managerial incentives from over-monitoring (e.g., Burkart, Gromb, and Panunzi (1997), Pagano and Röel (1998)) and potential blockholder opportunistic behavior (e.g., Bennedsen and Wolfenzon (2000)).

As emphasized by Edmans (2009) and others, blockholders can also play a role in firm governance via their trading decisions. In particular, if a blockholder recognizes that a firm is following a non-value maximizing strategy, this may motivate the blockholder to exit the firm before the negative information is fully impounded into the stock price. Edmans (2009) and Admati and Pfleiderer (2009) demonstrate that this exit threat can, in turn, serve a powerful governance role by providing ex-ante incentives for a manager to pursue a value-maximizing strategy (see Dasgupta and Piacentino (2015) for some caveats).

2.2 Blockholder Presence

We would expect potential blockholders to establish or maintain positions in firms when the private benefits of such a position, such as those described above, exceed the costs. Thus, empirical models predicting blockholder presence should provide insights regarding the circumstances that lead to the existence of these private net benefits. While some evidence on blockholder presence is reported by Dlugosz, Fahlenbrach, Gompers, and Metrick (2006) and

Holderness (2009) using samples from the 1990s, a comprehensive analysis of this type is absent from the literature.[1]

In our initial models, we include a laundry list of variables that have been suggested by the prior literature. These models can be viewed purely as empirical descriptions establishing an initial baseline of the factors that predict blockholder presence. However, if one is willing to make assumptions regarding what the empirical variables are likely capturing, it is possible to make some indirect inferences regarding blockholder motivations. For example, if some blockholders are more frequently observed in firms with characteristics that suggest high net benefits to monitoring, this would suggest that blockholders tend to play a monitoring role and privately capture some of the benefits created by their monitoring activity. Given this perspective, we do not hypothesize in advance what different theories may imply regarding factors that may predict blockholder presence. Instead, we briefly and less formally discuss possible interpretations of the evidence after the empirical factors that predict blockholder presence are identified.

2.3 Blockholder Interdependence

Several authors have noted that firms often have multiple blockholders (e.g., Holderness (2009)), and several studies demonstrate that multiple blocks are associated with certain firm outcomes.[2] However, none of these studies examine the circumstances that give rise to the multiple block structure. Many theories posit that the marginal benefit of establishing a block position will depend on the presence of other blockholders. In particular, monitoring-based

---

[1] See Zhu (2015) and Volkova (2018) for an expansion of this earlier evidence to larger and more recent samples.

[2] For studies of this type that use foreign data, see Faccio and Lang (2002), Maury and Pajuste (2005), Laeven and Levine (2007), Attig, Guedhami, and Mishra (2008), and Cai, Hillier, and Wang (2015). For more recent studies using U.S. data, see Konijn, Kräussl, and Lucas (2011), Volkova (2018), and Crane, Koch, and Michenaud (2018).

theories emphasize the inefficiency of multiple blocks at the same firm arising from free-rider problems (e.g., Winton (1993)). In a complementary vein, Zwiebel (1995) illustrates that multiple block structures may inefficiently allocate the private benefits of control. These theories predict a negative relationship between different potential blockholders' decisions to establish or maintain a position in a firm, an outcome we refer to as negative interdependence.

In contrast to these earlier models, Edmans and Manso (2011) demonstrate a benefit to the multiple block structure via enhanced managerial incentives when blockholders compete to collect and trade on information. Along different lines, Dhillon and Rosetto (2015) posit that blockholders may monitor each other, thus leading to net efficiency gains. Models by Bloch and Hege (2003), Gomes and Novaes (2006), and Song (2017) also highlight the potentially beneficial role of the multiple blockholder structure. These theories suggest that positive blockholder interdependence may arise as an optimizing structure in some firms.[3]

We know little empirically about blockholder interdependence. The one notable exception is univariate evidence reported by Zwiebel (1995) indicating negative interdependence in a small U.S. sample in 1981 (see also Laporta, Lopez-de-Silanes, and Shleifer (1999) for international evidence). A principal goal of our study is to comprehensively study these interdependence relations in a large modern sample.

2.4 Empirical Strategy

As discussed above, we first estimate models predicting blockholder presence as a function of firm characteristics identified from the prior literature. We then turn to the main

[3] The cited theories assume that blockholders act independently. It is possible that blockholders coordinate their actions so that they effectively function as a single block, which also could lead to positive interdependence. For some evidence on coordination, see Matvos and Ostrovsky (2010) and Crane, Koch, and Michenaud (2018).

issue of blockholder interdependence by augmenting our models to include variables related to the presence of other blockholders at the firm. This allows us to assess whether the likelihood of a blockholder appearing at a firm is higher or lower than would otherwise be expected given the firm's characteristics. A positive (negative) coefficient is taken as an indication of positive (negative) blockholder interdependence.

There are some subtleties in conducting these interdependence tests, as it is unclear how to incorporate elements of a firm's blockholder portfolio into both the dependent and independent variables. As we detail later, we overcome this challenge by using a randomization device to exogenously assign blockholder-year-firm matches into mutually exclusive groups. We use these groupings to code the key dependent and independent variables related to certain blocks. This approach provides a simple way to estimate the relation between blockholders' participation decisions while conditioning on a full set of controls.

In our preliminary analysis of blockholder presence as a function of firm characteristics, we seek largely to understand the correlation structure in the data, so concerns about the direction of causality are not of primary concern. However, when we consider the relation between different blockholder investment decisions, the usual causality concerns arise, as (endogenously selected) blockholder presence is incorporated into the explanatory variables. To address this issue, we (a) identify cases in which the resulting bias would only tend to weaken the reported results, and (b) exploit cases in which we can identify exogenous variation in the blockholder explanatory variable arising from deaths/health/age (for nonfinancial individual blockholders) or a mutual fund scandal (for financial blockholders).[4]

[4] Prior studies that exploit exogenous changes in the blockholder environment include studies of blockholder deaths (Slovin and Sushka (1993)), market liquidity shocks (Bharath, Jayaraman, and Nagar (2013)), and index membership changes (Appel, Gormley, and Keim (2016)). See also Becker, Cronqvist, and Fahlenbrach (2011) for a study that exploits exogenous geographic variation.

Prior empirical research documents that firms have many distinct types of blockholders (Cronqvist and Fahlenbrach (2009), Dou, Hope, Thomas, and Zou (2018)). Characterizing this heterogeneity is challenging, as the data can be categorized at varying levels of granularity. As more distinct categories are considered, the number of findings to interpret grows exponentially. To keep our analysis parsimonious, as we detail below, we focus largely on two broad groupings. Since information is necessarily lost in the aggregation process, we also report some findings using finer blockholder groupings.

3. Sample Construction and Description

3.1 Sample Selection

We collect ownership data from Factset, a data source that reports all 5% ownership positions revealed in public filings. The ownership data files are fairly comprehensive starting in 2001, and thus our sample period is from 2001 to 2014. We construct an annual snapshot of each firm's ownership structure as of June 30th. This assures that proxy statement information for firms with December fiscal year endings will have been incorporated into the subsequent June ownership listing. We match the Factset data with Compustat/CRSP by using common identifiers, followed by hand checking of ambiguous cases. We match all Compustat records for the most recent fiscal year ending that falls on or before June 30th with the associated June 30th ownership snapshot. The final sample includes 41,833 firm-years of data.

As we report in Table 1, the book assets of sample firms are similar to what others have reported for broad Compustat-based samples. The sample is tilted towards larger than average Compustat firms, but less so than samples restricted to Execucomp/S&P 1500 firms. The vast majority of sample firms are in the Russell 3000 index list (over 90%). We have fewer firms as the sample moves back in time, as our success rate in matching identifiers declines monotonically. However, there do not appear to be any systematic patterns to this decreasing success rate. Thus, one can think of our panel as including almost all of the larger public U.S. firms, less a random set of non-survivors that is largest near the start of the sample period.

3.2 Categorizing Blockholders

After assembling the sample, we consolidate together related positions that are listed separately, for example, individuals with the same last name or institutions that are both parts of the same parent entity. All positions below 5% are dropped from the sample, as this is the minimum threshold that is uniformly reported for all blockholder types. As we report in Table 1, the resulting sample has 113,941 blockholder-years of data.

We assign blockholders to mutually exclusive categories using Factset labels, algorithms, and hand coding. We assign 48% of blockholders to a category entirely via algorithms or Factset labels, with the remaining 52% assigned manually using news/directory/web searches 13-D and 13-G filings, proxy statements, etc. We initially group together blockholders that are likely to have similar economic motivations, monitoring skills, and investment strategies, resulting in a final set of six broad categories plus an "other" category. A finer categorization is possible, but this results in an unwieldy number of block types. In the appendix, we provide a detailed overview of our blockholder categorization procedure.

We identify two types of individual blockholders, referred to as affiliated and unaffiliated. The affiliated category includes blockholders who are likely to have a close attachment to the firm. We assign a block to this category if the last name matches that of any individual listed in the top four executives/directors of the firm at any point between 1990 and the observation year using the Compustat executive name file (see Fee, Hadlock, and Pierce

(2013)). All other individuals are assigned to the unaffiliated individual group. As we report in Table 1, 11.6% and 6.4% of all blockholdings are assigned to these two groups, respectively.

The third category, public company blockholders, is a small (2.2% of all blocks) but potentially interesting group. Prior research suggests that these blocks are often formed as part of a product market relationship (Allen and Phillips (2000), Fee, Hadlock, and Thomas (2006)). We place in a fourth category private company blockholders (1.4% of the sample), where we attempt to include in this private company group only actual private operating companies, rather than financial entities or investment vehicles.

A large number of blockholders are described as private equity and/or hedge funds. We assign all of these blockholders to a category we refer to as strategic investors. While this group will include a variety of investors with differing styles, it will generally include pools of strategic equity capital that are intermediated in nature, but potentially more involved in monitoring and governance than traditional financial institutions (see Edmans and Holderness (2017)). This category represents 12.7% of the sample of all blockholder-year observations.

The final category is composed of generic financial institutions. This is by far the largest group and is mostly composed of relatively passive (with respect to direct monitoring/voice) financial entities. The vast majority of these investors (over 97%) are 13F filers and represent owners that have been widely studied in the institutional investor literature.

Over 97.5% of all blocks can be placed in one of these mutually exclusive six categories. We place the remaining blocks in the "other" category. These blocks include non-profit/government entities, public pension funds, firms' pension funds, and ESOPs.

Much of the prior literature on institutional investors suggests that our generic financial institution block group largely participates in firm governance indirectly through their trading activity. The other categories certainly have the potential to monitor directly through voice, although the exact extent of these activities for each group individually, and all groups pooled together, is difficult to ascertain. In what follows, we will usually group all of the blocks except the generic financials into a single "nonfinancial" category, with the expectation that monitoring/voice is likely to be much more prevalent in this nonfinancial group. Clifford and Lindsey (2016) report findings consistent with this expectation.

3.3 Description of Blockholder Prevalence, Positions, and Heterogeneity

Consistent with prior studies, the first column of Table 1 indicates that the vast majority of firms (91.9%) have at least one blockholder, and the majority (74.0%) have more than one. The statistics in columns 2 and 3 for the first and last sample years reveal that the likelihood that a firm has at least one block, and the likelihood of observing multiple blocks, both have increased over time. The multiple block trend is prominent, with an increase in frequency of almost 20% (from 61.6% to 81.2%), and an upward shift in the median from 2 blocks to 3. The tabulated figures also reveal a sharp increase in the presence of strategic and financial blocks over time, a trend that is partially offset by moderate declines in the presence of other blocks. Table 1 also reveals that the majority of firms have at least one financial block (73.7%), and a majority also have at least one nonfinancial block (59.0%). Given that both types of blockholders appear widely prevalent, understanding the behavior of both distinct groups is clearly necessary for evaluating the potential role of blockholders in firm governance.

The final rows of Table 1 indicate that financial blocks are generally the smallest. Pooling all other categories together into a single nonfinancial group, the difference between the nonfinancials' median position size pooled across all years (9.0%) and the financial group's median (7.1%) is substantial (mean differences are larger, 13.5% vs. 8.4%). Figures below (see Table 5) derived from models of block exits imply an average block duration of 4.29 years for the nonfinancial group and 3.29 for the financial group. In untabulated figures, we find that nonfinancial blockholders generally have many fewer block positions in a given year compared to financials (mean of 1.39 versus 11.75). Thus, it appears that a simple sorting of firms into nonfinancial and financial blocks yields quite distinct groups.

4. Factors Associated with Blockholdings

We estimate logit models predicting blockholder presence as a function of a large set of explanatory variables. These controls are primarily selected from the inside ownership models of Himmelberg, Hubbard, and Palia (1999) and Helwege, Pirinky, and Stulz (2007). Following the recommendations of Edmans and Holderness (2017), we also include firm age. All models include year and 2-digit industry dummies. Given the importance of indexes in many investment decisions (Appel, Gormley, and Keim (2016) and Crane, Michenaud, and Weston (2016)), we also include a set of index membership dummy variables. All continuous variables except firm size are standardized by the sample standard deviation. Variable definitions are detailed in the appendix.

We create dependent variables that assume a value of 1 when a firm has at least one blockholder of a specified type in a given year and 0 otherwise. To aid in interpreting the model estimates, we report estimated marginal effects derived from the underlying logit model estimates (i.e., the marginal change in the implied probability of observing a blockholder per unit change in the explanatory variable), holding all other variables at their sample means.[5] In all cases, these estimated marginal effects agree with the underlying logit coefficients in sign and

[5] Marginal effects are estimated using the "margins" command in Stata 13. Marginal effects in Table 2 are calculated for an infinitesimal change in the explanatory variable. In later tables, when the key explanatory variable indicates blockholder presence, marginal effects are calculated for a discrete unit change in this indicator.

significance level. Moreover, they are usually quite similar to the corresponding estimates from linear probability models (i.e., OLS regressions) predicting blockholder presence. Standard errors are clustered at the firm level.

The first two columns of Table 2 report estimates from a baseline model predicting nonfinancial and financial blockholder presence respectively. In this table, we order our presentation of coefficient estimates by first listing estimates for variables that are significant in predicting nonfinancial block presence, followed by any additional variables that are significant in predicting financial blocks, followed by all other variables. The estimates in column 1 reveal six firm characteristics that are significantly related to the presence of nonfinancial blocks. In particular, these estimates indicate that a firm is more likely to have a nonfinancial block if it is smaller, younger, riskier (measured by return volatility), has a less liquid stock, a lower Tobin's Q value, or higher leverage.

While these models are intended to serve as a baseline for our later analysis, the reported relations are of some independent interest. In particular, Demsetz and Lehn (1985) hypothesize that the benefits of monitoring are likely to be elevated in high-risk environments and might, in fact, more than counteract any increase in risk-bearing costs. If nonfinancial blockholders typically assume a monitoring role and are privately able to capture some the associated net benefits, our finding of a positive relation between risk and nonfinancial blocks is consistent with the Demsetz and Lehn (1985) hypothesis.

The negative role for liquidity in predicting nonfinancial block presence, complemented by the relatively small size and youth of firms with these blockholders, is also interesting, since many authors have suggested that rapid blockholder exit will be limited in these environments. This, in turn, could enhance incentives to monitor (see Bhide (1993)). Thus, this evidence, while not conclusive, appears generally consistent with a monitoring role for nonfinancial blockholders that has enhanced private and social value in setting with a high cost of blockholder exit.[6]

Turning to the column 2 estimates for financial blocks, the coefficient on only one of the six aforementioned variables, Tobin's Q, has the same sign and significance as in the nonfinancial block model.[7] The significant negative role for risk and positive role for liquidity in financial block formation are particularly interesting, as they contrast sharply with the nonfinancial blocks. If financial blockholders do not directly monitor firms to apply their voice, the negative role of risk could indicate elevated risk-bearing costs being borne by financial blockholders in high-risk firms with no commensurate offsetting benefits. The negative role for liquidity is consistent with financial blockholders being particularly concerned with entry and exit costs when entering into larger positions, which in turn could have a substantive effect on the value of any governance through trading roles that these blockholders provide.[8]

Information may be lost in aggregating groups together into the nonfinancial category. Thus, for completeness, we predict in columns 3-7 of Table 2 the presence of each of the five different types of blockholders that compose the nonfinancial group (excluding "other"). While there are too many coefficient estimates to discuss each in detail, they are generally consistent with what we find for the group as a whole. In particular, there are only two cases out of 30 (5 models x 6 variables) in which the coefficient estimate on a variable that is significant in the

---

[6] The formal theory underlying this prediction is subtle. See Bolton and von Thadden (1998), Kahn and Winton, (1998), and Maug (1998). A lack of liquidity will increase the return to monitoring, as exiting is less feasible, but it may also affect the ex-ante returns to establishing a block, and this relation can be of ambiguous sign.

[7] The most plausible interpretation of the negative and significant coefficient on Tobin's Q for both nonfinancial and financial blocks is unclear. To the extent that high Q proxies for a lack of managerial agency problems, the negative coefficients are consistent with a low net marginal governance benefit to blockholder presence through both monitoring/voice or trading. However, this interpretation is admittedly somewhat speculative.

[8] Again, the underlying theory behind liquidity effects is subtle and in some cases ambiguous. See Heflin and Shaw (2000), Rubin (2007), and Edmans, Fang, and Zur (2013) for prior studies of liquidity and ownership.

column 1 nonfinancial model is significant and of opposite sign in these alternative models. One of these, the positive coefficient on firm size for public firm blocks, is consistent with these investors having relatively deep pockets, allowing them to take higher dollar value positions than others. The other, the positive coefficient on liquidity for strategic investor blocks, is consistent with the shorter holding periods of these investors leading to a preference for liquidity in order to enter and exit at low cost.[9]

In summary, our evidence indicates that there are some significant differences in the factors that predict nonfinancial versus financial blockholder presence. Nonfinancial blocks are more likely to be present at smaller, younger, riskier, less liquid and more highly levered firms. These patterns are either not evident for financial firms, or, in the case of risk and liquidity, are opposite in sign. However, both types of blockholders are less likely to be present in high Q firms. There are, not surprisingly, some substantive nuances to these findings when the data is parsed at a finer level.[10] While there are multiple possible explanations for our findings, the collective evidence appears broadly consistent with the hypothesis that nonfinancial blockholders tend to establish or maintain positions in firms in which there are net benefits to direct blockholder monitoring and voice, while financial blockholders are more likely to appear in firms in which there is more scope to participate in governance through trading.

5. Blockholder Interactions and Multiple Blocks

5.1 Blockholder Interdependence

---

[9] The expected holding period of strategic investors is 2.65 years, versus 6.28 for other nonfinancials. Related hedge-fund evidence is reported by Edmans, Fang, and Zur (2013) and Norli, Ostergaard, and Schindele (2015).

[10] We have estimated models of position size as a function of the Table 2 explanatory variables and find little agreement in the factors that predict position presence versus position size, conditional on block presence.

We now turn to the main issue of examining the interdependence of potential blockholder participation decisions. Modeling interdependence for different block types is straightforward, as we can predict whether a firm has, for example, a financial blockholder, as a function of a nonfinancial blockholder indicator variable. For blockholders in the same group, the analysis is less straightforward, since it is not immediately apparent how to include information on the same type of blocks into *both sides* of the regression equation.

Zwiebel (1995) addresses this issue by using the fact that if blocks tend to repel (attract) others of the same type, there should be an abnormally high number of outcomes in which a firm has one or few (two or many) blocks. Unfortunately, gauging baseline rates for these tests requires an assumption on the relevant probability distribution under the null of no interdependence. Zwiebel (1995) assumes that all blockholders are equally likely to appear at any firm. Unfortunately, this assumption will surely be violated in large and diverse samples such as ours. For example, small firms appear more likely to attract blockholders. Ignoring this systematic variation will tend to reveal an inflated rate of clustering together by blockholders, as they will jointly appear at firms that naturally attract blocks, even if the underlying block investment decisions are independent.

To address this possibility, we would like to condition on a full set of covariates that are related to blockholder presence and to then investigate whether the presence of one blockholder is contemporaneously correlated with the presence of others. This conditional correlation can be estimated by assigning blocks to one of the two sides of the regression equation using an assignment procedure that is independent of all model covariates. To do this, we randomly assign each blockholder-firm-year observation into one of two equally likely groups (referred to as the A and B groups). We then categorize the dependent variable (independent variables) regarding block presence using information only from blocks that are randomly assigned to the A group (B group). This allows us to treat similar blocks as if they are different in an exogenous manner, thus permitting an estimation of whether blocks tend to display positive or negative correlation in their appearances, conditional on a full set of controls.[11]

If we neglect to include an adequate set of controls, it may appear that blocks cluster together because they are attracted to one another, when in fact this reflects their common propensity to appear at firms with certain (omitted from the model) characteristics. Clearly, we cannot control for all possibly relevant firm characteristics, as some are unobserved. This suggests that our estimates will, if anything, be biased towards finding a positive relation between the dependent variable (A block presence) and key independent variable (B block presence). Given this directional bias, we believe any evidence of significant negative interdependence should be viewed as particularly compelling.

We first consider a model in which the dependent (key independent) variable assumes a value of 1 if the firm has an A (B) blockholder of any type in the observation year. Coefficient estimates on the included full set of controls are not tabulated. As we report in the first row and column of Table 3, the estimated (discrete) marginal effect on the blockholder presence variable is negative and significant, indicating a 2.2% decrease in the likelihood of observing an A blockholder when a B blockholder is present at the firm. Thus, similar to Zwiebel (1995), when all blocks are grouped together, the data indicate a small negative interdependence relation.

When we add the size of the largest B block position to the model, as in column 2 of Table 3, the coefficient is negative and highly significant, suggesting that larger block positions tend to strongly repel others. The (continuous) marginal effect estimate indicates that a firm with a B blockholder holding a position that is 10% larger than the mean is 7.8% less likely to have an

[11] There are other ways to estimate whether the conditional likelihood of blockholder presence is related to the presence of other blockholders, but our approach imposes fewer parametric restrictions than most others.

A blockholder compared to a similar firm with a mean position-size B blockholder (-.782 x .10 = -.0782). Relative to the sample likelihood of A blockholder presence of 73.2%, this 7.8% reduction is substantial.[12]

Turning next to the two blockholder groups modeled separately, the estimates for models 3 and 4 of Panel A of Table 3 indicate a significant negative relation in nonfinancial block participation decisions. The likelihood of observing a nonfinancial A block decreases by 3.5% when a B-group nonfinancial blockholder is present, a substantial marginal effect when measured relative to a 38.4% average likelihood. In contrast, the corresponding estimates for financial blocks in columns 5 and 6 indicate a strong positive relation, suggesting that small financial blocks are attracted to one another, or to common unobserved factors.

To more closely examine the interdependence of large blockholders, we consider in Panel B models that use a higher 10% ownership threshold (rather than 5%) to classify blockholders. As expected, the evidence here for negative interdependence is stronger. For all blocks grouped together, the highly significant estimate in column 1 implies that the presence of a large B block is associated with a 9.7% lower likelihood of observing a large A block. This figure equals almost one-third of the overall sample likelihood of large A block presence of 32.2%. The other columns of Panel B indicate a negative relation for both nonfinancial and financial blockholders considered separately, but the relation is much larger and more significant for the nonfinancial blocks.

In Panel C, we conduct the same analysis using 15% blocks. In this case, we find evidence of significant blockholder repulsion for all blocks (columns 1 and 2) and for the

[12] Marginal effects for the discrete blockholder presence explanatory variables are calculated for a discrete unit change. For continuous variables, such as ownership percentage, the marginal effects are technically estimated for an infinitesimal continuous change, so the indicated 7.8% change when ownership changes 10% is only an approximation. To facilitate comparisons, the ownership percentage variable is demeaned in all models and set equal to 0 if the blockholder explanatory variable assumes a value of 0.

nonfinancial blocks (columns 3 and 4). For financial blocks, the estimated relation appears basically flat (columns 5 and 6), which is unsurprising given the rarity of financial blocks of this size. The magnitudes of some of these estimates are quite large. For example, the presence of one large 15% B blockholder is associated with a 6.2% decrease in the likelihood of observing a large A blockholder, a figure that is more than 40% of the sample average frequency.

Collecting this evidence, the case for blockholder interactions in which the presence of one blockholder inhibits the presence of others appears strongest when we consider larger (above 10%) blocks of any type and nonfinancial blocks of any size. Thus, it appears that theories of negative blockholder interdependence, for example Zwiebel (1995), are supported by the data when it comes to the behavior of all blocks except small financial blocks. This evidence is particularly convincing given the natural bias against detecting this result in the presence of positively correlated investment styles related to unobservable firm characteristics.

5.2 Robustness of Initial Findings on Blockholder Interdependence

We have experimented with dropping all of the control variables (except year and industry). Not surprisingly, with this alteration, the coefficients on the blockholder presence explanatory variable in almost all cases move in the positive direction, indicating that omitted factors that are incorporated into the error term are almost surely positively correlated with the blockholder presence variable, a correlation that will bias the coefficient estimate upwards (i.e., in the positive direction). Our aim is to include enough controls that the residual correlation is negligible. However, to the extent that we are unsuccessful, we will understate (overstate) the case for negative (positive) blockholder interdependence.

One may be concerned that we over-control for firm-characteristics in the Table 3 models, as there may be some feedback from block presence to firm characteristics. To account for this possibility, we have experimented with including only the firm size variable in the odd column Table 3 models, along with year and industry dummies. Our findings change only slightly with this conservative alteration, with the two least significant negative coefficients from odd numbered columns of Table 3 becoming insignificant. However, the general character of the results remains the same, with strong evidence of negative blockholder interdependence for all large (> 10%) blocks and all nonfinancial blocks.

We have also experimented with altering the odd column Table 3 models by (a) excluding all firms with dual-class shares,[13] (b) eliminating all cases in which a blockholder holds more than 70% of the firm's shares, and (c) disregarding all blocks held by blockholders that have 100 or more block positions in different firms in a given year.[14] The results with these alterations have little effect on the coefficients reported in Table 3, although in some cases the two least significant negative coefficients in the table become insignificant.

Finally, we have experimented with dividing the sample in half by whether size, idiosyncratic risk, Q, or liquidity are above or below the sample median, and also by the observation year (2007 or earlier, 2008 or later). While there are some small differences across models, none of these are strong. In particular, in almost all cases the coefficients agree in sign with what is reported in Table 3, and there is no sample split in which the coefficient on the blockholder presence explanatory variable is significant and of opposite sign across the two subsamples. Moreover, for the large (> 10%) all blocks and nonfinancial blocks models, the estimate on the blockholder presence explanatory variable remains negative and significant for all resulting subsamples.

---

[13] A firm is classified as dual class if: (a) the firm is listed as dual class in the GMI/IRRC database, (b) there are two listings for the firm on CRSP, or (c) the difference in shares outstanding on Compustat (which aggregates across classes) and CRSP (which does not aggregate) is more than 1% for both the current and prior fiscal year.

[14] Edmans, Levit, and Reilly (2018) model the unique incentives of blockholders with a large number of positions.

5.3 Relation between Different Blockholder Types

While the preceding analysis considers the relation between blockholders of the same group, it may also be informative to consider the relation between different groups. To investigate, in column 1 (column 2) of Table 4 we report coefficients from models predicting the presence of a nonfinancial (financial) block as a function of the presence of a financial (nonfinancial) block. We estimate separate models for blocks in the three different block size groups (>5%, >10%, >15%) and report only the estimated marginal effects for one group on the other. As the figures indicate, these two distinct blockholder groups display strong negative correlation in their investment decisions, with significant negative coefficients in all cases.

To further explore, we report in columns 3-7 estimates from models predicting the presence of each specific type of nonfinancial blockholder as a function of whether there is at least one blockholder not of that type at the firm. As the figures indicate, all of the 15 coefficients are negative, and almost all are statistically significant. Clearly, the evidence seems quite compelling that blockholders tend to avoid firms with a different type of blockholder on board. In many cases, the estimated relation is quite large relative to the baseline rates.

We have also considered models in which we predict blockholder presence for each type as a function of separate indicators for each of the other block types. The resulting estimates are relegated to the appendix, as the full set is quite unwieldy. The pattern that emerges from this analysis is that blockholder presence is generally negatively related to the likelihood of observing blocks of other types, and sometimes one's own type, with stronger evidence of same-type negative correlation in the case of larger block positions. However, for a few type pairs, there is evidence of positive interdependence, most notably a positive relation between strategic investor and financial blocks. These models also reveal a particularly strong negative relation between affiliated individuals and all non-individual blockholders.

5.4 Blockholder Dynamics

The preceding findings could arise from interdependence in blockholder exit decisions, entry decisions, or some combination thereof. To investigate, we explore these dynamics. For exits, we predict a block dissolution at the blockholder-year level as a function of the contemporaneous presence of other blockholders.[15] Entry is modeled at the firm-year level with a dependent variable that assumes a value of 1 if the firm obtains at least one new blockholder during a year as a function of whether there is already a block at the firm. All models include the full set of start-of-year controls, plus the firm's most recent annual market-adjusted return.

We present the resulting estimates for exit (entry) in the odd (even) numbered columns of Table 5. For all blocks, the positive and highly significant estimate of .050 in column 1 indicates that the presence of at least one other blockholder is associated with an increased annual exit probability of 5.0%. The annual block exit rate is 27.8%, so this increase is large in a relative sense and suggests negative blockholder interdependence. (i.e., multiple block coexistence is an uneasy alliance).[16] However, the column 2 entry model indicates that the presence of a blockholder is also a significant positive predictor of blockholder entry, with an implied 7.2% increase in entry rate, a substantial figure relative to a baseline entry rate of 52.0%. Thus, viewing all blocks together, existing blockholders are associated with both increased exit but also

[15] Our earlier evidence may reflect a block's presence decreasing shares available for purchase, thus crowding out other potential blockholders. Exit behavior should not be affected by this possibility, as the blocks are already established. Thus, the exit analysis may allow a more direct examination of the relative ease of co-existence.

[16] The reciprocal of the exit rate can be taken as an estimate of block duration assuming a negative binomial distribution. We report these implied durations in Table 5.

more entry. This suggests that the small overall sample-wide negative interdependence relation reflects exit behavior dominating the offsetting entry relation.

Turning to nonfinancial blocks, the picture is much clearer. The column 3 estimates indicate a large increase in the exit rates of nonfinancial blockholders when others are present, while the column 4 model suggests a very small entry relation in the opposite direction. Thus, for nonfinancial blockholders, it appears that the earlier negative blockholder interdependence relation almost entirely reflects behavior in which nonfinancial blockholder coalitions tend to break down fairly quickly (i.e., strong exit dynamics and close-to-neutral entry dynamics).

Not surprisingly, the picture is quite different for financial blocks. The column 5 estimates indicate that the exit behavior of financial blocks has only a small relation with the presence of others, but the column 6 model indicates a highly elevated probability of financial blockholder entry when others are already present. This suggests that our earlier findings of positive financial blockholder interdependence largely reflects correlated entry behavior of (mostly small) financial blocks.

We have experimented with replacing the blockholder definition in the Table 5 models with a 10% or above ownership threshold. Consistent with our earlier findings of stronger negative interdependence for larger positions, the coefficients on the blockholder presence explanatory variable are substantial in magnitude and highly significant in the exit regressions (odd columns of Table 5, exit is accelerated), while the corresponding coefficients in the entry models become negative and insignificant for all blocks and nonfinancial blocks, and positive but much smaller and less significant for financial blocks (marginal effect drops from .111, as reported in model 6 of Table 5, to .005, p=.044). Thus, the evidence is fairly compelling that the underlying dynamics lead to negative interdependence for large blocks of any type and/or nonfinancial blocks of any size.

5.5 Exogenous Shocks to Nonfinancial Block Ownership

To strengthen a causal interpretation on our negative interdependence findings, it would be useful to identify exogenous variation in nonfinancial blockholder presence to examine whether this variation is related to the presence of other blocks. To do this, we identify cases in which a nonfinancial blockholder departs from a firm for what are likely exogenous reasons. In particular, we consider the disappearance of blocks held by individuals who either die, succumb to cancer within three years of the block dissolution (our proxy for illness), or who were over the age of 75 at the time of block dissolution.[17] Prior studies of CEO departures often use death/health/age as a proxy for exogenous events (e.g., Fee, Hadlock, and Pierce (2013)).

Our search yields a sample of 207 "exogenous" blockholder departures by individuals between time t and t+1. We then ask whether the change in the number of other blockholders (i.e., excluding the exogenous departure) is abnormally high around the time of these shocks to a firm's blockholder structure. The comparison group in this experiment is composed of other firms with an individual blockholder who did not depart between time t and t+1. In the case of candidate comparison firms with multiple individual blocks, one of these blocks is randomly selected to evaluate whether the firm is assigned to the comparison group. We code an exogenous departure variable as a 1 for firms in the exogenous departure group, 0 for firms in the comparison group, and missing for all others (i.e., cases with an endogenous individual blockholder departure or firms with no individual blocks).

[17] Departures due to death or illness are identified from news searches. Age data is collected from news searches and various directories and databases. The age of 75 is chosen as it represents the top sample decile cutoff point. We identify 45/5/157 departures related to death/illness/age respectively.

In Panel A of Table 6, we present OLS regression estimates predicting the change in the number of blockholders at the firm over one-year (t to t+1) and three-year (t to t+3) windows (column 1-2 and 3-4 respectively). We estimate parsimonious models that include only industry and year controls, and comprehensive models with the full set of control variables (odd and even columns respectively). As the figures indicate, in all cases the coefficients are positive and significant, with larger coefficients and significance levels over the longer window, suggesting that it may take some time for other actual and potential blockholders to adjust to the departure. The three-year window estimates suggest that firms with an exogenous departure tend to have a net change in the number of blocks on the order of +.40 compared to the baseline (point estimates of .366 and .396). This suggests the presence of a fairly substantial repelling effect of blockholder presence that is removed upon an exogenous blockholder departure.

In Panel B of Table 6, we present a parallel analysis, but we use a 10% threshold for coding blocks (applied to both the dependent and independent variables). Given our earlier evidence, we expect the estimated effects to be larger in this panel. As we report, this is indeed the case. In all Panel B models, the coefficient on the exogenous departure variable is significant and on the order of +.50 (point estimates of .525 and .536), suggesting that when a large individual blockholder departs exogenously, they are replaced with another large block approximately half of the time.

To check the robustness of the Table 6 findings, we have experimented with (a) excluding industry effects from the models, (b) adding the size of the largest individual block and the number of blockholders to the models, (c) using a 15% threshold for large blocks in place of 10%, and (d) using a two year window to measure net changes in blockholders. In all cases, the results are substantively unchanged to what we report in the table. We have also conducted a placebo analysis by running the same regressions assuming that the exogenous change occurred at time t-3 rather than at time t. The coefficient on the exogenous block departure variable is never positive and significant in this placebo analysis, and in many cases, the point estimate is actually negative. Thus, the evidence seems robust that exogenous blockholder departures invite abnormally high net blockholder entry, consistent with the presence of negative blockholder interdependence.

5.6 Exogenous Shocks to Financial Block Ownership

The findings in the preceding section add to our confidence that the overall negative interdependence relation between larger and/or nonfinancial blockholders is causal. However, the causal interpretation of the earlier positive interdependence relation between small financial blocks remains unclear. It may be that these blocks are attracted to firms because the firm has other blocks of the same type (i.e., the relation is causal), or it may be that these blocks are simply attracted to firms with similar unobserved/unmodeled firm characteristics.

To investigate this issue, we follow Anton and Polk (2014), Koch, Ruenzi, and Starks (2016), and Crane, Koch, and Michenaud (2018) by exploiting an exogenous shock to financial block ownership arising from the 2003 mutual fund scandal in which 25 financial institutions were accused of illegal trading in September of 2003. As Kisin (2011) illustrates, these institutions experienced large fund outflows, which in turn may result in a decrease in their block positions. If these exogenous block departures tended to break up coalitions of financial blocks that were causally attracted to one another, we would expect to observe a resulting net decrease in the presence of other financial blocks soon after the shock.

To validate this strategy, we re-estimate our earlier financial block exit prediction model (i.e., the column 5, Table 5 model), modified both by restricting attention to the (June) 2003 to 2004 window and by adding a dummy variable for whether the block at the start of the observation window was owned by a scandal-associated institution. The resulting coefficient on the scandal dummy is positive and highly significant (untabulated), indicating that blocks owned by scandal-associated funds had exit rates immediately after the scandal that were elevated by approximately 70% relative to the baseline. This indicates that the scandal had a large causal effect on the dissolution of certain block positions.

Turning to whether these departures precipitated a net decrease in the presence of other financial blockholders, as would be expected if there were a causal positive interdependence relation, we consider two slightly different empirical approaches. First, we exploit only cases in which a block owned by a scandal-tainted financial institution did exit. If these departures are purely exogenous, this approach should maximize test power. However, if some of these departures have an endogenous component unrelated to the scandal, coefficient from models based solely on actual departures may be biased. Thus, as an alternative, we also consider models that rely only on whether a firm had a block owned by a scandal firm immediately before the scandal, regardless of whether the block departed. This approach leads effectively to a reduced form version of an IV model in which the scandal serves as an instrument for an exogenous blockholder departure.[18]

In column 1 of Table 7, we report OLS regression coefficient estimates predicting the change in number of financial blockholders at a firm between 2003 and 2004, exclusive of blocks held by scandal-tainted firms. In all Table 7 models we only include firms with at least one non-scandal associated financial block as of 2003 and include the full set of control variables. The small, positive, and insignificant coefficient on the scandal departure variable in column 1 offers no evidence of a net decrease in financial blockholder presence after a firm

[18] The earlier model of departures as a function of scandal ownership can be seen as a first-stage validation of the relevancy condition. A full 2SLS model is not straightforward to implement in the current context.

experiences an exogenous departure. In column 2, we add the number of non-scandal financial blocks at the start of the year as an additional control, but this has no substantive effect on the scandal departure coefficient. Certainly, there is no evidence of a net decrease in financial blockholders via some combination of increased exit or decreased entry when a financial block leaves the firm for suspected exogenous reasons.

In columns 3 and 4 of Table 7, we present findings from parallel models in which the key explanatory variable is whether the firm had a block owned by a scandal-associated institution as of 2003, without adding the requirement that this block disappeared in the subsequent year. Similar to the findings in the earlier columns, the coefficients on the scandal variable are in both cases small and insignificant (negative in column 3, positive in column 4). Taken as a whole, the evidence in Table 7, suggests no abnormal changes in non-scandal financial blockholder presence around an episode in which scandal-associated financial blocks departed at substantially elevated rates for exogenous reasons. This evidence suggests that the positive correlation found between financial blockholder presence documented earlier largely reflects a non-causal relation in which (smaller) financial blocks are attracted to similar types of firms based on unobservable or unmodeled firm characteristics.

6. Summary and Conclusion

In this paper, we explore the factors associated with the appearance of block positions in a large and recent sample of public U.S. firms. We find substantial heterogeneity across blockholder types, with significant variation in holding periods, position sizes, number of positions taken, and firm characteristics associated with block investments. Slightly more than 1/3 of all blocks are owned by blockholder types that are not mutual funds or other generic financial institutions. Compared to generic financial blocks, nonfinancial blocks tend to be larger, more durable, and held by owners with more focused portfolios. Additionally, they are more likely to be observed in smaller, riskier, younger, and less liquid firms. These appearance propensities are either not evident, or are reversed, for financial blocks. Our findings offer varying levels of support for different theories of blockholder motivations. While far from conclusive, the evidence appears to us to be broadly consistent with a governance role for nonfinancial blockholders arising primarily from direct monitoring/voice, and for financial blocks through trading.

After examining these baseline models, we focus our attention on the interdependence of blockholder investment decisions. In particular, we consider whether blockholders tend to avoid collocating in the same firm as suggested by Zwiebel (1995) (negative interdependence), or whether they instead tend to cluster together at firms as suggested by alternative theories (positive interdependence). In the case of larger blocks (above 10%) of any type, or nonfinancial blocks of any size, we find strong evidence consistent with the presence of a negative interdependence relation. This negative relation is often substantial in magnitude, with the presence of one blockholder in some cases being associated with a more than one-third reduction in the likelihood of observing another blockholder at the firm. The evidence is compelling, as the presence of any omitted variables should bias us against detecting these findings. Further strengthening the case for a causality interpretation, we find abnormally high net entry of new blocks after exogenous nonfinancial block departures associated with death, health, or advanced age.

In contrast to nonfinancial blocks, we do detect some evidence of a positive correlation in the appearance of small financial blocks in firms. We are hesitant to interpret this as indicative of causal positive interdependence behavior, as it could reflect an omitted variable bias. When we consider a set of exogenous financial blockholder departures associated with a trading scandal, we do not detect subsequent abnormal changes in the presence of other financial blocks. This casts doubt on a causality explanation for the observed positive correlation in the presence of financial blocks, pointing instead to an explanation based on correlated investment styles related to unobserved/unmodeled firm characteristics.

In addition to offering insights on existing theories, we present a rich empirical picture of blockholder ownership that we hope may stimulate further theoretical and empirical thinking. There are many different types of blockholders within the broad groups we study, and it would be interesting to clarify each of their respective behaviors and governance roles. In addition, there are broad time trends in blockholder ownership and composition that do not appear to follow immediately from existing theories. These and related issues await future research.

References

Admati, Anat R., and Paul Pfleiderer. 2009. "The 'Wall Street Walk' and Shareholder Activism: Exit as a Form of Voice." *The Review of Financial Studies* 22-7: 2645-2685.

Allen, Jeffrey W., Gordon M. Phillips. 2000. "Equity Ownership, Strategic Alliances, and Product Market Relationships." *Journal of Finance* 5-6: 2791-2815.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5-1: 31–56.

Anton, Miguel, and Christopher Polk. 2014. "Connected Stocks." *The Journal of Finance* 69-3: 1099-1127.

Appel, Ian R., Todd A. Gormley, and Donald B. Keim. 2016. "Passive Investors, not Passive Owners." *Journal of Financial Economics* 121-1: 11-141.

Attig, Najah, Omrane Guedhami, and Dev Mishra. 2008. "Multiple Large Shareholders, Control Contests, and Implied Cost of Equity." *Journal of Corporate Finance* 14-5: 721–737.

Balakrishnan, Karthik, Mary Brooke Billings, Bryan Kelly, and Alexander Ljungqvist. 2014. "Shaping Liquidity: On the Causal Effects of Voluntary Disclosure." *Journal of Finance* 69-5: 2237-2278.

Becker, Bo, Henrik Cronqvist, and Rüdiger Fahlenbrach. 2011. "Estimating the Effects of Large Shareholders Using a Geographic Instrument." *Journal of Financial and Quantitative Analysis* 46-4: 907–42

Bennedsen, Morten, and Daniel Wolfenzon. 2000. "The Balance of Power in Closely Held Corporations." *Journal of Financial Economics* 58-1: 113–39.

Bharath, Sreedhar T., Sudarshan Jayaraman, and Venky Nagar. 2013. "Exit as Governance: an Empirical Analysis." *Journal of Finance* 68-3: 2515-2547.

Bhide, Amar. 1993. "The Hidden Cost of Stock Market Liquidity." *Journal of Financial Economics* 34-1: 31-51.

Bloch, Francis, and Ulrich Hege. 2003. "Multiple Shareholders and Control Contests." HEC Paris Working Paper.

Bolton, Patrick, and Ernst-Ludwig von Thadden. 1998. "Blocks, Liquidity, and Corporate Control." *Journal of Finance* 53-1: 1–25.

Burkart, Mike, Denis Gromb, and Fausto Panunzi. 1997. "Large Shareholders, Monitoring, and the Value of the Firm." *Quarterly Journal of Economics* 112-3: 693–728.

Cai, Charlie X., David Hillier, and Jun Wang. 2015. "The Cost of Multiple Large Shareholders." *Financial Management* 45-2: 401-430.

Clifford, Christopher P. and Laura Lindsey. 2016. "Blockholder Heterogeneity, CEO Compensation, and Firm Performance." *Journal of Financial and Quantitative Analysis* 51-5: 1491-1520.

Crane, Alan D., Andrew Koch, and Sebastien Michenaud. 2018. "Institutional Investor Cliques and Governance." *Journal of Financial Economics*, forthcoming.

Crane, Alan D., Sebastien Michenaud, and James Weston. 2016. "The Effect of Institutional Ownership on Payout Policy: Evidence from Index Thresholds." *Review of Financial Studies* 29-6: 1377-1408.

Cronqvist, Henrik, and Rüdiger Fahlenbrach. 2009. "Large Shareholders and Corporate Policies." *Review of Financial Studies* 22-10: 3941–76.

Dasgupta, Amil., and Giorgia Piacentino. 2015. "The Wall Street Walk when Blockholders Compete for Flows." *The Journal of Finance* 70-6: 2853-2896.

Demsetz, Harold, and Kenneth Lehn. 1985. "The Structure of Corporate Ownership: Causes and Consequences." *Journal of Political Economy* 93-6: 1155–77.

Denis, David J., and Atulya Sarin. 1999. "Ownership and Board Structures in Publicly Traded Corporations." *Journal of Financial Economics* 52-2: 187–223.

Dhillon, Amrita, and Silvia Rosetto. 2015. "Ownership Structure, Voting, and Risk." *Review of Financial Studies* 28-2: 521-560.

Dlugosz, Jennifer, Rüdiger Fahlenbrach, Paul Gompers, and Andrew Metrick. 2006. "Large blocks of stock: Prevalence, size, and measurement." *Journal of Corporate Finance* 12-3: 594–618.

Dou, Yiewei, Ole-Kristian Hope, Wayne B. Thomas, and Youli Zou. 2018. "Blockholder Exit Threats and Financial Reporting Quality." *Contemporary Accounting Research* 35-2: 1004-1028.

Edmans, Alex, and Clifford Holderness. 2017. "Blockholders: A Survey of Theory and Evidence." *The Handbook of the Economics of Corporate Governance*, Elsevier.

Edmans, Alex, and Gustavo Manso. 2011. "Governance through Trading and Intervention: a Theory of Multiple Blockholders." *Review of Financial Studies* 24-7: 2395–428.

Edmans, Alex, Doron Levit, and Devin Reilly. 2018. "Governing Multiple Firms." *Review of Financial Studies*, forthcoming.

Edmans, Alex, Vivian W. Fang, and Emanuel Zur. 2013. "The Effect of Liquidity on Governance." *Review of Financial Studies* 26-6: 1443-1482.

Edmans, Alex. 2009. "Blockholder Trading, Market Efficiency, and Managerial Myopia." *Journal of Finance* 64-6: 2481–513.

Edmans, Alex. 2009. "Blockholders and Corporate Governance." *Annual Review of Financial Economics 6*-1: 23–50.

Faccio, Mara, and Larry Lang. 2002. "The Ultimate Ownership of Western European Corporations." *Journal of Financial Economics* 65-3: 365–95.

Fahlenbrach, Rüdiger, and René M. Stulz. 2009. "Managerial Ownership Dynamics and Firm Value." *Journal of Financial Economics* 92-2: 342-361.

Fee, C. Edward, Charles J. Hadlock, and Joshua R. Pierce. 2013. "Managers with and Without Style: Evidence using Exogenous Variation." *Review of Financial Studies* 26-3: 567-601.

Fee, C. Edward, Charles J. Hadlock, Shawn Thomas. 2006. "Corporate Equity Ownership and the Governance of Product Market Relationships." *Journal of Finance* 61-3: 1217-1250.

Gomes, Armando, and Walter Novaes. 2006. "Sharing of Control versus Monitoring as Corporate Governance Mechanisms." Working paper, Washington University in St. Louis.

Heflin, Frank, and Kenneth W. Shaw. 2000. "Blockholder Ownership and Market Liquidity." *Journal of Financial and Quantitative Analysis*, *35*-4: 621-633.

Helwege, Jean, Christo Pirinsky, and René M. Stulz. 2007. "Why do Firms Become Widely Held?" *Journal of Finance* 62-3: 995–1028.

Himmelberg, Charles P., R. Glenn Hubbard, and Darius Palia. 1999. "Understanding the Determinants of Managerial Ownership and the Link between Ownership and Performance." *Journal of Financial Economics* 53-3: 353–384.

Holderness, Clifford G. 2009. "The Myth of Diffuse Ownership in the United States." *Review of Financial Studies* 22-4: 1377–408.

Holderness, Clifford G. 2003. "A Survey of Blockholders and Corporate Control," *Economic Policy Review* 9-1: 51-63.

Kahn, Charles, and Andrew Winton. 1998. "Ownership Structure, Speculation, and Shareholder Intervention." *Journal of Finance* 53-1: 99–129.

Kisin, Roni. 2011. The Impact of Mutual Fund Ownership on Corporate Investment: Evidence from a Natural Experiment. Working paper.

Koch, Andrew, Stefan Ruenzi, and Laura Starks. 2016. "Commonality in Liquidity: A Demand-side Explanation." *The Review of Financial Studies* 29-8: 1943-1974.

Konijn Sander J. J., Roman Kräussl, and André Lucas. 2011. "Blockholder Dispersion and Firm Value." *Journal of Corporate Finance* 17-5: 1330–9.

Laeven, Luc, and Ross Levine. 2007. "Complex Ownership Structures and Corporate Valuations." *Review of Financial Studies* 21-2: 579–604.

Laporta, Rafael, Florencio Lopez-de-Silanes and Andrei Shleifer. 1999. "Corporate Ownership around the World." *Journal of Finance* 54-2: 471-517.

Matvos, Gregor, and Michael Ostrovsky. 2010. "Heterogeneity and Peer Effects in Mutual Fund Proxy Voting." *Journal of Financial Economics* 98-1: 90-112.

Maug, Ernst. 1998. "Large Shareholders as Monitors: Is There a Trade-Off between Liquidity and Control?" *Journal of Finance* 53-1: 65–98.

Maury, Benjamin, and Anete Pajuste. 2005. "Multiple Large Shareholders and Firm Value." *Journal of Banking and Finance* 29-7: 1813-1834.

Morck, Randall, Andrei Shleifer, and Robert W. Vishny. 1988. "Management Ownership and Market Valuation: An Empirical Analysis." *Journal of Financial Economics* 20-1: 293-315.

Norli, Øyvind, Charlotte Ostergaard, and Ibolya Schindele. 2015. "Liquidity and Shareholder Activism." *The Review of Financial Studies* 28-2: 486–520.

Pagano, Marco, and Alisa Röell. 1998. "The Choice of Stock Ownership Structure: Agency Costs, Monitoring, and the Decision to go Public." *Quarterly Journal of Economics* 113-1: 187–225.

Rubin, Amir. 2007. "Ownership Level, Ownership Concentration and Liquidity." *Journal of Financial Markets*, *10*-3: 219-248.

Shleifer, Andrei, and Robert Vishny. 1986. "Large Shareholders and Corporate Control." *Journal of Political Economy* 94-3: 461–88.

Slovin, Myron B., and Marie E. Sushka. 1993. "Control Activity, and Firm Value: Evidence from the Death of Inside Blockholders." *Journal of Finance* 48-4: 1293-1321.

Song, Fenghua. 2017. "Blockholder Short-term Incentives, Structures, and Governance." Working paper, Pennsylvania State University.

Volkova, Ekaterina. 2018. "Blockholders' Diversity and Company Value." Working paper, Cornell University.

Winton, Andrew. 1993. "Limitation of Liability and the Ownership Structure of the Firm." *Journal of Finance* 48-2: 487–512.

Zhu, Guangyao. 2015. "The Extinction of Widely Held Public Companies." Working paper, Erasmus University.

Zwiebel, Jeffrey. 1995. “Block Investment and Partial Benefits of Corporate Control.” *The Review of Economic Studies* 62-2: 161–185.

Table 1: Sample Description

	All Years	2001	2014	Smallest Quintile Firms	Largest Quintile Firms
Number of firm-years	41,833	2,262	3,231	8,362	8,362
Mean (winsorized) firm book-assets in mil. 2014 $	8,932.8	6,637.6	11,298.1	60.2	41,346.3
Median firm book assets in mil. 2014 $	726.7	632.4	1,061.1	53.0	11,110.2
Number of block-years	113,941	4,884	10,027	21,307	16,042
Affiliated individual blocks as fraction of total	.116	.167	.077	.214	.059
Unaffiliated individual blocks as fraction of total	.064	.090	.044	.134	.027
Public company blocks as fraction of total	.022	.031	.018	.032	.025
Private company blocks as fraction of total	.014	.029	.008	.026	.010
Strategic investor blocks as fraction of total	.127	.069	.140	.203	.067
Generic financial blocks as fraction of total	.635	.580	.699	.376	.781
Other blocks as fraction of total	.022	.033	.015	.016	.031
Firm-years with at least 1 block	.919	.862	.955	.917	.828
Firm-years with at least 2 blocks	.740	.616	.812	.712	.570
Firm-years with at least 3 blocks	.516	.381	.602	.477	.314
Firm-years with at least 4 blocks	.308	.188	.388	.265	.135
Firm-years with at least one affiliated individual block	.267	.299	.211	.434	.107
Firm-years with at least one unaffiliated individual block	.144	.158	.115	.270	.045
Firm-years with at least one public company block	.056	.062	.051	.077	.046
Firm-years with at least one private company block	.036	.060	.023	.062	.019
Firm-years with at least one strategic investor block	.250	.127	.301	.343	.101
Firm-years with at least one generic financial block	.737	.650	.794	.536	.741
Firm-year with at least one nonfinancial block	.590	.567	.565	.806	.320
Median size of block: all blocks	.076	.082	.072	.084	.071
Median size of block: affiliated individual blocks	.108	.108	.108	.114	.110
Median size of block: unaffiliated individual blocks	.079	.083	.080	.078	.086
Median size of block: public company blocks	.130	.125	.162	.105	.166
Median size of block: private company blocks	.121	.111	.165	.119	.134
Median size of block: strategic investor blocks	.081	.085	.081	.083	.083
Median size of block: generic financial blocks	.071	.077	.068	.076	.068
Median size of block: all nonfinancial blocks	.090	.096	.088	.091	.094

Note.- The sample is composed of all block-years and corresponding firm-years for firms listed on Compustat and CRSP from 2001 to 2014 with ownership data available from Factset and nonmissing values for the explanatory variables used in later models. Ownership is measured as a percentage of all common shares as of June 30^{th} of each year. Blocks are assigned to mutually exclusive categories using the procedure outlined in the text and appendix. Figures for each block category are for the blocks in the specific indicated category, except for figures for nonfinancial blocks which are calculated over all individual categories except the generic financial blocks. All of the block (firm) statistics are calculated over the indicated population of block-years (firm-years). Size quintiles are defined using annual quintile breakpoints over the population of firms in the sample in a given year, with size measured using inflation-adjusted book assets as of fiscal year-end.

Table 2: Factors Associated with Blockholder Presence

	All Nonfinancial (1)	Generic Financial (2)	Affiliated Individual (3)	Unaffiliated Individual (4)	Public Company (5)	Private Company (6)	Strategic Investor (7)
Log of book assets	-.068***	.006	-.063***	-.028***	.007***	.000	-.020***
	(.006)	(.005)	(.005)	(.003)	(.001)	(.001)	(.004)
Firm Age	-.023***	-.000	-.013***	.003	-.008***	-.001	-.034***
	(.005)	(.004)	(.005)	(.003)	(.002)	(.001)	(.004)
Idiosyncratic risk	.025***	-.041***	-.003	.002	.003**	.002**	.013***
	(.007)	(.004)	(.004)	(.002)	(.001)	(.001)	(.004)
Liquidity	-.025***	.036***	-.026***	-.013***	-.001	-.003***	.047***
	(.008)	(.005)	(.005)	(.003)	(.002)	(.001)	(.005)
Tobin's Q	-.046***	-.024***	-.016***	-.009***	.001	-.000	-.035***
	(.006)	(.004)	(.005)	(.003)	(.001)	(.001)	(.005)
Book Leverage	.018***	.003	-.009	.005	-.001	.001	.024***
	(.007)	(.005)	(.006)	(.003)	(.002)	(.001)	(.004)
EBITDA/Assets	-.001	.018***	.025***	.001	-.007***	-.004***	-.010**
	(.008)	(.005)	(.006)	(.003)	(.002)	(.001)	(.005)
Sales growth	.001	.008***	-.002	-.003*	-.001**	-.002***	.003
	(.003)	(.002)	(.003)	(.002)	(.001)	(.001)	(.002)
Asset Tangibility	.016	-.016**	.010	.003	.000	.003	-.019***
	(.011)	(.007)	(.010)	(.006)	(.003)	(.002)	(.007)
Dividend dummy	.016	-.043***	.052***	.010	.001	.001	-.088***
	(.013)	(.009)	(.011)	(.007)	(.005)	(.003)	(.009)
R&D/Assets	-.013	.003	-.041***	-.010***	-.000	-.002	.021***
	(.008)	(.005)	(.008)	(.004)	(.001)	(.001)	(.005)
Advertising/Assets	.011	.002	-.001	.002	.001	-.000	.003
	(.007)	(.004)	(.005)	(.003)	(.001)	(.001)	(.004)
Capex./Assets	.005	.002	.021***	.001	-.001	-.001	.001
	(.006)	(.004)	(.005)	(.003)	(.001)	(.001)	(.004)
Pseudo R^2	.163	.171	.133	.119	.106	.103	.128
Number of Obs.	41,669	41,669	41,590	41,599	40,896	40,451	41,318

Note.- Each column reports estimated marginal effects from a logit model estimated at the firm-year level for a dependent variable that assumes a value of 1 if the firm has a blockholder of the indicated type as of the observation year and a 0 otherwise. Marginal effects are calculated by setting all explanatory variables at their sample means and deriving the marginal change in the implied probability of observing a blockholder of the indicated type per unit change in the explanatory variable, holding all other variables at their sample means. Robust standard errors clustered at the firm level are reported in parentheses and are calculated using the delta method. Each model includes a full set of year, 2-digit industry, and index membership dummy variables. All explanatory variables are calculated using CRSP or Compustat data for the fiscal year ending immediately preceding the ownership observation date. Variable constructions are reported in the appendix and each continuous variable except size is normalized by its sample standard deviation. Blockholders are assigned to one of the six mutually exclusive categories indicated in the headings to column 2-7 or to an "other" category. The dependent variable in column 1 is based on whether the firm has a nonfinancial blockholder which is a group composed of all of blocks except generic financial blocks. The dependent variables in columns 2-7 are based on whether the firm has a blockholder of the specific indicated type. Each model is estimated over the set of all sample observations that are not dropped by the logit estimation procedure. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Table 3: Models of Blockholder Interdependence

Panel A: Type of Blockholder Presence Predicted – 5 Percent A Blocks

	All	All	Nonfinancial	Nonfinancial	Financial	Financial
	(1)	(2)	(3)	(4)	(5)	(6)
Same blockholder dummy	-.021***	-.017**	-.035***	-.031***	.074***	.073***
	(.008)	(.007)	(.009)	(.009)	(.008)	(.008)
Largest position (demeaned)		-.782***		-.721***		-.597***
		(.030)		(.044)		(.082)
Sample rate of A block presence	.732	.732	.384	.384	.523	.523

Panel B: Type of Blockholder Presence Predicted – 10 Percent A Blocks

	All	All	Nonfinancial	Nonfinancial	Financial	Financial
	(1)	(2)	(3)	(4)	(5)	(6)
Same blockholder dummy	-.097***	-.103***	-.065***	-.068***	-.013**	-.014**
	(.007)	(.007)	(.006)	(.006)	(.005)	(.005)
Largest position (demeaned)		-.612***		-.373***		-.134*
		(.039)		(.032)		(.080)
Sample rate of A block presence	.322	.322	.193	.193	.153	.153

Panel C: Type of Blockholder Presence Predicted – 15 Percent A Blocks

	All	All	Nonfinancial	Nonfinancial	Financial	Financial
	(1)	(2)	(3)	(4)	(5)	(6)
Same blockholder dummy	-.062***	-.069***	-.053***	-.057***	.000	.000
	(.005)	(.005)	(.004)	(.004)	(.006)	(.006)
Largest position (demeaned)		-.298***		-.187***		-.032
		(.026)		(.021)		(.035)
Sample rate of A block presence	.151	.151	.120	.120	.035	.035

Note.- The reported coefficients on the dummy variables are the estimated discrete change in the implied probability of observing a blockholder belonging to the group/type indicated in the header row and assigned to the randomized A half of the sample for a firm that has a randomized B group blockholder in the indicated group/type compared to a firm with no such B group blockholder. The largest position variable is set equal to the largest ownership position of a firm's B blockholders of the type modeled in each column/panel, less the sample mean of this variable. For firms with no blockholder of the indicated type, the largest position variable is set equal to 0. In the even columns, the implied probability for the blockholder dummy variable is calculated holding the maximum position size variable at 0 (i.e., ownership at the mean if the firm has a block). The coefficients on the largest positon dummy are the estimated marginal change in probability when ownership as measured by the largest position by a B blockholder in the model is increased from its mean level (i.e., the demeaned maximum position variable is perturbed from 0) and the block dummy explanatory variable is set equal to 1. All other model variables are set equal to their sample means in calculating marginal effects. Robust standard errors clustered at the firm level are reported in parentheses under each estimate and are calculated using the delta method. Each model includes the full set of explanatory variables included in the Table 2 models. Column (1) and (2) models predict the presence of any blockholder in the randomized A group (half the sample of blocks) as a function of the presence of any blockholder in the randomized B group (the other half). The subsequent columns present parallel model estimates in which we only consider blockholders of the indicated type in the coding of both the dependent and independent variable. Financial blocks include only generic financial blockholders and nonfinancial blocks include all other blocks. Panel A treats all 5% or greater positions as blocks, while Panel B (Panel C) only considers a position to be a block in the coding of both the dependent and independent variables if the owner holds at least 10% (15%) of the firm's shares. The sample rate of block presence is the fraction of firm-years in the estimated model in which the dependent variable is coded as a 1 rather than a 0. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Table 4: Models of Interactions Across Different Blockholder Types

	Block Size	All Nonfinancial (1)	Generic Financial (2)	Affiliated Individual (3)	Unaff. Individual (4)	Public Company (5)	Private Company (6)	Strategic Investor (7)
Indicator for presence of different type block	5%	-.081***	-.055***	-.107***	-.030***	-.042***	-.027***	-.013
		(.012)	(.008)	(.015)	(.010)	(.009)	(.007)	(.012)
	10%	-.091***	-.086***	-.074***	-.018***	-.017***	-.011***	-.031***
		(.008)	(.008)	(.006)	(.003)	(.003)	(.002)	(.003)
	15%	-.055***	-.022***	-.051***	-.010***	-.013***	-.002***	-.020***
		(.011)	(.004)	(.004)	(.002)	(.002)	(.000)	(.002)
Rate of block presence	5%	.587	.721	.275	.153	.057	.041	.250
	10%	.339	.280	.164	.053	.035	.025	.093
	15%	.226	.067	.110	.026	.026	.018	.053

Note.- Reported coefficients are derived from logit model coefficients and indicate the estimated change in the implied probability of observing a blockholder of the indicated type in the column heading when the explanatory dummy variable indicating the presence of at least one block of a different type is changed from 0 to 1, holding all other model variables at their sample means. Robust standard errors clustered at the firm level are reported in parentheses under each estimate and are calculated using the delta method. Each model includes the full set of explanatory variables included in the Table 2 models (coefficients not reported). Each model is estimated over the set of all sample firm-years that are not dropped in the process of the logit model estimation. The dependent variable in each model assumes a value of 1 if the firm has at least one block of the type indicated in the header row and that block exceeds the minimum size indicated in the "Block Size" column. The independent variables are dummy variables coded based on whether a firm has a block of the same minimum size of any type except the type incorporated into the dependent variable. Nonfinancial blockholders include any block except a generic financial block. The sample rate of block presence is the fraction of firm-years in the corresponding estimated model in which the dependent variable is coded as a 1 rather than a 0. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Table 5: Dynamics of Blockholder Exit and Entry

	Exit Any (1)	Entry Any (2)	Exit Nonfincl. (3)	Entry Nonfincl. (4)	Exit Fincl. (5)	Entry Fincl. (6)
Any block present	.050***	.072***				
	(.004)	(.012)				
Nonfinancial block present			.051***	.010**		
			(.005)	(.005)		
Generic financial block present					.017***	.111***
					(.004)	(.008)
Number of observations	101,821	37,689	37,619	37,676	64,202	37,689
Unconditional exit or entry rate	.278	.520	.233	.176	.304	.416
Expected block duration	3.61		4.29		3.29	

Note.- All exit models are estimated at the blockholder-year level over the set of blockholders of the indicated type. In these models, the reported coefficients are the estimated change in the implied probability of exit of the indicated type in the column heading when the explanatory variable indicating the contemporaneous presence of another blockholder of the indicated type is changed from 0 to 1 derived from a logit model. Robust standard errors clustered at the blockholder-firm level are reported in parentheses under each exit model estimate and are calculated using the delta method. The unconditional exit rate is the percentage of all blocks modeled in the column dependent variable that exit as fraction of all observation years. Expected block duration is the reciprocal of the exit rate. All entry models are estimated at the firm-year level over the set of all firm-years. The reported coefficients in the entry models are the estimated change in the implied probability of entry by at least one new blockholder of the indicated type in the column heading when the explanatory variable indicating the presence of another blockholder of the indicated type is changed from 0 to 1 derived from a logit model. Robust standard errors clustered at the firm level are reported in parentheses under each estimate and are calculated using the delta method. The unconditional entry rate is the percentage of firm-years in the model for which the dependent variable is coded as a 1. All other model variables are set equal to their sample means in calculating marginal effects. All block groupings and categories are defined as in the earlier tables. Each model includes the full set of explanatory variables from the Table 2 models plus the firm's most recent fiscal year market-adjusted stock return. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Table 6: Blockholder Changes after Exogenous Individual Blockholder Departures

	Change in Blocks by T+1		Change in Blocks by T+3	
Panel A: All blocks	(1)	(2)	(3)	(4)
Exogenous block departure	.207*	.245**	.366**	.396**
	(.110)	(.109)	(.169)	(.172)
Number of Observations	14,653	12,319	11,614	9,656
R^2	.028	.040	.032	.047
Full set of controls	No	Yes	No	Yes

	Change in Blocks by T+1		Change in Blocks by T+3	
Panel B: Blocks > 10%	(1)	(2)	(3)	(4)
Exogenous block departure	.479***	.482***	.525***	.536***
	(.114)	(.105)	(.165)	(.175)
Number of Observations	14,532	12,219	11,529	9,588
R^2	.008	.012	.010	.017
Full set of controls	No	Yes	No	Yes

Note.- Panel A reports coefficients from an OLS regression model predicting the change in the number of blockholders (of any type) at the firm between year t and the year indicated (t+1 or t+3), not including the individual block that either did or did not experience an exogenous departure. Panel B estimates the same models as Panel A, but defines blockholders as ownership positions of at least 10% ownership in the creation of both the dependent variable and the key explanatory variable. The exogenous individual departure variable is a dummy variable that assumes a value of 1 if an individual blockholder leaves the firm between t and t+1 either because of death or illness or the individual is over the age of 75. All firms with no individual blockholder at time t are excluded. If the firm has a single individual blockholder who left for endogenous reasons between t and t+1, the exogenous departure variable is set equal to missing. For firms with multiple individual blockholders, none of who left for exogenous reasons, we randomly select one such individual and code the exogenous departure variable based on whether that blockholder is still with the firm at time t+1. All models include year and industry effects. The models in the even columns include the full set of explanatory variables from the Table 2 models plus the firm's most recent fiscal year market-adjusted stock (coefficients not reported). Robust standard errors clustered at the firm level are reported in parentheses. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Table 7: Financial Block Changes after Exogenous Financial Block Shocks

	Change in Number of Non-scandal Financial Blocks			
	(1)	(2)	(3)	(4)
Scandal block departed	.017	.042		
	(.134)	(.125)		
Scandal block present			-.022	.038
			(.096)	(.089)
Number of financial non-scandal blocks		-0.356***		-.356***
		(.026)		(.025)
Number of Observations	1,685	1,685	1,763	1,763
R^2	0.049	0.172	0.051	0.174

Note.- This table reports coefficients for OLS regression models in which the dependent variable is the change in the number of financial blocks at a firm between 2003 and 2004 excluding all blocks associated with financial institutions tainted by the 2003 mutual fund scandal. The sample in all models is restricted to all sample firms with at least one financial block owned by a non-scandal associated financial institution as of 2003. The scandal block departed variable assumes a value of 1 if the firm had a block owned by a scandal associated fund in 2003 that was no longer present in 2004, and 0 if the firm did not have any blocks owned by scandal associated funds as of 2003. This variable is set equal to missing for all other firms. The scandal block present variable assumes a value of 1 if the firm had a block owned by a scandal associated fund in 2003, regardless of whether that block departs, and 0 if the firm did not have any blocks owned by scandal associated funds as of 2003. The number of financial non-scandal blocks variable is the number of financial blocks at the firm as of 2003, exclusive of any blocks owned by scandal associated financial institutions. All models include year and industry effects and the full set of explanatory variables from the Table 2 models plus the firm's most recent fiscal year market-adjusted stock (coefficients not reported). Robust standard errors clustered at the firm level are reported in parentheses. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Appendix

A.1 Variable Definitions

All explanatory variables are constructed using Compustat or CRSP data for the most recent fiscal year that ends on or before the June 30th date for which we have an ownership snapshot of the firm's blockholders. All continuous variables that are not ratios or returns are inflation adjusted to 2014 dollars. Each variable is constructed using the procedure outlined in the table below. After constructing each variable, we standardize all variables except the dummy variables, firm age, and the firm size variable by dividing by the sample standard deviation calculated over all blockholder-year observations. This standardization eases the comparison of coefficient magnitudes.

Variable	Definition/Construction
Log of book assets	Logarithm of the firm's total book assets
Idiosyncratic risk	We first calculate the standard deviation of the residuals in a regression of the firm's daily stock return against the CRSP value-weighted return over the course of the fiscal year. The logarithm of 1 plus the resulting standard deviation of these residuals is the risk measure. This variable is winsorized at the sample 1st and 99th percentiles.
Tobin's Q	(Total assets – book common equity + market common equity)/Total assets. This variable is winsorized at the sample 1st and 99th percentiles.
R&D/Assets	Annual R&D spending divided by total year-end assets. Missing R&D values assumed to be 0. This variable is winsorized at the values of 0 and 1.
Liquidity	We first calculate the Amihud (2002) illiquidity measure using the construction outlined by Balakrishnan, Billings, Kelly and Ljungqvist (2014). Following Edmans, Fang, and Zur (2013) we then define liquidity as –ln(1+Ahimud illiquidity measure). This variable is winsorized at the sample 1st and 99th percentiles.
Sales growth	Logarithm of (total sales in most recent year / total sales in preceding year). This variable is winsorized at the values of -1 and +1.
EBITDA/Assets	The firm's annual earnings before interest, taxes, and depreciation divided by end of year total assets. This variable is winsorized at the values of -1 and +1.
Advertising/Assets	Annual advertising spending divided by total year-end assets. Missing advertising values assumed to be 0. This variable is winsorized at the values of 0 and 1.
Asset tangibility	Net property plant and equipment divided by end of year total book assets. This variable is winsorized at the values of 0 and 1.
Capex/Assets	The firm's annual capital expenditures divided by end of year total book assets. This variable is winsorized at the values of 0 and 1.
Book leverage	The sum of the firm's short-term plus long-term debt divided by end of year total book assets. This variable is winsorized at the values of 0 and 1.
Dividend payer dummy	Variable assumes a value of 1 if the firm paid cash dividends during the most recent year and 0 otherwise.
Firm age	The number of decades the firm has been listed on Compustat with a non-missing end-of-fiscal-year stock price as of the observation year.
Abnormal stock return	The firm's buy-and-hold stock return over the most recent fiscal year minus the return on the CRSP value-weighted index over this same period. This variable is winsorized at the sample 1st and 99th percentiles.
Index dummies	These are binary variables indicating whether the firm was in each of the following indexes as of the observation year: Dow Jones 30, S&P 500/600/400, Russell 1000/2000.

A.2 Ownership Data Algorithm

Factset assigns each block to a single blockholder-type category (in a few cases the category entry is missing, these were coded manually). There are 33 such categories. Since this is a relatively new data source, and some of the Factset category titles are ambiguous, we examine at least 20 blocks in each category in detail (or all such blocks if there are under 20), to determine whether the group does in fact reliably include a single blockholder type that fits within one of our broad blockholder-type groups Of the 33 Factset categories, we determined via this procedure that 22 are sufficiently homogenous in nature and unambiguous in labeling that an automatic assignment to one of the groups was appropriate. In what follows, Factset category titles are always listed with quotes, and the category titles we assign them to for our analysis in the paper are listed in italics.

The 2 Factset categories of "Individuals" and "Trust/Trustee" were automatically assigned to the *individual blockholder* groups. All of the trusts we investigated include a reference to the name of an individual or a family and were clearly associated with an individual or small set of related individuals. These blocks were then assigned to the affiliated and unaffiliated individual groups using the procedure outlined in the body of the paper. The single Factset category of "Public Company" was automatically assigned to the *public company* group.

A set of 5 Factset categories that contained a reference to the words/phrase "venture", "hedge," or "private equity" were automatically assigned to the *strategic investor* group. These categories included: "Hedge Fund," "Hedge Fund Manager," "Fund of Hedge Funds," "Family of Fds (VC/PvtEq)," and "Venture Capital Fund." In addition, a set of 6 Factset categories were automatically assigned to the *generic financial* group including: "Mutual Fund Manager," "Mutual Fd-Open End," "Bank Investment Division," "Insurance Company," "Private Banking/Wealth Management," and "Broker." The following 5 Factset categories were initially assigned to a non-profit subgroup which is then subsumed into our *other* blockholder group: "College/University," "Foundation/Endowment," "Foundation/Endowment Manager," "Non-Profit Organization," and "Government." Finally, 4 categories were initially assigned to a pension subgroup, which was also then subsumed into our *other* blockholder group. These categories were: "Pension," "Pension Fund," "Pension Fund Manager, and "Emp Stk Ownership Plan."

While the preceding 22 (out of 33) Factset categories could be assigned automatically, the remaining 11 exhibited sufficient heterogeneity or ambiguity upon inspection that a manual coding was employed. In completing this coding, we consulted websites, directories, and filings to ascertain the underlying organizational structure and objective/strategy of the blockholder. Our basic procedure was to continue to consult sources until we were confident in the correct assignment. When available, we consulted, in order, the Bloomberg description of the blockholder, websites of the blockholder, Factiva news searches of the blockholder, and finally 13D/13G/proxy filings.

Of these 11 Factset groups, a set of 6 had a small number of blocks, aggregating to only 27 blockholders. Thus, we do not discuss the assignment of blocks within this set of 6 in detail, except to emphasize that we use the exact same criteria for manually assigning these blocks as we do for the remaining 5 Factset categories discussed in detail below. This set of 6 Factset groups that were manually classified but contained only a small set of blocks included the categories: "Operating Division," "Arbitrage," "Family Office," "Financing Subsidiary/SPE," "Joint Venture," and "Fund of Funds Manager." In addition, there were 151 blocks with a missing blockholder type assignment by Factset that were all manually coded.

The remaining 5 Factset groups (33 total minus 22 assigned automatically minus 6 small groups assigned manually) represent larger groups in which there was sufficient heterogeneity upon inspection that a manual coding was undertaken. If the underlying blockholder was determined to be an investment vehicle of a single individual or family, it was assigned to the *individual* blockholder groups. If we could identify that the blockholder or its parent entity was a public non-financial firm, the block was automatically assigned to the *public company* group. If the firm was a private non-financial entity that was engaged in producing goods or services, it was assigned to the *private company* group. If the firm was a financial entity and the name of the block or a description of the firm's investment activities included references to the words/phrase "hedge," "private equity," or "venture," the block was assigned to the *strategic investor* group. All other financial entities were assigned to the *generic financial* group.

The largest and most heterogeneous of these 5 categories is the set of investors assigned to the "Private Company" group by Factset (1,200 blocks). A significant minority of these blockholders are in fact private operating companies of the type we assign to our *private company* group, for example the well-known Canadian private firm Cargill or Victory Oil Co., a firm that operates crude oil wells. However, a substantial number of these blockholders are instead assigned to the *strategic investor* category, for example Telcom Ventures LLC, which Bloomberg describes as a venture capital and private equity firm focused on the telecommunications industry. In addition, some of these blockholders are assigned to the *individual* blockholder group as they represent a family investment vehicle (e.g., "Sammon Family LP"). Finally, some of these blocks are *generic financial* institutions, for example Compass Financial Advisors LLC, a firm that is self-described on their website as a wealth management firm.

The second largest group is the set of block investors categorized by Factset as "Investment Advisers" (615 blocks). Not surprisingly, the vast majority (approx. 95%) of these block investors are assigned to the *generic financial* category, for example West Coast Asset Management, Inc., an investment firm that manages accounts for individuals, and corporations. However, our manual coding revealed that a small number of these blocks actually represent *strategic investors* according to our criteria, for example Cantillon Capital Management LLC, an entity that Bloomberg categorizes as a hedge fund.

The third largest group we manually categorized is a blockholder category referred to by Factset as a "Subsidiary" (397 blocks). Many of these entities represent *strategic investors*, for example Boston Millennia Partners, which describes itself on its website as a private equity and venture capital fund focusing on specific industries. Another substantial subset of this Factset category represent non-financial *private companies*, for example Biomec, Inc., a firm involved in medical technology R&D and manufacturing.

The final two groups are smaller with 159 blockholders in the Factset category of "Extinct" and 39 in the category "Holding Company." Our investigation reveals that most of these blockholders are either *private companies* (e.g., Barnato Exploration Ltd. and Healthmarkets, Inc.) or *generic financial* institutions (e.g., Terra Trust Investment AG and North Penn Mutual Holding Company).

We believe that manually coding the data from 11 of the 33 Factset categories yields an economically meaningful assignment of blockholders into truly distinct groups. If future researchers using Factset block data wanted to economize on data collection costs, given the small heterogeneity in the very large "Investment Adviser" category, minimal information would be lost by assigning all of these blocks to the *generic financial* category. The other 10 groups and the missing category exhibit more heterogeneity, so clearly hand-collection/manual-inspection is the first-best option. However, if one wanted to use a purely algorithmic approach, the most accurate such approach would be to assign each of these 10 Factset categories (plus the blocks with a missing Factset block category label) to the block group with the largest percentage of observations.

Given this possibility, we report here our most common manual assignment to a group, along with the associated percentage, for each of these Factset categories. We report these in order based on the prevalence of the Factset category in the overall sample. Factset category: Private Company; most common assignment using our procedure, *strategic investors* with 43.6%. Factset category - Subsidiary: most common assignment, *strategic investors* with 36.8%.

Factset category - Extinct: most common assignment, *private company* with 40.3%. Factset category missing: most common assignment, *strategic investors* with 35.1%. Factset category - Holding Company: most common assignment, *private company* with 28.1%. Factset category - Operating Division: most common assignment, *strategic investor* with 81.3%. Factset category - Family Office: most common assignment, *strategic investor* with 75.0%. Factset category - Joint Venture: most common assignment, *strategic investor* with 66.7%. Factset category - Fund of Funds Manager: most common assignment, *generic financial* with 100%. Factset category - Financing Subsidary/SPE: most common assignment, *public company* with 100%. Factset category - Arbitrage: most common assignment, *generic financial* with 100%.

Table A1: Disaggregated Models of Blockholder Interactions

Panel A – Predicting all blocks	Affil. Indiv	Unaff. Indiv.	Public Co.	Private Co.	Strat. Invest.	Generic Financial
	(1)	(2)	(3)	(4)	(5)	(6)
Indiv affil block dummy		.026*** (.008)	-.020*** (.004)	-.011*** (.002)	-.066*** (.008)	-.073*** (.010)
Indiv unaff block dummy	.046*** (.014)		-.012** (.003)	.000 (.003)	-.007 (.010)	-.068*** (.012)
Public block dummy	-.093*** (.016)	-.031*** (.010)		.003 (.005)	-.020 (.013)	-.085*** (.019)
Private block dummy	-.099*** (.018)	-.001 (.013)	.004 (.008)		-.042*** (.016)	-.097*** (.023)
Strategic block dummy	-.070*** (.009)	-.001 (.006)	-.005* (.003)	-.005** (.002)		.039*** (.008)
Financial block dummy	-.073*** (.011)	-.034*** (.007)	-.017*** (.004)	-.013*** (.003)	.048*** (.008)	
Sample rate of block presence	.275	.153	.057	.041	.250	.721

Panel B – Predicting A Blocks	Affil. Indiv	Unaff. Indiv.	Public Co.	Private Co.	Strat. Invest.	Generic Financial
Indiv affil block dummy	-.049*** (.006)	.011*** (.004)	-.008*** (.002)	-.005*** (.001)	-.035*** (.005)	-.092*** (.010)
Indiv unaff block dummy	.023*** (.007)	.024*** (.007)	-.005*** (.002)	-.000 (.002)	-.007 (.005)	-.076*** (.011)
Public block dummy	-.050*** (.008)	-.019*** (.005)	-.002 (.004)	.002 (.002)	-.010 (.008)	-.102*** (.017)
Private block dummy	-.045*** (.009)	.007 (.008)	.004 (.004)	.004 (.004)	-.024*** (.009)	-.118*** (.020)
Strategic block dummy	-.030*** (.005)	.000 (.003)	-.000 (.002)	-.003** (.001)	.053*** (.006)	.007 (.009)
Financial block dummy	-.034*** (.006)	-.017*** (.004)	-.009*** (.002)	-.007*** (.002)	.025*** (.005)	.063*** (.008)
Sample rate of block presence	.150	.085	.029	.021	.144	.523

Panel C – Predicting A blocks	Affil. Indiv	Unaff. Indiv.	Public Co.	Private Co.	Strat. Invest.	Generic Financial
Diagonal estimates – 10% blocks	-.031*** (.004)	.000 (.005)	-.001 (.003)	-.001 (.002)	.013*** (.004)	-.017*** (.005)
Diagonal estimates – 15% blocks	-.021*** (.003)	-.003 (.003)	-.005*** (.001)	-.001*** (.000)	.005 (.003)	-.001 (.005)

Note.- This reported coefficients are derived from logit model coefficients and indicate the estimated change in the implied probability of observing a blockholder of the indicated type when each explanatory dummy variable is changed from 0 to 1, holding all other model variables at their sample means. Robust standard errors clustered at the firm level are reported in parentheses under each estimate and are calculated using the delta method. Each model includes the full set of explanatory variables included in the Table 2 models (coefficients not reported). Each model is estimated over the set of all sample firm-years that are not dropped in the process of the logit model estimation. The dependent variable in each model assumes a value of 1 if the firm has at least one block of the indicated type. In Panel A all blocks are used in coding the dependent variable. In panels B and C only the blocks that are randomly assigned to the A group (half of all blocks) are used to code the dependent variable. In these two panels the independent variable corresponding to the block type of the dependent variable is coded using information only from the B blocks (the other half of the randomization procedure). All explanatory variables for blocks other than the type included in the dependent variable are coded using information on all blocks. Panel A and B are for models in which any 5% block is coded as a block. In Panel C we estimate models corresponding to Panel B but require that blocks be at least 10% (row 1 of the panel) or 15% (row 2 of the panel) in ownership position size. In Panel C we only report the estimated marginal effect of a given B type predicting the presence of the same type of owner in the A group (corresponding to the diagonal coefficients in Panel B). The estimated marginal effects for the other block categories are omitted from this panel. The sample rate of block presence is the fraction of firm-years in the estimated model in which the dependent variable is coded as a 1 rather than a 0. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.