Blockholder Heterogeneity, Multiple Blocks, and the Dance between Blockholders

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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 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, a behavior that appears causal. Small financial blocks often coexist in the same firm, an outcome that appears to reflect correlated investment styles. (*JEL* G30)

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 113,941 blockholdings (5% ownership or above) distributed over 41,833 Compustat 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 identify 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 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 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 59.0% and 73.7%, 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. For financial blocks, however, these patterns are either not evident or of the opposite sign.

Holding constant these factors associated with blockholder 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 between blockholders, which in turn could affect 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, as well as for nonfinancial blocks of any position size. Thus, except for small financial blocks, the data appear consistent with the models of Zwiebel (1995) and others predicting 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 a 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 blocks in firms. This could reflect a causal positive interdependence relation, or it may reflect small financial blockholders' common attraction to similar firms on unmodeled/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.

In summary, 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 our collective evidence suggests that these negative relations are causal.

In addition to our main findings, we fill in some important empirical details regarding blockholder behavior. In particular, we document a trend over time toward 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.

1. Blockholder Activity and Presence

1.1 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 (2009b), 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 (2009a) 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 (2009a) and Admati and Pfleiderer (2009) demonstrate that this exit threat can, in turn, serve a governance role by providing ex ante incentives for a manager to pursue a value-maximizing strategy (see Dasgupta and Piacentino 2015 for some caveats).

1.2 Blockholder presence

We would expect potential blockholders to establish or maintain positions in firms when the benefits they derive from 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 net benefits. Although some evidence on blockholder presence is reported by Dlugosz et al. (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 predicting blockholder presence, we include a laundry list of explanatory variables that have been suggested by the prior literature. These models can be viewed as empirical descriptions establishing an initial baseline. However, if one is willing to make assumptions regarding what the explanatory variables are likely capturing, it is possible to make some indirect inferences regarding blockholder motivations. For example, if some

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

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 might 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.

1.3 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 distinct firm outcomes.[2] However, none of these studies examine the circumstances that give rise to a 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 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

[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).

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 potential benefits 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 from 1981 (see also Laporta, Lopez-de-Silanes, and Shleifer 1999 for international evidence). A principal goal of our study is to investigate the nature of blockholder interdependence relations in a large recent sample.

1.4 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 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 the

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

independent variables. As we will 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 key explanatory variables. To address this issue, we (a) identify cases in which the resultant 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]

Prior empirical research documents that firms have many distinct types of blockholders (Cronqvist and Fahlenbrach 2009; Dou et al. 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 succinct, as we will detail below, we largely focus on two broad groupings. Because information is necessarily lost in the aggregation process, we also report some findings using finer blockholder groupings.

[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.

2. Sample Construction and Description

2.1 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 30. 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 30 to the associated June 30 ownership snapshot. The final sample includes 41,833 firm-years of data.

Table 1 reports that the book assets of sample firms are similar to what others have reported for broad Compustat-based samples. The sample is tilted toward 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, because 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 nonsurvivors that is largest near the start of the sample period.

2.2 Categorizing blockholders

After assembling the sample, we consolidate related positions that are listed separately, most notably individuals with the same last name and institutions that belong to 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. Table 1 reports the resultant 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. The appendix provides 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 or directors of the firm at any point between 1990 and the observation year as reported in the Compustat executive name file (see Fee, Hadlock, and Pierce 2013). All other individuals are assigned to the unaffiliated individual group. Table 1 reports 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 into a fourth category private company blockholders (1.4% of the sample), a group comprises 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.

Our final category, comprising generic financial institutions, is, by far, the largest group. It primarily includes 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 nonprofit/government entities, public pension funds, firms' pension funds, and employee stock ownership plans (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.

2.3 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, have both increased over time. The multiple block trend is prominent, with an increased frequency of almost 20% (from 61.6% to 81.2% between 2001 and 2014), and an upward shift in the median from 2 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 types of blocks. Table 1 also reveals that a 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, mean of 13.5% vs. mean of 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 vs. 11.75). Thus, it appears that a simple sorting of firms into nonfinancial and financial blocks yields quite distinct groups.

3. 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 the firm's age. All models include both year and 2-digit industry dummies. Given the importance of indexes in many investment decisions (Appel, Gormley, and Keim 2016; 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. The appendix details the variable definitions.

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 significance level. Moreover, they are usually quite similar to the corresponding estimates from linear probability models (i.e., ordinary least squares (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, respectively, nonfinancial and financial blockholder presence. In this table, we order our presentation of coefficient estimates by first listing estimates for variables that are significant in

[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 the indicator variable.

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, or riskier (measured by return volatility) or has a less-liquid stock, a lower Tobin's q value, or a 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 they suggest that this elevation in benefits may, in fact, exceed 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, because 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 value in settings with a high cost of blockholder exit.[6]

[6] A subtle formal theory underlies this prediction. 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. However, it also may affect the ex ante returns to establishing a block, and this relation can have an ambiguous sign.

Turning to the Column 2 estimates for financial blocks, the coefficient on only 1 of the 6 aforementioned variables, Tobin's q, has the same sign and significance found 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"). Although 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 2 of 30 (5 models x 6 variables) cases in which the coefficient estimate on a variable that is significant in the Column 1 nonfinancial model is significant and of the opposite sign compared to each of the corresponding coefficients reported in Columns 3–7. One of these, the positive coefficient on firm size for public firm blocks, is consistent with these investors having relatively deep pockets,

[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, signs are ambiguous. See Heflin and Shaw (2000), Rubin (2007), and Edmans, Fang, and Zur (2013) for prior studies of liquidity and ownership.

allowing them to take higher dollar value positions than others. The other, the positive coefficient on liquidity for strategic investor blocks, is consistent with 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 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, 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 are parsed at a finer level.[10] Although our findings have multiple possible explanations, 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, whereas financial blockholders are more likely to appear in firms in which there is more scope to participate in governance through trading.

4. Blockholder Interactions and Multiple Blocks

4.1 Blockholder interdependence

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

[9] The expected holding period of strategic investors is 2.64 years versus 6.27 for other nonfinancials. Edmans, Fang, and Zur (2013) and Norli, Ostergaard, and Schindele (2015) report related hedge fund evidence.

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

nonfinancial blockholder indicator variable. For blockholders in the same group, the analysis is less straightforward, because 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 is surely 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 blockholders clustering together, 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 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 dependent variables (independent variables) regarding block presence using information from blocks 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 toward 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 first 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, like 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

[11] Whether the conditional likelihood of blockholder presence is related to the presence of other blockholders can be estimated other ways, but our approach imposes fewer parametric restrictions than most others.

an 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, we demean the ownership percentage variable in all models and set it 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 or 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.

4.2 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 upward (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 overcontrol 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-numbered column Table 3 models, along with year, index, 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 nonfinancial blocks of any size.

We have also experimented with altering the odd-numbered 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). Although there are some small differences across the models, none of these differences 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 the large (> 10%) nonfinancial blocks models, the estimate on the blockholder presence explanatory variable remains negative and significant for all resultant subsamples.

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[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.

4.3 Relation between different blockholder types

While the preceding analysis considers the relation between blockholders of the same group, it also may 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.

As a further exploration, we report estimates in Columns 3–7 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 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 resultant 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 nonindividual blockholders.

4.4 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.

The odd- (even-) numbered columns of Table 5 present the resultant estimates for exits (entries). 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

[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 coexistence.

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

but also more entry. This suggests that the small, overall sample-wide negative interdependence relation reflects exit behavior slightly 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, and 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 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 significant in the exit regressions (odd-numbered columns in 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 nonfinancial blocks of any size.

4.5 Exogenous shocks to nonfinancial block ownership

To strengthen a causal interpretation for our negative interdependence findings, we identify plausibly exogenous variation in nonfinancial blockholder presence and examine whether this variation is related to the presence of other blocks. In particular, we consider the disappearance of blocks held by individuals who die, succumb to cancer within 3 years of the block dissolution (our proxy for illness), or 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 comprises 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).

Panel A of Table 6 presents OLS regression estimates for models predicting the change in the number of blockholders at the firm over 1-year (t to $t + 1$) and 3-year (t to $t + 3$) windows

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

(Columns 1 and 2 and 3 and 4, respectively). We estimate simple models that include only industry and year controls, and comprehensive models with the full set of control variables (odd- and even-numbered 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 3-year window estimates suggest that firms with an exogenous departure tend to have a net change in the number of other blocks of almost +.40 (point estimates of .366 and .396) compared to the baseline. This suggests the presence of a fairly substantial repelling effect of blockholder presence that is removed upon an exogenous blockholder departure.

Panel B of Table 6 presents 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 2-year window to measure net changes in blockholders. In all cases, the results are substantively unchanged from 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.

4.6 Exogenous shocks to financial block ownership

The findings in the preceding section add to our confidence that the detected overall negative interdependence relations within the set of larger blocks and also within the set of all nonfinancial blockholders are 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 2003. As Kisin (2011) illustrates, these institutions experienced large fund outflows, which is likely to 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 resultant net decrease in the presence of other financial blocks soon after the shock.

To validate this strategy, we reestimate 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 resultant 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 block 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]

Column 1 of Table 7 exploits the first approach and reports 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 we 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

[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.

a firm experiences an exogenous departure. In Column 2, we add the number of nonscandal 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.

Columns 3 and 4 of Table 7 turn to the second approach and 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 nonscandal financial blockholder presence around an episode in which scandal-associated financial blocks departed at substantially elevated rates for likely exogenous reasons. This evidence suggests that the positive correlation in the presence of financial blockholder documented earlier largely reflects a noncausal relation in which (smaller) financial blocks are attracted to similar types of firms based on unobservable or unmodeled firm characteristics.

5. Summary and Conclusion

In this paper, we identify factors associated with the appearance of block positions in a large and recent sample of public U.S. firms. We uncover 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 one third 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 broadly consistent with a governance role for nonfinancial blockholders primarily arising 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 colocating 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 plausibly exogenous individual 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 or 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. Many different types of blockholders exist within the broad groups we study, and it would be interesting to clarify each of their respective behaviors and governance roles. In addition, broad time trends in blockholder ownership and composition do not appear to immediately follow from existing theories. These and related issues await future research.

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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

The sample comprises 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 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 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 the 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's 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

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 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. The appendix reports the variable constructions, and each continuous variable, except size is normalized by its sample standard deviation. Blockholders are assigned to 1 of the 6 mutually exclusive categories indicated in the headings to Columns 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 comprising all 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. $*p < .1$; $**p < .05$; $***p < .01$.

Table 3
Models of blockholder interdependence

	A. Type of blockholder presence predicted, 5% 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
	B. Type of blockholder presence predicted, 10% 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
	C. Type of blockholder presence predicted, 15% 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

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 and 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-numbered 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 represent the estimated marginal change in probability of observing an A blockholder 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. The models in Columns 1 and 2 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, and 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. *$p < .1$; **$p < .05$; ***$p < .01$.

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

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. **p* < .1; ***p* < .05; ****p* < .01.

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	3.60		4.29		3.29	

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 from a logit model 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. 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 from a logit model 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. 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 like 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. *$p < .1$; **$p < .05$; ***$p < .01$.

Table 6
Blockholder changes after exogenous individual blockholder departures

	Change in blocks by t + 1		Change in blocks by t + 3	
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	
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

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 estimated in 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 because 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-numbered 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. *p < .1; **p < .05; ***p < .01.

Table 7
Financial block changes after exogenous financial block shocks

	Change in number of nonscandal financial blocks			
	(1)	(2)	(3)	(4)
Scandal block departed	.017 (.134)	.042 (.125)		
Scandal block present			-.022 (.096)	.038 (.089)
Number of financial nonscandal blocks		-0.356*** (.026)		-.356*** (.025)
Number of observations	1,685	1,685	1,763	1,763
R^2	.049	.172	.051	.174

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 nonscandal 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. *$p < .1$; **$p < .05$; ***$p < .01$.

Appendix

Table A1. 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 30 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. After constructing each variable, we standardize all variables, except the dummy variables, firm's 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 resultant 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's age	The number of decades the firm has been listed on Compustat with a nonmissing 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, and Russell 1000/2000

Appendix A. 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). Thirty-three such categories exist. Because 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 two 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 six 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 five Factset categories were initially assigned to a nonprofit subgroup which is then subsumed into our *other* blockholder group: “College/University,” “Foundation/Endowment,” “Foundation/Endowment Manager,” “Nonprofit Organization,” and “Government.” Finally, four 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 (of 33) Factset categories could be automatically assigned, the remaining 11 exhibited sufficient heterogeneity or ambiguity upon inspection that a manual coding was employed. In completing this coding, we consulted Web sites, 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, Web sites of the blockholder, Factiva news searches of the blockholder, and, finally, 13D/13G/proxy filings.

Of these 11 Factset groups, a set of six had a small number of blocks, aggregating to only 27 blockholders. Thus, we do not discuss the assignment of blocks within this set of six in detail, except to emphasize that we use the exact same criteria for manually assigning these blocks as we do for the remaining five Factset categories discussed in detail below. This set of six 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, 151 blocks had a missing blockholder type assignment by Factset that were all manually coded.

The remaining five 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 nonfinancial firm, the block was automatically assigned to the *public company* group. If the firm was a private nonfinancial 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 five 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 Web site 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 Web site as a private equity and venture capital fund focusing on specific industries. Another substantial subset of this Factset category represent nonfinancial *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 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

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***	-.020***	-.011***	-.066***	-.073***
		(.008)	(.004)	(.002)	(.008)	(.010)
Indiv unaff block dummy	.046***		-.012**	.000	-.007	-.068***
	(.014)		(.003)	(.003)	(.010)	(.012)
Public block dummy	-.093***	-.031***		.003	-.020	-.085***
	(.016)	(.010)		(.005)	(.013)	(.019)
Private block dummy	-.099***	-.001	.004		-.042***	-.097***
	(.018)	(.013)	(.008)		(.016)	(.023)
Strategic block dummy	-.070***	-.001	-.005*	-.005**		.039***
	(.009)	(.006)	(.003)	(.002)		(.008)
Financial block dummy	-.073***	-.034***	-.017***	-.013***	.048***	
	(.011)	(.007)	(.004)	(.003)	(.008)	
Sample rate of block presence	.275	.153	.057	.041	.250	.721

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

C. Predicting A blocks	Affil. indiv	Unaff. indiv.	Public co.	Private co.	Strat. invest.	Generic financial
Diagonal estimates, 10% blocks	-.031***	.000	-.001	-.001	.013***	-.017***
	(.004)	(.005)	(.003)	(.002)	(.004)	(.005)
Diagonal estimates, 15% blocks	-.021***	-.003	-.005***	-.001***	.005	-.001
	(.003)	(.003)	(.001)	(.000)	(.003)	(.005)

The reported coefficients are derived from logit models 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 latter two panels, the independent variable corresponding to the block type of the dependent variable is coded using information 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. Panels A and B are for models in which any 5% block is coded as a block. Panel C estimates models corresponding to panel B but requires that blocks be at least 10% (row 1 of the panel) or 15% (row 2 of the panel) in ownership position size. For brevity, Panel C only reports 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. **p* < .1; ***p* < .05; ****p* < .01.