Return Predictability Through Board Links*

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ABSTRACT

We find that investors fail to immediately account for information in past prices among firms with interconnected boards: a long-short portfolio, formed based on these links, yields an annual alpha of 6.5%. This predictability is limited to the period of the board link and not driven by industry or previously identified links. Investor inattention plays a key role: the predictability is concentrated among the largest firms, the long-end and in semi-private, hand-collected data on board links. Insider trading is a key mechanism: filtering on the trades of the linked director yields an annual alpha of 15%.

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Boards of directors influence firms both by exercising control rights and providing valuable information and advice to managers. Directors often sit on multiple boards, creating links among firms. Shared directors provide a common influence and channel for information diffusion across firms. In efficient markets, investors should quickly incorporate this shared influence across firms into prices, eliminating predictability among board-linked firms. We find, however, that a firm’s returns can be predicted by the prior returns of those firms with which they share a director.

Is it reasonable to expect sufficient commonality among board-linked firms to generate the comovement in returns necessary for return predictability? Extensive research has shown that board-linked firms tend to behave more similarly and experience similar events than non-linked firms behave and experience. Firms with linked boards are more likely to adopt similar governance structures such as poison pills (Davis, 1991; Davis and Greve, 1997). Board-linked firms are also more likely to adopt similar accounting techniques such as their choice of stock option expensing methods (Reppenhagen, 2010), willingness to backdate executive options (Bizjak, Lemmon, and Whitby, 2009) or use corporate life insurance tax shelters (Brown, 2011). Some of these more aggressive accounting techniques exemplify the general tendency of linked firms to engage in similar earnings management. This results in firms with shared directors to jointly be more likely to restate those earnings (Chiu, Teoh, and Tian, 2013). In the extreme case, a firm is more likely to be sued for fraud if one of its directors sits on the board of another firm that has been sued for fraud (Fich and Shivdasani, 2007).

Outside of governance and accounting practices, firms with linked boards share other common behaviors. They are more likely to make the switch from the NYSE to NASDAQ together (Rao, Davis, and Ward, 2000), thereby increasing their visibility and access to capital. Firms sharing directors also have similar acquisition patterns with acquisitions by one firm making the other board-linked firm more likely to make an acquisition (Haunschild,

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1For an overview of the influence of boards see the recent reviews by Hermelin and Weisbach (2003); Adams, Hermelin, and Weisbach (2010) and the references therein.
Moreover, board-linked firms pay similar premia for their targets (Haunschild, 1994). Board-linked firms are also more likely to be jointly acquired by private equity companies (Stuart and Yim, 2010) than non-linked firms.

These joint actions raise the question of what value effects exist for firms with shared directors? Researchers have studied the value effects of these common actions and reputational effects of similar governance with short window event studies. Ferris, Jagannathan, and Pritchard (2003) and Fich and Shivdasani (2006) use returns on board member appointments and departures to study the value effects of busy boards. Fich and Shivdasani (2007) uses the returns to linked firms on the announcement dates of fraud lawsuits against firms with shared directors as a measure of the reputational cost to allowing poor governance. For these returns to be accurate measures of the value effects due to actions at firms across the board network, investors must immediately and accurately update prices after such events. We ask the question, how quickly do investors incorporate the information about firms linked through shared directors?

We answer this question by using two sources of data to map the networks of firms with shared directors between 1996 and 2014. The first is the readily available “public” databases RiskMetrics and BoardEx. The second is a hand-collected database of directors obtained from mutual fund voting records filed with the SEC. Though technically publicly available, because it is less readily available, we call this a “semi-private” database.

After mapping the director network, we follow the methodology of Cohen and Frazzini (2008) and apply the correction of Burt and Hrdlicka (2016) to test for delayed price discovery among board links. We form a long-short trading strategy by sorting firms into quintiles each month based on the average of the prior month’s idiosyncratic returns of firms with which each firm shares at least one director. The five-factor alpha of the value weighted long-short portfolio is 6.5% per year. This alpha is both economically and statistically significant, indicating that investors process the common influences of linked boards into stock prices with a delay. Though we find a large effect with a delay of one month, the predictability
dissipates thereafter showing investors ultimately become aware of the relevant information in board links.

We find that this return predictability and, hence, delayed price discovery is concentrated among the largest firms and at the long end of the portfolio. Together, these findings suggest that investor inattention is important to this predictability, and trading frictions are not the sole source of the delayed price discovery.

Further evidence that investor inattention, rather than trading frictions, is responsible for the delayed price discovery comes in two forms. First, we find that predictability flows from small firms to big firms. In fact, there is almost no predictability flowing from big firms to small firms. Second, we find that when using only the public data on director links, return predictability is substantially muted. Including the semi-private, hand collected data on directors increases the predictability, as measured with alpha, by almost 50%.

The similar behavior among board-linked firms may come from three channels. First, common directors may transmit information across firms such as which management practices and actions should be taken to respond to the current economic environment. Second, firms with linked boards are more likely to share governance features (and failures) due to a common director’s experiences, predilections, or willingness to exert time and effort on governance. Third, links among firms’ boards may reveal more fundamental connections between the firms that make linked boards beneficial.

We attempt to distinguish among these channels by excluding from all results linked firms in the same industry and other economics link between firms. We exclude links that coincide with customer and suppliers relationships (Cohen and Frazzini, 2008), links between firms which are both part of the same strategic alliance (Cao, Chordia, and Lin, 2015), and firms with head quarters in the same MSA.\textsuperscript{2,3} Despite having removed these links, we find that

\textsuperscript{2}The predictability we find also appears to be different from that documented by Cao et al. (2015) among joint ventures because their predictability is concentrated among small firms while the predictability we find is concentrated among the largest firms.

\textsuperscript{3}Gulati and Westphal (1999) shows that a linked board affects the likelihood of a joint venture between the linked firms. However, whether this effect is positive or negative depends upon the ratio of insiders to outsiders on the board.
return predictability among board-linked firms remains.

To overcome the concern that shared directors proxy for another separate underlying economic link, we also perform an out-of-sample test using the links. Specifically, we form a sample of linked firms from shared directors 1-3 years before (after) a shared director link begins (ends). If the shared director is a proxy for another underlying economic link unrelated to the director, we expect to find that these out-of-sample links should yield similar return predictability. However, we find just the opposite. Using the out-of-sample links from 1-3 years before and after a link exists, we find the return predictability becomes economically small and statistically insignificant. If we use the sample period of 2-4 years before (after) a shared director link begins (ends), we find the economic magnitude decays further. Thus, the shared director links yield return predictability among firms.

We investigate the mechanism driving the observed predictability. We rule out the intra-industry effect documented by Hou (2007) and the big to small firm information flow of Lo and MacKinlay (1990). Given the predictability is in the long end of the portfolio and we are investigating predictability of firms linked by insiders we consider the mechanism of these insiders trades. Filtering on trades of the linked board members we find the return predictability increases giving a five-factor model long-short alpha of 15% per year.

Overall, the predictability provides further evidence of investor inattention, especially to small firms whose board are poorly covered by commercially available databases. Moreover we present a variety of evidence that the predictability is driven by the presence of a shared director. The delayed incorporation of information regarding these board-linked firms into prices suggests that short-horizon event studies of boards’ value effects understate the true effects of corporate boards. Nevertheless, the fact that returns of such linked firms move together, even with a delay, provides further evidence that the common actions of boards, even just one director, have important value effects on firms.
I. Data

We identify firms which share at least one director and use these board links to test for return predictability. Our data on directors comes from three primary sources. For two of our sources, we use the relatively public and easily accessible databases, RiskMetrics and BoardEx. The RiskMetrics Directors Database tracks the directors of S&P 1500 firms annually for the years 1996 to 2014. For the years 1999 and earlier, RiskMetrics includes director information for some additional firms beyond the S&P1500. BoardEx includes annual information on boards of directors for the years 2000-2015, including some firms which are not in the S&P 1500. The BoardEx and RiskMetrics database use differing unique identifiers for each unique director. We hand-match directors across the databases on their name, year of service and firm to obtain the unique number of shared directors per firm. Combining the databases provides coverage of over 2000 firms. Our sample is the set of these firms which share at least one director with another firm. Given the ease of accessibility to this data, we refer to this sample as our “public” sample.

For our third source, we supplement the public sample with hand-collected data on directors from Mutual Fund’s SEC filings on director elections. Mutual Funds are required to file a Form N-PX annually regarding their votes on each proxy statement proposal for each firm the mutual fund holds. This voting data includes votes cast for or against directors up for election and is available for download starting in 2002 on the SEC Edgar website. Using two general assumptions, we construct a second sample of firms which share at least one director with another firm. First, we assume that a director who is up for election is elected. Second, if a director appears in the data for a given firm in any two non-consecutive years, we assume the director was an active director in the years omitted. Both of these assumptions could potentially inflate the number of board connections and the average length of time for which two firms are connected. However, in our case, the misidentification of connected boards would only induce noise in our sample, and hence, bias our findings downward. To identify the firms with connected boards, we use a fuzzy matching process on director
names. The fuzzy matching leads to noise in our identification of the board links, but this also would only bias our findings downward. We exclude any firm-to-firm overlaps with our public sample. Although the mutual fund voting data is public, given that it is less easily accessible than the directors data in our public sample, we refer to the board links derived from this data as our “semi-private” sample.

We combine our public and semi-private sample into a “full” sample. We use this sample for most of our analysis throughout the paper. Two firms are considered linked at the end of each calendar year in which a director is active. We define a director as active for the first time after the first annual report following the election of a director. We combine monthly returns from CRSP with our full sample of board-linked stocks to test for slow price discovery following the methodology of Cohen and Frazzini (2008) with the correction of Burt and Hrdlicka (2016). We limit our data to common stocks (share codes 10 and 11) traded on the NYSE, AMEX and NASDAQ. We also exclude utilities and financial firms from the predicted side of the link.

Table I provides summary statistics for our sample at the end of each calendar year for the years 1997-2015. Panel A shows that the full sample covers, on average, 92% of the total market capitalization of the CRSP universe each year. This accounts for approximately 2,055 firms per year, which is 45%, on average, of the total common stocks in the CRSP Universe of firms. In later years, the number of firms in the total sample grows due to the additional data from the semi-private sample. Hence the maximum number of firms is 2,632 firms in a given year. Over our entire sample, the mean firm size percentile (based on NYSE percentiles) is 0.48 while the average firm book-to-market percentile is 0.46. For a given firm in our sample, the median firm is linked to 3 other firms.\footnote{Due to the fuzzy match a few firms end up with many matches due to common director names. This noise in our links biases us against finding anything.}

Panels B provides an overview of the public portion of our sample. The mean annual number of firms between the years 1997 and 2014 is 1,491, which represents approximately 34% of the total number of common stocks traded in the NYSE, AMEX, NASDAQ. Risk-
Table I Summary Statistics  This table shows summary statistics as of December of each year. Panel A includes an summary of the overall sample. Panel B provides an overview of the public sample, which is all board links identified based on directors listed in the RiskMetrics and BoardEx Databases for the years 1997-2015. Panel C summarizes the board links based on the unique set of firms with shared directors added to the overall sample through hand-collection from mutual fund voting records. This sample is summarized before removing links overlapping with the public sample. Percent coverage of CRSP Universe (EW) is the number of stocks with a valid board link to one or more firms divided by the total number of CRSP stocks. Percent coverage of CRSP Universe (VW) is the total market capitalization of stocks with a valid board link to one or more firms divided by the total market value of all CRSP stocks. Book-to-market is the Compustat book value of equity divided by the market value of equity. Size is the firm’s market value of equity. Book-to-market and size percentiles are based on the percentile rankings of NYSE stocks only. Number of unique links per firm is the number of stocks with a valid board link connected to a firm, regardless of the number of shared directors in each link.

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<td>Number of firms in the sample each year</td>
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<td>Full sample % coverage of CRSP Universe (EW)</td>
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<td>Full sample % coverage of CRSP Universe (VW)</td>
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<td>Firm size percentile (NYSE)</td>
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<td>Firm book to market percentile (NYSE)</td>
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<td>Number of Unique Links Per Firm</td>
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<th>Panel B: Public Sample (18 Yearly Observations, 1997 - 2015)</th>
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<td>Number of firms in the sample each year</td>
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<td>Full sample % coverage of CRSP Universe (EW)</td>
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<td>Full sample % coverage of CRSP Universe (VW)</td>
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<td>Firm size percentile (NYSE)</td>
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<td>Firm book to market percentile (NYSE)</td>
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<td>Number of Unique Links Per Firm</td>
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<th>Panel C: Semi-Private Sample - Unique Firms (11 Yearly Observations, 2004 - 2015)</th>
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<td>Number of firms in the sample each year</td>
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<td>Full sample % coverage of CRSP Universe (EW)</td>
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<td>Full sample % coverage of CRSP Universe (VW)</td>
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<td>Firm size percentile (NYSE)</td>
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<td>Firm book to market percentile (NYSE)</td>
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<td>Number of Unique Links Per Firm</td>
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Metrics data set consists of S&P 1500 firms, while BoardEx contributes some additional firms outside the S&P 1500. RiskMetrics’ focus on S&P 1500 firms means that fewer smaller firms are included in our sample. Thus, the public sample represents only 31% of the total number of firms in the CRSP universe each year, but comprises 88.9% of the total market capitalization of common stocks in the CRSP universe. Firms in the public sample tend to be bigger than those in the overall sample. The average firm size percentile based 0.57 and the average book-to-market percentile is 0.45. These firms also have a higher number of unique links due to shared directors than the full sample of firms, with an average number of unique links of 4.67 and a median of 4.

Panels C provides an overview of the semi-private portion of our sample. The hand-collected data comes from votes cast in most funds owned by Fidelity, Vanguard and Dimensional Fund Advisors. Thus, it includes both large firms and small firms. We show the summary statistics for only the unique firms identified through the hand-collection process. The mean annual number of firms between the years 1997 and 2015 is 728, which represents approximately 18% of the total number of common stocks traded in the NYSE, AMEX, NASDAQ. In contrast to the public sample, however, the firms in the semi-private sample are considerably smaller. Thus, the semi-private sample represents 2.3% of the total market capitalization of the CRSP universe. Firms in the semi-private sample have a mean firm size percentile of 0.16 compared to the mean size percentile of 0.48 in the public sample. The average book-to-market percentile of the semi-private sample is 0.51. The number of unique links per firm is also less for the semi-private sample. With a median of 2 links per firm, small firms in the semi-private sample appear to have about half as many unique board links than firms in the public sample.
II. Predictable Returns

If markets are efficient prices, should respond quickly to relevant news events. However, identifying ex-ante relevant news events is difficult, especially once one moves beyond the largest of firm events. Economically linked firms present an opportunity to exploit financial markets’ impounding of relevant news, visible via returns, as proxy for relevant news at the related firms. This allows the study of the effect of the continuous flow of often small or not directly observable news events into market prices.

We follow the methodology of detecting slow price discovery among economically linked firm originated by Cohen and Frazzini (2008); Menzly and Ozbas (2004, 2010) and refined by Burt and Hrdlicka (2016). For each firm in our sample at each month, \( t \), we form an equal-weighted portfolio of the prior period’s, \( t - 1 \), idiosyncratic shocks to each firm with which our first firm is linked via common directors. We refer to this portfolio of idiosyncratic shocks as the board-links return (\( BLRET \)). We then sort firms into quintile portfolios at time \( t \) based on this board-links return. We consider these quintile portfolios both value-weighted and equal-weighted rebalancing them monthly. Our key statistic of interest is the five-factor alpha of the long-short portfolio of the extreme quintiles (Fama and French, 1993, 1996; Carhart, 1997; Pástor and Stambaugh, 2003). As shown in Burt and Hrdlicka (2016) positive alphas in this long-short portfolio indicate slow price discovery.

The idiosyncratic shocks used in the sorting are calculated from a five-factor model rolling regression, estimated using one year of prior monthly data: \( t - 13 \) to \( t - 2 \). Idiosyncratic shocks, rather than excess returns, are used for the sorting to remove bias in the predictability due to shared model misspecification (correlated alphas) that would arise using excess returns. Additionally using show idiosyncratic shocks provides a more powerful test of delayed price discovery, improving the signal-to-noise ratio by eliminating noise from both model misspecification and common systematic shocks. (See Burt and Hrdlicka (2016) for an analysis of this methodology.)

To provide an opportunity for investors to learn of the firm links stemming from shared
directors, we impose a six-month gap between the end of the link observation year and portfolio formation. New links, as measured by shared directors at the end of the previous calendar year, come into use in July of each year and continue through the following June. To overcome potential micro-cap effects, we exclude all stocks whose previous month’s price was less than $5 from the side of the link being predicted. This methodology results in 216 monthly observations for five quintile portfolios.

Table II shows the alphas of five quintile portfolios (value- and equal-weighted) along with the long-short portfolio formed from quintiles 5 and 1. We see that, regardless of the asset pricing model used, the alpha of the value-weighted long-short portfolio is highly economically and statistically significant. The five-factor alpha of the value-weighted long-short portfolio is 54 basis points per month or 6.5% per year. The equal-weighted alpha is essentially zero, so we focus on the more interesting value-weighted results for the remainder of the paper. This positive alpha indicates slow information diffusion.

The larger value-weighted alpha shows the predictability is stronger in the largest firms, which tend to be more liquid. Furthermore, the predictability is concentrated in the long end of the portfolio where short-selling constraints do not bind. The concentration of predictability in large firms and in the long end of the portfolio suggests that investor inattention or limited information processing drives the predictability rather than only trading frictions.

Though the alphas due to predictability from board links over one-month horizon are large, the additional predictability (alphas) becomes statistically insignificant thereafter. The subsequent disappearance of the predictability shows investors eventually respond to the relevant information contained in the returns of these linked firms. Importantly, investors need never become aware of the link or past idiosyncratic shocks to linked firms for this eventual price discovery. The information could come out through a separate channel, such as a news report specific to the firm slow to respond or that firm’s earnings announcement.

In the following sections we show that the link between firms through their shared director is responsible for this return predictability. And we demonstrate that this link is not simply
Table II Abnormal Returns of Board-Linked Sorted Portfolios, 1997-2015

This table shows monthly abnormal returns for value- (equal-) weighted portfolios of board-linked stocks. In month $t$ (returns at $t + 1$), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month $t$. The five portfolios are rebalanced monthly to maintain value- (equal-) weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using the selected asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pastor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1 (Low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5 (High)</th>
<th>L/S</th>
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<tbody>
<tr>
<td>Excess Returns</td>
<td>0.407</td>
<td>0.638</td>
<td>0.588</td>
<td>0.386</td>
<td>0.989</td>
<td>0.581</td>
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<tr>
<td></td>
<td>(1.005)</td>
<td>(2.001)</td>
<td>(2.017)</td>
<td>(1.225)</td>
<td>(2.311)</td>
<td>(2.722)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>-0.189</td>
<td>0.155</td>
<td>0.149</td>
<td>-0.095</td>
<td>0.371</td>
<td>0.560</td>
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<td></td>
<td>(-1.210)</td>
<td>(1.576)</td>
<td>(1.569)</td>
<td>(-1.042)</td>
<td>(2.039)</td>
<td>(2.604)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>-0.153</td>
<td>0.184</td>
<td>0.172</td>
<td>-0.088</td>
<td>0.428</td>
<td>0.581</td>
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<td></td>
<td>(-1.071)</td>
<td>(1.907)</td>
<td>(2.052)</td>
<td>(-0.969)</td>
<td>(2.522)</td>
<td>(2.672)</td>
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<tr>
<td>4-Factor Alpha</td>
<td>-0.118</td>
<td>0.184</td>
<td>0.183</td>
<td>-0.122</td>
<td>0.474</td>
<td>0.592</td>
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<td>(-0.825)</td>
<td>(1.887)</td>
<td>(2.173)</td>
<td>(-1.373)</td>
<td>(2.801)</td>
<td>(2.698)</td>
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<tr>
<td>5-Factor Alpha</td>
<td>-0.110</td>
<td>0.146</td>
<td>0.166</td>
<td>-0.123</td>
<td>0.440</td>
<td>0.550</td>
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<td></td>
<td>(-0.754)</td>
<td>(1.487)</td>
<td>(1.945)</td>
<td>(-1.350)</td>
<td>(2.561)</td>
<td>(2.468)</td>
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<tr>
<th>Equal Weights</th>
<th>Q1 (Low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5 (High)</th>
<th>L/S</th>
</tr>
</thead>
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<tr>
<td>Excess Returns</td>
<td>0.819</td>
<td>0.801</td>
<td>0.836</td>
<td>0.855</td>
<td>0.960</td>
<td>0.141</td>
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<td></td>
<td>(1.907)</td>
<td>(2.072)</td>
<td>(2.218)</td>
<td>(2.249)</td>
<td>(2.243)</td>
<td>(1.268)</td>
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<tr>
<td>1-Factor Alpha</td>
<td>0.202</td>
<td>0.246</td>
<td>0.295</td>
<td>0.307</td>
<td>0.348</td>
<td>0.146</td>
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<td></td>
<td>(1.081)</td>
<td>(1.463)</td>
<td>(1.793)</td>
<td>(1.881)</td>
<td>(1.834)</td>
<td>(1.300)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>0.004</td>
<td>0.043</td>
<td>0.098</td>
<td>0.102</td>
<td>0.138</td>
<td>0.133</td>
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<td></td>
<td>(0.032)</td>
<td>(0.342)</td>
<td>(0.792)</td>
<td>(0.882)</td>
<td>(1.037)</td>
<td>(1.175)</td>
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<tr>
<td>4-Factor Alpha</td>
<td>0.116</td>
<td>0.130</td>
<td>0.183</td>
<td>0.172</td>
<td>0.225</td>
<td>0.109</td>
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<tr>
<td></td>
<td>(0.956)</td>
<td>(1.122)</td>
<td>(1.587)</td>
<td>(1.561)</td>
<td>(1.807)</td>
<td>(0.957)</td>
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<tr>
<td>5-Factor Alpha</td>
<td>0.045</td>
<td>0.035</td>
<td>0.095</td>
<td>0.068</td>
<td>0.162</td>
<td>0.117</td>
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<td></td>
<td>(0.375)</td>
<td>(0.317)</td>
<td>(0.854)</td>
<td>(0.653)</td>
<td>(1.305)</td>
<td>(1.011)</td>
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proxying for other previously identified relationships between firms. We then provide further
evidence that investor inattention is responsible for the slow information diffusion. Finally
we investigate the mechanism by which information about the linked firms originally enters
the market, finding trading by insiders is one important channel. This connection to insider
trading provides further identification that the link between the firms is indeed due to the
shared directors.

III. Robustness and Identification

Though two firms sharing a common director is a good summary statistics for a relation-
ship between the two firms, we now establish that such a link provides a measure of similarity
between firms over and above previously identified measures. Moreover, we argue that the
return predictability found in our main result is at least in part due to similar actions or
experiences among firms with shared directors due to the influence of the shared directors.

We employ three approaches in an attempt to distinguish the channels of general firm
similarity and the influence of directors. First, we exclude firms linked by directors that are
also in the same industry. Second, we exclude firms also linked by previously documented
economic links. Third, we show that the return predictability is limited to the time period
of the director link.

In Table III we show the predictability obtained when we exclude linked firms in the
same industry. Using 3 or 4-digit SIC codes as our industry measure we obtain virtually
identical results to our main specification: statistically significant five-factor monthly alphas
56 and 50 bps. Even excluding linked firms that share the same industry at the very coarse
2-digit SIC level, we still obtain statistically significant 42bps per month alpha.

In the last three columns of Table III we exclude firms linked at the industry level (3-digit
SIC) and firms linked by the customer-supplier relationships, strategic alliances or that share
the same MSA. We obtain the customer-supplier links network by following the method of
Cohen and Frazzini (2008) to replicate their network and extend the link relationships to the present. We find economically and statistically significant five-factor alphas for the long-short portfolio of 53 bps per month or 6.4% per year. Excluding firms linked by alliances as identified in Cao et al. (2015) we again find that the five-factor alphas for the long-short portfolios remain economically large and statistically significant: 51 bps per month. The reason for such small differences from excluding these sets of links is that there is little overlap between firms with shared directors and firms with customer-supplier relationships and alliances.

One might hypothesize that firms share director because they have similar location and thus the director link simply picks up common exposure to local economic variables. To show that such local effects do not drive our results we exclude linked firms with headquarters in the same MSA. We continue to find an economically and statistically significant alpha of 43 bps per month or 5.2% per year.

As an alternative test of whether the return predictability is due to the influence of the shared directors or simply similar firms sharing directors, we look at return predictability in the period before the link begins and after the link ends. Table IV reports the long-short alpha derived based on quintile portfolios formed by using out-of-sample director-linked firms. We first link firms one to three years before or after (or combined) the periods in which the firms share a director. In comparison to the statistically significant in-sample alpha of 54 basis points, we find that the five-factor alpha of the value-weighted long-short portfolio using the out-of-sample links is neither economically and nor statistically. It is -5 bps per month in the one to three years before the link begins and 11 bps per month in the one to three years after the link ends. Even combining the before and after periods to improve the power or consider the sample window two to four years before and after, we continue to find no evidence return predictability.

That predictability among firms with shared directors occurs only when the shared director link exists, suggests that the commonality among these firms flows through the director.
Table III Robustness: Abnormal Board-Linked Stock Returns Excluding Commonly Known Economic Links, 1997-2015

This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks. In month \( t \) (returns at \( t + 1 \)), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month \( t \). The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003). The alphas of the portfolios that are long the highest quintile and short the lowest quintile are shown below. Each column excludes links which are commonly known or previously documented. The first column is the main result from Table II. The next 3 columns exclude all board-linked stocks in the same industries identified by SIC-2, SIC-3 or SIC-4 codes. The “Customer-Supplier” column excludes board-linked stocks that are also customer-supplier links identified in Cohen and Frazzini (2008) and extended to 2015. The “Alliances” column excludes board-linked stocks that are in the same alliance as identified by Cao et al. (2015). The “Same MSA” column excludes board-linked stocks of firms with headquarters in the same census-defined metropolitan statistical area (MSA). Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Main Result</th>
<th>Industry SIC-4</th>
<th>Industry SIC-3</th>
<th>Industry SIC-2</th>
<th>Customer-Supplier</th>
<th>Alliance Member</th>
<th>Same MSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.581</td>
<td>0.454</td>
<td>0.564</td>
<td>0.423</td>
<td>0.537</td>
<td>0.491</td>
<td>0.456</td>
</tr>
<tr>
<td></td>
<td>(2.722)</td>
<td>(2.173)</td>
<td>(2.731)</td>
<td>(2.131)</td>
<td>(2.607)</td>
<td>(2.367)</td>
<td>(2.218)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>0.560</td>
<td>0.495</td>
<td>0.561</td>
<td>0.410</td>
<td>0.535</td>
<td>0.493</td>
<td>0.456</td>
</tr>
<tr>
<td></td>
<td>(2.604)</td>
<td>(2.365)</td>
<td>(2.695)</td>
<td>(2.052)</td>
<td>(2.573)</td>
<td>(2.356)</td>
<td>(2.198)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>0.581</td>
<td>0.486</td>
<td>0.579</td>
<td>0.431</td>
<td>0.553</td>
<td>0.520</td>
<td>0.472</td>
</tr>
<tr>
<td></td>
<td>(2.672)</td>
<td>(2.295)</td>
<td>(2.753)</td>
<td>(2.149)</td>
<td>(2.633)</td>
<td>(2.467)</td>
<td>(2.250)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>0.592</td>
<td>0.498</td>
<td>0.539</td>
<td>0.393</td>
<td>0.515</td>
<td>0.498</td>
<td>0.425</td>
</tr>
<tr>
<td></td>
<td>(2.968)</td>
<td>(2.327)</td>
<td>(2.552)</td>
<td>(1.950)</td>
<td>(2.440)</td>
<td>(2.341)</td>
<td>(2.022)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>0.550</td>
<td>0.499</td>
<td>0.556</td>
<td>0.415</td>
<td>0.531</td>
<td>0.507</td>
<td>0.427</td>
</tr>
<tr>
<td></td>
<td>(2.468)</td>
<td>(2.291)</td>
<td>(2.591)</td>
<td>(2.027)</td>
<td>(2.476)</td>
<td>(2.347)</td>
<td>(1.996)</td>
</tr>
</tbody>
</table>
This methodology cannot fully reject that shared directors do not indicate economic connections between firms other than that caused by the director. But for such other connections to be driving the predictability, they would have to vary in exactly the same points in time as the directors’ appointments.

Given these timing results and the results that other economic connections (Table III) do not explain our results suggests that the economic connection is driven by the common influence of directors on both firms. Combining these results with the fact that most links between firms are attributable to one director (see Table I), the extent of predictability we find suggests that even one director can wield significant influence on a firm. This is consistent with the findings a large literature on common actions and risk exposures among firms with shared directors.\(^5\)

### IV. Inattention to Costly Information

The return predictability we document in Table II is concentrated in the long-end of the value weighted portfolio. That there is an alpha due to return predictability available in a long only position for trades primarily in the largest most liquid firms (of S&P1500 firms) suggests investor inattention rather than trading frictions is responsible. To further explore the extent to which investor inattention plays a role in the return predictability through board links, we decompose this predictability into that attributable to different information sets about shared directors. These information sets are constructed to vary in the degree to which they are publicly available and readily accessible.

Our overall sample of board links comes from two sources. Our first data source is the director databases: RiskMetrics and BoardEx. Though these databases are available for a fee, they are both widely accessed databases. Moreover they are easy to use and covers the largest most actively followed firms in the market, primarily S&P1500 firms. Finally, these

\(^5\)See for example Davis (1991); Haunschild (1993, 1994); Davis and Greve (1997); Rao et al. (2000); Fich and Shivdasani (2007); Bizjak et al. (2009); Reppenhagen (2010); Stuart and Yim (2010); Brown (2011); Chiu et al. (2013).
This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks. We use only the returns that are 1-3 (2-4) years before and after a link exists, creating an out-of-sample test. Using these out-of-sample links, in month $t$ (returns at $t + 1$), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director. The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pastor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

<table>
<thead>
<tr>
<th>Link Timing</th>
<th>Value Weights</th>
<th>1-3 years</th>
<th>2-4 years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main Result</td>
<td>Before</td>
<td>After</td>
</tr>
<tr>
<td>Excess Returns</td>
<td>0.581 (-0.265)</td>
<td>0.165 (0.677)</td>
<td>0.058 (0.300)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>0.560 (-0.136)</td>
<td>0.192 (0.786)</td>
<td>0.112 (0.572)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>0.581 (-0.273)</td>
<td>0.192 (0.784)</td>
<td>0.102 (0.517)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>0.592 (-0.240)</td>
<td>0.157 (0.640)</td>
<td>0.087 (0.433)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>0.550 (-0.253)</td>
<td>0.131 (0.524)</td>
<td>0.108 (0.531)</td>
</tr>
</tbody>
</table>

databases provide unique director ids that make matching director across firms and therefore discovering which firms are linked easy even for a relatively unsophisticated investor. For these reasons of easy and pervasive access we label this as public data.

Our second data source consists of hand collected data on firm directors. We collect this data from mutual funds’ director voting records filed with the SEC. This second source, while technically publicly available, is much less readily usable. It requires text conversion from PDF files to identify the director up for election at each firm. This data only contains votes cast at particular dates, and therefore requires careful analysis of feasible director terms to establish when a director is likely in office. Moreover these filings only provide director names only without unique director ids. The absence of these ids requires and additional step of hand matching with both firm directors collected from this source and with those directors

17
in our first data source. Finally, this data covers firms not in the publicly available databases and, therefore, it consists primarily of small firms with likely smaller investor followings.\textsuperscript{6} We see small firm makeup from Table I where the new firms identified through this hand collected database represent on average across years 18\% of the CRSP universe by count but only 2\% by market cap. Due to the difficulty of its collection, the steps required to make it usable and focus on small firms, we refer to it as semi-private data.

If investor inattention, even rational inattention, is important to the return predictability, we would expect to see a larger-long short portfolio alpha in the portfolio constructed using the combined public and semi-private databases compared to the alpha from the trading strategy constructed using only the publicly available data. Table V shows the alpha available using only the publicly available data along with the alpha when the public data is combined with the semi-private data (also in Table II). We see that using only the public data there is an economically significant long-short alpha of 38 bps per month, though it is only statistically significant at the 10\% level. Again this alpha is concentrated in the long-end of the portfolio, consistent with investor inattention.

In the last column, we see by adding the semi-private data, the long-short alpha increases to 55 bps per month, a nearly 50\% increase in the amount of return predictability. Thus it appears that investors are relatively more (though not completely) attentive to easily accessible public data that has been processed into usable databases. However, investors are relatively less attentive to data that, while technically public, is much less readily accessible.

That this semi-private data covers small firms, but the predictability occurs in the value weighted portfolio, shows investors are inattentive to signals originating in small poorly followed firms that could be used to trade in large liquid firms. That we find this result in our noisy semi-private data is even more suggestive.\textsuperscript{7} All these findings combined point to investor inattention as playing an important role in the delayed price discovery we document.\textsuperscript{6}

\textsuperscript{6}The director voting records include both large and small firms. However, we only include in this second source of data those firms not included in the publicly available databases.

\textsuperscript{7}The data is noisy due to both the hand matching of directors by name and because only probable rather than exact director terms are available via this data source.
Table V Abnormal Board-Linked Stock Returns Segmented on Public and Semi-Private Data

This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks. In month \( t \) (returns at \( t + 1 \)), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month \( t \). The column “Public” shows the results based on using data in RiskMetrics and BoardEx databases only. The column “Public + Semi-Private” includes all links in the Public set as well as hand-collected links described in the paper. The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1(Low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5(High)</th>
<th>Public</th>
<th>Public+Semi-Private</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.553</td>
<td>0.606</td>
<td>0.566</td>
<td>0.418</td>
<td>0.947</td>
<td>0.394</td>
<td>0.581</td>
</tr>
<tr>
<td></td>
<td>(1.367)</td>
<td>(1.906)</td>
<td>(1.956)</td>
<td>(1.318)</td>
<td>(2.306)</td>
<td>(1.848)</td>
<td>(2.722)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>-0.041</td>
<td>0.124</td>
<td>0.134</td>
<td>-0.066</td>
<td>0.354</td>
<td>0.395</td>
<td>0.560</td>
</tr>
<tr>
<td></td>
<td>(-0.257)</td>
<td>(1.265)</td>
<td>(1.326)</td>
<td>(-0.737)</td>
<td>(2.027)</td>
<td>(1.837)</td>
<td>(2.604)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>0.013</td>
<td>0.153</td>
<td>0.158</td>
<td>-0.048</td>
<td>0.420</td>
<td>0.407</td>
<td>0.581</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(1.577)</td>
<td>(1.786)</td>
<td>(-0.536)</td>
<td>(2.566)</td>
<td>(1.872)</td>
<td>(2.672)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>0.044</td>
<td>0.152</td>
<td>0.168</td>
<td>-0.060</td>
<td>0.439</td>
<td>0.394</td>
<td>0.592</td>
</tr>
<tr>
<td></td>
<td>(0.305)</td>
<td>(1.557)</td>
<td>(1.887)</td>
<td>(-0.663)</td>
<td>(2.659)</td>
<td>(1.796)</td>
<td>(2.698)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>0.050</td>
<td>0.122</td>
<td>0.149</td>
<td>-0.058</td>
<td>0.429</td>
<td>0.380</td>
<td>0.550</td>
</tr>
<tr>
<td></td>
<td>(0.335)</td>
<td>(1.233)</td>
<td>(1.650)</td>
<td>(-0.632)</td>
<td>(2.559)</td>
<td>(1.701)</td>
<td>(2.468)</td>
</tr>
</tbody>
</table>
Although not conclusive proof of causality, seeing that the amount of return predictability varies with the publicity of the director links between firms also provides further evidence that the return predictability flows through the director channel. If the shared directors were simply proxying for another link between the firms, the publicity of such a link would need not vary exactly with the publicity of the director link. And thus, we would not expect to see variation in the predictability of returns based on the publicity of the director link.

V. Mechanism

We now investigate possible mechanisms for the observed return predictability. We have already shown in Table III that the predictability we document is not driven by the inter-industry predictability documented in Hou (2007). We next check whether it originates from big firms leading small firms as documented by Lo and MacKinlay (1990).

In Table VI we split the sample based on firm size. In Panel A we look at the ability of large firms to predict small firms by only including predictor firms (firms used for sorting) that are smaller than the predicted firms. We see there is no economically or statistically significant predictability as the five-factor long-short alpha is only 19 bps per month. This lack of predictability is not due to simply spitting our sample. In Panel B we only include predictor firms smaller than the predicted firms. We find an economically significant predictability of 44 bps per month which is significant at the 10% level. This predictability is only slightly smaller than that in the full sample showing that predictability is driven by small firms predicting big firms. Thus contrary to previously documented predictability this predictability does not flow from large firms to small firms.

A natural mechanism to investigate as the source of return predictability across firms with linked directors is the trading behavior of firm insiders. This is a particularly plausible mechanism given our findings of return predictability concentrated in the long end of the portfolio. Though return predictability could arise in several ways from insiders’ attempts
Table VI Abnormal Board-Linked Stock Returns Segmented on Linked Firms’ Relative Sizes

This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks. In month $t$ (returns at $t+1$), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month $t$. Panel A only includes predictor firms in the sorting portfolio that are larger than the predicted firm. Panel B only includes predictor firms in the sorting portfolio that are smaller than the predicted firm. The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

**Panel A: Big-to-Small.**

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1 (Low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5 (High)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.594</td>
<td>0.566</td>
<td>0.556</td>
<td>0.544</td>
<td>0.757</td>
<td>0.162</td>
</tr>
<tr>
<td></td>
<td>(1.669)</td>
<td>(1.800)</td>
<td>(1.728)</td>
<td>(1.709)</td>
<td>(2.178)</td>
<td>(0.828)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>0.066</td>
<td>0.099</td>
<td>0.078</td>
<td>0.080</td>
<td>0.253</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td>(0.507)</td>
<td>(0.867)</td>
<td>(0.667)</td>
<td>(0.620)</td>
<td>(1.752)</td>
<td>(0.946)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>0.058</td>
<td>0.057</td>
<td>0.056</td>
<td>0.010</td>
<td>0.241</td>
<td>0.184</td>
</tr>
<tr>
<td></td>
<td>(0.437)</td>
<td>(0.519)</td>
<td>(0.494)</td>
<td>(0.086)</td>
<td>(1.654)</td>
<td>(0.921)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>0.081</td>
<td>0.055</td>
<td>0.095</td>
<td>0.039</td>
<td>0.275</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>(0.610)</td>
<td>(0.498)</td>
<td>(0.850)</td>
<td>(0.331)</td>
<td>(1.884)</td>
<td>(0.965)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>0.059</td>
<td>0.038</td>
<td>0.056</td>
<td>-0.028</td>
<td>0.251</td>
<td>0.193</td>
</tr>
<tr>
<td></td>
<td>(0.437)</td>
<td>(0.341)</td>
<td>(0.492)</td>
<td>(-0.242)</td>
<td>(1.694)</td>
<td>(0.940)</td>
</tr>
</tbody>
</table>

**Panel B: Small-to-Big.**

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1 (Low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5 (High)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.624</td>
<td>0.544</td>
<td>0.477</td>
<td>0.957</td>
<td>0.427</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.304)</td>
<td>(1.930)</td>
<td>(1.845)</td>
<td>(1.443)</td>
<td>(2.220)</td>
<td>(1.921)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>-0.068</td>
<td>0.137</td>
<td>0.107</td>
<td>-0.028</td>
<td>0.330</td>
<td>0.397</td>
</tr>
<tr>
<td></td>
<td>(-0.431)</td>
<td>(1.301)</td>
<td>(0.987)</td>
<td>(-0.306)</td>
<td>(1.867)</td>
<td>(1.779)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>-0.056</td>
<td>0.164</td>
<td>0.152</td>
<td>0.007</td>
<td>0.361</td>
<td>0.417</td>
</tr>
<tr>
<td></td>
<td>(-0.395)</td>
<td>(1.556)</td>
<td>(1.638)</td>
<td>(0.072)</td>
<td>(2.128)</td>
<td>(1.851)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>-0.032</td>
<td>0.162</td>
<td>0.165</td>
<td>-0.005</td>
<td>0.395</td>
<td>0.427</td>
</tr>
<tr>
<td></td>
<td>(-0.226)</td>
<td>(1.529)</td>
<td>(1.764)</td>
<td>(-0.056)</td>
<td>(2.320)</td>
<td>(1.878)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>-0.039</td>
<td>0.118</td>
<td>0.150</td>
<td>-0.008</td>
<td>0.406</td>
<td>0.445</td>
</tr>
<tr>
<td></td>
<td>(-0.269)</td>
<td>(1.105)</td>
<td>(1.576)</td>
<td>(-0.086)</td>
<td>(2.343)</td>
<td>(1.923)</td>
</tr>
</tbody>
</table>
to exploit their private information about the joint prospects of linked firms through opportunistic trading, in all cases insiders would have a preference for purchasing their own company stock: revealing good news and concentrating the predictability in the long-end of the portfolio. This preference for purchases rather than sells is driven by the differential liability and even prosecution probability for insider trading in each direction.

We consider three hypotheses about insider trading behavior. First, insiders could trade simultaneously in both linked firms. If the market is more aware of one trade than the other or the firms have different price impact then we would expect to see returns in the more closely watched/sensitive firm lead those in the other firm.

Our second hypothesis is that insiders might trade sequentially in linked firms as they become aware of the prospects of firms. For example if they trade in January in one firm and February in the second firm, we could see the returns of the first firm lead those of the second if either the market becomes sequentially aware of their trades or simply through the sequential timing of the price impact from these trades.

Our third hypothesis is that an insider might choose to trade in only one firm. They might choose this strategy if they have taken similar actions at both firms on which they are a director. If they learn about the outcome of that action earlier at one firm and expect the same outcome at the second firm, they may choose to trade in the second firm where they plausibly do not yet have material information.

All three hypotheses have the same implication: upon filtering the predictive signal on insider trading behavior, we should find a stronger predictability (larger long-short alpha) if insider trading is important. For this filtering we use only non-routine insider trades as defined by Cohen, Malloy, and Pomorski (2012). In Table VII we show the return predictability where we only retain firms in the first and fifth quintiles when the direction of the net-trades of insiders in the predicting firm at $t$ agree with the return of the quintile at $t$. That is we only keep firms in quintile one where insiders are selling and only keep firms in quintile five when insiders are buying. To make sure this is a tradable strategy we only use data on
insider trades that is publicly available through filings to the SEC by the of month $t$.

In Panel A we consider all board members’ trades under the hypothesis that the linked board member may share his or her knowledge either explicitly or inadvertently with fellow board members. We find under this filter, the five-factor model long-short alpha increases to 83 bps per month consistent with insider trading playing an important role. In Panel B we only consider the trades of the linked director to see if the information appears to originate with him or her. The return predictability increases further giving a long-short alpha of 93 bps per month or 11% annually. This confirms that the insider who sits on both boards is a key component in the return predictability, providing further identification that return predictability is not simply flowing through shared board membership serving as a general proxy of firm similarity. Finally, in both panels the predictability is primarily in the long end, consistent with insiders preferring to buy rather than sell when trading on potentially opportunistic information.

In Table VIII we show the number of firm month observations in the first and fifth quintiles for the full sample and after applying filters on all insider trades in agreement and only the linked insider trades in agreement with the portfolio assignment. We also list the five-factor long-short alpha for of each filter for comparison. By construction there is an equal number of observations in the full sample for the two quintiles. When we filter on either type of insider trading, we see that there are 60 percent more buy observations (Q5) than sell observations (Q1). This is consistent both with insiders preferring to buy rather than sell and our findings of the predictability concentration in the long-end of the portfolio. Comparing the two different insider trading filters, we see that the trades by the linked board member represent approximately 80% of the sample of all insider trades. This again confirms that it is the behavior of the linked director driving the predictability observed.

Given that we have established insider trading behavior is an important mechanism, we now attempt to differentiate among the three hypothesis by looking directly at the trading behavior in both of the linked firms. In Table IX we continue to restrict the sample to firms
Table VII Abnormal Board-Linked Stock Returns With Links Restricted to Insider Trades

This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks intersected with insider trades. In month $t$ (returns at $t + 1$), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month $t$. Panel A restricts the links to those stocks for which at least one of the linked stocks has an opportunistic insider trade during month $t$. Panel B restricts the links to those stocks for which at least one of the linked stocks has a linked director’s opportunistic insider trade during month $t$. Insider trades are defined as opportunistic if the insider has not traded in the same month in any of the 3 years prior (Cohen et al., 2012). The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

**Panel A:** Board links restricted to having any opportunistic trades during month $t$ executed by any board member.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1(Low)</th>
<th>Q5(High)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.387</td>
<td>1.174</td>
<td>0.787</td>
</tr>
<tr>
<td></td>
<td>(0.812)</td>
<td>(2.663)</td>
<td>(2.142)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>-0.128</td>
<td>0.673</td>
<td>0.800</td>
</tr>
<tr>
<td></td>
<td>(-0.428)</td>
<td>(2.684)</td>
<td>(2.165)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>-0.162</td>
<td>0.674</td>
<td>0.837</td>
</tr>
<tr>
<td></td>
<td>(-0.551)</td>
<td>(2.686)</td>
<td>(2.242)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>-0.126</td>
<td>0.697</td>
<td>0.824</td>
</tr>
<tr>
<td></td>
<td>(-0.426)</td>
<td>(2.758)</td>
<td>(2.188)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>-0.179</td>
<td>0.654</td>
<td>0.834</td>
</tr>
<tr>
<td></td>
<td>(-0.597)</td>
<td>(2.553)</td>
<td>(2.180)</td>
</tr>
</tbody>
</table>

**Panel B:** Board links restricted to having any opportunistic trades during month $t$ executed by the linked director.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1(Low)</th>
<th>Q5(High)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td>0.283</td>
<td>1.131</td>
<td>0.848</td>
</tr>
<tr>
<td></td>
<td>(0.605)</td>
<td>(2.538)</td>
<td>(2.318)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td>-0.211</td>
<td>0.639</td>
<td>0.849</td>
</tr>
<tr>
<td></td>
<td>(-0.696)</td>
<td>(2.384)</td>
<td>(2.305)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td>-0.249</td>
<td>0.646</td>
<td>0.894</td>
</tr>
<tr>
<td></td>
<td>(-0.829)</td>
<td>(2.389)</td>
<td>(2.414)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td>-0.222</td>
<td>0.692</td>
<td>0.914</td>
</tr>
<tr>
<td></td>
<td>(-0.733)</td>
<td>(2.553)</td>
<td>(2.446)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td>-0.265</td>
<td>0.660</td>
<td>0.925</td>
</tr>
<tr>
<td></td>
<td>(-0.862)</td>
<td>(2.399)</td>
<td>(2.436)</td>
</tr>
</tbody>
</table>
Table VIII Number of Observations of Agreeing Insider Trades  This table shows the number of firms months in first and fifth quintile portfolios for the full sample and two samples filtered on the presence of trades by insiders at the predicting firms. The last column shows the five-factor model long-short alpha from the value weight portfolio associated with the trading strategy formed using each sample. The first insider trading filter includes only firm months where the direction of any board member’s trading at the predicting firm agrees with the quintile portfolio. That is the board member is selling the predicting firm’s shares when it falls in the first quintile or is buying the predicting firm’s shares when it falls in the fifth quintile. The second insider trading filter includes only firm months where the direction of the linked board member’s trading at the predicting firm agrees with the quintile portfolio. That is the linked board member is selling the predicting firm’s shares when it falls in the first quintile or is buying the predicting firm’s shares when it falls in the fifth quintile.

<table>
<thead>
<tr>
<th></th>
<th>Q1 (low)</th>
<th>Q5 (High)</th>
<th>L/S Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Sample</td>
<td>58,688</td>
<td>58,520</td>
<td>0.550</td>
</tr>
<tr>
<td>Insiders Agree</td>
<td>7,754</td>
<td>12,670</td>
<td>0.834</td>
</tr>
<tr>
<td>Linked Directors Agree</td>
<td>6,570</td>
<td>10,328</td>
<td>0.925</td>
</tr>
</tbody>
</table>

in which insiders in predictor firm have trades at t that agree with the quintile portfolio assignment. For each of these quintiles we tabulate how insiders trade at predicted (lagging) firm contemporaneously (t) and in the following period (t + 1). In Panel A we consider the trades of any board member, and in Panel B we consider only the trades of the linked board member.

If insiders trade simultaneously across both firms we would expect to see a large percentage of the trades in the upper-left and lower-right corners of the table for the time t trades. Across both panels, we see a slight agreement in the trades comparing across the buys and sells but the effect is economically tiny. This is evidence against the first hypothesis. If insiders were trading first in the predicting firms and in the predicted firms in the following period we would expect a large percentage of trades in the upper-left and bottom-right of the time t + 1 table. Again across both panels we see only a slight agreement, which is evidence against the second hypothesis.

Instead we see evidence for the third hypothesis that insiders are trading only in the predicting firm. Across both quintiles, both panels and both dates (t or t + 1) 85% of the time there is a trade in the predicting firm, we see no trade in the predicted firm. This
Table IX Opportunistic Insider Transactions Among Board-Linked Stocks This table shows the percentage of opportunistic trades by insiders for board-linked stocks in the Q1(low) and Q5 (high) quintiles. The opportunistic transactions for the leading (A) firms occur during month $t$. The opportunistic transactions for the lagging (B) firms during months $t$ and $t+1$ are shown below. Panel A restricts the links to those stocks for which at least one of the linked stocks has an opportunistic insider trade during month $t$. Panel B restricts the links to those stocks for which at least one of the linked stocks has a linked director’s opportunistic insider trade during month $t$. Insider trades are defined as opportunistic if the insider has not traded in the same month in any of the 3 years prior (Cohen et al., 2012). All numbers shown are in percentage points.

**Panel A**: Board links restricted to having any opportunistic trades during month $t$ or $t+1$ executed by any board member.

<table>
<thead>
<tr>
<th>Portfolio Number</th>
<th>Trade in leading (A) stock during month $t$</th>
<th>Trade in lagging (B) stock during month $t$</th>
<th>Trade in lagging (B) stock during month $t+1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Sell None Buy</td>
<td>Sell None Buy</td>
</tr>
<tr>
<td>Q1 (Low)</td>
<td>Sell</td>
<td>6.94 83.73 9.34</td>
<td>6.50 85.00 8.50</td>
</tr>
<tr>
<td>Q5 (High)</td>
<td>Buy</td>
<td>6.27 82.71 11.02</td>
<td>5.99 84.53 9.48</td>
</tr>
</tbody>
</table>

**Panel B**: Board links restricted to having any opportunistic trades during month $t$ or $t+1$ executed by the linked director.

<table>
<thead>
<tr>
<th>Portfolio Number</th>
<th>Trade in leading (A) stock during month $t$</th>
<th>Trade in lagging (B) stock at $t$</th>
<th>Trade in lagging (B) stock at $t$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Sell None Buy</td>
<td>Sell None Buy</td>
</tr>
<tr>
<td>Q1 (Low)</td>
<td>Sell</td>
<td>6.39 85.41 8.21</td>
<td>5.89 86.83 7.29</td>
</tr>
<tr>
<td>Q5 (High)</td>
<td>Buy</td>
<td>5.51 84.78 9.72</td>
<td>5.49 86.21 8.30</td>
</tr>
</tbody>
</table>
suggests that the linked board members are trading in one firm based on information they have in the other firm on whose board they sit.

One might suspect that the linked board members would vary the intensity of their opportunistic trading with either the strength of their information or confidence in it. To test this hypothesis we restrict the firms included in the quintiles to those where the linked board members trades at the predicting firm fall in the most extreme quintile of trades that agree with the assigned quintile. That is in the first quintile we only keep firms where insiders net-trades (e.g., sales) fell in the bottom quintile of all board members trades in that quintile.

Table X shows the return predictability that results from this filter. For the first time, we find a strong negative alpha in the short-end of the portfolio. This suggests that while the majority of the time insiders prefer to make opportunistic purchases they are willing to make opportunistic sales when they have an extreme signal. Overall, we find a five-factor long-short portfolio alpha of 125 bps per month or 15% annually. This suggests that insiders do vary the intensity of their trades based on the strength of their cross-firm information.

VI. Conclusion

Firms which share common directors exhibit similar behavior including adopting common governance structures, accounting methods and acquisition premiums. Such linked firms also experience common events such as lawsuits for fraud or being targeted for private equity takeovers. We show that investors fail to immediately incorporate into share prices the information from experiences of firms linked by common directors. Sorting firms based on the lagged idiosyncratic shocks experienced by firms with which they share a director, we form a long-short trading strategy that generates an alpha of over 6.5% per year. We present a variety of evidence to show that the link of between the firms formed by the shared director is key to this predictability. This evidence culminates with our finding that the return
Table X Abnormal Board-Linked Stock Returns With Links Restricted to Extreme Insider Trades

This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks intersected with extreme insider trades. In month $t$ (returns at $t+1$), stocks are assigned to one of five portfolios based on the equal-weighted portfolio of the five-factor model’s idiosyncratic returns of all stocks with which the firm shares at least one director in month $t$. Within each portfolio, stocks are ranked in five quintiles based on the linked stocks’ opportunistic insider trades during month $t$. In the Q1 (low) portfolio, stocks are retained only if one of its linked stocks has an opportunistic trade (sell) in the lowest quintile of insider trades. In the Q5 (high) portfolio, stocks are retained only if one of its linked stocks has an opportunistic trade (buy) in the highest quintile of insider trades. Insider trades are defined as opportunistic if the insider has not traded in the same month in any of the 3 years prior (Cohen et al., 2012). The five portfolios are rebalanced monthly to maintain value-weighting. Alpha is the intercept on a regression of the monthly excess return for the portfolio using various asset pricing models. The models include the CAPM 1-factor model, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003). L/S is the alpha of a portfolio that is long the highest quintile and short the lowest quintile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

<table>
<thead>
<tr>
<th>Value Weights</th>
<th>Q1(Low)</th>
<th>Q5(High)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns</td>
<td></td>
<td>-0.146</td>
<td>1.144</td>
</tr>
<tr>
<td></td>
<td>($-0.294$)</td>
<td>(2.005)</td>
<td>(2.539)</td>
</tr>
<tr>
<td>1-Factor Alpha</td>
<td></td>
<td>-0.647</td>
<td>0.576</td>
</tr>
<tr>
<td></td>
<td>($-1.910$)</td>
<td>(1.450)</td>
<td>(2.401)</td>
</tr>
<tr>
<td>3-Factor Alpha</td>
<td></td>
<td>-0.609</td>
<td>0.593</td>
</tr>
<tr>
<td></td>
<td>($-1.787$)</td>
<td>(1.490)</td>
<td>(2.334)</td>
</tr>
<tr>
<td>4-Factor Alpha</td>
<td></td>
<td>-0.615</td>
<td>0.695</td>
</tr>
<tr>
<td></td>
<td>($-1.788$)</td>
<td>(1.752)</td>
<td>(2.541)</td>
</tr>
<tr>
<td>5-Factor Alpha</td>
<td></td>
<td>-0.579</td>
<td>0.669</td>
</tr>
<tr>
<td></td>
<td>($-1.660$)</td>
<td>(1.663)</td>
<td>(2.388)</td>
</tr>
</tbody>
</table>
predictability is concentrated in periods with trading by the linked director. Restricting the sample to the top and bottom quintiles of these directors’ trades, more than doubles the alpha on the strategy to 15% per year.

Delayed price discovery suggests that event studies aimed at measuring the importance of boards’ actions can understate the true effect of boards. That the returns of board-linked firms eventually move together after a one month delay provides additional evidence that the common actions of boards influence firm value. Moreover, the dissipation of the predictability after a one-month lag suggests that event study windows should be expanded from the common window of days to one month or more. Finally, we show a new way in which shared directors attempt to trade opportunistically on their knowledge of the joint prospects of the firms on whose boards they sit.
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