Essays on Information Diffusion and Financial Markets

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Abstract

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My dissertation is a compilation of three separate research studies that explore how information diffuses in financial markets. The first chapter examines how non-uniform information diffusion through distinct networks segments U.S. financial markets. Using changes in newspaper ownership networks, I document that a network link between different geographic areas leads to increased comovement of turnover and returns between stocks headquartered in those areas. Consistent with delayed content sharing within a network, the largest increase in comovement is observed using weekly data. I show that the network-driven comovement is not driven by fundamentals and is weaker for large firms with high institutional ownership and decreases over time. I also document that a network link causes price levels of linked stocks to become more similar. My findings show that segmented information networks lead to segmented financial markets with implications for market efficiency, home bias, and the effects of changes in the U.S. media landscape on financial markets.

The second chapter shows that investors do not fully monitor the information about directors available in the past prices of firms within the network the directors oversee. A long-short portfolio using this information yields an annual alpha of 6.6%. This predictability is limited to when firms share a director and is not driven by industry or previously identified economic links between firms. The predictability is largest in the long end, when small firms predict big firms, and when information on shared directors is costlier to obtain. Trading by

the shared directors is a key mechanism: filtering on their trades increases the annual alpha to 15%.

The third chapter studies the econometric properties of a commonly used network-based measure of information diffusion between economically linked firms. Previous studies use this measure to document failures of market efficiency with price discovery requiring up to a year. The measure is constructed as the long-short alpha of portfolios formed sorting on the preceding returns of firms economically linked to portfolio firms. We show that correlated alphas between linked firms bias these measures. Existing studies have monthly biases as large as a factor of two. This bias creates predictability even after price discovery completes. Subtracting the predicted return from the sorting firms' returns removes this bias. Eliminating this bias reveals a more efficient market than previously documented: price discovery takes one month.

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DEDICATION

To my loving wife, Meredith,
my children, Alisa, Benjamin, Abigail, Bethany, Anna and Rebekah
and my supportive parents, Paul and Susan.

Chapter 1

INFORMATION NETWORKS AND MARKET SEGMENTATION

1.1 Introduction

A large body of research in finance explores the factors that segment financial markets focusing on those arising from geographic borders while often implicitly assuming uniform information diffusion. However, information diffuses non-uniformly through distinct and separate information networks, both across and within geographic borders. In this paper, I investigate how segmentation in information diffusion also contributes to equity market segmentation.

I characterize equity market segmentation through the increased trading and price commonality between stocks whose marginal investors become exposed to the same information network. Commonality in information within a network induces common demand shocks among network-linked investors. These common demand shocks result in trading pressure that gives rise to increased covariance in turnover. If arbitrageurs are unable to fully absorb these shocks, the trading pressure leads to an increase in covariance of returns as well as convergence in price levels between network-linked stocks. All three measures reflect financial market segmentation wrought by distinct information networks.

To identify the effects of distinct information networks on equity markets, three conditions are required. First, information produced and disseminated must differ from information in other networks. Second, the information network that an investor belongs to must be observable. Third, the set of stocks for which an investor is the marginal investor must be identifiable.

Changes in newspaper ownership networks are a novel way to reveal changes in investors' information sets that satisfy these necessary conditions. First, heterogeneity across networks arises as newspapers within a network share content, for example, through shared bureaus or internal newswires (Soloski, 1979). Second, several studies provide evidence that local investors include the local newspaper in their information set (Engelberg and Parsons, 2011; Gurun and Butler, 2012). Third, consistent with the extant literature on home bias (Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010), I identify the set of stocks affected by newspaper networks as locally headquartered stocks by assuming that local investors are the marginal investors in local stocks (Hong, Kubik, and Stein, 2008; Korniotis and Kumar, 2013). I observe these newspaper networks using hand-collected data covering 1989 to 2006.

To identify the causal impact of the ownership network on stocks of a given area, I exploit annual changes in local newspaper ownership. Specifically, I construct bilateral pairs of all U.S. metropolitan statistical areas (MSAs) to estimate the effect of belonging to the same newspaper network on commonality in trading, returns, and price levels between MSAs in the presence of MSA pair and year fixed effects. As these networks do not evolve randomly, I address endogeneity concerns in two ways. First, I use a difference-in-differences framework to control for unobservable commonalities of network-linked areas. Second, using earnings data of firms belonging to an MSA pair, I verify that network changes do not coincide with changes in fundamentals of these paired firms.

I first test for a network-driven increase in the covariance of daily turnover and returns between two network-linked areas relative to non-linked areas. I repeat these tests using covariances calculated from weekly, bi-weekly and monthly data to understand the speed of information diffusion within a network.

I also explore the stock characteristics that increase the influence of network-driven demand shocks. A firm's non-local ownership should be inversely related to measures of segmentation. Therefore, factors known to mitigate the local bias, such as firm size, institutional ownership and number of analysts should be negatively associated with the networks' segmenting effect (Coval and Moskowitz, 1999). In contrast, the network may report more regarding local firms which advertise in local newspapers, potentially amplifying the segmentation effects of the network on those firms.[1]

While the segmentation results on returns and turnover are presented in the form of covariances, I also study the effects of network membership on differences in price levels using a market segmentation measure from the international finance literature on capital market integration. To understand whether commonality in information-induced demand has price effects, I consider the standard deviation of average industry-weighted valuations (earnings yields) within MSA pairs.[2] A decrease in the standard deviation of stock valuations in an MSA pair linked through a newspaper network relative to non-linked pairs reflects valuation similarities within networks and segmented valuations across networks.

My main results can be summarized as follows. First, using daily turnover and returns data, I find that the covariance between two MSAs increases in the presence of a newspaper network link. The biggest increase in covariance between two linked areas occurs with weekly data. Relative to the average covariance of non-linked MSA pairs, the network causes a 31.8% increase in covariance of turnover and a 9.18% increase in covariance of returns between two linked MSAs. I find no corresponding increase in the comovement of cash flows. Cross-sectional tests reveal the returns commonality decreases for firms with larger market capitalization, a higher percentage of institutional ownership and a higher number of analysts and increases with a firm's advertising expenditures and the total network circulation. I also find that a network linkage reduces the difference in average price levels between two linked MSAs by 4.22% relative to that of non-linked pairs.

I explore two extensions to my findings. First, I explore how the effect changes over time. The onset of the internet has substantially reduced the costs to investors' accessing of news sources beyond the local newspaper. Thus, the local newspaper's weight in an investor's information set may have declined over time. This should lead to a decrease in

[1]Gurun and Butler (2012) suggests that newspapers report more favorably on local firms. However, the direction of bias is not needed for the segmenting effect to occur.

[2]For a similar approach in international finance, see Bekaert, Harvey, Lundblad, and Siegel (2011, 2013).

the effect I document, particularly in the post-internet era. I extend my main sample to include newspaper ownership linkages for the years 2007-2015 and show, as predicted, that the network's effect decreases over time.

The second extension studies whether firm-specific news is disseminated by the network. My findings of increased returns covariances and price similarities between network-linked areas suggest investors are exposed to network-driven commonalities in systematic news. However, the reporting of local newspapers on local firms may also lead to firm-specific news being disseminated within a network, leading to commonality in firm awareness among network-linked investors. Consistent with this effect, I find that a newspaper network leads to increased similarity of portfolio allocations for individual investors residing in informationally linked areas.

Overall, my results show that information diffusion through newspaper ownership networks cause commonality in trading, returns, and valuations among stocks whose marginal investors are exposed to the network. The increased returns comovement and price similarities reflect network-driven pricing differentials in the U.S. market. As I observe no similar increase in the comovement of cash flows, the pricing differentials are not due to commonalities in underlying fundamentals. Alternatively, as a market is (financially) segmented if similar assets are priced differently, these pricing differentials likely reflect differences in investors discount rates or growth expectations. Thus, my findings suggest that segmented information causes market segmentation.

My results contribute primarily to the market segmentation literature. One strand of the market segmentation literature argues that capital constraints give rise to market-specific discount factors that lead to segmentation of micro asset markets, such as mortgage-backed securities (Gabaix, Krishnamurthy, and Vigneron, 2007) and corporate bonds (Collin-Dufresne, Goldstein, and Martin, 2001).[3] My analysis suggests that segmentation occurs even within the much larger U.S. equity market. A second strand focuses on geographic clienteles and

[3]Other micro asset markets shown to be segmented include the catastrophe insurance (Froot and O'Connell, 1999) and index options markets (Garleanu, Pedersen, and Poteshman, 2009).

local economic environments as factors segmenting the U.S. equity market (Becker, 2007; Becker, Ivković, and Weisbenner, 2011; Korniotis and Kumar, 2013). In a similar vein, the literature on international market segmentation has also extensively focused on factors associated with geographic borders.[4] In contrast to focusing on geographic factors, my findings suggest that separate information networks segment markets in addition to these factors.

My analysis also contributes to the literature on excess comovement. First, I provide a test of the information diffusion hypothesis on comovement by Barberis, Shleifer, and Wurgler (2005). In that respect, my analysis is similar to Israelsen (2016), which shows that correlated analyst coverage gives rise to returns comovement among a small number of stocks followed by a single analyst. It is also consistent with Grullon, Underwood, and Weston (2014), who argue that investment banking networks give rise to comovement among stocks which have the same underwriter during their equity offerings. In addition to returns comovement, I show that information diffusion leads to comovement in turnover as well. Moreover, I am able to measure the speed at which information flows through the network. Newspaper ownership networks also provide a direct measure of the predictions of Veldkamp (2006) that argues that comovement arises due to common subsets of information among investors. My findings that newspaper ownership networks cause increased comovement among network-linked stocks also provide one potential channel for the strong local comovement documented in Pirinsky and Wang (2006) and, possibly, the systematic correlations in retail investor trading documented in Kumar and Lee (2006). In addition, my use of pairwise covariances provides a robust alternative framework that overcomes the shortcomings of the widely-used bivariate regression tests in the comovement literature documented by (Chen, Singal, and Whitelaw, 2016a).

[4]Jorion and Schwartz (1986) argue that government-enacted barriers give rise to segmentation, such as capital controls (Gultekin, Gultekin, and Penati, 1989), withholding taxes (Chan, Covrig, and Ng, 2005) and ownership restrictions (Bailey and Jagtiani, 1994). Cross-country segmentation is also attributed to differences in investor protections (Shleifer and Wolfenzon, 2002; Albuquerue and Wang, 2008), regulatory frameworks (Bekaert, 1995; Hail and Leuz, 2006) and stock market development (Bekaert et al., 2011). Other studies use indirect evidence of cross-listings to argue that investor recognition affects cross-country segmentation (Merton, 1987; Foerster and Karolyi, 1999; Fernandes and Ferreira, 2008).

This paper also contributes to the literature on the mass media and financial markets. Specifically, my study complements those of Engelberg and Parsons (2011) and Peress (2014) by providing a new setting to identify the causal effects of media. In addition, as the previous literature has focused on the effects of either local (Engelberg and Parsons, 2011; Gurun and Butler, 2012) or national (Tetlock, 2007; Solomon, Soltes, and Sosyura, 2014) news sources, newspaper ownership networks reveal a new dimension through which the media affects stocks. Finally, consistent with the recent research of Heston and Sinha (2016), I find that information diffuses through the media up to a month rather than the 1-2 days previously documented.

My findings provide evidence on why home bias might arise among professional and individual investors in domestic settings (Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005). One common explanation is that information (or awareness) leads to home bias (Merton, 1987; Barber and Odean, 2008).[5] However, the inherent unobservability of information makes this channel difficult to identify. Thus, studies resort to proxy variables for information assymetries such as cross-listings (Ahearne, Griever, and Warnock, 2004), stock market development (Chan et al., 2005), and culture or language (Grinblatt and Keloharju, 2001). My results suggest that information flowing through discrete networks affects portfolio composition as network-linked individual investors have more similar portfolios.

Lastly, my findings also have implications for the extensive debate over the consequences of concentrated media ownership in the U.S. (Bagdikian, 2014). While the existing literature has focused on whether these monopolies can propagate ideological slant (Gentzkow and Shapiro, 2010) and influence political outcomes (DellaVigna and Kaplan, 2007; Gentzkow, Shapiro, and Sinkinson, 2011), I show that changes in media ownership impacts financial markets as well.

[5] For a more comprehensive summary of explanations, see Karolyi and Stulz (2003).

1.2 Data and Empirical Design

1.2.1 Data

1.2.1.1 Newspaper ownership networks

Each year between 1988 and 2006, *Bowker's Media Directory*[6] published a directory of all (approximately 1,500) daily local newspapers in the United States, including detailed information on publication, ownership, and circulation.[7] I select all local newspapers that are published at least each weekday and have non-missing circulation data. I then hand-collect information on the parent ownership, publication days, average weekday circulation, and newspaper headquarters for each daily newspaper.

I assign each newspaper to the primary metropolitan statistical area (MSA) of its local headquarters.[8] If an owner owns more than one newspaper in a given MSA, I sum the circulation of all newspapers in the MSA of the same owner.

As many newspapers only reach a relatively small fraction of local readers, these newspapers are unlikely to affect the aggregate demand of local investors. Therefore, I only include local newspapers with a circulation market share of at least 25%. I examine alternative cut-offs in Section 2.3.

For each year, I drop MSAs with less than ten firms headquartered in the MSA at the end of the previous calendar year. The minimum number of firms is imposed purely to minimize noise when forming MSA-level portfolios, which consist of all the local stocks in the MSA. Consistent with the literature on home bias (Coval and Moskowitz, 1999), I match each firm

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[6]Prior to 2002, this was known as *Working Press of the Nation*.

[7]A newspaper is classified as daily if it is printed more than once per week. Almost all newspapers are classified as local, with the exceptions of *The Wall Street Journal*, *USA Today*, and the *Christian Science Monitor*, which are considered national newspapers.

[8]The use of MSA as a newspaper's market follows George and Waldfogel (2003). MSA definitions are provided by the Office of Management and Budget (OMB). The OMB defines a primary MSA as consisting of "one or more counties that have substantial commuting interchange." See http://factfinder.census.gov/help/en/primary_metropolitan_statistical_area_pmsa.htm for more detail.

to an MSA using the firm's headquarters listed in Compustat as a proxy for its location.[9]

A newspaper ownership network is defined as the set of MSAs with local newspapers belonging to the same owner. An MSA with multiple newspapers of different owners is assigned to multiple networks. To avoid any spurious effects arising from the ambiguity in the timing of the link formation, I set the link observation to missing for the publication year of the book that first documents the ownership link.

As newspaper networks are not formed exogenously, newspapers by the same owner are more likely to be located in the same state. This common location of ownership may give rise to regional economic effects which would confound my analysis. Therefore, to account for the endogeneity of regional economic effects, when forming a network, I only include the linked MSA with the largest newspaper circulation in that state.

Table 1.1 Panel A presents the newspaper network summary statistics for each year of my sample. The average total number of networks in my sample period is 31.8. The decline in networks from 36 in 1989 down to 23 in 2006 is due to the increasing consolidation of the newspaper industry over time.

On average over the sample period, a network consists of 5.1 MSAs, although the network owner may own additional newspapers outside the MSAs included in the network. The upward skewness of the mean of 5.1 MSAs relative to the median of 3.8 is primarily due to the three largest networks in my sample, which, based on the average network size over time, are the Gannett Company (17.6 MSAs), Thomson Newspapers (13.8), and Knight Ridder, Inc. (11.6).

The mean number of firms in an MSA is 54.7 over the entire sample period. The increase in the mean number of firms in the mid-1990s follows a similar increase in the total number of publicly listed firms during that same period. The three largest MSAs, on average over

[9] One concern with the Compustat data is that it only provides the *current* headquarters of the firm. Therefore, if a firm has moved its headquarters any time after my sample begins, the firm may be assigned to an incorrect MSA. This should have a minimal effect given how few firms change headquarters location. In addition, this noisy mis-assignment of a firm to an MSA portfolio will introduce a downward bias, providing a more conservative estimate of any network effects I find.

time, are New York (305 MSAs), Los Angeles (227) and Chicago (193).

The key explanatory variable throughout my analysis is a network indicator variable equal to 1 if an MSA pair is linked through a newspaper ownership network. Table 1.1 Panel B shows summary statistics for the number of MSA pairs each year and the indicator variable used in my empirical tests. On average, each year there are 4,323 total MSA pairs, of which 4.77% are linked through a common newspaper ownership network. In addition, in a given year, the average percentage of MSA pairs that change their link status (from non-linked to linked or vice versa) is 0.9%.

Table 1.1 Summary Statistics, Newspaper Ownership Networks 1989-2006 This table shows summary statistics as of December of each year for newspaper ownership networks. A newspaper ownership network is the unique set of metropolitan statistical areas (MSAs) which have one or more local newspapers owned by the same owner. To be included in the network, the local newspaper must have more than 25% market share of the MSA's total newspaper circulation. Panel A includes summary statistics for the newspaper networks, the network-linked areas, and the firms in network-linked areas. Total networks is the number of distinct newspaper networks that have at lease 2 local newspapers in separate MSAs. Number of firms per MSA is the total number of firms for each MSA in that year. MSAs per network is the number of MSAs in a network. Panel A reports the number of newspapers, owners and networks used as the basis for the sample. Panel B presents statistics on the number of MSA pairs that are linked and not-linked and the number that change from linked to non-linked or vice-versa in a given year. Panel C presents summary statistics for the (annualized) covariance of turnover, and returns between two MSAs at different frequencies as well as the absolute difference in valuations between two MSAs. All numbers are in percent. See Section 2.1 for a description of these variables.

Panel A: Summary statistics: Newspaper networks over time

Year	Total networks	MSAs per network				Number of firms per MSA			
		Mean	Median	Max	SD	Mean	Median	Max	SD
1989	36	5.27	4	21	4.41	51.9	29	329	57.1
1990	35	5.09	4	20	4.25	51.6	30	316	56.3
1991	33	5.06	4	21	4.12	52.1	30	307	56.7
1992	34	4.88	4	16	3.69	53.2	29	299	57.7
1993	36	4.64	3	17	3.84	54.1	27	317	60.9
1994	36	4.81	3.5	17	3.78	57.0	28	332	64.5
1995	37	4.84	4	17	3.78	57.8	28.5	341	66.3
1996	35	4.89	4	20	3.85	61.6	30	368	71.6
1997	34	5.15	4	21	4.08	61.5	29	366	72.4
1998	36	4.69	3.5	19	3.72	60.1	28	356	69.1
1999	35	4.71	3	17	3.54	59.3	31	351	68.1
2000	28	4.82	3	18	3.86	59.5	31.5	341	67.5
2001	28	4.96	3.5	17	3.75	54.0	30	277	59.0
2002	31	4.90	3	17	3.84	50.9	29	255	54.6
2003	27	5.33	4	17	3.90	50.8	33	237	51.1
2004	26	5.23	3	16	3.86	49.3	30.5	229	50.9
2005	22	6.05	5	19	4.17	49.6	32	228	50.4
2006	23	5.78	5	19	4.04	49.6	29	247	50.8
Sample average	31.8	5.1	3.8	18.3	3.9	54.7	29.7	305.3	60.3

Table 1.1 Continued

Panel B: Summary statistics: MSA pairs over time

Year	MSA pairs		
	Total	% linked	% change link status
1989	4,179	4.83	-
1990	4,003	4.92	0.20
1991	3,916	4.29	0.10
1992	4,005	4.59	0.47
1993	4,753	4.08	1.03
1994	5,048	4.44	0.30
1995	5,150	4.19	0.62
1996	5,252	4.36	0.48
1997	5,562	4.91	0.49
1998	5,560	4.30	0.49
1999	4,949	3.90	0.53
2000	4,556	4.35	0.92
2001	4,179	4.67	0.96
2002	3,741	5.59	1.44
2003	3,486	5.77	2.32
2004	3,239	4.79	2.50
2005	3,158	6.27	1.27
2006	3,079	5.62	0.97
Sample average	4,323	4.77	0.9

Table 1.1 Continued

Panel C: Summary statistics: Segmentation measures over time

Year	Pairwise MSA turnover covariance (%)				Pairwise MSA returns covariance (%)				Mean absolute pairwise MSA difference in valuations (%)
	Daily	Weekly	Bi-weekly	Monthly	Daily	Weekly	Bi-weekly	Monthly	
1989	0.09	0.06	0.08	0.21	13.36	10.16	13.70	17.99	3.53
1990	0.09	0.25	0.31	0.37	23.80	30.98	33.74	30.79	3.79
1991	0.10	0.17	0.20	0.19	27.37	46.82	76.98	104.91	2.88
1992	0.18	0.55	0.80	1.86	25.41	58.28	76.84	154.05	2.53
1993	0.10	0.20	0.31	0.50	17.33	24.89	28.82	35.27	2.63
1994	0.14	0.17	0.18	0.31	17.04	18.30	20.29	22.27	2.73
1995	0.28	0.69	0.77	1.08	13.24	14.30	16.36	26.37	2.79
1996	0.51	1.45	2.18	3.42	26.26	35.70	40.56	52.68	2.56
1997	0.18	0.66	1.18	1.92	26.55	48.77	56.07	110.49	2.02
1998	0.54	1.99	3.64	5.22	57.72	86.36	103.63	51.66	2.66
1999	0.75	2.53	3.96	9.63	30.47	65.89	108.63	108.88	2.71
2000	2.63	9.85	17.22	35.96	89.67	160.93	217.03	111.30	3.38
2001	0.61	1.73	2.35	3.51	64.36	101.93	113.87	184.35	2.33
2002	0.44	1.02	1.51	2.11	41.53	67.10	92.17	66.90	2.48
2003	1.23	3.59	6.05	10.54	22.95	42.62	55.68	65.72	2.14
2004	1.16	4.49	7.62	16.15	18.83	26.47	32.74	26.20	1.91
2005	0.30	0.91	1.24	1.88	11.61	15.82	13.97	10.57	2.12
2006	0.53	0.80	1.04	0.68	12.63	18.66	21.07	15.96	2.26
Sample Average	0.55	1.73	2.81	5.31	30.01	48.56	62.34	66.46	2.64

1.2.1.2 Commonality and segmentation

My main hypothesis is that newspaper networks drive commonality in information to network-linked areas, and thus cause local investors to experience similar demand shocks in those areas. If information across networks is heterogeneous, then this increased similarity of investor demand within networks implies segmented demand across networks. To observe the increased similarity of investor demand for network-linked stocks, I use the covariance of turnover between two network-linked MSAs.

Following Lo and Wang (2000), I construct turnover by dividing the daily share volume by the lagged total shares outstanding for each stock s. As I am interested in the idiosyncratic turnover effect from the newspaper network, in each year, I run regressions of each stock's daily turnover on the share-weighted market turnover and industry turnover:

$$TURN_{s,t} = \alpha_s + \beta_s^{MKT} * TURN_{s,t}^{MKT} + \beta_s^{IND} * TURN_{s,t}^{IND} + \epsilon_{s,t} \tag{1.1}$$

Using each stock's daily residual, $\epsilon_{s,t}$, I form equal-weighted as well as share-weighted MSA-level portfolios of the daily idiosyncratic turnover $TURN_{m,t}^{port}$ for all stocks in MSA m.

For each year y, I calculate the covariance of the daily turnover between MSA i and MSA j for all unique MSA pairs.

$$COV_{i,j,y}^{TURN} = \text{Cov}[TURN_{i,t}^{port}, TURN_{j,t}^{port}] \tag{1.2}$$

I also infer differences across networks by examining similarities in returns and price levels within networks. If investors are the marginal investors in local stocks, any network-specific demand shocks could lead to similar price impacts of network-linked stocks.

I calculate the covariance of returns analogously to the covariance of turnover. I extract the return residual for each stock through annual regressions of each stock's daily return on the value-weighted market and the stock's SIC-2 industry return. Using the residual accounts for any common market and industry factor exposures that may confound my results. For each MSA, I form equal-weighted and value-weighted daily portfolios $R^{port}_{m,t}$ using the local stocks' idiosyncratic returns. I then calculate the pairwise covariance in each year y between the daily MSA portfolio idiosyncratic returns:

$$COV^{RET}_{i,j,y} = \text{Cov}[R^{port}_{i,t}, R^{port}_{j,t}] \tag{1.3}$$

I repeat the pairwise turnover and pairwise returns covariance calculation using weekly, bi-weekly and monthly data. For both returns and turnover, a week is defined using the Wednesday to Wednesday convention. For comparison purposes, I display annualized covariances of these measures throughout the paper.

To understand the network effect on price levels, I use a measure of segmentation found in the international literature that computes the average difference in industry valuations between MSAs for all MSA pairs in my sample. Specifically, I follow Bekaert et al. (2011, 2013) and construct the following bilateral segmentation measure based on earnings yields differences:

$$DIFF\_PRICES_{i,j,y} = \sum_{k=0}^{N_{i,j,y}} IW_{k,y} |EY_{i,k,y} - EY_{j,k,y}| \tag{1.4}$$

$DIFF\_PRICES_{i,j,y}$ is the average absolute value of the value-weighted difference in earnings yields (EY) for industry k in year y between MSA i and MSA j. The industry weights ($IW_{k,y}$) used are the portion of the industry's summed market capitalization relative to the combined market capitalization across both areas. I form this measure at the end of each calendar year for the entire combination of all MSA pairs.

The measure can be interpreted as a scaled version of the standard deviation of price levels (valuations) of all stocks within an MSA pair. As a newspaper network drives shocks to a common discount factor of investors in the network, a network link between two MSAs should lead to valuation similarities among local stocks in the MSA pair. The increased similarities within the network implies valuation differences across networks, or segmented financial markets.

Table 1.1 Panel C shows summary statistics for the covariance of turnover, $COV^{TURN}_{i,j,y}$, the covariance of returns, $COV^{RET}_{i,j,y}$, and the measure of pairwise valuation differences, $DIFF\_PRICES_{i,j,y}$ used as dependent variables in my empirical tests. I include annualized measures of covariances calculated using daily, weekly, bi-weekly and monthly and winsorize all variables by 2.50% on each end of the distribution.

The average annualized covariance of daily turnover between two MSAs is about $0.5\%^2$ over the sample period. The average annualized covariance of daily returns between two MSAs is about $30\%^2$ over the sample period. As a benchmark, assuming the market return variance is 16%, the market covariance would be approximately $256\%^2$. Therefore, the pairwise covariance of returns is approximately 10% of the market variance.

The mean absolute difference in valuations between two MSAs is approximately 2.6%. As noted above, this can be interpreted as the cross-sectional standard deviation of industry-weighted valuations for all stocks in an MSA pair. The decline in the segmentation measure, particularly after the year 2000, suggests that the U.S. market as a whole is becoming more integrated over time.

1.2.2 Empirical design

I use the turnover covariance, $COV^{TURN}_{i,j,y}$, the returns covariance, $COV^{RET}_{i,j,y}$, and the valuations differential, $DIFF\_PRICES_{i,j,y}$, between two MSAs as outcome variables in a difference-in-differences framework to examine the effects of a newspaper network on stocks in network-linked areas. The linear regression model is:

$$OUTCOME_{i,j,y} = \alpha + \beta_{NET} NET_{i,j,y} + \beta_X X_{i,j,y} + \delta_{i,j} + \gamma_y + \epsilon_{i,j,y} \tag{1.5}$$

where $NET_{i,j,y}$ is a network indicator equal to 1 if in year y if the pair of MSAs i and j are linked through a newspaper ownership network. I include $\delta_{i,j}$ and γ_y to control for MSA-pair fixed effects and year fixed effects. The coefficient β_{NET} reveals the effect of a network linkaage on the outcome variables relative to those of randomly matched network pairs. For turnover and returns covariance, a coefficient $\beta_{NET} > 0$ suggests that a network linkage causes covariance between two linked MSAs to increase relative to non-linked MSAs. For the valuations differential, a coefficient $\beta_{NET} < 0$ suggests increased similarity in prices between two linked MSAs relative to non-linked MSAs. The increased covariance and price levels for MSA pairs linked through a network relative to non-linked MSA pairs is evidence of market segmentation.

The turnover and returns covariance could, alternatively, be measured using a methodology common in the comovement literature first introduced by Barberis et al. (2005).[10] The approach, in my setting, would involve running bivariate regressions of an MSA return on two explanatory variables: the currently linked network portfolio return and the return of the previously linked network portfolio. A statistically significant increase in the beta on the currently linked portfolio relative to the beta on the previously linked portfolio could be interpreted as increased comovement.

Despite the widespread use of the bivariate regression approach in measuring comovement, I instead use a difference-in-differences framework for two reasons. First, Chen et al. (2016a) show that "bivariate results are unreliable in terms of assessing the economic magnitude of any excess comovement." My framework provides a directly interpretable measure of the economic magnitude of the increase in comovement between network-linked areas relative to non-linked areas. Second, including MSA pair fixed effects controls for time-invariant MSA pair characteristics that give rise to ownership commonality.

Finally, I account for the pairwise nature of my outcome variables when calculating the standard errors. My analysis uses paired, or dyadic, data to estimate the effects of a network linkage on the turnover covariance, returns covariance and similarity in valuations between two MSAs. Dyadic data has a particularly complex correlation structure among the error

[10]This approach has been used extensively to understand excess comovement of stocks. Numerous studies have documented excess comovement among index additions and deletions (Barberis et al., 2005; Greenwood, 2008; Boyer, 2011). Other studies using this bivariate approach have found excess comovement among stocks headquartered in the same MSA (Pirinsky and Wang, 2006) and stocks with similar price levels (Green and Hwang, 2009).

terms because a single component of a pair may be common to multiple pairs, or dyads.[11] For instance, in the outcome variables of my analysis, the same MSA may show up in either component of the pair. This correlation leads to a potential understatement in the standard errors. I account for this correlation using the dyadic cluster robust variance estimator derived by Aronow et al. (2015).[12]

1.3 Main Results: Market Segmentation Effects

1.3.1 Comovement Results: Turnover and Returns

If newspaper ownership networks lead to segmented information diffusion, the trading of investors within a given network should be more correlated than trading by investors outside the network. To the extent that investors inside a given network are the marginal investors, correlated trading would also lead to increased return comovement among stocks traded by investors inside the network and, thereby, to reduced return comovement among stocks traded by investors that do not belong to the same network. In this section, I compare the covariances in stock turnover and returns between network-linked areas to that of non-linked areas.

[11] Examples of other types of dyadic data would be pairwise stock correlations or trade flows between country pairs. See Aronow, Samii, and Assenova (2015); Cameron and Miller (2014) for a thorough analysis of dyadic clustering.

[12] One-way clustering using MSA only ignores the second MSA in a pair. Clustering by MSA pairs does not account for the correlation between all the MSA pairs that share at least one common MSA. Two-way clustering by each individual component in the pair also may not account for all the correlation among dyads. To understand why two-way clustering does not account for all the correlation in dyadic data, consider an MSA pair as being made up of two variables MSA1 and MSA2, each with the same domain of all the MSAs. To obtain the unique set of pairs, take the set of all MSA pairs such that MSA1 is less than MSA2. Assuming each MSA is numbered starting from 1, then the first MSA only appears in the MSA1 variable as it is paired with every other MSA, which each show up in the MSA2 variable. However, the second MSA appears in the MSA2 variable in a pair with the first MSA and it appears in the MSA1 variable as it is paired with all other MSAs. Dyadic clustering iteratively accounts for an MSA showing up in either the MSA1 or MSA2 of the pair.

1.3.1.1 Turnover

Table 1.2 presents the results of a regression of annual MSA-pair covariances of daily turnover on a network indicator that is equal to one if the two MSAs in the pair belong to the same network and zero otherwise. Panel A shows the results using equal-weighted MSA portfolios of local stock turnover. Panel B shows the results using value-weighted MSA portfolios. I annualize all coefficients for ease of interpretation.

The first column of Panel A reports a statistically significant coefficient estimate associated with the network link indicator of $0.156\%^2$. As shown in the second and third specifications, the coefficient estimate remains largely unchanged in the presence of additional control variables.

The coefficient estimates suggests that the covariance of stock turnover between two areas linked by a newspaper network is $0.156\%^2$ higher than the turnover covariance between two non-linked areas. Given that the average covariance is $0.548\%^2$ for non-linked MSA pairs, this represents an increase of 28.46%, suggesting that newspaper networks drive substantial commonality in demand shocks for local stocks among local investors. Using value-weighted MSA portfolios in Panel B, the coefficient on the network indicator is statistically insignificant.

Taken together, the results suggest that newspaper networks induce strong demand shocks among investors in network-linked areas. Consistent with the proposed economic mechanism, local investors are likely to make up a greater proportion of traders in smaller local stocks. Thus, the lack of a value-weighted result suggests network-driven effect on trading is primarily in smaller stocks.

1.3.1.2 Returns

Table 1.3 shows the effect of network-induced commonality in demand shocks on the pairwise covariance of returns between two MSAs. Column 1 of Panel A shows that the average annualized equal-weighted pairwise covariance of daily returns increases by $2.23\%^2$ if two

Table 1.2 Newspaper Network Effect on Annual Pairwise Covariance of Daily Idiosyncratic Turnover This table shows the effect of a newspaper network on the covariance of daily turnover between two MSAs. For all years between 1988 and 2006, I obtain a stock's idiosyncratic turnover from the residual of the regression of that stock's turnover on the market turnover and the turnover of that stock's own SIC-2 industry. At each date, for each MSA, I form an equal-weighted (value-weighted) portfolio turnover of all stocks headquartered within that MSA. For every pair of MSAs, I calculate an annual covariance between the two MSA portfolios of daily idiosyncratic turnover. This covariance is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than 25% and 0 otherwise. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Panel A shows the results for the specifications using the equal-weighted turnover. Panel B shows the results for the specifications using the value-weighted turnover. All coefficients are annualized and are in percent. All numbers are in percent. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

Panel A: Equal-Weighted Portfolios

	Dependent var: $COV^{TURN}_{i,j,y}$		
	(1)	(2)	(3)
Network indicator	0.156**	0.158**	0.158**
	(0.066)	(0.067)	(0.067)
Number of firms (MSA pair)		0.004***	0.004***
		(0.001)	(0.001)
MCAP (MSA pair)			0.119
			(0.099)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	80,881	80,881	80,881
% same network	4.27%	4.27%	4.27%

Panel B: Value-Weighted Portfolios

	Dependent var: $COV^{TURN}_{i,j,y}$		
	(1)	(2)	(3)
Network indicator	0.022	0.022	0.022
	(0.040)	(0.040)	(0.040)
Number of firms (MSA pair)		-0.001	0.000
		(0.001)	(0.001)
MCAP (MSA pair)			-0.125***
			(0.045)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	79,700	79,700	79,700
% same network	4.27%	4.27%	4.27%

Table 1.3 Annual Pairwise Covariance of Daily Idiosyncratic Returns Aggregated at the MSA Level This table shows the effect of a newspaper network on the covariance of daily returns between two MSAs. For all years between 1988 and 2006, I obtain a stock's idiosyncratic returns from the residual of the regression of that stock's return on the market return and the return of that stock's own SIC-2 industry. At each date, for each MSA, I form an equal-weighted (value-weighted) portfolio return of all stocks headquartered within that MSA. For every pair of MSAs, I calculate an annual covariance between the two MSA portfolios of daily idiosyncratic returns. This covariance is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than 25% and 0 otherwise. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Panel A shows the results for the specifications using the equal-weighted return. Panel B shows the results for the specifications using the value-weighted returns. All coefficients are annualized and are in percent. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

Panel A: Equal-Weighted Portfolios

	Dependent var: $COV^{RET}_{i,j,y}$		
	(1)	(2)	(3)
Network indicator	2.231*	2.393**	2.390**
	(1.164)	(1.100)	(1.089)
Number of firms (MSA pair)		0.208***	0.190***
		(0.030)	(0.028)
MCAP (MSA pair)			3.975***
			(1.292)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	80,975	80,975	80,975
% same network	4.27%	4.27%	4.27%

Panel B: Value-Weighted Portfolios

	Dependent var: $COV^{RET}_{i,j,y}$		
	(1)	(2)	(3)
Network indicator	0.451	0.437	0.440
	(0.581)	(0.584)	(0.580)
Number of firms (MSA pair)		-0.018	0.008
		(0.012)	(0.011)
MCAP (MSA pair)			-5.837***
			(1.164)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	80,975	80,975	80,975
% same network	4.27%	4.27%	4.27%

MSAs are linked through a common newspaper network. Column 3 shows that the coefficient increases to $2.39\%^2$ after controlling for the number of firms and total market capitalization of the local firms in an MSA pair. In all three specifications, the results are statistically significant at the 5% level. As the average covariance of returns between two non-linked MSAs is $30.4\%^2$, the coefficient of $2.39\%^2$ suggests that a newspaper network causes a 7.83% increase in the covariance of returns between linked MSAs.

Similar to the value-weighted turnover covariance results, the pairwise daily returns covariance using value-weighted MSA portfolios is both statistically and economically insignificant, reinforcing that the information network effect on returns covariance is concentrated among smaller firms. Acknowledging this, the rest of my paper focuses only on equal-weighted MSA portfolios.

1.3.1.3 Covariance differences at longer data frequencies

My findings using daily data are consistent with most of the previous literature findings that the mass media affects turnover and returns over 1 to 2 days. However, Heston and Sinha (2016) show that news aggregated at the weekly level can predict stock returns up to a quarter. As information within a network likely diffuses with a delay, I investigate the pairwise covariances of turnover and returns using different time horizons of the data. Specifically, I use weekly, bi-weekly and monthly data to calculate annual pairwise covariances and employ the same difference-in-differences framework to test the network linkage effect on these returns and turnover covariances.

Table 1.4 shows the effect of network linkages on equal-weighted pairwise returns and turnover covariances using daily, weekly, bi-weekly and monthly data. As before, coefficients shown are annualized for ease of comparison. In absolute terms, at the monthly horizon, the increase in the covariance of turnover of $1.143\%^2$ is the biggest absolute increase of the four frequencies shown, but is statistically insignificant. Relative to non-linked MSA covariances, however, the increase in turnover covariance of $0.524\%^2$ using weekly returns is the largest, representing a network-driven increase in turnover covariance of 30.41%. Importantly, the

Table 1.4 Pairwise Covariance of Idiosyncratic Turnover and Returns at Varying Frequencies This table shows the effect of a newspaper network on the covariance of turnover and returns between two MSAs calculated using daily, weekly, biweekly and monthly frequencies of data. For all years between 1988 and 2006, I obtain a stock's idiosyncratic turnover (return) from the residual of the regression of that stock's turnover (return) on the market turnover (return) and the turnover (return) of that stock's own SIC-2 industry. At each date, for each MSA, I form an equal-weighted (value-weighted) portfolio turnover (return) of all stocks headquartered within that MSA. For every MSA pair , I calculate an annual covariance between the two MSA portfolios of idiosyncratic turnover (returns). This covariance is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than 25% and 0 otherwise. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Panel A shows the results for specifications using the equal-weighted turnover. Panel B shows the results for the specifications using the equal-weighted returns. Dyadically clustered standard errors are in parentheses. All coefficients are annualized and are in percent. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

Panel A: Pairwise covariance of MSA idiosyncratic turnover

	$COV^{TURN}_{i,j,y}$ by frequency			
	Daily (1)	Weekly (2)	Biweekly (3)	Monthly (4)
Network indicator	0.158**	0.524**	0.762*	1.143
	(0.067)	(0.253)	(0.420)	(0.752)
Number of firms (MSA pair)	0.004***	0.012**	0.020**	0.036**
	(0.001)	(0.005)	(0.008)	(0.018)
MCAP (MSA pair)	0.119	0.388*	0.353***	2.146*
	(0.099)	(0.214)	(0.127)	(1.278)
MSA Pair fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes	Yes
Total observations	80,881	80,881	80,881	80,881
% same network	4.27%	4.26%	4.26%	4.27%

Panel B: Pairwise covariance of MSA idiosyncratic returns

	$COV^{RET}_{i,j,y}$ by frequency			
	Daily (1)	Weekly (2)	Biweekly (3)	Monthly (4)
Network indicator	2.390**	4.493**	5.929***	4.402*
	(1.089)	(1.767)	(2.180)	(2.264)
Number of firms (MSA pair)	0.190***	0.372***	0.422***	0.258***
	(0.028)	(0.052)	(0.062)	(0.054)
MCAP (MSA pair)	3.975***	3.025**	1.572**	12.529***
	(1.292)	(1.243)	(0.650)	(4.441)
MSA Pair fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes	Yes
Total observations	80,975	80,975	80,975	80,975
% same network	4.27%	4.27%	4.27%	4.28%

coefficient using weekly returns is statistically significant at the 5% level.

Panel B shows the results for regressions using pairwise returns covariances at different frequencies. In absolute terms, the increase in returns covariance due to a network link is biggest at the bi-weekly horizon, with a statistically significant coefficient of $5.929\%^2$. However, similar to the turnover covariances, the relative magnitude of the statistically significant increase of $4.493\%^2$ at the weekly horizon is the largest, representing an increase in returns covariance of 9.18% relative to the average covariance for non-linked MSA pairs.

Consistent with a non-instantaneous delay in information diffusion within a network, the biggest relative increase in both the turnover and returns covariance between two network-linked MSAs occurs when using weekly data.

1.3.1.4 Cross-sectional differences in firm and network characteristics

Newspaper networks induce commonality in demand of local investors in geographically separate areas, giving rise to increased covariance in trading and returns of network-linked local stocks. The mechanism assumes the local investors, due to home bias, are the marginal investors in the local firms. Thus, several implications arise for the characteristics of firms mostly likely affected by the information segmentation effect observed using newspaper networks.

First, as firm size increases, the investor base becomes more geographically diversified, implying that firm size should be negatively correlated with the network effect. The effect should also be negatively correlated with the percent of institutional ownership. Institutional owners are more likely to focus on fundamentals, have access to larger information sets and are less likely influenced by news sentiment. In addition, the number of analysts following a stock should also decrease the network effect on a stock. On the other hand, as advertising is often done in local newspapers, a newspaper network has an incentive to cover the firm more. Thus, a firm's advertising expenditure should be positively correlated with the network.

Network characteristics may also affect the covariance between a firm and its corresponding network. The total circulation summed across the network should also amplify the network effect, as a larger network can benefit more from cost savings of content sharing and consolidated news production, leading to stronger commonality in information disseminated throughout the network. At the same time, the number of newspapers in a specific MSA may be negatively correlated with the effect for two reasons. First, individual investors could read multiple newspapers mitigating the information effect from one newspaper. Second, the investor base of a stock may be split across which newspapers the investors read, leaving an insufficient number of investors to affect stock prices.

To test these predictions, I first estimate the covariance between a firm's weekly stock returns and the weekly portfolio returns of the network to which a firm belongs. The network return is the equal-weighted return of all network-linked stocks excluding stocks in the firm's own MSA. I calculate the covariance between a firm's returns and its network returns for each firm-network combination in each year similar to the pairwise covariances in previous tests. Appendix Table 1.A.2 provides summary statistics for this variable and the firm characteristics predicted.

The annual firm-network covariances are then regressed on the firm characteristics averaged over the year of the covariance measure as well as the network characteristics for that year. I include both firm and year fixed effects and cluster by network.[13]

Table 1.5 shows the results for the regression of the firm-network covariance on various firm and network characterstics. In the first specification, I include firm size as the only independent variable. Consistent with the cross-sectional prediction, the coefficient of -0.254 is negative and highly statistically significant. In the second specification, I include the firm's institutional ownership, number of analysts and advertising expenditure as explanatory variables. I exclude firm size as it is highly correlated with these variables and the collinearity may obscure any inference. Consistent with my hypotheses, the coefficients for these three

[13] Although the dependent variable is a pairwise measure, dyadic clustering used in earlier tests does not apply here. In previous tests, both components in the pair were an MSA. This resulted in the same MSA showing up in either component of the pair. In contrast, the firm-network pair is formed using two separate variables—the firm and the network, suggesting two-way clustering should be used. However, in this specification, the firm fixed effects are assumed to absorb any within-firm correlation, obviating the need to cluster by firm. See Cameron and Miller (2015) for more details.

Table 1.5 Cross-sectional Determinants of Firm Covariance with Network This table shows the various characteristics of a firm and its stock that explain the annual covariance of the firm's weekly return with the equal-weighted weekly return of all MSAs linked to the firm through a newspaper network. For all years between 1988 and 2006, I obtain a stock's idiosyncratic return from the residual of the regression of that stock's return on the market return and the return of that stock's own SIC-2 industry. Both the market and industry returns are weighted by market capitalization. At each date, for each firm, I form an equal-weighted portfolio return of all local stocks in that firm's newspaper network, excluding those stocks in the firm's MSA. In each year, an annual covariance is calculated between a firm's weekly idiosyncratic returns and the firm's corresponding network portfolio return. Market capitalization is the natural log of the market capitalization of a firm. % institutional is the percent of institutional holdings from Thomson-Reuters s34 instiutional holdings database divided by the total market capitalization of the firm. Number of analysts is the total number of analysts with a valid earnings estimate for the next upcoming quarter.Advertising is the firm's total expenditure on advertising as reported in its 10-k. Total network circulation is the number of subscribers summed across all the network's newspapers. The number of newspapers in the MSA is the count of all daily newspapers in the MSA. All variables are averaged over each year. Network clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

	Dependent Var: Firm-Network Covariance				
	(1)	(2)	(3)	(4)	(5)
Market capitalization (ln)	-0.254***				-0.237***
	(0.017)				(0.016)
% institutional ownership		-0.998***		-1.011***	-0.586***
		(0.065)		(0.065)	(0.058)
Number of analysts		-0.007***		-0.007***	0.011***
		(0.002)		(0.002)	(0.003)
Advertising (ln)		0.021**		0.021**	0.039***
		(0.009)		(0.009)	(0.009)
Total network circulation (ln)			0.028*	0.028*	0.028*
			(0.015)	(0.015)	(0.015)
Number of papers in MSA			-0.002	-0.003	-0.005
			(0.006)	(0.006)	(0.007)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Network cluster	Yes	Yes	Yes	Yes	Yes
Number of firm-network years	181,617	181,617	181,617	181,617	181,617

variables are highly statistically significant and have the predicted sign.

The third specification includes both the total network circulation and number of papers in the MSA where the firm is located. The coefficients on both explanatory variables have the predicted sign. However, only the coefficient on the network's total circulation variable is significant. In the fourth specification, I include all explanatory variables except for firm size to show that the effects are independent of each other. After including firm size in column 5, the coefficient on the firm's % institutional ownership decreases by nearly half and the coefficient on the number of analysts changes sign. These changes are due to firm size capturing much of the same variation that institutional ownership and number of analysts captures.

1.3.1.5 Robustness

1.3.1.5.1 Economic fundamentals I argue the increase in turnover and returns covariance between two network-linked MSAs is due to network-driven commonality in demand shocks. An alternative channel, however, could be that owners acquire newspapers located in areas with common underlying economic fundamentals. These economic commonalities should also be reflected in the covariance of the growth rates of local stocks' cash flows between two MSAs. The increase in returns could then simply be a reflection of changes in the stocks' underlying cash flows.

To test this alternative hypothesis, I use quarterly earnings as a proxy for firm cash flows (Ball and Brown, 1968; Dechow, 1994). For each local stock and calendar quarter, I calculate the quarter-over-quarter (QoQ) and year-over-year (YoY) difference in quarterly earnings. The year-over-year difference in quarterly earnings is particularly useful because any seasonality effects in earnings are subtracted out. To create comparability across firms, I scale both earnings differences by the lagged book equity obtaining an earnings growth rate for the firm.

For each MSA and each quarter, I form an equal-weighted portfolio of all local stocks' earnings growth rates. A firm must have at least 8 previous quarters of non-missing earnings data to be included in the portfolio. I calculate the covariance in earnings growth across MSAs using each year's worth of data. For both the QoQ and YoY earnings growth ratio variables, I calculate the annual pairwise covariance of earnings growth between two MSAs each year for all MSA pairs. Summary statistics for the QoQ and YoY covariances are included in Appendix Table 1.A.2.

I regress the annual pairwise covariance of earnings growth rates between two MSAs on the network indicator variable defined previously. As in my prior tests, both MSA-pair fixed effects and year fixed effects are included as well as controls for the total number and total market capitalization of all local firms in the MSA pair.

Table 1.6 shows the results of these regressions. Panel A documents the results for quarter-over-quarter earnings growth rates. As before, I compute three separate regressions including controls for the total number and total market capitalization of firms in the two MSAs. All three specifications yield the same statistically insignificant coefficient of -0.0010 on the network indicator, suggesting that the average covariance of earnings growth rates for MSA pairs linked by a newspaper network is indistinguishable from that of non-linked pairs. Panel B shows a similar null result for the covariance of year-over-year earnings growth rates.

Overall, the results suggest that the increase in returns and turnover covariance between two linked MSAs is not due to the covariance in the underlying cash flows, suggesting the network linkages are not the result of endogenous matching on similarities among firms in those areas.

1.3.1.5.2 Importance of newspaper market share Throughout my previous tests, I define two MSAs as being linked through a network if the commonly owned local newspapers' both have at least 25% market share in terms of newspaper circulation in the area. To explore the effect of this cutoff, I vary the cutoff from 0% to 50% and re-run the same difference-in-differences pairwise turnover and returns covariance regressions used previously. I focus on the pairwise covariances calculated using weekly data, although the results are similar for all other frequencies.

Table 1.6 Annual Pairwise Covariance of Earnings Growth Rates at the MSA Level This table shows the covariance of quarterly earnings growth rates of local stocks between two metropolitan statistical areas (MSA). The earnings growth rate is calculated using quarter-over-quarter (QoQ) or year-over-year (YoY) changes in earnings. Both the market and industry returns are equal-weighted. At each date, for each MSA, I form an equal-weighted portfolio earnings growth rate of all local stocks in that area. A stock is considered local if its corporate headquarters is located within that MSA. In each year, for every pair of MSAs, I calculate the covariance of the idiosyncratic earnings growth rates between the two MSAs. This annual covariance measure is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than 25% and 0 otherwise. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Panel A shows the results for the specifications using quarter-over-quarter growth rates. Panel B shows the results for the specifications using year-over-year earnings growth rates. Dyadically clustered standard errors are in parentheses. All coefficients are annualized and are in percent. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

Panel A: Quarter-over-quarter earnings growth rates

	Dependent var: QoQ earnings growth rate		
	(1)	(2)	(3)
Network indicator	-0.0010	-0.0010	-0.0010
	(0.0025)	(0.0025)	(0.0024)
Number of firms (MSA pair)		0.0000	0.0000
		(0.0000)	(0.0000)
MCAP (MSA pair)			-0.0008
			(0.0007)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	72854	72854	72854
% same network	4.46%	4.46%	4.46%

Panel B: Year-over-year earnings growth rates

	Dependent var: YoY earnings growth rate		
	(1)	(2)	(3)
Network indicator	-0.0007	-0.0007	-0.0007
	(0.0022)	(0.0022)	(0.0022)
Number of firms (MSA pair)		0.0000	0.0000
		(0.0000)	(0.0000)
MCAP (MSA pair)			-0.0010
			(0.0007)
MSA-Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	75935	75935	75935
% same network	4.37%	4.37%	4.37%

Table 1.7 shows the regression results with varying cutoffs of network strength while controlling for the total number of firms and total market capitalization of stocks in the MSA pair. Panel A focuses on turnover, while Panel B focuses on returns. Column 4 in both panels shows the results from the previous regressions of turnover and returns covariance using data shown in Column 3 of Table 1.4.

The first two specifications of Panel A show statistically insignificant coefficients on the network indicator. In the third specification, the coefficient on the network indicator increases slightly relative to the coefficients in the first two specifications. The fourth specification using the cutoff of 25% shows a statistically significant coefficient of 0.524 on the network indicator. This implies that a network link causes the covariance in turnover between two MSAs to increase by $0.524\%^2$. Relative to the mean of 1.72% for non-linked MSA pairs, the network link causes a 31.4% increase in turnover covariance. The fifth specification using a cutoff of 30% has a statistically insignificant coefficient on the network indicator. However, the coefficient is not statistically different than that of the fourth or sixth specifications. Moreover, given that the coefficients on the sixth and seventh specifications are both statistically significant, the overall conclusion is that a newspaper must have at least 25% market share in terms of circulation to have a substantial segmenting effect on local stocks.

Focusing on returns, the first specification of Panel B yields a coefficient on the network indicator of 2.371, representing the effect of a network linkage defined at a cutoff of 0% on the pairwise covariance of returns between two MSAs. In addition to being statistically insignificant, the coefficient is nearly 60% smaller in magnitude than the coefficient found using a cutoff of 25% (shown in column 3). The regression results using links with a cutoff of 10% in column 2 reflect an effect similar to the 0% cutoff, with the statistically insignificant coefficient on the network indicator of 1.839 being statistically indistinguishable from that obtained using a 0% cutoff.

Table 1.7 Pairwise Covariance of Turnover and Returns at Different Cutoffs for Network Link This table shows the covariance of weekly idiosyncratic turnover and returns of local stocks between two linked and non-linked metropolitan statistical areas (MSA) for varied cutoffs of linked areas. . For all years between 1988 and 2006, I obtain a stock's idiosyncratic turnover (return) from the residual of the regression of that stock's turnover (return) on the market return and the turnover (return) of that stock's own SIC-2 industry. Both the market and industry turnover (returns) are weighted by market capitalization. At each date, for each MSA, I form an equal-weighted portfolio return of all local stocks in that area. A stock is considered local if its corporate headquarters is located within that MSA. In each year, for every pair of MSAs, I calculate the covariance of the paired MSAs' idiosyncratic turnover (returns) using weekly data. This covariance is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than or equal to the cutoff specified below. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Panel A shows results for turnover while Panel B shows results for returns. All coefficients are annualized and are in percent. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

Panel A: Covariance of Turnover at Different Cutoffs for Network Links

	Dependent Var: $COV_{i,j,y}^{TURN}$						
	Market share cutoff for network indicator						
	0% (1)	10% (2)	20% (3)	25% (4)	30% (5)	40% (6)	50% (7)
Network indicator	0.271	0.203	0.361	0.524**	0.438	0.608**	0.597*
	(0.181)	(0.190)	(0.223)	(0.253)	(0.276)	(0.297)	(0.328)
Number of firms (MSA pair)	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
MCAP (MSA pair)	0.400*	0.389*	0.389*	0.388*	0.389*	0.388*	0.390*
	(0.212)	(0.214)	(0.214)	(0.214)	(0.213)	(0.214)	(0.213)
MSA Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observations	80,881	80,881	80,881	80,881	80,881	80,881	80,881
% same network	9.82%	6.11%	4.56%	4.26%	3.89%	3.13%	2.32%

Table 1.7 Continued

Panel B: Covariance of Returns at Different Cutoffs for Network Links

	Dependent Var: $COV^{RET}_{i,j,y}$						
	Market share cutoff for network indicator						
	0%	10%	20%	25%	30%	40%	50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Network indicator	2.371	1.839	3.009*	4.493**	3.646**	3.877**	2.707*
	(1.531)	(1.303)	(1.670)	(1.767)	(1.770)	(1.621)	(1.505)
Number of firms (MSA pair)	0.369***	0.372***	0.372***	0.372***	0.372***	0.372***	0.372***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
MCAP (MSA pair)	2.998**	3.023**	3.023**	3.025**	3.027**	3.026**	3.035**
	(1.244)	(1.243)	(1.243)	(1.243)	(1.243)	(1.243)	(1.244)
MSA Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observations	80,975	80,975	80,975	80,975	80,975	80,975	80,975
% same network	9.82%	6.04%	4.57%	4.27%	3.90%	3.14%	2.33%

As shown in the third specification, the coefficient on the network indicator defined using a cutoff of 20% increases to 3.009 and becomes statistically significant at the 10% level. This suggests that network-linked local newspapers require approximately 20% market share in an area to influence a sufficient number of local investors to drive commonality in stock returns.

The fourth specification of Panel B reveals a coefficient of 4.493 on the network indicator variable defined for network linkages between two MSAs as having 25% circulation market share. Columns 5 to 7 show that the network linkage effect is persistent and similar in magnitude for cutoffs above 25%. The coefficient magnitudes for the larger cutoffs of 30% and 40% are statistically indistinguishable from the coefficient on the network indicator using a 25% cutoff. At the cutoff of 50% shown in Column 7, the coefficient on the network indicator decreases slightly to 2.707 and becomes statistically weaker with significance at the 10% level. The decrease in magnitude and statistical significance occurs for two reasons. First, those MSA pairs that are linked using cutoffs between 25% and 50% are now included as non-linked pairs. This inclusion decreases the difference between the linked and non-linked set of pairs, resulting in a decreased ability of the test to distinguish the covariance among linked MSA pairs from that non-linked MSA pairs. Second, the decreased statistical significance can be attributed to a lack of power as the number of changes in MSA pairs decreases.

Overall, for both turnover and returns, the results of using different cutoffs in defining a network suggest 25% to be the minimum market share needed for a newspaper network to have a measurable effect on the trading and returns covariances of local stocks. The 25% provides additional evidence that newspaper networks are causing the increase in covariance rather than the selection of newspaper ownership based on economic fundamentals. If local newspaper ownership is due to economic fundamentals, then MSAs linked by smaller newspapers with 25% or less market share in terms of circulation would also cause a similar effect. As this is not the case, my findings confirm that newspaper ownership networks cause the increase in returns comovement.

1.3.2 Valuation differences

In this section, I consider the similarities of price levels between linked MSAs. Market efficiency implies that, in a well-integrated market, after controlling for leverage and growth differences, a dollar of earnings should be priced similarly (i.e., have the same price-to-earnings ratio). In my sample of all MSA pairs in the U.S. market, similar assets in different geographic areas of a given MSA pair should have similar valuations.

I continue to employ the same regression framework using the measure of price level differentials, $DIFF\_PRICES_{i,j,y}$ (described in Section 1.2.1.2), as the dependent variable. In addition to the number of firms and the market capitalization, I follow Bekaert et al. (2013) and control for the absolute difference in return volatility, the absolute difference in leverage and the absolute difference in earnings growth volatilities between two MSAs.[14]

Table 1.8 shows the results of regressing MSA-pair valuation differentials on a network indicator and varying sets of controls as specified in equation 1.5. The first specification shows a statistically significant coefficient of -0.120 on the network indicator, suggesting that a network link between two MSAs causes the average difference in the two MSAs' earnings yields to decrease by -0.120 percentage points. The second specification reveals a slight increase in the network indicator coefficient of -0.121 relative to the first specification after controlling for noise in the segmentation measure by including the number of firms and combined market capitalization of all firms in an MSA pair. As expected, the coefficient on the control for the total market capitalization of firms in the MSA pair is negative and highly significant.

[14]The total number of firms and total market capitalization in a particular industry affects the precision of the average industry earnings yield. Thus, a small number of firms will result in a noisier measure of the industry earnings yield, and hence, the absolute value of the difference in industry valuation ratios will be biased upwards. In addition, geographic-specific differences in financial leverage may cause valuation ratios to vary across assets. The differences in earnings growth rate volatility and discount rate volatility may vary across geographies, but will nonetheless be priced in, affecting valuation ratios.

Table 1.8 Network Effect on Pairwise Valuation Differences at the MSA Level This table shows the bilateral segmentation differences of MSA pairs that are linked through ownership of their local common newspaper compared to all non-linked MSA pairs in the sample. For all years between 1988 and 2006, I obtain a bilateral segmentation measure between two MSAs for all MSA pairs. The bilateral segmentation measure ($DIFF\_PRICES_{i,j,y}$) is the absolute value of the difference in same industry valuations as measured by earnings yields weighted by the total industry market capitalization and summed across all industries common to the two MSAs. I regress this pairwise measure on a network link equal to 1 if both MSAs have commonly owned local daily newspapers with market shares greater than or equal to 25%. As controls, I include the absolute differences in return volatility, leverage and earnings volatility which are defined in the appendix. Other controls include the sum of all firms headquartered in either of the paired MSAs and the sum of the market cap of all firms headquartered in either of the paired MSAs. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

	Dependent Var: $DIFF\_PRICES_{i,j,y}$			
	(1)	(2)	(3)	(4)
Network indicator	-0.120**	-0.121**	-0.115*	-0.117**
	(0.059)	(0.057)	(0.059)	(0.057)
Abs (return volatility difference)			4.176***	4.105***
			(0.822)	(0.803)
Abs (leverage difference)			0.311*	0.273
			(0.181)	(0.179)
Abs (earnings growth volatility difference)			0.100***	0.096***
			(0.027)	(0.028)
Number of firms (MSA pair)		0.047		0.032
		(0.030)		(0.029)
MCAP (MSA pair)		-0.307***		-0.295***
		(0.094)		(0.093)
MSA-Pair fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes	Yes
Total observations	44,135	44,135	44,135	44,135
% same network	4.07%	4.07%	4.07%	4.07%

The third specification includes the controls for the absolute differences in return volatility, financial leverage and earnings growth volatility between two MSAs in the MSA pair. The coefficient of -0.115 on the network indicator is only slightly smaller to that in the first and second specification, but it is also statistically weaker at the 10% level. However, after including the additional controls for number of firms and market capitalization, the fourth specification shows a coefficient of -0.117 that is similar to all other specifications and is statistically significant at the 5% level. As predicted, segmentation is positively related to the differences in return volatility, leverage, and earnings growth volatility.

The results suggest that a network link between two MSAs causes price levels of stocks in those two areas to become more similar. Given the average segmentation measure over the sample period for non-linked pairs is 2.768%, the decrease of 0.117% suggests that valuations are 4.22% more similar for two network-linked MSAs than for non-linked MSA pairs.

Overall, my results provide evidence that segmentation in information along network lines causes segmentation in financial markets. The increased covariance of turnover between network-linked areas relative to non-network linked areas reflects network-induced commonality in demand shocks to local investors. These common demand shocks lead to differential pricing manifested through the network-driven increase in the covariance of returns as well as the increased similarity in valuations. Given the absence of a difference in the covariance of cash flows between linked areas relative to non-linked areas, the differential pricing is consistent with network-driven differences in investors' discount rates or growth expectations, suggesting segmentation in information causes financial segmentation.

1.4 Extensions

1.4.1 Effect over time

My main results focus on the time period between 1988 and 2006. During this period, newspapers likely represented a primary source of mass media through which local investors obtained their news. Since the onset of the internet in the early 2000's, however, investors' access to news beyond their local newspapers has increased substantially. Thus, in the internet age, newspapers are likely to constitute a smaller weight in investors' information sets, weakening the effect I document.

I test whether the ownership network effect weakens over time by extending my sample of newspaper ownership linkages through the year 2015. I employ the same difference-in-differences framework to test the network linkage effect on weekly returns covariances for different sample periods.

Table 1.9 presents the results of the difference-in-differences regression of pairwise covariances of weekly returns on the network indicator equal to 1 if the two MSAs are linked through a newspaper ownership network for the extended sample period of years 1988 to 2015. Column 1 shows that the average annualized equal-weighted pairwise covariance of weekly returns increases by $3.642\%^2$ if two MSAs are linked through a common newspaper network. This is a 18.9% decrease relative to the coefficient of $4.493\%^2$ obtained from runnig the same regression for the main sample years 1988 to 2006 (shown in Column 4 and Table 1.4). The decrease suggests that the effect has declined over time as the weight of local newspapers has also declined among investors' information sets[15].

The effect's decline in time is more evident by decomposing the extended sample into two subsamples of the pre-internet period of 1988-2002 and the post-internet period 2002-2016. Splitting the sample in 2002 captures the effect of the internet's proliferation. Column 2 shows that the coefficient on the pre-internet subsample is $4.904\%^2$, which is larger than the effect measured using the main sample or the complete extended sample. As expected with the local newspaper's decline over time, column 3 shows that in the post-internet period, the effect's magnitude declines to only $2.502\%^2$ and becomes statistically insignificant. The decrease in the economic magnitude and statistical significance over time provides additional identification to my results. If newspaper ownership endogeneity is driving my results, the results should be similar in both the pre-internet and post-internet subsamples.

[15]The number of observations declines substantially in the later years of the extended sample. This decline is due to the total number of CRSP firms declining over time.

Table 1.9 Segmentation Effect Over Time This table shows the effect of a newspaper network on the covariance of weekly returns between two MSAs over different time periods. For all years between 1988 and 2015, I obtain a stock's weekly idiosyncratic returns from the residual of the regression of that stock's return on the weekly value-weighted market return and the weekly return of that stock's own SIC-2 industry. At each date, for each MSA, I form an equal-weighted portfolio return of all stocks headquartered within that MSA. To be included in the sample, an MSA is required to have at least 10 stocks. For every pair of MSAs, I calculate an annual covariance between the two MSA portfolios of weekly idiosyncratic returns. This covariance is then regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than 25% and 0 otherwise. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Column 1 is the results for the main sample of years 1988 to 2006. Columns 2-4 use the extended sample time period from 1989-2015. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

	Covariance by Frequency (Annualized)			
	Extended Sample			Main Sample
	1988-2015	1988-2002	2003-2015	1988-2006
Network link = 1	3.642**	4.904*	2.132	4.493**
	(1.523)	(2.719)	(1.524)	(1.767)
Total number of firms summed across MSAs	0.274***	0.494***	0.230***	0.372***
	(0.046)	(0.063)	(0.042)	(0.052)
Total market cap summed across MSAs	1.981*	4.293***	-2.884	3.025**
	(1.179)	(1.479)	(2.556)	(1.243)
MSA Pair Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dyadic Cluster	Yes	Yes	Yes	Yes
Total Observations	100647	64969	35678	80975
% Major network	4.19%	3.94%	4.64%	4.27%

1.4.2 Asset allocation effects

The segmentation effect documented likely arises from systematic news being shared within the network. However, my cross-sectional findings that show the network effect is positively associated with a firm's advertising expenditures also suggest firm-specific news may be transmitted. In this section, I explore whether firm-specific news is shared within the network.

If newspapers are more likely to print stories about local firms (i.e., firm-specific news) and these stories are shared within the network, this could increase awareness of network-linked, yet geographically separate, stocks by capturing the attention of investors in linked areas (Barber and Odean, 2008; Merton, 1987). A key implication is that investor holdings in one area relative to another should become more similar after the areas become connected through a newspaper network.

To test whether firm-specific news is propagated through the network, I use data on retail investors' monthly portfolio holdings data from Barber and Odean (2000). The data is a sample of monthly holdings of retail trading accounts from a large discount brokerage firm for the years 1991-1996. Investors are identified by account and household. Summing the household holdings by firm, I form holdings based calendar-time portfolios for each MSA. Using these MSA-level holdings portfolios, I then calculate the difference in portfolio holdings between two MSAs as follows:

$$DIFF\_HOLDINGS_{i,j,y} = \sum_{f \in F_{i,j,y}} |weight_{f,i,y} - weight_{f,j,y}| \tag{1.6}$$

where $DH_{i,j,y}$ is the sum of the absolute value of the difference in portfolio weights of a firm f in the two aggregated portfolios for a pair of MSAs i and j in year y. For each MSA of an MSA pair (i, j), the portfolio weight for each firm f is calculated as the total MSA-level firm holdings at time t divided by the total holdings of the set of all firms, F, in either MSA portfolio of the pair, averaged over year y. Summary statistics for the $DIFF\_HOLDINGS_{i,j,y}$ variable is included in Appendix Table 1.A.2.

Using the difference-in-differences framework from before, I regress the pairwise difference in holdings on the network link indicator and controls. Table 1.10 shows the results of regressing the difference in individual investor holdings weights for an MSA pair on a network indicator and the controls used previously. The first specification yields a statistically significant coefficient on the network indicator of -0.172 that is both negative and statistically significant at the 10% level. As shown in the second and third specification, the result is nearly identical even after controlling for the total number and total market capitalization summed across MSAs in a pair. The coefficient of -0.172 suggests that a network link increases the similarity in portfolio holdings among individual investors of areas linked through the network relative to investors not exposed to the network. Given the average net difference for non-linked MSA pairs is 6.755%, this suggests that a newspaper ownership network causes a 2.54% increase in the similarity of the holdings of individual investors in network-linked areas.

1.5 Conclusion

This paper shows that distinct information networks lead to equity market segmentation, as measured by trading and price commonality that arise between stocks with marginal investors that are exposed to the same information network. I argue that commonality in information within a network induces common demand shocks among network-linked investors. These demand shocks result in trading pressure exhibited by increased covariance in the turnover of network-linked stocks. This trading pressure leads to an increase in covariance of returns and similarities in prices among stocks with marginal investors exposed to the network.

Using changes in newspaper ownership networks, I find that a network link between two MSAs increases the covariance of both turnover and returns between the stocks in the MSA pair. The network-driven increase in covariance of turnover and returns is strongest when calculated using weekly data, consistent with a delay in information diffusion within a network. For turnover, a network link increases the covariance between two linked MSAs by 30.1% relative to the average covariance of two non-linked MSAs. For returns, the network-

Table 1.10 Network Effect on Difference in Individual Investor Holdings This table shows the difference in portfolio weights of individual investors' holdings between two MSAs. For each local stock in each pair of MSAs, I calcluate the total holdings in that stock. I weight each holding by the total market capitalization of all local firms located in either area of the paired MSAs. For each stock in each month of each MSA pair, I compute the absolute value of the difference in portfolio allocation to that stock. For each MSA, the sum of the holdings differentials is regressed on a dummy variable that is equal to 1 if both MSAs in the pair have commonly owned local newspapers with market shares greater than or equal to 25%. I include the total number and total market cap of local firms summed across the two MSAs as control variables. Dyadically clustered standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by ***, ** and *, respectively.

	Diff. in portfolio weights		
	(1)	(2)	(3)
Network indicator	-0.172*	-0.172*	-0.172*
	(0.102)	(0.102)	(0.102)
Number of firms (MSA pair)		0.002	0.002
		(0.002)	(0.001)
MCAP (MSA pair)			0.000
			(0.000)
MSA-Pair fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Dyadic cluster	Yes	Yes	Yes
Total observations	243,609	243,609	243,609
% same network	4.44%	4.44%	4.44%

driven increase in covariance between two linked MSAs is 9.18%. The network effect decreases for larger stocks with high institutional ownership, and a greater number of active analysts. Using earnings growth ratios as a proxy for cash flows, I show that the comovement measured is not driven by changes in underlying cash flows.

In addition to returns, I measure segmentation in price levels along network lines. However, I also find increased similarity in price levels between network-linked areas. Using a measure of bilateral valuation differences from the international market segmentation literature, I find that a network link causes valuations to become 4.22% more similar between two MSAs relative to non-linked MSA pairs.

The increased comovement of turnover is a result of network-driven demand shocks. The commonality in demand shocks leads to an increased comovement of returns and similarity in prices between two-network linked areas, consistent with the network driving a common discount rate or growth expectations among network-linked investors. Taken together, my findings imply that segmentation in (public) information leads to financial segmentation.

Although the segmentation effect is likely driven by systematic news shared within a network, I also find that network-driven commonality in firm-specific news leads to increased similarity in portfolio allocations of individual investors.

My findings suggest opportunities for future research on the changing media landscape and the home bias. Additional research should explore the degree to which the mass media mitigates the home bias by increasing investor awareness of network-linked stocks. Alternatively, as the mass media tends to cluster geographically, the home bias may be exacerbated by increased consolidation of news ownership in a given region.

1.A Appendix Tables

Table 1.A.1 Variable Definitions and Construction This table defines all the variables used in my analysis.

Variable	**Description**
Network Indicator	Indicator equal to 1 if both MSAs belong to the same newspaper network and 0 otherwise. An MSA's local newspaper must have at least 25% market share in terms of circulation for the MSA to be included in a network.
Segmentation measures	
Pairwise covariance of turnover	I obtain stock turnover data from CRSP for all stocks in MSAs with greater than 10 stocks. For each stock, I extract the turnover residual obtained by regressing stock turnover on the share-weighted market turnover and that stock's share-weighted SIC-2 industry turnover. For each MSA, I form an equal-weighted (share-weighted) portfolio of stock turnover for all locally headquartered stocks. For each year, I compute the annual pairwise covariance between two MSAs. Turnover is measured using daily, weekly, bi-weekly or monthly data, where a week is defined from Wednesday-to-Wednesday. Constructed for all MSA pairs.
Pairwise covariance of returns	I obtain stock return data from CRSP for all stocks in MSAs with greater than 10 stocks. For each stock, I extract the return residual obtained by regressing stock return on the value-weighted market return and that stock's value-weighted SIC-2 industry return. For each MSA, I form an equal-weighted (value-weighted) portfolio of returns for all locally headquartered stocks. For each year, I compute the annual pairwise covariance between two MSAs. Returns are measured using daily, weekly, bi-weekly or monthly data, where a week is defined from Wednesday-to-Wednesday. Constructed for all MSA pairs.
DIFF_PRICES	The industry value-weighted average of the absolute difference between the average earnings yields of two MSAs. Constructed for all MSA pairs. See Bekaert et al. (2011, 2013) for more details.
Robustness and extensions measures	
Pairwise covariance of earnings	I obtain quarterly earnings from Compustat for all stocks in MSAs with greater than 10 stocks. For each MSA and each quarter, I form an equal-weighted portfolio of earnings for all locally headquartered stocks. I require a stock to have at least 8 non-missing quarterly observations. For each year, I compute the annual pairwise covariance in earnings between two MSAs. Constructed for all MSA pairs.
DIFF_HOLDINGS	I obtain monthly holdings data of individual investors for the years 1991-1996 (Barber and Odean, 2000). For each MSA in each MSA pair, I compute the weight held in each firm by taking the total dollar amount in that firm divided by the total MSA holdings in all firms common to either MSA of the pair. In each month, I take the difference between the firm weights in the two portfolios of an MSA pair. Constructed for all MSA pairs.

Table 1.A.1 continued

Variable	Description
Measure-induced controls	
Number of firms (MSA pair)	The total number of locally headquartered stocks in an MSA pair.
MCAP (MSA pair)	The total market capitalization of locally headquartered stocks in an MSA pair.
Abs (return volatility difference)	Using returns data from CRSP, I obtain industry log earnings growth volatility by calculating the 60-month standard deviation of SIC-2 industry log returns for all industries in a given MSA. I require at least 24 non-missing returns for the calculation. Industry returns are the value-weighted returns of all firms with a given SIC-2 code in an MSA. I form the weighted average of the absolute difference between the industry return volatilities of two MSAs, using total industry market values as weights. See Bekaert et al. (2011, 2013) for more details.
Abs (leverage difference)	At the end of each year, I obtain the total liabilities and total equity for the most recent annual report. For each firm, I calculate a leverage ratio by dividing the long-term interest bearing debt by total assets. For each industry in each MSA, I compute a weighted average leverage ratio of all locally headquartered stocks, weighting each observation by total assets. I form the weighted average of the absolute difference between the industry leverage ratios of two MSAs using total industry market values as weights. See Bekaert et al. (2011, 2013) for more details.
Abs (earnings growth volatility difference)	For each industry in a given MSA, I obtain industry log earnings growth volatility by calculating the 20 quarter standard deviation of quarterly log growth rates of 12-month earnings. I require at least 8 quarters of observations for the calculation. Industry earnings are the sum of all firm's earnings in that industry in each quarter. I form the weighted average of the absolute difference between the industry log earnings growth volatilities of two MSAs, using total industry market values as weights. See Bekaert et al. (2011, 2013) for more details.

Table 1.A.1 continued

Variable	Description
Cross-sectional determinants	
Market capitalization (ln)	The natural logarithm of the total market capitalization of a stock as of end of each year.
% institutional ownership	The fraction of the number of shares held by institutional investors (obtained from Thomson Reuter's 13f) divided by the total number of shares outstanding.
Number of analysts	The total number of analysts with a current estimate
Advertising (ln)	The total advertising expenditure captured in the most recent 10-k as of the end of the previous year.
Total network circulation (ln)	The natural logarithm of the total circulation for all newspapers in previous year.
Number of papers in MSA	The total number of daily newspapers in the MSA as of the end of the previous year.

Table 1.A.2 Additional Summary Statistics This table provides summary statistics of all variables used in the paper. Definitions are given in Appendix Table 1.A.1

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Variable	**Mean**	**Std**	**Min**	**Max**
Network Indicator	0.043	0.202	0.000	1.000
Segmentation measures				
Pairwise covariance of (weekly) turnover	1.728	8.108	-54.315	112.154
Pairwise covariance of (weekly) returns	48.555	63.969	-54.959	551.515
$DIFF\_PRICES$	2.637	1.792	0.131	12.409
Robustness and extensions measures				
Pairwise covariance of QoQ earnings growth rates	0.056	2.257	-27.636	51.512
Pairwise covariance of YoY earnings growth rates	0.108	3.062	-102.661	72.804
$DIFF\_HOLDINGS$	6.656	7.509	0.000	61.530
Measure-induced controls				
Abs (leverage difference)	0.140	0.097	0.000	1.145
Abs (earnings growth volatility difference)	0.674	0.558	0.000	5.294
Number of firms (MSA pair)	111.217	88.057	20.000	659.000
MCAP (MSA pair) (ln)	14.862	1.147	7.947	18.423
Cross-sectional determinants				
Market capitalization (ln)	12.540	1.768	9.037	17.268
% institutional ownership	43.016	28.048	0.000	100.000
Number of analysts	6.704	7.218	0.000	50.000
Advertising (ln)	15.423	2.382	0.000	22.795
Total network circulation (ln)	11.615	3.688	0.000	15.475
Number of papers in MSA	2.129	1.471	0.000	8.000

Chapter 2

THE VALUE OF A DIRECTOR ON ORDINARY DAYS

A central concern in corporate governance is the alignment of incentives between shareholders and boards of directors. To ensure adequate alignment, shareholders must monitor directors or, at least, the performance of the directors' firms. The literature evaluates investors' monitoring of directors using major firm-related events, such as directors' votes on anti-takeover provisions (Coles and Hoi, 2003), initiations of fraud investigations (Fich and Shivdasani, 2007) and the announcement of departures or additions to boards (Ferris, Jagannathan, and Pritchard, 2003; Fich and Shivdsani, 2006). Studies using these large pre-identified corporate events–when the monitoring is most likely to occur–provide evidence of investors' attention to directors. In contrast, we show that shareholders are inattentive to the performance of directors' firms in more routine times.

To show this inattention, we exploit that directors sitting on multiple boards create links among firms. These links occur in part through the directors' common influence, making firm performance across these networks another channel to evaluate shareholders' monitoring of directors. In this paper, we investigate how closely investors monitor this network of directorships by measuring the profitability of a trading strategy rebalanced monthly based on information contained within this network.

To form this trading strategy, we map the network of shared directorships between 1996 and 2014. We begin with the readily available "public" databases RiskMetrics and BoardEx. We then extend these sources with a hand-collected database of directors obtained from mutual fund voting records filed with the SEC.

With these links, we implement a long-short trading strategy. Each month we sort firms into quintiles based on the prior month's (five-factor) idiosyncratic return, not of the firm itself, but instead the portfolio of the firms with which the firm being sorted shares at least one director.[1] Going long the top quintile and short the bottom quintile yields a value-weighted five-factor alpha of 6.5% per year.[2] This economically and statistically significant alpha shows both that there is cross-firm value relevant information contained in the director network and that investors process this information into prices with a delay.

We show that directors are aware of the common information within this network by examining their personal trading. When we restrict the long and short ends of the portfolio to only firms where the linked director at the predicting firm is in the top or bottom quintile of insiders trading, the alpha on the long-short portfolio increases to 15% per year. These directors' trades appear highly profitable, yielding statistically significant cumulative abnormal returns in the following 60 trading days of 4.5% for purchases and -4.6% for sales. That the return predictability is tied to directors' trades and the CAAR of these trades grow for several months provide further evidence that shareholders' do not fully monitor directors. The directors' profitable trades on information in their portfolio of directorships extends the literature by showing that directors are aware of more than just the idiosyncratic factors affecting their firms (e.g., Ravina and Sapienza (2010)).[3]

There is a long literature showing common influence of directors over their portfolio of firms.[4] Nevertheless, the return predictability among board-linked firms may arise because

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[1]This sorting method follows the standard lead-lag sorting methodology in the literature with the bias correction provided in Burt and Hrdlicka (2016). See additional references on the methodology therein.

[2]The asset pricing model is the Fama and French (1993) 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003)

[3]This is consistent with the findings of Alldredge and Cicero (2015) that insiders trade successfully on related firms and of Anginer, Hoberg, and Seyhun (2015) that insiders trade in the same director of anomalies.

[4]For example, 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). Firms with shared directors are jointly more likely to restate earnings (Chiu, Teoh, and Tian, 2013). They are more likely to make the switch from the NYSE to NASDAQ together (Rao, Davis, and Ward, 2000). Firms sharing directors also have similar acquisition patterns and pay similar premia for their targets. (Haunschild, 1993, 1994) Board-linked firms are also more likely to be jointly acquired by private equity companies (Stuart and Yim, 2010) and are more likely to form a joint venture

connected boards proxy for another relationship between the firms. We address this concern using two robustness settings. First, we exclude connected firms that share observable economic commonalities, such as firms in the same industry or firms linked through previously documented economic channels such as customer-supplier relationships, strategic alliances, or headquarters in the same MSA.[5] The predictability remains after these exclusions.

Second, in an attempt to exclude board-linked firms with unobservable commonalities, we also perform an out-of-sample test. We form a sample of linked firms from those with shared directors 1 to 3 years (also 2 to 4 years) before a shared director link begins and after the link ends. If the shared director is a proxy for another underlying economic link unrelated to the director, we should find that these out-of-sample links yield similar return predictability. We find just the opposite: using the out-of-sample links makes the return predictability disappear. Though we are unable to fully exclude the possibility that the missing relationship happens to vary in exactly the same way as shared directorships, our robustness tests combined with the trading behavior of the directors themselves make a strong case that the director linkages themselves are key to the predictability.[6]

The predictability could arise from either trading frictions or investor inattention to director networks. Our evidence suggests inattention as the predictability is present primarily in the long end of the value-weighted portfolio. Moreover, we find that the predictability flows almost entirely from small firms to big firms (contrary to the direction found in other settings, e.g., Lo and MacKinlay (1990)). Thus, to eliminate much of the documented predictability investors would need only to buy, not short, some of the largest and most liquid stocks in the market, suggesting trading frictions is not driving our results.

Contrasting the predictability across two information sets that vary in their degree of

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(Gulati and Westphal, 1999). For a more extensive overview of the influence of boards, see the recent reviews by Hermalin and Weisbach (2003); Adams, Hermalin, and Weisbach (2010) and the references therein.

[5]See Hou (2007), Cohen and Frazzini (2008) and Cao, Chordia, and Lin (Forthcoming).

[6]This absence of out of sample predictability also suggests the predictability is not simply due to a missing factor in the asset pricing model, though the methodology of Burt and Hrdlicka (2016) already lessens such a possibility. See the discussion of missing factors therein.

publicness also suggests that information, rather than trading frictions, drive the predictability. We find that when using only the "public" data on director links from RiskMetrics and BoardEx, return predictability is present but substantially muted. Including our hand collected data on directors from mutual fund voting records, which we term "semi-private" due to its lower accessibility to investors, increases the predictability by almost 50%.[7]

Finally, the trading behavior of directors themselves suggests they are attempting to exploit investor inattention to trade profitably while avoiding detection. The directors who trade, trade primarily in the firm that predicts the idiosyncratic returns of the other firms on whose boards they sit. 85% of the time, in both the concurrent month and in the following month (the month where we observe the return predictability), the director makes no trades in the predicted firms. Thus, the directors appear to deliberately leave money on the table to avoid detection.

Overall, this return predictability provides evidence of investor inattention, implying that shareholders do not fully monitor firm performance across directorship networks. This predictability has implications both for our understanding of information diffusion and the functioning of the directorship labor market. We also provide unique evidence that directors are aware not only of what the idiosyncratic outcomes of individual firms in their portfolio will be, but they are also aware of outcomes that are systematic to the firms on whose boards they sit. We show a novel way to use mutual fund voting records to extend our knowledge of the directorship network to small firms not covered by standard commercial databases. Finally, the delayed incorporation of information regarding these board-linked firms into prices suggests that the short-horizon event studies of boards' value effects (e.g., Ferris et al. (2003); Fich and Shivdsani (2006) and Fich and Shivdasani (2007)) potentially understate the importance of corporate boards.

[7]One could equally term this "semi-public" data. What is important is the increased difficulty for investors of obtaining this information compared to that in the "public" database. As Jensen (1978) writes "the precise meaning of publicly available' must be defined ... exactly where those boundaries are in a general sense is something that will profitably receive more attention in the future."

2.1 Data

We form annual firm links for the years 1996 to 2015 by identifying firms that share at least one director. We use data on directors from three primary sources: RiskMetrics, BoardEx and SEC records on mutual fund votes in director election.

2.1.1 Construction of Public Sample

We use the two 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 2015. For the years 1999 and earlier, RiskMetrics includes director information for some additional firms beyond the S&P 1500. BoardEx includes annual information on boards of directors for the years 2000-2015, including some firms which are not in the S&P 1500. As the BoardEx and RiskMetrics databases use different unique identifiers for each unique director, we hand-match directors across the databases on their name, year of service and firm. Combining these databases provides coverage of over 2000 firms. We refer to the shared directorships identified as our "public" sample.

2.1.2 Construction of Semi-Private Sample

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 (there are no useful observations until 2004). 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 directorships derived from these voting records as the "semi-private" sample. To make this distinct from the public sample, we remove any overlap from the semi-private sample.

We use two assumptions to convert the data on votes to a panel of shared directorships.

First, we assume that a director who is up for election is elected.[8] Second, we assume one-year terms unless a director appears in the data for a given firm in any two non-consecutive years. In this case, we assume the director was an active director in the intervening years. For example, a director appearing on the ballot in 1999 is coded as a director in 1999. While a director on the ballot in 2000 and 2003 is coded as a director in 2000, 2001, 2002 and 2003. To match directors across firms, we use a fuzzy matching process on director names. The assumptions about director tenure and the fuzzy matching are intentionally conservative. Erroneous firm links arising from either assumption lead to noise in our sample which biases against finding evidence of return predictability.

2.1.3 Firm Links Through Shared Directors

Our total sample of linked firms consists of three sets of links: (1) the links identified solely from directorships listed in BoardEx and RiskMetrics which make up our public sample, (2) the links identified solely from directorships listed in our semi-private data, and (3) the links identified from one directorship listed in either BoardEx or RiskMetrics and one directorship listed in our semi-private data. The last two sets of links constitute our semi-private sample. We use the total sample for our analysis unless otherwise noted.

The links between firms in our sample are dynamic and explicitly account for turnover among directors. We define a director of a firm as active at the end of the calendar year following the first annual report in which he or she is listed (i.e., the first annual report after election). We form links between firms beginning six months (July 1) after they begin sharing an active director. This link continues one year until the following June. A link continues each year (July to June) thereafter as long as the firms continue to share an active director. Figure 2.1 provides two examples of the link formation dates with respect to the observable firm events and director elections.

The timing convention used to map links between firms has a deliberately delayed start.

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[8]Cai, Garner, and Walkling (2009) and Fos, Li, and Tsoutsoura (2017) document close to 100% election rates of nominated directors.

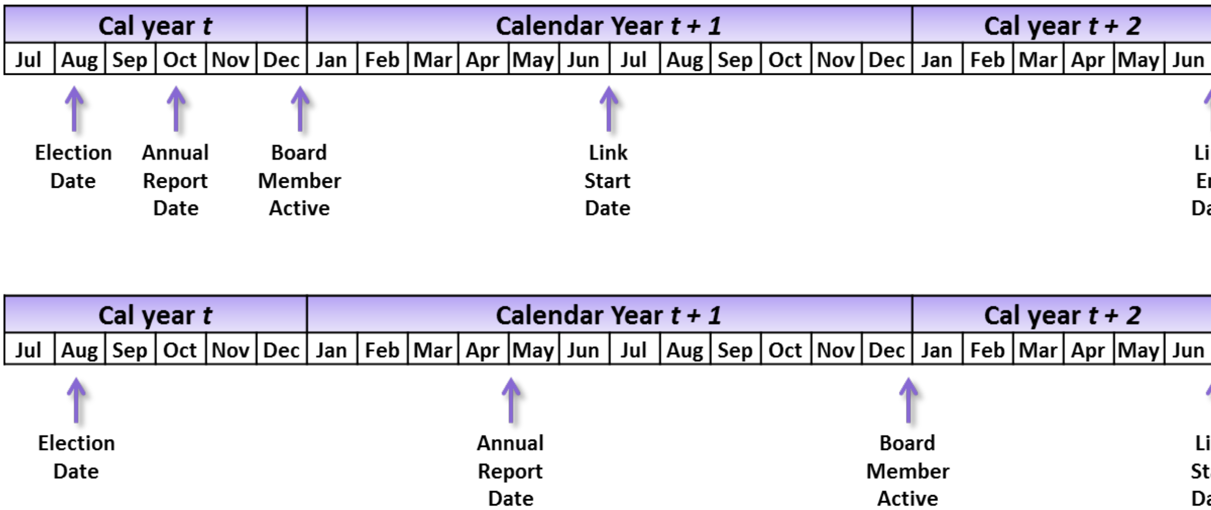


Figure 2.1. This figure provides two examples of how the links are formed in time relative to the oberved directors presence on the board of directors.

At the firm level, the delay allows for directors to begin acting on their firms. In link formation between firms, the delay ensures that investors have sufficient time to learn of the new directorships to begin monitoring. This timing convention allowing investors time to learn information is common in the literature following Fama and French (1992).

We combine the data on firms that share at least one director with accounting data from Compustat, monthly returns from CRSP and factor returns from Ken French's website. We limit our data to common stocks (share codes 10 and 11) traded on the NYSE, AMEX and NASDAQ. We exclude utilities and financial firms from the predicted side of the link. To eliminate 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.

2.1.4 Summary Statistics

Table 2.1 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

Table 2.1 Summary Statistics This table shows summary statistics as of December of each year. Panel A covers of the overall sample. Panels B and C summarize non-overlapping partitions of this overall sample. Panel B summarizes the public sample: all firms and the links between them identified solely based on directors listed in the RiskMetrics and BoardEx Databases for the years 1997-2015. Panel C summarizes the semi-private sample: all firms and links from them that require the use of at least one director added to the overall sample through hand-collection from mutual fund voting records. 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.

Panel A: Full Sample (19 Yearly Observations, 1997 - 2015)

	Min	Q1	Median	Q3	Max	Mean	Std.
Number of firms in the sample each year	1226	1630	2148	2504	2632	2055	518
Full sample % coverage of CRSP Universe (EW)	16.3	29.3	48.8	63.2	66.3	44.9	18.5
Full sample % coverage of CRSP Universe (VW)	80.1	90.2	93.5	94.6	96.0	91.6	4.8
Firm size percentile (NYSE)	0.01	0.2	0.45	0.75	0.99	0.48	0.3
Firm book to market percentile (NYSE)	0.01	0.2	0.45	0.7	0.99	0.46	0.3
Number of Unique Links Per Firm	1	2	3	7	24	5.24	5.41

Panel B: Public Sample (19 Yearly Observations, 1997 - 2015)

	Min	Q1	Median	Q3	Max	Mean	Std.
Number of firms in the sample each year	1111	1226	1582	1671	1793	1491	223
Full sample % coverage of CRSP Universe (EW)	16.3	29.0	32.6	36.0	39.5	31.0	6.9
Full sample % coverage of CRSP Universe (VW)	80.1	88.0	90.8	92.0	92.8	88.9	4.2
Firm size percentile (NYSE)	0.01	0.35	0.55	0.8	0.99	0.57	0.28
Firm book to market percentile (NYSE)	0.01	0.2	0.4	0.7	0.99	0.45	0.29
Number of Unique Links Per Firm	1	2	4	8	24	5.67	5.2

Panel C: Semi-Private Sample - Unique Firms (12 Yearly Observations, 2004 - 2015)

	Min	Q1	Median	Q3	Max	Mean	Std.
Number of firms in the sample each year	283	700	813	835	887	728	182
Full sample % coverage of CRSP Universe (EW)	5.9	15.1	20.0	21.6	22.6	17.9	5.4
Full sample % coverage of CRSP Universe (VW)	0.7	1.5	2.1	2.9	4.4	2.3	1.1
Firm size percentile (NYSE)	0.01	0.05	0.1	0.2	0.99	0.16	0.16
Firm book to market percentile (NYSE)	0.01	0.2	0.5	0.8	0.99	0.51	0.33
Number of Unique Links Per Firm	1	1	2	3	21	2.14	2.21

firms per year, which is, on average, 45% 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. 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.

Panels B provides an overview of the public portion of our sample. RiskMetrics 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 public sample. The mean annual number of firms between the years 1997 and 2015 is 1,491. 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. Based on NYSE percentiles, the average firm size percentile, is 0.57 while 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 5.67 and a median of 4. This greater connectivity is to be expected in a sample that contains the largest public firms.

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 firm links identified through the hand-collection process. That is, Panels B and C show non-overlapping partitions of the overall data.

In the semi-private sample, the mean annual number of firms between the years 1997 and 2015 is 728, which represents 17.9% 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 mean of 2.14 and 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.

2.2 Predictable Returns

The extent of market efficiency is a function of the extent of investors' monitoring of directors. If investors monitor in real time the performance of all the firms on which a director sits, any cross-firm value-relevant information should be simultaneously reflected in the prices of all these firms. Therefore, it should not be possible to form a profitable trading strategy using news about one firm a director presides over to trade a month later in the others firms that director presides over.

Basing such a trading strategy only on large highly visible corporate events only measures the monitoring of a small subset of events. To study how investors monitor the continuous flow of often small events not directly observable to econometricians, we exploit financial markets' impounding of relevant news, visible via firms' idiosyncratic returns. Because this signal may miss some news events, its inability to produce a profitable trading strategy cannot confirm attentive monitoring. However, the presence of a profitable strategy using the signal can provide evidence of inattentive monitoring.

2.2.1 Trading Strategy Construction

We use idiosyncratic returns as our signal to avoid contamination from systematic exposures and firms' average returns that are present in raw returns. The intuition is similar to the use of abnormal returns in event studies rather than raw returns. We estimate these idiosyncratic returns from rolling regressions of a five-factor model (Fama and French, 1993, 1996; Carhart, 1997; Pástor and Stambaugh, 2003), using one year of prior monthly data: $t-13$ to $t-2$. This estimation window balances the trade-off between estimation precision from more data with the need to estimate betas that vary greatly through time (Fama and French, 1997; Lewellen and Nagel, 2006). Any noise in these estimates, makes it less likely to find evidence of predictability. Nevertheless, we obtain similar estimates using longer horizons.[9]

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, not of the firm itself, but instead of each firm with which it shares a common director. This average of idiosyncratic shocks gives us a predictive signal based on the average performance in the preceding period of the other firms at which each director presides. We sort firms into quintile portfolios at time t based on these average idiosyncratic returns. We consider both value-weighted and equal-weighted portfolios with monthly rebalancing, though we show only value-weighted results unless otherwise noted.

Once firms are sorted into portfolios, our key statistic of interest is the five-factor alpha of the long-short portfolio of the extreme quintiles. Positive alphas in this long-short portfolio indicate both slow price discovery and the presence of value-relevant cross-firm information in the network of shared directors. These alphas are a direct measure of the economic importance of these effects.

2.2.2 Main Predictability Results

Table 2.2 shows the alphas of the five quintile portfolios (value- and equal-weighted) along with the long-short portfolio formed from quintiles 5 and 1. We see that, across all asset pricing models, 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 55 basis points per month or 6.6% per year. This economically and statistically significant alpha shows both that cross-firm value-relevant information is contained in the director network and that investors process this information into prices with a delay. As the equal-weighted alpha is essentially zero, we focus on the more interesting value-weighted results

[9] We do not use higher frequency data because the liquidity factor of Pástor and Stambaugh (2003) is not available at the daily frequency and the literature shows that asset pricing models can vary systematically across frequencies (Hawawini, 1983; Handa, Kothari, and Wasley, 1989; Gilbert, Hrdlicka, Kalodimos, and Siegel, 2014; Boguth, Carlson, Fisher, and Simutin, 2016).

Table 2.2 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 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.

Value Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S
Excess Returns	0.407	0.638	0.588	0.386	0.989	0.581
	(1.005)	(2.001)	(2.017)	(1.225)	(2.311)	(2.722)
1-Factor Alpha	-0.189	0.155	0.149	-0.095	0.371	0.560
	(-1.210)	(1.576)	(1.569)	(-1.042)	(2.039)	(2.604)
3-Factor Alpha	-0.153	0.184	0.172	-0.088	0.428	0.581
	(-1.071)	(1.907)	(2.052)	(-0.969)	(2.522)	(2.672)
4-Factor Alpha	-0.118	0.184	0.183	-0.122	0.474	0.592
	(-0.825)	(1.887)	(2.173)	(-1.373)	(2.801)	(2.698)
5-Factor Alpha	-0.110	0.146	0.166	-0.123	0.440	0.550
	(-0.754)	(1.487)	(1.945)	(-1.350)	(2.561)	(2.468)

Equal Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S
Excess Returns	0.819	0.801	0.836	0.855	0.960	0.141
	(1.907)	(2.072)	(2.218)	(2.249)	(2.243)	(1.268)
1-Factor Alpha	0.202	0.246	0.295	0.307	0.348	0.146
	(1.081)	(1.463)	(1.793)	(1.881)	(1.834)	(1.300)
3-Factor Alpha	0.004	0.043	0.098	0.102	0.138	0.133
	(0.032)	(0.342)	(0.792)	(0.882)	(1.037)	(1.175)
4-Factor Alpha	0.116	0.130	0.183	0.172	0.225	0.109
	(0.956)	(1.122)	(1.587)	(1.561)	(1.807)	(0.957)
5-Factor Alpha	0.045	0.035	0.095	0.068	0.162	0.117
	(0.375)	(0.317)	(0.854)	(0.653)	(1.305)	(1.011)

for the remainder of the paper.

The slow information diffusion that gives rise to the observed alphas could be caused by either investor inattention or trading frictions. If investors actively monitor this information about directors but trading frictions prevent them from exploiting it, then we expect to see the strongest predictability among small firms. In addition, the predictability should be primarily in the short-end of the portfolio where shorting constraints bind. Our results show the opposite and provide evidence that is more consistent with inattention.

The larger value-weighted alpha shows the predictability is stronger in the largest firms, which tend to be more liquid and, hence, less susceptible to trading frictions. In addition to finding alpha in the long-short portfolio, we find the alpha of the top quintile is economically and statistically significant. The predictability's concentration in the long end of the value-weighted portfolio, where short-selling constraints do not bind, shows that an investor only needs to buy some of the largest most liquid stocks to profit from this strategy. We provide additional evidence to distinguish investor inattention from trading frictions in Section 2.4.

The alphas we find show that the commonality among firms with shared directors is more observable at longer return horizons. The eventual price responses in the related firms, however, does not necessarily mean that investors eventually monitor directors by looking at the past performance of all the firms they oversee. Nor does it require that investors even become aware of directors shared among firms. Investors can learn the information that ultimately moves prices from separate firm-level announcements even if they don't observe the commonality in value effects among these firms.

For example, consider a series of information events consistent with director-linked firms having an increased propensity to jointly backdate options due the directors' influence as in Bizjak et al. (2009). Suppose firms A, B, and C share a director, and we observe a negative idiosyncratic shock today in firm A due to the revelation of its option backdating. A month later, we could see similar negative returns at B and C, when the information comes out that those firms are also backdating options. None of these price responses require investors to have monitored the shared director's behavior across the three firms or even become aware of the shared director.

We provide evidence consistent with the return predictability that we document arises from the shared director as in this example. Alternatively, the predictability may occur because a shared director proxies an unobservable economic commonality between the firms. In the next section, we attempt to rule out this alternative.

2.3 Robustness and Identification

We use two methods to distinguish the role of a shared director from that of an unobservable commonality between firms. First, we exclude connected firms that share observable economic commonalities, such as firms in the same industry or firms linked through previously documented economic channels such as customer-supplier relationships, strategic alliances, or headquarters in the same MSA. Second, we perform a placebo test using synthetic non-existent links between firms.

2.3.1 Predictability Remains After Removing Other Connections

Table 2.3 shows the alpha of the value-weighted long-short portfolio for our main sample in the first column. Columns two through four show the alpha after excluding firms in the same industry. Columns five through seven show the alphas after excluding firms with customer-supplier relationships, strategic alliances and headquarters in the same MSA.

Using 3 or 4-digit SIC codes as our industry measure to exclude firms, we obtain virtually identical results to our main specification: statistically significant five-factor monthly alphas of 56 and 50 bps. Even after excluding linked firms that share the same industry at the very coarse 2-digit SIC level, we still obtain statistically and economically significant 42 bps per month alpha. Thus, the documented predictability is not an industry effect.

In addition to controlling for industry, we also control for previously documented links. 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. Excluding these firms, we find economically and statistically significant five-factor alphas virtually

Table 2.3 Robustness: Abnormal Board-Linked Stock Returns Excluding Other 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 a different set of known links. The first column is the main result from Table 2.2. 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. (Forthcoming). 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.

Value Weights	Main Result	Industry SIC-4	Industry SIC-3	Industry SIC-2	Customer-Supplier	Standalone-Conglomerate	Alliance Member	Same MSA
Excess Returns	0.581	0.454	0.564	0.423	0.537	0.608	0.491	0.456
	(2.722)	(2.173)	(2.731)	(2.131)	(2.607)	(2.711)	(2.367)	(2.218)
1-Factor Alpha	0.560	0.495	0.561	0.410	0.535	0.537	0.493	0.456
	(2.604)	(2.365)	(2.695)	(2.052)	(2.573)	(2.549)	(2.356)	(2.198)
3-Factor Alpha	0.581	0.486	0.579	0.431	0.553	0.586	0.520	0.472
	(2.672)	(2.295)	(2.753)	(2.149)	(2.633)	(2.574)	(2.467)	(2.250)
4-Factor Alpha	0.592	0.498	0.539	0.393	0.515	0.586	0.498	0.425
	(2.698)	(2.327)	(2.552)	(1.950)	(2.440)	(2.547)	(2.341)	(2.022)
5-Factor Alpha	0.550	0.499	0.556	0.415	0.531	0.545	0.507	0.427
	(2.468)	(2.291)	(2.591)	(2.027)	(2.476)	(2.335)	(2.347)	(1.996)

identical to that of the full sample: 53 bps per month or 6.4% per year. Excluding firms linked by alliances as identified in Cao et al. (Forthcoming) we again find that the five-factor alphas nearly identical to the full sample: 51 bps per month. The small alpha differences after excluding these sets of links is due to minimal overlap between firms with shared directors and firms with customer-supplier relationships and alliances. Thus, the predictability is not due to previously identified relationships among firms.

One might hypothesize that firms share a director, because they have a similar location and thus the director link simply picks up common exposure to local economic variables (e.g., Korniotis and Kumar (2013)). 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, showing firm links using shared directors pick up more than geographic commonalities.

2.3.2 No Predictability in Placebo Test

Table 2.3 shows that sharing a director does not simply proxy for pre-identified observable links between firms. To address concerns that sharing a director proxies for other unobservable relationships between the firms, we use a placebo test. For this placebo test, we construct a set of synthetic non-existent links on which we rerun our predictability analysis.

For a convincing placebo test, we want these synthetic non-existent links to share as many properties with our original links as possible. We construct these synthetic links from the actual linked firms in our sample, but use only the periods before and after the link is active. Specifically, we consider one to three years and two to four years before or after (and combined) the period in which firms actually share a director. Figure 2.2 illustrates an example of how these synthetic links are formed.

Table 2.4 reports the long-short portfolio alpha using the actual links and the synthetic links. If the common director proxies for some other unobservable relationship between the firms, we would expect the alpha using these synthetic placebo links to be similar to the 55 bps five-factor alpha we find using the actual links. We find the opposite. Using

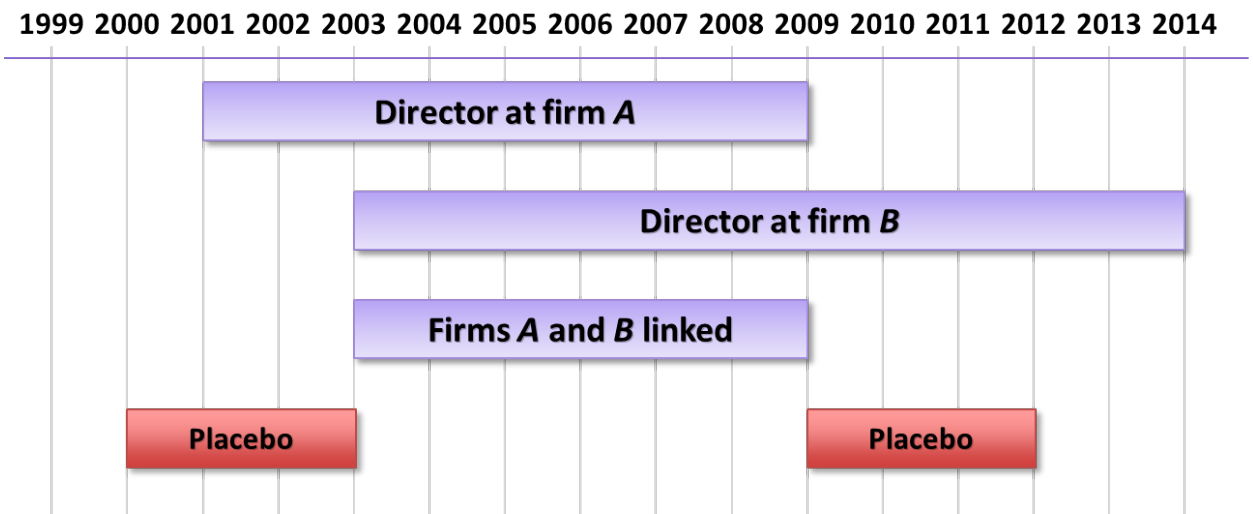


Figure 2.2. This figure provides an example of the in-sample period and out-of-sample periods before and after the link formation used in the placebo test.

synthetic links of one to three years before an actual link, the alpha is -5 bps per month, while using synthetic links in the one to three years after an actual link ends yield only 13 bps per month. Combining these two sets of links to improve the test's power or considering a sample window two to four years before and after, we also find no evidence of return predictability. In summary, the five-factor alpha of the value-weighted long-short portfolio using the placebo links is neither economically nor statistically significant.

Our results show that the timing of a director's overlapping tenure at both firms is critical to identifying the effect. Although this is suggestive of commonality among these firms flowing through the director, our methodology cannot reject an unobservable commonality that happens to vary in exactly the way across both firms and time as the directors' appointments.

2.4 Inattention to Costly Information

The return predictability shown in Table 2.2 is concentrated in the long end of the value-weighted portfolio. This concentration is consistent with investor inattention to director networks rather than trading frictions. In this section we further explore the extent to which

Table 2.4 Placebo Test: Abnormal Board-Linked Stock Returns Using Out-of-Sample Links, 1997-2015 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 a placebo 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 Pástor and Stambaugh (2003). Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

Link Timing *Value Weights*	Main Result	1-3 years Before	1-3 years After	1-3 years Before & After	2-4 years Before & After
Excess Returns	0.581	-0.047	0.165	0.058	0.033
	(2.722)	(-0.265)	(0.677)	(0.300)	(0.187)
1-Factor Alpha	0.560	-0.025	0.192	0.112	0.087
	(2.604)	(-0.136)	(0.786)	(0.572)	(0.487)
3-Factor Alpha	0.581	-0.049	0.192	0.102	0.067
	(2.672)	(-0.273)	(0.784)	(0.517)	(0.374)
4-Factor Alpha	0.592	-0.044	0.157	0.087	0.109
	(2.698)	(-0.240)	(0.640)	(0.433)	(0.601)
5-Factor Alpha	0.550	-0.047	0.131	0.108	0.119
	(2.468)	(-0.253)	(0.524)	(0.531)	(0.650)

investor inattention leads to return predictability. We decompose the predictability into that attributable to the two different public and semi-private information sets about shared directors. These two sets are constructed to vary in the degree to which they are publicly available and readily accessible.

2.4.1 Comparison of Public and Semi-Private Data

Our total sample of shared directorships comes from two sources. Our first data source is the director databases, RiskMetrics and BoardEx. Although these databases are available for a fee, they are both widely accessed databases. Moreover, they are easy to use and cover the largest most actively followed firms in the market, primarily S&P 1500 firms. Finally, these databases provide unique director IDs that make matching directors across firms and, therefore, discovering which firms are linked easy, even for a relatively unsophisticated investor. Given its ease of access and pervasiveness, we label this as public data.

Our second data source consists of hand-collected data on firm directors. We collect this data from SEC filings by mutual funds regarding their votes on directors. This second source, while technically publicly available, is much less readily usable. It requires web scraping 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. As these filings provide director names without unique director IDs, hand-matching by director names is required to identify board-connected firms. Due to the difficulty of the collection of this data, the steps required to make the data usable and its focus on smaller firms, we refer to this as semi-private data.

2.4.2 Predictability is Larger with Semi-Private Data

If investor inattention, even rational inattention, is important to the return predictability documented, we 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 2.5 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 2.2). We see that using only the public data generates an economically significant long-short alpha of 38 bps per month, however, it is only statistically significant at the 10% level. Consistent with investor inattention, this alpha is concentrated in the long end of the portfolio.

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. Moreover, the alpha is statistically significant at the 1% level. Thus, it appears that investors are relatively more (though not completely) attentive to easily accessible public data that has been processed into usable databases, while relatively less attentive to data that, while

Table 2.5 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 columns labeled "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.

	Public						Public+Semi-Private
Value Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S	L/S
Excess Returns	0.553	0.606	0.566	0.418	0.947	0.394	0.581
	(1.367)	(1.906)	(1.956)	(1.318)	(2.306)	(1.848)	(2.722)
1-Factor Alpha	-0.041	0.124	0.134	-0.066	0.354	0.395	0.560
	(-0.257)	(1.265)	(1.326)	(-0.737)	(2.027)	(1.837)	(2.604)
3-Factor Alpha	0.013	0.153	0.158	-0.048	0.420	0.407	0.581
	(0.089)	(1.577)	(1.786)	(-0.536)	(2.566)	(1.872)	(2.672)
4-Factor Alpha	0.044	0.152	0.168	-0.060	0.439	0.394	0.592
	(0.305)	(1.557)	(1.887)	(-0.663)	(2.659)	(1.796)	(2.698)
5-Factor Alpha	0.050	0.122	0.149	-0.058	0.429	0.380	0.550
	(0.335)	(1.233)	(1.650)	(-0.632)	(2.559)	(1.701)	(2.468)

technically public, is much less readily accessible.

Our results show that the predictability occurs in the value-weighted portfolio and is strongest using the semi-private data covering smaller firms. Because this is the value-weighted portfolio, the additional smaller firms have little impact when included in the quantile portfolio returns. The smaller firms however have a large impact on the sorting signal because the signal portfolio is an equal-weighted average of idiosyncratic shocks. Taken together, this shows that investors are inattentive to signals originating in smaller less followed firms that could be used to trade in larger more liquid firms. In the next section, we provide further evidence of the signal flowing from small to big firms.

The variation in predictability with the publicness of the director links between firms provides evidence for the importance of investor inattention. This variation also provides further evidence that the predictability flows through the director channel. If the shared directors were simply proxying for another link between the firms, we would not expect to see variation in the return predictability based on the publicness of the director links.

2.5 Mechanism

We now investigate possible mechanisms for the observed return predictability. We have already shown in Table 2.3 that the predictability we document is not driven by the inter-industry predictability documented in Hou (2007). We now assess whether the predictability originates from big firms leading small firms as documented by Lo and MacKinlay (1990) and then explore the role played by directors' trades.

2.5.1 Role of Firm Size

In Table 2.6 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. The five-factor long-short alpha on this sample is an economically and statistically insignificant 19 bps per month. Contrary to the findings in other settings, the predictability we document does not flow from large firms to small firms.

This lack of predictability is not due to simply splitting 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 our overall predictability is driven by small firms predicting big firms.

2.5.2 Role of Directors' Trades

A natural mechanism to investigate as the source of return predictability across firms with shared directors is the trading behavior of directors. The concentration of predictability in the long end of the portfolio hints at this mechanism. Due to differential liability and even prosecution probabilities for purchasing versus selling stocks based on inside information, directors should have a preference for purchasing their own company stock. Such purchases could reveal the good news and concentrate predictability in the long end of the portfolio.

Return predictability could arise in several ways from directors' attempts to trade on their private information about the joint prospects of firms they oversee. We, therefore, consider three hypotheses about insider trading behavior. First, directors could trade simultaneously in both linked firms. If the market is more aware of one trade than the other or the stocks have different price impacts, then we would expect to see returns in the more closely watched/price-sensitive stocks lead the other stock return.

Our second hypothesis is that directors might trade sequentially in linked firms as they become aware of the prospects of the two firms. For example, suppose a director trades in January in one firm and February in another firm. We could see the returns of the first firm lead those of the second through either the market becoming sequentially aware of their trades or the sequential timing of the price impact from these trades.

Our third hypothesis is that a director might choose to trade in only one firm. Directors might choose this strategy if they have taken similar actions at both firms they oversee but they learn the outcome sequentially. Specifically, if they learn about the outcome of that

Table 2.6 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.

<u>Panel A</u>: Big-to-Small.

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

<u>Panel B</u>: Small-to-Big.

Value Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S
Excess Returns		0.624	0.544	0.477	0.957	0.427
	(1.304)	(1.930)	(1.845)	(1.443)	(2.220)	(1.921)
1-Factor Alpha	-0.068	0.137	0.107	-0.028	0.330	0.397
	(-0.431)	(1.301)	(0.987)	(-0.306)	(1.867)	(1.779)
3-Factor Alpha	-0.056	0.164	0.152	0.007	0.361	0.417
	(-0.395)	(1.556)	(1.638)	(0.072)	(2.128)	(1.851)
4-Factor Alpha	-0.032	0.162	0.165	-0.005	0.395	0.427
	(-0.226)	(1.529)	(1.764)	(-0.056)	(2.320)	(1.878)
5-Factor Alpha	-0.039	0.118	0.150	-0.008	0.406	0.445
	(-0.269)	(1.105)	(1.576)	(-0.086)	(2.343)	(1.923)

action earlier at one firm and expect the same outcome at the second firm, to lessen the chance of prosecution for insider trading, they may choose to trade in the second firm where they plausibly do not yet have material information directly from that firm.

2.5.2.1 Predictability Increases When Directors Trade

All three hypotheses have the same implication: upon filtering the predictive signal on director trading behavior, we should find stronger predictability (i.e., a larger long-short alpha) if director trading is important. For this filtering, we use only non-routine insider trades as defined by Cohen, Malloy, and Pomorski (2012). Their algorithm eliminates routine trades such as selling shares when they vest. To make sure our filters result in tradeable strategies, we only use data on insider trades that is publicly available through SEC filings at the end of the prior month (e.g., sorts for February use director trades executed and published in January).

We first filter on the direction of the directors' trades. We only retain firms in the first and fifth quintiles when the direction of the net trades of directors in the predicting firm at t agree with the sign of the return of the quintile at t. That is, we only keep stocks in quintile one linked to firms that directors are selling. Similarly, we only keep stocks in quintile five linked to firms that directors are buying. Table 2.7 shows the return predictability from this filter.

In Panel A we consider all board members' trades under the hypothesis that the shared board member may share his or her knowledge either explicitly, or inadvertently, with fellow board members. Applying this filter, the five-factor model long-short alpha increases to 83 bps per month, consistent with director trading playing an important role.

In Panel B we only consider the trades of the *shared* 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 director who sits on both boards is a key component in the return predictability, providing further identification that return predictability is not simply arising from an underlying economic similarity for which the shared board membership proxies. 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.

2.5.2.2 How Directors Trade

In Table 2.8 we show the number of firm-month observations in the first and fifth quintiles for the full sample as well as two subsamples obtained by restricting to firms for which directors' trades agree with the portfolio assignment. The first subsample includes all directors' trades while the second subsample uses only the shared directors' trades. For comparison, we also list the five-factor long-short alpha obtained using each sample. By construction, in the full sample, Q1 and Q5 have the same number of observations. However, when we filter the sample on either type of insider trading, Q5 has 60 percent more buy observations than sell observations in Q1. The difference is consistent with our findings of the predictability concentrated in the long end of the portfolio. It suggests when trading on information directors prefer to buy rather than sell the stocks of firms they preside over.

Comparing the two different insider trading filters, the trades by the shared board members represent approximately 80% of the sample of all director trades. This explains why the increase in alpha (83 bps to 93 bps in Table 2.7) is small when we restrict the sample from all director trades to only shared director trades. The large proportion of agreeing trades by shared directors further ties the observed predictability to the shared director. Specifically, this trading by the shared director shows the information is specific both to the network of firms the shared director oversees and that director. If the predictability were due to some connection between the firms unobservable to us, the non-shared directors should be equally informed as the shared directors about such a link. They would then be able to trade on the information related to it and we should see more trades by non-shared directors than shared directors.

We differentiate among the three hypotheses by looking at the directors' trading behavior in both of the linked firms. In Table 2.9 we continue to restrict the sample to firms in which

Table 2.7 Abnormal Board-Linked Stock Returns With Links Restricted to Director Trades This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks intersected with director 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 director trade during month t. Panel B restricts the links to those stocks for which at least one of the linked stocks has a *shared* director's opportunistic trade during 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). 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.

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

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

Value Weights	Q1(Low)	Q5(High)	L/S
Excess Returns	0.283	1.131	0.848
	(0.605)	(2.538)	(2.318)
1-Factor Alpha	-0.211	0.639	0.849
	(-0.696)	(2.384)	(2.305)
3-Factor Alpha	-0.249	0.646	0.894
	(-0.829)	(2.389)	(2.414)
4-Factor Alpha	-0.222	0.692	0.914
	(-0.733)	(2.553)	(2.446)
5-Factor Alpha	-0.265	0.660	0.925
	(-0.862)	(2.399)	(2.436)

Table 2.8 Number of Observations of Agreeing Director Trades This table shows the number of firm-months in the first and fifth quintile portfolios for the full sample and two subsamples restricted to firms with director trades agreeing with the firm's portfolio assignment. The last column shows the five-factor model long-short alpha from the value-weighted portfolio associated with the trading strategy formed using each sample. The first director 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 director trading filter includes only firm months where the direction of the *shared board member's* trading at the predicting firm agrees with the quintile portfolio. That is, the shared 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.

	Q1 (low)	Q5 (High)	L/S Alpha
Full Sample	58,520	58,520	0.550
Directors Agree	7,754	12,670	0.834
Shared Directors Agree	6,570	10,328	0.925

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

If insiders trade simultaneously across both firms, then 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 then in the predicted firms the following period, we would expect a large percentage of trades in the upper-left and bottom-right of the time $t + 1$ table. As evidence against the second hypothesis, we again see only a slight agreement.

We find 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 when

Table 2.9 Opportunistic Director Transactions Among Board-Linked Stocks This table shows the percentage of opportunistic trades by directors 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 director trade during month t. Panel B restricts the links to those stocks for which at least one of the linked stocks has a *shared* director's opportunistic insider trade during month t. 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.

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

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

Portfolio Number	Trade in leading (A) stock during month t	Trade in lagging (B) (B) stock at t			Trade in lagging (B) (B) stock at t+1		
		Sell	None	Buy	Sell	None	Buy
Q1 (Low)	Sell	6.39	85.41	8.21	5.89	86.83	7.29
Q5 (High)	Buy	5.51	84.78	9.72	5.49	86.21	8.30

there is a trade in the predicting firm, we see no trade in the predicted firm. This suggests that the shared board members are trading in one firm based on information they have in the other firms on whose board they sit.

2.5.2.3 Predictability Increases with the Intensity of Directors' Trades

As a further test to determine whether directors appear to be trading on information, we check if the shared board members vary the intensity of their opportunistic trading with the strength of their information. Large trades by directors may provide a stronger signal that reveals even more predictability. To test this hypothesis, we sort directors' trades into quintiles. Using these quintiles, we filter on the direction and the magnitude of the directors' trades. We include only firms in the extreme return quintiles that also have a shared director's trade at the predicting firm in the same quintile. That is, in the first quintile of returns, we only keep firms where shared directors trades (e.g., sells) fell in the bottom quintile of all board members' trades.

Table 2.10 shows the return predictability that results from this filter. For the first time, we find a significant 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 sells when they have a strong signal. Overall, we find a five-factor long-short portfolio alpha of 125 bps per month or 15% annually. This suggests that directors vary the intensity of their trades based on the strength of their information with cross-firm value-relevance. The results provide additional evidence that directors are aware of information that, although idiosyncratic to the overall market, nevertheless systematically affects the portfolio of firms they oversee.

2.5.2.4 Profitability of and Attention Paid to Directors' Trades

As additional evidence that directors are trading on information that they know rather than simply responding to returns they see in the market, we show that directors appear to profit on their trades in the predicting firm. Figure 2.3 plots the cumulative average abnormal

Table 2.10 Abnormal Board-Linked Stock Returns With Links Restricted to Top and Bottom Quintiles of Directors' Trades This table shows monthly abnormal returns for value-weighted portfolios of board-linked stocks intersected with shared directors' trades that fall in the top and bottom quintiles of all directors 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. Stocks are ranked in five quintiles based on the linked stocks' opportunistic director trades during month t. In the Q1 (low) portfolio, stocks are retained only if one of its linked stocks has an opportunistic trade (sell) by the shared director in the lowest quintile of director trades. In the Q5 (high) portfolio, stocks are retained only if one of its linked stocks has an opportunistic trade (purchase) by the shared director in the highest quintile of director trades. 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.

Value Weights	Q1(Low)	Q5(High)	L/S
Excess Returns	-0.146	1.144	1.290
	(-0.294)	(2.005)	(2.539)
1-Factor Alpha	-0.647	0.576	1.223
	(-1.910)	(1.450)	(2.401)
3-Factor Alpha	-0.609	0.593	1.202
	(-1.787)	(1.490)	(2.334)
4-Factor Alpha	-0.615	0.695	1.309
	(-1.788)	(1.752)	(2.541)
5-Factor Alpha	-0.579	0.669	1.249
	(-1.660)	(1.663)	(2.388)

return (CAAR) over the following 60 trading days after the trade of the shared director (same trades as in Table 2.10).[10]

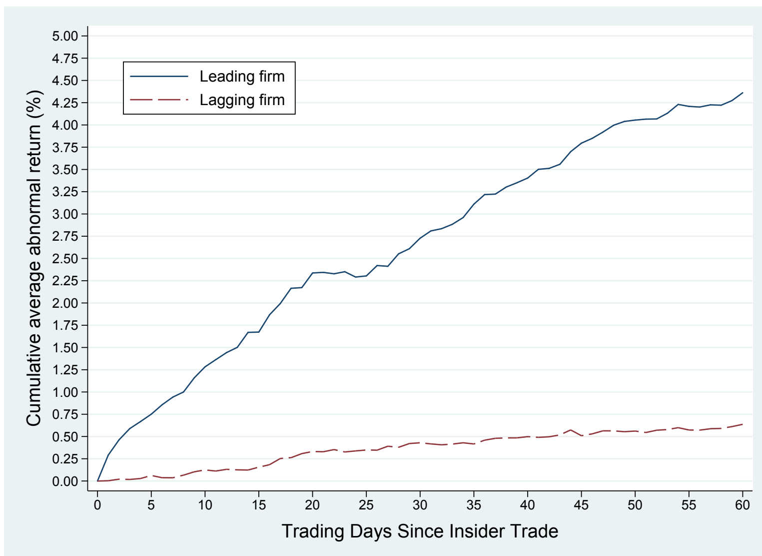
Over these 60 trading days, the CAAR on the buy side is 4.41% and on the sell side is -4.92%. Both CAARs are highly economically and statistically significant across all test statistics.

To see if the shared directors' trades contribute to the return information we use to form

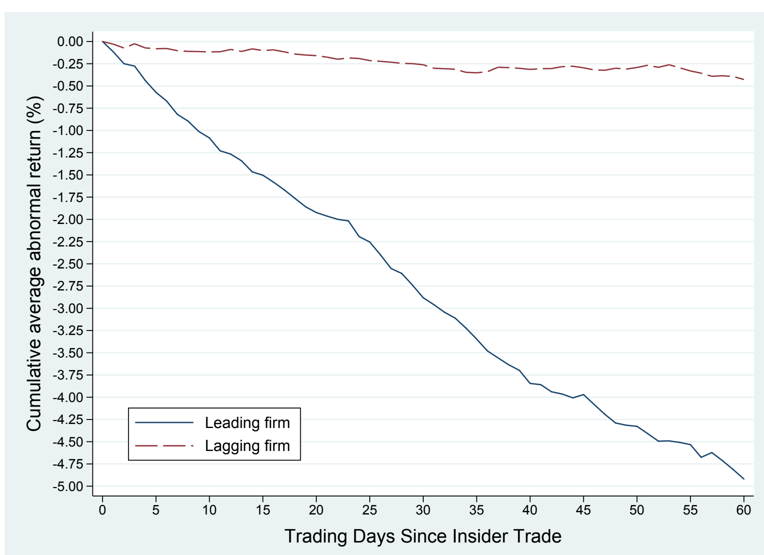
[10] We obtain virtually the same values when we use the SEC report date instead (typically 3 days later).

Figure 2.3. Shared Director Trading Profitability This figure shows the cumulative average abnormal return to the trade made by the shared director over the next 60 tradings days after the director's trade date in the leading firm. For comparison, the return to a hypothetical trade in the lagging firm at the same time is also shown. Panel A shows the CAAR following the top quintile of director trades (i.e., purchases) that are also in the top quintile of predicting firms. Panel B shows the CAAR following the bottom quintile of director trades (i.e., sells) that are also in the bottom quintile of predicting firms. The trades used are the same as those used to identify the sorts used in Table 2.10.

Panel A: Top Quintile–Purchase Side



Panel B: Bottom Quintile–Sells Side



our trading strategy, we calculate the CAARs using multiple event windows. Table 2.11 shows tests of their statistical significance. As the literature contains a variety of competing test statistics for the null hypothesis that the CAARs are equal to zero, we present a selection of test statistics used in Fidrmuc, Goergen, and Renneboog (2006), and recommend the excellent discussion therein of the properties of each statistic.

On average (untabulated), the shared directors trade 10 trading days before the end of the month whose return we use as a sorting signal. The CAAR over the 10 trading days after the shared directors trades is an economically and statistically significant 1.32% on the buy side and -0.89% on the sell side. These CAARs suggest that the directors are trading on information related to what we pick up in our sorting signal. It also suggests that their trades could be one source of this information. We find similar results for CAAR windows over the 5 and 20 trading days following the insider transaction.

Although these CAARs suggest that directors' trades could be a source of the signal we detect, it does not mean that investors directly monitor the trades of the shared directors. For instance, their trading could simply induce price pressure, albeit larger than typical if it displays features that make market participants think it is informed trading. To test if investors are monitoring the directors' trades directly, we measure the persistence of the CAARs. If investors actively monitor the directors' trades, then we would expect to see a CAAR over the first few days and no abnormal returns thereafter as prices in the predicting firm quickly respond to the information about directors' trading.

The CAAR over the first 20 trading days of the event window is biased for testing investor attention to directors' trades, because these trades are for firms selected to have had large absolute returns over that period. This bias is not present for event windows starting on day 21 and later. Therefore, to cleanly measure the attention to the shared directors' trades, we consider the CAARs over the 21 to 60 trading days following their trades. In Table 2.11 we see the economically and statistically significant CAARs over this window are 2.03% for buys and -2.99% for sells. These CAARs suggest that, in addition to not actively monitoring the performance of the firms with shared directors, investors do not actively monitor these

Table 2.11 Profitability of Shared Directors' Trades This table shows the cumulative average abnormal return (CAAR) to the trades made by the shared director during the interval between the trade date and up to 60 tradings days afterwards. Panel A shows CAARs following the top quintile of director trades (i.e., purchases) that are also in the top quintile of predicting firms. Panel B shows CAARs following the bottom quintile of director trades (i.e., sales) that are also in the bottom quintile of predicting firms. The trades used are the same as those used to identify the sorts used in Table 2.10. We use three parametric test statistics of the null hypothesis that the CAAR is zero: $tCAAR$ based on Barber and Lyon (1997), and J_1 and J_2 based on Campbell et al. (1997). For additional robustness we use Corrado (1989) non-parametric rank test statistic to test the same null. See Fidrmuc et al. (2006) for a detailed discussion of these test statistics.

Panel A: Top Quintile–Purchase Side

	CAAR(0,5)	CAAR(0,10)	CAAR(0,20)	CAAR(0,60)	CAAR(21,60)
CAAR	0.78%	1.32%	2.38%	4.41%	2.03%
tCAAR	4.71	6.09	7.42	7.50	4.94
J1	5.79	7.17	8.89	10.24	5.15
J2	4.61	5.92	8.11	10.06	5.42
tRank	3.02	3.24	4.16	3.54	2.33

Panel B: Bottom Quintile–Sells Side

	CAAR(0,5)	CAAR(0,10)	CAAR(0,20)	CAAR(0,60)	CAAR(21,60)
CAAR	-0.57%	-1.08%	-1.92%	-4.92%	-2.99%
tCAAR	-3.38	-5.21	-7.72	-10.39	-7.56
J1	-3.13	-5.90	-7.29	-11.73	-7.19
J2	-3.54	-5.70	-8.25	-11.91	-8.32
tRank	-2.86	-4.29	-5.99	-5.86	-5.09

directors' trades.

2.6 Conclusion

Sorting firms based on the lagged idiosyncratic shocks of firms with which they share a director, we form a long-short trading strategy that generates an alpha of over 6.6% 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 return predictability is concentrated in periods with trading by the shared director. Restricting the sample to when these directors' trades fall in the top and bottom quintiles more than doubles the alpha on the strategy to 15% per year.

This delayed price discovery provides evidence of inattention to the performance of firms linked through shared directors. This has implications for both the efficiency of financial markets and the director labor market. Failure to monitor the real-time performance of all firms a director oversees prevents investors from timely intervening in the directorship of firms.

This predictability also provides evidence that firms with shared directors have correlated performance. We show that directors are aware of this commonality and trade opportunistically on their knowledge of the joint prospects of their firms.

Chapter 3

UNDERSTANDING NETWORK-BASED MEASURES OF INFORMATION DIFFUSION

The study of price discovery underlies our understanding of financial markets. The finance literature has identified many settings with slow information diffusion marked by the presence of lead-lag cross-autocorrelations among stocks at various time horizons. Lo and MacKinlay (1990) is among the earliest papers to document the lead-lag effect at short horizons, showing that lagged *weekly* returns of big firms explain current weekly returns of small firms but not vice versa. Cohen and Frazzini (2008) sparked a large extension of this literature with the insight that economic links between firms, such as those between customers and suppliers, provide an instrument for measuring delays in information diffusion.[1]

This large literature uses these economic links to form a long-short portfolio trading strategy. The alpha of this strategy is used as a measure of slow information diffusion with an immediately interpretable economic magnitude. The portfolios for this strategy are formed by sorting firms, e.g., suppliers, into quantile portfolios based on the lagged excess return of an economically linked firm (or portfolio of firms), e.g., customers. Using this sorting strategy, many studies, including Menzly and Ozbas (2004), Cohen and Frazzini (2008), Cohen and Lou (2012) and Huang (2015), have reported positive and economically significant alphas persisting over long horizons of many months up to an *entire year*. This

[1] Menzly and Ozbas (2004) released a working paper at approximately the same time also exploiting such an insight. For other examples, see Chen, Chen, and Li (2009), Menzly and Ozbas (2010), Easton, Gao, and Gao (2010), Rizova (2010), Kulak and Schmidt (2011), Cohen and Lou (2012), Nguyen (2012), Scherbina and Schlusche (2013a), Scherbina and Schlusche (2013b), Noh (2014), Lim (2014), Liu (2015), Agarwal, Konana, Kumar, and Leung (2015), Albuquerque, Ramadorai, and Watugala (2015), Gao, Moulton, and Ng (2016), Hoberg and Phillips (2015), Huang (2015), Cao et al. (Forthcoming), Parsons, Sabbatucci, and Titman (2016), Chava, Hsu, and Zeng (2016), Chen, Khan, Kogan, and Serafeim (2016b), Kumar and Moon (2016), and Cen, Hertzel, and Schiller (2017).

extreme delay incorporating past price information into the prices of economically linked firms casts doubt on even weak form market efficiency.

We show that these surprising results arise from a bias in this measure of slow information diffusion and we provide a method for removing this bias. As such, our paper contributes to the financial markets econometrics literature that identifies biases and provides corrections (e.g., Lyon, Barber, and Tsai, 1999; Berk, 2000; Ferson, Sarkissian, and Simin, 2003, 2008; Asparouhova, Bessembinder, and Kalcheva, 2010; Lewellen, Nagel, and Shanken, 2010; Kan, Robotti, and Shanken, 2013; Asparouhova, Bessembinder, and Kalcheva, 2013; Gospodinov, Kan, and Robotti, 2014; Pástor, Stambaugh, and Taylor, 2015; Ferson and Chen, 2015; Harvey, Liu, and Zhu, 2016).

The source of this bias we identify in measures of slow information diffusion is the misspecification (alpha) inherent in the underlying asset pricing model. This misspecification causes bias, because economically linked firms have correlated alphas. This correlation makes sorting on the economically linked firms' (customers') returns, which include alphas, an implicit sort on the the alphas of the firms being predicted (suppliers). The implicit sort on the predicted firms' (suppliers') alphas mechanically raises the long-short portfolio alpha and even causes a positive long-short portfolio alpha after information diffusion completes. [2]

We show that subtracting the asset pricing model's predicted return from the return of the sorting firm (customers) removes this model misspecification bias. Applying this solution to existing studies, we find the bias to be economically large: up to a factor of two at the one month horizon. Critically, removing this bias shows that price discovery completes within one month rather than taking an entire year.

A simple example illustrates this bias. Consider the hypothesis that investors pay insuf-

[2]The economically linked firms may also have correlated risk exposures that would create time variation in the conditional betas of the sorted portfolios. These betas will be a function of the sorting periods factor exposure. Thus to the extent that the factor exposures are close to iid these conditional betas will not contribute meaningfullly to the alphas of the sorted portfolios, when measured with uncondtional regressions. See Lewellen and Nagel (2006) for additional details on when variation in conditional betas contributes to alphas.

ficient attention to a firm's own returns and that, with this inattention, news takes 10 years to be fully incorporated into prices. We exploit the economic link between a firm and its past self to test this hypothesis. Applying the method of Cohen and Frazzini (2008) each month, we sort all CRSP firms into quintile portfolios based on each firm's own return 10 years prior. Consistent with this hypothesis of slow information diffusion, the light red bar in Figure 3.1 shows that the long-short portfolio of the extreme quintiles yields a monthly 5-factor alpha of 62 basis points which is statistically significant at the 1% level.[3] However, this positive alpha is due to model misspecification: a firm mispriced by the asset pricing model 10 years ago has a similar mispricing today.

To see that this alpha is caused by model misspecification bias and not a 10 year delay in information diffusion, we use future returns to predict past returns. Because information cannot flow from the future to the past, any long-short alpha for portfolios based on this reverse sort comes from persistent model misspecification. Taking the difference in long-short alphas from the two sorts provides a measure of slow price discovery free of model misspecification bias.[4] To apply this correction, we sort firms into quintile portfolios based on each firm's own return 10 years in the *future* and obtain alphas on the long-short portfolio that are nearly identical to the alphas from the original sort. The dark blue bars in Figure 3.1 show the quasi-difference-in-differences between these sorts is economically and statistically insignificant, rejecting a 10 year lag in information diffusion.

In Section 3.1 we show that model misspecification bias is present whenever the alphas are correlated across the economic link used. This bias grows with the measurement horizon and the strength of the economic link. The quasi-difference-in-differences correction illustrated, works in the special case where information flows with a delay only in one direction along the economic link, such as from the past to the future. In Section 3.1, we also derive a correction robust to delayed information flow in both directions along the economic link.

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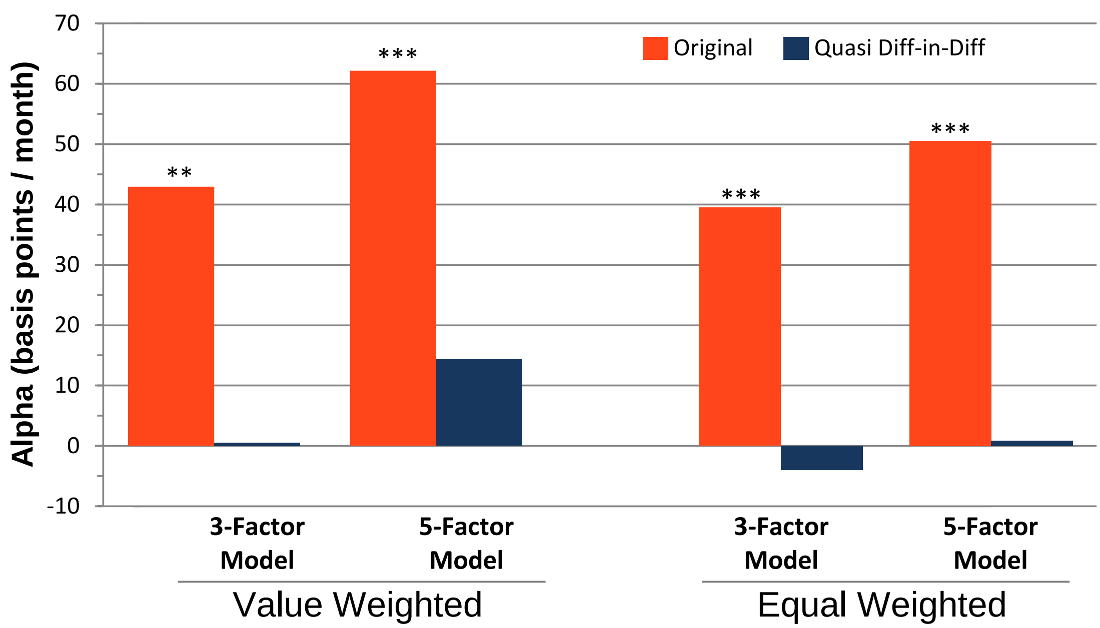
[3]This effect is consistent with the findings in Heston and Sadka (2008) and Keloharju, Linnainamaa, and Nyberg (2015).

[4]See the Online Appendix for necessary conditions and a proof of this statement.

Figure 3.1. Stock Predictability of Itself A Decade Later: Slow Price Discovery or Model Misspecification? This figure shows two measures of slow price discovery for a stock's decade old return predicting its current return. Original denotes the methodology following Cohen and Frazzini (2008) and quasi-difference-in-differences denotes our bias-removing methodology. The original specification uses the time t monthly return of a stock to assign that same stock into quintile portfolios 10 years later at $t+119$ (returns at $t+120$). The reported alpha (percent per month) is that of the long-short portfolio of the extreme quintiles using various asset pricing models. The quasi-difference-in-differences methodology removes the bias from model misspecification by exploiting a reverse sorting specification. The reverse specification uses the time t return of a stock to assign that same stock into quintile portfolios at $t-121$ (returns at $t-120$). Alpha is the difference between the long-short portfolio alpha from the original specification and the alpha of the long-short portfolio of extreme quintiles in the reverse specification. The asset pricing models used are the Fama and French (1993) 3-factor model and the 5-factor model, which is the 3-factor model augmented with momentum (Carhart, 1997) and liquidity (Pástor and Stambaugh, 2003). We include all common stocks traded on the NYSE, NASDAQ and AMEX from 1975 to 2011. ** and *** represent 5% and 1% significance.



This correction is to subtract the asset pricing model's predicted return from the sorting return.

By subtracting the asset pricing model's predicted returns, the corrected test sorts firms based on the idiosyncratic news shock of the firms (or portfolios) to which they are linked. Intuitively, these idiosyncratic returns capture the news shocks of interest in measuring slow information diffusion. And importantly, sorting on the idiosyncratic news shocks *purges* the sorting variable of model misspecification before it biases the long-short portfolio alpha. As such, we refer to this as the *purging method*.

In Section 3.2 we explore the economic magnitude of this bias by applying the purging method to the settings of customer-supplier links and standalone-conglomerate links (Cohen and Frazzini, 2008; Cohen and Lou, 2012).[5] We show that the originally reported one-month alphas substantially overstate the delay in the price discovery process. Specifically, Cohen and Frazzini (2008) report that customers' excess returns predict suppliers' excess returns yielding a Fama French 3-factor alpha of 155 basis points over one month and that this predictability lasts up to 12 months.[6] When we apply our corrected methodology, we find the value-weighted portfolio's one month 3-factor alpha drops to only 83 basis points. The 5-factor alpha drops to 69 basis points and becomes statistically insignificant. The same correction applied to the equal-weighted portfolio shows the alpha is overstated by more than 100%. Applying our correction to Cohen and Lou (2012) we find similar, though smaller, biases at the monthly horizon. In both cases after the correction, there is no statistically significant cumulative alpha beyond the first month in any specification. This shows that information diffusion occurs within one month rather than taking 6 to 12 months previously documented.

Two key forces determine the size of the bias. The bias increases when the correlation of alphas across the link is larger. The bias decreases when the true delay in price discovery is larger. The relative size of these forces explains the different magnitudes of the bias across our two applications. With customer-supplier links, where the model misspecification bias is larger, the shared alpha correlation is 11 times that of the slow price discovery correlation. This contrasts to a ratio of 4 to 1 for the pseudo-conglomerate to conglomerate links.

In Section 3.2.3 we address an attenuation bias present in both the original method and

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[5]See the Online Appendix for an application of the reverse sort to settings of Cohen and Frazzini (2008); Cohen and Lou (2012). In these cases, the quasi-difference-in-differences method yields similar results to the more robust method on which we focus.

[6]Here we focus on the portfolios that Cohen and Frazzini (2008) highlight in their abstract.

our implementation of the purging method. The original method's sorting on excess returns is a noisy sort on the true idiosyncratic shock. Excess returns are the true idiosyncratic shock plus noise from the alphas and the systematic factor realizations. This noisy sort on excess returns introduces an attenuation bias in the original specification. The noisy sort bias depends on the cross-sectional dispersion in the alphas and factor exposures (betas) in the firm returns used for sorting. With the purging method, when the asset pricing model parameters are known, one can observe the true idiosyncratic shocks (relative to the reference model) on which to sort. This purging method thereby removes both the model misspecification bias and the noisy sort bias.

However, when one must estimate the asset pricing parameters, one can then only estimate the idiosyncratic shocks. When these estimates are unbiased, such as those from linear factor model regressions, the purging method, albeit noisy, still removes the model misspecification bias. However, because one is now subtracting a noisy estimate of the noise (the alphas plus the systematic factor realizations) in the original specification, this implementation of the purging method cannot completely remove the noisy sort bias. The amount of noisy sort bias in the purging method depends upon the precision with which one can estimate the asset pricing model.

We use a calibrated simulation to answer the empirical question of how much attenuation bias remains with the estimated purging method. We find that, although the original method has a large total upward bias, this upward bias is mitigated by the noisy sort bias. The noisy sort bias contributes a 10% downward bias in both sets of economic links studied. The purged method fully removes the model misspecification bias but only partially removes this noisy sort bias, leaving a 5% downward bias. Thus, even after estimating the asset pricing model, the purging method is a superior measure of slow information diffusion.

Our analysis and correction are related to the joint hypothesis problem identified in Fama (1970). The joint hypothesis problem is that one cannot identify whether deviations from an asset pricing model are due to mispricing or failures of the model. In the context of measuring slow price discovery, the joint hypothesis problem is that measures of slow information diffusion are always relative to a reference asset pricing model.

Even though all asset pricing models suffer from misspecification, i.e., stocks have true alpha relative to the model, we show how to separate this persistent model misspecification from slow information diffusion. In making this separation, the source of this misspecification as an omitted risk factor or a behavioral effect does not matter for the model misspecification bias we identify, so we take no stand on its source. The critical point is that the original measures of slow information diffusion based on economic links fail to make this separation, leaving the measures biased even relative to their reference asset pricing model. By making this separation, our measure is free of this model misspecification bias, capturing only slow information diffusion relative to the reference asset pricing model.

Our paper contributes to several additional strands of the literature in addition to the financial econometrics literature. Our correction adds to the understanding of lead-lag relationships among stock returns. It applies primarily to papers, such as those listed in footnote 1, that exploit close economic links and use long-short portfolios alphas as a measure of slow information diffusion.

The biases we identify have analogs in the lead-lag literature that uses the cross-autocorrelations among firms to measure slow price discovery. These papers measure the cross-autocorrelations by regressing excess returns on lagged excess returns of linked firms. The biases can be corrected by measuring the cross-autocorrelation instead through regressing idiosyncratic shocks on idiosyncratic shocks of linked firms. Lo and MacKinlay (1990) were among the first to use this framework to show that information diffuses from big firms to small firms with a delay. Their findings have been confirmed in a subsequent literature.[7]

Though these analogous biases are present in this set of papers, in most cases the biases only change magnitudes slightly. The bias is dampened because of the short measurement

[7]Subsequent studies explored various channels that causes this information delay, including time-varying expected returns, nonsynchronous trading, transaction costs, market microstructure effects and investor inattention (see Brennan, Jegadeesh, and Swaminathan (1993), Mech (1993), Badrinath, Kale, and Noe (1995), McQueen, Pinegar, and Thorley (1996) , Chordia and Swaminathan (2000), Hou and Moskowitz (2005) and Hou (2007)).

horizon (e.g., weekly) and weakness of the economic link between big and small firms. Lo and MacKinlay (1990) discuss, but dismiss due to its small quantitative size in their setting, the bias related to the model misspecification bias we highlight.[8] Many other papers use this regression framework to measure slow price discovery over either longer horizons or among more strongly linked firms. In both cases we would expect to find larger biases, though many papers attempt to mitigate the biases with ad hoc control variables.[9]

Our analysis also applies to momentum (Jegadeesh and Titman, 1993) which comes from a sort based on the link between a firm and its past self. Our analysis highlights that the ongoing debate whether momentum is due to mispricing or differences in expected returns is one about what is the correct relative asset pricing model and how to interpret variation in model misspecification over time.[10] We see this most strongly in our example in Figure 3.1 which could be viewed as 10-year momentum. The findings of Grundy and Martin (2001) that momentum returns are concentrated in the preceding 6-month alphas of returns is consistent with our analysis. Realizing that industries provide a cleaner sort on alphas compared to individual firms, the findings in Moskowitz and Grinblatt (1999) that momentum is concentrated in industries is also consistent with our findings.

The biases we identify also have analogs in the event study context.[11] The noisy sort bias is related to the question of whether to use returns adjusted merely by past means or an estimated asset pricing model (see Brown and Warner, 1980). And the model misspecification

[8]An additional reason for the small magnitude of the bias in Lo and MacKinlay (1990) is they split firms only at the median rather than into quintiles or deciles which can magnify the bias.

[9]See for example Boudoukh, Richardson, and Whitelaw (1994), Shahrur, Becker, and Rosenfeld (2010), Hou (2007), Rapach, Strauss, and Zhou (2013), Cen, Chan, Dasgupta, and Gao (2013), Aobdia, Caskey, and Ozel (2014), Wu and Birge (2014), Madsen (2016) and Leung, Agarwal, Konana, and Kumar (Forthcoming).

[10]See among many others Conrad and Kaul (1988); Berk, Green, and Naik (1999); Jegadeesh and Titman (2001, 2002); Chordia and Shivakumar (2002).

[11]Event studies have been the primary tool for exploring the price discovery process since Fama, Fisher, Jensen, and Roll (1969). However, event studies are limited to showing the effects of information from a set of pre-identified events and for a small subset of days around these events (Brown and Warner, 1980, 1985, provide an analysis of short horizon event studies) Using a long-short trading strategy among economically linked firms dramatically increases the sample size and power of tests of information diffusion compared to event studies, because it allows researchers to include *all* days with returns, as opposed to only days with pre-specified information events.

bias, which grows with horizon, is related to the poor performance of long-horizon event studies (see Kothari and Warner, 1997).

3.1 Model Misspecification and Noise Biases: Existence, Properties and Correction

In this section, we show the alpha of a long-short portfolio based on lead-lag sorts among economically linked firms is a biased measure of slow information diffusion. We also show how this bias grows with horizon. We then derive a method that reduces this bias. We present the case of single economic links. This setup equivalently describes the links between two individual firms or a portfolio and a single firms, e.g., one supplier linked to one customer or a portfolio of customers.

3.1.1 Portfolio Alphas

Let M be the asset pricing model relative to which we wish to measure the price discovery process.[12] The unconditional expected return of asset i under the asset pricing model is M_i, but this model is misspecified by a component α_i. Misspecification is defined as the difference between the unconditional expected return and the unconditional prediction of the model:

$$\alpha_i \equiv E[r_{i,t}] - M_i \tag{3.1}$$

where $r_{i,t}$ is the excess return of asset i.

This asset pricing model predicts the excess return $M_{i,t}$ for each firm i at time t. For example, in the case of the CAPM: $M_{i,t} = \beta_i(R_{mkt,t} - R_{f,t})$.

Let $\epsilon_{i,t}$ be the period-specific *news* shock to the excess return. It is the component of

[12] For simplicity, we consider a world with fixed exposures to the risks quantified in the asset pricing model. For now, we set aside any issues (e.g., estimation error) in estimating this asset pricing model. We return to these model estimation issues in Section 3.1.3.

returns not predicted by the asset pricing model (or misspecification):

$$\epsilon_{i,t} \equiv r_{i,t} - M_{i,t} - \alpha_i. \tag{3.2}$$

In the spirit of a factor pricing model, we assume that $\epsilon_{i,t}$ is orthogonal to $M_{i,t}$. It has mean zero by construction. Slow information diffusion arises from the propagation of this news shock, $\epsilon_{i,t}$, to other firms' returns over time.

Information link: To understand this news propagation, Cohen and Frazzini (2008) and numerous other studies focus on economically linked firms (or portfolios of firms).[13] We formalize these links as follows. Consider two sets of firms, set A and set B (e.g., customers and suppliers), where each firm in each set has a link to one firm in the other set. Equivalently a "firm" in set A may be a portfolio of firms. A link between firms means that, on average, news affects the linked firms in the same direction (as measured by returns). Furthermore, the news sometimes affects firms in set A before affecting firms in set B. This (delayed) link between firm i in set A and firm j in set B can be written as

$$\epsilon_{j,t+1} = \rho_{\epsilon,i,j}\epsilon_{i,t} + \psi_{i,j,t+1}, \quad j \in B, i \in A \tag{3.3}$$

where $\psi_{i,j,t+1}$ is a normal shock independent of both $\epsilon_{i,t}$ and $M_{j,t+1}$. The assumption that news affects linked firms in the same direction means that a positive cross-autocorrelation exists between linked firms. That is, $\rho_{\epsilon,i,j} \geq 0$ for all i and j which are linked.

Model misspecification link: Firms are linked through their information shocks because they share similar economic exposures. However, firms sharing similar economic exposures are also likely to share similar model misspecification, or alphas. We write this alpha link between firms in set A and set B as

$$\alpha_j = \rho_{\alpha,i,j}\alpha_i + \eta_{i,j}, \quad j \in B, i \in A \tag{3.4}$$

[13] We list other studies applying this technique in the introduction.

where $\rho_{\alpha,i,j} > 0$ for linked firms, $\eta_{i,j}$ is mean 0, and $\rho_{\alpha,i,j}$, α_i and $\eta_{i,j}$ are independent. $\eta_{i,j}$ and $\rho_{\alpha,i,j}$ allow for variation in the strength of this alpha link in the cross-section of linked firms.

Sorting method: To learn about information diffusion in the set of linked firms, the econometrician can follow the method of Cohen and Frazzini (2008). At each date t, the econometrician sorts the firms in set A by their excess return at time t into N quantiles (e.g., quintiles, deciles, etc.). A portfolio (either value-weighted or equal-weighted) is then formed at time t of the linked stocks in set B that correspond to this sorting of stocks in set A (returns are at $t+1$). Each period, portfolios are rebalanced by repeating this procedure. This procedure results in a time-series of N portfolio returns formed from stocks in set B.

Let $B(P)$ be the Pth such portfolio; the Nth portfolio is that formed from those firms linked to the highest excess return stocks in set A each period.

Alphas of sorted portfolios: The alphas of the $B(P)$ portfolios, which are the key statistic of interest in Cohen and Frazzini (2008) as their measure of slow information diffusion, have the following properties.

PROPOSITION 1. *If the firms in sets A and B are linked via news shocks only per Equation* (3.3) *and via model misspecification per Equation* (3.4) *and if there is cross-sectional dispersion in the alphas of firms in set A, then the expected alpha of the portfolio $B(P)$ can be decomposed into two pieces:*

$$E\left[\alpha_{B(P)}\right] = \varrho_{\alpha,P} + \varrho_{\epsilon,P} \tag{3.5}$$

The first component, $\varrho_{\alpha,P}$, is due to model misspecification and the second component, $\varrho_{\epsilon,P}$, *is due to slow information diffusion. Moreover*

$$\varrho_{\alpha,P} \begin{cases} > \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \textit{If } B(P) \textit{ is entirely above the median break-point.} \\ \gtreqless \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \textit{If } B(P) \textit{ spans the median break-point.} \\ < \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \textit{If } B(P) \textit{ is entirely below the median break-point.} \end{cases} \tag{3.6}$$

where $\bar{\rho}_{\alpha,i,j}$ is the cross-sectional average of the $\rho_{\alpha,i,j}$ and $\bar{\alpha}_A$ is the cross-sectional average alpha of linked stocks in set A.

This proposition's proof along with all others are in Appendix 3.B.

3.1.1.1 Model misspecification bias

From this proposition, we can immediately see the alpha of the long-short portfolio $B(LS)$ formed from $B(N)$ and $B(1)$.

COROLLARY 1. *Under the assumptions of Proposition 1, the expected alpha of the long-short portfolio $B(LS)$ is composed of two pieces as follows*

$$E\left[\alpha_{B(LS)}\right] = (\varrho_{\alpha,N} - \varrho_{\alpha,1}) + (\varrho_{\epsilon,N} - \varrho_{\epsilon,1}). \tag{3.7}$$

The first component, $\varrho_{\alpha,N} - \varrho_{\alpha,1}$, is due to model misspecification and is positive. The second component, $\varrho_{\epsilon,N} - \varrho_{\epsilon,1}$, is due to the slow price discovery process described in Equation (3.3)*.*

$\varrho_{\alpha,N} - \varrho_{\alpha,1}$ is the upward model misspecification bias in the long-short portfolio alpha used as a measure of slow information diffusion.

The size of this bias depends upon two features of the data: the amount of cross-sectional variation in the alphas of the firms in set A and how tightly linked the alphas are between the firms in sets A and B.

COROLLARY 2. *Under the assumptions of Proposition 1, when the cross-sectional variance of the alphas (model misspecification) for firms in set A increases then, all else constant, $\varrho_{\alpha,N} - \varrho_{\alpha,1}$ becomes more positive.*

The intuition for this result is that when there is more spread in the alphas, a larger portion of the sort is driven by them. One can see this most clearly in the degenerate case where all firms in set A have the same alpha, there is no model misspecification bias.

So long as there is a spread in these alphas, if more tightly linked firms share more similar model misspecification as described by larger average $\rho_{\alpha,i,j}$, then this bias increases with the strength of the economic link.

COROLLARY 3. *Under the assumptions of Proposition 1, when the average $\rho_{\alpha,i,j}$ are larger, all else constant, $\varrho_{\alpha,N} - \varrho_{\alpha,1}$ becomes more positive.*

The bias remains even after information diffusion has completed. To see this persistent bias, define information diffusion links over longer horizons, h, between firm i in set A and firm j in set B as

$$\epsilon_{j,t+h} = \rho_{\epsilon,i,j,h}\epsilon_{i,t} + \psi_{i,j,t+h} \tag{3.8}$$

where $\psi_{i,j,t+h}$ is a normal shock independent of both $\epsilon_{i,t}$ and $M_{j,t+h}$. $\rho_{\epsilon,i,j,h}$ is positive when information diffusion is still occurring and zero when it has completed. Let H be the horizon at which information diffusion completes: $\rho_{\epsilon,i,j,h} = 0$ for all $h \geq H$, all firms i in set A and all firms j in set B.

Define longer horizon predictive portfolios $B(P,h)$ as the portfolio of firms in set B formed following the previous sorting method except that portfolio formation occurs at $t+h-1$ and returns are measured at $t+h$ for sorts that occur at t. The previous $B(P)$ is equivalent to $B(P,1)$. $B(LS,h)$ is the long short portfolio of $B(N,h)$ and $B(1,h)$.

COROLLARY 4. *Under the assumptions of Proposition 1 and the longer horizon information diffusion link described in Equation* (3.8), *the expected alpha of the long-short portfolio*

$B(LS,h)$ is composed of only model misspecification bias for all $h \geq H$. Specifically

$$E\left[\alpha_{B(LS,h)}\right] = \varrho_{\alpha,N} - \varrho_{\alpha,1}, \quad \forall\, h \geq H. \tag{3.9}$$

Thus, if one fails to account for the misspecification bias, information diffusion appears artificially slow.

3.1.1.2 Noisy sort bias

In addition to the bias from model misspecification, a second bias exists. This second bias is a downward one created from sorting stocks in set A on their total returns rather than the news shock alone. This bias manifests in the slow information diffusion component, $\varrho_{\epsilon,N} - \varrho_{\epsilon,1}$, and depends on the distribution (cross-sectional and time-series) of all the components of the return, rather than just the news shock component.

COROLLARY 5. *Under the assumptions of Proposition 1 plus the assumption that the link between firms in set A and B (from Equation (3.3)) is independent in the cross-section from the model misspecification, the model predicted returns and the news shocks to firms in set A, then the slow information diffusion component, $\varrho_{\epsilon,P}$, of Equation (3.5) can be written as*

$$\varrho_{\epsilon,P} = c_P\, \bar{\rho}_\epsilon \tag{3.10}$$

where $\bar{\rho}_\epsilon$ is the cross-sectional average of the $\rho_{\epsilon,i,j}$ and c_P is a constant dependent upon the portfolio number and the distribution of cross-sectional variance of the alpha and model predicted return and news shocks. Moreover, the spread from the long-short portfolio

$$\varrho_{\epsilon,N} - \varrho_{\epsilon,1} = (c_N - c_1)\bar{\rho}_\epsilon \tag{3.11}$$

is decreasing in the cross-sectional variance of the alpha and the model predicted returns, $M_{i,t}$, and increasing in the size of the time-series variances of the news shocks.

In the case of linear factor models, the $M_{i,t}$ distribution is driven by the cross-sectional variances of betas and the time-series variance of the factor shocks.

3.1.2 Bias Corrections

We provide a method to remove both the misspecification bias and the noisy sort (attenuation) bias. This method operates by sorting on the idiosyncratic news shocks, defined in Equation (3.2), of firms in set A instead of sorting on their excess returns.[14] Such a sort is essentially *purged* of model misspecification, making the long-short portfolio exclusively a measure of the delayed information diffusion effect.

Denote the portfolios of linked firms in set B formed using news shocks instead of returns as $B'(P)$.

PROPOSITION 2. *If the firms in sets A and B are linked via news shocks per Equation* (3.3) *and via model misspecification per Equation* (3.4)*, and the distribution of $\epsilon_{i,t}$ is independent of the model misspecification α_j for linked firms i and j, then the expected alpha of the portfolio $B'(P)$ can be decomposed into two pieces:*

$$E[\alpha_{B'(P)}] = \bar{\alpha}_B + \varrho'_{\epsilon,P}. \tag{3.12}$$

The first component, $\bar{\alpha}_B$, is the average misspecification of stocks in set B and is the same for all the quantile portfolios. The second component, $\varrho'_{\epsilon,P}$, is due to slow information diffusion.

[14] If the model misspecification is due to an omitted factor such as HML, then the model misspecification will be time-varying due to the factor realizations. That is, we can rewrite Equation (3.2) as

$$\varepsilon_{i,t} \equiv r_{i,t} - M_{i,t} - \alpha_{i,t}$$

where $\alpha_{i,t}$ is the time-varying model misspecification. Purging with the misspecified model only allows us to recover α_i and, hence, $\epsilon_{i,t}$. So long as the omitted factor is i.i.d., then this purging will still remove the bias from the time-varying model misspecification. However, if the omitted factor is positively auto-correlated (e.g., HML), then some model misspecification bias may remain. The potential for time-varying model misspecification means one should purge using the best available asset pricing model.

3.1.2.1 Model misspecification bias

Notice that compared to the original method, the first term is identical across all sorted portfolios. Thus, the long-short portfolio, denoted $B'(LS)$, as a (first) difference eliminates this term, making the long-short portfolio alpha an unbiased measure of slow information diffusion.

COROLLARY 6. *The long-short portfolio of the extreme portfolios has expected alpha:*

$$E[\alpha_{B'(LS)}] = \varrho'_{\epsilon,N} - \varrho'_{\epsilon,1}. \tag{3.13}$$

3.1.2.2 Noisy sort bias

Purging the sorting variables of both the model misspecification (alpha) and the model predicted return ($M_{i,t}$) has the additional benefit of removing the noise in the sorting process. The sort is thus based only on the idiosyncratic new shocks. One can call this purged long-short alpha of Equation (3.13) the *true* slow information diffusion alpha because of the following.

COROLLARY 7. *The expected long-short alpha of Equation* (3.13) *is unaffected by the distribution of the model misspecification or model predicted returns of the firms in set A.*

Furthermore, this cleaner sort produces the largest possible alphas due to slow information diffusion, leading to an increased chance of finding slow information diffusion if truly present.

COROLLARY 8. *Under the assumptions of Proposition 2 and Corollary 5 the slow information diffusion component, $\varrho'_{\epsilon,P}$, of Equation* (3.12) *can be written as*

$$\varrho'_{\epsilon,P} = c'_P \, \bar{\rho}_\epsilon. \tag{3.14}$$

Moreover the slow information diffusion component of Equation (3.13) *is greater than or* *equal to that of Equation* (3.7)*:*

$$\varrho'_{\epsilon,N} - \varrho'_{\epsilon,1} \geq \varrho_{\epsilon,N} - \varrho_{\epsilon,1} \tag{3.15}$$

equivalently

$$c'_N - c'_1 \geq c_N - c_1. \tag{3.16}$$

The inequality is strict whenever there is a cross-sectional spread in the model misspecification or model predicted returns.

Thus so long as we are not in the degenerate case where all firms in set A have the identical model misspecification and model predicted returns, e.g., alphas and betas, the purging method provides a stronger test of slow information diffusion.

3.1.3 Effects of Estimating the Asset Pricing Model

The preceding discussion assumes that the asset pricing model, though imperfect, is known. In most cases, however, the asset pricing model must also be estimated. We now focus on the case of linear factor models estimated via regression on historical data. When such model estimation is required, purging still removes the bias due to model misspecification. However, it only partially removes the bias stemming from the noise in the sorting.

The purging method requires the estimation of the asset pricing model before sorting stocks into portfolios. Let $\hat{\alpha}_i$ be the estimated model misspecification, $\hat{M}_{i,t}$ be the estimated model predicted returns and the estimated idiosyncratic news shocks be

$$\hat{\epsilon}_{i,t} \equiv r_{i,t} - \hat{M}_{i,t} - \hat{\alpha}_i. \tag{3.17}$$

Denote the portfolios of linked firms in set B formed using news shocks instead of returns as $B''(P)$.

PROPOSITION 3. *If the firms in sets A and B are linked via news shocks per Equa-*

tion (3.3) *and via model misspecification per Equation* (3.4)*, and the distribution of* $\epsilon_{i,t}$ *is independent of the model misspecification* α_j *for linked firms* i *and* j*, then the expected alpha of the portfolio* $B''(P)$ *can be decomposed into two pieces:*

$$E[\alpha_{B'(P)}] = \bar{\alpha}_B + \varrho''_{\epsilon,P}. \tag{3.18}$$

The first component, $\bar{\alpha}_B$*, is the average misspecification of stocks in set* B *and is the same for all the quantile portfolios. The second component,* $\varrho''_{\epsilon,P}$*, is due to slow information diffusion.*

The intuition for obtaining a decomposition in Proposition 3 similar to that in Proposition 2 is that the estimation error of the alpha using a regression is mean zero and independent of the true model misspecification.

3.1.3.1 Model misspecification bias

Because the first term is again constant across all portfolios, the long-short portfolio, denoted $B''(LS)$, as a first difference eliminates this term, giving a measure of the slow price discovery free of bias from model misspecification.

COROLLARY 9. *The long-short portfolio of the extreme portfolios has expected alpha:*

$$E[\alpha_{B''(LS)}] = \varrho''_{\epsilon,N} - \varrho''_{\epsilon,1}. \tag{3.19}$$

Thus, purging with estimates of the model leads to estimates of the information diffusion effect free of the model misspecification bias.

3.1.3.2 Noisy sort bias

Because the idiosyncratic news shock used for sorting is now measured with noise, model estimation reduces the measure of the slow information diffusion compared to when the asset pricing model is known.

COROLLARY 10. *Under the assumptions of Proposition 2, Corollary 5 and Proposition 3 the slow information diffusion component,* $\varrho''_{\epsilon,P}$*, of Equation* (3.18) *can be written as*

$$\varrho''_{\epsilon,P} = c''_P \, \bar{\rho}_{\epsilon}. \tag{3.20}$$

The slow information diffusion component of Equation (3.19) *is less than that of Equation* (3.19)*:*

$$\varrho''_{\epsilon,N} - \varrho''_{\epsilon,1} < \varrho'_{\epsilon,N} - \varrho'_{\epsilon,1} \tag{3.21}$$

equivalently

$$c''_N - c''_1 < c'_N - c'_1. \tag{3.22}$$

We can rewrite the estimated idiosyncratic news shocks as combination of the true idiosyncratic news plus the estimation error:

$$\hat{\epsilon}_{i,t} = \epsilon_{i,t} + \underbrace{(\alpha_i + M_{i,t}) - (\hat{\alpha}_i + \hat{M}_{i,t})}_{\text{estimation error}} \tag{3.23}$$

From this we see that whether we obtain a larger or smaller measure of the slow information diffusion component from (1) the purged specification using an estimated asset pricing model compared to (2) that portion from the original specification, depends upon (a) the size of the cross-sectional distribution of alpha and model predicted returns relative to (b) that of the estimation error for our asset pricing model. Writing this more formally gives our next corollary.

COROLLARY 11. *Whether the slow price discovery component of Equation* (3.19) *is greater than or less than that of Equation* (3.7) *depends upon the cross-sectional distribution of the model misspecification, model predicted returns and the model estimation error:*

$$\varrho''_{\epsilon,N} - \varrho''_{\epsilon,1} \lessgtr \varrho_{\epsilon,N} - \varrho_{\epsilon,1} \tag{3.24}$$

equivalently

$$c''_N - c''_1 \lesseqgtr c_N - c_1. \tag{3.25}$$

Provided there is a wide cross-section in model misspecification and we can estimate our asset pricing model relatively well, the purging method provides a better measure of slow information diffusion than the original specification. Ultimately, the amount of the noisy sort bias the implementable purging method can remove is an empirical question which we address in Section 3.2.3

3.2 Bias in Published Price Discovery Studies

To show the magnitude of the bias described in our preceding analysis, we apply our corrections to Cohen and Frazzini (2008) and to Cohen and Lou (2012). The first paper, Cohen and Frazzini (2008), shows that return predictability exists across economically linked firms by using customer returns data at t to predict supplier returns at $t + 1$. The second paper, Cohen and Lou (2012), uses business segments data to demonstrate return predictability from simple firms at t to complex firms at $t + 1$. We replicate each paper's original findings. Then, by applying our corrections, we demonstrate that the one-month alphas are biased upward and the corrected cumulative abnormal returns over longer horizons are considerably smaller than previously measured. Hence, the speed of information diffusion is substantially faster than previously documented.

3.2.1 Application to Cohen and Frazzini (2008)

Cohen and Frazzini (2008) use the economic link between customers and suppliers to measure slow information diffusion. They obtain data on these links from regulation SFAS No. 131, which requires each firm to report any customer whose sales represent more than 10% of the firm's total sales. The authors argue that shocks to a supplier's customers (as measured by a portfolio of the supplier's customer returns) will propagate through to the supplier itself. Motivated by information processing constraints and the complexity of customer-supplier relationships, Cohen and Frazzini (2008) hypothesize and confirm that this propagation from customers to suppliers is delayed. They find this delay manifests itself as customer returns predicting future supplier returns for periods up to one year. In contrast, after applying our bias corrections, we find that this predictability, as measured by portfolio alphas, is overstated by more than 70%. The corrected alphas are both economically and statistically less significant. The value-weighted case even becomes statistically insignificant. Moreover, information diffusion is complete within one month rather than the 12 months originally argued.

3.2.1.1 Data Overview and Original Results

Following their method, we successfully replicate the key results of Cohen and Frazzini (2008). Using the U.S. Customer Supplier Links data made available by the authors on Andrea Frazzini's website, we calculate the equal-weighted excess return for a portfolio of customers of each supplier in each month.[15] We then rank customer portfolio returns in month t in ascending order. We use the customer portfolio return rankings at t to assign linked supplier firms at t into quintile portfolios. We calculate the value and equal-weighted $t+1$ excess returns of all suppliers in each quintile portfolio to generate a monthly time series of portfolio returns. To measure the return predictability, or alpha, associated with holding the long-short portfolio of the extreme quintiles, we apply four different factor models: the CAPM, the Fama French 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003).

In the column labelled original specification, Table 3.1 shows that the key results replicated are quantitatively very similar to those in the original paper: large alphas on long-short portfolios.[16] Specifically, using the Fama French 3-factor model, customer returns in month t predict supplier returns in month $t+1$ yielding a monthly alpha on the long-short portfolio of 155 basis points for the value-weighted portfolio and 116 basis points for the equal-weighted

[15] See http://www.econ.yale.edu/~af227/data_library.htm

[16] See Appendix Table 3.A.1 for a full replication of the main Table III of Cohen and Frazzini (2008).

portfolio. Both of these alphas are economically large and statistically significant at the 1% level.

3.2.1.2 Correcting the Bias by Purging Model Misspecification

Following Corollary 6, we show the effect of our purging method. The purging method sorts customers on their idiosyncratic news shocks instead of their excess returns. These idiosyncratic news shocks are the customers' excess returns purged of the both model misspecification and the component of returns due to systematic factor shocks.

We implement this purging method by first forming equal-weighted portfolios of customers linked to each supplier. Then we estimate the 4-factor loadings and alphas for each portfolio of customers at each month t using the previous 12 months of daily data ($t-12$ to $t-1$). We obtain similar results if, instead of purging the portfolio of customers, we perform the purging at the individual customer firm level or purge with the 5-factor model using monthly data.[17]

We use daily data to obtain estimates of the asset pricing model with the smallest possible estimation error while maintaining a sample as close as possible to that of the original specification. The lowest possible model estimation error minimizes the noisy sort bias. Using a longer estimation window (and monthly data) yields similar results, but causes a substantial loss in observations.

We extract the idiosyncratic news shock of each portfolio of customers at t using these parameter estimates combined with the current factor realizations.[18] At t, we rank the portfolio of customers in ascending order into quintiles based on their idiosyncratic shocks. Using these rankings, at t we form value or equal-weighted quantile portfolios of the suppliers (excess returns at time $t+1$). Per Corollary 6, the alpha of the long-short portfolio of the

[17] To minimize the bias one should purge with the best available asset pricing model (see Footnote 14). We use the 4-factor model because there is no daily Pástor and Stambaugh (2003) liquidity factor.

[18] The daily alpha estimates are scaled to monthly values using the number of trading days in the current month.

Table 3.1 Purging Method: Supplier Abnormal Returns This table replicates the main result of Cohen and Frazzini (2008). It shows the alphas of long-short portfolios using the original specification of Cohen and Frazzini (2008) and the purging specification. The original specification uses time t portfolio returns of a supplier's principal customers to assign suppliers into quintile portfolios at t (returns at $t+1$). The purged specification uses portfolio returns of a supplier's principal customers' idiosyncratic news shocks at t to sort suppliers into quintile portfolios at t (returns at $t+1$). For each customer, we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each customer's idiosyncratic news shock at t. Alpha is the intercept on a regression of the monthly returns for the long-short portfolio using various asset pricing models. Alpha is reported in percent per month. The models used are the CAPM, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum (Carhart, 1997) and liquidity (Pástor and Stambaugh, 2003). Overstatement (%) is the amount by which the original specification's alpha exceeds the purged specification's alpha. t-statistics are in parentheses. Following the original paper, the sample period is from 1981 to 2004.

Value Weights	Original	Purged	Overstatement (%)
Excess Returns	1.389	0.761	82.6
	(3.637)	(2.169)	
1-Factor Alpha	1.361	0.697	95.3
	(3.526)	(1.971)	
3-Factor Alpha	1.547	0.826	87.3
	(3.875)	(2.243)	
4-Factor Alpha	1.347	0.789	70.7
	(3.319)	(2.090)	
5-Factor Alpha	1.303	0.694	87.8
	(3.179)	(1.828)	

Equal Weights	Original	Purged	Overstatement (%)
Excess Returns	1.160	0.541	114.5
	(4.967)	(2.681)	
1-Factor Alpha	1.164	0.526	121.2
	(4.930)	(2.582)	
3-Factor Alpha	1.155	0.605	90.8
	(4.717)	(2.848)	
4-Factor Alpha	1.067	0.586	82.1
	(4.266)	(2.689)	
5-Factor Alpha	1.057	0.504	109.7
	(4.180)	(2.316)	

extreme quintiles reveals the slow information diffusion effect associated with these economic links. We investigate the extent of the remaining noise bias in Section 3.2.3.

Table 3.1 shows the results of this purging method. Across both value-weighted and equal-weighted portfolios and for all asset pricing models, the purged alphas are substantially smaller than the alphas from the original specification. For example, the 3-factor alphas on value-weighted and equal-weighted portfolios shows the original specification overstates the slow information diffusion by 87% and 91%. The overstatement is even larger for the 5-factor alpha at 88% for the value-weighted portfolio and 110% for the equal-weighted portfolio. Correcting for the overstatement from model misspecification bias leads to 5-factor alpha estimates of only 69 basis points for the value-weighted portfolio and 50 basis points for the equal-weighted portfolio. Not only is the overstatement economically large, but the corrected alphas also become statistically insignificant for the value-weighted portfolio under the 5-factor model. The alphas remain statistically significant for the other cases, though substantially less so than in the original specification.

3.2.1.3 Implications of Bias on the Speed of Information Diffusion

The preceding analysis shows the alpha measured under the original specification of Cohen and Frazzini (2008) is biased upwards due to model misspecification. In Figure 3.2, we plot the cumulative alphas out to 12 months for the original specification using the 3-factor alpha and our purged specification using the 3-factor and 5-factor alphas.[19] The cumulative alpha of the original specification continually grows out to 12 months, while the alphas of the purged specification remains flat after one month. The divergence arising from the upward bias due to model misspecification makes information diffusion appear to take much longer than it actually is. This appearance of the extended delay in information diffusion is explained by Corollary 4, which shows that, even after price discovery has completed, the incremental alpha of the original long-short portfolio remains positive for each additional period.

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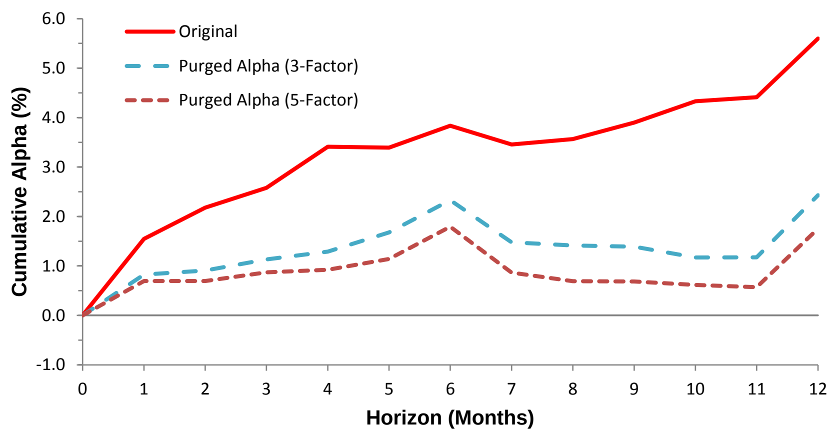
[19] We use the 12 month horizon to be consistent with the original paper.

Figure 3.2. Cumulative Alphas Over Time: Supplier Portfolios This figure shows the cumulative alphas to supplier portfolios over the following year using the original specification of Cohen and Frazzini (2008) and this paper's proposed purging correction. At each horizon h, we calculate the Fama and French (1993) 3-factor model monthly alpha under the original specification and the purging specification. The cumulative alpha is the sum of alphas for each of the periods through horizon h. The original specification uses time t portfolio returns of a supplier's principal customers to assign suppliers into quintile portfolios at $t+h-1$ (returns at $t+h$). The purged specification uses portfolio returns of a supplier's principal customers' idiosyncratic news shocks at t to sort suppliers into quintile portfolios at $t+h-1$ (returns at $t+h$). To calculate these idiosyncratic new shocks, for each customer we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each customer's idiosyncratic news shock at t. The sample period following the original paper is from 1981 to 2004. Panel A shows value-weighted portfolios, and Panel B shows equal-weighted portfolios.

Panel A: Value-Weighted Portfolios



Panel B: Equal-Weighted Portfolios

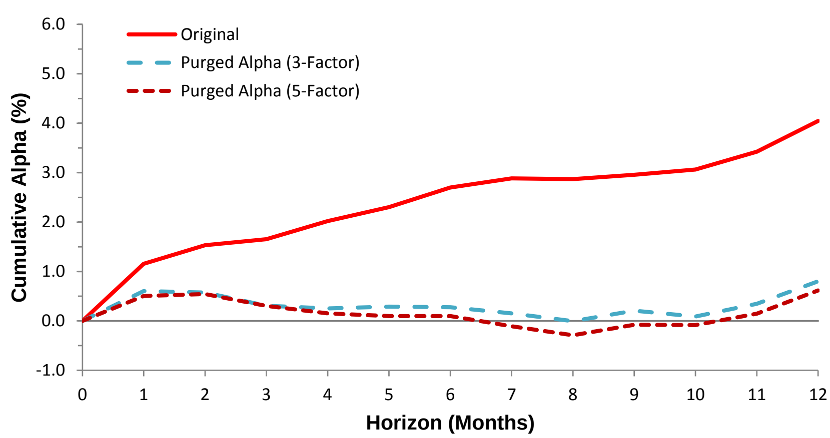


Table 3.2 quantifies the effect that model misspecification has on the cumulative alpha of value and equal-weighted portfolios at the 1-month, 6-month and 12-month horizons for both the 3-factor and 5-factor models. Panel A includes the first month and Panel B shows the cumulative alphas excluding the first month. Under the original specification (Panel A), the cumulative 3-factor alpha for a value (equal) weighted portfolio increases from 155 (116) basis points at a one month horizon to 560 (404) basis points at a 12 month horizon, suggesting that information diffusion in supplier returns is still taking place 12 months after the initial news shock to customer returns, casting doubt on market efficiency.

Table 3.2 Cumulative Alphas at Various Horizons: Supplier Abnormal Returns
This table shows the cumulative alpha to supplier portfolios at different horizons using the original method of Cohen and Frazzini (2008) and this paper's proposed purging correction. At each horizon h, we calculate the monthly alpha under the original and the purging specifications. The cumulative alpha is the sum of alphas for each of the periods through horizon h. The original specification uses time t portfolio returns of a supplier's principal customers to assign suppliers into quintile portfolios at $t+h-1$ (returns at $t+h$). The purged specification uses portfolio returns of a supplier's principal customers' idiosyncratic news shocks at t to sort suppliers into quintile portfolios at $t+h-1$ (returns at $t+h$). For each customer, we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each customer's idiosyncratic news shock at t. Alpha is the intercept on a regression of the monthly returns for the long-short portfolio using various asset pricing models. Alpha is reported in percent per month. The models used are the Fama and French (1993) 3-factor model and the 3-factor model augmented with momentum (Carhart, 1997) and liquidity (Pástor and Stambaugh, 2003). t-statistics are in parentheses. We assume independence of the standard errors between across months when calculating the t-statistics for the cumulative returns and 6 and 12 months. Following the original paper, the sample period is from 1981 to 2004. Panel A shows the cumulative alphas including the first month. Panel B shows the cumulative alphas excluding the first month.

Panel A: Month 1 Onward

	Value-Weighted Portfolios			Equal-Weighted Portfolios		
3-Factor Model	Month 1	Months 1-6	Months 1-12	Month 1	Months 1-6	Months 1-12
Original	1.547	3.835	5.600	1.155	2.698	4.044
	(3.875)	(4.098)	(4.116)	(4.717)	(4.633)	(4.871)
Purged	0.826	2.332	2.431	0.605	0.277	0.801
	(2.243)	(2.534)	(1.875)	(2.848)	(0.508)	(1.052)

Table 3.2 Continued

Panel B: Summary statistics: MSA pairs over time

	Value-Weighted Portfolios			Equal-Weighted Portfolios		
5-Factor Model	Month 1	Months 1-6	Months 1-12	Month 1	Months 1-6	Months 1-12
Original	1.303	2.082	2.437	1.057	1.507	1.880
	(3.179)	(2.184)	(1.759)	(4.180)	(2.559)	(2.237)
Purged	0.694	1.793	1.754	0.504	0.099	0.617
	(1.828)	(1.887)	(1.310)	(2.316)	(0.176)	(0.785)

Panel B: Month 2 Onward

	Value-Weighted Portfolios			Equal-Weighted Portfolios		
3-Factor Model	Month 2	Months 2-6	Months 2-12	Month 2	Months 2-6	Months 2-12
Original	0.632	2.288	4.052	0.377	1.543	2.889
	(1.573)	(2.703)	(3.116)	(1.612)	(2.920)	(0.793)
Purged	0.081	1.506	1.605	-0.030	-0.329	0.196
	(0.211)	(1.786)	(1.291)	(-0.136)	(-0.657)	(0.268)
	Value-Weighted Portfolios			Equal-Weighted Portfolios		
5-Factor Model	Month 2	Months 2-6	Months 2-12	Month 2	Months 2-6	Months 2-12
Original	0.326	0.779	1.133	0.241	0.450	0.823
	(0.794)	(0.905)	(0.856)	(1.016)	(0.847)	(1.027)
Purged	-0.001	1.099	1.060	0.040	-0.405	0.113
	(-0.001)	(1.261)	(0.826)	(0.172)	(-0.783)	(0.150)

However, for the purged specifications, the cumulative 3-factor and 5-factor alphas increase only marginally with horizon beyond one month. More importantly, under both corrected specifications, the cumulative alpha becomes statistically insignificant at the 6 month and 12 month horizons. Panel B shows there is no statistically significant cumulative alpha after the first month. Thus we see that the bias from model misspecification increases over time, leading to an increasingly larger overstatement of alpha at longer horizons. Correcting for this overstatement shows that very little, if any, information diffusion occurs after 1 month.

3.2.2 Application to Cohen and Lou (2012)

Cohen and Lou (2012) demonstrate return predictability of complex conglomerate firms based on a portfolio of of simple firms' returns. These simple firms are single-industry firms in the industries in which the conglomerate has operating segments. Assuming information processing constraints, the authors argue that conglomerate firms are more difficult to analyze than single-industry firms, and therefore, a portfolio of single-industry firms should lend itself to predicting the returns of conglomerate firms. They follow the method of Cohen and Frazzini (2008) and confirm the delay in information incorporation into conglomerate prices. Moreover, they show that this delay persists over 6 months casting doubt on market efficiency. In contrast, after applying our bias correction, we find this predictability, as measured by portfolio alphas, is overstated by 30 to 60% (depending upon the specification) and has substantially lower statistical significance. Most importantly, we find that information diffusion is complete within one month.

3.2.2.1 Data Overview and Original Results

Following Cohen and Lou (2012), we use data on operating and business segments from the Compustat segment files to identify firms as single-industry firms or as conglomerates. We use 2 digit SIC codes to identify the segment. Using the single-industry firms only, we calculate the industry portfolio returns of these firms in each 2 digit SIC code.

For the conglomerates, we identify each of its principal operating and business segments that represent more than 10% of a firm's sales. We use operating segments of each conglomerate firm along with each segment's industry return (calculated from single-industry firms) to form a value-weighted portfolio return, which, using the naming convention from the original paper, we call the pseudo-conglomerate returns.

At each time t, we rank the pseudo-conglomerate returns in ascending order into deciles. Using these rankings, we assign the corresponding conglomerate firms at t to the (value or equal-weighted) decile portfolios (returns at $t + 1$). To measure the return predictability, or alpha, associated with holding the long-short portfolio of the extreme deciles, we apply four different factor models: the CAPM, the Fama French 3-factor model, and the 3-factor model augmented with momentum of Carhart (1997) and liquidity of Pástor and Stambaugh (2003).

In the column labelled original specification, Table 3.3 shows that the key results replicated are quantitatively similar to those of Cohen and Lou (2012).[20] Using the Fama French 3-factor model, this long-short strategy results in an abnormal return of 116 and 123 basis points per month using value and equal-weighted portfolios of conglomerate returns. The results are similar across the various asset pricing models.

3.2.2.2 Correcting the Bias by Purging Model Misspecification

Following Corollary 6, we show the effect of our purging method. We implement this purging method by estimating the 4-factor loadings and alphas for each pseudo-conglomerate portfolio at each date t using the previous 12 months of daily data ($t - 12$ to $t - 1$). We obtain similar results if, instead of purging the pseudo-conglomerate portfolio return, we perform the purging at the individual single industry firm level or purge with the 5-factor model using monthly data.

We use daily data to obtain estimates of the asset pricing model with the smallest possible

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[20] See Appendix Table 3.A.2 for a full replication of the main Table 2 of Cohen and Lou (2012).

Table 3.3 Purging Method: Conglomerate Abnormal Returns This table replicates the main result of Cohen and Lou (2012). It shows the alphas of long-short portfolios using the original specification of Cohen and Lou (2012) and the purging specification. The original specification uses time t portfolio returns of a conglomerate's principal industries to assign conglomerates into decile portfolios at t (returns at $t+1$). The purged specification uses portfolio returns of a conglomerate's principal industries' idiosyncratic news shocks at t to sort conglomerates into decile portfolios at t (returns at $t+1$). For each customer, we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each industry's idiosyncratic news shock at t. Alpha is the intercept on a regression of the monthly returns for the long-short portfolio using various asset pricing models. Alpha is reported in percent per month. The models used are the CAPM, the Fama and French (1993) 3-factor model, and the 3-factor model augmented with momentum (Carhart, 1997) and liquidity (Pástor and Stambaugh, 2003). Overstatement (%) is the amount by which the original specification's alpha exceeds the purged specification's alpha. t-statistics are in parentheses. Following the original paper, the sample period is 1977 to 2009.

Value Weights	Original	Purged	Overstatement (%)
Excess Returns	1.094	0.775	41.1%
	(3.996)	(2.859)	
1-Factor Alpha	1.130	0.770	46.7%
	(4.102)	(2.817)	
3-Factor Alpha	1.157	0.729	58.6%
	(4.120)	(2.619)	
4-Factor Alpha	0.967	0.748	29.3%
	(3.428)	(2.634)	
5-Factor Alpha	0.994	0.760	30.7%
	(3.473)	(2.638)	

Equal Weights	Original	Purged	Overstatement (%)
Excess Returns	1.280	0.979	30.7%
	(5.572)	(4.405)	
1-Factor Alpha	1.275	0.946	34.7%
	(5.508)	(4.232)	
3-Factor Alpha	1.233	0.870	41.7%
	(5.239)	(3.831)	
4-Factor Alpha	1.184	0.904	31.0%
	(4.938)	(3.903)	
5-Factor Alpha	1.257	0.925	35.9%
	(5.186)	(3.937)	

estimation error while maintaining a sample as close as possible to that of the original specification. The lowest possible model estimation error minimizes the noisy sort bias. Using a longer estimation window (and monthly data) yields similar results, but causes a substantial loss in observations.

We extract the idiosyncratic news shock of each pseudo-conglomerate portfolio at t using these parameter estimates combined with the current factor realizations.[21] At t, we rank these pseudo-conglomerate idiosyncratic news shocks in ascending order into deciles. Using these rankings, at t we form value or equal-weighted decile portfolios of the conglomerate firms (excess returns at time $t + 1$). The alpha of the long-short portfolio of the extreme deciles reveals the slow information diffusion effect associated with these economic links. We investigate the extent of the remaining noise bias in Section 3.2.3.

Table 3.3 shows the results of this purging method. Across both value-weighted and equal-weighted portfolios and for all asset pricing models, the purged alphas are substantially smaller than the alphas obtained from the original specification. For example, the 3-factor alpha on value-weighted and equal-weighted portfolios is 73 basis points and 87 basis points, meaning the original specification overstates the slow information diffusion by 59% and 42%. Nevertheless, the alpha estimates still remain statistically significant, indicating the presence of some slow information diffusion at the one month horizon.[22]

3.2.2.3 Implications of Bias on the Speed of Information Diffusion

The preceding analysis shows that the alpha measured under the original specification of Cohen and Lou (2012) is biased upward due to model misspecification. In Figure 3.3, we plot the cumulative alphas out to 6 months for the original specification using the 3-factor

[21]The daily alpha estimates are scaled to monthly values using the number of days in the current month.

[22]In a robustness test, measure information diffusion Cohen and Lou (2012) with a regression framework, which has analogous biases to those we document. In this setting, the authors partially control for the bias, we highlight by including the lagged conglomerate return. An unbiased regression framework would instead regress the conglomerate's idiosyncratic shocks on the pseudo-conglomerate's lagged idiosyncratic shocks.

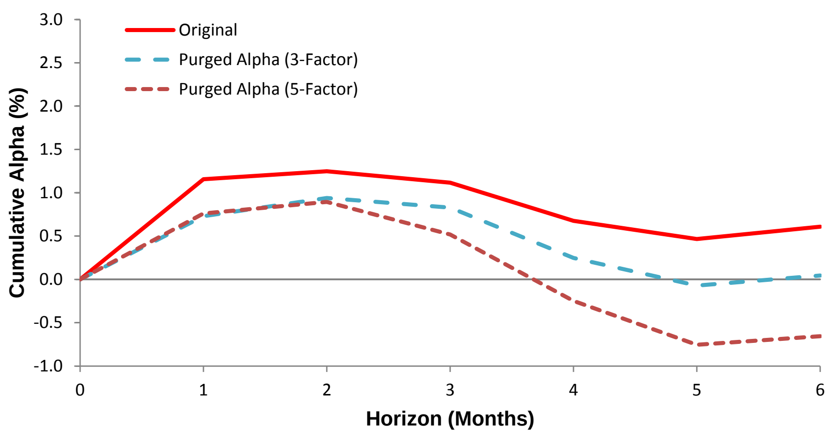
alpha and our purged specification using the 3-factor and 5-factor alphas.[23] We see that the cumulative alpha for the equal-weighted original specification continually grows, while, under the bias-corrected specification, after one month the cumulative alphas remains flat. From this divergence, we see that the upward bias in the long-horizon alphas due to model misspecification makes information diffusion appear to take much longer than it actually does. This appearance of the extended delay in information diffusion can be explained by Corollary 4, which shows that, even after price discovery has completed, the incremental alpha of the original long-short portfolio for each additional period remains positive.

Table 3.4 shows the effect that model misspecification has on the cumulative alpha of value and equal-weighted portfolios at the 1 month and 6 month horizons for both the 3-factor and 5-factor models. Panel A includes the first month and Panel B shows the cumulative alphas excluding the first month. Under the original specification, the cumulative 3-factor alpha for the equal-weighted portfolio increases from 123 basis points at a one month horizon to 258 basis points at a 6 month horizon. This increase suggests that information diffusion in conglomerate returns is still taking place 6 months after the initial news shock to customer returns, casting doubt on market efficiency.

[23]We use the 6 month horizon to be consistent with the original paper.

Figure 3.3. Cumulative Alphas Over Time: Conglomerate Portfolios This figure shows the cumulative alphas to conglomerate portfolios over the following year using the original specification of Cohen and Lou (2012) and this paper's proposed purging correction. At each horizon h, we calculate the Fama and French (1993) 3-factor model monthly alpha under the original specification and the purging specification. The cumulative alpha is the sum of alphas for each of the periods through horizon h. The original specification uses time t portfolio returns of a conglomerate's principal industries to assign conglomerates into quintile portfolios at $t+h-1$ (returns at $t+h$). The purged specification uses portfolio returns of a conglomerate's principal industries' idiosyncratic news shocks at t to sort conglomerates into quintile portfolios at $t+h-1$ (returns at $t+h$). To calculate these idiosyncratic new shocks, for each industry we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each customer's idiosyncratic news shock at t. The sample period following the original paper is from 1977 to 2009. Panel A shows value-weighted portfolios, and Panel B shows equal-weighted portfolios.

Panel A: Value-Weighted Portfolios



Panel B: Equal-Weighted Portfolios

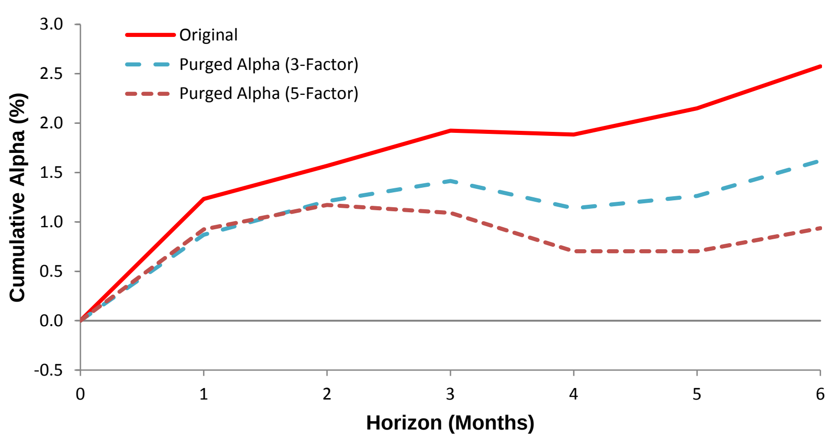


Table 3.4 Cumulative Alphas at Various Horizons: Conglomerate Abnormal Returns This table shows the cumulative alpha to conglomerate portfolios at different horizons using the original method of Cohen and Lou (2012) and this paper's proposed purging correction. At each horizon h, we calculate the monthly alpha under the original and the purging specifications. The cumulative alpha is the sum of alphas for each of the periods through horizon h. The original specification uses time t portfolio returns of a conglomerate's principal industries (pseudo-conglomerate returns) to assign conglomerates into quintile portfolios at $t+h-1$ (returns at $t+h$). The purged specification uses portfolio returns of a conglomerate's principal industries' idiosyncratic news shocks at t to sort conglomerates into quintile portfolios at $t+h-1$ (returns at $t+h$). For each pseudo-conglomerate, we estimate the alphas and loadings of the 4-factor model (Fama and French, 1993; Carhart, 1997) by using the previous 12 months of daily data ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to extract each pseudo-conglomerate's idiosyncratic news shock at t. Alpha is the intercept on a regression of the monthly returns for the long-short portfolio using various asset pricing models. Alpha is reported in percent per month. The models used are the Fama and French (1993) 3-factor model and the 3-factor model augmented with momentum (Carhart, 1997) and liquidity (Pástor and Stambaugh, 2003). t-statistics are in parentheses. We assume independence of the standard errors between across months when calculating the t-statistics for the cumulative returns at 6 months. Following the original paper, the sample period is 1977 to 2009. Panel A shows the cumulative alphas including the first month. Panel B shows the cumulative alphas excluding the first month.

Panel A: Month 1 Onward

	Value-Weighted Portfolios		Equal-Weighted Portfolios	
3-Factor Model	Month 1	Months 1-6	Month 1	Months 1-6
Original	1.157	0.608	1.233	2.575
	(4.120)	(0.848)	(5.239)	(4.771)
Purged	0.729	0.044	0.870	1.619
	(2.619)	(0.061)	(3.831)	(2.902)
	Value-Weighted Portfolios		Equal-Weighted Portfolios	
5-Factor Model	Month 1	Months 1-6	Month 1	Months 1-6
Original	0.994	-1.109	1.257	1.306
	(3.473)	(-1.553)	(5.186)	(2.439)
Purged	0.760	-0.656	0.925	0.936
	(2.638)	(-0.884)	(3.937)	(1.638)

Table 3.4 Continued

Panel B: Month 2 Onward

	Value-Weighted Portfolios		Equal-Weighted Portfolios	
3-Factor Model	Month 2	Months 2-6	Month 2	Months 2-6
Original	0.092	-0.548	0.335	1.342
	(0.323)	(-0.830)	(1.574)	(2.763)
5-Factor Purged	0.211	-0.685	0.340	0.749
	(0.742)	(-1.028)	(1.604)	(1.470)
	Value-Weighted Portfolios		Equal-Weighted Portfolios	
5-Factor Model	Month 2	Months 2-6	Month 2	Months 2-6
Original	-0.216	-2.103	0.040	0.049
	(-0.761)	(0.654)	(0.192)	(0.103)
5-Factor Purged	0.134	-1.417	0.248	0.011
	(0.458)	(-2.072)	(1.133)	(0.022)

However for the purged specifications, the cumulative 3-factor alpha increases only marginally after one month and, in some cases, decreases. More importantly, under all purged specifications, the cumulative alpha becomes statistically insignificant at the 6 month horizon. Panel B shows that the all the cumulative alphas after 1 month are statistically insignificant. Thus we see that the bias from model misspecification increases over time leading to an increasingly large overstatement of alpha at longer horizons. Correcting for this bias, we find that information diffusion occurs largely within the first month.

3.2.3 Decomposing the Biases

The original specification of testing for slow information diffusion by sorting on a set of firms' returns has two biases. The first bias from model misspecification is upward. The second bias from having a noisy sort is downward. The noise comes from including both the model misspecification and systematic return components in the sort in addition to signal of interest: the idiosyncratic news.

Purging the returns of the model misspecification and systematic return components reveals the idiosyncratic shocks when one knows the asset pricing model parameters. Sorting on these idiosyncratic shocks removes both biases. However, when one must estimate the asset pricing model parameters to use for purging, one can only attain estimates of the idiosyncratic shocks. Nevertheless, the idiosyncratic shock estimates are unbiased, so sorting on them still removes the upward bias from model misspecification.

The effect that sorting on the estimated idiosyncratic shocks has on reducing the noisy sort bias, however, is an empirical question. The noisy sort bias will be reduced if the estimation error of the asset pricing model is small compared to the amount of cross-sectional variation in the model misspecification and systematic return components.

We provide a simulation method for the case of linear factor models based on parameters calibrated for each slow price discovery test setting. With this simulation, we estimate the total bias in the original specification and find numbers that closely match those reported in preceding subsections (Tables 3.1 and 3.3). We then use the simulation to decompose the total bias into the fraction of the original specification's reported alpha that is due to model misspecification. We also estimate how the slow information diffusion components of both the original specification and our purged specification compare to the hypothetical case of purging with known asset pricing model parameters.

We recognize that these simulation estimates are limited by our ability to accurately calibrate the simulation. We therefore provide a sensitivity analysis of these estimates to variation in the calibration parameters to demonstrate the robustness of our results.

3.2.3.1 Calibration Parameter Discussion

For the bias magnitudes, the average level of slow information diffusion between firms in set A and B ($\bar{\rho}_\epsilon$) and the average linkage of their model misspecification ($\bar{\rho}_\alpha$) are crucially important. Just as in the preceding empirical section, these calibrations are based on the portfolios in set A rather than at the individual firm level. These values are the cross-sectional averages of the coefficients from time-series regressions (analogous to Equations (3.3) and (3.4)) for each portfolio-firm link in the sample.

Panel A of Table 3.5 shows the two calibration parameters for the link in model misspecification $\bar{\rho}_\alpha$ and slow information $\bar{\rho}_\epsilon$ across customer-supplier and pseudo-conglomerate links. In both cases, the average alpha linkage is economically large and statistically significant which explains the upward bias. We see that there is a much tighter link in the model misspecification for pseudo-conglomerates than for customers and suppliers (0.63 v. 0.22). Despite this tighter model misspecification link, we find the model misspecification bias to be much larger for the customer-supplier link setting. This apparent discrepancy is because there is also a much larger slow information diffusion link for the pseudo-conglomerates (0.16 v. 0.02). The combined effect of the two parameters is clear when one looks at the ratios between the parameters. The ratio of the misspecification link to the slow information link is 11:1 for the customer supplier links and only 4:1 for the pseudo-conglomerate links. The larger ratio for the customer supplier links helps explain why the bias is larger for that case despite the stronger model misspecification links for the pseudo-conglomerate case.

The sizes of the model misspecification and noisy sort biases are also determined by the distribution of firms (or portfolios of firms) in set A. The key features of the distribution that matter are the cross-sectional variance of the alphas (σ^2_α), the cross-sectional variance of the factor betas (Σ_β), the distribution of the time-series variances of the idiosyncratic shocks ($\vec{\sigma}^2_\epsilon$).[24] These values are all calibrated from the cross-sectional distribution of α, β and ϵ estimates from time-series regressions for each firm (portfolio) in set A.

For a list of the other parameter values used and further details of the calibration of these parameters, see Appendix Tables 3.A.3 and 3.A.4.

[24]We bootstrap from the the vector of idiosyncratic shock variances in the data, because variances must be positive and they are not normally distributed.

Table 3.5 Decomposition of Bias This table shows estimates of the key bias-determining parameters and simulation results decomposing the total bias into the model misspecification and noisy sort components. Panel A shows the average correlation in the model misspecification ($\bar{\rho}_\alpha$) and the average cross-autocorrelations of the idiosyncratic shocks ($\bar{\rho}_\epsilon$) across the economic links. These are the key parameters used in the simulation. The values are calculated as the cross-sectional average of the regression coefficients of time series regressions for each portfolio-firm link of either the alphas or idiosyncratic shocks using the same data windows as in the original papers. t-statistics are in parentheses. Panels B and C show the expected bias and its decomposition into the model misspecification component and the noisy sort (attenuation) component. The results are shown for the original method and the purging method where the asset pricing model parameters are estimated. The bias and decompositions are relative to the purging method when the asset pricing model parameters are known. The model misspecification bias is the difference of the total bias and the attenuation bias. Panel B shows the bias decomposition results for Cohen and Frazzini (2008). Panel C shows the bias decomposition results for Cohen and Lou (2012). Results are based on the means from 1000 simulation runs. The calibrated parameters used in the simulation are in Appendix Table 3.A.3.

Panel A: Model Misspecification and Slow Information Parameters

	$\bar{\rho}_\alpha$	$\bar{\rho}_\epsilon$	Ratio
Customer-Supplier Links	0.22	0.02	11:1
	(6.60)	(1.02)	
Pseudo-Conglomerate Links	0.63	0.16	4:1
	(15.74)	(5.33)	

Panel B: Customer-Supplier Links

	Bias (%)		
Specification	Total	Attenuation	Model Misspecification
Original	69.6	-9.1	77.7
Purged	-4.6	-4.6	0.0

Panel C: Pseudo-Conglomerate Links

	Bias (%)		
Specification	Total	Attenuation	Model Misspecification
Original	23.5	-7.8	31.2
Purged	-4.7	-4.7	0.0

3.2.3.2 Simulation Procedure and Results

For each run of our simulation, we use the parameters discussed in the preceding section to draw a random sample of firms (portfolios) in set A of the same size as the average number of firms in the actual data. The panel dimension of the random data comes from drawing daily factor shocks from the mean and variance covariance matrix of the four factors: market excess return, SMB, HML and momentum. Finally, for each firm we draw its idiosyncratic shocks based on the idiosyncratic variance we drew for that firm. We set the panel length to be the length of actual data.

From this panel of random data we perform three sorts, splitting firms each month (assuming 21 trading days) into quintiles for the customer-supplier links simulation and deciles for the pseudo-conglomerate links simulation. The first sort mirrors the original lead-lag specification using excess returns as the sorting variable. The second sort mirrors our implemented purge specification, sorting on the lagged estimated idiosyncratic shocks. These shocks are calculated using parameters from the four factor model estimated with the preceding year's worth (252 days) of data. The third sort uses the true idiosyncratic shocks, which are known since we generated the sample data.

For each sort, we calculate the average of the true alphas and idiosyncratic shocks within the extreme portfolios. These averages are within each portfolio at each sorting date, then across each date in the panel, and finally, across all 1000 simulation runs. We denote these $\alpha_{P,Sim,Sort}$ and $\epsilon_{P,Sim,Sort}$. These values are known since we generated the simulation data. From these values, we decompose the biases contributing to the reported long-short portfolio alpha of firms in set B. The total alpha for each sort is[25]

$$\alpha_{LS,Sim,Sort} = \rho_\alpha(\alpha_{N,Sim,Sort} - \alpha_{1,Sim,Sort}) + \rho_\epsilon(\epsilon_{N,Sim,Sort} - \epsilon_{1,Sim,Sort}). \tag{3.26}$$

[25]This equation comes from the decomposition described in Corollary 5 and a similar decomposition that can be obtained for the $\varrho_{\alpha,P}$ by imposing similar independence assumptions used in that corollary. The average alphas and epsilons from the simulation are the constants of interest in those decompositions.

The slow information diffusion component of this alpha is

$$\epsilon_{LS,Sim,Sort} = \rho_\epsilon(\epsilon_{N,Sim,Sort} - \epsilon_{1,Sim,Sort}). \tag{3.27}$$

The sort on known idiosyncratic shocks is the baseline (free of both biases) against which the biases in the other sorts are measured.

Table 3.5 reports the bias decomposition. Column 1 reports the total bias: the long-short alpha divided by that of the sort with known idiosyncratic shocks

$$\frac{\alpha_{LS,Sim,Sort}}{\alpha_{LS,Sim,Purged\,Known}}. \tag{3.28}$$

Column 2 reports the attenuation bias: the slow information diffusion component of the long-short alpha relative to that from the sort with the known idiosyncratic shocks

$$\frac{\epsilon_{LS,Sim,Sort}}{\epsilon_{LS,Sim,Purged\,Known}} - 1. \tag{3.29}$$

Column 3 reports the model misspecification bias: the difference between the total bias and the attenuation bias. The simulation uses the four-factor model with equal-weighted averages. The results in Table 3.5 should be compared to the bias (overstatement %) in equal-weighted four-factor alphas shown in Tables 3.1 and 3.3.

Panel A reports simulation results for customer-supplier links and Panel B reports simulation results for the pseudo-conglomerate links. In both panels, the total bias of the original specification closely matches that obtained from the actual data (Tables 3.1 and 3.3). We see that though the original method has an overall upward bias, this bias is due to a large upward bias from the model misspecification and a smaller downward bias from the noisy sort.

In both panels the purged specification has a small overall downward bias of 4.6% and 4.7% due entirely to the noisy sort bias. The last column shows that the purged specification completely removes the model misspecification bias. However, the model estimation error, prevents the purged specification from completely removing the downward noisy sort bias. The similar downward bias across both sets of links arises because the precision with which the asset pricing model can be estimated is similar across both cases. This purged specification has less noisy sort (attenuation) bias than the original specifications' attenuation of -9.1% and -7.8%.

3.2.3.3 Sensitivity analysis

Decomposing the biases in Table 3.5 depends upon the calibration parameters. Figure 3.4 shows a sensitivity analysis varying the calibration parameters from 50% to 150% of the baseline values. Panel A shows results for the customer-supplier links and Panel B shows results for the pseudo-conglomerate links. The first subpanel shows the total bias of the original specification. The second subpanel shows the noisy sort (attenuation) bias for both the original and purged specifications as a percentage relative to the slow information diffusion component of the known purged specification. The main result remains over this wide range of parameters: the original specification has an economically significant upward bias while the purged specification has no upward bias and a smaller noisy sort bias than the original.

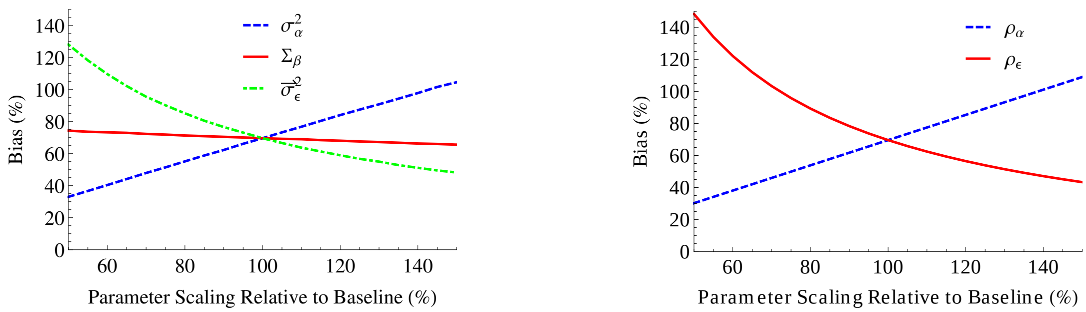
This sensitivity analysis also shows that the biases change as a function of the parameters, consistent with the predictions of our theory section. The first subpanel shows that the total (percentage) bias increases in both the amount of cross-sectional variation in alphas for set A firms (σ_α^2) and the strength of the alpha link across A and B firms ($\bar{\rho}_\alpha$). The total percentage bias decreases in both the size of the idiosyncratic news shocks ($\vec{\sigma}_\epsilon^2$) and the size of the slow price discovery link ($\bar{\rho}_\epsilon$). This decrease comes from the actual amount of slow information diffusion increasing rather than the absolute bias decreasing. Finally, due to an increase in the downward noisy sort bias, the total percentage bias decreases in the cross-sectional variance of betas.

The second subpanel shows the downward noisy sort bias in the original specification increases in the amount of noise, i.e., the cross-sectional variance of alphas and betas for firms in set A. The noisy sort bias decreases in the size of the idiosyncratic shocks ($\vec{\sigma}_\epsilon^2$). The

Figure 3.4. Bias Sensitivity Analysis: Simulations This figure shows a sensitivity analysis of the bias to the underlying parameters. Panel A shows the results for Cohen and Frazzini (2008). Panel B shows the results for Cohen and Lou (2012). Subpanel 1 shows the total bias of the original method relative to the purged method with known asset pricing model parameters. Subpanel 2 shows the size of the of the true slow information diffusion component of the total alpha relative to the true slow information diffusion alpha as calculated by the purged method using known parameters for the asset pricing model. All plots show variation from the scaling of individual parameters relative to their baseline calibrated values. A full list of the baseline calibration parameters is in Appendix Table 3.A.3.

Panel A: Customer-Supplier Links

Panel A1: Total Bias of Original



Panel A2: Slow Information Diffusion Component Relative to True Slow Information Diffusion Component

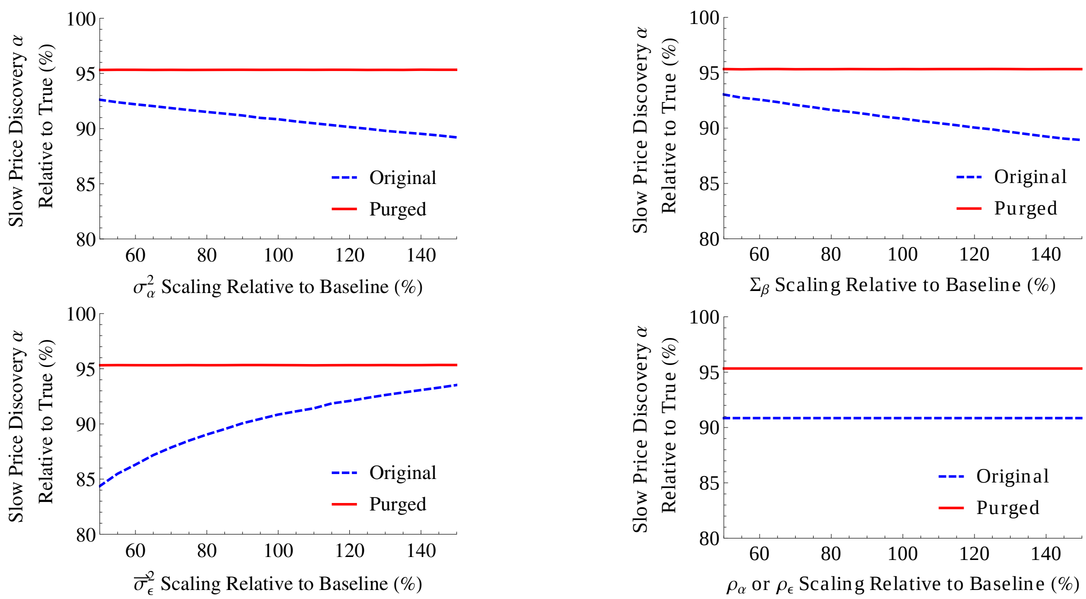
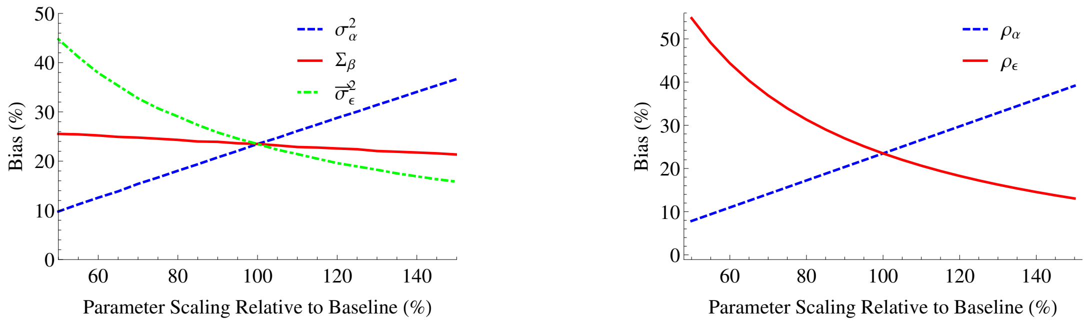


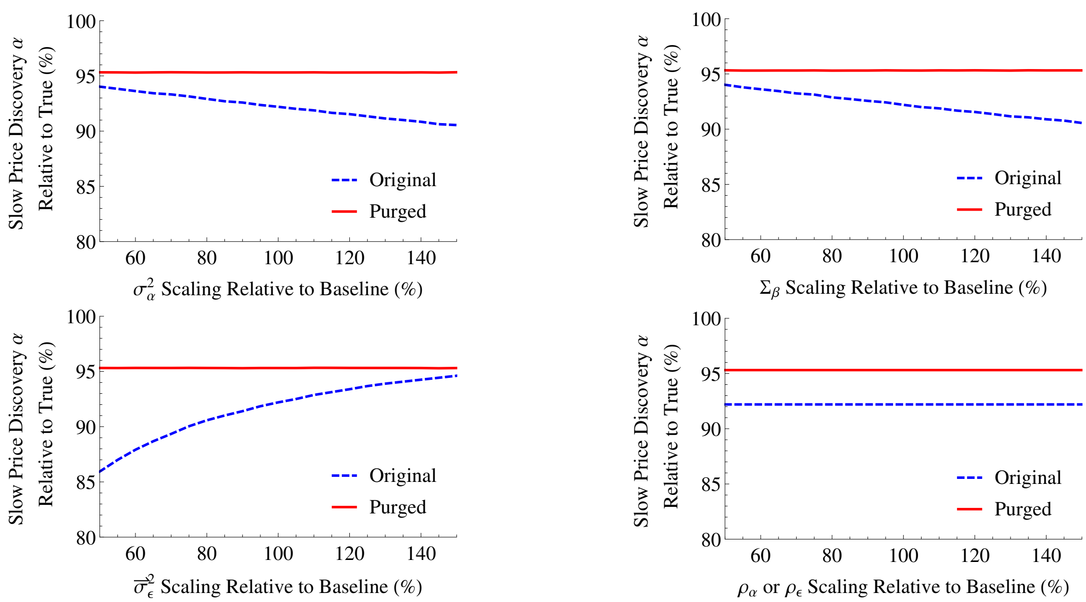
Figure 3.4. Bias Sensitivity Analysis: Simulations–continued

Panel B: Pseudo-Conglomerate Links

Panel B1: Total Bias of Original



Panel B2: Slow Information Diffusion Component Relative to True Slow Information Diffusion Component



noisy sort bias (percentage) is invariant to the strength of both the model misspecification links and slow price discovery links ($\bar{\rho}_\alpha$ and $\bar{\rho}_\epsilon$).[26]

The noisy sort bias of the purged specification is relatively insensitive to variation in the parameter values. The insensitivity to the cross-sectional dispersion of α and β is because the purged method removes this dispersion. Thus, the noisy sort bias is primarily a function of the average estimation accuracy. This estimation accuracy depends upon the variance of the idiosyncratic shocks. However, with larger idiosyncratic shocks that increase the absolute bias comes a larger true slow information diffusion effect. These changes offset each other leaving a relatively constant percentage bias (the slope is too small to be seen). This relative insensitivity of the purged specification's attenuation bias is consistent with the similar values for this bias we find across the two different sets of economic links.

3.3 Conclusion

Understanding the rate of information diffusion is central to the understanding of financial markets. Building on the method of Cohen and Frazzini (2008), our paper provides an improvement necessary to ensure accurate measurement of the price discovery process. We show that the widely used long-short portfolio alphas formed by sorting firms into quintiles based on the lagged return of economically linked firms (e.g., those used in Cohen and Frazzini (2008)) are a biased measure of slow information diffusion. The bias comes primarily from the correlation in model misspecification (alpha) among economically linked firms. This model misspecification bias increases in both the strength of the economic link and the measurement horizon. A secondary component of the bias comes from noise in the sorting variable. This noise arises from both the model misspecification and the systematic factor realizations obscuring the true idiosyncratic news shocks.

We provide a correction based on purging the returns of model misspecification prior to sorting. Intuitively, purging returns reveals the idiosyncratic news shocks that are of interest

[26] In equations (3.27) and (3.29), $\bar{\rho}_\alpha$ does not enter. $\bar{\rho}_\epsilon$ appears in both the numerator and denominator of equation (3.29).

when measuring information diffusion. Sorting on unbiased estimated idiosyncratic shocks eliminates the bias from model misspecification. Purging with an estimated asset pricing model, however, cannot completely eliminate the noisy sort bias, but will lessen it whenever the noise induced by estimating the asset pricing model is less than that induced by the cross-sectional dispersion in model misspecification and factor exposures.

Applying our corrections to two published studies (Cohen and Frazzini, 2008; Cohen and Lou, 2012), we find that our purging methodology has a smaller bias (-5%) due to noisy sorting than the original methodology (-10%). Further, we find that the original methodology results in a total bias that overstates the one-month slow price discovery alphas up to a 100%. Most importantly, we find that information diffusion completes in just one month rather than the six to twelve months previously argued, showing markets are more efficient than previously thought.

3.A Appendix Tables

3.B Proofs and Additional Details

3.B.1 Portfolio Alphas

Proof of Proposition 1. Portfolio $B(P)$ is formed of firms in set B linked to firms in set A that, at time t, fell into the Pth highest quantile of returns. Let $\iota_{j,t,P}$ be an indicator function of whether firm j is included in portfolio P at time t. In the case of inclusion, it has value 1. It has value 0 otherwise.

Let the portfolio weights each period be denoted $w_{j,t,P}$. Which, in the case of equal weighting,

$$w_{j,t,P} = \frac{\iota_{j,t,P}}{\sum_{k\in B}\iota_{k,t,P}}. \tag{3.30}$$

And, in the case of value weighting,

$$w_{j,t,P} = \frac{\iota_{j,t,P}P_{j,t}}{\sum_{k\in B}\iota_{k,t,P}P_{k,t}}, \tag{3.31}$$

where $P_{k,t}$ is the market value of firm k at time t.

The unconditional expected alpha of portfolio $B(P)$ can be found using iterated expectations over the expected alpha at a particular date t for portfolio $B(P)$:

$$E\Big[E_t\Big[\alpha_{B(P),t+1}\Big]\Big] = E\Big[E_t\Big[\sum_{j\in B} w_{j,t,P}(r_{j,t+1} - M_{j,t+1})\Big]\Big]. \tag{3.32}$$

The portfolio weights are known at time t, so we pull them out of the inner expectation. And the set of firms B is known unconditionally,

$$= \sum_{j\in B} E\left[w_{j,t,P} E_t[r_{j,t+1} - M_{j,t+1}]\right]. \tag{3.33}$$

By the definition in Equation (3.2), we can rewrite the difference between the realized return and the model predicted return as a sum of the model misspecification and the period-specific shock,

$$= \sum_{j\in B} E\left[w_{j,t,P} E_t[\alpha_j + \epsilon_{j,t+1}]\right]. \tag{3.34}$$

α_j is known at t and is independent of $\epsilon_{j,t+1}$, giving

$$= \sum_{j\in B} E\left[w_{j,t,P}\right]\alpha_j + \sum_{j\in B} E\Big[w_{j,t,P} E_t[\epsilon_{j,t+1}]\Big]. \tag{3.35}$$

Use the information link between firms, per Equation (3.3), to simplify the second term.

$$= \sum_{j\in B} E\left[w_{j,t,P}\right]\alpha_j + \sum_{j\in B} E\left[w_{j,t,P}\,\epsilon_{i,t}\right]\,\rho_{\epsilon,i,j}. \tag{3.36}$$

Define the first and second terms as $\varrho_{\alpha,P}$ and $\varrho_{\epsilon,P}$,

$$= \varrho_{\alpha,P} + \varrho_{\epsilon,P}. \tag{3.37}$$

$\varrho_{\epsilon,P}$ depends upon the information linkages in Equation (3.3) and, hence, is a function of the slow price discovery process.

$\varrho_{\alpha,P}$ depends upon the model misspecification of firms in set A and varies with portfolio $B(P)$. To be more precise about $\varrho_{\alpha,P}$, we must notice the dependence in the cross-section between the expected unconditional weights of stock j in portfolio P and α_j by looking at the link in the model misspecification per Equation (3.4). The α_i plays a key role in both the value of α_j and the expectation of whether firm j is included in portfolio P. Thus we have:

$$\varrho_{\alpha,P} \equiv \sum_{j\in B} E\left[w_{j,t,P}\right]\alpha_j \tag{3.38}$$

$$= \sum_{j\in B} E\left[w_{j,t,p}\right](\rho_{\alpha,i,j}\alpha_i + \eta_{i,j}). \tag{3.39}$$

By the independence between $\eta_{i,j}$, $\rho_{\alpha,i,j}$ and α_i in the cross section, $\eta_{i,j}$ is independent of the weights so that portion of the summation is zero:

$$= \sum_{j\in B} E\left[w_{j,t,P}\right]\rho_{\alpha,i,j}\,\alpha_i. \tag{3.40}$$

Notice that this summation can be re-expressed in terms of the cross-sectional moments of the linked firms, denoted by a CS subscript. Also let N_L be the number of linked firms in set B,

$$= N_L E_{CS}\Bigg[E\left[w_{j,t,P}\right]\rho_{\alpha,i,j}\,\alpha_i\Bigg] \tag{3.41}$$

$$= N_L\left[E_{CS}\big[E[w_{j,t,P}]\big]\,E_{CS}[\rho_{\alpha,i,j}\alpha_i] + \mathrm{cov}_{CS}\,\big[E[w_{j,t,P}],\,\rho_{\alpha,i,j}\,\alpha_i\big]\right]. \tag{3.42}$$

Noticing that $N_L E_{CS}\big[E[w_{j,t,P}]\big] = 1$ gives

$$= E_{CS}[\rho_{\alpha,i,j}\alpha_i] + N_L\ \mathrm{cov}_{CS}\,\big[E[w_{j,t,P}],\,\rho_{\alpha,i,j}\,\alpha_i\big]. \tag{3.43}$$

Using the independence of $\rho_{\alpha,i,j}$ and α_i, and defining $\bar{\alpha}_A$ as the cross-sectional average alpha of linked stocks in set A gives

$$= \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A + N_L\ \mathrm{cov}_{CS}\,\big[E[w_{j,t,P}],\,\rho_{\alpha,i,j}\,\alpha_i\big]. \tag{3.44}$$

The cross-sectional covariances between the weights and the α_i are positive when the portfolio $B(P)$ is entirely above the median break-point, indeterminate when portfolio $B(P)$ spans the median break-point and negative when portfolio $B(P)$ is entirely below the median break-point.[27] This gives

$$\varrho_{\alpha,P}\begin{cases} > \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \text{If } B(P) \text{ is entirely above the median break-point.} \\ \gtreqless \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \text{If } B(P) \text{ spans the median break-point.} \\ < \bar{\rho}_{\alpha,i,j}\bar{\alpha}_A & \text{If } B(P) \text{ is entirely below the median break-point.} \end{cases} \tag{3.45}$$

□

[27] This statement is true except for perverse cases of cross-sectional dependence between the time series variances of $M_{i,t}$, $\epsilon_{i,t}$ and the model misspecification α_i for firm i in set A.

The proof of Corollary 1 is immediate.

Proof of Corollary 2. When the cross-sectional variance of alpha increases, the magnitude of the cross-sectional covariance term in Equation (3.44) increases. Thus $\varrho_{\alpha,N}$ becomes larger and $\varrho_{\alpha,1}$ becomes smaller making $\varrho_{\alpha,N} - \varrho_{\alpha,1}$ more positive. □

Proof of Corollary 3. When the average $\rho_{\alpha,i,j}$ increases, the magnitude of the cross-sectional covariance term in Equation (3.44) increases. Thus $\varrho_{\alpha,N}$ becomes larger and $\varrho_{\alpha,1}$ becomes smaller making $\varrho_{\alpha,N} - \varrho_{\alpha,1}$ more positive. □

Proof of Corollary 4. The proof follows that of Proposition 1 altering the timing subscripts where appropriate. Notice that for the equivalent of Equation (3.36), the second term

$$\sum_{j \in B} E\left[w_{j,t+h,P}\, \epsilon_{i,t}\right]\, \rho_{\epsilon,i,j,h} = 0 \tag{3.46}$$

for all $h \geq H$ since $\rho_{\epsilon,i,j,h} = 0$ for all such h. Thus,

$$B(P,h) = \varrho_{\alpha,P}, \quad \forall\, h \geq H. \tag{3.47}$$

Our result immediately follows.

□

Proof of Corollary 5. Recall the definition of $\varrho_{\epsilon,P}$

$$\varrho_p = \sum_{j \in B} E\left[w_{j,t,P}\, \epsilon_{i,t}\right]\, \rho_{\epsilon,i,j} \tag{3.48}$$

by the independence assumption of $\rho_{\epsilon,i,j}$ specified in the corollary and an argument similar to that made for the analysis of the $\varrho_{\alpha,P}$ we can rewrite this in terms of cross-sectional moments

$$= E_{CS}\left[\sum_{j \in B} E\left[w_{j,t,P}\, \epsilon_{i,t}\right]\right]\, \bar{\rho}_{\epsilon} \tag{3.49}$$

Labelling this sum c_P gives

$$= c_P \, \bar{\rho}_\epsilon. \tag{3.50}$$

Using an argument similar to that in our analysis of $\varrho_{\alpha,N} - \varrho_{\alpha,1}$ we see that $c_N - c_1$ is decreasing the in cross-sectional variance of alpha and model predicted returns but increasing the time series variance of the news shocks. □

3.B.2 Bias Corrections

Proof of Proposition 2. Portfolio $B'(P)$ is formed of firms in set B linked to firms in set A that in the previous period fell into the Pth highest quantile of news shocks $\epsilon_{i,t}$. Let $\iota''_{j,t,p}$ be an indicator function of whether firm j is included in portfolio P at time t. In the case of inclusion, it has value 1. It has value 0 otherwise.

Let the portfolio weights each period be denoted $w''_{j,t,P}$. Which, in the case of equal weighting,

$$w''_{j,t,P} = \frac{\iota''_{j,t,P}}{\sum_{k \in B} \iota''_{k,t,P}}. \tag{3.51}$$

And, in the case of value weighting,

$$w''_{j,t,P} = \frac{\iota''_{j,t,P} P_{j,t}}{\sum_{k \in B} \iota''_{k,t,P} P_{k,t}}. \tag{3.52}$$

where $P_{k,t}$ is the market value of firm k at time t.

The unconditional expected alpha of portfolio $B'(P)$ can be found using iterated expectations over the expected alpha at a particular date t for portfolio $B'(P)$

$$E\Big[E_t\Big[\alpha_{B'(P),t+1}\Big]\Big] = E\Big[E_t\Big[\sum_{j \in B} w''_{j,t,P}(r_{j,t+1} - M_{j,t+1})\Big]\Big]. \tag{3.53}$$

The portfolio weights are known at time t, so we pull them out of the inner expectation. And the set of firms B is known unconditionally,

$$= \sum_{j \in B} E\left[w''_{j,t,P} E_t[r_{j,t+1} - M_{j,t+1}]\right]. \tag{3.54}$$

By the definition in Equation (3.2), we can rewrite the difference between the realized return and the model predicted return as a sum of the model misspecification and the period-specific shock

$$= \sum_{j \in B} E\left[w''_{j,t,P} E_t[\alpha_j + \epsilon_{j,t+1}]\right]. \tag{3.55}$$

α_j is known at t and is independent of $\epsilon_{j,t+1}$. Moreover, the distribution of $\epsilon_{i,t}$ is independent of α_j. Thus we have

$$= \sum_{j \in B} E\left[w''_{j,t,P}\right] \alpha_j + \sum_{j \in B} E\Big[w''_{j,t,P} E_t[\epsilon_{j,t+1}]\Big]. \tag{3.56}$$

Use the information link between firms, per Equation (3.3), to simplify the second term:

$$= \sum_{j \in B} E\left[w''_{j,t,P}\right] \alpha_j + \sum_{j \in B} E\left[w''_{j,t,P}\, \epsilon_{i,t}\right]\, \rho_{\epsilon,i,j}. \tag{3.57}$$

Noticing that the first term can be re-expressed in terms of the cross-sectional moments gives

$$= N_L\, E\Big[E\left[w''_{j,t,P}\right] \alpha_j\Big] + \sum_{j \in B} E\left[w''_{j,t,P}\, \epsilon_{i,t}\right]\, \rho_{\epsilon,i,j} \tag{3.58}$$

Using the independence of the weights and the α_j gives the first term as the average misspecification of linked firms in set B and then define the second term to be ϱ.

$$= \bar{\alpha}_B + \varrho'_{\epsilon,P}. \tag{3.59}$$

□

The proofs of Corollaries 6 and 7 are immediate.

Proof of Corollary 8. Recall that $c_N - c_1$ is increasing in the cross-section variance of the model misspecification and model predicted returns. Then notice that $c'_N - c'_1$ is the same as the degenerate case where these cross-sectional variances go to zero. □

3.B.3 Effects of Estimating the Asset Pricing Model

Proof of Proposition 3. The proof follows that of Proposition 2 combined with the fact the model estimation error for a model estimated with historical data is unbiased and uncorrelated with the current idiosyncratic news shocks. □

The proofs of Corollaries 9, 10 and 11 are immediate.

Table 3.A.1 Abnormal Supplier Returns Sorted on Previous Month's Customer Returns This table replicates Table III of Cohen and Frazzini (2008). It shows monthly abnormal returns for value- (equal-) weighted portfolios of supplier stocks. In month t (returns at $t+1$), supplier stocks are assigned to one of five portfolios based on the equal-weighted return of the supplier's principal customers 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 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.

Value Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S
Excess Returns	-0.752	0.057	0.263	0.621	0.637	1.389
	(-1.859)	(0.161)	(0.701)	(1.672)	(1.477)	(3.637)
1-Factor Alpha	-1.459	-0.604	-0.444	-0.034	-0.098	1.361
	(-5.371)	(-2.768)	(-1.989)	(-0.140)	(-0.331)	(3.526)
3-Factor Alpha	-1.419	-0.555	-0.337	0.026	0.128	1.547
	(-5.269)	(-2.616)	(-1.496)	(0.102)	(0.464)	(3.875)
4-Factor Alpha	-1.127	-0.515	-0.238	0.002	0.220	1.347
	(-4.262)	(-2.368)	(-1.036)	(0.008)	(0.781)	(3.319)
5-Factor Alpha	-1.128	-0.492	-0.194	-0.004	0.175	1.303
	(-4.219)	(-2.239)	(-0.839)	(-0.016)	(0.616)	(3.179)

Equal Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	L/S
Excess Returns	-0.394	0.219	0.386	0.653	0.766	1.160
	(-0.956)	(0.597)	(1.072)	(1.816)	(1.972)	(4.967)
1-Factor Alpha	-1.133	-0.495	-0.288	-0.040	0.030	1.164
	(-4.246)	(-2.418)	(-1.323)	(-0.197)	(0.133)	(4.930)
3-Factor Alpha	-1.141	-0.647	-0.442	-0.112	0.014	1.155
	(-5.989)	(-4.366)	(-2.815)	(-0.842)	(0.084)	(4.717)
4-Factor Alpha	-0.901	-0.501	-0.244	-0.044	0.166	1.067
	(-4.895)	(-3.419)	(-1.609)	(-0.329)	(0.996)	(4.266)
5-Factor Alpha	-0.912	-0.479	-0.200	-0.027	0.145	1.057
	(-4.900)	(-3.238)	(-1.312)	(-0.194)	(0.862)	(4.180)

Table 3.A.2 Abnormal Conglomerate Returns Sorted on Previous Month's Segments' Industry Returns
This table replicates Table 2 of Cohen and Lou (2012). It shows monthly abnormal returns for value- (equal-) weighted portfolios of conglomerate stocks. Each month, the average industry return of all single-industry firms is calculated. A pseudo-conglomerate return is then calculated by taking the value-weighted return of a conglomerate's principal segments' industry returns. In month t (returns at $t+1$), conglomerate stocks are assigned to one of ten portfolios based on their pseudo-conglomerate's return in the previous month t. The ten 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 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 decile and short the lowest decile. Alphas are in monthly percent and t-statistics are shown in parentheses below the coefficient estimates.

Value Weights	Q1(Low)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10(High)	L/S
Excess Returns	-0.163	0.358	0.450	0.458	0.273	0.662	0.408	0.946	0.662	0.931	1.094
	(-0.510)	(1.238)	(1.498)	(1.520)	(0.917)	(2.213)	(1.450)	(3.075)	(2.074)	(3.123)	(3.996)
1-Factor Alpha	-0.729	-0.179	-0.104	-0.049	-0.245	0.133	-0.097	0.420	0.174	0.401	1.130
	(-3.622)	(-1.061)	(-0.581)	(-0.241)	(-1.265)	(0.698)	(-0.553)	(2.047)	(0.729)	(2.132)	(4.102)
3-Factor Alpha	-0.891	-0.252	-0.216	-0.192	-0.410	-0.018	-0.126	0.259	0.129	0.266	1.157
	(-4.457)	(-1.477)	(-1.210)	(-0.939)	(-2.132)	(-0.097)	(-0.708)	(1.267)	(0.531)	(1.414)	(4.120)
4-Factor Alpha	-0.736	-0.163	-0.233	0.015	-0.351	-0.007	-0.059	0.156	0.083	0.231	0.967
	(-3.682)	(-0.946)	(-1.278)	(0.077)	(-1.797)	(-0.039)	(-0.325)	(0.754)	(0.337)	(1.208)	(3.428)
5-Factor Alpha	-0.724	-0.215	-0.305	-0.075	-0.386	0.024	-0.107	0.131	-0.045	0.269	0.994
	(-3.573)	(-1.233)	(-1.660)	(-0.370)	(-1.947)	(0.120)	(-0.584)	(0.624)	(-0.182)	(1.388)	(3.473)

Equal Weights	Q1(Low)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10(High)	L/S
Excess Returns	-0.004	0.165	0.402	0.562	0.536	0.906	0.807	1.031	0.929	1.276	1.280
	(-0.013)	(0.567)	(1.372)	(1.966)	(1.806)	(3.033)	(2.943)	(3.472)	(2.816)	(3.914)	(5.572)
1-Factor Alpha	-0.583	-0.379	-0.151	0.029	0.005	0.363	0.305	0.495	0.400	0.692	1.275
	(-3.086)	(-2.280)	(-0.907)	(0.175)	(0.025)	(1.996)	(1.850)	(2.708)	(1.692)	(3.404)	(5.508)
3-Factor Alpha	-0.887	-0.652	-0.366	-0.231	-0.276	0.078	0.141	0.236	0.171	0.346	1.233
	(-5.347)	(-4.695)	(-2.559)	(-1.627)	(-1.723)	(0.510)	(0.969)	(1.512)	(0.782)	(2.021)	(5.239)
4-Factor Alpha	-0.739	-0.552	-0.316	-0.136	-0.257	0.138	0.202	0.234	0.204	0.445	1.184
	(-4.487)	(-3.963)	(-2.179)	(-0.951)	(-1.567)	(0.890)	(1.368)	(1.469)	(0.915)	(2.577)	(4.938)
5-Factor Alpha	-0.758	-0.518	-0.342	-0.168	-0.307	0.163	0.185	0.214	0.113	0.498	1.257
	(-4.543)	(-3.676)	(-2.322)	(-1.167)	(-1.855)	(1.041)	(1.232)	(1.321)	(0.505)	(2.854)	(5.186)

Table 3.A.3 Simulation Parameters This table outlines the parameters calibrated for the simulation model used to decompose the biases in both Cohen and Frazzini (2008) and Cohen and Lou (2012). Panel A shows the parameters for Cohen and Frazzini (2008). Panel B shows the parameters for Cohen and Lou (2012). The cross-sectional distribution of the factor betas are presented with standard deviations on the diagonals and correlations on the off-diagonals. Detailed descriptions for all parameters are in Appendix Table 3.A.4.

Panel A: Customer-Supplier Links

Average linkage of model misspecification: $\bar{\rho}_\alpha$	0.22
Average level of slow price discovery: $\bar{\rho}_\epsilon$	0.02
Ratio of model misspecification linkage to price discovery linkage	11:1

Cross-sectional standard deviation of alpha estimates (annualized): σ_α^2	2.20%

Cross-sectional distribution of the factor betas: Σ_β

	MKTRF	SMB	HML	UMD
MKTRF	0.41			
SMB	0.45	0.65		
HML	0.42	0.23	0.88	
UMD	-0.10	-0.10	-0.02	0.61

Cross-sectional mean of beta estimates: $\bar{\hat{\beta}}$

MKTRF	SMB	HML	UMD
1.08	0.11	0.17	-0.15

Panel B: Pseudo-Conglomerate Links

Average linkage of model misspecification: $\bar{\rho}_\alpha$	0.63
Average level of slow price discovery: $\bar{\rho}_\epsilon$	0.16
Ratio of model misspecification linkage to price discovery linkage	4:1

Cross-sectional standard deviation of alpha estimates (annualized): σ_α^2	1.18%

Cross-sectional distribution of the factor betas: Σ_β

	MKTRF	SMB	HML	UMD
MKTRF	0.20			
SMB	0.73	0.23		
HML	0.00	-0.07	0.27	
UMD	-0.01	-0.14	-0.06	0.21

Cross-sectional mean of beta estimates: $\bar{\hat{\beta}}$

MKTRF	SMB	HML	UMD
0.87	0.83	0.19	-0.08

Table 3.A.4 Simulation Parameters Description This table describes the calibrated parameters of the simulation model and their calculations.

Parameter	Description	Calculation
σ_{α}^2	Cross-Sectional Variance of Alpha Estimates	We calculate the variance of the pooled alpha estimates of each customer (pseudo-conglomerate) portfolio. Alpha is obtained from a regression using the Fama-French 3-factor model augmented with the Carhart momentum factor.
Σ_{β}	Cross-sectional variance of Beta Estimates	The variance-covariance matrix of the beta estimates of each customer (pseudo-conglomerate).
$\bar{\hat{\beta}}$	Cross-sectional mean of Beta Estimates	The unconditional pooled mean of the beta estimates of customers (pseudo-conglomerates).
$\vec{\sigma}_{\epsilon}^2$	Distribution of the Time-series Variances of the Idiosyncratic Shocks	A vector of idiosyncratic shock variances, extracted from a regression using the Fama-French 3-factor model augmented with the Carhart momentum factor. We adjust for degrees of freedom to account for estimation of residuals.
$\bar{\rho}_{\alpha}$	Average Linkage of Model Misspecification	For each supplier, we regress the supplier (conglomerate) alpha on the customer (pseudo-conglomerate) alpha with no intercept. Alpha is obtained from a regression using the Fama-French 3-factor model augmented with the Carhart momentum factor. We adjust for outliers in the beta coefficient on the customer (pseudo-conglomerate) independent variable by truncating the most extreme coefficients at the 0.5% level. We then calculate the cross-sectional average of the coefficients.
$\bar{\rho}_{\epsilon}$	Average Level of Slow Price Discovery	For each supplier, we regress the supplier (conglomerate) alpha on the customer (pseudo-conglomerate) alpha with no intercept. The idiosyncratic shock is the residual obtained from a regression using the Fama-French 3-factor model augmented with the Carhart momentum factor. We adjust for outliers in the beta coefficient on the customer (pseudo-conglomerate) epsilon by truncating the most extreme coefficients at the 0.5% level. We then calculate the cross-sectional average of the coefficients.

Table 3.A.5 Alpha and Epsilon Correlations This table outlines the parameters calibrated for the simulation model used to decompose the biases in both Cohen and Frazzini (2008) and Cohen and Lou (2012). Panel A shows the parameters for Cohen and Frazzini (2008). Panel B shows the parameters for Cohen and Lou (2012). The cross-sectional distribution of the factor betas are presented with standard deviations on the diagonals and correlations on the off-diagonals. Detailed descriptions for all parameters are in Appendix Table 3.A.4.

	Customer-Supplier	Conglomerate-Standalone	Alliance Partner
Average linkage of model misspecification: $\bar{\rho}_\alpha$	0.22	0.63	0.22
Average level of slow price discovery: $\bar{\rho}_\epsilon$	0.16	0.07	0.07
Ratio of model misspecification linkage to price discovery linkage	11:1	4:1	3:1

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