Network Centrality and Managerial Market Timing Ability

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Abstract

We document that long-run excess returns following announcements of share buyback authorizations and insider purchases are a U-shaped function of firm centrality in the input-output trade flow network. These results conform to a model of investors endowed with a large but finite capacity for analyzing firms. Additional links weaken insiders' informational advantage in peripheral firms (simple firms whose cash flows depend on few economic links) provided investors' capacity is large enough, but eventually amplify that advantage in central firms (firms with many links) due to investors' limited capacity. These findings shed light on the sources of managerial market timing ability.

JEL classification: G32; O32

Keywords: Buybacks, Market Timing, Network Centrality, Insider Trading, Market Efficiency

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I Introduction

It is well documented that the announcement of a repurchase authorization is, on average, followed by long-term positive excess returns (see, e.g., Ikenberry, Lakonishok, and Vermaelen (1995), Peyer and Vermaelen (2009), Dittmar and Field (2015), Evgeniou, de Fortuny, Nassuphis, and Vermaelen (2018), and Manconi, Peyer, and Vermaelen (2019)).[1] The most widely accepted interpretation of this phenomenon is that firms tend to buy back stock when their stock is undervalued. This *market timing* hypothesis assumes that managers have an information advantage over financial markets, which raises two natural questions. First, what specific factors determine the extent of information asymmetry and thus managers' ability to time the market? Second, is there actually a relation between those factors and long-term abnormal returns? Scholars have reported that some firm characteristics such as size and idiosyncratic volatility influence the link between post-buyback abnormal returns and market timing due to information asymmetry.[2] However, most assessments have been of a general nature and do not identify the sources of management's information advantage.

The purpose of this paper is to study a specific potential *economic* driver of information asymmetry between company insiders and outside investors: *firm centrality* in the supplier-customer network. We use this firm centrality as a test of the market timing

[1] Fu and Huang (2016) argue that the anomaly has disappeared in the U.S. in the 2003-2010 period. However, Manconi et al. (2019) confirm (see their Table 9) that excess returns in the short period 2003-2010 are smaller than the returns reported by e.g. Peyer and Vermaelen (2009) but they are still economically and statistically significantly positive. They also point out (footnotes 24,25) that long-term excess returns reported on buyback events since 1980 vary over time, which should not be surprising as information asymmetries vary over time. Note that the time horizon covered by this paper (1996-2015) is longer than the time horizon of past research. In our robustness section below, we confirm the persistence of the buyback anomaly by presenting results for the recent period 2005-2015.

[2] Peyer and Vermaelen (2009) argue that this ability is larger for small firms as they are followed by fewer analysts, while Evgeniou et al. (2018) show that it is larger for firms with high idiosyncratic volatility because the value of such firms is driven mainly by company-specific information, which could give management an advantage. Such firm characteristics encompass many possible drivers of information asymmetry.

hypothesis in the context of share repurchases, and also confirm it in the case of direct insider buying. A firm is "central" in the product market network if it does business with several customers and suppliers, or in other words, has many direct economic links as measured by its degree of centrality (Freeman (1977)).[3] Shocks originating from or transmitted through a firm's direct trade partners affect its stock price as the cash flows of supplier and customer firms are typically correlated (for supporting evidence, see, e.g., Cohen and Frazzini (2008) and Menzly and Ozbas (2010)).

We develop a parsimonious model (Section V) in which a firm's value is driven by two types of cash flows: those resulting from its economic interactions with other (i.e., supplier or customer) firms; and cash flows not related to other firms (e.g., management ability, retail sales, etc). We refer to these as, respectively, "link-related" and "link-unrelated" cash flows. Two groups of agents trade the firm's stock: outside investors, or simply "outsiders", and "insiders" (i.e., firm managers). Insiders trade indirectly through share repurchases or directly with their own personal funds.

Agents differ only in their information about the firm. They do so along two dimensions, of which the first is cost. Insiders receive some (imperfect) information about cash flows for free - that is, simply as a by-product of managing the firm - whereas learning is costly to outsiders. In other words, inside information is costless to obtain and cannot be made more accurate.[4] Hence, in contrast to the outsiders, the precision of the insider's information does

[3]Second-order effects may also arise from the inter-firm trade relations and the complexity of directly linked firms, as captured by other centrality measures, such as eigenvector centrality (Bonacich (1972)). We use other measures of centrality in robustness tests.

[4]The assumption that inside information cannot be improved can be relaxed by endowing the insider, in addition to her costless technology, with a technology to learn about links, similar to the outsider's, provided that the insider's learning capacity is smaller than the outsider's.

not vary with the firm's centrality. More specifically, outsiders in the model are endowed with a limited budget, or "capacity", for analyzing firms; this assumption is consistent with the notion that acquiring and processing information requires cognitive and monetary resources.[5] Under these circumstances, the quality of outsiders' information decreases with the number of links (i.e., with firm centrality). The second dimension along which agents differ pertains to what can be learned about link-unrelated cash flows. Insiders' information about these cash flows is perfect (unlike their information about link-related cash flows). In contrast, outsiders do not have the technology to learn about these cash flows.[6] This assumption ensures that insiders enjoy a base information advantage over outsiders. Outsiders' finite capacity, in turn, implies that the magnitude of that advantage depends on firm centrality.

Our model's main implication is that, provided their learning capacity is large enough, outsiders (using any related information, for example about the firm, its customers, suppliers, and the market) know more than insiders about the link-related cash flows of peripheral firms. Peripheral firms have so few links that the outsider can thoroughly analyse them all, and thus he understands the cash flow implications of these links better than the insider does. For such firms, each additional link is better understood by the outsider than the insider, and therefore reduces the insider's informational advantage and her expected profit. In contrast, for central

[5]This assumption is consistent with empirical evidence indicating that limited attention and information processing costs lead investors to ignore some customer-supplier links. For example, Cohen and Frazzini (2008) show that stock prices of suppliers underreact to shocks affecting the stock price of their major customers. These authors show that a long-short strategy based on this underreaction generates an impressive alpha of 1.5% per month.

[6]This assumption captures parsimoniously, in our single-stock setup, the notion that rational investors favor information that can predict the cash flows of multiple firms (e.g., information about link-related cash flows) over information that can predict only one firm's cash flows (e.g., information about link-unrelated cash flows). Theories incorporating this notion include, for example, Lin and Xiong (2006) and Veldkamp (2006). Empirically, Hameed, Morck, Shen, and Yeung (2015) report that analysts disproportionately follow firms whose fundamentals are highly correlated with those of many other firms. See also the large literature in accounting that documents between-firm information transfers within and across industries (e.g., Foster (1981) and Han and Wild (1990)).

firms - that is, firms with more links than the outsider (given his limited learning capacity) can comprehend - the insider knows more than the outsider about the link-related cash flows. For such firms, adding links magnifies the insider's advantage and thereby increases her expected profit. The resulting pattern for the insider's expected profit is a U-shaped function of the firm's centrality. In the context of share buybacks and insider buying, our model predicts a U-shaped relation between centrality and post-event long-term abnormal returns. Though our modelling assumptions are obviously specific, our results are not sensitive to the exact nature of the learning technology we postulate. Rather, they depend on (i) outsiders' learning capacity being sufficiently large that they understand links of peripheral firms better than insiders can, and (ii) that advantage being diminished for firms that are relatively more central. We believe both features to be plausible.

We first test our theory in the context of share repurchases, using the centrality of a firm's *industry* as a proxy for that *firm*'s centrality following Ahern (2012). We measure industry centrality based on the inter-industry trade flow network constructed using the Input-Output (I-O) tables from the U.S. Bureau of Economic Analysis (BEA). There are several reasons for using this proxy: (1) the I-O industry classification is at a detailed level (e.g., 410 industries in 2002), and so the number of firms in each industry is small;[7] (2) our target sample consists of public firms in the major exchanges that can be considered as representative of their industry; and (3) firms of the same industry are closer to each other in terms of centrality than firms from different industries. Moreover, we want to capture the

[7] In the regressions we report below we also control for industry fixed effects - in addition to controlling for year effects. The companies in our sample belong on average across years in 8 one-digit SIC industries, 48 two-digits SIC industries, and have 215 different centrality values while there are 420 buyback events from 368 unique companies on average per year. Hence the centrality measures we use are close to being company specific for our sample.

effect from both public and private trade partners and economic links between them. To the best of our knowledge, I-O tables are the best data available for such a complete trade-flow network of all public and private firms in the United States, as also argued by others, including Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Ahern and Harford (2014).

As mentioned above, we measure centrality as the number of direct economic links, a.k.a. degree centrality. For example, in the 2002 I-O network, the Wholesale Trade industry has 372 substantial direct connections with other industries, and its degree centrality is ranked the highest of all industries. To value a firm in this industry – such as TESSCO Technologies Incorporated (NASDAQ: TESS), an electronic parts and equipment merchant wholesaler – an outside investor may need to use information about up-to-date sales/input contribution from all directly linked industries. However, as it is hard for an investor to follow all 372 industries at the same time, the *information processing costs* are very high for these firms. On the other end, the Computer Storage Device Manufacturing industry has only ten substantial direct trade relationships in the 2002 I-O network and thus its degree centrality is ranked among the lowest (376^{th} out of 410 industries). To value a firm in this industry - such as NetApp, Inc. (NASDAQ: NTAP), a storage and data management company and a component of the S&P 500 - investors face on average much lower information processing costs as they need to cover only the ten industries that are directly linked to the Computer Storage Device Manufacturing industry. However, any information availability advantage insiders may have for each of these ten cash flow relations can be relatively (marginally) more important.

To test whether management's information advantage when repurchasing shares depends on firm centrality, we use 8,401 open-market share repurchase authorization announcements of U.S. firms between October 1996 and December 2015. To construct the centrality measures, we use BEA I-O reports published in 1997, 2002, and 2007. We start our empirical investigation by confirming the premise of our theory, namely that more central firms have businesses that are harder to analyze and predict. Using both parametric and non-parametric tests, we report strong evidence that the volatility of operating cash flows is increasing in centrality.

We then turn to examining whether inter-industry network centrality is related to long-run excess returns after buyback authorization announcements, proceeding in four steps. First, we sort all CRSP firms according to their centrality score in each calendar month and split buyback events into five groups using these centrality scores (Q1 to Q5, from the least central to the most central). Second, we compute the post-announcement long-run excess returns for each centrality subgroup for up to 48 months after the announcement. Third, using double sorting we test whether centrality acts as a proxy for other predictors of long-term excess returns reported in the share repurchase anomaly literature (see, e.g., Peyer and Vermaelen (2009), and Evgeniou et al. (2018)), such as volatility, idiosyncratic volatility, prior returns, market to book, firm size, and analyst coverage. Finally, we regress long-run excess returns on centrality (and centrality squared), controlling for the above known factors.

All of these tests show that the relation between long-run Cumulative Abnormal Returns (CAR) and centrality is U-shaped. In other words, excess returns are largest in the low and high centrality samples. Moreover, after controlling for idiosyncratic volatility (a proxy for firm-specific information in stock prices), analyst coverage (a proxy for the quality of the information environment), return volatility (a proxy for the option value of buyback announcements), and the U-index (the Peyer and Vermaelen (2009) proxy for the likelihood of firm undervaluation), the U-shaped relation between centrality and long-term excess returns is still significant.

Next, we test for the robustness of this finding by examining whether, and how, insider trading profits depend on the centrality of the firm, where insiders include the firm's CEO, CFO, and Chairman of the Board. A large literature supports the hypothesis that insiders can beat the market (see, e.g., Seyhun (1986), Seyhun (2000), Lakonishok and Lee (2001), Jeng and Zeckhauser (2003), and Cohen, Mallow, and Pomorski (2012)). Moreover, as in the case of buybacks, the market underreacts to disclosures of insiders' trades and the underreaction is most pronounced for small firms. The main difference between insider buying and share repurchases is that, in the case of buybacks, insiders are buying with their own money only to the extent they are long-term shareholders in the firm.

We conduct the same analysis as for the shares repurchasing data above using insider data for the period 2007 to 2015: after sorting all CRSP firms according to their centrality score in each calendar month, and assigning insider trading events to five groups using these centrality scores (Q1 to Q5, from the least to the most central), we compute the post-announcement long-run excess returns for each centrality subgroup for up to 48 months after the announcement of insider purchases. We consider only events where an insider buys shares of the firm. We find the same pattern as in the repurchase sample, i.e. a U-shaped relation between long-run cumulative excess returns after insider buying and centrality.

To summarize, we document that long-run excess returns following announcements of share buyback authorizations and insider purchases are a U-shaped function of firm centrality.

Note that we don't claim that network centrality determines whether buybacks take place, or in other words, that centrality causes buybacks. Buybacks are motivated by considerations such as a firm's excess cash, debt capacity, or investment opportunities that are unrelated to a firm's centrality. Rather, our argument is that centrality is a determinant of managers' ability to *time* the buyback, as reflected by how much value they generate for long-term shareholders. In short, given a buyback authorization, we relate the manager's ability to time open-market share repurchases to the firm's position in the input-output network.

In summary, this paper contributes to the literature on managerial market timing ability in the context of direct and indirect insider buying (i.e. share repurchase). It also relates to the literature of investors' delayed and biased reactions to information. The theme of this literature is that, to the extent that investors have limited resources and capacity to collect, interpret, and finally trade on value-relevant information, asset prices will incorporate information only gradually (see, e.g., Hong and Stein (1999), Hong, Lim, and Stein (2000), Cohen and Frazzini (2008), and Cohen and Lou (2012)). Our paper shows that the effects of such limited capacity depend on the complexity of the firm, as proxied by its firm centrality in the product network.

Our paper also relates to recent work that studies networks in finance.[8] Acemoglu et al. (2012) show theoretically that microeconomic idiosyncratic shocks can lead to aggregate fluctuations when there is a small number of central suppliers. Building on this theory, Ahern (2013) and Aobdia, Caskey, and Ozel (2014) find that central industries in the inter-industry trade flow network covary more with aggregate fluctuations. Consistent with this result, we report that peripheral firms have higher idiosyncratic volatility, which may partially explain

[8]See also Allen and Babus (2009) for a recent summary paper.

the high long-run excess returns after buyback announcements (Evgeniou et al. (2018)).

The paper is organized as follows. We start in Section II by describing our data and variables. Section III presents our main tests, namely whether centrality predicts long-run excess returns following share repurchases. Section IV displays various robustness checks. We start by confirming that our findings hold under alternative centrality measures (Section IV.C). We then replicate our main results using insider trades (Section IV.D) and perform further robustness analyses. We confirm that the results of the paper have not disappeared in recent years by studying the 2005-2015 subsample. We also confirm that when individual firms announce a buyback after a change in centrality, excess returns move as predicted by our model. In Section V we present a simple model that formalizes the main hypotheses about the relation between centrality and the information advantage of a firm's insiders. Section VI concludes. The Appendix A features the proofs of the model.

II Data and Variables

A Share Repurchases

Our sample of buyback announcements spans the period from October 1996 to December 2015. We start in October 1996 because analyst recommendation data are sparse prior to 1996 (Boni and Womack (2006)). Also, the first supplier-customer network after 1996 is constructed in 1997, with the U.S. federal government's 1997 fiscal year starting on October 1, 1996. We retrieve buyback authorization announcements from the Securities Data Corporation (SDC) database.

We combine all open market repurchase announcements from both the SDC Repurchases database and the SDC U.S. mergers and acquisitions (M&A) database, ending up with a total of 15,706 repurchase events. We remove the following events: (1) no network centrality is available; (2) no CRSP returns are available; (3) not all relevant Compustat data are available; (4) the percentage of shares authorized is larger than 50%, or the one month pre-announcement closing price is less than $3, or the primary stock exchange is not the NYSE, NASDAQ, or AMEX; (5) the firm belongs to the Financial or Utilities sector. We obtain a final sample containing 8,401 buyback events made by 2,979 firms. Figure 1 shows the number of announcements per year in the sample period as well as the (standardized) level of the $S\&P$ 500 index. The average percent of shares authorized for these firms is 7.40% (median of 6%), the average market capitalization at announcement is $7066.20 million (median of $1025.30 million), while the BE/ME is on average 0.50 (median of 0.40). We also collect consensus analyst recommendations in the two months prior to the buyback announcement. In the month before the buyback announcement 1,983 firms were downgraded, 1,792 were upgraded, and in 4,626 cases the recommendation consensus remained unchanged.

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Figure 1 at end of Section II.A

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B Insider Trading Data

Our data source for insiders trades is the Thomson Reuters TFN Insider Filling database which covers all insider activity as reported on SEC forms 3, 4, 5, and 144. The database defines as corporate insiders broadly those who have “access to non-public, material, insider information” and are required to file SEC form 3, 4, and 5 when they trade their companies’ stock. Our data comes from the Form 4 fillings (“Change in an insider’s ownership position”), considered to be the most important insider document forming the basis of the main Insiders dataset. The data are available from January 2007 to December 2015. We therefore use only the 2007 I-O report available from BEA for this analysis. We have only used insider data of the highest quality (i.e., for which the “Cleanse Indicator” is R, H, or L). After aggregating all insider trades during a month into a single “event”, we ended up with 23,802 insider trading event months. We ignore insider sales and only consider insider buys aggregated at the permno-month level. Past research on insider trading (e.g. Lakonishok and Lee (2001)) shows that insider sales are not information driven. Figure 2 shows the number of insider events over the sample period as well as the (standardized) level of the $S\&P$ 500 index. The average market capitalization at event month is $2074.90 million (median of $221 million), while the BE/ME is on average 1 (median of 0.80).

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Figure 2 at end of Section II.B

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C Supplier-Customer Network and Centrality Measures

We define firm centrality using an industry-level supplier-customer trade network, as it is very difficult to build a firm-level trade network because of data limitations. Following Ahern (2012), we construct a network of industries connected by inter-industry trade flows (e.g., Acemoglu et al. (2012), and Ahern and Harford (2014)) and measure a firm's centrality in the network as that of its industry. Since 1947, the Bureau of Economic Analysis (BEA) has provided Input-Output (I-O) accounts of dollar flows between all producers and purchasers in the U.S. economy. Producers include all industrial and service sectors as well as household ones. Purchasers include industrial sectors, households, and government entities. The I-O tables are based primarily on data from the Economic Census and are updated every five years with a five-year lag, so we use three I-O reports (1997, 2002, and 2007).

As argued by Ahern (2012) using industry-level network centrality as a proxy for firm centrality is reasonable. Indeed, the inter-industry trade flow data are currently the best available data for a supplier-customer network that covers all sectors in the economy and accounts for trade relations between all public and private firms. Possible error in using the industry position as a proxy for firm position is smaller than it appears for three reasons: (1) the industry classification used for our analysis is very narrowly defined – we consider, for example, 410 detailed I-O industries in 2002 – which reduces the firm heterogeneity in each industry, (2) firms in our study are publicly traded firms followed by analysts, and they are also relatively large firms (the mean percentile of market equity at the month of the buyback announcement is 0.70, which is statistically significantly different from the all CRSP firms cross-sectional percentile mean of 0.5 ($t > 10$), so our firms are more likely to be representative for their industry), and (3) firms of the same industry are closer to each other in terms of centrality than those from different industries.

The construction of the trade-flow network in each I-O report year follows Ahern and Harford (2014). From the Use and Make tables, we create matrices that record flows of inputs and outputs between industries (the left graph in Figure 3). To avoid any biases due to some large dollar-value trade flows, each trade flow is standardized by its purchaser's total input (the middle graph in Figure 3), which gives an asymmetric and directed I-O network, namely the supplier network. Selecting the larger number of the two directed links between two industries generates an undirected supplier network (the right graph in Figure 3). This network captures each I-O industry's role as both a customer and a supplier of directly linked industries. Economic shocks transmit through the supplier network via the impact, for example, of input quantity or price. For example, members of the Petroleum Refineries industry (e.g., Exxon Mobile) supply an excess quantity of gasoline, which lowers oil prices. As a result, transportation companies (e.g., U.S. Xpress and FedEx) may have lower costs, and later, companies in the Retail Trade industry (e.g., Gap Inc. and Amazon.com) may be more profitable. Finally, after excluding household and government industries, as well as exports and imports, we are left with 470, 410, and 368 industries in 1997, 2002, and 2007, respectively.

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Figure 3 about here

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A number of measures have been developed to quantify centrality in networks, including degree, closeness, betweenness, and eigenvector centrality. Degree centrality measures the number of direct connections a node has if the network is unweighted (Freeman (1977)). A corresponding weighted measure is strength centrality (Barrat, Barthélemy, Pastor-Satorras, and Vespignani (2004)). In this case the weights are the "strength" of each industry-pair link – that is, the percentage of input supplied by the linked industry. Closeness centrality provides higher centrality scores to nodes that are situated closer to members of their component (the set of reachable nodes, both directly and indirectly) (Freeman (1977)). Betweenness centrality bestows larger centrality scores on nodes that lie on a larger proportion of shortest paths linking pairs of other nodes (Anthonisse (1971), and Freeman (1977)). Eigenvector centrality can indicate how important a node is by being large if a node has many neighbors, important neighbors, or both (Bonacich (1972)). One limitation of eigenvector centrality in our context is that it does not allow connection values to decay when industry distance increases, while one should expect that the effect of complexity is smaller for more distant industries. A modified version of eigenvector centrality, the Katz-Bonacich (K-B, henceforth) centrality (see, e.g., Li, Rajgopal, and Venkatachalam (1953), Bonacich (1987), and Bonacich and Lloyd (2001)) deals with this limitation of the eigenvector centrality.

Because degree centrality is more straightforward to understand as it captures the first-order effect of firm centrality on management's information advantage relative to the markets, we employ degree centrality as our primary measure in the main analysis. In the robustness tests, we also use the strength, betweenness, eigenvector, and K-B centrality measures as they are appropriate proxies for our context (Section IV.C).[9]

D Firm and Other Data

Monthly returns and market capitalization data are taken from CRSP, Book value of equity (BE), cash flow and industry classifications (NAICS and SIC) are taken from

[9] All of our network measures are calculated with the Stata package "netsis" provided by Miura (2012).

Compustat. For diversified firms or firms with non-classified industry codes (i.e., the first two digits of historical NAICS/SIC are 99), we use the Compustat Segment data.[10] The Fama-French factors are downloaded from Kenneth French's website. Our source for analyst recommendation data are the I/B/E/S Summary History Recommendation file.

E Merging Firm Data with I-O Industry Network Data

To merge firms with I-O industry codes, we rely mainly on concordance tables between NAICS (or SIC) and I-O codes provided by the Bureau of Economic Analysis (BEA). We assume that I-O accounts follow the U.S. federal government's fiscal year, which runs from October 1^{st} of the previous calendar year to September 30^{th}. Note that we have I-O industry classifications only in 1997, 2002, and 2007. Hence, for firm-month observations from October 1996 (2002) to September 2001 (2006) we use the I-O industry classification of 1997 (2002) and for firm-months from October 2006 to December 2015 we use the I-O table of 2007.

Table 1 reports the summary statistics of I-O industries in each of the three supplier networks. Panel A describes the centrality statistics of all industries. The mean degree centrality of all I-O industries in 1997, 2002, and 2007 is 23.08, 24.5, and 24.1, respectively. While the mean degree centrality varies little over time, the total number of I-O industries

[10] To locate a firm in the Input-Output network, we match its historical NAICS or SIC to IO code, following Ahern (2012) and Ahern and Harford (2014). We firstly use the historical NAICS/SIC in the Compustat Fundamental data to identify a firm's industry and replace missing or non-classified industry codes (i.e., the first two digits of historical NAICS/SIC are 99) with historical NAICS/SIC from the nearest past or future year. For diversified firms or firms with missing and non-classified industry codes, we further turn to the Compustat Historical Segment data for more detailed industry classification. For every firm with multiple reported segments in the segment database, we rank the primary NAICS codes by its total revenue from high to low, and then map them to IO industry codes (secondary NAICS or SIC codes are used if no mapping is found with the primary NAICS). In our reported results, we use the highest-ranked mapped IO to get the centrality for diversified or non-classified-industry firms. Other methods of computing centrality, e.g., equal weighted or revenue weighted average, give similar results to all analysis.

decreased from 1997 to 2007, as industries became more intensely connected in the trade-flow network. These supplier networks exhibit "small-world" properties: across the 368 to 470 industries, depending on the year, a typical industry is only about two connections away from any other industry, and the maximum shortest path between any two industries is only three.

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Table 1 about here

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The centrality distribution is highly skewed with a few extremely central industries (i.e., hubs) in every supplier network. For example, in the 2002 supplier network the top two central industries, Wholesale Trade and Management of Companies and Enterprises, have a degree centrality of 372 and 367, respectively; all other industries' degree values are lower than 230. Tables 2 and 3 report the 15 most and least central industries in each of these supplier networks according to degree centrality. The top three most central industries in every network are Wholesale Trade, Management of Companies and Enterprises, and Truck Transportation. The least central industries are Religious Organizations and Schools.

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Tables 2 and 3 about here

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About 90% of I-O industries have some public firms (with data available in CRSP/Compustat merged database); they range from the most to the least central industries (Panel B, Table 1). On average, about 67% of I-O industries in our final sample have repurchase announcements, and they have no significant difference in terms of industry-level centrality with other industries (Panel C, Table 1).

III Evidence from Share Repurchases

In this section, we start by investigating the premise of our theory, namely that more central firms have businesses that are harder to analyze and predict. Then we present our main empirical findings on centrality and long-run returns following buyback announcements.

A The Relation Between Centrality and the Volatility of Operating Cash Flows

Our argument is that, as it rises, a firm's centrality, at first, is advantageous to outsiders (who can cope with the associated increased complexity better than insiders), and then reaches a point where it is harmful (because outsiders have exhausted their capacity for analyzing additional links). A premise underlying this argument is that the business of more central firms is harder to analyze. To appraise this premise, we check whether cash flows are more volatile for more central firms.[11]

Following prior work (e.g., Minton and Schrand (1999)), we measure the volatility of

[11]To be clear, our analysis does not focus on cashflow volatility per se, but rather on the firm's complexity, i.e. on how difficult its operations are to understand, and as a result, on how challenging it is for outsiders to interpret and forecast its cashflows. Volatility is one manifestation of that complexity. But it has many other determinants. For instance, an oil producer might have highly volatile cash flows due to the volatility of oil prices, and yet be easy for outsiders to comprehend because it depends on few suppliers. Conversely, a firm that relies on a complex supply network, but enjoys market power in its product market might have stable cashflows because it can pass on supply shocks to its customers. In other words, our main prediction is not that volatility in general produces a U-shaped pattern with respect to insiders' informational advantage, but that volatility due to complexity does. Accordingly, we focus on network centrality as a determinant of that complexity: each economic link has to be examined by outsiders and that requires time and effort.

operating cash flows (OCF) for all firms in our sample as the (logarithm of the) coefficient of variation of a firm's quarterly OCF, defined as the standard deviation of OCF scaled by the absolute value of the mean OCF (and so is unitless), and denoted "OCF Volatility". We estimate the standard deviation and mean OCF using quarterly OCF over the 24 quarters preceding each buyback announcement. A buyback event is included in the sample if the announcing firm has at least ten quarterly observations of OCF in the preceding 24 quarters. Following Hribar and Collins (2002), we get quarterly OCF directly from the quarterly Statement of Cash Flows (net cash flow from operating activities – extraordinary items and discontinued operations).[12]

To assess the relation between cash flow volatility and centrality, we run a panel regression of OCF Volatility on Centrality. In a one specification, we control for firm size. In another specification, we include a firm fixed-effect to account for unobservable firm determinants of OCF Volatility. We also carry out a non-parametric sign test. Specifically, we compare two announcements made by the same firm to check whether the announcement made at a time when the firm is more central is indeed associated with higher volatility. If a firm makes more than one announcement over our sample period, we select the two announcements with the highest difference in centrality so that the power of the test is maximized. We conduct one final test using paired announcements, namely whether firms displaying a larger increase in centrality between two buyback announcements also exhibit a larger increase in volatility. To do so, we regress, in the cross-section of firms, differences in

[12]Results were robust when we measured quarterly OCF as Sales less Cost of Goods Sold less Selling, General and Administrative Expenses (excluding R&D and advertising expenses when available) less the change in working capital for the period. Under GAAP, firms are required to expense R&D costs in the year spent rather than capitalize them. This practice tends to artificially amplify volatility. Results were also not sensitive to whether or not we excluded R&D and advertising expenses.

volatility within buyback pairs on differences in centrality within the pairs.

The results of these tests are displayed in Table 4. All three tests reveal a positive and statistically significant relationship between OCF Volatility and Centrality. The t-stat equals 5.9 in the panel regression (Panel A), the p-value equals 0.06 in the sign test (Panel B), and t-stat equals 1.74 in the cross-sectional test (Panel C). In terms of economic magnitude, the effect is relatively modest. The coefficient estimate in the regression indicates that an increase in Centrality of 0.24 (one standard deviation, which corresponds to a 52% relative increase given a sample mean for centrality of 0.46) is associated with an increase in OCF Volatility of 8.9% ($= 0.24 \times 0.37$). The estimates from the paired sample used in the sign test yield similar magnitudes. The mean difference in OCF Volatility across two announcements made by the same firm is 5.4%, for a change in Centrality of 0.13.

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Table 4 about here

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To conclude, we find strong evidence that OCF Volatility is increasing in Centrality: as assumed in our model, the larger complexity deriving from having more links is associated with more volatile, and therefore less predictable, cash flows.

B Main Results

Following the literature on the long-run anomaly of share repurchases (e.g., Ikenberry et al. (1995) and Peyer and Vermaelen (2009)), we first apply the Ibbotson's Returns across Time and Securities (IRATS) procedure (1975). For each event month t we run cross-section regressions of stock returns against the Fama-French factors. Note that all events are equally weighted. Value-weighting events introduces a systematic bias against finding excess returns as small firms are more likely to be mispriced (Peyer and Vermaelen (2009)). The intercept in the regression measures the average abnormal excess return in event month t. We then accumulate these excess returns over various time horizons (up to 48 months after the event). Table 5 shows the excess returns using the Fama and French (1993) three-factor model (Panel A) and the Fama and French (2015) five-factor model (Panel B). The first columns show the excess returns for all buyback events, which are statistically significantly positive over all horizons with both models. The five-factor IRATS model adjusts for more risk factors and thus generates lower excess returns than the three-factor model (15.68% vs. 20.32% after 48 months).

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Table 5 about here

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To examine the relation between centrality and long-run excess returns, we start with a single-sort approach and split all buyback events into subgroups based on their centrality. Because the raw centrality values are from three different I-O networks, they are not comparable over time. To make buyback events from different times comparable by centrality, we first create a cross-sectional centrality score ranging from 0 to 1, as the percentile of the centrality of a firm across all firms in the CRSP universe in each calendar month. This construction gives a mean Centrality Score of 0.52 for all CRSP firms over the sample period (note that the mean is not exactly 0.5 as centrality is measured at a sector level). Our sample of buyback announcements is made by less central firms as the mean Centrality Score of buyback events is 0.46, significantly smaller than 0.52 ($p < 0.01$).

We rank all buyback events by Centrality Score and split them into five quintile groups: Q1 indicates the least central group; Q2, Q3, and Q4 indicate increasing centrality; and Q5 indicates the most central group. Table 5 and Figure 4 also report the long-run excess returns (CAR) for each of these centrality subgroups. The results show that there is a U-shaped relation between CAR and centrality, over all horizons, with the lowest CAR in Q4 and the highest CARs in Q1 and Q5. The U-shaped relation appears in both the three-factor and the five-factor models but is more pronounced in the latter one. Specifically, with the Fama-French five-factor model, after 48 months the CAR difference between the Q1 and Q4 quintiles is 28.05% ($t = 7.45$) and the CAR difference between Q5 and Q4 is 22.39% ($t = 5.74$). Note that the CAR in Q4 is never significantly different from zero at the 1% level, regardless of the investment horizon. These results indicate that both of our hypothesized effects may play a role: the *information processing cost* hypothesis is more pronounced for the more central firms, and the *information availability asymmetry* hypothesis plays a more important role for the more peripheral firms.

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Figure 4 about here

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One critique of the Ibbotson (1975) IRATS method is that the results may be time-specific and the cumulative abnormal returns are dominated by periods when there is a large number of events. So we also use the Calendar Time method: in each calendar month we form an equally weighted portfolio of all firms that had announced a buyback in the previous t months. We then run a time series regression of the portfolio returns against the factors. The intercept of the regression is the average monthly excess return in the t months after the event.

Table 6 reports the results from the three-factor and five-factor Calendar Time Abnormal Returns (AR). Both models show to some extent a similar pattern for the relation between post-event monthly excess returns and centrality. Although the AR for the Q5 sample is always higher than the AR for the Q4 sample, the differences are never statistically significant at the 5% level when we use the three-factor model. When we use the five-factor model the difference becomes statistically significant at the 5% level. Nevertheless, as Figure 4 also shows, there is a clear U-shaped relation between excess returns and centrality for both the IRATS CAR and the Calendar Time method AR. Therefore, for simplicity in the remainder of the paper we will focus on results from the five-factor Fama-French IRATS method.[13]

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Table 6 about here

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C Centrality vs. Other Predictors of Long-Run Excess Returns

Could the observed U-shaped relation between long-run excess returns and centrality be explained because centrality is a proxy for other firm characteristics that affect the benefit

[13]Calendar Time AR results and three-factor Fama-French results are available upon request. Conclusions are qualitatively similar.

of repurchasing undervalued stocks? Some examples of such firm characteristics can be firm size, market-to-book ratio, and prior return (combined in an Undervaluation Index (U-index) by Peyer and Vermaelen (2009)), plus analyst coverage, idiosyncratic volatility, and total volatility combined with the U-index in an Enhanced Undervaluation index (EU-index) by Evgeniou et al. (2018).

To check the power of alternative explanations, we perform double-sort tests and check whether/how the U-shaped relation varies with these firm characteristics. Following the same procedure to calculate the Centrality Score we also standardize the return volatility, $(1 - R^2)$, market beta, analyst coverage, market equity, prior 11-months returns, and book-to-market ratio (BE/ME) using cross-sectional percentiles across all CRSP firms for each calendar month as characteristic scores. By construction, the mean value across all CRSP firms in each month is 0.5 for each of these scores. Table 7 reports the average value of each firm standardized characteristic for all buyback events and every centrality subgroup. Note that all characteristics are, on average, significantly different from 0.5 (t-statistics not shown), and note that the U- and EU- indices are not standardized between 0 and 1. For example, in the universe of CRSP firms, buyback firms are less central as the average centrality score is 0.46. On the other hand, with a score of 0.67 they are covered by relatively more analysts than the average CRSP firm, as they also are relatively larger. They are less risky than average when risk is measured by (idiosyncratic) risk or volatility and riskier when risk is measured by market beta. The Q3 group has the lowest values for volatility, the U-index, and the EU-index and contains relatively larger firms. Finally, idiosyncratic risk $(1 - R^2)$ decreases with centrality as found by Ahern (2013).

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Table 7 about here

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While Table 7 reveals no obvious U-shaped relation between centrality and any of the company characteristics (except volatility, the U-index, and the EU-index), it may still be the case that each of these characteristics can at least partially explain the relation between long-run excess returns and centrality. For example, Peyer and Vermaelen (2009) suggest that the post-event excess returns are higher for smaller firms as they are followed by fewer analysts. To test whether our results can be explained by size or analyst coverage we independently double-sort firms by size (analyst coverage) and centrality: two size (analyst coverage) groups and five centrality groups (2×5). Results from the five-factor IRATS method (Tables 8 and 9) show that larger firms or higher-analyst-coverage firms experience lower excess returns. Specifically, small (large) firms earn long-run excess returns after 48 months of 23.48% (8.05%), while firms with low (high) analyst coverage earn excess returns of 18.87% (10.42%). More important, the U-shaped relation between IRATS CAR and centrality is unconditional on the group splitting based on firm size or analyst coverage.

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Tables 8 and 9 about here

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In each case the CAR of the Q4 sample is significantly smaller than the CAR in the Q1 and Q5 samples. Note that the Q4 sample (not the Q3 one, as in Table 7) is consistently the sample with the lowest excess returns. This is especially striking for the larger-size and higher-analyst-coverage samples where the firms in the Q4 quintile always earn negative and significantly lower excess returns than the most central and peripheral firms, for all horizons. The highly significant negative long-run excess returns of close to -13% after 48 months experienced by the high-analyst-coverage/large firms after buyback announcements is, to our knowledge, unprecedented in the buyback literature.

We hypothesize that buybacks made by low centrality firms in Q1 are followed by large excess returns because of the information advantage of firm managers. An alternative explanation may be that the larger excess returns are a result of the higher idiosyncratic volatility of these firms (see Table 7). Central firms are more connected in the economy and have greater exposure to systematic risk, so the explanatory power of the standard risk factors is expected to be higher for central firms, i.e., the idiosyncratic volatility $(1 - R^2)$ is lower for central firms than for peripheral ones (Ahern (2013)). Moreover, Evgeniou et al. (2018) find that long-run excess returns after buyback announcements are positively correlated with idiosyncratic volatility. To test for the relevance of idiosyncratic volatility, we double-sort firms as above by idiosyncratic volatility and centrality (2×5). Our results (Table 10) show that the U-shaped relation between IRATS CAR and centrality exists for both high- and low-idiosyncratic firms: repurchase announcements by firms in the Q4 group are followed by the lowest (and not statistically significant) long-run excess returns. So while it is true that high idiosyncratic volatility is associated with larger long-run excess returns, it cannot explain why peripheral firms with low idiosyncratic risk are doing so well relative to more central firms.

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Table 10 about here

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Table 7 suggests that there is to some extent a U-shaped relation between volatility and centrality with the lowest mean volatility in Q3. Evgeniou et al. (2018) find that high-volatility firms experience greater post-buyback excess returns because the value of the option to take advantage of an undervalued stock price is positively correlated with the volatility of the underlying firm (Ikenberry and Vermaelen (1996)). So perhaps a third alternative explanation is that the U-shaped relation between IRATS CAR and centrality is driven by firm volatility. The results from double-sorting (volatility $\times$ centrality) in Table 11 show that low-volatility firms indeed experience very small CAR (4.37% over 48 event months) compared to high-volatility firms (27.57% over 48 months). However, the U-shaped relation between CAR and centrality holds for both high- and low-volatility firms. These findings indicate that firm volatility may not be the only driver of the higher post-buyback excess returns of the high and low central firms.

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Table 11 about here

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Finally, the high CAR of the most and least central firms may be driven by the U-shaped relation between the undervaluation index (U-index in Peyer and Vermaelen (2009)) or the EU-index (Evgeniou et al. (2018)) and centrality, as shown in Table 7. The results from the double-sorting method (U-index × centrality and EU-index × centrality) in Tables 12 and 13 show that the U-shaped relation between CAR and centrality shows up in all cases, although less clearly in the high-U-index and high-EU-index groups. For high U-index firms, CAR appears higher in Q2 than in Q1 (40.54% vs 36.98%) while the lowest CAR is in Q3 (16.07%). Similarly for the high EU-index firms the highest CAR appears in the Q2 group (42.59%). Nevertheless, as in our basic results, the U-shaped relation between centrality and excess returns still exists regardless of whether the firm has a high or low U- or EU-index. We can therefore conclude that the U-index and EU-index cannot explain the CAR-centrality U-shaped relation. Moreover, as centrality provides additional explanatory power for the IRATS CAR on top of the EU-index, it seems that the predictive capacity of the EU-index can be further improved by adding the centrality dimension, as we discuss below.

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Tables 12 and 13 about here

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Summarizing, we find a U-shaped relation between excess returns and centrality with the IRATS method. Specifically, firms in centrality quintile Q4, the second most central group, tend to have significantly lower long-run excess returns after buyback announcements than firms in centrality quintiles Q1 and Q5. Double-sorting firms by centrality and size, analyst coverage, $(1 - R^2)$, or volatility does not affect this U-shaped relation. These results partially solve the concern that the centrality effect is simply a proxy for other factors associated with long-run excess returns. While the same U-shaped relation shows up in low-U-index or low-EU-index firms, the pattern changes somewhat in high-U-index or high-EU-index firms as buybacks by firms in Q1 are followed by higher long-run excess returns in Q2.

D Network Centrality and Buyback Decisions

Table 14 tests whether the probability of a buyback depends on network centrality, using all CRSP firm-month decisions during the same period. To a large extent we use the model of Massa, Rehman, and Vermaelen (2007) to predict whether, ceteris paribus, network centrality increases the likelihood of a share buyback. Both Logistic and Probit regressions show that a share repurchase is more likely if the firm has announced a repurchase during the previous 2 years, if it has low returns in the previous 6 months, has low leverage, large profitability, a high book-to-market ratio, or low capital expenditures. So firms with significant debt capacity and few investment opportunities are more likely to buy back stock. Ownership structure also matters: firms with more institutional investors and higher institutional ownership are more likely to buy back stock. One interpretation is that these investors put more pressure on management to reduce the agency costs of free cash flow. More relevant for our purpose is that the regression coefficient on the network centrality variable in Table 14 is statistically indistinguishable from zero. Thus, network centrality does not appear to determine whether a buyback occurs.[14] But it does affect the manager's ability to time their purchases of shares and thus long-run stock returns, as we show next.

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Table 14 about here

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[14] This alleviates concerns about the endogeneity of the buyback decision with respect to a firm's network centrality.

E Cross-Sectional Analysis of Centrality and Long-Run Excess Returns

To evaluate the explanatory power of centrality for excess returns above and beyond known factors, we estimate regressions of long-run monthly excess returns on centrality (and a squared centrality term (Lind and Mehlum (2010)) and a number of control variables. Following Brennan, Chordia, and Subrahmanyam (1998), we first estimate factor loadings $\beta_{jk,\tau}$ for each event j, risk factor k, and event month τ using data from the 60 months prior to the event month τ (requiring that there are at least 24 return observations during those 60 months). The risk factors used in our study are the Fama and French (2015) five factors ($R_M - R_F$, SMB, HML, RMW, and CMA). Factor loadings $\beta_{jk,\tau}$ are obtained from the following time series regression:

(1) $R_{jt} - R_{Ft} = a_{j\tau} + b_{j\tau}(R_{Mt} - R_{Ft}) + s_{j\tau}SMB_t + h_{j\tau}HML_t + r_{j\tau}RMW_t + c_{j\tau}CMA_t + e_{jt} =$

$$a_{j\tau} + \sum_{k=1}^{5} \beta_{jk,\tau} F_{kt} + e_{jt},$$

where F_{kt} indicates the k^{th} risk factor in month t, and t ranges over the 60 months before the event month τ for which returns are available.

Next, for each stock j in event month τ, we calculate the estimated risk-adjusted return $\Delta R_{j\tau}$ using the estimated $\beta_{jk,\tau}$ factor loadings:

(2) $\Delta R_{j\tau} = (R_{j\tau} - R_{F\tau}) - [b_{j\tau}(R_{M\tau} - R_{F\tau}) + s_{j\tau}SMB_\tau + h_{j\tau}HML_\tau + r_{j\tau}RMW_\tau + c_{j\tau}CMA_\tau] =$

$$(R_{j\tau} - R_{F\tau}) - \sum_{k=1}^{5} \beta_{jk,\tau} F_{k\tau}$$

Then for all event stocks in each post-event month τ (from the 1^{st} to the 48^{th} month following the buyback announcement), we run the following cross-section regression:

$$\Delta R_{j\tau} = c_{0\tau} + \sum_{m=1}^{M} c_{m\tau} Z_{mj} + \mathrm{Y}ear Dummies + \mathrm{I}ndustry Dummies + \epsilon_{j\tau}, \tag{3}$$

where Z_{mj} are the m^{th} characteristic of stock j in the month prior to the buyback announcement, such as centrality, total volatility, $(1 - R^2)$, analyst coverage, U-index, etc.

Finally, we compute the average of the monthly regression coefficient estimates $c_{m\tau}$ over the event months 3 through 48, C_m^n for n in 3 to 48. We calculate standard errors of the aggregated coefficients using the standard Fama-MacBeth approach Fama and Macbeth (1973): the t-statistics for testing the hypothesis that $C_m^n = 0$ are:

$$t(C_m^n) = (C_m^n)/(s(C_m^n)/\sqrt{n}) \tag{4}$$

where n is the number of post-event months to calculate C_m^n and $s(C_m^n)$ is the standard deviation of the monthly estimates, $c_{m\tau}$ for τ in 1 to n. We do this for four different time horizons n: 1 to 12 months, 1 to 24 months, 1 to 36 months, and 1 to 48 months.

In Table 15 we regress long-run monthly excess returns on individual standardized firm characteristics. The significance of the characteristics depends on the investment horizon. For the 36- and 48-month horizons (long-run), we find results that are largely consistent with past research: small firms, firms with a high EU-index, volatility, and $(1 - R^2)$ experience larger long-run excess returns. However, besides volatility and EU-Index, centrality squared (centrality) is the only variable that is statistically significant over all (the last three) investment horizons at 1% (5%) level. These results support the hypothesis that centrality is a significant determinant of long-run excess returns and the relation is indeed U-shaped.[15]

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Table 15 about here

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In Tables 16 and 17 we run multivariate cross-sectional regressions. In Table 16 we use the U-index as an independent variable, together with other variables that are not components of this index.[16] In Table 17 we replace the U-index with its components (size, market to book, and prior return). The message from both tables is similar: we find that the relation between post-event long-run excess returns (36- and 48-month horizons) and centrality is still U-shaped. The coefficients in the 48-month horizon regression indicate that the average monthly excess return reaches the lowest level when the de-meaned Centrality Score is 0.08 and the original Centrality Score is about 0.54. This corresponds to the 61^{st} percentile across centrality scores, which is in subgroup Q4 and consistent with the single and double-sort results above. From the control variables, only volatility is significantly positively correlated with long-run excess returns over all horizons. The results indicate that centrality and volatility have more robust effects on long-run excess returns than other undervaluation proxies.

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[15] To avoid co-linearity between the linear and square terms for centrality, we subtract from every centrality score the mean score in each event month, generate a squared term of the de-mean centrality score, and then use these in the cross-section regressions.

[16] We do not use the EU-index of Evgeniou et al. (2018) as we include volatility and $(1 - R^2)$.

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Tables 16 and 17 about here

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Peyer and Vermaelen (2009) find that open market repurchases are a response to a market overreaction to bad news, such as significant analyst downgrades. While, consistent with the literature, we find significant negative excess returns in the six months prior to the buyback announcement, for firms in all centrality groups, we also test whether indeed it makes a difference whether analysts were (at least partially) responsible for the stock price decline. Table 18 shows regression coefficients on the centrality squared term for buyback announcements following analyst downgrades (Panel A) and upgrades (Panel B) in the month prior to the repurchase announcement. The relation between excess returns and centrality is almost flat for downgraded firms and has a significant U shape for upgraded firms at the 10% level. Note that we do not have many events that were downgraded (1,983 events) or upgraded (1,792 events) before the repurchase announcement, which may partly explain the lack of significance of the results. This indicates that while the management of all firms can take advantage of clear misvaluation caused by analyst mistakes, the management of central and peripheral firms have an information advantage even when analysts are optimistic. Such information advantage may be due to the markets' slow reaction to good news (including the news that may have led to the analyst upgrade).

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Table 18 about here

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F Combining Centrality With Other Return Predictors: The Central EU-Index

Based on the results so far, we extend the EU-index of Evgeniou et al. (2018) by adding to it the centrality dimension. Because the CAR-centrality relation is U-shaped, we assign a score of 0 to the second most central quintile group (Q4) where CAR tends to be the lowest, a score of 1 to the middle groups (Q2 and Q3), and a score of 2 to the least and most central quintile groups (Q1 and Q5). Then we add these centrality scores to the EU-index to get a central EU-index (CEU-index). The CEU-index ranges from 0 to 8 and has a symmetric distribution with a mean of 4.25 (Figure 5). There are very few buyback events with a CEU-index of 8, which means that few firms with an EU-index of 6 have a centrality score of 2. This is again evidence that centrality is different from known factors that predict the success of market timing after buyback announcements.

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Figure 5 about here

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The excess returns of every CEU-index score are reported in Table 19 and Figure 6. The results show a monotonically increasing relation between CAR and the CEU-index except for firms with CEU-index of 0 (only 22 such events): firms with a CEU-index of 1 have the lowest CAR of -8.04% and those with a CEU-index of 8 have the highest CAR of 87.60%, over 48 months after their buyback announcement. In unreported tables, we also find a similar pattern between Calendar Time monthly excess returns and the CEU-index.

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Table 19 and Figure 6 about here

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IV Robustness Tests

In this section, we examine the robustness of our empirical results. We start by confirming that the results hold in recent times and under alternative centrality measures. Next we examine a subsection of companies that repurchased before and after a change in centrality. Finally, we replicate our main results using insider trades.

A Stability over Time

Fu and Huang (2016) and Manconi et al. (2019) report that the buyback anomaly became less pronounced over the period 2003-2010. In order to test whether the buyback anomaly and the U-shaped relation we document survive the test of time, we repeat the analysis of Tables 5, 6 and 16 using data only from the 2005-2015 period. The results, presented in Tables 20, 21 and 22 confirm that they do: long-term excess returns after buyback announcements remain significantly positive, especially in the highest and lowest centrality quantiles. Regardless of the factor model used or the event study methodology, excess returns tend to be significantly lower in Q4 than in Q1 and Q5.

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Tables 5, 6 and 16 about here

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B Changes in Firm Centrality and Long-term Returns

In this section we run two additional tests to improve the evidence that it is indeed centrality that drives the relation between returns and the centrality metrics. The tests are based on subsamples of firms which announce a repurchase program before and after a change in their centrality during the time period we study.

In the first test we identify companies in our sample whose centrality changed from low (quantiles 1 or 2) to medium (quintile 4) or vice versa, as well as those that changed from high (quantile 5) to medium (quantile 4) and vice versa. We use quantile 4 as the medium centrality quantile, consistent with our existing results, and combine quantiles 1 and 2 in order to increase the number of events. There are 143 firms in our repurchases data that moved between low and medium centrality quantiles, and 145 that moved between high and medium centrality quantiles. The first group features 383 (resp., 321) repurchase events involving firms in the low (resp., medium) centrality group. The second group features 347 (resp., 323) events involving firms in the high (resp., medium) centrality group. We estimate the cumulative abnormal returns of these 4 types of events (both using IRATS and calendar methods), and compare how these returns change as firms migrate from one group to another, i.e., compare buybacks returns announced when firms belong to the low (resp., high) centrality group to when they belong to the medium centrality group.

The results, shown in Tables 23 and 24, are consistent with our previous results based on all repurchase events: in all cases returns are lower when firms are in the medium centrality quantile than when they are in the low or high ones. Despite the very low number of events in each group (less than 400 from a sample of 8,401 repurchase events), the difference between high (low) and medium centrality quantiles is strongly significant with the IRATS method, regardless of the investment horizon or factor model. As in our main tests, the results are weaker with the calendar time method. The fact that calendar time results are always less significant is well known as it is a less powerful method to detect abnormal returns (Loughran and Ritter (2000)). They are only significant over every investment horizon when we use the 5-factor model and consider firms moving from low to medium centrality quantiles. But regardless of the factor model and the investment horizon, firms moving to medium centrality quantiles always display lower long-term returns. The results further support that the effect we document is not driven by unobserved time-invariant firm characteristics.

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Tables 23 and 24 about here

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C Alternative Measures of Centrality

We evaluate the sensitivity of our findings to how we measure centrality. To do so, we reproduce our main test using measures of centrality other than degree centrality. First, we consider the strength centrality (Barrat et al. (2004)). While degree centrality gives equal weight to all direct links, strength centrality puts more weight on industries with stronger links with the focal industry. Thus, it can be considered as a proxy for a "weighted" complexity of a firm's supplier-customer portfolio. Second, we consider two global centrality measures: eigenvector centrality (Bonacich (1972)) and K-B centrality (see, e.g., Li et al. (1953), Bonacich (1987), and Bonacich and Lloyd (2001)). These two measures account for the centrality of linked industries and thus capture the second order complexity of a firm's portfolio, which comes from the inter-industry trade relations between trade partners and the complexity of trade partners. If our theory is correct – that is, the management's information advantage relative to outsiders increases with centrality due to information processing complexity and decreases with centrality due to information availability difference – then we predict a U-shaped relation between post-buyback excess returns and each of our three centrality measures. Table 25 shows evidence that the U-shaped relation is robust with respect to different centrality measures. Indeed, in all cases the coefficient on centrality squared is significantly positive for the (long-run) 36- and 48-month horizons.

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Table 25 about here

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Finally, we consider the betweenness centrality (Anthonisse (1971), and Freeman (1977)), which measures an industry's role as a broker in the economy. In theory, betweenness centrality shows a node's importance in the network along a different dimension than degree centrality and the other three measures above. But in the I-O supplier network, betweenness centrality and degree centrality are highly correlated (with a correlation coefficient of 0.88), so important industries in the U.S. product network happen to be both "brokers" (measured by betweenness centrality) and "resource aggregators" (measured by degree centrality). Given this network structure, we expect a similar U-shaped relation between post-buyback excess returns and betweenness centrality. Table 25 shows that the U-shaped relation is indeed significant for the long-run horizons.

D Evidence from Insider Trading

Finally, to corroborate our findings regarding the effect of centrality on managers' informational advantage, we replicate the main results from the analysis of share repurchases using insider trades. Note that, as in the case of repurchases, the ability of insiders to take advantage of inside information depends on their personal debt capacity and alternative investment opportunities.

1 Centrality and Insider Trading Profits

We proceed as we did for share buybacks, sorting insider buy events on their Centrality Score into five quintiles, from Q1 for the least central group to Q5 for the most central group. Table 26 Panel A displays the CAR for each of these quintiles using the Ibbotson (1975) IRATS method. The results show that there is a U-shaped relation between CAR and centrality, over all horizons, with the lowest CAR achieved in Q3 and the highest CARs in Q1 and Q5. The U-shaped relation is shown whether we use the three-factor or the five-factor model (see Table 26 Panel B). The CAR in Q3 is always significantly smaller than the CAR in Q1, across investment horizons. It is also significantly smaller than the CAR in Q5, at least for horizons of 36 months and longer.

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Table 26 about here

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Table 27 reports the results from the analysis of the three-factor and five-factor Calendar Time Abnormal Returns (AR). Both models show to some extent a similar pattern for the relation between post-event monthly excess returns and centrality, with the middle quintile Q3 standing out as the sample with the smallest excess returns. Moreover, regardless of the factor model and of the investment horizon, excess returns in that quintile are significantly (at the 10% level or less) smaller than those in the Q1 sample. This time the firms in Q5 have larger returns than the firms in Q3 but the difference is not statistically significant. Hence the U shape continues to hold with the Calendar Time method, albeit less clearly than with the IRATS.

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Table 27 about here

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2 Cross-Sectional Analysis of Insider Trading Profits

To test whether centrality has explanatory power for excess returns above and beyond known factors, we replicate the analysis of Table 17 in Table 28 by running regressions of long-run monthly excess returns following insider buy events on centrality (and a centrality squared term (Lind and Mehlum (2010)) and a number of control variables. Past research on insider trading (e.g. Lakonishok and Lee (2001)) has shown that insider trading profits are concentrated in small firms so we include size as a dependent variable. We also add a number of controls that are used in the buyback tests of Table 17, i.e. the book-to-market ratio and prior return. To the extent that buybacks can be considered a form of indirect insider buying, we would expect the same control variables to be relevant for predicting excess returns following insider buy events. Table 28 shows that indeed insider buying is significantly more profitable over all horizons in small firms. Also, consistent with the results in Table 17, centrality is significantly (at the 10% or less) negatively related to excess returns over all horizons. However, we find no significant positive relation between centrality squared and excess returns.

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Table 28 about here

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V A Model of Centrality and Managers' Information Advantage

In this section we propose a parsimonious model that can rationalize the U-shaped relation which we observe in the data between firm centrality and the profitability of insiders' share purchases. Our purpose is to demonstrate that this pattern can indeed result from rational agents subject to information constraints trading with one another. The model focuses on a single firm linked to several other firms, or "business partners". In our empirical analysis, we considered links established with the firm's customers and suppliers; here we are agnostic about the exact nature of this link. An insider (e.g., CEO, CFO, a Board member) buys the firm's stock, either for her own account or on behalf of long-term shareholders through a share buyback program (the model does not distinguish these two types of purchases). Many firm outsiders (e.g., investors, analysts) also trade the stock. Both categories of agents maximize their expected profit subject to attention constraints. We investigate theoretically how the firm's centrality affects the profitability of the insider's trades. Derivations and proofs are presented in the Appendix A.

The model features three periods, labelled 0, 1, and 2. In period 0, agents choose how much information to acquire; in period 1, they trade; in period 2, they consume.

A Model Setup

1 Firms

We assume the firm has excess cash or debt capacity that allows it to finance a repurchase without destroying shareholder value, and wants to repurchase stock to benefit from reducing the agency costs of free cash flow and/or tax benefits from increasing debt. Note that these conditions are consistent with the results of our probit/logit analysis of Table 14. The firm generates a cash flow F in period 2. As the outcome of the firm's interactions with its partners, this cash flow can be decomposed into a sum of random, link-specific cash flows or "shocks":

$$F = \varphi + \sum_{n=1}^{N} f_n \tag{5}$$

where f_n is the cash flow associated with link n ($n = 1, \ldots, N$), N is the number of such links, and φ is a cash flow unrelated to any business partner. The term f_n is positive (resp., negative) if the firm's dealings with partner n leads to a profit (resp., a loss) – as when, for example, partner n is one of the firm's customers (resp., suppliers). The parameter N

measures the firm's centrality: firms that are more central are connected to a larger number of other firms (i.e., have more partners).

We assume that the cash flows f_n are independent and identically distributed across links. In the analysis that follows, we study how the predictability of a firm's cash flow F depends on its centrality N. In order to hold a firm's average size (as reflected by its total cash flow or market capitalization) constant as we vary N, we assume that $E(f_n) = 0$. This assumption avoids mis-attributing to centrality any effect of size. We also assume (without loss of generality) that φ is independent of the f_n and that $E(\varphi) = 0$. All random variables are normally distributed. We denote the (prior) precisions (i.e., the inverse of the variance) of φ and f_n ($n = 1, \ldots, N$) as τ^{φ} and τ^{f}, respectively.

Finally, a claim (the stock) to the firm's cash flow F is traded competitively in period 1. This stock has a price P and a fixed supply $\bar{X}$. A riskless bond in perfectly elastic supply is also available; its gross return is normalized to 1.

2 Agents

The model features two types of risk-neutral agents, *outsiders* and *insiders*, who seek to maximize their expected profit from trading the stock. For that purpose, they attempt to predict in period 1 (the trading period) the firm's cash flow F, which will be revealed in period 2. We assume that they do not learn from the price; that is, they "agree to disagree". Agents – outsiders or insiders – differ on how they access information about the firm's cash flow, as described next.

Outsiders

A representative outsider ("he") can learn about the firm's cash flow at a cost. This cost can be interpreted as cognitive or monetary. Under the cognitive interpretation, outsiders receive a large number of (raw) signals for free; processing these signals requires time and attention, both of which are in limited supply. Under the monetary interpretation, agents must expend physical resources (e.g., purchase data or hire analysts) in exchange for (processed) signals. We assume that outsiders are endowed with a fixed learning budget, or "capacity", for processing these signals (under the former interpretation) or purchasing them (under the latter interpretation).

We assume that the outsider cannot learn φ, the cash flow unrelated to any link, but that he may acquire a private signal about each of the link-related cash flows: $s_{nO} = f_n + \epsilon_{nO}$, $(n = 1, \ldots, N)$, where ϵ_{nO} is normally distributed (with mean 0 and precision τ^{ε}_{nO}) and uncorrelated with all other random variables.

We consider three common learning technologies. All three impose an upper bound on the degree to which the outsider can reduce the uncertainty he faces, but they differ in terms of how a reduction in uncertainty is measured. Also, we impose a "no forgetting" constraint in all three cases, which ensures that agents cannot erase what they know about one link in order to improve their knowledge about another.

The first learning technology expresses the reduction in uncertainty as the difference between the posterior variance of F and its prior variance, and then caps this difference:

$$Var(F) - Var(F|\mathcal{F}_O) \leq k \tag{6}$$

where $k \geq 0$ is a constant that represents the agents' learning capacity and where

$\mathcal{F}_O = \{s_{nO}, n = 1, \ldots, N\}$ denotes the outsider's information set. Our no-forgetting constraint takes the following form: $Var(F) \geq Var(F|\mathcal{F}_O)$.

The second learning technology posits that the cost of learning is linear in a signal's precision. This technology imposes an upper bound on the sum of those costs:

$$\sum_{n=1}^{N} \tau_{nO}^{\varepsilon} \leq k' \tag{7}$$

In this case we use $k' \geq 0$ to denote the agents' learning capacity, and the no-forgetting constraint takes the form $\tau_{nO}^{\varepsilon} \geq 0$ for $n = 1, \ldots, N$.[17]

The third learning technology we consider uses the information-theoretic concept of entropy to measure the amount of information contained in a signal.[18] Under this approach, we restrict the mutual information (i.e., the reduction in conditional entropy) of prior and posterior beliefs about the N cash flow shocks:

$$\frac{|\Sigma_O|}{|\hat{\Sigma}_O|} \leq k'' \tag{8}$$

In this formulation, $k'' \geq 1$ is the learning capacity, $\hat{\Sigma}_O$ is the posterior variance-covariance matrix of the individual cash flow variables f_n ($n = 1, \ldots, N$), Σ_O is the prior posterior variance-covariance matrix, and $|\cdot|$ signifies the matrix determinant. The no-forgetting constraint now takes the form $\hat{\Sigma}_{Onn} \leq \Sigma_{Onn}$ for $n = 1, \ldots, N$, where $\hat{\Sigma}_{Onn}$ and

[17] Note that this learning technology is consistent with a model in which outsiders can acquire signals at a fixed cost, that is, pay a cost per signal (i.e., per link). In addition to this extensive margin adjustment (whether or not to learn about a link), this technology features an intensive margin adjustment (how much to learn about that link).

[18] In finance, entropy-based constraints are used by Sims (2003), Mondria (2010), Mackowiak and Wiederholt (2009), Mackowiak and Wiederholt (2015), Van Nieuwerburgh and Veldkamp (2010), and Kacperczyk, Nieuwerburgh, and Veldkamp (2014), among others.

Σ_{Onn} are (respectively) the n^{th} diagonal elements of the matrices $\hat{\Sigma}_O$ and Σ_O. Here we have exploited the independence of shocks and signal errors.

The entropy constraint (8) assumes learning to be a process of increasingly refined and increasingly costly search, whereas the constraints (6) and (7) represent learning as a sequence of independent yet equally costly draws (see Veldkamp (2011)). In contrast to (7) and (8), the variance constraint (6) allows the agent to achieve a perfect knowledge of link-related cash flows – provided he has sufficient learning capacity.

Insiders managers

The insider ("she") is a manager of the firm. Through her position, she has access to detailed and timely information about the firm's operations. We assume that she knows perfectly φ, the cash flow unrelated to any link, and that she receives noisy information about the link-related cash flows f_n, $(n = 1, \ldots, N)$. Such information might pertain, for example, to the odds of a customer order materializing or to the quality of a part manufactured by a supplier. In contrast to the outsider, the insider receives her information at no cost: it is simply a by-product of managing the firm and so is free.

We model the insider's information about f_n as a signal $s_{nI} = f_n + \epsilon_{nI}$, where ϵ_{nI} is normally distributed with mean 0 and precision $\tau^{\epsilon}_{nI} = \delta \geq 0$, and uncorrelated with all other random variables. Hence for the insider, the posterior precision of each f_n is equal to $\tau^f + \delta$. We denote $\mathcal{F}_I = \{\varphi; s_{nI}, n = 1, \ldots, N\}$ the insider's information set.

Based on her information, the insider assesses whether shares of the firm are underpriced and whether the firm (or the insider if she trades for her own personal account) can afford the buyback. Thus, whether a firm will respond to undervaluation with a share buyback depends not only on the extent of undervaluation but also on the availability of excess cash (or debt capacity), alternative investment opportunities and whether managers care about long-term shareholder value (agency costs). We see no reason to believe that the firm's position in the input-output network is related to these determinants. Hence network centrality by itself does not cause the buyback, which can therefore be considered a largely exogenous event. If the firm can afford the buyback the insider purchases shares in the open market through a share buyback program. The purpose of the model is to relate post-buyback stock returns to the manager's ability to time the buyback, and in turn to the firm's position in the input-output network.

If the firm can afford the buyback the insider purchases shares in the open market through a share buyback program. We assume that the stock price is not affected by the insider's purchase because of SEC's regulation of share buybacks restricting trading volume and price manipulation. We also ignore any short-term signalling effects (for empirical evidence, see, e.g., Vermaelen (1981)). Indeed, our focus is on the long-term effects of buyback programs, in contrast to the short term over which any signaling effect would be observed. In equilibrium then, the asset price reflects the outsider's information but not the insider's; the insider's information will only be revealed in the long run.

3 Equilibrium

An equilibrium consists of the stock demands by both agents, the stock price, and the outsider's information choice (i.e., signal precisions τ^{ε}_{nO} for $n = 1, \ldots, N$) such that three conditions are satisfied. First, outsider's information choice and investors' stockholding maximize their expected profit subject to the capacity constraints (6), (7), or (8). Second, the stock price clears the stock market. Third, beliefs are updated via Bayes' law. Our results are spelled out in the next section.

B Model results

1 Lemma: Outsiders' information choice and firm centrality

The outsider spreads his (limited) learning capacity across the N links. As a result, he knows more about the links of peripheral (low-N) firms than about the links of central (high-N) firms. Moreover, his information improves with his learning capacity.

Formally, as shown in the Appendix A, the signal precisions ($n = 1, \ldots, N$) chosen by the outsider in equilibrium are as follows:

- *Under the variance capacity constraint:* $\tau^{\varepsilon}_{nO} = +\infty$ *for* $N \leq k\tau^f$ *and* $\tau^{\varepsilon}_{nO} = \tau^f(\frac{N}{k\tau^f} - 1)^{-1}$ *for* $N > k\tau^f$;
- *Under the linear precision constraint:* $\tau^{\varepsilon}_{nO} = k'/N$;
- *Under the entropy constraint:* $\tau^{\varepsilon}_{nO} = \tau^f(k''^{1/N} - 1)$.

Although their functional forms vary, all three specifications have two important properties in common. The first is that outsiders' precision is (weakly) decreasing in the number of links N; that is, their information about each single link is less precise when there are more links to investigate. The second property is that this precision increases with the learning capacity (k, k', or k'').

We state next our main result – which concerns the effect of firm centrality on the returns to insider trading (buying shares at a price below the insider's expected value). These are defined as the profit per share bought, conditional on buying shares:

$E[F - P|E(F|\mathcal{F}_I) - P > 0]$.

2 Proposition: Insider's profit and firm centrality

There exists a threshold (defined in the Appendix A) such that:

- *If the outsider's learning capacity (k, k', or k'') is larger than the threshold, then the insider's expected trading profit is a U-shaped function of the firm's centrality N.*
- *If the outsider's learning capacity is smaller than the threshold, then the insider's expected trading profit is monotonically increasing in the firm's centrality N.*

The Proposition, proven in the Appendix A, is illustrated in Figure 7. It offers a rationalization of our main finding (of a U-shaped relation between centrality and the profitability of insider trades), provided that the outsider's learning capacity is not too small. It can be interpreted as follows. Suppose first his capacity exceeds the threshold. Peripheral firms have so few links that the outsider can thoroughly analyse them all, and thus he understands the cash flow implications of these links better than the insider does. For such firms, each additional link is better understood by the outsider than the insider, and therefore reduces the insider's informational advantage and her expected profit. In contrast, for central firms – that is, firms with more links than the outsider (given his limited learning capacity) can comprehend – the insider knows more than the outsider about the link-related cash flows. For such firms, adding links magnifies the insider's advantage and thereby increases her expected profit. The resulting pattern for the insider's expected profit is a U-shaped function of the firm's centrality.

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Figure 7 about here

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In the case in which the outsider's learning capacity is below the threshold, the downward-sloping branch of the U shape disappears. Indeed, the outsider's capacity is then so low that he is poorly informed even when there are only a few links to investigate; in such a situation, adding links amplifies the insider's relative advantage and expected profit starting from the very first link; that is, her expected profit is monotonically increasing in the firm's centrality.

C Discussion of the model's assumptions

Our theory proposes a mechanism that leads to the U-shaped relation between centrality and the profitability of insider trades that we observe in the data. This mechanism is based on the recognition that outside investors' capacity for analyzing firms is large but finite. More specifically, the key premise of the model is that the insider and the outsider are endowed with different learning technologies. On the one hand, the insider learns about links by virtue of managing her firm. Hence her information is costless and does not deteriorate as the number of links grows. On the other hand, the outsider must consume resources in order to learn, and because these resources are in limited supply, the precision of his information decreases in the number of links. The U shape arises from the interplay between these two learning technologies. Provided the outsider's capacity is large, he learns more than the insider about peripheral firms, which reduces the insider's relative advantage when links are added. But at some point his advantage is exhausted and the insider's advantage grows with centrality.

We believe that these assumptions capture realistic features of the market. A large literature builds on the premise that insiders develop a thorough understanding of their firm by managing operations. We acknowledge this informational advantage but also emphasize that it should be reduced when they pertain to aspects of firms' operations that are sensitive to the behaviour of other firms. Specifically, we argue that the insider is not as capable as the outsider of comprehending "link-related cash flows", that is, cash flows that involve firms other than her own. These cash flows indeed depend not only on the insider's firm but also on linked firms, and therefore on these firms' own links (e.g., their customers and suppliers) and so on. The outsider, in contrast, follows closely (and trades) many of the linked firms and is better equipped to understand complex connections (even if his understanding comes at a cost).

We could endow the insider with a technology to learn about links, similar to the outsider's (in addition to her costless technology). We conjecture that the U shape is preserved provided that the insider's capacity is smaller than the outsider's. In this case indeed, the insider's information deteriorates with the number of links at a faster rate than the outsider's.[19] This preserves the downward sloping branch of the U shape. The upward sloping branch continues to hold thanks to the insider's costless technology. Thus, the model's prediction holds if the outsider's learning capacity is large enough, namely larger than both the threshold discussed in the Proposition above and the insider's capacity.

[19]Indeed, the expressions for τ^{ϵ}_{n0} presented in the Lemma imply that $\frac{\partial}{\partial k}(\frac{\partial \tau^{\epsilon}_{nO}}{\partial N}) \geq 0$.

The model assumes further that the outsider cannot learn φ, the cash flow unrelated to any link. This assumption is meant to capture the notion that investors facing capacity constraints prefer learning about shocks common to many firms to shocks that affect only one firm (e.g., Lin and Xiong (2006)). The reason is that information about common shock can be used for valuing more than one firm. We conjecture therefore that the U shape is maintained in an extension of the model in which the outsider can learn about firm-specific shocks and invests in multiple stocks. In such a setup, the outsider chooses (endogenously) to prioritize information about link-related shocks (which involve several firms) over information about firm-specific shocks.

Last but not least, our results are not sensitive to the exact nature of the learning technology operated by the outsider. They hold across the three information capacity constraints we assume. What they depend on is: (i) the outsider being able to understand links of peripheral firms better than insiders can, provided his learning capacity is large enough, and (ii) that advantage being diminished for firms that are relatively more central. We believe both features to be plausible.

VI Conclusion

We study the relation between firm centrality in the product network and managers' market timing ability in the context of open-market share repurchases and insider purchases. Using U.S. data over the period 1996-2015, we find a U-shaped relation between long-run abnormal returns and firm centrality in the Input-Output (I-O) trade flow networks for repurchase announcements. We find similar results for insider trading for the period

2007-2015 for which insider data was available. This pattern is consistent with a model we develop in which investors are endowed with a limited capacity for analyzing firms. Consequently, they understand peripheral firms (whose cash flows depend on only a few economic links) better than they do central firms (whose cash flows depend on many such links). It follows that additional links attenuate insiders' informational advantage regarding peripheral firms (provided outsiders' learning capacity is large enough), whereas they amplify that advantage regarding central firms, making it a U-shaped function of firm centrality. The resulting pattern for the profit of insiders who repurchase shares below fair value is also a U-shaped function of firm centrality. Of course other mechanisms might produce a U-shape, hence alternative explanations for our empirical findings may be a fruitful future research direction that can lead to further refinements of our understanding of the potential market timing ability of managers.

TABLE 1
Summary Statistics of I-O Industry Centrality in the Supplier Networks.

Supplier networks are constructed with the Input-Output tables from the U.S. BEA in 1997, 2002, and 2007. Eigenvector centrality and K-B centrality are calculated using the symmetric supplier network of all industry pairs. Degree centrality, strength centrality, betweenness centrality, average shorted path, and maximum shorted path are all measured using the connections in each I-O network. A substantial connection is defined as a connection where one industry supplies at least 1% of the total inputs of the connected industry. Panel A reports summary statistics of all industries in each I-O network; Panel B reports summary statistics of I-O industries with observations in the CRSP/Compustat Merged database. Panel C reports summary statistics of I-O industries in the final sample of buyback announcements (satisfying all filters stated in the text).

Panel A: All I-O Industries in the Network

	I-O Supplier Network 1997						I-O Supplier Network 2002						I-O Supplier Network 2007					
	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N
Degree	23.08	16	2	443	34.45	470	24.5	17	5	372	32.83	410	24.1	18	4	338	29.41	368
Strength	0.00	0.00	0.00	0.06	0.00	470	0.00	0.00	0.00	0.05	0.00	410	0.00	0.00	0.00	0.05	0.00	368
K-B	3.76	3.28	0	29.77	2.03	470	4.62	4.01	0	40.14	2.71	410	4.61	3.80	0	32.39	3.02	368
Eigenvector	0.04	0.03	0.01	0.42	0.03	470	0.04	0.04	0.01	0.39	0.03	410	0.04	0.04	0.01	0.38	0.03	368
Betweenness	0.00	0.00	0	0.32	0.02	470	0.00	0.00	0	0.26	0.02	410	0.00	0.00	0	0.30	0.02	368
Avg. shortest path	1.97	1.97	1.05	2.65	0.10	470	1.95	1.96	1.09	2.36	0.09	410	1.96	1.96	1.08	2.57	0.12	368
Max shortest path				3		470				3		410				3		368

Panel B: I-O Industries with Observations in CRSP/Compustat Merged

	I-O Supplier Network 1997						I-O Supplier Network 2002						I-O Supplier Network 2007					
	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N
Degree	23.05	16	2	443	30.93	422	24.32	17	5	372	29.46	368	23.80	18	4	338	26.04	338
Strength	0.00	0.00	0.00	0.06	0.00	422	0.00	0.00	0.00	0.05	0.00	368	0.00	0.00	0.00	0.05	0.00	338
K-B	3.75	3.28	0	14.85	1.71	422	4.62	4.00	2.08	40.14	2.80	368	4.56	3.79	0	32.39	2.87	338
Eigenvector	0.04	0.03	0.01	0.42	0.03	422	0.04	0.04	0.01	0.35	0.02	368	0.04	0.04	0.01	0.38	0.03	338
Betweenness	0.00	0.00	0	0.32	0.02	422	0.00	0.00	0.00	0.26	0.01	368	0.00	0.00	0.00	0.30	0.02	338

Panel C: I-O Industries with Buyback Events in the Final Sample

	I-O Supplier Network 1997						I-O Supplier Network 2002						I-O Supplier Network 2007					
	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N	Mean	Median	Min.	Max.	SD	N
Degree	23.64	17	2	294	25.74	321	26.67	17	5	372	33.62	239	23.57	18	4	215	20.56	272
Strength	0.00	0.00	0.00	0.02	0.00	321	0.00	0.00	0.00	0.05	0.00	239	0.00	0.00	0.00	0.02	0.00	272
K-B	3.85	3.29	1.79	14.85	1.87	321	4.74	3.97	2.08	40.14	3.24	239	4.60	3.78	1.91	32.39	3.01	272
Eigenvector	0.04	0.03	0.01	0.16	0.02	321	0.04	0.04	0.01	0.35	0.03	239	0.04	0.04	0.01	0.27	0.03	272
Betweenness	0.00	0.00	0	0.10	0.01	321	0.00	0.00	0.00	0.26	0.02	239	0.00	0.00	0.00	0.09	0.01	272

TABLE 2
Most Central Industries in I-O Supplier Networks.

The top 15 most central industries in every Input-Output supplier network. Supplier networks are constructed with the Input-Output tables from the U.S. BEA in 1997, 2002, and 2007. All I-O detailed industries are ranked primarily by degree centrality. Degree centrality is an industry's number of inter-industry connections measured using the substantial connections in the U.S. BEA Input-Output Supplier Network at the detailed level. A substantial connection is defined as one where an industry supplies at least 1% of the total inputs of the connected industry.

I-O Supplier Network 1997

Rank	Degree	I-O Industry Name
1	443	Wholesale trade
2	408	Management of companies and enterprises
3	294	Truck transportation
4	181	Power generation and supply
5	147	Real estate
6	140	Iron and steel mills
7	135	Paperboard container manufacturing
8	108	Plastics plumbing fixtures and all other plastics products
9	99	Monetary authorities and depository credit intermediation
10	84	Lessors of nonfinancial intangible assets
11	80	Other basic organic chemical manufacturing
12	78	Scientific research and development services
13	76	Plastics packaging materials, film and sheet
14	75	Telecommunications
15	73	Petroleum refineries

I-O Supplier Network 2002

Rank	Degree	I-O Industry Name
1	372	Wholesale trade
2	367	Management of companies and enterprises
3	226	Truck transportation
4	204	Real estate
5	178	Electric power generation, transmission, and distribution
6	130	Monetary authorities and depository credit intermediation
7	101	Iron and steel mills and ferroalloy manufacturing
8	100	Lessors of non-financial intangible assets
9	99	Other plastics product manufacturing
10	96	Paperboard container manufacturing
11	86	Telecommunications
12	82	Employment services
13	80	Semiconductor and related device manufacturing
14	74	Scientific research and development services
15	73	Plastics packaging materials & unlaminated film & sheet manuf.

I-O Supplier Network 2007

Rank	Degree	I-O Industry Name
1	338	Wholesale trade
2	314	Management of companies and enterprises
3	215	Truck transportation
4	115	Real estate
5	112	Iron and steel mills and ferroalloy manufacturing
6	92	Electric power generation, transmission, and distribution
7	92	Monetary authorities and depository credit intermediation
8	80	Petroleum refineries
9	79	Paperboard container manufacturing
10	78	Lessors of non-financial intangible assets
11	78	Architectural, engineering, and related services
12	78	Insurance carriers
13	75	Other plastics product manufacturing
14	74	Turned product and screw, nut, and bolt manufacturing
15	74	Legal services

TABLE 3
Least Central Industries in I-O Supplier Networks.

The bottom 15 least central industries in every Input-Output supplier network. Supplier networks are constructed with the Input-Output tables at the detailed level from the U.S. BEA in 1997, 2002, and 2007. All I-O detailed industries are ranked primarily by degree centrality. Degree centrality is an industry's number of inter-industry connections measured using the substantial connections in the U.S. BEA Input-Output Supplier Network at the detailed level. A substantial connection is defined as one where an industry supplies at least 1% of the total inputs of the connected industry.

I-O Supplier Network 1997

Rank	Degree	I-O Industry Name
456	8	Insurance agencies, brokerages, and related
457	8	Offices of physicians, dentists, & other health practitioners
458	7	Stationery and related product manufacturing
459	7	Envelope manufacturing
460	7	Vitreous china and earthenware articles manufacturing
461	7	Funds, trusts, and other financial vehicles
462	7	Home health care services
463	7	Spectator sports
464	6	Hunting and trapping
465	6	Investigation and security services
466	5	Nursing and residential care facilities
467	5	Facilities support services
468	3	Colleges, universities, and junior colleges
469	2	Elementary and secondary schools
470	2	Religious organizations

I-O Supplier Network 2002

Rank	Degree	I-O Industry Name
396	9	Dental laboratories
397	9	Hospitals
398	9	Junior colleges, colleges, universities, and professional schools
399	9	Spectator sports
400	9	Religious organizations
401	8	Video tape and disc rental
402	8	Biological product (except diagnostic) manufacturing
403	8	Industrial process furnace and oven manufacturing
404	8	Support activities for printing
405	8	Museums, historical sites, zoos, and parks
406	7	Leather and hide tanning and finishing
407	7	Home health care services
408	6	Other amusement and recreation industries
409	5	Propulsion units and parts for space vehicles & guided missiles
410	5	Elementary and secondary schools

I-O Supplier Network 2007

Rank	Degree	I-O Industry Name
354	7	Commercial and industrial machinery and equipment repair and maintenance
355	7	Guided missile and space vehicle manufacturing
356	7	Spectator sports
357	7	Grantmaking, giving, and social advocacy organizations
358	6	Death care services
359	6	Custom computer programming services
360	6	Propulsion units & parts for space vehicles and guided missiles
361	6	Office administrative services
362	5	Funds, trusts, and other financial vehicles
363	5	Investigation and security services
364	5	Individual and family services
365	5	Residential mental retardation, mental health, substance abuse and other facilities
366	5	Elementary and secondary schools
367	5	Civic, social, professional, and similar organizations
368	4	Junior colleges, colleges, universities, and professional schools

TABLE 4
The Relation Between the Volatility of Operating Cash Flows and Network Centrality

This table shows how the volatility of operating cash flows (OCF Volatility) relates to network centrality. In Panel A, OCF Volatility is regressed on centrality for all buyback announcements, using either firm size (market capitalization) or firm fixed-effects as controls. Panel B presents the results of a sign test conducted on pairs of buyback announcements made by the same firm. The difference in OCF Volatility, centrality and size between the two announcements in a pair are denoted ΔOCF Volatility, ΔCentrality and ΔSize, respectively. Panel C presents estimates from a cross-sectional regression of differences in volatility within buyback pairs (ΔOCF Volatility) on differences in centrality within the pairs (ΔCentrality). In regressions, ***, ** and * denote significance levels at 1%, 5%, and 10%, respectively

Panel A: Panel regression for all buyback announcements

	OCF Volatility		**OCF Volatility**	
	Coeff.	t-stat	Coeff.	t-stat
Intercept	5.507***	136.65	4.552***	156.99
Centrality	0.134***	3.46	0.367***	5.92
Size	-0.119***	-24.04		
Firm fixed-effects	No		Yes	
Observations	8303		8303	

Panel B: Sign test on pairs of buyback announcements by the same firm

Sign of ΔCentrality: Positive for 1691 pairs (zero for 64)

Sign of ΔOCF Volatility:	**Observed**	**Expected**
Positive	798	767
Negative	736	767
Zero	59	59
All	1593	1593

Two-sided test that the median of ΔOCF Volatility equals zero:
p-value = 0.0597

Panel C: Regression across pairs of buyback announcements by the same firm

	ΔOCF Volatility	
	Coeff.	t-stat
Intercept	0.0309	1.15
ΔCentrality	0.221*	1.74
ΔSize	-0.142***	-6.09
Observations	1593	

TABLE 5
Firm Centrality and IRATS Cumulative Abnormal Returns (CAR) after Repurchase Announcements

The table presents the long-run IRATS Cumulative Abnormal Returns (CAR) for firms repurchase announcements using the three-factor (Panel A) and five-factor (Panel B) Fama-French models. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) = a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The numbers reported are sums of the intercepts of cross-sectional regressions over the relevant event-time-periods expressed in percentage terms. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 3-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-5.95**	-18.25	-5.66**	-7.98	-5.38**	-7.03	-7.01**	-9.53	-6.07**	-8.59	-5.8**	-7.96	0.41	0.41	0.27	0.27
+12	4.09**	7.97	7.88**	6.98	3.8**	3.38	1.58	1.4	1.16	1.07	5.53**	4.34	6.72**	4.3	4.37**	2.62
+24	10.07**	12.9	16.47**	9.74	9.3**	5.21	10.23**	5.88	1.04	0.65	12.74**	6.73	15.43**	6.63	11.69**	4.72
+36	16.35**	16.57	25.44**	11.89	15.6**	6.85	15.16**	6.99	5.05*	2.41	20.33**	8.71	20.39**	6.81	15.28**	4.87
+48	20.32**	17.52	30.02**	11.85	20.41**	7.6	19.22**	7.62	8.2**	3.26	23.79**	8.82	21.83**	6.11	15.6**	4.23
Observations	8401		1682		1681		1683		1675		1680		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-6.11**	-18.24	-5.79**	-7.87	-5.73**	-7.34	-6.43**	-8.49	-6.88**	-9.46	-5.7**	-7.63	1.09	1.05	1.17	1.13
+12	3.1**	5.81	6.84**	5.79	2.47*	2.13	1.88	1.59	-0.32	-0.28	4.68**	3.53	7.16**	4.4	5**	2.88
+24	7.91**	9.69	15.09**	8.51	8.85**	4.76	8.69**	4.72	-3.44*	-2.08	10.69**	5.39	18.53**	7.64	14.13**	5.47
+36	12.9**	12.42	22.95**	10.2	16.18**	6.76	10.64**	4.6	-1.84	-0.85	17.22**	6.99	24.79**	7.91	19.06**	5.8
+48	15.68**	12.76	26.38**	9.85	19.95**	7	13.38**	4.95	-1.67	-0.63	20.72**	7.24	28.05**	7.45	22.39**	5.74
Observations	8401		1682		1681		1683		1675		1680		-		-	

TABLE 6
Calendar Time Monthly Abnormal Returns (AR) after Repurchase Announcements

The table presents the Calendar Time monthly Abnormal Returns (AR) for firms repurchase announcements using the three-factor (Panel A) and five-factor (Panel B) Fama-French models. In this method, event firms that have announced an open market buyback in the last calendar months form the basis of the calendar month portfolio. A single time-series regression is run with the excess returns of the calendar portfolio as the dependent variable and the returns of factors used as the independent variables. The following regression is used for the five-factor model:

$$(R_t - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where R_t is the monthly return on the constructed portfolio in the calendar month t. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel B: 3-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q4		Q5-Q4	
	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat
-6	-0.77**	-6.09	-0.83**	-4.89	-0.74**	-3.83	-0.76**	-3.73	-0.78**	-4.19	-0.54**	-2.93	-0.05	-0.21	0.24	0.91
+12	0.34**	2.86	0.68**	4.82	0.39**	2.61	0.19	1.05	0.15	0.91	0.37*	2.26	0.53**	2.49	0.22	0.96
+24	0.38**	3.48	0.66**	5.24	0.35**	2.86	0.47**	3.01	0.1	0.7	0.43**	2.84	0.56**	2.94	0.33^{+}	1.6
+36	0.38**	3.63	0.66**	5.4	0.39**	3.19	0.35**	2.69	0.11	0.85	0.44**	2.96	0.55**	2.99	0.33^{+}	1.62
+48	0.34**	3.31	0.59**	4.99	0.37**	3.04	0.29*	2.45	0.1	0.76	0.39**	2.66	0.49**	2.73	0.29^{+}	1.45
Observations	8401		1682		1681		1683		1675		1680		-		-	

Panel B: 5-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q4		Q5-Q4	
	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat	AR	*t*-stat
-6	-0.82**	-6.46	-0.85**	-4.8	-0.79**	-3.9	-0.72**	-3.57	-0.99**	-5.3	-0.6**	-3.17	0.14	0.57	0.39^{+}	1.49
+12	0.28*	2.26	0.62**	4.22	0.28^{+}	1.78	0.24	1.38	0.01	0.03	0.32^{+}	1.92	0.61**	2.76	0.31^{+}	1.34
+24	0.3**	2.65	0.6**	4.63	0.31*	2.42	0.42**	2.62	-0.1	-0.67	0.39*	2.41	0.7**	3.63	0.49*	2.25
+36	0.29**	2.72	0.59**	4.66	0.36**	2.78	0.25^{+}	1.89	-0.05	-0.41	0.38**	2.46	0.64**	3.5	0.43*	2.13
+48	0.25*	2.42	0.52**	4.24	0.34**	2.64	0.19	1.56	-0.05	-0.4	0.34*	2.23	0.57**	3.16	0.39*	1.95
Observations	8401		1682		1681		1683		1675		1680		-		-	

TABLE 7
Relation between Firm Characteristics and Centrality.

Average values of firm characteristics in the final sample of buyback events (first row) and the *p*-value for their difference from 0.5 (second row), as well as the average values in each centrality quintile group (3^{rd}-7^{th} rows) and comparisons across centrality sub-groups (last two rows). All buyback events are ranked by Degree Centrality Score and then assigned into one of five quintile groups: Q1 indicates the least central group; Q2, Q3, and Q4 indicate increasing centrality; and Q5 indicates the most central group. Degree centrality is an industry's number of inter-industry connections and is measured using the substantial connections in the U.S. BEA Input-Output Supplier Network at the detailed level. A substantial connection is defined as a connection where one industry supplies at least 1% of the total inputs of the connected industry. All variables, except U-index and EU-index, are standardized scores ranging from 0 to 1, and the scores are calculated across all firms in the CRSP universe in the same calendar month.

	Centrality	Volatility	(1-R2)	Market_Beta	Analyst_Cov.	Market_Cap.	Prior_Returns	BE/ME	U-index	EU-index
All	0.46	0.37	0.35	0.59	0.67	0.7	0.41	0.45	8.2	3.05
p-value diff. 0.5	0	0	0	0	0	0	0	0	-	-
Centrality: 1	0.11	0.38	0.4	0.55	0.67	0.68	0.41	0.41	8.12	3.16
Centrality: 2	0.31	0.37	0.36	0.58	0.64	0.69	0.4	0.42	8.18	3.06
Centrality: 3	0.47	0.35	0.34	0.59	0.69	0.73	0.42	0.44	8	2.92
Centrality: 4	0.61	0.37	0.34	0.61	0.66	0.7	0.41	0.46	8.27	3.07
Centrality: 5	0.78	0.37	0.33	0.6	0.69	0.72	0.42	0.51	8.43	3.02
Q1-Q4 p-value	0	0.72	0	0	0.15	0.03	0.87	0	0.1	0.03
Q5-Q4 p-value	0	0.34	0.12	0.41	1.1e-03	0.03	0.73	0	0.06	0.3

TABLE 8
IRATS Cumulative Abnormal Returns after Double-sorting: Small versus large Firms

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms whose Market Capitalization (cross-sectional) score is below the median score of all events. Panel B reports the results for firms whose Market Capitalization (cross-sectional) score is above the median score of all events. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: Small (below median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-9.89**	-18.2	-10.19**	-8.91	-8.14**	-6.45	-10.55**	-8.02	-11.39**	-10.07	-9.28**	-7.47	1.2	0.74	2.11	1.26
+12	4.71**	5.33	9.61**	5.25	1.62	0.87	2.45	1.17	2.38	1.32	7.27**	3.08	7.23**	2.82	4.89+	1.65
+24	12.25**	8.91	19.28**	6.83	10.34**	3.39	12.46**	3.72	1.9	0.7	16.89**	4.82	17.38**	4.44	14.99**	3.38
+36	19.25**	10.95	28.45**	7.87	21.35**	5.35	13.85**	3.3	6.75+	1.86	25.32**	5.91	21.7**	4.23	18.57**	3.31
+48	23.48**	11.31	32.35**	7.43	28**	5.9	16.46**	3.35	9.25*	2.12	29.69**	6.03	23.1**	3.75	20.44**	3.11
Observations	4201		896		873		765		865		802		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: large (above median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.17**	-5.58	-0.9	-1.02	-2.58**	-2.96	-3.18**	-3.78	-1.87*	-2.09	-2.11*	-2.44	0.98	0.78	-0.23	-0.19
+12	1.3*	2.15	3.58*	2.49	3.69**	2.71	1.14	0.88	-3.33*	-2.55	2.14	1.58	6.91**	3.56	5.47**	2.91
+24	3.54**	3.95	10.31**	5.03	7.36**	3.65	4.89*	2.5	-9.29**	-4.91	5.74**	2.74	19.6**	7.03	15.03**	5.33
+36	6.39**	5.6	16.42**	6.38	10.46**	4.14	7.16**	2.89	-11.28**	-4.63	10.22**	3.77	27.7**	7.82	21.49**	5.9
+48	8.05**	5.85	19.11**	6.26	12.16**	3.97	9.65**	3.32	-13.6**	-4.45	13.61**	4.19	32.71**	7.57	27.22**	6.1
Observations	4200		786		808		918		810		878		-		-	

TABLE 9
IRATS Cumulative Abnormal Returns after Double-sorting: Centrality x (Analyst Coverage)

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms whose Analyst Coverage (cross-sectional) score is below the median score of all events. Panel B reports the results for firms whose Analyst Coverage (cross-sectional) score is above the median score of all events. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: low Analyst Coverage (below median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-6.97**	-12.97	-6.98**	-5.69	-7.15**	-6.48	-8.23**	-6.28	-6.68**	-5.85	-5.49**	-4.37	-0.3	-0.18	1.2	0.7
+12	3.09**	3.45	8.73**	4.52	-1.26	-0.7	3.32	1.61	1.03	0.58	4.32+	1.73	7.7**	2.93	3.29	1.07
+24	9.72**	6.99	18.63**	6.3	7.6*	2.54	10.19**	3.12	0.48	0.18	12.52**	3.4	18.16**	4.56	12.04**	2.64
+36	15.74**	8.86	27.05**	7.12	17.8**	4.57	10.63*	2.58	4	1.13	19.65**	4.34	23.05**	4.43	15.65**	2.72
+48	18.87**	8.99	28.8**	6.34	20.05**	4.35	14.27**	2.97	5.42	1.27	26.58**	5.03	23.38**	3.75	21.17**	3.12
Observations	3727		749		815		700		768		695		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: High Analyst Coverage (above median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-6.01**	-14.42	-4.96**	-5.4	-5.91**	-6.15	-6.03**	-6.53	-6.66**	-6.9	-6.63**	-7.35	1.7	1.28	0.03	0.02
+12	2.53**	3.83	4.82**	3.22	5**	3.22	0.95	0.67	-3.31*	-2.3	5.02**	3.4	8.13**	3.91	8.34**	4.04
+24	5.23**	5.32	10.05**	4.62	9.45**	4.08	6.6**	3.04	-8.83**	-4.18	9.3**	4.17	18.88**	6.23	18.12**	5.9
+36	8.76**	7.06	17.64**	6.45	12.75**	4.42	9.68**	3.56	-10.15**	-3.77	14.16**	5.01	27.79**	7.24	24.31**	6.23
+48	10.42**	7.04	21.92**	6.74	15.99**	4.65	11.13**	3.51	-12.86**	-3.85	15.81**	4.75	34.79**	7.46	28.67**	6.08
Observations	4203		833		768		901		822		879		-		-	

TABLE 10
IRATS Cumulative Abnormal Returns after Double-sorting: Centrality x (Idiosyncratic Risk)

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) = a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms whose Idiosyncratic Risk (cross-sectional) score is below the median score of all events. Panel B reports the results for firms whose Idiosyncratic Risk (cross-sectional) score is above the median score of all events. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: low Idiosyncratic Risk

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-5.21**	-12.19	-4.36**	-4.05	-5.28**	-5.42	-5.14**	-5.31	-6.07**	-6.63	-4.87**	-5.56	1.7	1.2	1.2	0.95
+12	2.25**	3.21	5.58**	3.13	2.39	1.52	1.57	1.01	-0.72	-0.48	3.49*	2.38	6.3**	2.7	4.21*	2
+24	5.79**	5.5	11.64**	4.56	8.63**	3.59	6.31**	2.64	-4.44*	-2.03	9**	3.96	16.08**	4.79	13.44**	4.27
+36	8.53**	6.44	16.46**	5.18	13.51**	4.47	7.1*	2.4	-5.21+	-1.85	13.87**	4.84	21.67**	5.1	19.08**	4.75
+48	8.47**	5.42	15.81**	4.25	12.99**	3.65	8.1*	2.36	-5.8+	-1.71	14.26**	4.22	21.62**	4.29	20.06**	4.19
Observations	4200		673		805		878		910		934		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: High Idiosyncratic Risk

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-6.96**	-13.56	-6.94**	-7.02	-6.16**	-5.16	-7.85**	-6.69	-7.19**	-6.22	-6.75**	-5.32	0.25	0.17	0.44	0.26
+12	4.12**	5.1	7.75**	4.93	2.62	1.54	2.67	1.48	0.24	0.14	6.57**	2.79	7.51**	3.29	6.34*	2.2
+24	10.17**	8.14	17.38**	7.19	9.39**	3.35	11.66**	4.11	-2.44	-0.96	12.78**	3.7	19.82**	5.64	15.22**	3.55
+36	17.54**	10.91	27.49**	8.84	18.9**	5.15	15.5**	4.29	2.25	0.66	21.46**	5.04	25.24**	5.45	19.21**	3.51
+48	23.56**	12.31	34.2**	9.14	26.82**	6.08	20.82**	4.88	3.25	0.78	30.25**	6.15	30.96**	5.51	27**	4.18
Observations	4201		1009		876		805		765		746		-		-	

TABLE 11
IRATS Cumulative Abnormal Returns after Double-sorting: Centrality x Volatility

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms whose Volatility (cross-sectional) score is below the median score of all events. Panel B reports the results for firms whose Volatility (cross-sectional) score is above the median score of all events. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: low Volatility (below median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.9**	-9.69	-1.29+	-1.9	-3.42**	-5.15	-3.13**	-4.79	-3.83**	-5.35	-2.83**	-4.42	2.53**	2.56	1	1.04
+12	-0.06	-0.11	1.93	1.52	0.45	0.36	-0.92	-0.8	-1.49	-1.25	0.56	0.46	3.41*	1.96	2.04	1.2
+24	0.39	0.48	6.23**	3.31	1.12	0.61	0.98	0.55	-6.02**	-3.25	0.51	0.27	12.25**	4.64	6.53**	2.45
+36	2.13*	1.96	9.41**	3.93	3.73	1.57	2.69	1.14	-6.85**	-2.81	2.2	0.86	16.26**	4.76	9.06**	2.55
+48	4.37**	3.28	11.29**	3.8	6.62*	2.21	3.63	1.29	-6.26*	-2.1	6.69*	2.13	17.55**	4.17	12.95**	2.99
Observations	4201		791		826		921		819		844		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: High Volatility (above median)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-8.86**	-14.98	-10.12**	-8.17	-7.33**	-5.3	-9.27**	-6.38	-9.24**	-7.51	-8.29**	-6.2	-0.88	-0.5	0.95	0.52
+12	6.12**	6.68	11.33**	5.91	3.79+	1.95	5.6*	2.54	1.1	0.6	8.55**	3.62	10.23**	3.84	7.44**	2.48
+24	15.51**	11.09	22.83**	7.89	15.45**	4.86	18.6**	5.39	0.01	3.4e-03	20.95**	6.05	22.82**	5.76	20.94**	4.76
+36	23.55**	13.35	34.69**	9.43	26.59**	6.47	20.42**	4.8	4.14	1.16	31.84**	7.62	30.56**	5.96	27.71**	5.04
+48	27.57**	13.35	39.7**	9.17	31.51**	6.53	26.29**	5.34	4.86	1.12	34.68**	7.29	34.84**	5.67	29.81**	4.62
Observations	4200		891		855		762		856		836		-		-	

TABLE 12
IRATS Cumulative Abnormal Returns after Double-sorting: Centrality x U-index

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms with high U-index (larger than 10). Panel B reports the results for firms with low U-index (smaller than 6). The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: low U-index (lower than 6)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	20.6**	23.03	18.65**	11.81	23.74**	8.99	18.27**	10.02	19.85**	11.25	23.01**	11.17	-1.2	-0.51	3.16	1.16
+12	1.69	1.49	0.83	0.36	4.34^{+}	1.68	7.17**	2.82	-6.71**	-2.81	-0.62	-0.21	7.54*	2.28	6.09^{+}	1.62
+24	3.45*	2.02	7.33*	2.12	6.05	1.51	9.26*	2.48	-12.45**	-3.57	3.32	0.74	19.78**	4.03	15.76**	2.77
+36	7.75**	3.63	17.27**	4.02	11.94*	2.39	10.66*	2.34	-12.07**	-2.64	8.51	1.51	29.34**	4.67	20.58**	2.84
+48	11.84**	4.7	20.97**	4.07	15.94**	2.66	16.88**	3.22	-9.23	-1.63	12.8*	2	30.2**	3.95	22.03**	2.58
Observations	1272		279		263		281		247		202		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: High U-index (greater than 10)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-26.73**	-34	-26.5**	-14.42	-25.03**	-15.63	-29.5**	-14.3	-27.96**	-16.51	-25.59**	-14.74	1.46	0.58	2.37	0.98
+12	3.06*	2	5.51^{+}	1.73	-3.19	-1.05	-0.08	-0.02	4.45	1.46	8.13^{+}	1.96	1.06	0.24	3.68	0.72
+24	16.07**	6.65	20.01**	3.82	14.12**	2.69	11.51*	1.98	7.25	1.55	26.5**	4.47	12.76*	1.82	19.25**	2.55
+36	25.06**	7.99	32.57**	4.76	26.47**	3.77	12.02	1.64	12.82*	1.98	41.35**	5.65	19.75*	2.1	28.53**	2.92
+48	32.67**	8.78	36.98**	4.57	40.54**	4.73	16.07^{+}	1.87	20.04**	2.6	47.53**	5.52	16.94^{+}	1.52	27.49**	2.38
Observations	1657		327		341		282		347		360		-		-	

TABLE 13
IRATS Cumulative Abnormal Returns after Double-sorting: Centrality x EU-index

The tables present the long-run IRATS Cumulative Abnormal Returns (CAR) for subsets of firms' repurchase announcements using the five factor Fama-French model. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. Panel A reports the results for firms with high EU-index (larger than 3). Panel B reports the results for firms with low EU-index (smaller than 2). The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 5-Factor IRATS Cumulative Abnormal Returns: low EU-index (lower than 2)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	6.82**	11.15	5.4**	4	8.16**	6.16	5.69**	4.47	9.32**	5.45	6.01**	4.71	-3.93*	-1.8	-3.32^{+}	-1.56
+12	0.19	0.18	-2.77	-1.11	3.28	1.48	2.05	0.88	-5.13^{+}	-1.96	1.95	0.9	2.36	0.65	7.08*	2.08
+24	0.87	0.54	0.03	0.01	3.8	1.13	4.7	1.33	-13.2**	-3.44	3.92	1.12	13.24**	2.46	17.12**	3.29
+36	3.58^{+}	1.74	10.15*	2.09	5.68	1.38	6.65	1.48	-18.06**	-3.63	8^{+}	1.73	28.21**	4.06	26.07**	3.84
+48	6.87**	2.78	12.29*	2.15	8.7^{+}	1.85	11.69*	2.18	-14.33*	-2.18	10.35^{+}	1.86	26.62**	3.06	24.68**	2.87
Observations	919		159		200		222		145		193		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns: High EU-index (greater than 3)

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-16.56**	-23.03	-17.19**	-12.01	-13.29**	-7.74	-19.14**	-10.84	-17.02**	-10.91	-16.66**	-10.37	-0.17	-0.08	0.36	0.16
+12	5.83**	5.04	11.03**	4.83	3.87	1.62	1.45	0.54	2.87	1.17	9.02**	2.87	8.16**	2.44	6.14^{+}	1.54
+24	16.35**	9.1	22.12**	6.23	16.94**	4.24	14.9**	3.51	2.12	0.58	23.37**	5	20**	3.92	21.26**	3.58
+36	25.53**	11.1	35.54**	7.74	30.59**	5.82	16.74**	3.14	7.05	1.45	34.67**	6.06	28.49**	4.26	27.61**	3.68
+48	31.7**	11.65	40.82**	7.41	42.59**	6.74	20.79**	3.31	10.87^{+}	1.86	38.37**	5.85	29.95**	3.73	27.5**	3.13
Observations	2832		622		586		512		557		555		-		-	

TABLE 14
The decision to repurchase: Logistic and Probit Regressions and Network Centrality

This table presents the results for the firm's decision to repurchase using logistic and probit regressions on firm-month observations. The dependent variable is a binary variable indicating whether there was a repurchase announcement in a given month by a given firm. **, * and + denote significance levels at 1%, 5%, and 10%, respectively. Year and industry controls are used. See the Appendix B for detailed definitions of the variables.

	Logistic		Probit	
	Coeff.	*t*-stat	Coeff.	*t*-stat
Intercept	-4.83**	-13.53	-2.38**	-17.33
Announced Repurchase in Previous 2 Years (0/1)	0.36**	13	0.15**	13.43
Market Cap.	0.63**	5.78	0.22**	5.07
BE/ME	0.25**	3.76	0.08**	3.22
Prior Returns	-0.78**	-15.36	-0.31**	-15.64
Total Payout in Event Year	2.9e-05	0.39	1.9e-05	0.59
Total Payout in Year before Event	-1.3e-04	-1.58	-6.2e-05^{+}	-1.8
Leverage	-0.55**	-7.47	-0.23**	-7.97
Profitability (ROA)	1.78**	10.02	0.6**	9.48
Operating Income (Percent assets)	0.55**	3.05	0.24**	3.54
Non-Operating Income (Percent assets)	0.29	0.21	0.15	0.28
Lag Dividend Payout Ratio	-0.28**	-4.89	-0.11**	-5.02
Liquid Assets (Percent assets)	0.05	0.52	0.02	0.61
Price/Earnings Ratio	2.4e-04	0.59	1e-04	0.64
Capital Expenditures (Percent assets)	-2.02**	-5.08	-0.78**	-5.15
Institutional Holdings	0.01**	6.69	2e-03**	6.55
Number of Institutions	1.4e-03**	7.35	6.2e-04**	8.04
Network Centrality	-3e-03	-0.03	-0.01	-0.14
Observations	516170		516170	

TABLE 15
Cross-Section Regressions: Univariate Analysis (one company feature per regression).

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998). The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on each firm characteristic in every post-buyback-announcement month gives the monthly coefficients. Centrality and centrality squared terms are in one regression. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the *t*-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	*t*-stat	Month	*t*-stat	Month	*t*-stat	Month	*t*-stat
Size Score	-6.17	-0.24	-12.91	-0.81	-45.05**	-2.84	-66.93**	-4.42
BE/ME Score	-48.96*	-3.01	-36.74**	-2.95	-22.81+	-2	1.5	0.13
Prior Returns Score	-42.68+	-1.97	-23.1	-1.44	10.38	0.67	12.96	1.08
U-index	-0.64	-0.29	-0.53	-0.38	-0.33	-0.28	1.62	1.4
EU-index	5.04	1.21	5.43+	1.78	8.94**	3.55	11.85**	4.81
Volatility	123.59**	3.45	100.73**	4.62	105.13**	6.26	104.75**	6.89
$(1-R^2)$	-24.5+	-1.94	-11.52	-0.8	30.28+	2.01	52.91**	3.94
Analyst Coverage Score	12.38	0.52	8.37	0.53	-9.83	-0.68	-21.34	-1.62
Centrality (Linear term)	-28.59	-1.25	-34.69*	-2.18	-25.94*	-2.04	-24.36*	-2.23
Centrality (Square term)	224.66**	3.85	157.52**	3	162.44**	3.99	136.81**	3.99
Observations	12		24		36		48	

TABLE 16
Cross-Section Regressions: Multivariate Analysis (all variables in one regression, including U-index).

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998). The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every post-buyback-announcement month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term, U-index, volatility, $(1-R^2)$, and analyst coverage. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	31.1	0.47	-22.59	-0.54	-15.02	-0.41	-49.79	-1.4
U-index	-3.35	-1.22	-3.22	-1.68	-4.53**	-2.77	-2.67^{+}	-1.85
Volatility	160.33**	4.46	132.56**	5.53	122.71**	6.45	109.2**	6.65
$(1-R^2)$	-57.85**	-3.41	-39.92*	-2.19	10.56	0.58	28.04^{+}	1.88
Analyst Coverage Score	15.43	0.59	11.18	0.53	2.36	0.14	2.21	0.15
Centrality (Linear term)	-39.6	-1.52	-41.21*	-2.31	-28.56^{+}	-1.98	-23.3^{+}	-1.92
Centrality (Square term)	237.19**	4.1	162.58**	2.89	173.56**	3.83	142.79**	3.8
Observations	12		24		36		48	

TABLE 17
Cross-Section Regressions: Multivariate Analysis (all variables in one regression, including components of U-index).

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998). The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every post-buyback-announcement month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term, size, book-to-market, prior returns, volatility, $(1-R^2)$, and analyst coverage. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	1.69	0.02	-43.86	-0.81	-37.11	-0.79	-51.51	-1.28
Size Score	88.61	1.67	50.43	1.34	-20.08	-0.51	-43.85	-1.34
BE/ME Score	-44.65*	-2.32	-38.71*	-2.28	-32.74*	-2.36	-18.61	-1.44
Prior Returns Score	-40.81+	-1.8	-20.97	-1.23	22.6	1.35	24.04+	1.86
Volatility	171.08**	4.35	136.58**	5.07	113.01**	5.03	96.98**	5.18
$(1-R^2)$	-43.32+	-2.14	-32.69+	-1.72	2.67	0.16	17.25	1.25
Analyst Coverage Score	-31.3	-0.89	-14.44	-0.49	19.91	0.74	28.95	1.34
Centrality (Linear term)	-37.11	-1.43	-39.06*	-2.19	-27.31+	-1.88	-22.48+	-1.85
Centrality (Square term)	240.36**	4.1	165.26**	2.91	175.48**	3.87	144.33**	3.83
Observations	12		24		36		48	

TABLE 18
Multivariate Cross-Section Regressions: Downgraded vs. Upgraded Events.

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998), for firms experiencing analyst recommendations downgrade (Panel A) and upgrade (Panel B) in the month prior to buyback announcement. The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every post-buyback-announcement month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term, U-index, volatility, $(1 - R^2)$, and analyst coverage. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: All variables in one model, only Downgraded events

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	-23.07	-0.2	-74.14	-0.77	-146.77$^+$	-1.86	-127.14$^+$	-1.82
U-index	-3.79	-0.62	-4.12	-1.09	-0.97	-0.32	-2.8	-1.08
Volatility	262.51**	3.69	204.11**	4.32	159.04**	4.41	148.18**	4.95
$(1 - R^2)$	-92.18	-1.78	-106.65**	-2.82	-60.14$^+$	-2.03	-21.17	-0.74
Analyst Coverage Score	5.68	0.07	56.53	1.06	66.41$^+$	1.69	51.82	1.61
Centrality (Linear term)	-46.87	-1.51	-42.61	-1.42	-30.21	-1.2	-45.92$^+$	-2.01
Centrality (Square term)	172.35	1.22	156.29	1.54	89.8	1.19	80	1.26
Observations	12		24		36		48	

Panel B: All variables in one model, only Upgraded events

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	39.11	0.45	-68.29	-0.98	-53.55	-0.79	-48.13	-0.73
U-index	-14.08*	-2.34	-7.62$^+$	-1.71	-11.63**	-3.28	-9.2**	-2.9
Volatility	108.37	1.6	163.86**	4.01	148.26**	4.22	132.7**	4.38
$(1 - R^2)$	-49.39	-1.66	-40.62	-1.19	2.84	0.1	16.31	0.66
Analyst Coverage Score	23.34	0.6	75.51$^+$	1.87	33.07	0.87	7.4	0.23
Centrality (Linear term)	-62.65*	-2.5	-46.54	-1.58	-54.41*	-2.4	-41.99$^+$	-1.91
Centrality (Square term)	415.33*	2.34	288.58*	2.44	215.6*	2.38	187.91*	2.38
Observations	12		24		36		48	

TABLE 19
Buyback announcements Calendar Time for all CEU-index Values

IRATS five factor cumulative abnormal returns after open market repurchase announcements for each Central Enhanced Undervaluation Index (CEU-index) value from 0 to 8. For each CEU-index value, we report the monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method combined with the Fama and French (2015) five-factor model for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The numbers reported are sums of the intercepts of cross-sectional regressions over the relevant event-time-periods expressed in percentage terms. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors.

	CEU-index 0		CEU-index 1		CEU-index 2		CEU-index 3		CEU-index 4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	8.1*	2.32	9.64**	7.1	3.78**	5.22	-0.72	-1.16	-3.87**	-6.43
+12	-9.87	-1.59	-2.86	-1.36	0.66	0.55	-0.43	-0.45	2.57**	2.61
+24	-9.33	-0.95	-8.85**	-2.82	0.57	0.31	-0.86	-0.6	5.66**	3.76
+36	-1.89	-0.14	-10.69**	-2.66	0.05	0.02	3.05	1.64	9.39**	4.9
+48	1.1	0.05	-8.04	-1.62	-0.43	-0.15	3.14	1.43	11.08**	4.87
Observations	22		194		813		1646		2144	

	CEU-index 5		CEU-index 6		CEU-index 7		CEU-index 8	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-7.92**	-9.93	-16.08**	-14.5	-21.88**	-12.05	-31.17**	-8.35
+12	3.94**	3.34	5.66**	3.22	8.28**	2.81	18.85^{+}	1.71
+24	10.81**	6	16.63**	5.9	25.97**	5.38	43.58**	3.24
+36	15.44**	6.7	24.72**	6.93	44.35**	7.01	67.1**	4.11
+48	18.82**	6.8	31.31**	7.41	54.96**	7.39	87.6**	4.75
Observations	1892		1076		486		128	

TABLE 20
Firm Centrality and IRATS Cumulative Abnormal Returns (CAR) after Repurchase Announcements, 2005-2015

The table presents the long-run IRATS Cumulative Abnormal Returns (CAR) for firms repurchase announcements using the three-factor (Panel A) and five-factor (Panel B) Fama-French models for only the period 2005-2015. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The numbers reported are sums of the intercepts of cross-sectional regressions over the relevant event-time-periods expressed in percentage terms. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 3-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.52**	-6.9	-2.58**	-3.5	-2*	-2.1	-2.53**	-3.25	-3.75**	-4.55	-2.11**	-2.72	1.17	1.05	1.64^{+}	1.45
+12	2.62**	4.75	5.54**	4.65	1.29	1.02	2.78*	2.21	0.57	0.46	2.49*	2.07	4.97**	2.88	1.92	1.11
+24	6.58**	7.63	13.32**	7.26	5.51**	2.76	9.52**	4.89	-1.4	-0.73	4.9*	2.53	14.73**	5.55	6.31*	2.32
+36	10.68**	9.38	18.77**	7.9	9.91**	3.85	12.57**	5.1	1.56	0.58	9.71**	3.67	17.22**	4.78	8.16*	2.15
+48	15.76**	11.01	22.5**	7.69	17.7**	5.31	13.81**	4.7	5.66	1.65	17.71**	5.19	16.84**	3.73	12.05**	2.49
Observations	4276		948		887		827		775		839		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q4		Q5-Q4	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.69**	-7.12	-2.42**	-3.17	-1.92^{+}	-1.95	-3.3**	-4.08	-3.88**	-4.57	-2.36**	-2.95	1.46	1.28	1.52^{+}	1.3
+12	2.78**	4.8	6.01**	4.8	1.22	0.92	2.28^{+}	1.72	-1.2e-03	-9.2e-04	3.85**	3.02	6.01**	3.33	3.85*	2.11
+24	6.78**	7.52	14.74**	7.68	5.51**	2.63	9.53**	4.67	-3.82^{+}	-1.92	7.35**	3.61	18.56**	6.72	11.17**	3.92
+36	10.94**	9.21	20.63**	8.34	10.38**	3.86	11.14**	4.32	-0.97	-0.34	12.84**	4.63	21.6**	5.74	13.81**	3.48
+48	16.75**	11.19	24.88**	8.17	18.46**	5.26	12.11**	3.94	3.26	0.9	23.54**	6.57	21.61**	4.58	20.28**	3.99
Observations	4276		948		887		827		775		839		-		-	

TABLE 21
Calendar Time Monthly Abnormal Returns (AR) after Repurchase Announcements, 2005-2015

The table presents the Calendar Time monthly Abnormal Returns (AR) for firms repurchase announcements using the three-factor (Panel A) and five-factor (Panel B) Fama-French models for only the period 2005-2015. In this method, event firms that have announced an open market buyback in the last calendar months form the basis of the calendar month portfolio. A single time-series regression is run with the excess returns of the calendar portfolio as the dependent variable and the returns of factors used as the independent variables. The following regression is used for the five-factor model:

$$(R_t - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where R_t is the monthly return on the constructed portfolio in the calendar month t. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel B: 3-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q4		Q5-Q4	
	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat
-6	-0.47**	-4.94	-0.46**	-3.04	-0.43*	-2.24	-0.44**	-2.56	-0.68**	-3.14	-0.25	-1.32	0.22	0.84	0.43^{+}	1.49
+12	0.22*	2.34	0.47**	3.48	0.15	0.87	0.2	1.4	0.03	0.14	0.27*	2.15	0.44*	1.91	0.24	1.08
+24	0.24*	2.41	0.5**	3.61	0.17	1.17	0.35*	2.41	-0.08	-0.5	0.26*	2.09	0.58**	2.81	0.34*	1.71
+36	0.24*	2.45	0.48**	3.54	0.21	1.48	0.32*	2.37	-0.05	-0.31	0.28*	2.22	0.53**	2.59	0.33*	1.66
+48	0.23*	2.29	0.42**	3.18	0.21	1.5	0.29*	2.35	-0.04	-0.22	0.3*	2.19	0.46*	2.22	0.34^{+}	1.6
Observations	4276		948		887		827		775		839		-		-	

Panel B: 5-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q4		Q5-Q4	
	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat
-6	-0.48**	-4.92	-0.4**	-2.57	-0.33^{+}	-1.74	-0.58**	-3.38	-0.72**	-3.22	-0.31	-1.62	0.32	1.19	0.41^{+}	1.4
+12	0.23*	2.32	0.5**	3.54	0.13	0.72	0.17	1.17	0	-0.01	0.36**	2.82	0.5*	2.07	0.36^{+}	1.54
+24	0.23*	2.29	0.52**	3.6	0.16	1.04	0.31*	2.17	-0.15	-0.93	0.34**	2.75	0.67**	3.13	0.49**	2.44
+36	0.23*	2.25	0.49**	3.55	0.18	1.26	0.26*	1.96	-0.1	-0.67	0.34**	2.64	0.59**	2.86	0.44*	2.2
+48	0.23*	2.16	0.44**	3.23	0.19	1.31	0.25*	1.98	-0.09	-0.55	0.37**	2.66	0.53**	2.5	0.46*	2.14
Observations	4276		948		887		827		775		839		-		-	

TABLE 22
Cross-Section Regressions: Multivariate Analysis (all variables in one regression, including U-index), 2005-2015.

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998), using only the 2005-2015 events The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every post-buyback-announcement month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term, U-index, volatility, $(1 - R^2)$, and analyst coverage. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	-19.55	-0.56	-56.65^{+}	-1.8	-36.61	-1.11	14.69	0.41
UIndex	-4.07	-1.13	-2.5	-1.18	-2.87	-1.43	-1.13	-0.65
Volatility	-19.94	-0.58	-19.22	-0.81	-29.8	-1.51	-40.48*	-2.18
OneMRsq	12.81	0.47	47.45	1.57	79.86**	3.22	80.19**	4.02
AnalystCoverage	-26.07	-1.64	-14.93	-0.8	-11.63	-0.72	-22.08	-1.4
CentralityDemean	-37.2	-1.72	-65.26**	-3.99	-52.12**	-3.35	-50.59**	-3.79
CentralityDemeanSquare	252.78**	4.73	127.3*	2.16	152.63**	3.2	119.71**	3.02
Observations	12		24		36		48	

TABLE 23
Firm Centrality and IRATS Cumulative Abnormal Returns (CAR) after Repurchase Announcements for Firms with Changing Centrality.

The table presents the 3 and 5-factor long-run IRATS Cumulative Abnormal Returns (CAR) for firms repurchase announcements using the three-factor and five-factor Fama-French models for firms whose centrality has changed between low and medium quantiles (Panel A), or between high and medium quantiles (Panel B) during the period. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms that announced an open market share repurchase plus various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the repurchase announcement. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The numbers reported are sums of the intercepts of cross-sectional regressions over the relevant event-time-periods expressed in percentage terms. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: IRATS Cumulative Abnormal Returns for Firms with Centrality changing between Low and Medium

	3-Factor: Low Centr.		Mid Centr.		Low-Mid		5-Factor: Low Centr.		Mid Centr.		Low-Mid	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-0.43	-0.35	-2.06	-1.31	1.63	0.82	-1.19	-0.96	-3.48*	-2.15	2.29	1.12
+12	9.71**	4.89	3.85+	1.83	5.86*	2.03	7.52**	3.64	2.01	0.94	5.52*	1.86
+24	16.78**	5.76	5.28+	1.74	11.51**	2.74	14.42**	4.71	-0.59	-0.19	15.01**	3.46
+36	23.13**	6.47	13.8**	3.57	9.34*	1.77	20.29**	5.39	3.43	0.87	16.86**	3.09
+48	28.53**	6.96	15.39**	3.36	13.14*	2.14	23.29**	5.37	1.47	0.31	21.82**	3.4
Observations	383		321		-	-	383		321		-	

Panel B: IRATS Cumulative Abnormal Returns for Firms with Centrality changing between High and Medium

	3-Factor: High Centr.		Mid Centr.		High-Mid		5-Factor: High Centr.		Mid Centr.		High-Mid	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.26	-1.59	-1.8	-1.37	-0.46	-0.24	-2.68+	-1.81	-3.47*	-2.55	0.79	0.39
+12	12.04**	3.42	1.94	1.06	10.1**	2.55	9.26*	2.48	-0.63	-0.33	9.88**	2.37
+24	21.05**	4.9	-0.4	-0.15	21.45**	4.24	14.09**	3.09	-5.77*	-2.11	19.86**	3.73
+36	29.91**	6.11	1.16	0.33	28.75**	4.75	17.41**	3.35	-6.04	-1.65	23.45**	3.68
+48	32.66**	6.11	7.11	1.59	25.55**	3.67	14.26*	2.51	-2.94	-0.63	17.21**	2.34
Observations	347		323		-	-	347		323		-	

TABLE 24

Firm Centrality and Calendar Time Monthly Abnormal Returns (AR) after Repurchase Announcements for Firms with Changing Centrality.

The table presents the 3 and 5-factor Calendar Time monthly Abnormal Returns (AR) for firms repurchase announcements using the three-factor and five-factor Fama-French models for firms whose centrality has changed between low and medium quantiles (Panel A), or between high and medium quantiles (Panel B) during the period. In this method, event firms that have announced an open market buyback in the last calendar months form the basis of the calendar month portfolio. A single time-series regression is run with the excess returns of the calendar portfolio as the dependent variable and the returns of factors used as the independent variables. The following regression is used for the five-factor model:

$$(R_t - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where R_t is the monthly return on the constructed portfolio in the calendar month t. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: Calendar Time Method Monthly Abnormal Returns for Firms with Centrality changing between Low and Medium

	3-Factor: Low Centr.		Mid Centr.		Low-Mid			5-Factor: Low Centr.		Mid Centr.		Low-Mid	
	CAL	t-stat	CAL	t-stat	CAL	t-stat		CAL	t-stat	CAL	t-stat	CAL	t-stat
-6	-0.14	-0.49	-0.32	-0.77	0.18	0.35		-0.36	-1.2	-0.6	-1.42	0.24	0.46
+12	1.03**	4.57	0.38	1.37	0.66*	1.83		0.78**	3.4	0.15	0.52	0.63*	1.73
+24	0.72**	3.63	0.27	1.12	0.45^{+}	1.45		0.59**	2.87	-0.08	-0.35	0.68*	2.15
+36	0.61**	3.26	0.42^{+}	1.96	0.19	0.68		0.52**	2.69	0.11	0.54	0.41^{+}	1.44
+48	0.56**	3.13	0.33	1.62	0.23	0.83		0.46*	2.49	0.06	0.32	0.4^{+}	1.44
Observations	383		321		-		-	383		321		-	

Panel B: Calendar Time Method Monthly Abnormal Returns for Firms with Centrality changing between High and Medium

	3-Factor: High Centr.		Mid Centr.		High-Mid			5-Factor: High Centr.		Mid Centr.		High-Mid	
	CAL	t-stat	CAL	t-stat	CAL	t-stat		CAL	t-stat	CAL	t-stat	CAL	t-stat
-6	0.05	0.15	-0.08	-0.21	0.12	0.26		-0.22	-0.74	-0.31	-0.83	0.08	0.18
+12	0.64*	2.25	0.39	1.58	0.25	0.67		0.48^{+}	1.67	0.05	0.19	0.44	1.15
+24	0.64**	2.79	0.3	1.43	0.34	1.09		0.48*	2.07	-0.08	-0.39	0.56*	1.82
+36	0.64**	2.87	0.26	1.38	0.37	1.27		0.43^{+}	1.93	-0.02	-0.08	0.45^{+}	1.53
+48	0.54*	2.43	0.28	1.44	0.27	0.9		0.31	1.38	0.03	0.17	0.28	0.93
Observations	347		323		-		-	347		323		-	

TABLE 25
Robustness Tests: Cross-Section Regressions with Different Centrality Measures.

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998), with different centrality measures from the Input-Output supplier networks. Supplier networks are constructed with the Input-Output tables at the detailed level from the U.S. BEA in 1997, 2002, and 2007. Eigenvector centrality and K-B centrality are calculated from the symmetric supplier network of all industry pairs. Strength centrality and betweenness centrality are measured using the substantial connections in each I-O network. A substantial connection is defined as a connection where one industry supplies at least 1% of the total inputs of the connected industry. The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every post-buyback-announcement month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term, U-index, volatility, $(1-R^2)$, and analyst coverage. Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	27.37	0.42	-25.63	-0.61	-17.98	-0.49	-52.14	-1.46
U-index	-3.32	-1.23	-3.21	-1.68	-4.52**	-2.79	-2.65$^+$	-1.84
Volatility	165**	4.62	134.54**	5.63	123.98**	6.5	110.05**	6.69
$(1-R^2)$	-60.31**	-3.38	-40.48*	-2.17	11.14	0.59	29.02$^+$	1.91
Analyst Coverage Score	16.21	0.61	11.88	0.57	3.29	0.19	3.08	0.21
Betweenness	-45.63	-1.79	-37.43$^+$	-2.06	-19.12	-1.26	-13.51	-1.05
Betweenness Square	244.26**	3.58	176.01**	3	171.65**	3.64	129.73**	3.14
Observations	12	12	24	24	36	36	48	48
Intercept	24.93	0.37	-27.48	-0.64	-20.91	-0.57	-55.55	-1.55
U-index	-3.42	-1.25	-3.33$^+$	-1.73	-4.65**	-2.84	-2.8$^+$	-1.95
Volatility	162.73**	4.63	133.17**	5.61	122.68**	6.47	109.37**	6.68
$(1-R^2)$	-51.82*	-3	-33.71$^+$	-1.82	16.68	0.91	32.98*	2.22
Analyst Coverage Score	17.9	0.69	13.36	0.64	4.04	0.24	3.3	0.23
Strength	-19.62	-0.72	-10.59	-0.6	2.52	0.17	-1.4	-0.11
Strength Square	129.83$^+$	1.97	82.53	1.62	89.82*	2.18	99.64**	2.76
Observations	12	12	24	24	36	36	48	48
Intercept	14.45	0.21	-34.74	-0.8	-27.36	-0.73	-61.56$^+$	-1.71
U-index	-3.45	-1.26	-3.36$^+$	-1.76	-4.66**	-2.86	-2.82$^+$	-1.96
Volatility	157.77**	4.45	129.75**	5.42	119.65**	6.33	105.93**	6.46
$(1-R^2)$	-48.76*	-2.88	-31.46$^+$	-1.73	18.97	1.05	35.61*	2.41
Analyst Coverage Score	16.91	0.65	12.7	0.61	3.73	0.22	3.13	0.21
Eigenvector	-9.96	-0.6	-2.99	-0.24	12.31	1	13.19	1.19
Eigenvector Square	185.5*	2.45	122.1*	2.7	108.17**	2.79	104.99**	2.86
Observations	12	12	24	24	36	36	48	48
Intercept	21.48	0.3	-27.2	-0.62	-23.38	-0.63	-58.92	-1.64
U-index	-3.32	-1.21	-3.24	-1.7	-4.56**	-2.8	-2.73$^+$	-1.9
Volatility	159.79**	4.49	131.83**	5.52	121.98**	6.45	108.24**	6.63
$(1-R^2)$	-52.41**	-3.12	-34.85$^+$	-1.94	15.68	0.87	32.37*	2.2
Analyst Coverage Score	16.92	0.65	12.79	0.61	3.54	0.21	2.76	0.19
K-B	-30.18$^+$	-1.91	-23.06$^+$	-1.72	-10.3	-0.99	-10.72	-1.14
K-B Square	154.47$^+$	2.1	85.68$^+$	1.75	106.73*	2.68	117.94**	3.01
Observations	12		24		36		48	

TABLE 26
Firm Centrality and IRATS Cumulative Abnormal Returns (CAR) after Insider Trading Permno-Month Events

The table presents the long-run IRATS Cumulative Abnormal Returns (CAR) for firms with insider purchases during a month using the three-factor (Panel A) and five-factor (Panel B) Fama-French models. The tables report monthly cumulative average abnormal returns (CAR) in percent using the Ibbotson (1975) returns across time and security (IRATS) method for the sample of firms for which there was insider purchasing for various subsamples. The following regression is run each event month j for the five-factor model:

$$(R_{i,t} - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on security i in the calendar month t that corresponds to the event month j, with $j = 0$ being the month of the insider trading. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The numbers reported are sums of the intercepts of cross-sectional regressions over the relevant event-time-periods expressed in percentage terms. The standard error (denominator of the t-statistic) for a window is the square root of the sum of the squares of the monthly standard errors. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel A: 3-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q3		Q5-Q3	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-4.3**	-17.55	-4.12**	-6.78	-4.18**	-6.37	-6.4**	-11.45	-1.93**	-4.69	-4.46**	-9.37	2.29**	2.77	1.94**	2.64
+12	2.84**	6.51	9.27**	7.29	6.42**	5.89	-2.84**	-3.02	4.51**	6.84	-2.23**	-2.7	12.11**	7.66	0.61	0.49
+24	10.26**	15.45	17.72**	10.19	20.36**	11.99	1.41	0.9	11.21**	10.2	2.06^{+}	1.66	16.31**	6.96	0.65	0.32
+36	14.06**	17.64	20.19**	9.78	25.7**	12.68	-1.42	-0.76	18.58**	13.28	8.78**	5.93	21.61**	7.75	10.2**	4.27
+48	18.33**	19.73	22**	9.25	32.97**	13.95	-4.83*	-2.2	25.15**	14.54	18.21**	10.87	26.83**	8.29	23.04**	8.34
Observations	23802		4761		4766		4754		4847		4674		-		-	

Panel B: 5-Factor IRATS Cumulative Abnormal Returns

	All		Q1 (Low) CAR		Q2 CAR		Q3 CAR		Q4 CAR		Q5 (High) CAR		Q1-Q3		Q5-Q3	
	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
-6	-2.65**	-10.19	-1.75**	-2.7	-2.25**	-3.21	-5.13**	-8.62	-1.26**	-2.93	-2.61**	-5.12	3.39**	3.86	2.52**	3.22
+12	7.2**	15.63	15.07**	11.22	11.11**	9.62	1.57	1.58	5.96**	8.66	3.02**	3.43	13.49**	8.08	1.45	1.09
+24	16.39**	23.84	25.18**	13.93	26.51**	15.04	8.32**	5.12	13.24**	11.77	9.84**	7.51	16.87**	6.94	1.52	0.73
+36	21.23**	25.74	29.38**	13.76	32.09**	15.25	6.8**	3.5	21.48**	15	16.83**	10.76	22.58**	7.82	10.03**	4.02
+48	26.31**	27.37	32.12**	13.08	40.53**	16.49	3.65	1.6	29.68**	16.69	25.63**	14.52	28.47**	8.49	21.98**	7.62
Observations	23802		4761		4766		4754		4847		4674		-		-	

TABLE 27
Calendar Time Monthly Abnormal Returns (AR) after Insider Trading Permno-Month Events

The table presents the Calendar Time monthly Abnormal Returns (AR) for firms for which there has been insider share purchase during a month using the three-factor (Panel A) and five-factor (Panel B) Fama-French models. In this method, event firms for which there has been insider trading in the last calendar months form the basis of the calendar month portfolio. A single time-series regression is run with the excess returns of the calendar portfolio as the dependent variable and the returns of factors used as the independent variables. The following regression is used for the five-factor model:

$$(R_t - R_{f,t}) \quad = \quad a_j + b_j(R_{m,t} - R_{f,t}) + c_j SMB_t + d_j HMl_t + e_t RMW_t + f_t CMA_t + \epsilon_{i,t},$$

where R_t is the monthly return on the constructed portfolio in the calendar month t. $R_{f,t}$ and $R_{m,t}$ are the risk-free rate and the return on the equally weighted CRSP index, respectively. SMB_t, HMl_t, RMW_t, and CMA_t are the monthly returns on the size, book-to-market factor, profitability factor and investment factor in month t, respectively. The three-factor model does not use factors RMW_t and CMA_t. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

Panel B: 3-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q3		Q5-Q3	
	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat
-6	-0.65**	-3.71	-0.57*	-2.36	-0.52^{+}	-1.84	-1**	-3.57	-0.44*	-2.2	-0.5^{+}	-1.83	0.43	1.17	0.5	1.28
+12	0.2	0.95	0.68*	2.12	0.39	1.27	-0.3	-1	0.44*	2.12	-0.03	-0.1	0.98*	2.23	0.27	0.69
+24	0.22	1.08	0.52^{+}	1.91	0.46^{+}	1.65	-0.22	-0.77	0.28^{+}	1.67	0.05	0.17	0.74*	1.87	0.27	0.68
+36	0.22	1.06	0.45^{+}	1.64	0.48^{+}	1.74	-0.22	-0.77	0.26	1.5	0.02	0.08	0.67*	1.7	0.24	0.62
+48	0.22	1.08	0.43	1.6	0.51^{+}	1.82	-0.18	-0.65	0.23	1.33	0.03	0.1	0.61^{+}	1.59	0.21	0.54
Observations	23802		4761		4766		4754		4847		4674		-		-	

Panel B: 5-Factor Calendar Time Method Monthly Abnormal Returns

	All		Q1 (Low) CAL		Q2 CAL		Q3 CAL		Q4 CAL		Q5 (High) CAL		Q1-Q3		Q5-Q3	
	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat
-6	-0.42**	-2.57	-0.25	-1.12	-0.26	-0.92	-0.8**	-2.83	-0.33	-1.59	-0.36	-1.29	0.55^{+}	1.53	0.44	1.1
+12	0.49*	2.41	1.12**	3.68	0.65*	2.11	-0.02	-0.07	0.58**	2.76	0.17	0.64	1.14**	2.67	0.19	0.48
+24	0.5**	2.52	0.89**	3.42	0.71**	2.54	0.06	0.21	0.41*	2.45	0.27	1.02	0.83*	2.15	0.21	0.55
+36	0.49**	2.5	0.82**	3.19	0.72**	2.6	0.05	0.19	0.43*	2.48	0.25	0.93	0.77*	2.02	0.2	0.5
+48	0.49**	2.51	0.79**	3.11	0.76**	2.72	0.08	0.29	0.41*	2.36	0.25	0.95	0.71*	1.9	0.17	0.44
Observations	23802		4761		4766		4754		4847		4674		-		-	

TABLE 28
Cross-Section Regressions for Insider Trading Analysis: Multivariate Analysis (all variables in one regression).

Monthly average coefficients of each firm characteristic estimated with the cross-section analysis following Brennan, Chordia and Subrahmanyam (1998). The five-factor Fama-French model is used to estimate the factor loadings for each stock in every month and, thus, monthly excess returns. Regressing monthly excess returns on all firm characteristics in every insider trading month gives the monthly coefficients. The firm characteristics are centrality, centrality squared term.... Coefficients reported in this table are the average of monthly coefficient estimates over the corresponding post-event window. The standard error (denominator of the t-statistic) for a window is the standard deviation of the monthly estimated coefficients divided by the square root of the number of months in the window. Year and industry dummies are included. The significance levels are indicated by +, *, and ** and correspond to a significance level of 10%, 5%, and 1% respectively, using a two-tailed test.

	month 12		month 24		month 36		month 48	
	Month	t-stat	Month	t-stat	Month	t-stat	Month	t-stat
Intercept	-1.69**	-4.43	-0.12	-0.21	-0.21	-0.54	-0.43	-1.39
Size Score	-1.29**	-6.93	-1.51**	-10.78	-1.39**	-12.41	-1.3**	-13.62
BE/ME Score	0.15	0.96	0.15	1.39	0.14	1.61	0.14	1.65
Prior Returns Score	0.27	1.56	-0.01	-0.06	0.11	0.99	0.13	1.4
Centrality (Linear term)	-0.92**	-5.05	-0.86**	-5.89	-0.57**	-4.44	-0.42**	-3.47
Centrality (Square term)	-0.86	-1.62	-1.77**	-4.04	-1.08**	-2.89	-0.43	-1.29
Observations	12		24		36		48	

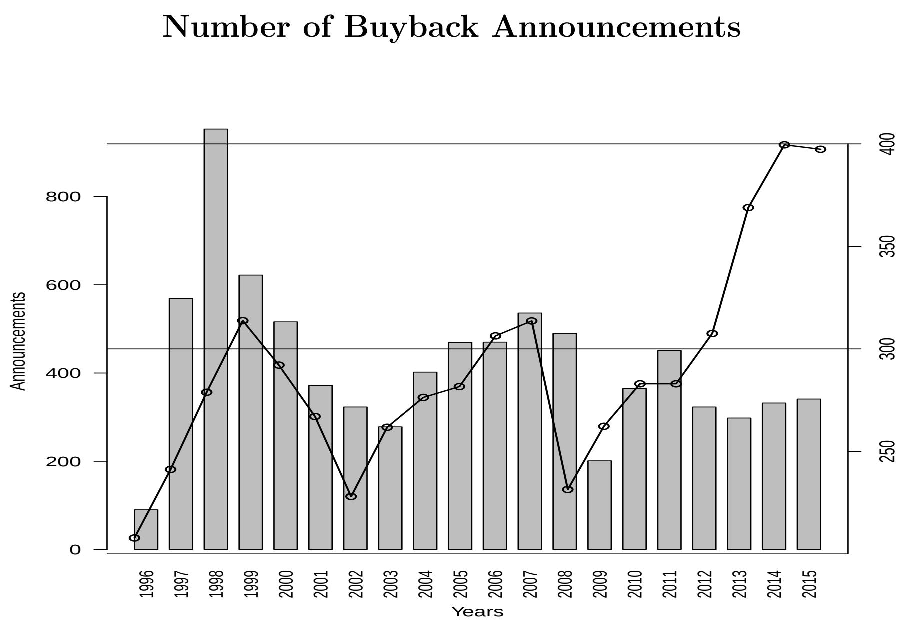

FIGURE 1. Number of buyback announcements per year (bar chart and left hand axis). Solid line and right hand axis show the $S\&P$ index at the end of each year, starting from 100 in October 1996. Buyback activity rises prior to stock market increases and tends to fall afterwards.

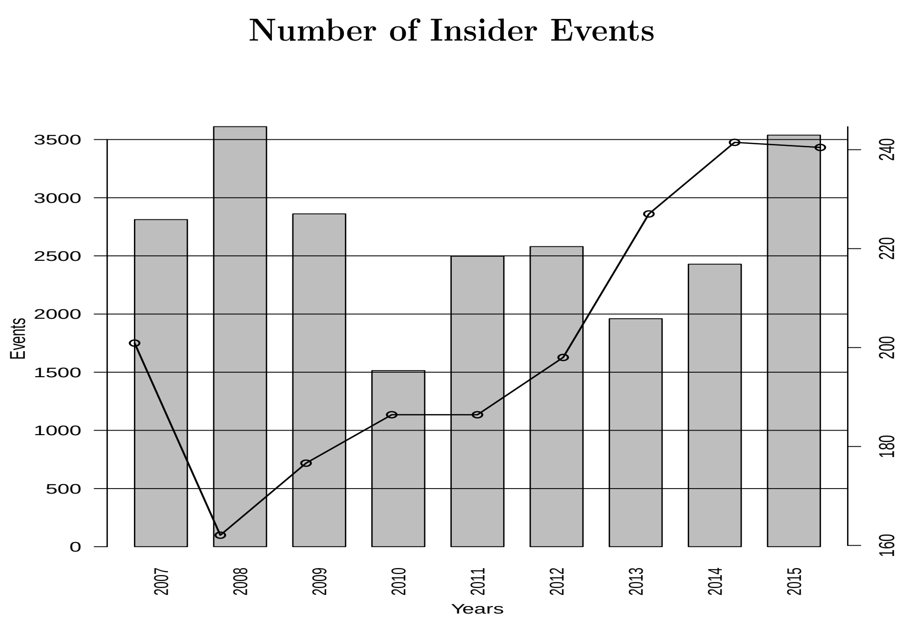

FIGURE 2. Number of insider events per year (bar chart and left hand axis). Solid line and right hand axis show the $S\&P$ index at the end of each year, starting from 100 in January 2007. All insider buys of a given firm's shares during a given month are aggregated into a single (month, firm) event.

Construction of the Trade-flow Network

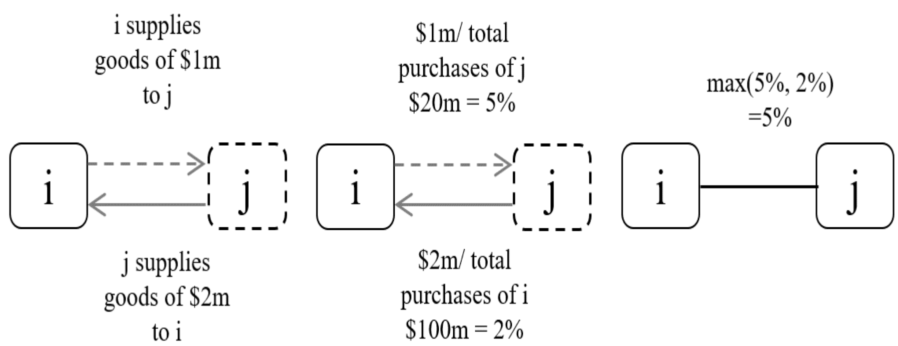

FIGURE 3. In the adjacency matrix A of a supplier network, a_{ij} represents the link strength between industries i and j. The left graph shows the dollar values of goods flowed from i to j (a_{ij} = \$1 million) and from j to i (a_{ij} = \$2 million). These values are calculated from the Input-Output Make and Use tables from BEA. The middle graph shows the link strength standardized by total purchases of an industry. Industry j's (i's) total purchases from all other industries are \$20 million (\$100 million) in this example, so $a_{ij} = 5\%$ ($a_{ij} = 2\%$) which means that among all industry suppliers of j (i), industry i (j) accounts for 5% of j's (i's) total inputs. These standardized link strengths give an asymmetric matrix and hence a directed network. The right graph makes a symmetric matrix by selecting the larger number between a_{ij} and a_{ij}. This results to an undirected network.

Firm Centrality and Excess Returns

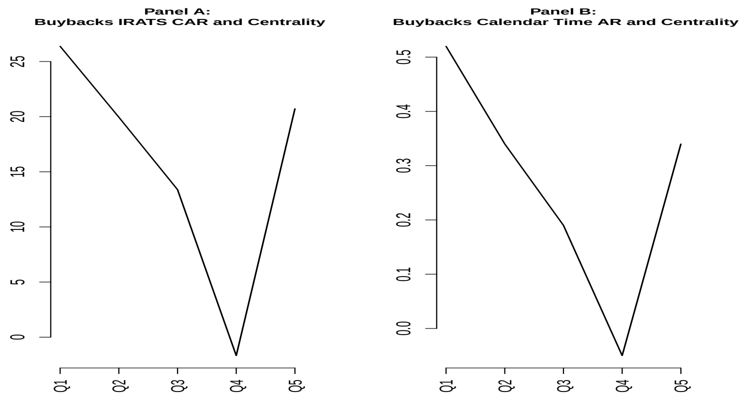

FIGURE 4. Long-run IRATS Cumulative Excess Returns (CAR) (left) and Calendar Monthly Abnormal Returns (AR) (Right) for different subgroups of firms defined according to firm centrality: Q1 is the bottom and Q5 the top quintile of firms in terms of their centrality score one month prior to the repurchase announcement. Centrality Score is constructed with degree centrality. CAR (monthly AR) are calculated using the Fama-French five-factor model and the horizon is 48 months post buyback announcement, as in Tables 5 and 6, respectively.

CEU-Index Distribution

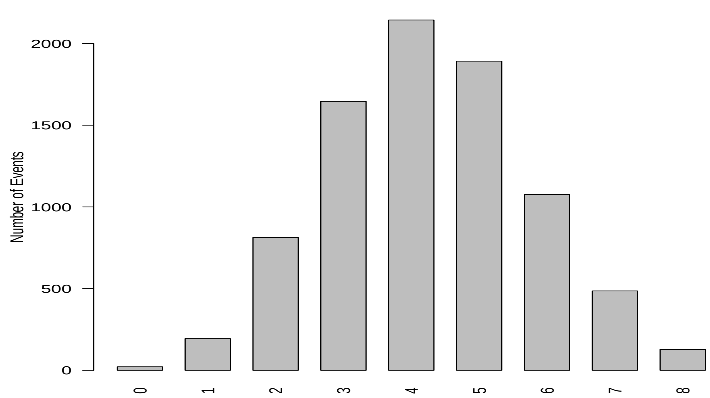

FIGURE 5. Distribution of the CEU-index of all buyback events.

Cumulative Abnormal Returns and the CEU-Index

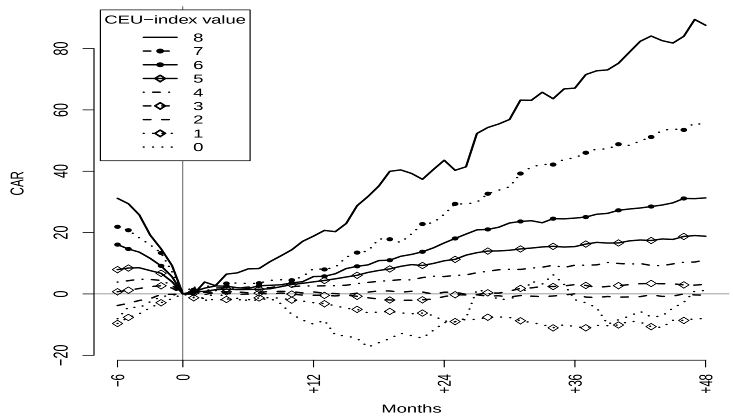

FIGURE 6. Long-run IRATS five factors cumulative abnormal returns of buybacks depending on the CEU-index. From the highest to the lowest lines: solid line is for CEU-index 8, dashed with dots for CEU-index 7, solid with dots for CEU-index 6, solid with diamonds for CEU-index 5, dotted-dashed for CEU-index 4, dashed with diamonds for CEU-index 3, dashed for CEU-index 2, dotted with diamonds for CEU-index 1, and finally the lowest dotted line is for CEU-index 0. The x-axis indicates months from the date of the event announcement.

The Insider's Expected Profit as a Function of a Firm's Centrality

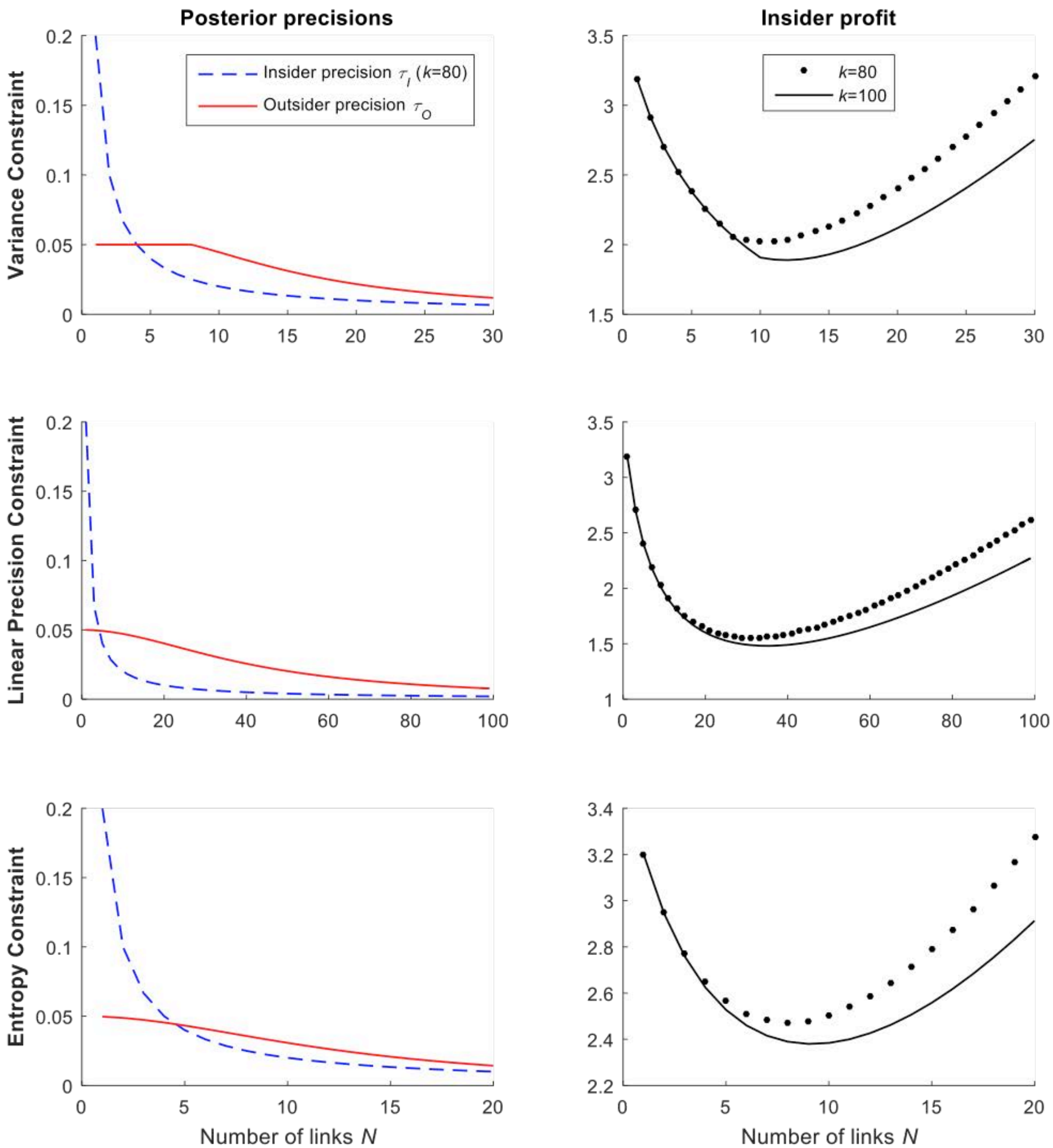

FIGURE 7. The model is plotted for three learning technologies: the variance capacity constraint (top row), the linear precision constraint (middle row) and the entropy constraint (bottom row). For each learning technology, we plot, as a function of the firm's centrality (i.e., of number of links N): i) in the left column, the posterior precisions of outsiders, τ_O, and of the insider, τ_I for a learning capacity $k = 80$; ii) in the right column, the insider's expected profit for learning capacities $k'' = 80$ and $k'' = 100$. The other model parameters are set as follows: $\tau^f = \delta = 0.1$ and $\tau^\varphi = 0.05$.

Appendix

A Proofs of the Model

1 Proof of Lemma: Outsider's information choice and firm centrality

The model solved by backward induction starting from period 1, then proceeding to period 0.

1.1 The Period-1 Stock Price

In period 1, the stock price is pinned down in equilibrium by the representative outsider's expectation of the firm's cashflow, since he is risk neutral and unconstrained: $P = E(F|\mathcal{F}_O)$, where $\mathcal{F}_O = \{s_{nj}, n = 1, \ldots, N\}$ denotes the outsider's information set.

We conjecture that the outsider chooses precisions that are identical across shocks, i.e., $\tau^{\varepsilon}_{nO} = \tau^{\varepsilon}_{O}$ for $n = 1, \ldots, N$. We shall confirm this conjecture later. From Bayes law:

$$E(F|\mathcal{F}_O) = \sum_{n=1}^{N} \frac{\tau^{\varepsilon}_{O}}{\tau^f + \tau^{\varepsilon}_{O}} s_{nO}, \tag{A.1}$$

and $\tau_O^{-1} \equiv Var(F|\mathcal{F}_O) = Var(\varphi + \sum_{n=1}^{N} f_n|\mathcal{F}_O) = Var(\varphi) + \sum_{n=1}^{N} Var(f_n|\mathcal{F}_O) = \tau^{\varphi^{-1}} + N(\tau^f + \tau^{\varepsilon}_{O})^{-1}$.

1.2 The Period-0 Learning Problem of Outsiders

We turn to the determination of the outsider's signal precisions. We assume that he chooses signal precisions that maximize his posterior precision, τ_O, about the firm's cash flow, subject to his capacity constraint, either (6), (7), or (8), taking other outsiders' behaviour as given. We prove below that this intuitive objective indeed maximises the outsider's expected profit (see Section A.1.3).

Since $\tau_O \equiv 1/Var(F|\mathcal{F}_O) = [\tau^{\varphi^{-1}} + \sum_{n=1}^{N}(\tau^f + \tau^{\varepsilon}_{nO})^{-1}]^{-1}$, maximizing the posterior precision is equivalent to minimizing the variance of the sum of the link-related cashflows,

$\sum_{n=1}^{N} Var(f_n|\mathcal{F}_O) = \sum_{n=1}^{N} (\tau^f + \tau_{nO}^{\varepsilon})^{-1}$.

We solve this optimization problem for each of the three learning technologies we consider.

1.2.1 Variance capacity constraint

Under the variance capacity constraint, the outsider's optimization problem is

$$max_{\{\tau_{nO}^{\varepsilon}\}_{n=1}^{N}} - \sum_{n=1}^{N} Var(f_n|\mathcal{F}_O)$$

subject to: $\sum_{n=1}^{N} Var(f_n|\mathcal{F}_O) \geq N/\tau^f - k$ and $\tau_{nO}^{\varepsilon} \geq 0$ $for\, n = 1, \ldots, N$.

The constraint binds at the optimum, leading to a posterior variance and precision equal to $\sum_{n=1}^{N} Var(f_n|\mathcal{F}_O) = Max(0, N/\tau^f - k)$ and $1/Var(F|\mathcal{F}_O) = (\tau^{\varphi^{-1}} + N/\tau^f - k)^{-1}$, respectively. Individual variances are not determined, only their sum is; focusing on a symmetric equilibrium (i.e., identical τ_{nO}^{ε} across links), we obtain the following optimal precisions:

(A.2)

- $N \leq k\tau^f$, $\tau_{nO}^{\varepsilon} = +\infty$ for $n = 1, \ldots, N$, and $\tau_O = \tau^{\varphi}$
- $N > k\tau^f$, $\tau_{nO}^{\varepsilon} = \tau^f(\frac{N}{k\tau^f} - 1)^{-1}$ for $n = 1, \ldots, N$, and $\tau_O^{-1} = \tau^{\varphi^{-1}} + \frac{N}{\tau^f} - k$.

With this learning technology, it is possible for the outsider to know the $f_n's(n = 1, \ldots, N)$ without error, provided his capacity is large enough relative to the number of links ($N \leq k\tau^f$).

1.2.2 Linear precision constraint

Under the linear precision constraint, the outsider's optimization problem is

$$max_{\{\tau_{nO}^{\varepsilon}\}_{n=1}^{N}} - \sum_{n=1}^{N} (\tau^f + \tau_{nO}^{\varepsilon})^{-1}$$

subject to: $\sum_{n=1}^{N} \tau_{nO}^{\varepsilon} \leq k'$ and $\tau_{nO}^{\varepsilon} \geq 0$ $for\, n = 1, \ldots, N$.

Maximizing the Lagrangian leads to the following first-order conditions

$$(\tau^f + \tau^{\varepsilon}_{nO})^{-2} = \nu' \qquad for \quad n = 1, \ldots, N,$$

where ν' is the Lagrange multiplier on the capacity constraint. This system of equations implies that the $\tau^{\varepsilon}_{nO}{}'s$ are equated across links n:

$$\text{(A.3)} \qquad \tau^{\varepsilon}_{nO} = \frac{k'}{N} \qquad for \quad n = 1, \ldots, N.$$

It follows that $\tau_O^{-1} = \tau^{\varphi^{-1}} + N(\tau^f + k'/N)^{-1}$.

1.2.3 Entropy constraint

Because all random variables (shocks and signal errors) are i.i.d., the prior and posterior variance-covariance matrices are diagonal. The determinant of these matrices is simply the product of their diagonal elements: $|\sum| = \prod_{n=1}^{N} \tau^{f^{-1}} = \tau^{f^{-N}}$ and $|\widehat{\sum}| = \prod_{n=1}^{N} (\tau^f + \tau^{\varepsilon}_{nO})^{-1}$.

The outsider's optimization problem is

$$max_{\{\tau^{\varepsilon}_{nO}\}_{n=1}^{N}} - \sum_{n=1}^{N} (\tau^f + \tau^{\varepsilon}_{nO})^{-1}$$

subject to: $\quad \prod_{n=1}^{N} (\tau^f + \tau^{\varepsilon}_{nO}) \leq k'' \tau^{f^N} \quad$ and $\quad \tau^{\varepsilon}_{nO} \geq 0 \quad for\, n = 1, \ldots, N.$

Maximizing the Lagrangian leads to the following first-order conditions

$$(\tau^f + \tau^{\varepsilon}_{nO})^{-2} = \nu'' \prod_{m=1, m \neq n}^{N} (\tau^f + \tau^{\varepsilon}_{mO}) \qquad for \quad n = 1, \ldots, N,$$

where ν'' is the Lagrange multiplier on the capacity constraint. The first-order conditions imply

$$(\tau^f + \tau^{\varepsilon}_{nO})^{-1} = \nu'' \prod_{m=1}^{N} (\tau^f + \tau^{\varepsilon}_{mO})^{-1} = \nu'' k'' \tau^{f^N} \qquad for \quad n = 1, \ldots, N,$$

where the second equality results from the capacity constraint being binding. This system of equations implies that the τ^{ε}_{nO}'s are equated across links n:

(A.4) $$\tau^{\varepsilon}_{nO} = \tau^{f}(k''^{1/N} - 1) \quad for \quad n = 1, \ldots, N.$$

It follows that $\tau_O^{-1} = \tau^{\varphi^{-1}} + N(\tau^f k''^{1/N})^{-1}$.

Despite their differences, all three specifications imply that i) outsiders' precision is (weakly) decreasing in the number of links N (i.e., their information about each single link is less precise when there are more links to investigate), and ii) this precision is increasing in the learning capacity (k, k', or k'').

1.3 Proof that the outsider's optimal decision is to maximize $\tau_O \equiv 1/Var(F|\mathcal{F}_O)$, the precision of his information about the firm's total cashflow

When solving the outsider's learning problem, we postulated that he chooses signals such that the precision of his information about the firm's total cashflow, $\tau_O \equiv 1/Var(F|\mathcal{F}_O)$, is maximised. Here, we demonstrate that this intuitive rule is indeed optimal.

Under risk neutrality and in the absence of any restriction on trading (e.g., on borrowing or short-selling), the outsider's learning strategy is undetermined. Indeed, consider an outsider, labelled $O*$, who takes as given the information choice of the representative outsider. His expected profit in period 1 is infinite since he will buy (respectively, sell) an infinite number of shares if his expectation of the firm's cashflow F is greater (respectively, smaller) than that of the representative outsider. [A1] It follows that his profit expected in period 0 is also infinite, regardless of his precision choices, which therefore are indeterminate.

To break this indeterminacy, we solve the learning problem faced by a risk averse outsider and then drive his risk aversion to zero. We will establish that a risk averse outsider finds it optimal to maximise τ_O regardless of his degree of risk aversion. It follows that a risk averse outsider whose risk aversion is infinitesimally small—in other words, a risk neutral outsider—also finds this rule optimal.

We assume that the outsider's utility exhibits constant absolute risk aversion (CARA), where the coefficient of risk aversion is denoted γ. Risk neutrality corresponds to $\gamma = 0$. We normalize the outsider's

[A1] Of course, in equilibrium, the expectations of $O*$ and of the representative outsider are identical, so that the price equals the expectation of the representative outsider.

initial wealth to 0, without loss of generality. Hence his terminal wealth is equal to the profit earned from portfolio investments, $\pi_O = X_O(F - P)$, where X_O denotes his stockholding. Thus, his objective is to maximize his expectation of $U \equiv -e^{-\gamma X_O(F-P)}$.

We proceed by backward induction as before, solving first for the equilibrium price in period 1 given arbitrary precisions, and then progressing to period 0 to determine optimal precisions.

1.3.1 The Period-1 Portfolio Problem of the Outsider

We solve for the outsider's optimal portfolios decision, taking his information choices as given. At this point, we conjecture that he chooses precisions that are identical across shocks, i.e., $\tau^{\varepsilon}_{nO} = \tau^{\varepsilon}_{O}$ for $n = 1, \ldots, N$. We shall confirm this conjecture later.

The outsider optimal portfolio is given by $X_O = \frac{\tau_O[E(F|\mathcal{F}_O)-P]}{\gamma}$, where τ_O and $E(F|\mathcal{F}_O)$ are given in equation (A.1). Aggregating asset demands across investors, neglecting the insider's demand who is assumed infinitesimal, and imposing market clearing, leads to the following equilibrium price P:

$$P = E(F|\mathcal{F}_O) - \frac{\gamma\bar{X}}{\tau_O} \tag{A.5}$$

Note that by setting γ to zero in the portfolio holding and price equations above, one reverts to the economy with risk neutral outsiders.

To solve for the outsider's information choice in period 0, we consider an outsider, labelled $O*$, who takes as given the information choice of the representative outsider. (At this stage outsider $O*$ differs from the representative outsider, but in equilibrium, they will be identical). It will prove useful to define the outsider $O*$'s Sharpe Ratio:

$$SR_O* \equiv [E(F|\mathcal{F}_{O*}) - P]\sqrt{\tau_{O*}} = \gamma X_{O*}/\sqrt{\tau_{O*}}, \tag{A.6}$$

Substituting in this formula the expression for the price yields:

$$SR_O* \equiv [E(F|\mathcal{F}_{O*}) - E(F|\mathcal{F}_O) + \frac{\gamma\bar{X}}{\tau_O}]\sqrt{\tau_{O*}} \tag{A.7}$$

$$= [\sum_{n=1}^{N} \frac{\tau_{O*}^{\varepsilon}}{\tau^f + \tau_{O*}^{\varepsilon}} s_{nO*} - \sum_{n=1}^{N} \frac{\tau_{O}^{\varepsilon}}{\tau^f + \tau_{O}^{\varepsilon}} s_{nO} + \frac{\gamma \bar{X}}{\tau_O}] \sqrt{\tau_{O*}}$$

$$= [\sum_{n=1}^{N} (\frac{\tau_{O*}^{\varepsilon}}{\tau^f + \tau_{O*}^{\varepsilon}} - \frac{\tau_{O}^{\varepsilon}}{\tau^f + \tau_{O}^{\varepsilon}}) f_n + \sum_{n=1}^{N} \frac{\tau_{O*}^{\varepsilon}}{\tau^f + \tau_{O*}^{\varepsilon}} \varepsilon_{nO*} - \sum_{n=1}^{N} \frac{\tau_{O}^{\varepsilon}}{\tau^f + \tau_{O}^{\varepsilon}} \varepsilon_{nO} + \frac{\gamma \bar{X}}{\tau_O}] \sqrt{\tau_{O*}}$$

Trading profits (and terminal wealth) equal $\pi_{O*} = X_{O*}(F - P)$. The mean and variance of trading profits, as of period 1, are given by the following expressions, after substituting out X_{O*}:

Substituting in this formula the expression for the price yields:

(A.8) $$E(\pi_{O*}|\mathcal{F}_{O*}) = [E(F|\mathcal{F}_{O*}) - P] X_{O*} = \frac{SR_{O*}^2}{\gamma};$$

and

(A.9) $$Var(\pi_{O*}|\mathcal{F}_{O*}) = \frac{X_{O*}^2}{\tau_{O*}} = \frac{SR_{O*}^2}{\gamma^2}.$$

Because π_{O*} is normally distributed conditional on period-1 information, the outsider's expected utility equals:

(A.10) $$E(U|\mathcal{F}_{O*}) = E(-e^{-\gamma W}|\mathcal{F}_{O*}) = E(-e^{-\gamma \pi_{O*}}|\mathcal{F}_{O*})$$

$$= -e^{-\gamma E(\pi_{O*}|\mathcal{F}_{O*}) + \gamma^2 Var(\pi_{O*}|\mathcal{F}_{O*})/2} = -e^{-\frac{SR_{O*}{}^2}{2}}.$$

1.3.2 The Period-0 Learning Problem of the Outsider

In period 0, outsider $O*$ has expected utility:

$$E[E(U|\mathcal{F}_{O*})] = -E(e^{-\frac{SR_{O*}^2}{2}}).$$

At that time, SR_{O*} is normally distributed so this expected utility is the mean of the exponential of a chi-square distributed random variable. Hence,

$$E[E(U|\mathcal{F}_{O*})] = -\frac{1}{\sqrt{Var(SR_{O*})+1}}e^{-\frac{1}{2}\frac{E(SR_{O*})^2}{Var(SR_{O*})+1}}$$

We compute next the mean and variance of SR_{O*} for an outsider with arbitrary signal precisions τ^{ε}_{nO*} for $n = 1, \ldots, N$ which might differ across shocks. Taking the expectation of equation (A.7) yields

$$E(SR_{O*}) = \sqrt{\tau_j}\frac{\gamma\bar{X}}{\tau_O} \tag{A.11}$$

since all random variables have mean zero. Likewise, taking the variance of equation (A.7) yields

$$Var(SR_{O*}) = \tau_{O*}[\sum_{n=1}^{N}(\frac{\tau^{\varepsilon}_{nO*}}{\tau^f+\tau^{\varepsilon}_{nO*}} - \frac{\tau^{\varepsilon}_{O}}{\tau^f+\tau^{\varepsilon}_{O}})^2\frac{1}{\tau^f} + \sum_{n=1}^{N}\frac{{\tau^{\varepsilon}_{nO*}}^2}{(\tau^f+\tau^{\varepsilon}_{nO*})^2}\frac{1}{\tau^{\varepsilon}_{nO*}} + \frac{{\tau^{\varepsilon}_{O}}^2}{(\tau^f+\tau^{\varepsilon}_{O})^2}\frac{N}{\tau^{\varepsilon}_{O}}]$$

Expanding the square, rearranging and simplifying leads to

$$Var(SR_{O*}) = \frac{\tau_{O*}}{\tau_f}[\sum_{n=1}^{N}\frac{\tau^{\varepsilon}_{nO*}}{\tau^f+\tau^{\varepsilon}_{nO*}} + \frac{N\tau^{\varepsilon}_{O}}{\tau^f+\tau^{\varepsilon}_{O}} - 2\frac{\tau^{\varepsilon}_{O}}{\tau^f+\tau^{\varepsilon}_{O}}\sum_{n=1}^{N}\frac{\tau^{\varepsilon}_{nO*}}{\tau^f+\tau^{\varepsilon}_{nO*}}]$$

Rearranging further implies

$$Var(SR_{O*}) = \frac{1}{\tau^f+\tau^{\varepsilon}_{O}}[a\tau_{O*} - \tau^f + \tau^{\varepsilon}_{O}] \tag{A.12}$$

where $a \equiv N + \frac{\tau^f - \tau^{\varepsilon}_{O}}{\tau^{\varphi}}$.

Plugging in the expressions for $E(SR_{O*})$ and $Var(SR_{O*})$ yields the following expression for outsider $O*$'s expected utility:

$$E[E(U|\mathcal{F}_{O*})] = -\frac{\sqrt{\tau^f+\tau^{\varepsilon}_{O}}}{\sqrt{a\tau_{O*}+2\tau^{\varepsilon}_{O}}}e^{-\frac{c}{2}\frac{\tau_{O*}}{a\tau_{O*}+2\tau^{\varepsilon}_{O}}}$$

where $c \equiv (\gamma\bar{X}/\tau_O)^2(\tau^f+\tau^{\varepsilon}_{O}) \geq 0$.

Outsider $O*$ maximises this expression with respect to his signals precisions, τ^{ε}_{nO*} (for $n = 1, \ldots, N$), subject to his capacity constraint, either (6), (7), or (8), taking other outsiders' behaviour, represented by τ^{ε}_{O}, as given.

$E[E(U|\mathcal{F}_{O*})]$ is increasing in the outsider's posterior precision τ_{O*}. To see why, first note that $E[E(U|\mathcal{F}_{O*})]$ increasing in τ_{O*} is equivalent to

$$f(\tau_{O*}) \equiv -2ln[E[E(U|\mathcal{F}_{O*})]] = ln(a\tau_{O*} + 2\tau_O^{\varepsilon}) + \frac{c\tau_{O*}}{a\tau_{O*} + 2\tau_O^{\varepsilon}} - ln(\tau^f + \tau_O^{\varepsilon})$$

increasing in τ_{O*}. Since $f'(\tau_{O*}) = \frac{a(\tau_{O*}+2\tau_O^{\varepsilon})+2c\tau_O^{\varepsilon}}{(a\tau_{O*}+2\tau_O^{\varepsilon})^2}$ where $c \geq 0$, f is increasing in τ_{O*} if $a > 0$. It is a priori unclear what the sign of a is. Let's suppose $a < 0$. In that case, the outsider's expected utility is decreasing in his posterior precision τ_{O*}, leading to an optimal signal precision, τ_{nO*}^{ε}, of zero across all shocks n. As a result, $\tau_O^{\varepsilon} = 0$ in equilibrium, which in turn leads to $a > 0$ and contradicts our premise. Thus, a must be positive in equilibrium, and the outsider's expected utility is increasing in his posterior precision τ_{O*}.

Hence, a risk averse outsider's optimization problem amounts to choosing signals precisions, τ_{nO}^{ε} (for $n = 1, \ldots, N$) that maximize his posterior precision τ_O subject to his capacity constraint. By continuity, this rule remains optimal for a risk neutral outsider—one with an infinitesimally small risk aversion.

2 Proof of Proposition: Insider's profit and firm centrality

We study the (period-0) expectation of the insider's profit, conditional on the insider buying shares. The insider's profit per share purchased equals $F - P$. She purchases shares if and only if she considers them underpriced, i.e. if $E(F|\mathcal{F}_I) - P > 0$. Hence, her expected profit, denoted π_I, is given by:

$$\pi_I = E[F - P|E(F|\mathcal{F}_I) - P > 0].$$

Substituting in the expressions for the cash flow and the equilibrium price yields:

$$F - P = (\varphi + \sum_{n=1}^{N} f_n) - E(F|\mathcal{F}_O) = (\varphi + \sum_{n=1}^{N} f_n) - (\sum_{n=1}^{N} \tau_O^{\varepsilon}(\tau^f + \tau_O^{\varepsilon})^{-1} s_{nO})$$

$$= \varphi + \sum_{n=1}^{N} \tau^f(\tau^f + \tau_O^{\varepsilon})^{-1} f_n - \sum_{n=1}^{N} \tau_O^{\varepsilon}(\tau^f + \tau_O^{\varepsilon})^{-1} \varepsilon_{nO},$$

and

$$E(F|\mathcal{F}_I) - P = E(F|\mathcal{F}_I) - E(F|\mathcal{F}_O)$$

$$= \varphi + \sum_{n=1}^{N} \frac{\tau^f(\delta - \tau_O^\varepsilon)}{(\tau^f + \delta)(\tau^f + \tau_O^\varepsilon)} f_n - \sum_{n=1}^{N} \frac{\tau_O^\varepsilon}{\tau^f + \tau_O^\varepsilon} \varepsilon_{nO} + \sum_{n=1}^{N} \frac{\delta}{\tau^f + \delta} \varepsilon_{nI},$$

where we used that $\tau_{nI}^\varepsilon = \delta$ for $n = 1, \ldots, N$, by assumption.

The expectation of a mean-zero random variable x conditioned on another mean-zero random variable y being positive is

$$E(x|y > 0) = q \frac{Cov(x, y)}{\sqrt{Var(y)}},$$

where $q \equiv \frac{\phi(O)}{1-\Phi(O)} \approx 0.8$, ϕ and Φ are the probability and cumulative density functions of the standard normal distribution. Applying this formula to the insider's expected profit yields:

$$\pi_I = q \frac{Cov(F - P, E(F|\mathcal{F}_I) - P)}{\sqrt{Var(E(F|\mathcal{F}_I) - P)}}$$

where

$$Cov(F - P, E(F|\mathcal{F}_I) - P) = \frac{1}{\tau^\varphi} + \frac{N\delta}{(\tau^f + \delta)(\tau^f + \tau_O^\varepsilon)}$$

and

$$Var(E(F|\mathcal{F}_I) - P) = \frac{1}{\tau^\varphi} + \frac{N\tau^f(\delta - \tau_O^\varepsilon)^2}{(\tau^f + \delta)^2(\tau^f + \tau_O^\varepsilon)^2} + \frac{N\tau_O^\varepsilon}{(\tau^f + \tau_O^\varepsilon)^2} + \frac{N\delta}{(\tau^f + \delta)^2}$$

$$= Cov(F - P, E(F|\mathcal{F}_I) - P) + \frac{N\tau_O^\varepsilon}{(\tau^f + \delta)(\tau^f + \tau_O^\varepsilon)}.$$

The effect of the number of links N on π_I can be decomposed into two parts, as shown in the following equation:

$$\frac{d\pi_I}{dN} = \frac{\partial \pi_I}{\partial N} + \frac{\partial \pi_I}{\partial \tau_O^\varepsilon} \frac{d\tau_O^\varepsilon}{dN}.$$

The first term,

$$\frac{\partial \pi_I}{\partial N} = \frac{q}{Var(E(F|\mathcal{F}_I) - P)^{3/2}} \frac{(\delta - \tau_O^\varepsilon)(\tau^f + \delta)/\tau^\varphi + N\delta}{(\tau^f + \delta)^2(\tau^f + \tau_O^\varepsilon)},$$

represents the direct effect of N on π_I, i.e., keeping τ_O^ε, the precision of outsiders' signals, constant. Its sign depends on τ_O^ε.

- If $\tau_O^\varepsilon > \delta(1 + N\tau^\varphi/(\tau^f + \delta))$, then $\frac{\partial \pi_I}{\partial N} < 0$. Intuitively, increasing the number of link-related shocks increases uncertainty for the insider more than that for outsiders, since the latter knows each shock much better than the former does. Therefore, the insider's information advantage relative to the outsider, and hence her expected profit, decrease.
- If instead $\tau_O^\varepsilon < \delta(1 + N\tau^\varphi/(\tau^f + \delta))$, then $\frac{\partial \pi_I}{\partial N} > 0$. The intuition is now reversed: as the number of links grows, the insider's information advantage relative to outsiders, and hence her expected profit, increase.

The second term, $\frac{\partial \pi_I}{\partial \tau_O^\varepsilon} \frac{d\tau_O^\varepsilon}{dN}$, represents the indirect effect of the number of links N on π_I, through outsiders' information choice. Since

$$\frac{\partial \pi_I}{\partial \tau_O^\varepsilon} = -\frac{q}{Var(E(F|\mathcal{F}_I) - P)^{3/2}} \frac{N}{(\tau^f + \delta)(\tau^f + \tau_O^\varepsilon)^2} [\frac{\tau^f + \delta}{\tau^\varphi} + \frac{N\delta}{\tau^f + \tau_O^\varepsilon} + \frac{2N\delta\tau_O^\varepsilon}{(\tau^f + \delta)(\tau^f + \tau_O^\varepsilon)}]$$

is negative and $\frac{d\tau_O^\varepsilon}{dN} < 0$, this term is positive. Through this channel, the insider performs better as N increases because the outsider needs to reduce his signal precision as he spreads his scarce learning capacity more thinly across the N shocks (τ_O^ε lower); this improve the insider's information advantage relative to the outsider.

The net effect of N on the insider's profit depends on the sign and magnitude of these two channels. These, in turn, depend on the number of links and the outsider's learning capacity.

- If there are few links (e.g., $N = 1$) and a large capacity, then τ_O^ε is large, so $\frac{\partial \pi_I}{\partial N}$ is negative and large in absolute value, and hence $\frac{d\pi_I}{dN} < 0$. In words, adding links leads to a reduction in the insider's profit, because the outsider is better informed than the insider about link-related shocks.
- If instead N is large, then τ_O^ε is small, so $\frac{\partial \pi_I}{\partial N} > 0$ and hence $\frac{d\pi_I}{dN} > 0$. In that case, adding links increases the insider's expected profit, because her informational advantage grows.

Thus, the insider's profit is U-shaped as a function of the number of links N, provided the outsider's learning capacity is large enough. If instead this capacity is low, then the profit increases with N for all N.

We establish next this result formally for each of the three learning technologies. We start with the case of the variance capacity constraint:

- When $N \leq k\tau_f$, $\tau_O^\varepsilon = +\infty$; so taking limits in the above expressions yields

$$Var(E(F|\mathcal{F}_I) - P) \approx \frac{1}{\tau^\varphi} + \frac{N}{\tau^f + \delta}, \frac{\partial \pi_I}{\partial N} \approx -\frac{q}{Var(E(F|\mathcal{F}_I) - P)^{3/2}} \frac{1/\tau^\varphi}{\tau^f + \delta} < 0$$

  and $\frac{\partial \pi_I}{\partial \tau_O^\varepsilon} \approx 0$, leading to $\frac{d\pi_I}{dN} < 0$.

- When N is large, $\tau_O^\varepsilon = (N/k\tau_f - 1)^{-1}$ which converges towards zero as N grows to infinity. It follows that

$$Var(E(F|\mathcal{F}_I) - P) \approx \frac{N\delta}{\tau^f(\tau^f + \delta)}$$

  grows to infinity, and that

$$\frac{\partial \pi_I}{\partial N} \approx \frac{q}{Var(E(F|\mathcal{F}_I) - P)^{3/2}} \frac{N\delta}{(\tau^f + \delta)\tau_f}$$

  converges towards zero, leading to $\frac{d\pi_I}{dN} \geq 0$.

The resulting pattern is a U shape, provided that $k > 1 \ / \ \tau^f$. Intuitively, adding links favours the outsider as long as $N \leq k\tau^f$ because the outsider is able to learn each link-related shock perfectly; but beyond a number of links, he can no longer keep pace and his information per link deteriorates, giving a greater advantage to the insider.

The other two constraints also lead to similar U–shaped patterns for π_I. The only difference relative to the case of the variance capacity constraint is that the downward-sloping branch is now less pronounced because the outsider's information about link-related shocks is imperfect even at low levels of N: the outsider's precision about these shocks starts to deteriorate as links are added starting from the very first link (whereas in the variance capacity constraint case, it remains infinite up to τ^f links). Again, the U shape obtains only if the capacity is large enough, because it ensures that the outsider is well informed about link-related shocks when there are few links, and thus that adding links reduces his disadvantage relative to the insider (who knows perfectly the shock φ but not the link-related shocks f_n).

- Formally, substitute $N = 1$ into the expressions for $\frac{\partial \pi_I}{\partial N}$ and $\frac{\partial \pi_I}{\partial \tau_O^\varepsilon}$; the condition $\frac{d\pi_I}{dN} < 0$ is then equivalent to

$$\text{(A.13)} \qquad \tau^{\varphi}\delta - (\tau^f + \delta + \frac{\tau^{\varphi}\delta}{\tau^f + \tau_O^{\varepsilon}} + \frac{2\tau^{\varphi}\delta\tau_O^{\varepsilon}}{(\tau^f + \delta)(\tau^f + \tau_O^{\varepsilon})})\frac{d\tau_O^{\varepsilon}}{dN} < (\tau_O^{\varepsilon} - \delta)(\tau^f + \tau_O^{\varepsilon}),$$

where τ_O^{ε} and $\frac{d\tau_O^{\varepsilon}}{dN}$ are evaluated at $N = 1$. Under the linear precision constraint, $\tau_O^{\varepsilon} = \frac{k'}{N} = k'$ and $\frac{d\tau_O^{\varepsilon}}{dN} = -\frac{k'}{N^2} = -k'$ for $N = 1$ so condition (A.13) can be stated as:

$$\frac{\tau^{\varphi}\delta(\tau^f + k') + (\tau^f + \delta)(\tau^f + k')k' + \tau^{\varphi}\delta + \frac{2\tau^{\varphi}\delta}{\tau^f + \delta}k'^2}{(k' - \delta)(\tau^f + k')^2} < 1.$$

The numerator of the ratio on left-hand side of this inequality grows with k' to infinity at a rate k'^2 while its denominator grows to infinity at a rate k'^3. Hence, there exist a threshold, $\bar{k}'$, such that, for any $k' > \bar{k}'$, this ratio is smaller than 1. Likewise, under the entropy constraint, $\tau_O^{\varepsilon} = \tau^f(k''^{1/N} - 1) = \tau^f(k'' - 1)$ and

$$\frac{\tau_O^{\varepsilon}}{dN} = \frac{-\tau^f(ln(k''))k''^{1/N}}{N^2} = -\tau^f k'' ln(k'')$$

for $N = 1$ so condition (A.13) is equavilent to:

$$\frac{\tau^{\varphi}\delta + ((\tau^f + \delta)k'' + \frac{\tau^{\varphi}\delta}{\tau^f} + \frac{2\tau^{\varphi}\delta\tau^f(k''-1)}{(\tau^f+\delta)\tau^f})\tau^f ln(k'')}{\tau^f k''(\tau^f(k'' - 1) - \delta)} < 1.$$

The numerator of the ratio on left-hand side of this inequality grows with k'' to infinity at a rate $k''ln(k'')$ while its denominator grows to infinity at a rate k'^2. Hence, there exist a threshold, $\bar{k}''$, such that, for any $k'' > \bar{k}''$, this ratio is smaller than 1. Thus, under both the linear precision and entropy constraints, there exist a threshold such that condition (A.13) is satisfied for any capacity larger than this threshold. In words, if the outsider's learning capacity is large enough, the downward-sloping branch of the U shape obtains.

- The upward-sloping branch of the U shape obtains, as in the case of the variance capacity constraint, because τ_O^{ε} converges to 0, regardless of the learning technology employed. That is, eventually (i.e., for high enough number of links N), the outsider lacks the resources to investigate all links.

B Variable Definitions

BE/ME: Ratio of the book value of equity to the market value of equity. We follow Fama and French (2001) to calculate the book value of equity. This is calculated using the following CCM variables: SEQ, CEQ, PSTK, PSTKRV, TXDITC, PRBA, DLC, DLTT, AT, LT. Market value of equity is calculated as the price per share multiplied by the number of shares outstanding: CCM and CRSP Monthly Stocks.

Capital Expenditures: Ratio of capital expenditure to the total assets of the firm: CCM data 128/CCM data 6 (CAPX/AT). Equal-weighted moving average over the past three years.

Institutional Holdings: Ratio of firm's shares held by the institutional investors relative to the total shares outstanding: CDA/Spectrum Database.

Leverage: The ratio $debt/(debt + equity)$. Debt is the sum of the Compustat variables DLC+ DLTT. Equity is the Compustat variable SEQ. We make the winsorization and other data adjustments as in `http://www.ivo-welch.info/professional/leverage.placebo/`.

Liquid Assets: Current assets minus current liabilities, divided by the total assets: (CCM data 4 - CCM data 5)/CCM data 6 (ACT-LCT)/AT. Equal-weighted moving average over the past three years.

Market Cap.: Market value of equity, calculated as the price per share multiplied by the number of shares outstanding: CRSP Monthly Stocks.

Operating Cash Flow (OCF): Net Cash Flow from Operating Activities less Extraordinary Items and Discontinued Operations (quarterly measure, items from Statement of Cash Flows).

OCF Volatility: the (log. of the) coefficient of variation of a firm's quarterly Operating Cash Flow (OCF) (ratio of the standard deviation of OCF to the absolute value of the mean OCF) estimated over the preceding 24 quarters.

Non-Operating Income: Ratio of non-operating income to total assets: CCM data 61/CCM data 6 (NOPI/AT). Equal-weighted moving average over the past three years.

Number of Institutions: Number of Institutions holding shares of the firm: CDA/Spectrum Database

Operating Income: Ratio of operating income to total assets: CCM data 13/CCM data 6 (OIBDP/AT). Equal-weighted moving average over the past three years.

Percent Shares: The percentage of shares authorized for repurchase in the case of buybacks, or issued for the case of issuers: SDC Database.

Price/Earnings Ratio: Share price divided by the basic earnings per share: CCM data 24/CCM data 58 (PRCC/EPSPX). Equally-weighted moving average over the past three years.

Prior Returns: Cumulative return for the previous 6 months: CRSP Daily Stocks.

Profitability (ROA): Return on Assets: CCM data 18/CCM data 6 (IB/AT)

Total Payout: Sum of repurchases and dividends as percent of earnings: CCM data 115 + CCM data 21 (DVC + PRSTKC)

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