A Network Analysis of Information Diffusion in the Financial Sector*

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This version: January 9, 2020

Abstract

We create and test two novel network-based measures of interconnectedness in the financial industry during 1996 to 2013. A network based on informed trading in financial firms predicts firm-specific risk and performance, while one formed on financial firm returns predicts future macroeconomic risk. The measure of informed trading is robust to variable order arrival rates more common in modern algorithmic trading. A trading strategy based on informed trading network centrality in the financial sector delivers an annualized risk-adjusted return of 7.73%. This risk-adjusted return shows that the network centrality has an economic impact that is relevant beyond the statistical results of the paper.

Keywords: Asset Pricing, Network Analysis, VPIN, Systemic Risk

JEL classification: G12, G14, C55, G20

*The authors would like to thank Brian Peterson, Joshua Ulrich, and the R/Finance community for their support.
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1 Introduction

We create and test two network-based measures of interconnectedness in the financial industry for the period of 1996 to 2013 at the intraday frequency: a network centrality based on informed trading measured using the Easley, de Prado, and O'Hara (2012) Volume Synchronized Probability of Informed Trading (VPIN) measure, and another on raw returns. These two network types originate in distinct signals and have distinct predictive value. We find that the VPIN network based on firm-specific informed trading predicts firm-specific risk and performance significantly better than the firm-specific return network. However, we find that return network completeness is a superior predictor of future macroeconomic risk, consistent with an underlying common risk factor in financial firm returns.

We make three contributions to the literature on financial sector interconnectedness and firm-specific and economy-wide risk. First, we create a novel measure of firm interconnectedness using informed trades measured using VPIN, rather than balance sheet or price data. Second, our method estimates a conditional correlation network across all firms simultaneously, rather than a simple pairwise unconditional correlation in the prior literature. Third, we calculate interconnectedness measures at the intraday frequency which captures information diffusion better than daily close data (Hou, 2007). These innovations have economic significance: a simple zero-cost trading strategy on the informed trading network formed on VPIN earns 7.73% per year in abnormal returns relative to the Carhart (1997) four-factor benchmark. Furthermore, the completeness of the return network is a strong predictor of future macroeconomic risk measured by the credit spread, VIX, and the S&P 500 volatility smirk.

The issue of correlation between firms as an indicator of systemic risk has been previously considered by Allen and Gale (2000), who propose that the interconnectedness of the financial system determines whether contagion will spread, and the key measure of interconnectedness is the cross holding of deposits. If the interbank market is complete, then a shock to one region may be adequately dispersed by banks in the immediate vicinity liquidating short-term assets. In the case of incomplete markets, the shock cannot be adequately absorbed by liquidating short term assets so banks must liquidate long-term assets causing contagion to spread to other regions. The combination of incomplete markets with a highly connected banking system causes the greatest amount of systemic risk. While untested, the authors suggest that contagion may also be spread by incomplete information. A shock in one region may predict information about another region in which case a crisis in one region would create the expectation for a crisis in another region. Our network measures allow us to test this since they cover all financial firms.

A network perspective on the stability of the financial system provides significant insight, as joint losses can exceed losses from individual failures because the surviving banks are less likely to immediately replace the lending capacity of the failed banks in the short term (Acharya, 2009). The author suggests that banks are likely to make correlated investments because any guarantee against a government bailout is less credible for a joint failure than for an individual failure. Under this theory, we should expect to see greater systemic risk as correlations between bank investments increase. If banks successfully take on risk and are rewarded for it, we would also expect to see correlations increasing over time. This is supported by the work of Allen, Babus, and Carletti (2012); Billio, Getmansky, Lo, and Pelizzon (2012); and Patro, Qi, and Sun (2013).

Our network measures proxy for systemic risk, which is likely to become greater when financial firms are more interconnected. Bad news affecting the value of securities on bank's balance sheet is more likely to be relevant to other firms in a more connected network (Allen, Babus, and Carletti, 2012). Fewer connections between firms are less likely to transmit information contagion and this results in great stability for the financial industry. Billio et al. (2012) show that financial firm connections increase prior to and during both the LTCM crisis of 1998 and the financial crisis of 2007-2009 relative to calm periods. Both cases are associated with credit and liquidity problems. They find that these connections are independent of Fama-French factors and macroeconomic factors such as inflation and industrial production. In a more recent application of network analysis to credit risk, Zareei (2015) combines the firm default probability from credit default swaps with networks formed from equity market data to show that centralized firms have a lower probability of default. Following the theory of Allen and Gale (2000), we would expect centralized firms in a well-connected network to benefit from spreading small shocks to the rest of the financial system.

The work closest in spirit to ours is that of Patro et al. (2013), who study pair-wise correlations in daily returns and idiosyncratic risk in bank holding companies. Over time, idiosyncratic risk declines but becomes more correlated between firms. They also find that higher correlations between idiosyncratic risks lead to higher systemic risk. Spikes in correlations occur during financial crises such as the 1998 Russian financial crisis, the 2001 recession, and the 2008 financial crisis. They conclude that average pair-wise correlations in bank stocks is a forward-looking measure of systemic risk. Peng and Xiong (2006) offer a different theory based on information quality. The average correlation between stocks within an industry is negatively related to the firm-specific information in prices. When the market processes firm-specific information efficiently, we should observe greater idiosyncratic variation and less industry correlation. While Patro et al (2013) is more empirical, the results may be explained with the model of Peng and Xiong (2006). A financial crisis may result from insufficient attention to firm specific information. If this were the case, we would expect to see higher correlations leading up to a crisis as investors limit their attention to industry and macroeconomic information rather than firm-specific information.

Network analyses have been previously used to provide insight into information diffusing in supply chain relationships: Gençay, Signori, Xue, Yu, and Zhang (2015) use similar supplier-customer-supplier data to construct a directed network. They find that counterparty risk is a significant determinant of credit spreads. Cohen and Frazzini (2008) utilize business to business relationships to form of network, constructing a trading strategy based on network information diffusion. We believe a network approach is even more suitable to the financial sector: Hirshleifer and Teoh (2003) develop a model that shows that the way accounting information is presented may produce negative long run abnormal returns due to overestimation of real cash flows. This suggests that investors may not fully incorporate the risks of off balance sheet liabilities which are particularly important for financial firms, which are further magnified by the high financial leverage typically used by firms in the industry. We would thus expect information diffusion to be more relevant in our setting.

Our study adds to this prior work not only by estimating simultaneous conditional correlations rather than pairwise ones, but also by taking an intraday perspective rather than focusing on end-of-day price changes. This is an important methodological improvement, as Hou (2007) finds that the lead-lag effect of Lo and MacKinlay (1990) is determined by intra-industry information diffusion. Once differences in information diffusion within an industry are accounted for, the market-wide lead-lag effect becomes insignificant. There is also an asymmetry to the speed of positive and negative information. Bad news takes longer to be incorporated into prices than good news. These results confirm earlier findings by Hong and Stein (2000) and lends credibility to the theory that there is significant variation in information diffusion within the financial industry that the intraday setting can help illuminate.

This study is also among the first large-scale applications of the Volume Synchronized Probability of Informed Trading (VPIN) introduced in Easley, López de Prado, O'Hara (2011) and further examined in Easley, López de Prado, O'Hara (2012) extends the seminal Probability of Informed Trading (PIN) adverse selection risk measure of Easley, Kiefer, O'Hara and Paperman (1996). The extension both allows for random information arrival and solves the problem of matching trades with quotes in a market that consists of both high-frequency and traditional traders.

By using a volume rather than a physical time clock, this market microstructure measure is designed to be more robust in a high-frequency setting with variable order arrival times. The introduction of volume, rather than physical, time also has beneficial distributional properties which are important in accurately modeling trades. Mandelbrot (1963) proposed that price changes have infinite variance which invalidates the use of the normal distribution for modeling returns. Consistent with the later innovation of the VPIN measure, Mandelbrot (1973) and Clark (1973) address this problem by making the return process subordinate to trading volume. Ane and Geman (2000) find that a method using cumulative trades is better than one using cumulative volume in generating normally distributed returns but do not address the loss of information quality described by Blume, Easley, and O'Hara (1994). Finally, Easley, López de Prado and O'Hara (2012) show that stock returns in volume time are approximately normally distributed. Simultaneously, the information from volume improves the signal quality from order imbalances.

The propagation of informed trading across firms in the financial sector represents systemic risk. In related work, Hong and Stein (1999) assume that information diffuses slowly to investors and creates a model with two types of traders: news watchers that collect and process information for long term investing and momentum traders that utilize price information for short term trading. The model explains both over and under reaction to information with changing proportions of the two groups of traders and the resulting changes to the momentum traders' risk tolerance. Stocks that are more likely to be driven by momentum have slow information diffusion and these stocks are also more likely to experience momentum reversals. Hong and Stein (2000) provide empirical evidence to support this theory and finds that bad information diffuses slower than good information. We would expect momentum reversals to be more significant in highly leveraged firms in the financial sector. Correlated momentum reversals may represent a threat to the stability of the financial system if they occur in a tight credit period.

This study demonstrates that a network analysis of the financial sector can be used both at the industry-wide and individual firm levels: the interconnectedness of the intraday return network is a meaningful predictor of the credit spread, S&P 500 implied volatility smirk, and VIX innovations as proxies for macroeconomic risk. Meanwhile, the centrality of individual firms in the adverse selection risk network, as measured by VPIN, is a significant predictor of their individual performance. The rest of the work is organized as follows: Section 2 describes the data and network centrality estimation, Section 3 describes the relation of financial firm network centrality with firm characteristics, Section 4 presents the relation of network centrality with firm-specific risk while Section 5 presents that of network centrality with macroeconomic risk, Section 6 describes a trading strategy based on information diffusion through the informed trading network, and Section 7 concludes.

2 Data and Methodology

We use SIC Industry codes to select financial firms from the NYSE TAQ data set. We eliminate firms with prices less than $5 per share and market capitalization of less than $1mm. We match firms with

CRSP, Compustat, OptionMetrics, and Federal Reserve data in order to incorporate firm characteristics, returns, implied volatilities as a measure of expected risk, and macroeconomic indicators in the analysis. The resulting sample contains 104 unique financial firms from 1996 through 2013. Variable construction is described in Appendix A.

We compute intraday volatility from TAQ trade data over the course of one day, and historical volatility from CRSP returns data over the past 30 days. For our ex-ante risk measures we use implied volatility data from OptionMetrics, and construct three implied volatility spreads from prior literature that measure different types of risk.

First, we construct the volatility premium similar to the approach of Goyal and Saretto (2009) as the spread between the at-the-money (ATM) implied volatility of the 30-day standardized call option from OptionMetrics and the historical volatility of the underlying:

$$IV_{prem} = IV_{call,30d} - Historical\ Volatility \tag{1}$$

Goyal and Saretto (2009) demonstrate that this spread corresponds to revisions to market risk expectations about the underlying asset, increasing when performance is poor and falling when it is good. Therefore, this spread provides a measure of investor beliefs about riskiness of the firms in the financial sector.

Second, we construct the put-call parity deviation IV spread similar to the approach of Cremers and Weinbaum (2010) as the difference between the ATM put and ATM call option implied volatilities for 30-day constant-maturity standardized options:

$$IV_{PCP} = IV_{put,30d} - IV_{call,30d} \tag{2}$$

Cremers and Weinbaum (2010) find that put-call parity deviations predict future returns to the underlying consistent with investor sentiment by informed market participants that take positions in options: if call implied volatility is higher than that of the put, the underlying asset has positive abnormal performance in the future. This spread provides a measure of investor sentiment about the expected performance of firms in the financial sector.

Third, we create the volatility skew spread similar to the approach of Bollen and Whaley (2004) and Xing, Zhang and Zhao (2010) as that between the implied volatilities of the out-of-the-money (OTM) put and ATM call standardized 30-day options. We define OTM puts as those with $\frac{S}{K} < .8$

$$IV_{skew} = IV_{put,OTM,30d} - IV_{call,ATM,30d} \tag{3}$$

Xing, Zhang, and Zhao (2010) find that a positive spread between OTM and ATM implied volatilities predicts abnormally negative underlying performance, consistent with market expectations about increased tail risk. This spread, therefore, provides and indicator of crash risk for financial firms.

We calculate daily CAPM beta using the Dimson (1979) aggregated coefficient method. Lo and MacKinlay (1990) show that some stocks may take up to a week to incorporate information, so we use a five-trading day lead/lag in the estimation of beta. Brennan et al (1993) confirm the usage of 5 lags in daily data to capture slow information diffusion.

$$R_{i,t} = \alpha_i + \sum_{k=-5}^{5} \beta_{1,i} Mkt_{t+k} + \epsilon_i \tag{4}$$

With this estimate of β, we next compute the Hou and Moskowitz (2005) price delay as a measure of trading frictions in financial firm. Following the authors' approach, we can recover the autoregressive coefficients ϕ by dividing the sum of the lagged factor loadings by the beta. The measure of price delay, the speed of information diffusion into the financial institution's stock price, is denoted by δ.

$$\delta_t = \sum \beta(\phi_{t-1} + \phi_{t-2} + \phi_{t-3} + \phi_{t-4} + \phi_{t-5}) \Big/ \beta = \sum_{k=-5}^{-1} \phi_{t+k} \tag{5}$$

The higher the δ, the longer market information takes to be incorporated in the price of a particular financial firm. We drop observations where the delay measure is greater than 10 in absolute terms. We also drop observations where the estimated daily beta is less than -2 as these observations are most likely mismeasured.

To investigate the relationship between information flow networks in the financial sector and the state of the economy, we collect several macroeconomic variables. We obtain the VIX, a measure of investor fears, from CBOE. We create three yield risk spreads using Federal Reserve data, the default premium DEF as the difference between the Moody's AAA and the one-month T-bill, the Credit Spread as the difference between Moody's BAA and AAA corporate bond yields, and the maturity premium TERM as the difference between the 10-year T-bond and one-month T-bill.

Table 1 describes our sample. Despite the focus on the more heavily regulated financial sector and the requirement of tradeable options biasing firm size upward relative to the overall population, we observe a substantial cross-section of market capitalization ranging from \$1.6bn to \$237bn. Similarly, although firms with traded options are often more liquid than the average, we observe a significant cross-section of turnover and Amihud (2002) illiquidity. Consistent with the higher leverage and pro-cyclical behavior of the financial sector, we observe an average beta of 1.2 in our sample, higher than the average 1.0 of the entire population. Notably, price delay is slightly negative, indicating that financial sector returns are on average slightly negatively related to recent market movements consistent with an investor overreaction. This is consistent with the pro-cyclical and systemically critical nature of the financial sector, which motivates our study of information flows in this sector in particular.

2.1 VPIN and Return Network Calculation

We calculate the Volume Synchronized Probability of Informed Trading (VPIN) according to Easley, López de Prado, and O'Hara (2012). Each firm has a unique volume bucket size and observation frequency depends on individual trading volume on any given day. Some days may have observations that occur within a minute while other days may only have a few observations over the course of the trading day. Aggregating the VPIN observations at the hourly frequency allows for comparison between securities while retaining higher frequency information and eliminating asynchronous trading errors in the panel. We use a time weighted average for aggregation and do not allow prior observations to continue beyond the hour after they occur.

We use a rolling 100 trading day window of hourly VPIN data to estimate the conditional correlation network of the VPIN measure. The network structure is estimated with a hill climbing algorithm that optimizes the BIC score of the network and includes restarts to avoid local maxima. This network of informed trading represents information flow through the financial sector. We also define an alternative network using a 100-day window of hourly returns data. This network does not directly address information flow, since informed trades can be firm-specific. For example, informed trading on good news about a specific financial institution would result in positive returns for that institution and potentially negative returns for its competitors, and vice versa. The return network, on the other hand, measures conditional correlation in the co-movement of financial institutions in response to sector-wide news.

The network structure is estimated with a hill climbing algorithm that optimizes the BIC score of the network and utilizes 10 random restarts to avoid local maxima. The estimated network structure is composed of nodes that represent firms and edges that represent conditional correlation. If a significant portion of the variation in a single firm is explained by its neighbors, an edge is drawn from the neighbors to the firm. The algorithm finds the optimal neighbors and number of neighbors for each node to maximize the individual firm variation explained by the neighbors of each node. We use the Baysian Information Criterion (BIC) rather than log likelihood because the maximum likelihood of any network is one where every node is connected to every other node. The BIC imposes a penalty for adding additional links in order to ensure the most informative network structure results from the estimation procedure.

Prior studies use averages of pair-wise correlations to study financial firms (Billio et al (2012) and Patro et al (2013)). The use of averages assumes that every financial firm in the sample has equal influence on the rest of the industry. We believe a better approach is to let the data tell us how much influence each firm has over the others. With the network estimated at a daily frequency, this method allows for the relative influence of each firm to change over time.

We use eigenvector centrality as our measure of the importance of each firm within the network. This follows related papers such as Billio et al. (2012). Eigenvector centrality recursively increases the score a of a vertex as the score of connected vertices increase. This gives the highest score to the vertex that is most connected to other well-connected vertices - in other words, financial firms that are central nodes of information diffusion through the sector will have higher eigenvector centrality than those that simply receive information at the periphery of the network.

We add aggregate measures of network structure connections in order to evaluate individual firm importance in the context of the state of the financial sector. We use edge density and transitivity to describe the overall network structure in each period. Edge density is the ratio of actual firm connections to the number of potential firm connections while transitivity describes the degree of clustering within the network. Transitivity increases when there is an increase in the likelihood that a firm's connections will also be connected.

3 Financial Network Centrality and Firm Characteristics

We begin by examining the relationship of financial firm characteristics with their network centrality according to both the VPIN informed trading measure and overall returns. Table 2 presents decile sorts on eigenvector network centrality for both VPIN and returns with average firm characteristics in each decile.

Within the conditional correlation networks formed on the VPIN measure of informed trading in Panel A of Table 2, there is a monotonic relationship between eigenvector centrality and market capitalization. stocks in the highest decile, which represent the most connected firms, are also the largest firms by market capitalization. This is consistent with an information flow interpretation of the VPIN conditional correlation network, as the biggest firms are also the most significant in the sector. Informed trading in these large firms is highly likely to affect smaller firms as well. Indeed, well-connected firms with high VPIN eigenvector centrality also have higher average daily VPIN levels and low, even negative, price delay. This indicates that more informed trading occurs in these larger, more central firms, and that market information is more quickly being priced into their value. Stocks with low VPIN eigenvector centrality ranking have higher delay measures. This indicates that stocks on the periphery of the network are slower to incorporate new market information, with that from several days prior still having a substantial effect on today's returns. These stocks also have less informed trading. Firms with highly connected informed trading tend to have lower turnover, higher signed VPIN, and smaller deviations from put-call parity. Characteristics not related to VPIN eigenvector centrality include Amihud illiquidity, daily return, CAPM beta, 30-day trailing volatility, implied volatility, the difference between implied volatility and trailing volatility, and volatility skew. It is important to note that the characteristics of volume, illiquidity, and volatility levels do not vary with VPIN eigenvector centrality levels, meaning the information network we create is not explained by these simpler characteristics.

Networks formed on hourly stock returns produce similar results to those formed on the VPIN measure. Panel B of Table 2 shows a monotonic relationship between eigenvector centrality and several firm characteristics that is similar to that in Panel A. Financial stocks that have a high return eigenvector centrality ranking, which have high conditional correlation with other highly conditionally correlated financials, are also larger and have lower price delay. Higher return eigenvector centrality is associated with higher VPIN and signed VPIN, lower turnover, and smaller deviations from put-call parity. Notably the network centrality formed on returns does produce cross-sectional sorts on turnover (volume) and Amihud illiquidity, suggesting that return comovement is more likely than informed trading to be explained by other fundamental firm characteristics.

4 Financial Network Centrality and Firm Risk

We next consider whether network centrality can predict future risks in the financial sector. We test whether network centrality in informed trading and returns can predict next day's intraday volatility and forward-looking risk measures for financial firms from the options market. We control for each financial firm's past risk using current intraday volatility and past historical volatility over the last 30 days, and for expected future risk using the IV spreads IV_{prem}, IV_{PCP}, and IV_{skew}. We also control for other contemporaneous firm characteristics: the current level of informed trading using VPIN, the CAPM beta, price delay, firm size, turnover, and illiquidity:

$$Y_{i,t} = \alpha + \beta X_{i,t-1} + \gamma_1 Y_{i,t-1} + \delta Z_{i,t-1} + \epsilon_{i,t} \tag{6}$$

where $Y_{i,t}$ is the next day's observation of the variable of interest, $X_{i,t-1}$ are network centrality, density, and transitivity, $Y_{i,t-1}$ is the current level of the variable of interest, and $Z_{i,t-1}$ are the firm-specific controls discussed above.

4.1 Intraday Volatility

First, we consider the short-term effects of network centrality on intraday volatility for the next day. We estimate each firm's future intraday volatility using tick data from TAQ, and regress it on the firm's current VPIN and return network centrality, network density and transitivity as measures of the overall state of the financial sector network, and control variables following Eq. (6).

Table 3 presents the results. We see that VPIN network centrality by itself does not have a significant effect on short-term future riskiness measured by next-day intraday volatility in financial firms in Model 1. As expected, current intraday volatility, historical volatility, the forward-looking IV spreads IV_{prem}, IV_{PCP}, and IV_{skew}, volume, and price delay all contribute positively to next-day volatility. Interestingly, CAPM beta actually reduces next-day volatility - stocks that have higher market exposure have less overall volatility throughout the following day. When we take into account both the firm-specific centrality in the VPIN network and the network-wide measures of completeness, the role of the network becomes highly significant in predicting next-day volatility in Models 2 and 3. That is, the significance of firm-specific centrality in the conditional correlation network of informed trades depends on the state of the overall network.

We consider two different summary measures of the state of the network, density and transitivity. Density measures the global completeness of the network as the ratio of observed to total possible connections in the network, increasing with the number of connections in existence. Transitivity measures the average local completeness as the number of connections between a node's immediate neighbors, increasing as a node's neighbors become more interconnected. In both Models 2 and 3 including density and transitivity respectively, the firm-specific VPIN centrality predicts future volatility with coefficients of 0.000264 and 0.000280 significant at the 5% level. This has economic significance as well, as a one standard deviation increase in VPIN centrality results in a 0.4218% and 0.4467% higher next-day volatility for Models 2 and 3 respectively. Similarly, VPIN network density in the financial sector increases next-day volatility for financial firms with a coefficient of 0.000745 while network transitivity increases it with a coefficient of 0.000331, both significant at the 1% level. A one standard deviation increase in financial sector network density increases next-day financial firm volatility by 0.1598% in Model 2 while the same increase in network transitivity increases next-day volatility by 0.1311% in Model 3. Notably, the interaction of firm-specific centrality and network-wide interconnectedness in Models 2 and 3 has a volatility-reducing effect significant at the 5% and 1% levels respectively. In other words, key financial firms in the network of informed trading are less risky in the short term when the VPIN network is more complete and firms are overall more interconnected, taking the emphasis off the central firms.

The financial sector return network in Models 4 through 6 of Table 3 shows that conditional correlation in returns, rather than in firm-specific informed trading specifically, is less useful as a predictor of short-term future financial firm volatility. Return network centrality in Model 4 reduces next day's volatility by 0.0000219 significant at the 1% level. Therefore, a one standard deviation change in return network centrality reduces volatility by 0.0389%. That is, firms that have higher conditional correlation with other highly conditionally correlated firms, those that experience more comovement with others in the industry, experience less short-term volatility consistent with herding behavior. However, measures of return network completeness dilute this significance in Models 5 and 6.

4.2 Implied Volatility Spreads

We next test the effect of informed trading and return networks on market expectations of longer-term risks in the financial sector using forward-looking risk measures from the options market. Table 4 shows the results for the put-call parity deviation demonstrated by Cremers and Weinbaum (2010) to measure informed investor trading related to expected performance of the firm as the dependent variable in Eq. (6). Models 1 through 3 test the power of the informed trading VPIN network to predict put-call parity deviations in the 30-day standardized call and put contracts from OptionMetrics.

As with intraday volatility, we find that firm-specific network centrality on its own has no predictive power for next-day deviations from put-call parity. Furthermore, once we also include the network-wide measures of completeness of density and transitivity, the VPIN network variables become statistically significant in Models 2 and 3 respectively. The centrality of a financial firm in the VPIN network make next-day put-call parity violations lower by -.0540 significant at the 1% level, with a one standard deviation change in network centrality making the put-call spread lower by 45.02%. Network density in Model 2 and network transitivity in Model 3 make the put-call parity spread more negative by -.1418 and -.0463 with significance at the 1% and 5% levels respectively. The interaction of network centrality with density and transitivity makes the spread more negative still by -.0059 in Models 2 and 3 respectively, both significant at the 1% level. The conditional correlation of informed trading in a given financial firm with other highly conditionally correlated ones in the same industry makes informed investors more pessimistic about the firm's prospects. Since highly central firms can be viewed as focal points of informed trading which then propagates throughout the VPIN network, this means that firms in which informed trades originate are viewed more negatively by the market when the completeness of the network is taken into account. Furthermore, the completeness of the network itself further depresses informed traders' expectations about outcomes for the firms, consistent with Allen and Gale (2000). Highly central firms in times when informed trading is particularly correlated among all the firms in the industry, such as times of crisis, makes informed investors' expectations about the future of the firms even more negative.

The return network in Models 4 through 6 of Table 4 shows a weaker predictive relationship with future put-call parity deviations consistent with their origins in informed trading[1] rather than in prior or current raw returns. Return network centrality itself is not statistically significant in Model 4, but its product with density in Model 5 has a coefficient of -.0064 significant at the 1% level. Return network transitivity by itself makes put-call parity deviations more negative with a coefficient of -.0177, weakly significant at the 10% level in Model 6, while its interaction with network centrality makes the implied volatility gap between puts and calls still more negative with a coefficient of -.0065 significant at the 1% level.

Table 5 presents the results for the skewness of expected returns measured by the slope of the implied volatility function following Bollen and Whaley (2005) and Xing, Zhang, and Zhao (2010). A larger difference between OTM and ATM implied volatilities is indicative of investor expectations about negative price jumps or crashes, and is therefore particularly relevant for the systemic risk dimension of the financial sector.

Model 1 of Table 5 fits Eq. (6) to the risk-neutral skewness implied volatility spread, finding that firm-specific VPIN centrality increases the spread between OTM and ATM IVs by .0010 significant at the 5% level. That is, a one standard deviation increase in a firm's network centrality increases the negative skewness spread by 0.16%. However, when we add the network-wide completeness measures of density and transitivity in Models 2 and 3 respectively, we find that the firm-specific centrality effect is dominated by the network-wide completeness measures and their interaction with firm centrality. In Model 2, the interaction of VPIN network density and firm-specific network centrality reduces the negative skewness IV spread by -.0022 significant at the 1% level. Model 3 shows that financial firm VPIN network transitivity itself increases negative skewness by .0128 with weak significance at the 10% level, while the interaction of transitivity with firm-specific centrality reduces the firm's expected crash risk by -.0022 significant at

[1] See Cremers and Weinbaum (2010).

the 1% level. Since VPIN network centrality is defined in terms of conditional correlation with informed trading in other firms, highly central firms in the network should experience the most informed trading, which then propagates outward to the less central firms. Consistent with Xing, Zhang, and Zhao (2010), informed investors take positions in the options market consistent with their expectations about crash risk as in Model 1. However, network completeness reduces the effect of these positions, consistent with higher counterparty risk in times of sector-wide informed trading correlation.

4.3 Informed Trading and Price Delay

If our VPIN conditional correlation network centrality selects financial firms that disseminate information through trading, we would expect these firms to have higher price efficiency and lower trading frictions than others. To test this, we regress the Hou and Moskowitz (2005) price delay measure on both VPIN and return network centrality with our standard battery of controls following Eq. (6).

Table 6 presents the results. Model 1 shows that firm-specific VPIN network centrality does reduce price delay with a coefficient of -.0237 significant at the 10% level. That is, firms that are at the center of the informed trading network do indeed experience lower price delay than those on the periphery. However, when we add the network-wide measures of VPIN network density and transitivity in Models 2 and 3 respectively, we find that the centrality effect is subsumed by the interactions with density and transitivity respectively.

Notably, both the density and transitivity interactions with firm-specific VPIN centrality increase the firm's price delay by .0843 and .0882 in Models 2 and 3 respectively, both significant at the 1% level. That is, when the network is more dense globally as in Model 2, or more complete locally, as in Model 3, firm centrality has an opposite, worsening, effect on price efficiency. While further work is necessary to confirm the cause of this reversal, it is consistent with a worsening of information quality during times when the network is less hierarchical and more interconnected. As the number of connections increases, and the hierarchy of the network decreases, VPIN network centrality is less likely to proxy for the transmission of informed trades from one firm to another. Furthermore, consistent with market overreaction during periods of substantial network-wide interconnectedness such as bubbles and crashes, the information itself is likely to be of a worse quality leading to a further delay in pricing in economy-wide fundamentals.

The return network in Models 4 through 6 in Table 6 has a similar effect on price delay, consistent with the importance of comovement in both informed trades and returns on price efficiency. Firm-specific network centrality reduces price delay by -.0268 unconditional of the overall state of the network in Model 4, significant at the 5% level. When sector-wide density and transitivity are included the interactions with centrality increase next day's price delay by .0835 and .0808 in Models 5 and 6 respectively, significant at the 1% level. As the returns network becomes more complete, systemically important firms that are more highly conditionally correlated with other highly correlated firms experience a worsening in price delay.

5 Financial Sector Interconnections and Macroeconomic Risk

We next turn to measures of macroeconomic risk to test whether the financial sector networks are leading indicators of systemic risk. We consider four daily measures of systemic risk and performance over the next day: the daily return on the S&P 500 index, the change in the Moody's Baa - Aaa credit spread, the change in the VIX index volatility measure, and the level of the risk-neutral skewness implied volatility spread IV_{skew} computed from S&P 500 options. Our predictive variables are the financial sector network-wide density and transitivity measures, which summarize the interconnectedness of financial sector intraday returns.

Figure 1 presents the relation between network density, transitivity, and the Baa - Aaa credit spread as a measure of macroeconomic credit risk. The graphical results are consistent with intraday return density and transitivity in the financial sector being leading indicators of increase in the credit spread, particularly during the financial crises of 2001 and 2008.[2] The increasing interconnectedness of the intraday return network in Figure 1 is consistent with the implications of Acharya (2009) for financial firm correlation and systemic risk.

Since the graphical results could be driven by confounding variables, we next consider the information in the financial sector's intraday return network interconnectedness in a multivariate regression context. We control for other well-known macroeconomic indicators: the term spread $TERM$, the default spread DEF, the 1-month US Treasury rate $UST1M$, and the current day's values of the credit spread, the change in credit spread, the S&P 500 index return, the current level and change in VIX, and the current level of IV_{skew} for the S&P 500 index:

$$Y_{i,t} = \alpha + \beta X_{i,t-1} + \gamma_1 Y_{i,t-1} + \delta Z_{i,t-1} + \epsilon_{i,t} \tag{7}$$

Table 7 presents the results for the model in Eq. (7) for the sector-wide measures of density and transitivity in the informed trading network based on VPIN. Notably, the results from the VPIN network have only weak predictive power for macroeconomic variables, with a 10% statistically significant increase

[2] We omit other macroeconomic time series from the plot for simplicity and brevity. The results are similar.

in credit spread for VPIN network density and a 10% statistically significant decrease in VIX for both density and centrality. However, these weak results are not surprising since VPIN is computed using firm-specific trade imbalances, which makes it much more suited to firm-specific rather than economy-wide information.

We obtain significantly better results for next-day macroeconomic variable prediction with the return network completeness measures in Table 8, in particular for returns network transitivity. We find that increases in the completeness of the financial sector returns network have significant predictive power for our three macroeconomic risk measures, though not for the S&P 500 index performance itself. Specifically, financial sector network density is a weakly significant positive predictor for next day's credit spread with a coefficient of .0002 with 10% significance level, but financial network transitivity is a stronger positive predictor with the same coefficient but 5% significance level. Return network transitivity is also a strong predictor of changes in future VIX, with a coefficient of 1.3224 significant at the 5% level. Thus, a one standard deviation change in return network transitivity produces an 8.76% change in VIX. Finally, both return network density and transitivity have a strong predictive factor on the S&P 500 IV_{skew}, otherwise known as the slope of the implied volatility smirk for the index (Bollen and Whaley, 2005). Return network density increases the next day's index IV_{skew} by .0078 and transitivity increases it by .0049 both significant at the 1% level. In other words, as the return conditional correlation network becomes more complete the credit spread widens, VIX increases, and the implied volatility smirk becomes more steep. All of these results about the relationship between measures of interconnectedness and economic outcomes are consistent with Allen and Gale (2000), Allen, Babus, and Carletti (2012), and Patro et al. (2013).

6 The Economic Value of Financial Network Centrality

6.1 Return Predictability

We now proceed to further quantify the economic significance of the VPIN and return networks in the financial sector. First, we consider the pricing effects of network centrality over the course of the subsequent month. We compute the monthly abnormal returns for each firm using the five-factor Pastor and Stambaugh (2003) model with coefficients determined over the prior five-year rolling window. We then regress next month's abnormal return on our VPIN and return network measures, the current month's abnormal return, and control variables that predict future returns such as historical volatility, the three option-based implied volatility spreads IV_{prem}, IV_{PCP}, and IV_{skew} previously documented to predict abnormal returns,[3] VPIN, price delay, CAPM beta, size, turnover, and Amihud (2002) illiquidity:

$$AR_{i,t} = \alpha + \beta X_{i,t-1} + \gamma_1 AR_{i,t-1} + \delta Z_{i,t-1} + \epsilon_{i,t} \tag{8}$$

where AR is the 5-factor monthly abnormal return relative to the Pastor and Stambaugh (2003) model, X is the vector of network variables, and Z is the vector of control variables. The results for estimating the model in Eq. (8) for the VPIN and return networks in Models 1-3 and 4-6 respectively are described in Table 9.

We find that VPIN network centrality is a significant predictor of next month's abnormal returns, but the state of the sector is also important. When conditioned on the density or transitivity of the network, we find that a central firm produces higher abnormal returns but more so when the network is less dense and has fewer clusters.

6.2 Trading Strategy

Next, we create a simple long-short trading strategy on network centrality. To do this, we form value-weighted portfolios by market capitalization on VPIN eigenvector centrality ranking from the previous trading day. Each portfolio is rebalanced daily based on end-of-day VPIN centrality. A decile arbitrage portfolio is formed by buying the tenth and shorting the first decile portfolio. Likewise, the quintile arbitrage portfolio is formed by buying the fifth and shorting the first quintile portfolio. The realized return from both arbitrage portfolios is tested for abnormal returns. Table 10 shows statistically significant positive abnormal returns in both the decile and quintile arbitrage portfolios formed using the VPIN network eigenvector centrality ranking. The average daily return for the quintile arbitrage portfolio on VPIN centrality is equivalent to an 11.88% annualized abnormal return while the average daily decile arbitrage portfolio produces and annualized abnormal return of 21.87%.

Table 10 also presents analogous results using return network eigenvector centrality ranking. We again form value-weighted portfolios based on centrality from the previous trading day. However, we find that both quintile and decile sorts on return network centrality produce arbitrage portfolios with no significant abnormal returns.

Our results suggest that investors should pay attention to the linkages between firms, particularly in informed trading measured using VPIN. In order to support this argument, we track the time-series

[3] See, e.g., Goyal and Saretto (2009), Cremers and Weinbaum (2010), Bali and Hovakimian (2009), and Xing, Zhang, and Zhao (2010).

performance of our long-short trading strategy with daily rebalanced value-weighted portfolios, as well as the long-only daily portion of the strategy to mitigate concerns about potential short-sale constraints.

Figure 2 shows the performance of the long-only leg of the daily trading strategy on VPIN (left panel) and return (right panel) network centrality from 1996 to 2013 with respect to the four-factor Carhart (1997) benchmark model. The long-only VPIN centrality portfolio that holds the most interconnected financial firms by informed trades exhibits consistent and significant growth, doubling portfolio value (100% abnormal growth) by 2003 and almost tripling it (200% abnormal growth) by 2013. The long-only return centrality portfolio that holds the most interconnected financials by returns exhibits much noisier and less reliable growth, reversing most gains made after 2005.

Figure 3 shows the performance of the zero-cost arbitrage strategy that combines the long leg of highly central firms in Figure 2 with a short leg of the least-central firms. The performance of the VPIN centrality zero-cost strategy is reported on the left, achieving 100% abnormal growth relative to the Carhart (1997) model by 2004 and 200% abnormal growth by 2012. The return centrality zero-cost strategy is shown on the right. This strategy is much more volatile, achieving a short-lived 300% growth during the end of the financial crisis in 2009 but losing most of those gains by 2013.

The difference in the economic significance of the two network measures illustrates the importance of linkages in informed trades specifically, rather than raw returns, in explaining the future performance of financial firms. The daily value-weighted zero-cost portfolio based on the VPIN network centrality delivers an average annualized abnormal return of 7.73% and an information ratio of 0.25. The same strategy based on return network centrality delivers only 0.57% annualized abnormal return with an information ratio of 0.02.

7 Conclusion

We create two novel measures of comovement in the financial sector by creating conditional correlation networks from informed trading, measured the Easley, de Prado, and O'Hara (2012) VPIN, and raw returns. We identify the importance of individual firms in these networks using eigenvector centrality, which captures the conditional correlation of the given financial firm with other highly-correlated firms in the financial sector. This type of centrality measure identifies firms that are drivers of firm-to-firm conditional correlation by each type of signal: informed trading for VPIN, and price movement for raw returns.

We also compute network-wide measures of completeness for each type of network, with network density describing the global completeness of the network relative to the maximum possible number of connections and transitivity describing the average local completeness of the network of each firm's immediate neighbors. These measures have strong predictive power for firm-specific risks, price efficiency, macroeconomic risk, and future firm performance.

We find that the VPIN network, defined using the firm-specific trade imbalance VPIN measure, has strong predictive power for firm-specific risks. A financial firm's VPIN network centrality predicts future firm intraday volatility, future expected risk from option implied volatility spreads, and future firm price delay. Notably, these firm-specific effects are conditional on the state of the overall network: during times of higher interconnectedness when the VPIN network is more complete, the effect of centrality is often reversed as in the cases of price delay and risk-neutral skewness from the option market. In other cases it is magnified, such as that for future put-call parity violations consistent with informed trading (Cremers and Weinbaum, 2010).

The return network is defined from raw price changes which have a greater exposure to sector-wide shocks than the firm-specific informed trading VPIN measure. While the return network is significantly less reliable in predicting firm-specific future risk, the network-wide interconnectedness measures of density and transitivity are significant predictors of macroeconomic risk. Consistent with prior findings by Allen and Gale (2000), Allen, Babus, and Carletti (2012), and Patro et al. (2013), higher returns network density results in higher future credit spread and a steeper S&P 500 implied volatility smirk, while transitivity has an even stronger positive effect for these as well as increases in the VIX index volatility measure, all of which are consistent with higher expected macroeconomic risk.

Finally, firm-specific VPIN network centrality has a strong effect on future firm performance, both at the monthly and daily level, relative to standard performance benchmarks. A daily trading strategy long firms with high VPIN centrality, which are the drivers of sector-wide correlation in informed trading, and short those with low VPIN centrality, which are on the periphery of the network, earns an abnormal 7.73% return per year.

These findings establish the importance of conditional correlation networks in the financial sector for firm-specific risk, macroeconomic risk, and firm-specific future performance. These results are extendable to other industries or representative sets of firms such as the S&P 500 constituents, though the processing time required to compute conditional correlations may place inherent limits on the number that can be simultaneously considered.

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Appendix A

We detail the construction of our variables below. Table 1 reports summary statistics.

Centrality
The eigenvector centrality of each firm within each day's network.

Density
The daily ratio of actual firm connections to the number of potential firm connections.

Transitivity
The daily measure of local clustering within the network.

VPIN
The hourly Volume Synchronized Probability of Informed Trading measure, following Easley, López de Prado, and O'Hara (2012) using bulk volume classification. Observations calculated in each security's volume time are time weighted to produce an hourly panel.

Signed VPIN
The hourly Volume Synchronized Probability of Informed Trading measure, following Easley, López de Prado, and O'Hara (2012), with the sign of the return averaged over a single day.

Intraday Volatility
The volatility of stock returns in a single day using trade data from the NYSE TAQ data set.

Historic Volatility
The volatility of underlying stock returns computed over the past 30 days.

Implied Volatility
The at-the-money implied volatility for a 30-day constant-maturity call option interpolated from trade data.

Volatility Premium
The spread between the Implied Volatility and Historic Volatility, following Goyal and Saretto (2009).

Put-Call Parity Deviation
The spread between the at-the-money 30-day standardized call and put Implied Volatilities, following Cremers and Weinbaum (2010).

Volatility Skew
The spread between the out-of-the-money put option ($\frac{S}{K} \leq .8$) and at-the-money call implied volatility following Bollen and Whaley (2004).

Price Delay
The daily sum of the five prior day market factor loadings divided by beta, following Hou and Moskowitz (2005).

CAPM Beta
The daily market factor loading estimated using the trailing 60 days.

Return
Daily returns are taken from CRSP and monthly returns are taken from Compustat

Turnover
The number of shares traded each day divided by the total number of shares outstanding

Amihud Illiquidity
The ratio of absolute value daily return to dollar daily volume, following Amihud (2002).

Market Capitalization
The price per share multiplied by shares outstanding (for the current/prior quarter?) in $ millions.

Size
The logarithm of Market Capitalization.

VIX
The level of the CBOE volatility index.

DEF
The difference between Moody's AAA corporate bond index yield and the yield on the 1 month treasury bill.

TERM
The difference between the yield on the 10 year treasury bond and the yield on the 1 month treasury bill.

Credit Spread
The difference between the yield on Moody's BAA corporate bond index and the yield on Moody's AAA corporate bond yield.

IV Slope
OTM Put delta$_{-.25}$ - ATM Put delta$_{-.50}$

Table 1: Summary Statistics. Market capitalization is measured in millions of dollars. Amihud illiquidity is multiplied by 10^{10} to improve readability. Variable construction is described in Appendix Appendix A.

Metric	Obs	Mean	Std Dev	1%	25%	50%	75%	99%
VPIN Centrality	105099	0.7085	0.1571	0.3587	0.5938	0.7090	0.8241	1.0000
Return Centrality	105098	0.6938	0.1765	0.2100	0.5838	0.7058	0.8187	1.0000
Market Capitalization	105099	24951	37364	1652	8091	13974	23079	236878
Turnover	105099	0.0088	0.0132	0.0010	0.0030	0.0053	0.0099	0.0564
Amihud Illiquidity	105099	2.8410	5.3449	0.0000	0.4526	1.2512	3.0765	23.0299
Daily VPIN	105099	0.3341	0.0853	0.0845	0.2895	0.3479	0.3940	0.4834
Daily Signed VPIN	105094	0.0023	0.1336	-0.3113	-0.0829	0.0025	0.0867	0.3187
Return	105099	0.0006	0.0290	-0.0770	-0.0107	0.0000	0.0113	0.0830
CAPM Beta	105099	1.2371	1.0744	-1.0175	0.6205	1.1156	1.6979	4.7747
Price Delay	105099	-0.0760	1.2673	-4.8102	-0.3008	0.0146	0.2444	4.3023
Intraday Volatility	105019	0.0581	3.5525	0.0001	0.0005	0.0011	0.0024	0.0411
Historic Volatility	105099	0.3595	0.3020	0.0912	0.1987	0.2828	0.4107	1.6417
Implied Volatility	100184	0.3550	0.2082	0.1331	0.2321	0.3071	0.4072	1.2358
Volatility Premium	100184	-0.0050	0.1716	-0.5994	-0.0340	0.0213	0.0644	0.2324
Put-Call Parity Deviation	100184	0.0076	0.0567	-0.0665	-0.0036	0.0041	0.0135	0.1008
Volatility Skew	89294	0.0405	0.0442	-0.0193	0.0188	0.0359	0.0539	0.1698
VIX	4165	22.1630	8.5458	10.5964	16.5800	20.7500	25.3900	54.9452
IV Slope	4167	0.0379	0.0148	0.0148	0.0277	0.0351	0.0450	0.0856
S&P 500 Return	4167	0.0003	0.0130	-0.0347	-0.0057	0.0007	0.0065	0.0371
VPIN Density	4167	0.2316	0.0198	0.1929	0.2169	0.2303	0.2446	0.2815
Return Density	4167	0.2037	0.0315	0.1403	0.1798	0.2020	0.2282	0.2688
VPIN Transitivity	4167	0.4717	0.0369	0.3932	0.4454	0.4699	0.4962	0.5621
Return Transitivity	4167	0.4045	0.0663	0.2678	0.3522	0.4094	0.4556	0.5340
UST 1M	2837	0.0164	0.0167	0.0000	0.0011	0.0117	0.0265	0.0522
TERM	2837	0.0216	0.0120	-0.0062	0.0147	0.0240	0.0321	0.0381
DEF	2837	0.0372	0.0156	0.0010	0.0280	0.0432	0.0493	0.0582
Credit Spread	2837	0.0103	0.0047	0.0055	0.0076	0.0091	0.0118	0.0310

Table 2: Eigenvector Centrality Deciles. We form deciles sorted on eigenvector centrality from conditional correlation networks estimated from the VPIN measure of informed trading. Deciles are formed each trading day and the reported metrics are the median of each decile across time. Market capitalization is reported in millions of dollars. Amihud illiquidity is multiplied by 10^{10} to improve readability. Variable construction is described in Appendix Appendix A.

Panel A: VPIN Network

Decile	1	2	3	4	5	6	7	8	9	10
Market Capitalization	12531	12878	13400	13257	13508	13800	14089	14540	14879	15911
Turnover	0.0055	0.0055	0.0055	0.0054	0.0054	0.0053	0.0052	0.0051	0.0052	0.0051
Amihud Illiquidity	1.2433	1.2279	1.1782	1.2531	1.2503	1.2579	1.2650	1.2852	1.2541	1.2735
Daily VPIN	0.3211	0.3356	0.3398	0.3440	0.3463	0.3507	0.3521	0.3558	0.3570	0.3604
Daily Signed VPIN	-0.0027	0.0020	0.0012	0.0029	0.0050	0.0027	0.0045	0.0026	0.0006	0.0047
Return	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
CAPM Beta	1.1679	1.1382	1.1479	1.1263	1.1176	1.1119	1.0939	1.0821	1.0900	1.1039
Price Delay	0.0639	0.0326	0.0243	0.0200	0.0203	0.0121	0.0110	0.0016	-0.0070	-0.0103
Intraday Volatility	0.0011	0.0011	0.0010	0.0011	0.0011	0.0011	0.0011	0.0010	0.0011	0.0011
Historic Volatility	0.2966	0.2848	0.2822	0.2902	0.2827	0.2824	0.2808	0.2757	0.2743	0.2810
Implied Volatility	0.3289	0.3118	0.3105	0.3126	0.3055	0.3074	0.3024	0.2986	0.2983	0.3044
Volatility Premium	0.0190	0.0224	0.0232	0.0211	0.0215	0.0225	0.0205	0.0206	0.0220	0.0197
Put-Call Parity Deviation	0.0045	0.0045	0.0043	0.0043	0.0043	0.0042	0.0042	0.0041	0.0037	0.0038
Volatility Skew	0.0362	0.0353	0.0356	0.0360	0.0352	0.0363	0.0360	0.0361	0.0361	0.0359

Panel B: Return Network

Decile	1	2	3	4	5	6	7	8	9	10
Market Capitalization	12824	13352	13378	13576	13732	13785	13980	14876	15157	15593
Turnover	0.0060	0.0055	0.0055	0.0053	0.0053	0.0053	0.0051	0.0052	0.0051	0.0050
Amihud Illiquidity	1.2875	1.2620	1.2793	1.3098	1.2853	1.2657	1.2705	1.1940	1.2037	1.1939
Daily VPIN	0.3438	0.3461	0.3461	0.3463	0.3471	0.3488	0.3479	0.3503	0.3490	0.3518
Daily Signed VPIN	0.0002	0.0009	0.0024	0.0029	0.0021	0.0063	0.0010	-0.0017	0.0020	0.0085
Return	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0002	0.0000
CAPM Beta	1.0823	1.1296	1.1242	1.1231	1.1196	1.1166	1.1171	1.1146	1.1022	1.1163
Price Delay	0.0754	0.0256	0.0212	0.0172	0.0177	0.0142	0.0118	0.0045	-0.0065	-0.0098
Intraday Volatility	0.0012	0.0011	0.0011	0.0011	0.0010	0.0011	0.0011	0.0011	0.0010	0.0010
Historic Volatility	0.2861	0.2869	0.2844	0.2849	0.2788	0.2853	0.2812	0.2821	0.2785	0.2806
Implied Volatility	0.3134	0.3151	0.3100	0.3093	0.3048	0.3091	0.3067	0.3033	0.3023	0.3023
Volatility Premium	0.0191	0.0222	0.0213	0.0231	0.0223	0.0213	0.0208	0.0205	0.0215	0.0199
Put-Call Parity Deviation	0.0043	0.0043	0.0043	0.0042	0.0042	0.0043	0.0042	0.0039	0.0040	0.0039
Volatility Skew	0.0339	0.0360	0.0361	0.0359	0.0354	0.0365	0.0359	0.0366	0.0362	0.0359

Table 3: Intraday Volatility Prediction. We use daily eigenvector centrality to predict the next trading day's intraday volatility. Estimates are scaled by 10^4 to improve readability. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates and each regression includes firm fixed effects. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN Network			Return Network		
Factor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Centrality	0.0698	2.6398**	2.7957***	−0.2187***	0.1091	0.0137
	0.8498	2.5135	2.7547	−3.1106	0.2316	0.0326
Density		7.4456***			0.5235	
		2.6604			0.3684	
Centrality x Density		−12.6058**			−1.7564	
		−2.4658			−0.6754	
Transitivity			3.3065***			0.2969
			2.8054			0.5205
Centrality x Transitivity			−5.8377***			−0.5853
			−2.6989			−0.5618
Current Intraday Volatility	95.2835***	95.3581***	95.3529***	95.1374***	95.1309***	95.1373***
	68.4434	68.4912	68.4887	68.3233	68.3102	68.3214
Historic Volatility	1.2939***	1.3127***	1.2995***	1.3015***	1.3004***	1.3017***
	16.7566	16.6188	16.6965	16.8445	16.8283	16.8424
Volatility Premium	0.3243***	0.3289***	0.3249***	0.3271***	0.3284***	0.3274***
	6.4676	6.5342	6.4745	6.5228	6.5467	6.5266
Put-Call Parity Deviation	0.5004***	0.5114****	0.5097***	0.5024***	0.5063***	0.5036***
	2.8172	2.8784	2.8693	2.8288	2.8502	2.8349
Volatility Skew	0.8219***	0.8194***	0.8084***	0.8506***	0.8838***	0.8535***
	3.8290	3.8169	3.7600	3.9594	4.0777	3.9209
Daily VPIN	0.1192	0.1224	0.1108	0.1431	0.1657	0.1429
	1.2131	1.2427	1.1271	1.4608	1.6502	1.4113
Price Delay	0.0129**	0.0128**	0.0129**	0.0129**	0.0128**	0.0129**
	2.2596	2.2395	2.2660	2.2629	2.2492	2.2578
CAPM Beta	−0.0176**	−0.0176**	−0.0179**	−0.0179**	−0.0174**	−0.0178**
	−2.3375	−2.3408	−2.3863	−2.3792	−2.3192	−2.3646
Size	0.0195	0.0213	0.0193	0.0296	0.0330	0.0298
	0.8262	0.8995	0.8170	1.2472	1.3756	1.2463
Turnover	5.8158***	5.9155***	5.8263***	5.8361***	6.0328***	5.8464***
	7.8219	7.9457	7.8317	7.8492	7.8972	7.6615
Amihud Illiquidity	1148.5360	1187.6574	1252.1365	1059.2484	840.7447	1034.5992
	0.7397	0.7647	0.8059	0.6824	0.5378	0.6615
Observations	88,845	88,845	88,845	88,845	88,845	88,845
Adjusted R^2	0.0299	0.0300	0.0300	0.0299	0.0299	0.0299

Table 4: Daily Put-Call Parity Deviations. We test whether the eignevector centrality of the network can predict Cremers and Weinbaum (2010) put-call parity. Estimates are scaled by 10^4 to improve readability. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates and each regression includes firm fixed effects. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN Network			Return Network		
Factor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Centrality	−7.0071	−540.4838***	−359.1188**	−19.5456	−100.3256	−111.8974
	−0.4879	−2.9456	−2.0252	−1.5918	−1.2203	−1.5314
Density		−1418.3005***			−360.0332	
		−2.9007			−1.4508	
Centrality x Density		−59.0538***			−63.8702***	
		−4.0810			−4.3827	
Transitivity			−462.9668**			−176.8883*
			−2.2481			−1.7761
Centrality x Transitivity			−59.0711***			−64.7225***
			−4.0861			−4.4345
Intraday Volatility	70.9292	69.4644	66.3329	65.8824	61.2720	63.3495
	0.4925	0.4823	0.4605	0.4573	0.4252	0.4397
Historic Volatility	92.1632***	92.2034***	89.8173***	92.9775***	93.2899***	93.7107***
	6.8464	6.6944	6.6199	6.9033	6.9254	6.9552
Volatility Premium	85.7802***	85.8564***	85.3513***	86.0361***	86.4644***	86.4083***
	9.7908	9.7629	9.7336	9.8184	9.8641	9.8576
Put-Call Parity Deviation	4319.6328***	4318.1461***	4318.1298***	4319.6580***	4320.4370***	4320.8400***
	139.5454	139.4584	139.4747	139.5496	139.5542	139.5414
Volatility Skew	−244.6005***	−244.1039***	−240.8375***	−242.2258***	−233.4489***	−229.8062***
	−6.5333	−6.5202	−6.4227	−6.4648	−6.1756	−6.0527
Daily VPIN	−39.8671**	−38.9463**	−38.6158**	−39.2857**	−31.8745*	−29.4520*
	−2.3218	−2.2625	−2.2480	−2.2949	−1.8160	−1.6641
Price Delay	2.2631**	2.2493**	2.2602**	2.2711**	2.2567**	2.2490**
	2.2701	2.2555	2.2672	2.2782	2.2636	2.2558
CAPM Beta	−7.4988***	−7.4377***	−7.4723***	−7.4939***	−7.4534***	−7.5028***
	−5.7092	−5.6594	−5.6868	−5.7068	−5.6704	−5.7118
Size	−18.1123***	−17.9337***	−18.3304***	−17.3389***	−16.2939***	−16.3397***
	−4.3956	−4.3303	−4.4394	−4.1754	−3.8894	−3.9078
Turnover	374.8015***	360.6122***	377.1854***	378.4917***	431.7719***	437.9803***
	2.9441	2.8295	2.9613	2.9732	3.3039	3.3555
Amihud Illiquidity	118.7429***	117.7009***	116.5797***	118.7956***	113.2982***	112.3638***
	4.3850	4.3462	4.3026	4.3884	4.1557	4.1190
Observations	88,813	88,813	88,813	88,813	88,813	88,813
Adjusted R^2	0.3189	0.3190	0.3189	0.3189	0.3189	0.3189

Table 5: Daily Implied Volatility Skew. We test whether the eignevector centrality of the network can predict Xing,Zhang, and Zhao (2010) volatility skew. Estimates are scaled by 10^4 to improve readability. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates and each regression includes firm fixed effects. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN Network			Return Network		
Factor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Centrality	10.4362**	85.2324	37.1109	20.7577***	−52.6089*	−30.0989
	1.9747	1.2610	0.5699	4.5913	−1.7478	−1.1236
Density		230.2762			222.1794**	
		1.2784			2.4425	
Centrality x Density		−22.0403***			−9.6132*	
		−4.1051			−1.7812	
Transitivity			127.6026*			142.3490***
			1.6873			3.8944
Centrality x Transitivity			−21.6541***			−6.0501
			−4.0381			−1.1202
Intraday Volatility	16.9906	17.6159	21.3579	22.0477	23.6773	19.0829
	0.3293	0.3414	0.4140	0.4273	0.4596	0.3705
Historic Volatility	107.6400***	108.6524***	112.6272***	107.0466***	110.0119***	109.1862***
	20.9556	20.6935	21.7457	20.8384	21.4404	21.3010
Volatility Premium	34.6221***	34.8746***	35.6627***	34.3645***	33.0914***	33.3867***
	10.2142	10.2495	10.5129	10.1385	9.7795	9.8740
Put-Call Parity Deviation	533.1805***	533.3991***	534.6461***	532.2313***	533.8404***	536.4641***
	36.1990	36.2061	36.2750	36.1513	36.2439	36.3745
Volatility Skew	8301.3203***	8301.2297***	8291.9415***	8297.9784***	8236.1559***	8205.9422***
	491.2249	491.1936	489.5845	490.7350	480.6431	475.6549
Daily VPIN	72.6288***	72.8021***	71.9269***	72.1968***	49.1351***	40.0340***
	11.4464	11.4493	11.3321	11.4150	7.5950	6.1458
Price Delay	−0.7603**	−0.7702**	−0.7782**	−0.7744**	−0.7009*	−0.6398*
	−2.0539	−2.0794	−2.1024	−2.0922	−1.8964	−1.7321
CAPM Beta	0.3592	0.3647	0.4052	0.3600	−0.0319	0.1175
	0.7382	0.7491	0.8326	0.7402	−0.0657	0.2421
Size	7.2641***	7.4054***	7.9438***	6.4029***	2.7167*	2.4276
	4.7761	4.8441	5.2132	4.1774	1.7587	1.5761
Turnover	720.1635***	724.3932***	707.9717***	711.3414***	473.9634***	427.3732***
	14.4352	14.5023	14.1885	14.2623	9.2566	8.3585
Amihud Illiquidity	−81.2403***	−81.0720***	−78.4848***	−81.7035***	−61.3891***	−56.1009***
	−7.9620	−7.9447	−7.6886	−8.0118	−5.9901	−5.4752
Observations	87,550	87,550	87,550	87,550	87,550	87,550
Adjusted R^2	0.7725	0.7725	0.7725	0.7725	0.7723	0.7722

Table 6: Explaining Price Delay with Network Centrality. We calculate daily price delay as the sum of the autoregressive coefficients on rolling CAPM estimates. Higher price delay indicates that past information is still affecting current prices while a price delay of zero represents a random walk. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates and each regression includes firm fixed effects. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN Network			Return Network		
Factor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Centrality	−0.0237*	−0.1460	−0.1447	−0.0268**	0.0406	0.0849
	−1.7205	−0.8242	−0.7080	−2.2656	0.5192	1.0450
Density		0.1860			0.0740	
		0.3945			0.3140	
Centrality x Density		0.0843***			0.0835***	
		6.0346			5.9366	
Transitivity			−0.0731			0.0607
			−0.2526			0.4596
Centrality x Transitivity			0.0882***			0.0808***
			6.3224			5.7344
Lagged Price Delay	0.8211***	0.8206***	0.8211***	0.8211***	0.8210***	0.8208***
	401.7504	401.1626	401.7015	401.6879	401.4479	401.1223
Size	−0.0135***	−0.0114***	−0.0130***	−0.0126***	−0.0117***	−0.0111***
	−3.3963	−2.8674	−3.2807	−3.1601	−2.9003	−2.7688
CAPM Beta	0.0105***	0.0108***	0.0106***	0.0106***	0.0107***	0.0106***
	8.3742	8.5959	8.4214	8.3960	8.4704	8.4385
Historic Volatility	−0.0782***	−0.0625***	−0.0751***	−0.0772***	−0.0776***	−0.0762***
	−6.0564	−4.7321	−5.7735	−5.9785	−6.0069	−5.9030
Volatility Premium	−0.0274***	−0.0232***	−0.0267***	−0.0272***	−0.0268***	−0.0264***
	−3.2285	−2.7245	−3.1481	−3.2002	−3.1603	−3.1122
Put-Call Parity Deviation	0.0071	0.0106	0.0073	0.0070	0.0082	0.0100
	0.2362	0.3517	0.2421	0.2315	0.2725	0.3303
Volatility Skew	−0.1640***	−0.1636***	−0.1676***	−0.1609***	−0.1514***	−0.1414***
	−4.5674	−4.5577	−4.6608	−4.4782	−4.1759	−3.8820
VPIN	0.0094	0.0156	0.0092	0.0086	0.0153	0.0222
	0.5712	0.9466	0.5595	0.5239	0.9100	1.3048
Turnover	0.1974	0.2137*	0.1890	0.2044*	0.2573**	0.2922**
	1.6417	1.7749	1.5705	1.6992	2.0825	2.3684
Amihud Illiquidity	0.5070	0.3859	0.6368	0.5652	−0.0289	−0.5111
	0.2000	0.1522	0.2510	0.2230	−0.0113	−0.2000
Observations	79,134	79,134	79,134	79,134	79,134	79,134
Adjusted R^2	0.6950	0.6951	0.6950	0.6950	0.6950	0.6950

Table 7: The Predictive Value of the VPIN Network. We utilize two daily measures of aggregate network connectedness, density and transitivity, to predict macro variables. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	S&P500 Return_{t+1}		Δ Credit Spread_{t+1}		Δ VIX_{t+1}		IV Slope_{t+1}	
Density	0.0005		0.0004*		−2.5604*		−0.0015	
	0.0409		1.8126		−1.7320		−0.4903	
Transitivity		−0.0013		0.0001		−1.4068*		0.0001
		−0.1971		0.7513		−1.8522		0.0609
TERM	0.1904**	0.1834*	0.0001	−0.0001	−65.6657***	−67.8610***	−0.0484**	−0.0453*
	1.9924	1.8829	0.0867	−0.0353	−5.8951	−5.9765	−2.0685	−1.8994
DEF	−0.2834***	−0.2767***	−0.0032**	−0.0029*	84.3678***	85.7561***	0.0320	0.0287
	−2.8163	−2.7269	−2.0866	−1.8895	7.2122	7.2708	1.3052	1.1640
UST 1M	−0.0011***	−0.0011***	−0.0000***	−0.0000***	0.2332***	0.2279***	−0.0002*	−0.0002*
	−2.8567	−2.8569	−3.5176	−3.3579	5.2646	5.1621	−1.9111	−1.9543
Credit Spread	−0.0293	−0.0298	−0.0107***	−0.0109***	27.1981***	28.6777***	0.0041	0.0055
	−0.4048	−0.4160	−9.7744	−10.0531	3.2998	3.5139	0.2376	0.3166
Δ Credit Spread	−0.2297	−0.2209	0.0373***	0.0383***	143.3762	141.1983	−0.0609	−0.0696
	−0.2474	−0.2382	2.6731	2.7459	1.3688	1.3488	−0.2700	−0.3087
S&P 500 Return	−0.0242	−0.0243	−0.0004	−0.0004	5.0144	4.9970	0.0352***	0.0354***
	−0.8571	−0.8618	−0.9234	−0.9110	1.5248	1.5191	5.0713	5.0865
VIX	0.0001	0.0001	0.0000***	0.0000***	−0.0707***	−0.0719***	0.0001***	0.0001***
	1.4424	1.3977	6.3078	6.2034	−7.9648	−8.0509	2.8738	2.9201
Δ VIX	0.0003	0.0003	0.0000	0.0000	−0.0030	−0.0023	0.0002***	0.0002***
	1.1884	1.1856	0.1797	0.2142	−0.1209	−0.0927	4.3443	4.3502
IV Slope	0.0057	0.0059	−0.0011**	−0.0011**	3.0791	3.4986	0.9263***	0.9265***
	0.1608	0.1669	−2.0295	−2.0482	0.7470	0.8485	106.5678	106.6147
Observations	2,717	2,717	2,596	2,596	2,716	2,716	2,717	2,717
Adjusted R^2	0.0072	0.0071	0.0461	0.0450	0.0558	0.0560	0.9621	0.9621

Table 8: The Predictive Value of the Return Network. We utilize two daily measures of aggregate network connectedness, density and transitivity, to predict macro variables. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	S&P500 Return$_{t+1}$		Δ Credit Spread$_{t+1}$		Δ VIX$_{t+1}$		IV Slope$_{t+1}$	
Density	−0.0029		0.0002*		0.7229		0.0078***	
	−0.3172		1.7588		0.6787		3.4273	
Transitivity		−0.0035		0.0002**		1.3224**		0.0049***
		−0.7215		2.2739		2.3239		4.0713
TERM	0.1883**	0.1974**	−0.0003	−0.0007	−60.6680***	−63.4200***	−0.0418*	−0.0558**
	2.0042	2.0870	−0.2113	−0.5206	−5.5459	−5.7641	−1.8210	−2.4138
DEF	−0.2834***	−0.2967***	−0.0024	−0.0019	79.5027***	84.1764***	0.0317	0.0483**
	−2.8679	−2.9403	−1.6209	−1.2334	6.9286	7.1955	1.3210	1.9713
UST 1M	−0.0011***	−0.0012***	−0.0000***	−0.0000**	0.2305***	0.2541***	−0.0001	−0.0001
	−2.8446	−2.9201	−2.8772	−2.5469	5.0947	5.4942	−1.2817	−0.7649
Credit Spread	−0.0261	−0.0235	−0.0111***	−0.0111***	28.1415***	26.8958***	−0.0030	−0.0027
	−0.3633	−0.3273	−10.2387	−10.2753	3.4344	3.2869	−0.1714	−0.1573
Δ Credit Spread	−0.2205	−0.2141	0.0381***	0.0381***	122.4507	114.7143	−0.0900	−0.0948
	−0.2380	−0.2310	2.7379	2.7405	1.1707	1.0969	−0.4006	−0.4221
S&P 500 Return	−0.0236	−0.0225	−0.0004	−0.0005	5.0134	4.5189	0.0342***	0.0334***
	−0.8343	−0.7943	−0.9869	−1.0342	1.5201	1.3699	4.9138	4.8009
VIX	0.0001	0.0001	0.0000***	0.0000***	−0.0672***	−0.0661***	0.0001***	0.0001***
	1.3323	1.3438	6.4012	6.3253	−7.4535	−7.4454	3.7272	3.3863
Δ VIX	0.0003	0.0003	0.0000	0.0000	−0.0040	−0.0063	0.0002***	0.0002***
	1.2056	1.2272	0.1189	0.1393	−0.1601	−0.2551	4.1845	4.1643
IV Slope	0.0099	0.0138	−0.0014**	−0.0014**	2.2595	0.4093	0.9164***	0.9164***
	0.2685	0.3771	−2.4712	−2.5474	0.5272	0.0966	101.9204	102.9642
Observations	2,717	2,717	2,596	2,596	2,716	2,716	2,717	2,717
Adjusted R^2	0.0072	0.0073	0.0458	0.0465	0.0541	0.0554	0.9622	0.9623

Table 9: Monthly Abnormal Return Prediction. We test whether the network's eigenvector centrality can predict the next month's abnormal return for each firm. We use the prior 60 months to estimate the factor loadings in the 5-factor model. Estimates are scaled by 10^2 to improve readability. Variable construction is described in Appendix Appendix A. T-statistics are below the estimates and each regression includes firm fixed effects. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN Network			Return Network		
Factor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Centrality	6.0851***	75.3272**	92.2549**	−0.9941	28.1781*	28.5795
	2.7731	2.2172	2.1714	−0.5277	1.7329	1.3605
Density		199.5743**			101.3367**	
		2.1367			2.1655	
Centrality x Density		−341.4216**			−157.4406*	
		−2.0467			−1.8547	
Transitivity			126.6739**			58.7020*
			2.0665			1.8098
Centrality x Transitivity			−223.3604**			−85.4427
			−2.0318			−1.4489
Current Abnormal Return	−0.0678***	−0.0691***	−0.0694***	−0.0650***	−0.0655***	−0.0653***
	−3.8078	−3.8809	−3.8973	−3.6411	−3.6822	−3.6676
Historic Volatility	−11.7520***	−10.8812***	−11.4757***	−11.7796***	−11.9977***	−12.2396***
	−5.7952	−5.1441	−5.5971	−5.7863	−5.9037	−5.9993
Volatility Premium	−7.1529***	−6.8319***	−7.0825***	−7.1750***	−7.6283***	−7.7259***
	−4.3869	−4.1763	−4.3464	−4.3898	−4.6470	−4.6917
Put-Call Parity Deviation	−7.3462	−7.1370	−6.4123	−6.3509	−7.2791	−7.8253
	−0.7779	−0.7557	−0.6783	−0.6715	−0.7694	−0.8265
Volatility Skew	13.3743*	11.6289	12.1195	14.5616*	13.4212*	12.7154
	1.7379	1.5037	1.5646	1.8884	1.7317	1.6356
VPIN	4.2384	4.7537	5.3186	5.5706	7.3351	6.7734
	0.7411	0.8187	0.9138	0.9754	1.2730	1.1829
Price Delay	0.1139	0.0760	0.0810	0.1249	0.1317	0.1461
	0.6826	0.4537	0.4841	0.7474	0.7887	0.8737
CAPM Beta	0.2647	0.2558	0.2518	0.2351	0.2132	0.2296
	1.5576	1.5054	1.4818	1.3840	1.2520	1.3523
Size	−0.3691	−0.3066	−0.3304	−0.1745	−0.2154	−0.1862
	−0.6201	−0.5134	−0.5528	−0.2909	−0.3595	−0.3109
Turnover	26.6383*	27.4937*	27.7255*	26.5603	23.0464	22.3196
	1.7703	1.8304	1.8446	1.7622	1.5200	1.4722
Amihud Illiquidity	92.3916***	90.8891***	92.6210***	93.7140***	101.6567***	103.0986***
	5.2727	5.1839	5.2919	5.3339	5.6946	5.7965
Observations	2,184	2,184	2,184	2,184	2,184	2,184
Adjusted R^2	0.0414	0.0427	0.0423	0.0384	0.0412	0.0414

Table 10: Trading Strategy Tests. We form value-weighted portfolios using eigenvector centrality ranking and market capitalization from the previous trading day. Each portfolio is rebalanced daily. A decile arbitrage portfolio is formed by buying the tenth decile portfolio and shorting the first decile portfolio. Likewise, the quintile arbitrage portfolio is formed by buying the fifth quintile portfolio and shorting the first quintile portfolio. The realized return from both arbitrage portfolios is tested for abnormal returns. *, **, * indicates significance at the 1%, 5%, and 10% levels respectively.**

	VPIN		Return	
Factor	Quintiles	Deciles	Quintiles	Deciles
Alpha	0.0004***	0.0008***	0.0001	0.0003
	2.6458	3.3131	0.4925	1.3786
MRP	−0.0533***	0.0026	0.0298**	0.0527**
	−3.6610	0.1256	2.0440	2.5072
SMB	−0.0680**	−0.1472***	0.0404	0.0810**
	−2.4446	−3.7310	1.4513	2.0537
HML	−0.2576***	−0.2193***	−0.0339	0.0253
	−8.8880	−5.3054	−1.1842	0.6129
UMD	0.1411***	0.0871***	−0.0807***	−0.1570***
	7.2458	3.1573	−4.2042	−5.7290
Obs	4,156	4,027	4,158	4,043
Adj. R^2	0.0380	0.0110	0.0054	0.0105

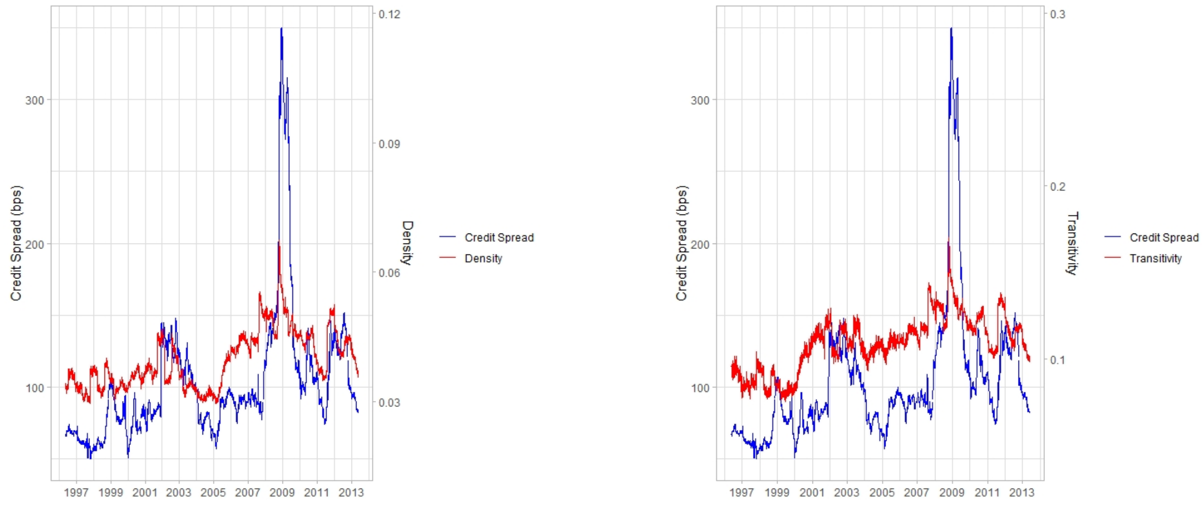


Figure 1: Return Network Properties and the Credit Spread. We graph the density (left) and transitivity (right) of the return network over time relative to the return on the spread between BAA and AAA rated bonds.

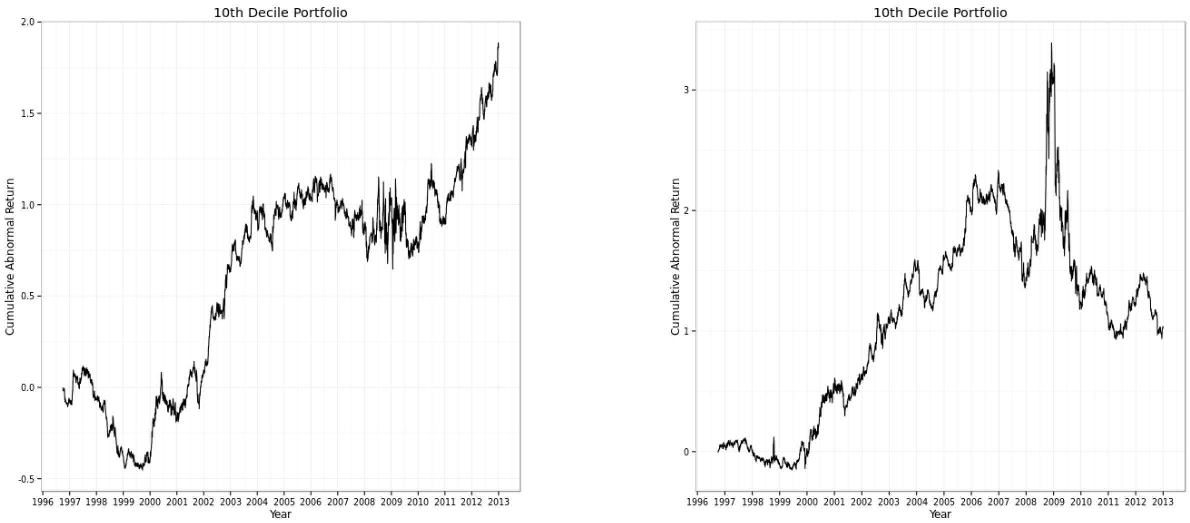
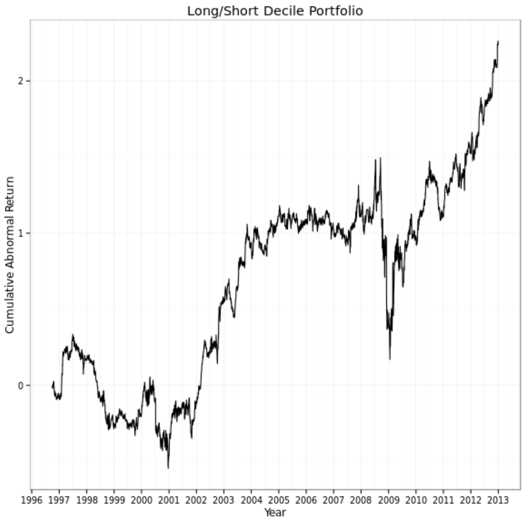


Figure 2: Cumulative Daily Abnormal Returns. We create a portfolio from the tenth decile of stocks ranked by network centrality and weighted by market capitalization. The portfolio constructed using VPIN network centrality is on the left and the return network is on the right. Abnormal returns were calculated using the 4 factor model and rebalanced daily.



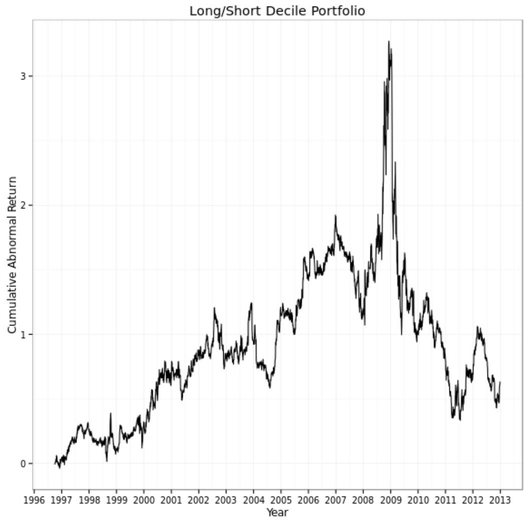


Figure 3: Cumulative Daily Abnormal Returns. We create a long/short portfolio from the first and tenth decile portfolios ranked by network centrality and weighted by market capitalization. The portfolio constructed using VPIN network centrality is on the left and the return network is on the right. Abnormal returns were calculated using the 4 factor model and rebalanced daily.