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Financial sector volatility connectedness and equity returns

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**FINANCIAL SECTOR VOLATILITY
CONNECTEDNESS AND EQUITY RETURNS**

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Financial Sector Volatility Connectedness and Equity Returns

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Abstract: We apply the Diebold and Yilmaz (2014) methodology to daily stock prices of the largest 40 U.S. financial institutions to construct a volatility connectedness index. We then estimate the contemporaneous return sensitivity of every non-financial U.S. company to this index. We find that there is a large statistically significant difference between the returns of firms with positive and negative exposures to financial connectedness. The four-factor alpha of a strategy that goes long in the bottom decile and short in the top decile of stocks sorted on their connectedness betas is roughly 15% per annum. Bivariate portfolio tests reveal that abnormal returns are robust to market beta, size, book-to-market ratio, momentum, debt, illiquidity, and idiosyncratic volatility. Abnormal returns are asymmetric; they are primarily driven by firms whose returns covary negatively with the index. These firms tend to be young and small, with poor past performance and low credit quality.

Keywords: Cross-section of returns, Anomalies, Financial connectedness, Vector autoregressions.

JEL codes: G12, G21, C32.

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1 Introduction

It is no surprise that research interest in networks and connectedness has increased tremendously since the global financial crisis in 2008. Whether it is the market, credit, counterparty, or systemic risk facing financial institutions, connectedness has become a central tenet of risk measurement and management practice. Understanding financial connectedness is also critical in assessing the limitations on financial sector’s ability to effectively undertake the intermediation function, which is of utmost concern to regulators.

Most of the empirical literature on financial connectedness (Acharya et al. (2017), Billio et al. (2012), Diebold and Yilmaz (2014), Brownlees and Engle (2015) and Adrian and Brunnermeier (2016)) focuses on estimation methods and building early warning systems for averting crises. Giglio et al. (2016) propose a composite index of alternative measures of systemic risk, which turns out to be closely related to the real economic activity. Despite these studies, the effects of financial connectedness are still not well understood, other than the fact that policy makers consider high levels of connectedness to be “bad” for financial markets. They also consider high inflation to be bad for the economy; but unlike the case of inflation there is a lack of empirical work which links connectedness to other economic variables of interest.¹ We try to fill this gap by using the Diebold-Yilmaz Connectedness Index (DYCI) methodology to estimate the financial sector volatility connectedness for the U.S., and investigate its effects on the risk premia of non-financial firms. Our contribution in the most general sense is to provide a robust tool for measuring financial connectedness and demonstrate a use case for its application in areas other than banking and regulation.

We estimate DYCI between 1965 and 2016 using the daily stock prices of the top 40 financial institutions in the U.S. As required, the time-series behavior of the index mirrors the behavior of the U.S. financial sector. Taken together or separately, the long-run trends and short-run fluctuations of the connectedness index capture relevant information about the performance of financial institutions. Broadly speaking, we observe three long-run phases of the connectedness index. To begin with, the index is quite low and stays low until the mid-1980s. It then follows an upward trend from mid-1980s until the end of 1990s, a period of steady financial deregulation in the U.S. (see Kroszner and Strahan (2014)). From 2000 onwards, the index fluctuates around a high level, peaking in 2008 during the global financial crisis. Apart from these long-running phases, we also observe short-term fluctuations in the

¹ One exception is Yang and Zhou (2017), where they show that quantitative easing was a major determinant of the volatility spillovers across 11 major economies. However, that paper studies the causes of financial connectedness rather than its effects.

index reflecting business cycles and developments in the U.S. and global financial markets.

Our main finding is that non-financial firms whose stock returns covary negatively with financial connectedness have high expected returns. These are mostly small firms with poor past performance, but not necessarily financially distressed. In terms of systematic or idiosyncratic risk, they rank only slightly ahead of firms with no sensitivity to financial connectedness, which makes their abnormal returns somewhat of an anomaly. The effect is relatively recent in history and economically large. Over the 1994-2016 period, the average risk-adjusted return (annualized 4-factor alpha) of non-financial firms that were the most sensitive to financial connectedness is 14% more than the least sensitive. In a long/short strategy these abnormal returns are driven entirely by the long side, hence large liquid stocks could be shorted if one wanted to implement it.

Alphas generated by portfolios of negative connectedness beta stocks are robust with respect to CAPM beta, market capitalization, book-to-market ratio, past 12-month return, leverage, illiquidity, and idiosyncratic volatility. In other words, sensitivity of a firm to financial connectedness is not just another proxy for known characteristics that explain the cross-sectional variation in stock returns. At the same time, because we find no linear relationship between connectedness betas and expected returns, financial connectedness does not appear to be a common risk factor. Our view is that financial connectedness has disproportional effects on firms that are more dependent on financial intermediation to satisfy their financing needs. Indeed, we find that firms' connectedness beta is directly related to its credit rating: Higher credit quality firms that have easier access to capital markets are less affected by financial connectedness. A similar pattern exists among unrated firms. Firms with higher levels of secured debt (a rough proxy for bank debt) are more adversely affected by connectedness.

In the next section, we briefly review the most relevant literature and position our paper. Section 3 introduces the Diebold-Yilmaz connectedness index methodology and the estimation of connectedness in a high dimensional setup. After estimating and constructing the financial sector volatility connectedness index we analyze the behavior of the connectedness index over time in Section 4. In Section 5 we estimate the connectedness beta – the contemporaneous return sensitivity to DYCI – for every non-financial public firm and show that there is a large and statistically significant difference between the returns of firms with positive and negative exposures. Section 6 provides evidence for the view that connectedness beta measures the dependence of a firm on financial intermediation. Section 7 provides additional robustness tests, and Section 8 concludes.

2 Literature Review

As our study is largely builds on the recent literature on financial networks and connectedness, a brief overview of this literature is in order. Theoretical contributions to the literature focuses for the most part on the stability of financial networks. Acemoglu et al. (2015) analyze the importance of the financial network architecture and the likelihood of systemic failures. The authors show that while densely connected financial networks are stable when the shocks to financial institutions are relatively small and infrequent, they become unstable in the face of sufficiently large shocks. Allen et al. (2012a), on the other hand, show that systemic risk is lower in the presence of separate bank clusters compared to a complete network. Elliott et al. (2014) show that both integration (greater dependence on counterparties) and diversification (more counterparties per organization) properties of networks have nonmonotonic effects on the occurrence of systemic failures.

On the empirical side, since the global financial crisis in 2008 developing systemic risk measures have become the major focus of the literature. Acharya et al. (2017) and Brownlees and Engle (2015) proposed to measure systemic contribution of a financial institution as the derivative of market expected shortfall with respect to its size. Adrian and Brunnermeier (2016), on the other hand, showed that the value at risk framework can be extended to measure the contribution of a financial institution to the systemic risk. Their measure is based on the difference between the market value at risk when the firm is in its distressed state (which they call CoVaR) and median state. Similarly, Hautsch et al. (2015) capture network spillover effects through quantile regressions of each institution's value-at-risk, defining the systemic risk beta as the marginal effect of a financial institution's value-at-risk on the system's value-at-risk.

As a time-series econometrics tool vector autoregressions (VARs) are also useful in developing connectedness measures. VAR framework allows for full multivariate dynamic cross-variable interaction, focusing on connectedness due to cross-variable interactions (Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014)). Diebold-Yilmaz connectedness framework mainly relies on forecast error variance decomposition obtained from the estimated model. As such, the variance decomposition enables the researchers to focus on connectedness due to innovation correlations as well as dynamic cross-variable interactions. Recently, Demirer et al. (2018) incorporate LASSO estimation into the Diebold-Yilmaz framework to extend it to high-dimensional environments.

Compared with other approaches to the measurement of connectedness and systemic risk, the Diebold-Yilmaz framework has minimal data requirements. This allows us to use the

high-dimensional extension of this framework to construct an index that goes all the way back to 1964. After we build that index, we use it to gauge the responsiveness of non-financial equity returns to financial sector connectedness.

By analyzing the relation between financial sector connectedness and non-financial stock returns, we aim to contribute to the ever-growing anomaly literature in empirical asset pricing. The defining characteristic of this literature is to uncover certain economic concepts that might have been overlooked in the standard models for determining expected returns. The most recent example is Bali et al. (2017b). Authors argue that sensitivity to economic uncertainty, in addition to traditional portfolio risk, should play a role in determining expected returns. They find that stocks with negative exposure to economic uncertainty earn much higher (risk-adjusted) returns than stocks with positive exposure. Ang et al. (2006) argue that aggregate volatility risk is priced in the cross-section of returns. They estimate the risk premium associated with time-varying volatility to be -1% per annum. For the most part, the intertemporal capital asset pricing model of Merton (1973) where investors try to hedge variations in the future investment opportunity set forms the basis of many contributions in this area.

Financial frictions may also give rise to mispricings relative to the idealized models. Liquidity is a prime example. Amihud (2002) and Pastor and Stambaugh (2003) show that both the liquidity level and the liquidity risk are priced in the cross-section, respectively. Short-sale constraints is another. If short selling is costly or prohibited, then stocks may become more mispriced. Nagel (2005) proxies short-sales constraints with institutional ownership and shows that anomalies are more pronounced for low institutional ownership stocks. Diether et al. (2002) argues that any kind of friction that prevents negative opinions to be reflected in prices will lead to overvaluation. They find that stocks with higher analyst earnings forecast dispersion (which represent more biased views) earn significantly lower future returns than otherwise similar stocks.

Other anomalies have been discovered thanks to the availability of novel datasets. Electronically searchable news archives is a good example. Using the LexisNexis database, Fang and Peress (2009) sort stocks according to their newspaper coverage and show that no-media stocks earn a significant return premium. Media coverage is also used in Da et al. (2014) to support the limited attention hypothesis which explains the momentum anomaly. Bali et al. (2017a) show that unusual news flow (using the Thompson-Reuters News Analytics data set) gives rise to idiosyncratic volatility shocks which in turn predict one month ahead returns in the cross-section.

This short list of studies is by no means a complete review of the vast literature on the cross-section of returns, but we believe that these examples capture the spirit of our approach. We try to explain the variation in the cross-section of returns and categorize firms according to their exposure to a market-wide index, similar to the studies cited above. In contrast to some of the work in this area we do not propose a new risk factor. We view financial connectedness as a market friction that raises the required rate of return demanded by investors for only a subset of firms.

3 DYCI Methodology

This section provides information about the estimation of connectedness measures. We first describe the DYCI methodology, followed by a short description of Lasso estimation method.

3.1 Variance Decompositions in an Approximating VAR

As an approximating model we use an N -variable VAR(p), $x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$, with A_0 an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$.

Standard variance decompositions based on Cholesky factorization depend on the ordering of the variables, significantly complicating the study of directional connectedness. Hence Diebold and Yilmaz (2012) suggest exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering. Instead of attempting to orthogonalize shocks, the generalized approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors.

3.1.1 Pairwise Directional Connectedness

Variable j 's contribution to variable i 's H -step-ahead generalized forecast error variance is

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, \dots, \quad (1)$$

where Σ is the covariance matrix for the error vector ε , σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and

zeros otherwise.

Because we work in the Koop-Pesaran-Potter-Shin generalized VAR framework, the variance shares do not necessarily add to 1: $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. Hence we normalize each entry of the generalized variance decomposition matrix (1) by the row sum:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}. \quad (2)$$

Now by construction $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

3.1.2 Total Directional Connectedness, “To” and “From”

Now we get less granular, moving from pairwise directional connectedness to total directional connectedness. Total directional connectedness to firm i from all other firms j is:

$$C_{i \leftarrow \bullet} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \quad (3)$$

Similarly, total directional connectedness from firm i to all other firms j is

$$C_{\bullet \leftarrow i} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ji}^g(H)}{N} \times 100. \quad (4)$$

3.1.3 Total Connectedness

Now we get still less granular, proceeding to a system-wide level. Using the normalized entries of the generalized variance decomposition matrix (2), we measure total connectedness as

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \quad (5)$$

Total connectedness is just the sum of total directional connectedness whether “to” or “from” (it doesn’t matter, because “exports” must equal “imports” at the “global” level). Note that, by construction, total connectedness index varies between 0 and 100.

3.2 Lasso

Least Absolute Shrinkage and Selection Operator (Lasso) is a regression method proposed by Tibshirani (1996) which penalizes the absolute size of the regression coefficients as well as the sum of error squares. It is an L1-norm regularization with an important advantage over L2-norm regularization (Ridge Regression): As it shrinks some of the variables exactly to zero, it is the preferred method for variable selection. The higher the penalty parameter λ , the lower would be the number of variables chosen.

$$\beta^L = \underset{n}{\operatorname{argmin}} \left\{ \sum_{n=i}^N (y_i - \beta_0 - \sum_{n=j}^P x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^P |\beta_j| \right\} \quad (6)$$

As the number of variables selected by lasso is highly sensitive to the penalty parameter, the choice of optimum λ is also a concern. In the literature, the most common method to determine λ is the *cross validation* method, which is borrowed from machine learning. In this method, the criterion to choose the penalty parameter is based on its forecast performance.

3.3 Discussion

At this point it would be helpful to note some of the benefits of DYCI approach. First of all, it does not require balance sheet or related data, which is generally unavailable on a high-frequency basis. Instead, one needs only daily stock return and/or volatility data, which is readily available.

Second, note that we want to impose sparsity on our approximating model, but we do not want to impose sparsity on the implied network, because in modern highly-integrated financial systems it is hard to imagine sparse bank networks: One way or the other, all banks in modern financial systems are linked. The approximating VAR is intentionally sparse, but the variance decomposition matrix that drives the connectedness measures is a non-linear transformation of the VAR coefficients and is therefore not generally sparse.

Relatedly, note that alternative frameworks that estimate connectedness directly from fitted VAR(1) coefficients (e.g., Bonaldi et al. (2015)) fall short on the desiderata mentioned above. They force sparse networks because they force a sparse VAR(1) coefficient matrix, and they force a one-step connectedness horizon by construction.

4 U.S. Financial Volatility Connectedness (1963-2016)

4.1 Data

The sample used to estimate the DYCI index is made up of the daily returns of the largest 40 financial and non-financial firms in the U.S (80 firms in total). The data is obtained from the Center for Research in Securities Prices database (CRSP) and the size breakpoints are calculated at the end of each year, independently for financial and non-financial firms. It is important to note that non-financial firm stocks do not directly contribute to the index. Once the VAR model is estimated using data on daily range volatilities for 80 firms, we calculate the financial sector volatility connectedness from the variance decompositions of the top 40 financial firms only. As a result, our financial sector volatility connectedness index is a conditional index, conditional on the presence of non-financial firms in the model.² Including the top 40 non-financial firm stocks in the VAR model allows us to make sure that any volatility shock stemming from outside the financial sector is correctly accounted for as a non-financial shock and hence will not be part of the financial sector volatility connectedness we aim to measure.

The number of firms used to estimate the index is in some ways arbitrary. Here we face with a trade-off between the feasibility of computation versus representativeness. Luckily, the skewness of the size distribution of financial institutions in the U.S. works in our favor. Just 40 firms make up no less than 95% of the market capitalization of the whole finance sector.

The analysis of volatility connectedness requires the use of daily stock return volatility, which is a latent variable to be estimated in the tradition of Garman and Klass (1980), Parkinson (1980) and Alizadeh et al. (2002). Since we do not have the opening and closing prices for all stocks in our sample period, we estimate daily variance stock returns using log of daily high (H) and low (L) prices only, following the formula proposed by Parkinson (1980):

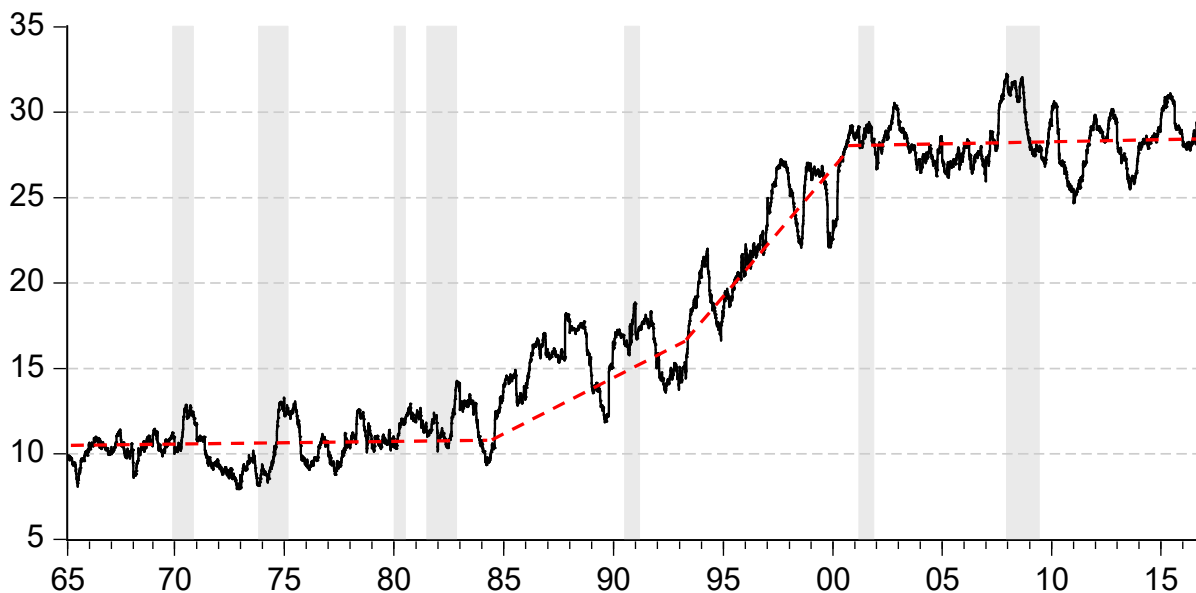
$$\tilde{\sigma}_{it}^2 = 0.361 (H_{it} - L_{it})^2$$

² We also estimated the “unconditional” volatility connectedness using only the top 40 financial firm stocks. The resulting index was more than 95% correlated with the “conditional” version in the paper, hence all our results carry through.

4.2 Time-Series Behavior of DYCI: A Historical Account

Our sample period is typical of empirical finance studies; it covers December 31, 1963 through December 31, 2016. Figure 1 plots the index between 1965 and 2016.³ Based on daily data covering more than 50 years, the index exhibits significant changes over time not only in terms of levels but also in terms of short-term fluctuations. Starting from a level around 10 in 1965, it reaches as high as 32 during the global financial crisis in 2008. The bird’s-eye view of the connectedness levels in the first and last two decades is a sign of significant changes in the riskiness of the U.S. financial system over this time period. An upward trend in the DYCI index in the mid-1980s is clearly visible in Figure 1. This is not a coincidence considering the financial history in the U.S.; 1980-2000 was actually a period of substantial deregulation.

Figure 1: U.S. Financial Volatility Connectedness Index



The underlying reason for deregulation was declining profitability and increasing competition in the banking sector. The average rate of return of the U.S. bank equities declined significantly from 14% in 1979 to an 8% in 1989-1991. The average rate of return on assets followed a similar downward path from 0.75% to 0.5% over the same period (see Boyd and Gertler (1993), p. 338). The decline in profitability was a result of several factors. First, in late

³ The index starts from December 30, 1964 because we use the market capitalization on December 31, 1963 to filter the firms that go into the VAR system and use a 250 trading day rolling window.

1970s and early 1980 financial institutions that held long-term fixed-rate mortgages (such as Savings and Loan Associations (S&Ls)) lost substantial amounts of money due to the rise in inflation. Second, the whole banking system suffered as a result of the anti-inflationist monetary policy of the Volcker Fed. Third, the Latin American debt crisis of 1982 led to further write-offs among the large U.S. banks.

Faced with increasing pressure on profits, the finance industry searched for ways to expand commercial banking activities, which had hitherto been restricted by laws that were mostly enacted after the Great Depression. Commercial banks and other depository institutions intensified their efforts to lower the regulatory burden, which also jibed with the political sentiment at the time. They were successful in getting favorable responses from the Carter and Reagan administrations. The Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn St. Germain Depository Institutions Act of 1982 were the early legislative attempts to slow down the outflow of savings from depository institutions to other investment vehicles. However, the haphazard way of deregulating S&Ls allowed these institutions to take more risks in the housing sector and led to a crisis in the S&L industry in 1984.⁴ The event marks roughly the beginning of the rise in the connectedness index. First, the index increases from 9.5 to close to 15 in 1984. As the huge scale of the crisis becomes evident, the index continues its upward move to reach 18 at the end of 1987.

Commercial and investment banks were next in line for deregulation. Many states have already begun removing restrictions on interstate banking throughout the 1980s (see McLaughlin (1995)). The Federal Reserve and the Office of the Comptroller of Currency (OCC) also did their share to loosen restrictions on bank participation in investment banking and insurance from mid-1980s onwards (see Kroszner and Strahan [2014]). Nevertheless, it took until 1994 for the lobbying efforts of big banks to finally bear fruit in the form of Riegle-Neal Interstate Banking and Branching Efficiency Act, which completely removed restrictions on opening bank branches throughout the whole country (see McLaughlin (1995)). We see connectedness increase along with interstate banking practices and accelerate its climb in the 1990s. After President Clinton signed the Riegle-Neal Act into law in September 1994, the major banking stock prices went into a rally that lasted more than three years. KBW Bank Index⁵ increased from less than 30 at the end of 1994 to 86 by August 1998 (one month

⁴ Nearly five hundred S&Ls were shut down and an equal number of them were forced to merge under the umbrella of the Resolution Trust Corporation set up by the Congress. Cleaning the S&L mess between 1986 and 1991 costed \$153 billion, \$124 billion of which was shouldered by the U.S. government (For more on S&L crisis see Ferguson (2008)).

⁵ KBW Bank Index is a large cap value-weighted stock index comprised of 24 U.S. banks.

before the collapse of LTCM hedge fund). Over the same period, volatility of major bank stocks as measured by the 12-month average range volatility of the KBW index increased to more than double (from 0.0016 to 0.0034).

From the mid-1990s to early 2000s, the profitability of the U.S. banking industry increased but so did the riskiness of their assets. Brokerage and trading activities grew in size and scope. Mergers and acquisitions paved the way for a handful of financial conglomerates to dominate the industry. OTC derivatives created new markets and offered innovative products but at the same spawned complex webs of obligations that were not visible on the balance sheet. After the repeal of the Glass-Steagall Act, banks turned into one-stop shops for any kind of financial service a client may desire. The steady increase in the connectedness index reflect these structural changes in the industry. We see the index inching its way up to 30 by 2000, and hit its peak of 32 in 2008. Despite the new financial regulations introduced after the global financial crisis such as the Dodd-Frank bill, the index stays at the level of 25-30, perhaps as a sign of the “new normal”.

Apart from these structural changes and their long-term effects on connectedness, there is also a correspondence between the short-run fluctuations of the DYCI and business cycle fluctuations.⁶ Despite the gradual renewal of data by the 250-day rolling window, the monthly updates of the index are still able to catch real world events. During the recession of 1969-1970 the index increases by 2.5 percentage points. Then, during the longer 1973-74 recession (16 months), we observe a 4 percentage point increase. The next two recessions, the short-lived one in 1980 and a longer one that starts in 1982 also correspond to roughly 2 and 3 percentage point increases in the index, respectively. All of these recessions have a temporary impact on the index, which has an average value of 10.6 percent between 1964 and 1984. The recessionary period from July of 1990 to March 1991 leads to a 1 percentage point uptick on the index, whereas the difference between April 1991 and March 2001 (the start of the next recessionary period) is more than 10 percentage points. Other noteworthy economic events such as the East Asian crisis of 1997 and the Russian (and the LTCM) crisis of 1998, also affected the index upticks of 3-4 percentage points – but the effects do not appear to have long lasting impact on the general level.

The major economic event of the 2000s is surely the subprime mortgage crisis, which is tracked almost perfectly by the connectedness index in Figure 1. The index hits its highest yearly average in 2008, roughly 31. After a slight comedown in 2009, the index rises again

⁶ Shaded areas in Figure 1 indicate U.S. recessions as determined by the NBER Business Cycle Dating Committee.

following the economic turmoil in Europe. The sovereign debt crisis in the EU, which started with Greece being downgraded and later bailed out by an EU-IMF package in 2010 continued to occupy the headlines in the subsequent four years. There were many episodes of write-downs, downgrades, bailout negotiations, and political unrest. These events also exposed the financial fragility of other Eurozone countries such as Spain and Italy, and the overreliance of European banks on government bonds to meet regulatory requirements. This turbulent era between 2011 and 2015 corresponds to an increase of about 5 points in our index.

To sum up, the behavior of the DYCI reveals substantial variation both in the short-run and in the long-run. Short-run adverse economic events push the index up temporarily. More structural changes in the finance sector have long lasting effects and suggest regime shifts. We realize that these claims are not based on statistical tests, however our goal here is not to model the time-series properties of connectedness index or come up with forecasts. We leave that task to another study. In the context of our study, we simply want to discern the economic rationale for the movements of the index. Had it been the case that our index did not reflect the historical developments of the finance industry, we would have less confidence in using it in further analyses.

5 Financial Connectedness and Non-financial Firms

In this section, we investigate how financial sector volatility connectedness affects the risk premia of non-financial firms. There is little theoretical work on casting risks borne out of the financial sector within a general asset pricing framework (Piccotti (2017) is a rigorous treatment of the subject), even though empirical evidence is in favor of systemic risk having an impact on expected returns (Allen et al. (2012b)). Our interest in this question comes mostly from exercising our economic logic. In a world with financial frictions, firms with varying degrees of dependence on the financial sector may find varying degrees of success in their businesses. For example, a firm may find it harder to access lines of credit at a time when connectedness is high (the aftermath of Lehman Brothers' bankruptcy comes to mind), as opposed to a time when connectedness is low. Similarly, the market for syndicated loans and private placements may be favorable or non-favorable for an industrial firm that wants to borrow and invest because of the cross-commitments and the capital requirements of financial institutions.⁷ If that is the case, investors might discount such firms more heavily

⁷ Other variables such as aggregate credit supply could also capture adverse market conditions for borrowers; however, connectedness is inherently a different concept. It is possible to have high degrees of connectedness with ample credit, as the subprime mortgage market demonstrated in the years prior to the

than what the classic asset-pricing models with frictionless finance markets would suggest. Our course of action then is to measure the sensitivity of (non-financial) firms to financial connectedness and see whether the variation in that dimension leads to a variation in their expected returns.

5.1 Connectedness Betas

We run the following time-series regression to estimate the sensitivity of non-financial stock returns to financial connectedness:

$$R_{it} - r_{ft} = \alpha_i + \beta_i^M MKT_t + \beta_i^C DYCI_t + \epsilon_{it} \quad (7)$$

where $R_{it} - r_{ft}$ is the excess return on stock i , MKT is the market excess return and $DYCI$ is the Diebold-Yilmaz financial volatility connectedness index, reported in Section 4, β_i^M is the market beta and β_i^C is the connectedness beta of stock i , $DYCI$ at time t uses daily data from 250 prior days. We use a rolling window size of 60 months and require at least 36 consecutive observations for each stock. We use the delisting return for the last observation of a stock's return when it leaves the CRSP tapes, or substitute negative 30% when delisting return is missing. We use common stocks (share codes 10 and 11) which trade on the NYSE, AMEX, and NASDAQ and exclude financial stocks (SIC codes between 6000-7000). If the closing price on the last day of the month is less than \$1, or is a bid-ask average rather than an actual trade we exclude that stock from the portfolio formation process in that month. We winsorize connectedness betas at the 1st and 99th percentile of the cross-sectional distribution. While this does not affect portfolio composition, it is there to reduce the effect of outliers when we examine the determinants of connectedness betas in Section 6. After these filters, we sort stocks by their connectedness betas and form decile portfolios. All portfolios are equal-weighted and rebalanced at the monthly frequency.

5.2 Portfolios Formed on Connectedness Beta

Table 1 reports the summary statistics for these 10 portfolios. The average connectedness beta ranges from -1.99 to 1.85 across the deciles. Negative connectedness betas indicate stocks whose returns go down when the level of connectedness goes up, hence stocks in portfolio 1 are the ones which are negatively affected by financial sector connectedness.

blow-up.

Table 1: Portfolio Summary Statistics

	Decile Portfolios (Equal-Weighted)									
	1	2	3	4	5	6	7	8	9	10
Connectedness Beta	-1.99	-0.98	-0.54	-0.26	-0.03	0.17	0.38	0.63	1.01	1.85
Market Beta	1.29	1.14	1.03	0.94	0.89	0.91	0.95	1.04	1.21	1.46
Market Cap. (Mil. \$)	137.0	291.3	476.0	667.0	832.8	883.6	815.5	655.3	451.1	241.1
Book-to-Market	0.47	0.53	0.54	0.55	0.55	0.54	0.53	0.53	0.53	0.48
Past Return (12 mo.)	-1.06%	-0.41%	-0.02%	0.28%	0.47%	0.65%	0.77%	0.91%	1.05%	1.53%
Debt-to-Assets	12.79%	15.38%	18.62%	20.68%	21.70%	21.81%	21.00%	19.44%	18.01%	17.42%
Amihud Illiquidity	0.15	0.06	0.04	0.03	0.02	0.02	0.02	0.03	0.07	0.20
Idiosyncratic Volatility	3.51%	2.74%	2.29%	1.99%	1.83%	1.79%	1.84%	1.99%	2.31%	2.97%

Table reports the time-series averages of median stock characteristics for the decile portfolios formed on Connectedness Betas. Decile 1 includes firms with the lowest connectedness betas and decile 10 with the highest connectedness betas. Connectedness betas are estimated prior to portfolio formation by running 60 month rolling time-series regressions of excess stock returns on the excess market return and the Diebold-Yilmaz connectedness index. Only non-financial firms which trade on NYSE, AMEX, and NASDAQ with prices greater than \$1 at the end of each month were included in the regressions. Estimates with less than 36 months of data are excluded. Portfolio formation starts at the beginning of 1994 and ends at the end of 2016.

As we will see in the next section, this group is the main driver of the abnormal returns we find in portfolio tests. The median stock in decile 5 has a connectedness beta of zero which implies no effect. It is natural to ask what kinds of firms are affected by financial connectedness (positively or negatively) and what kinds of firms appear to be immune. It is conceivable that high or low connectedness betas pick out certain types of companies and the dispersion in connectedness betas could be representing dispersion in some other firm-level variable.

Size stands out as an important characteristic (as is usually the case) when we glance across the deciles. Firms in decile 1 are the smallest with a median of \$137 million, whereas firms in decile 6 are the largest with \$884 million. As we move towards decile 10 size diminishes (\$241 million). This inverted U-shape tells us clearly that large firms are not affected by financial connectedness (in the statistical sense), perhaps because they find it easier to access capital. Large firms could either use their internal capital or issue bonds directly in capital markets, in contrast to small firms that are more dependent on bank financing and private placements. The fact that size is not monotonically increasing across the deciles at least alleviates the worry that connectedness beta may be a proxy for size or vice versa. Nonetheless, we further probe the issue of size in the robustness section.

High sensitivity to the financial sector may signal financial difficulties on the part of the firm. A firm with a lot of existing debt may find it difficult to borrow even for positive NPV projects, the problem known as debt overhang in the literature. We do not observe this to be the case for the firms in decile 1; in fact, these firms have the lowest debt-to-asset ratios. Firms with the highest leverage are the ones in the middle of the connectedness beta distribution, whose sensitivities to the financial sector are practically zero. We also do not observe signs of financial distress. Book-to-Market ratios across all the deciles are similar and all are less than 1. Overall, it is safe to say that firms which are negatively affected by financial connectedness (on the left tail of the distribution), are not exclusively suffering from debt overhang or financial distress.

Decile 1 firms tend to have higher market betas than Decile 5 firms (1.29 vs. 0.89), but lower than Decile 10 firms (1.29 vs. 1.46). Market beta is not monotonic across the deciles and exhibits little variation. Thus, any differences in the risk-premiums of these portfolios would be unlikely to be explained by market risk. Decile 1 portfolio has the highest idiosyncratic risk (3.51% per month) but once again, the differences among portfolios are small and non-monotonic. Based on these two commonly used risk measures, it would be hard to make the case that stocks with the lowest (most negative) connectedness betas

possess higher risk than stocks with the highest (most positive) connectedness betas.

One variable that does follow a monotonic pattern along with connectedness beta is the return of the firm over the past 12 months. The past (geometric) average monthly return is -1.06% for decile 1 and 1.53% for decile 10. This pattern alerts us to the importance of controlling for the momentum effect; however note that the momentum anomaly would imply lower returns for decile 1 (selling the losers) and higher returns for decile 10 (buying the winners) in the future. What shows up in our portfolio tests is the exact opposite, which we discuss next.

5.3 Univariate Portfolio Returns

We have seen that there is considerable variation in how non-financial stocks react to financial connectedness. The main question now is whether this variation drives a variation in returns. In Table 2 we present excess and risk-adjusted returns for the 10 portfolios we formed by sorting stocks on their connectedness betas.

There is a significant difference between the returns of low connectedness beta stocks and high connectedness beta stocks, regardless of the risk-adjustment method. The column labeled 1-10 represents a zero-net-investment portfolio that is long in low (negative) connectedness beta stocks and short in high (positive) connectedness beta stocks. The return difference is around 0.9% per month, or 11% per annum. CAPM alpha is slightly lower at around 0.7% and still statistically significant ($t=2.26$). Remember from Table 1 that portfolio 1 has lower past returns than portfolio 10 on average; hence the return continuation in subsequent months actually diminishes the effect attributable to the connectedness beta. As a result, controlling for momentum with the UMD factor of Carhart (1997) ends up increasing the magnitude and the t -statistic of the intercept term (alpha=1.2%, $t=3.29$). In economic terms, any hedge fund that could generate an annual return of 15% with no systematic risk would attract serious inflows.

An interesting feature of this alpha is that most of the abnormal return comes from portfolio 1 on the long side no “hedge” is necessary to profit from this anomaly. A long-only retail investor could invest in portfolio 1 and capture an alpha of 1.76% (per month) along with some systematic risk premiums. As we move into stocks with higher connectedness betas, the returns of portfolios begin to resemble each other. In the last column portfolio 1-5 is constructed similar to the 1-10 portfolio except that it shorts portfolio 5 instead of portfolio 10. The 4-factor alpha of this hedge portfolio is almost identical to the 1-10 portfolio, hence the choice of stocks on the short side is not crucial if one is aiming for a market neutral

Table 2: Univariate Portfolio Returns

	1	2	3	4	5	6	7	8	9	10	1-10	1-5
Excess returns	2.30 (3.70)	1.66 (3.62)	1.38 (3.44)	1.25 (3.74)	1.24 (3.73)	1.15 (3.63)	1.19 (3.88)	1.20 (3.66)	1.20 (3.16)	1.36 (3.02)	0.93 (2.75)	1.05 (2.54)
CAPM alpha	1.32 (2.98)	0.84 (3.01)	0.66 (2.71)	0.60 (3.16)	0.62 (3.26)	0.55 (2.94)	0.58 (3.42)	0.58 (3.22)	0.52 (2.42)	0.59 (2.27)	0.73 (2.26)	0.69 (1.78)
4-Factor alpha	1.76 (4.70)	1.04 (5.50)	0.74 (4.94)	0.62 (5.66)	0.61 (5.43)	0.52 (5.00)	0.51 (5.08)	0.50 (4.31)	0.41 (3.34)	0.54 (3.52)	1.22 (3.29)	1.15 (3.18)

Table reports the excess returns and risk-adjusted returns of portfolios formed on Connectedness Beta. Returns are given in percent per month. Decile 1 includes firms with the lowest connected betas and decile 10 with the highest connected betas. 1-10 column represents a zero-net-investment portfolio that is long in portfolio 1 and short in portfolio 10. Portfolios are equal-weighted and rebalanced monthly. 4-Factor alpha uses MKT, SMB, HML, and UMD as the systematic factors. Financial stocks are excluded. Time period is 1994-2016. T-statistics based on Newey-West standard errors are in parentheses

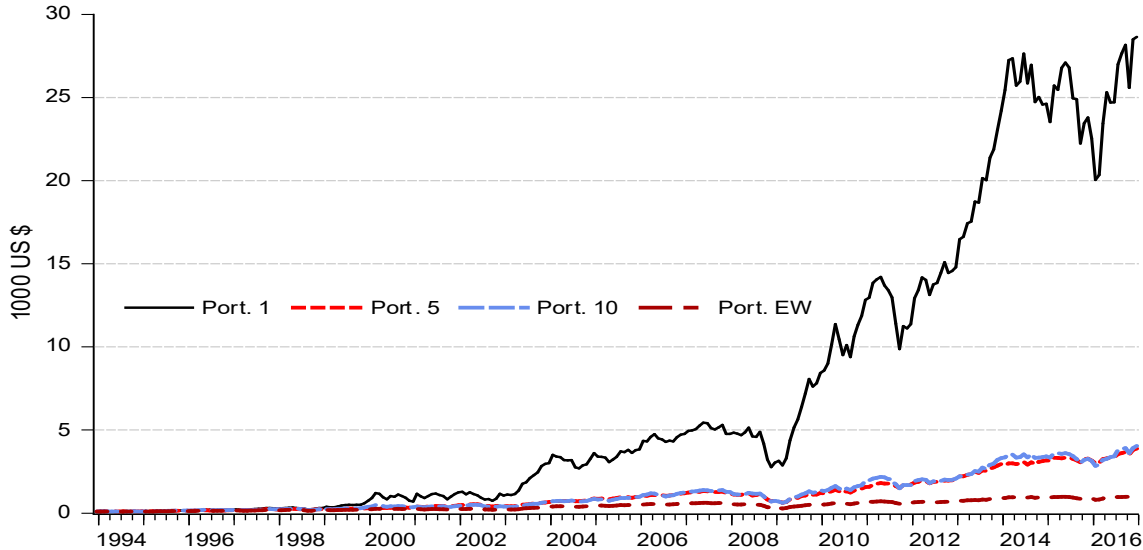
exposure. It is possible to generate many other long/short strategies with positive alphas as a result of portfolio 1's exceptionally high alpha.

To better understand the economic intuition behind these abnormal returns it is important to remember that the low beta stocks in portfolio 1 are actually high negative beta stocks. A negative beta stock performs worse when the financial sector connectedness increases, which may be due to the dependence of the firm on the financial sector. If investors are aware of this dependence, then they may value these firms lower than they otherwise would. These firms would then exhibit above average returns in the future, as it is observed here. A behavioral explanation would mark the firms in portfolio 1 as being "undervalued" since their systematic risk do not justify their return. But a risk-based explanation is also possible. Investors could be correctly pricing the risks in these firms that the 4-factor model misses. This is yet another example of the "joint-hypothesis problem" (Fama (1998)) that fuels the debates on market efficiency. We do not take sides in this debate but what we can say is that investors surely care about firms' dependence on the financial sector in their valuations.

One worry with systematic anomalies is that strategies based on them could be prone to crashes. A long stream of positive returns could be erased by a sudden negative shock, which is easy to miss when looking at arithmetic averages. In Figure 2, we plot cumulative returns of our low connectedness, zero connectedness, and high connectedness beta portfolios and the CRSP equal-weighted market index.

Despite its rocky climb, portfolio 1 dramatically tops every other portfolio depicted in the graph. \$100 invested at the end of 1993 would have grown to \$1014 in an equal-weighted market index by the end of 2016. Positive connectedness beta portfolio (10) would be at \$4050, zero connectedness beta portfolio (5) would be at \$3879, and the negative connectedness beta portfolio (1) would be at \$28646! This seven-fold increase in wealth (or twenty-eight-fold compared to the market) implies either significant mispricing, or an extremely lucky period. To foreshadow some of our results in Section 6, let us reveal that this kind of overperformance does not exist in the 1969-1993 period, therefore there is something special about the last two decades. We just do not think it is luck; financial connectedness has risen considerably in the 90s and the financial crisis of 2008 has made investors overly cautious about the financial sector. The exponential growth of portfolio 1 post crisis can be interpreted as the "correction" of investors' systematic bias against non-financial firms that are more dependent on the finance sector.

Figure 2: Cumulative Returns for Connectedness Beta Portfolios



5.4 Bivariate Portfolio Returns

Next, we examine bivariate portfolio returns. As we saw in Table 1 firms in different decile portfolios have different characteristics, hence we want to make sure that it is connectedness beta and not some other characteristic that is driving their returns. The bivariate portfolios are formed by first sorting stocks on the control variable (size, book-to-market, etc.), then by sorting on connectedness betas within those deciles. This procedure generates 100 portfolios. For each connectedness beta decile we average the returns across the control variable and estimate their 4-factor alphas. This procedure generates portfolios with roughly the same number of low and high beta stocks, or small, medium, and large stocks, or “loser” and “winner” stocks and so on.

The results in Table 3 corroborate our previous findings. The 1-10 hedge portfolio earns a statistically and economically significant abnormal return in each column. Alphas range from 0.67% per month to 1.26% per month and t-statistics range from 2.20 to 4.19. Controlling for CAPM beta or the book-to-market ratio - two major drivers of the cross-section of returns - has practically no effect on the alpha generated by the connectedness beta strategy. The controls that reduce alpha the most are size and idiosyncratic volatility. Because small firms are generally the ones with high idiosyncratic volatility this is not surprising. 1-10 alpha for the size/connectedness beta double-sorted portfolio is 0.67% per month, which is roughly half of what we found in the univariate case. Financial sector connectedness appears to affect

the risk premia of small firms much more than large firms, but as the bivariate portfolios have a uniform distribution of size, we conclude that the phenomenon is not restricted to small firms.

To summarize, we discover statistically and economically significant return differences between firms which are negatively and positively affected by financial connectedness. This difference is driven by firms which are the most sensitive to the DYCI index (inversely) and is robust with respect to market beta, size, book-to-market ratio, past return, leverage, illiquidity, and idiosyncratic volatility.

Table 3: Bivariate Portfolios

	BETA	SIZE	BTM	MOM	DEBT	ILLIQ	IVOL
Low Connectedness	1.78	1.14	1.79	1.27	1.70	1.33	1.19
Beta	(5.51)	(3.85)	(5.11)	(4.43)	(4.59)	(3.96)	(5.13)
2	0.88	0.80	1.01	0.97	0.92	0.92	0.85
	(5.07)	(4.29)	(5.19)	(6.15)	(5.47)	(5.01)	(5.25)
3	0.70	0.84	0.74	0.82	0.71	0.78	0.76
	(4.77)	(5.97)	(4.91)	(5.48)	(5.01)	(5.78)	(5.79)
4	0.70	0.72	0.62	0.72	0.68	0.75	0.79
	(6.46)	(5.37)	(5.41)	(5.78)	(5.70)	(5.84)	(5.64)
5	0.63	0.78	0.63	0.67	0.59	0.64	0.80
	(5.31)	(6.53)	(5.65)	(6.89)	(5.13)	(6.19)	(6.30)
6	0.52	0.57	0.51	0.71	0.51	0.57	0.59
	(4.94)	(5.59)	(5.24)	(6.24)	(4.55)	(5.11)	(5.30)
7	0.59	0.73	0.53	0.57	0.50	0.62	0.74
	(5.89)	(6.61)	(4.86)	(5.03)	(5.32)	(5.88)	(6.40)
8	0.42	0.64	0.48	0.58	0.47	0.64	0.58
	(3.98)	(5.04)	(4.45)	(4.89)	(4.11)	(5.28)	(4.95)
9	0.51	0.58	0.44	0.43	0.43	0.52	0.46
	(5.01)	(4.48)	(3.60)	(3.73)	(3.63)	(4.22)	(4.02)
High Connectedness	0.52	0.47	0.50	0.51	0.46	0.50	0.50
Beta	(3.92)	(3.24)	(3.38)	(3.64)	(2.77)	(3.34)	(3.77)
1-10	1.26	0.67	1.29	0.76	1.25	0.84	0.68
	(4.19)	(2.20)	(3.69)	(2.70)	(3.33)	(2.53)	(3.02)

Table reports 4-factor alphas of double-sorted decile portfolios. 4-Factor alpha uses MKT, SMB, HML, and UMD as the systematic factors. Units are percent per month. The first sort is always by the control variable in each column and the second sort is by connectedness beta with breakpoints dependent on the first sort. Of the resulting 10x10 portfolios, the returns are averaged across the control variable deciles for each connectedness beta decile. Portfolios are equal-weighted and rebalanced monthly. BETA is the coefficient on the market index, SIZE is the market value of equity at the end of each month, BTM is the log of book-to-market ratio, MOM is the return in the past 12 months skipping the most recent month, DEBT is the sum of Long-Term Debt and Debt in Current Liabilities divided by Total assets. ILLIQ is the Amihud illiquidity measure estimated from daily returns and volume each month. IVOL is the standard deviation of the residuals from a monthly regression of daily stock returns on the excess market return, SMB and HML factors. T-statistics based on Newey-West standard errors are in parentheses.

6 Determinants of Connectedness Beta

In the previous sections we alluded to the idea that firms with the negative connectedness betas may turn out to be the most bank-dependent firms and that they may be discounted more heavily by the investors. In this section we present supporting evidence for this hypothesis. Our tests revolve around taking the connectedness beta of a firm as a dependent variable and finding out which firm-level characteristics are correlated with it.

Our main variables of interest in explaining connectedness beta are the S&P credit rating of a firm and the ratio of its secured debt to its total debt. The rationale for these two variables is that lower the credit quality of a firm the more dependent it will become on the banking system, hence the lower (more negative) its connectedness beta will be. We encode Standard & Poor's Domestic Long Term Issuer Credit Rating numerical values between 1 and 22 (1=AAA, 2 =AA+, ..., 22=D) as in Avramov et al. (2007). Higher values indicate lower credit quality on this scale. For unrated firms (which make up more than half of the sample) we use secured debt as a proxy for credit quality. Higher fraction of secured debt to total implies lower credit quality, as investors are typically less willing to provide loans without collateral. In addition, because bank loans are almost always secured this variable can also be thought of as a proxy for the amount of bank financing a firm uses.

Table 4 presents the Fama and MacBeth (1973) regressions run separately for the rated and unrated universe of firms. Taking the rated group first (columns 1 and 2), the coefficient on credit rating is highly significant and negative. This is very much in line with our priors; non-investment grade firms (higher numerical values on the scale), would find it difficult to access capital markets and come to depend more on bank loans and private placements. These are the firms whose returns turn out to be inversely related to the financial connectedness index. Among the control variables AGE and R&D spending are of particular interest. A positive coefficient on AGE and a negative coefficient on R&D means that younger and more innovative firms tend to be negatively affected by financial connectedness. Again, this squares nicely with the stylized fact that market frictions tend to be more severe for new firms with asymmetric information.

In Section 5.1, two variables have caught our attention when we examined the portfolio characteristics: size and past return. We now get a chance to understand their relation to connectedness beta at the individual firm level. Our proxy for size is sales normalized by assets (we do not use market value of equity because of its collinearity with credit rating). Positive coefficient on sales implies larger firms having larger connectedness betas; the same pattern observed in Table 1. ROE is also positively related to connectedness beta which

implies that lower operating performance leads to lower connectedness beta. The relation between ROE and connectedness beta is consistent with the median past 12-month return going from negative to positive across the decile portfolios in Table 1. Both the stock performance and the accounting performance indicate that dependence on the financial sector increases in magnitude with declining success of the firm’s business.

Table 4: Determinants of Connectedness Beta

	Rated	Rated	Unrated	Unrated
RATING	-0.066 (-6.62)	-0.115 (-7.83)		
SEC. DEBT			-0.071 (-6.07)	-0.063 (-8.23)
BETA		0.126 (8.06)		0.115 (6.07)
BTM		-0.020 (-3.11)		-0.004 (-0.41)
SALES		0.052 (7.68)		0.001 (0.17)
AGE		0.052 (12.13)		0.060 (12.20)
R & D		-1.489 (-5.29)		-0.465 (-4.41)
ROE		0.013 (2.97)		0.009 (3.18)
CONSTANT	0.229 (10.59)	0.001 (0.02)	0.008 (0.45)	-0.297 (-11.03)
Observations	227,457	213,756	378,551	363,439
R-squared	0.008	0.096	0.002	0.085
Num. of months	276	276	276	276

Table reports Fama-MacBeth regressions of connectedness betas on firm characteristics. Reported coefficients are time series averages of coefficients estimated from separate monthly cross-sectional regressions. Dependent variable is the connectedness beta of each firm which is estimated previously by 60-month rolling regressions of firm excess returns on the excess market return and the Diebold-Yilmaz connectedness index. . RATING is the Standard & Poor’s Domestic Long Term Issuer Credit Rating coded into numerical values between 1 and 22 (1=AAA, 2 =AA+, ..., 22=D). SEC.DEBT is the ratio of secured debt to total debt, BETA is the coefficient on the market index, BTM is the log of book-to-market ratio, SALES is sales normalized by total assets, AGE is time in years from the date that the firm first appears in the CRSP database, R&D is Research and Development Expense normalized by total assets, ROE is net income divided by book value. Regressions in each column are run on the subset of firms which have a Standard & Poor’s Domestic Long Term Issuer Credit Rating on Compustat (Rated), and which do not (Unrated). Firms with zero debt are excluded from all regressions. All COMPUSTAT variables are winsorized at the 1% and 99% level, and lagged six months with respect to the dependent variable.

Moving onto columns three and four, results for the unrated group are similar to the rated group in that firms with higher levels of secured debt have lower (more negative) connectedness betas. If one views secured debt as a measure of bank debt (albeit a noisy one), then this is evidence that the firm’s connectedness beta measures its bank dependence.

Higher levels of financial connectedness hurt these firms as evidenced by their negative connectedness betas. All variables for the unrated subsample are related to connectedness beta in the same direction as the rated subsample. One difference is that for unrated firms book-to-market ratio and sales turn out to be insignificant which are significant for rated firms. The negative coefficient on book-to-market indicates value firms having lower connectedness betas, and the positive coefficient on sales indicate small firms having lower connectedness betas. It could be that growth firms are less dependent on the banking system due to the attention they receive from private equity and venture capital funds. Another story could be that value firms are the “fallen angels” and thus have less bargaining power with their banks. Similar stories could be told for small firms (less attention, less bargaining power, etc.). The fact that size and value distinctions do not fully account for the connectedness beta is an important lesson to take away from Table 4. For unrated firms these variables have no explanatory power.

To conclude, while we cannot directly observe the amount of non-bond debt financing in each firm’s capital structure, and neither the terms of those deals, it is not unrealistic to assume that firms with lower credit quality are more likely to be dependent on the banking system. The data bears this out. Firms with lower ratings from S&P, or with more secured debt, have a negative exposure to financial connectedness. In addition, we observe younger firms with poor past performance and high R&D spending to be more sensitive to financial connectedness. Size and valuation metrics exhibit partial success in explaining the sensitivity to financial connectedness.

7 Robustness

In this last section, we provide additional robustness checks and address certain questions that have come up through discussions with our colleagues. The first of these is whether our results are sensitive to the starting point of our sample. They are not. Our tests begin in 1994 because they neatly coincide with the passage of the Riegle-Neal act, which allowed for interstate banking in the U.S. Our prediction was that financial connectedness and its effects would be more prominent in the subsequent time period. Nevertheless, moving the starting point back a few years, or even a decade does not invalidate our findings.

In Table 5 we repeat the portfolio tests first presented in Table 2 for three different time periods. The first column covers the exact same time period as in Table 2, and presented here for ease of comparison. In the second column we move the starting point of our sample

Table 5: Portfolio Composition and Time Periods

<i>Weighting Scheme</i>	Time Period		
	1994-2016	1969-2016	1969-1993
Equal-Weighted: Full Sample	1.22 (3.29)	0.98 (3.76)	0.47 (1.83)
Equal-Weighted: Exc. smallest 10 percent	0.71 (2.21)	0.68 (3.05)	0.37 (1.60)
Value-Weighted: Full Sample	-0.01 (-0.02)	0.37 (1.42)	0.37 (1.09)
Value-Weighted: Exc. largest 10 percent	0.78 (2.05)	0.74 (2.78)	0.34 (1.23)
Value-Weighted: Log of Market Cap.	0.89 (2.64)	0.80 (3.34)	0.39 (1.59)

Table reports 4-factor alphas of 1-10 hedge portfolios formed on connectedness beta. 4-Factor alpha uses MKT, SMB, HML, and UMD as the systematic factors. Units are percent per month. Each column represents a different time period and each row represents a different portfolio weighing mechanism. In rows three and four firm size is measured as the market value of equity at the end of the previous calendar year. In row five firm size is measured as the natural logarithm of the market value of equity.

to 1969⁸ and obtain an alpha with an even higher level of statistical significance ($t=3.76$ vs 3.29). In the third column, we run the same test between 1969 and 1994. For this time period we do not obtain a statistically significant alpha (at the 1% level) although it is still positive. Its magnitude is also smaller which implies that the lack of statistical significance is not simply due to a smaller sample. The impact of financial connectedness on the risk premia of non-financial firms appears to be a relatively recent phenomenon. In our view, that is perfectly normal considering the fact that the financial markets of 60s and 70s were dramatically different from today's and "connectedness" was not even a scientific concept to be studied. Globalization, advances in information technology, and consolidation in the financial services sector have indeed made financial markets more connected in a structural way and thus the academic interest in this topic has grown. It is only recent that network modelling have crossed over into the economics literature and new statistical tools have been developed to study connectedness in financial markets. Thus, the 1969-1993 period does not properly constitute an out-of-sample test of the anomaly we find in 1994-2016. We would need to wait for future data from to provide a more accurate verdict.

The next issue we would like address is whether the effect we uncover only applies to a

⁸ To be more precise, our data actually begins in 1963. The first year of data is required to estimate the index, and the latter 5 years are used to estimate firms' betas with respect to the index. This makes the first portfolio return available in the first month of 1969.

very limited subset of stocks. This is a common criticism in the market anomaly literature, in that many of the anomalies do not matter much, because they would not be profitable if one tried to take advantage of them in the real world. In the second row in Table 5, we repeat our tests by excluding stocks smaller than the bottom 10th percentile of market capitalization at the end of each year. The 4-factor alpha is still significant at 0.71% per month with a t-statistic of 2.21. Based on our previous findings we already know that firms with the lowest connectedness betas also happen to be small firms, hence some reduction in alpha is to be expected. Nevertheless, the long/short strategy is still economically significant and attractive because it does not require short-selling of extremely small stocks.

From the third row onwards, we change the weighing scheme of the portfolios from equal-weighted to value-weighted. At first the value-weighted hedge portfolio does not generate a statistically significant alpha. The stark difference between the equal-weighted and the value-weighted results brings up a more general question that divides opinion: are cap-weighted or equal-weighted indexes more representative of the market? Should a few large firms “matter” so much more than many small firms? The size distribution of U.S. stocks have become so skewed in the recent decades that many cap-weighted indexes and passive ETFs are primarily driven by a handful of companies. This has given rise to alternative weighing schemes based on fundamentals or volatility. It is not our intention to investigate these methods here and argue for the “best” weighing scheme; nevertheless, we too are worried about a small number of stocks having a disproportional effect on the return of our portfolios. Therefore, in each of our portfolios we took a deeper look at the constituents. We saw many cases of few stocks dominating entire portfolios because of their high market capitalizations. We wondered how these portfolios would perform without the heavyweights. In row 4 we report the alphas of value-weighted portfolios with the largest 10th percent of stocks dropped from the sample. The alpha goes up to 0.78% per month with a t-statistic of 2.05. In row 5, we take another route to limit the effect of extremely large stocks. Instead of excluding them, we take the log of market value of equity before value-weighting the portfolio. The log transformation preserves the order of stocks but reduces the effect of outliers in the distribution. We find an alpha of 0.89% and a t-statistic of 2.64 in this case. Unless one is adamant about market-cap weighting, we believe that investors should pay attention to the connectedness beta of the stocks they own.

Overall, the picture that emerges is that the effect of financial connectedness on risk-premia is weak among large stocks, yet still applies to a large number of stocks. If one is investing strictly in blue-chips the effect can be ignored, but in our view there are lots

fund managers and individual investors concentrating on small stocks, hence the results are practically relevant. For the same reasons, we believe our results are of interest to policy makers as well. It would not be wise (or popular) if regulators were to only pay attention to issues pertaining to the largest firms in the economy. For example, it would be absurd to claim that bank financing for small businesses is not an essential part of the economy because large firms like Apple and Google do not require any bank financing. The fact that plenty of small firms are negatively affected by financial connectedness requires more attention, not less.

8 Conclusion

This study builds on the framework for understanding financial connectedness developed by Diebold and Yilmaz (2014) among others. The main advantage of this type of econometric approach is that the assumptions of the model are minimal and the only data that is needed for estimation is daily prices. While it is useful to be able to quantify a vague notion like connectedness, its effects on the economy are only partially understood. Our study offers a new application of connectedness in the equity market.

We start by estimating a VAR system of the daily volatilities of the largest 40 financial institutions in the U.S. for the 1963-2016 period. The estimation is performed on a rolling sample window and has no look-ahead bias. The resulting connectedness index reflects the state of connectedness on the last day of the sample window. The evolution of this index through time captures the regulatory changes that have occurred in the U.S. finance industry over the last four decades. We observe clear regime changes between the early parts of the sample when the industry mostly followed traditional banking practices, the deregulation period of the late 1980s and 1990s which led to massive expansion of the financial sector, and the post-2000 period of complex networks of too-big-to-fail institutions.

Our next step is to estimate the sensitivity of nonfinancial firms to the financial connectedness index. We do this by standard time-series regressions of (contemporaneous) stock returns on two factors, the market excess return and the connectedness index. The resulting connectedness betas vary between negative and positive values, showing wide cross-sectional dispersion. We then form portfolios by sorting stocks according to their connectedness betas. We find that the bottom decile portfolio has a median connectedness beta of -2 and earns a positive alpha of 21% per year, where alpha is measured with respect to market, size, value, and momentum factors. In comparison, the portfolio with an average connectedness beta of

zero earns an alpha of 7%. Statistical and economic significance of the alphas of hedge portfolios (decile 1 minus decile 10) survive the robustness checks with respect to market beta, market cap, book-to-market, past returns, leverage, illiquidity, and idiosyncratic volatility. The impact of financial connectedness on nonfinancial stocks appears to be an undiscovered anomaly.

We call the existence of these abnormal returns an anomaly because the evidence for a new risk factor is weak. First, if financial connectedness was an undiversifiable risk factor, then the stocks with positive connectedness betas would provide a natural hedge against the rise in connectedness, hence their expected returns would be reduced accordingly. We do not observe this to be the case. Decile 10 portfolio has roughly the same average returns as decile 5 portfolio. Second, the abnormal returns only exist in the most recent two decades and are concentrated mostly among small firms. It is unlikely that a connectedness factor could explain the full cross-section of returns. Regardless, we think there are good economic reasons not to view these results as spurious. Further investigation into the determinants of connectedness betas reveals that they are strongly correlated with the credit quality of the firms in the cross-section: Lower credit quality implies a lower connectedness beta (negative, and higher in absolute value). Since lower credit quality firms would find it more difficult to access capital markets, we interpret their negative connectedness beta as a proxy for their financial sector dependence. Investors are thus discounting such firms at a higher rate than otherwise comparable firms.

An important question is whether the relative underpricing of negative connectedness beta stocks will continue to hold in the future. We think that is likely to be the case because financial connectedness has not fallen substantially after the 2008 crisis, and many investors have good reasons to ‘dislike’ companies that are more sensitive to the whims of the bankers. These companies tend to be young with high R&D costs, implying high informational asymmetry. Their recent past performance and credit quality is poor, lowering their bargaining power with lenders. Irrespective of these characteristics reflecting the exposure to systemic (contagion, tail, etc.) risk or driving mispricing, we foresee that patient and disciplined investors should be able to earn a premium.

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