Financial Sector Volatility Connectedness and Equity Returns

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Abstract: The objective of this study is to analyze how financial connectedness impacts equity markets and potentially raises the cost of equity for firms that are more dependent on the financial sector. 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 find that there is a large statistically significant difference between the returns of non-financial firms with positive and negative exposures to this index. 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. Based on bivariate portfolio tests and Fama-MacBeth return regressions, abnormal returns are robust to market beta, size, book-to-market ratio, momentum, profitability, asset growth, debt, illiquidity, idiosyncratic volatility and downside beta. They are, however, driven by smaller firms whose returns covary negatively with the index. These firms tend to be of low credit quality which explains their dependence on financial institutions.

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 undesirable for financial stability and economic growth, somewhat similar to how they view high inflation. But unlike the case of inflation, there is a lack of empirical work studying the effects of financial connectedness on other economic and financial variables of interest.

We fill this gap by estimating financial sector volatility connectedness and investigating its effects in the cross-section of non-financial firms' stock returns. 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. The empirical results reveal that non-financial firms whose stock returns covary negatively with financial connectedness have high expected returns and this effect is orthogonal to systematic risk factors.

We start by estimating the Diebold-Yilmaz Connectedness Index (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. The long-run trends of the connectedness index track relevant events affecting the U.S. 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 the 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-run trends, we also observe short-term fluctuations in the index reflecting the effects of business cycles and developments in global financial markets.

Next, we estimate non-financial firms' connectedness beta; sensitivity of its stock return to DYCI. Firms with negative connectedness betas turn out to be mostly small firms with poor past performance, though not necessarily financially distressed. In terms of systematic or idiosyncratic risk, they don't differ substantially from others, which makes their high average returns somewhat of an anomaly. This effect is economically large and observed relatively recently. 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 ones. 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 to the CAPM beta, downside beta, market capitalization, book-to-market ratio, past 12-month return, gross profitability, asset growth, leverage, illiquidity, and idiosyncratic volatility. In other words, sensitivity of a firm to financial connectedness is not just another proxy for already known characteristics that explain the cross-sectional variation in stock returns. Yet, financial connectedness does not appear to be a common risk factor: There is no monotonic relationship between connectedness betas and average portfolio returns, post-formation portfolio connectedness betas turn out to be flat, and large firms do not exhibit the same patterns as the small firms.

Our view is that the observed abnormal returns are due to inefficiencies/frictions in financial markets. Financial connectedness has disproportional effects on firms that are more dependent on financial intermediation to satisfy their financing needs. We find that a firm's 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. As a result, investors may discount these firms at a higher rate than what common asset pricing models would imply. This behavior would give rise to the abnormal returns reported in this study.

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 its behavior over time in Section 4. In Section 5 we estimate the connectedness beta 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 7 provides evidence for the view that connectedness beta measures the dependence of a firm on financial intermediation. Section 8 provides additional robustness tests, while Section 9 considers risk-based and behavioral explanations of the anomaly, and Section 10 concludes.

2 Literature Review

As our study largely builds on the recent literature on financial networks and connectedness, a brief overview of this literature is helpful to set the scene. Theoretical contributions to the literature focus, 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 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. Overall, network theory has been instrumental in understanding systemic risk however, it has not yielded a simple model that can be put to practice by policy makers.

Ever since the global financial crisis in 2008, developing empirical systemic risk measures has gained urgency in the literature. Acharya et al. (2017) and Brownlees and Engle (2015) propose to measure the systemic contribution of a financial institution's solvency risk as the expected shortfall in a market decline. Adrian and Brunnermeier (2016) with their CoVaR measure show that the value-at-risk framework can be extended to measure the contribution of a financial institution to the amount of systemic risk in the economy. Their measure is based on the difference between the market value at risk when the firm is in its distressed state and the 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.

On the econometrics side, vector autoregressions (VARs) have proved to be useful for developing connectedness measures. The advantage of the VAR framework is that it allows for full multivariate dynamic cross-variable interactions. The Diebold-Yilmaz connectedness framework relies on forecast error variance decomposition obtained from the estimated VAR model (for more detail see (Diebold and Yilmaz, 2009, 2012, 2014)). As such, the variance decomposition enables the researcher 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 or systemic risk, the Diebold-Yilmaz framework has minimal data requirements. It can be estimated using index price series or interest rate spreads, most of which are publicly available at a high frequency. This feature allows us to use the high-dimensional extension of this framework to construct a financial connectedness index that can go further back in history than the other measures.

Estimating the connectedness index is only the precursor to most of the analyses we take on in this study. 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. (2017). 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. An earlier study by Ang et al. (2006c) argues 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 these risk-based stories, the intertemporal capital asset pricing model of Merton (1973) where investors try to hedge variations in the future investment opportunity set provides a theoretical basis.

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 form another type of friction that may cause stocks to be 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) argue 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 new datasets. Electronically searchable news archives are a technological innovation that has proven to be fruitful in understating how media and financial markets are linked. 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. (2017) 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 help put our study in context. We 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. As we will discuss in detail later on, the empirical evidence is more supportive of the view that financial connectedness is a type of market friction that raises the required rate of return demanded by investors for specific types 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 NxN coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN 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

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

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:

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

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:

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

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

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

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

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

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.

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

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 conditional on the presence of non-financial firms in the model.[1] 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.

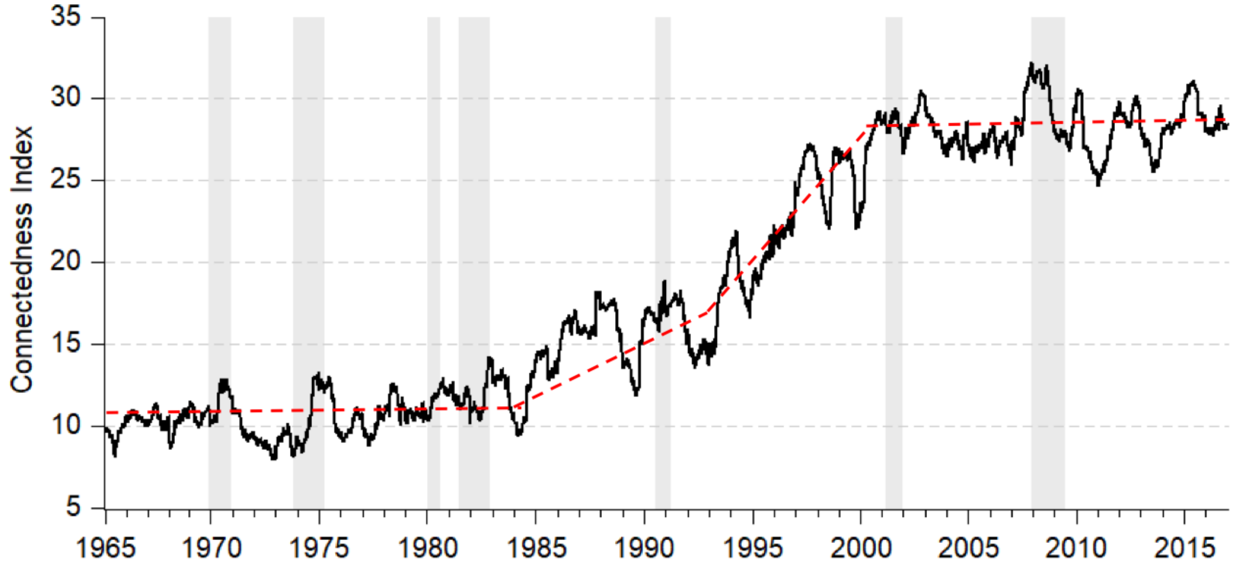
[1] We also estimated the "unconditional" connectedness index excluding the non-financial firm stocks. The resulting index, which is presented in Figure A.1 in the Appendix, is more than 95% correlated with the "conditional" index. Note that, because the unconditional index is obtained from the full variance decomposition matrix, rather than a submatrix of it, it ranges between 10 and 92. When we use the unconditional index all our results carry through.

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):

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

4.2 Time-Series Behavior of DYCI: A Historical Account

Figure 1: U.S. Financial Volatility Connectedness Index (1965-2016)



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.[2] 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 increases to reach 32 during the U.S. financial crisis of 2007-2008, indicating substantial impairments in the U.S. finance industry.[3] 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.

[2] 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.

[3] During the U.S. financial crisis, the "unconditional" financial sector connectedness index (Figure A.1) increases by 18 points to reach a maximum level of 92, only 8 points lower than 100 level which shows full scale connectedness.

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.

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 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 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

[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)).

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 Index[5] increased from less than 30 at the end of 1994 to 86 by August 1998 (one month 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 time 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

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

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

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 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. In this section we simply want to discern the economic rationale for the movements of the index and develop our intuition. Had it not been the case that our index reflected 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 stock returns of non-financial firms. There is little theoretical work on casting risks borne out of the financial sector within a general asset pricing framework, perhaps because modern portfolio theory takes the healthy functioning of financial markets as given. Nevertheless, the idea that investors may want to hedge against a scenario of financial sector collapse has certainly become more fitting after the 2008 financial crisis. As a reflection of this need, Allen et al. (2012b) introduced a catastrophic risk measure called CATFIN, which was calculated from the cross-sectional distribution of equity returns of financial firms. As the authors show, CATFIN can predict economic downturns and is priced in both the time series and cross-section of individual stocks. Another contribution in this direction, Piccotti (2017) develops a model of financial contagion and shows that stocks which co-move more strongly with contagious intermediaries earn higher average returns. The rationale behind these two studies is that investors would prefer to hold assets that pay off during times when their marginal utility of wealth is high.

Our motivation for exploring the link between financial connectedness and stock returns is different, although our results are consistent with the aforementioned studies. In a world with financial frictions, firms with varying degrees of dependence on the financial sector may find varying degrees of success financing 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 or private placements may not be favorable for an industrial firm that wants to borrow and invest because of the cross-commitments and the capital requirements of financial institutions. Contrast that with a firm with excess cash or one that can directly access capital markets. It is plausible that investors might discount bank-dependent firms more heavily than what the classic asset-pricing models would suggest.

In the following sections we measure the sensitivity of (non-financial) firms to financial connectedness, which we interpret as a characteristic of a firm. We then test to see whether the cross-sectional variation in this characteristic can lead to a variation in expected returns.

5.1 Connectedness Betas

We follow a standard approach in empirical asset pricing where individual stock returns are regressed onto a market-wide factor to estimate their betas. Specifically, we run the following time-series regression:

$$R_{it} - r_{ft} = \alpha_i + \beta_i^M MKT_t + \beta_i^{DYCI} DYCI_t + \epsilon_{it} \tag{7}$$

where $R_{it} - r_{ft}$ is the excess return on stock i, MKT is the market excess return and $DYCI$ is the Diebold-Yilmaz Connectedness Index, explained in Section 4, β_i^M is the market beta and β_i^{DYCI} 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 meant to reduce the effect of outliers when we examine the determinants of connectedness betas in Section 7. 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. We also examine value-weighted portfolios in Section 8.1.

5.2 Portfolios Formed on Connectedness Beta

Table 1 reports average values of these 10 portfolios from 1994 to 2016. This time period coincides with the passage of the Riegle-Neal act which allowed for interstate banking in the U.S. and has led to a dramatic rise in financial connectedness (Figure 1). The variables are chosen among firm characteristics that have been used to explain the cross-section of stock returns. We will use the same set of variables in Sections 5.4 and 6 later on. At this point, we simply report the median stock values for each portfolio to get a big picture view of what type of stocks are in these decile portfolios.

The average connectedness beta of the median stock in the portfolios 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. As we will see in the next section, this group is the main driver of the abnormal returns, hence our discussion is structured around comparing this group to the others. 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 are not. The other characteristics reported here provide some clues.

Size stands out as a 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 from 6 size diminishes to $241 million. This inverted U-shape tells us clearly that large firms are not

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	1.38	1.17	1.04	0.94	0.89	0.89	0.93	1.02	1.17	1.38
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%
Gross Profitability	0.32	0.33	0.33	0.32	0.32	0.33	0.34	0.34	0.34	0.34
Asset Growth	6.32%	6.33%	6.50%	5.71%	5.65%	5.69%	5.76%	5.70%	5.33%	5.24%
Debt-to-Assets	12.81%	15.39%	18.62%	20.68%	21.70%	21.81%	21.00%	19.44%	18.01%	17.41%
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%

This table reports the time-series averages of median stock characteristics for the decile portfolios formed on connectedness betas (β^{DYCI}). Decile 1 comprises of firms with the lowest β^{DYCI} and decile 10 with the highest β^{DYCI}. β^{DYCI} is estimated prior to portfolio formation by running 60-month rolling time-series regressions of excess stock returns on the excess market return and the DYCI. β^{DYCI} is winsorized at the 1^{st} and 99^{th} percentile. Only non-financial firms which trade on NYSE, AMEX, or NASDAQ with prices greater than $1 at the end of each month are included in the porfolios. Portfolio formation starts at the beginning of 1994 and ends at the end of 2016.

affected by financial connectedness (in a statistical sense), perhaps because they find it easier to access capital when needed. Large firms could either use internal capital or issue bonds directly in capital markets, whereas small firms are more dependent on bank loans and private placements. Stock level liquidity follows the same pattern as firm size. Based on the Amihud (2002) illiquidity measure, stocks in decile 5 are the most liquid, whereas stocks in deciles 1 or 10 are the least liquid. The fact that size or liquidity is not monotonically increasing across the deciles alleviates the concern that connectedness beta may be a proxy for these two variables.

High sensitivity to the behavior of the financial sector may be a signal of financial distress. A company with a lot of existing debt may find it difficult to borrow even for positive NPV projects, for example. We do not observe signs of financial distress for the stocks in decile 1; in fact, these stocks have the lowest debt-to-asset ratios. Firms with the highest level of debt are the ones in the middle of the connectedness beta distribution, whose sensitivities to the financial sector are practically zero. Book-to-Market ratios are similar across all deciles and all are less than 1 which makes it unlikely that firms in the first decile are financially distressed. Gross profitability is also very similar across the deciles and does not appear to be related to connectedness betas, and so is asset growth. Overall, we conclude that firms that are negatively affected by financial connectedness (on the left tail of the distribution), are not necessarily suffering from debt overhang or financial distress.

Decile 1 firms tend to have higher market betas than Decile 5 firms (1.38 vs. 0.89), but market beta is not monotonic across the deciles and exhibits low variation. Thus, any differences in average returns of these portfolios are unlikely to be explained by market risk. Decile 1 portfolio has the highest idiosyncratic risk with 3.51% per month, but once again, the differences among portfolios are small and non-monotonic. Based on these two commonly used risk measures, stocks with the lowest (most negative) connectedness betas do not appear to be riskier than stocks with the highest (most positive) connectedness betas.

One variable that does follow a monotonic pattern with connectedness beta is the stock return of the firm over the past 12 months. The past (geometric) average monthly return is negative 1.06% for decile 1 and positive 1.53% for decile 10. This pattern of underperformance versus overperformance as the connectedness beta increases alerts us to the importance of controlling for momentum; however, note that the momentum anomaly would indicate lower returns for decile 1 (selling the losers) and higher returns for decile 10 (buying the winners) in the near future, completely the inverse of what we show in the next section.

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 leads to differences in expected returns. In Table 2 we present excess and risk-adjusted returns for the 10 portfolios 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 0.93% per month, or 11% per annum (CAPM alpha is slightly lower at around 0.73%). Remember from Table 1 that portfolio 1 has on average lower past returns than portfolio 10; 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 (alpha=1.22%, t=3.29). The last row controls for the profitability (RMW) and investment (CMA) factors in Fama and French (2015) and alpha is larger still. To judge the economic significance of this finding, consider a hedge fund which were to report annual returns of 16% with no exposure to the systematic risk factors. No doubt it would see substantial 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 a 5-factor alpha of 1.81% (per month) albeit with some systematic risk premiums. As we move into stocks with higher connectedness betas, the returns of portfolios begin to resemble each other. The portfolio in the last column of Table 2 is constructed similar to the 1-minus-10 portfolio except that it shorts portfolio 5 instead of portfolio 10. The 4-factor and 5-factor alphas of the 1-5 hedge portfolio differs only by 7 basis points from the corresponding alphas of the 1-10 hedge portfolio, hence the choice of stocks on the short side is not crucial. Portfolio 5 firms for example are the largest and the most liquid, and are more likely to be available for shorting.

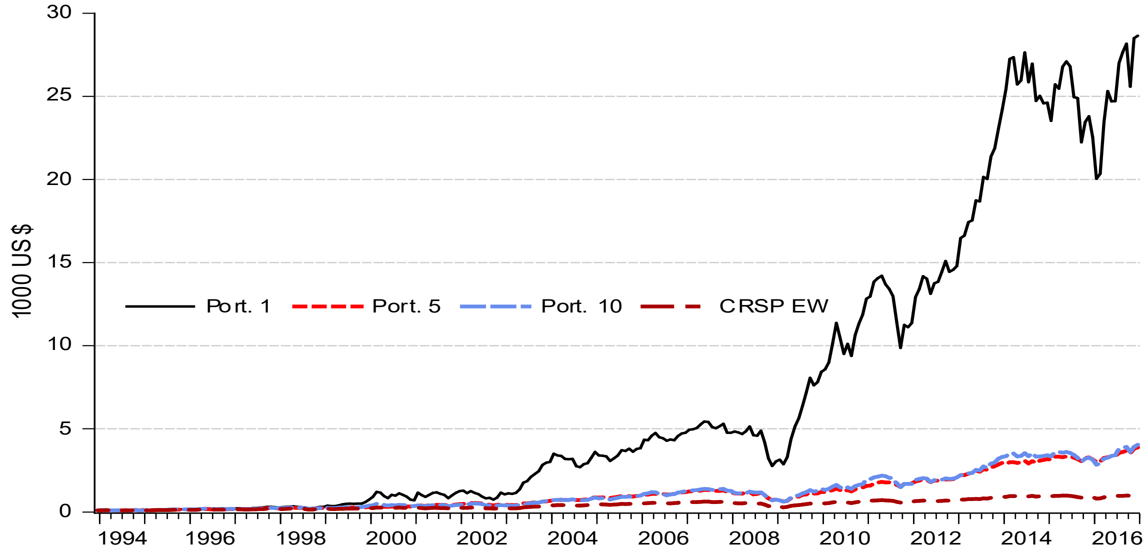
To better understand the economic intuition behind these abnormal returns it is important to realize that the low beta stocks in portfolio 1 are actually negative beta stocks. A negative beta stock performs worse when the financial sector connectedness increases, which we think is due to the dependence of the firm on the financial sector. Investors who are keenly aware of this dependence may value these firms lower than they otherwise would.

Table 2: Univariate Portfolio Returns

	Decile Portfolios (Equal-Weighted)											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1-10**	**1-5**
Excess returns	2.30	1.66	1.38	1.25	1.24	1.15	1.19	1.20	1.20	1.36	0.93	1.05
	(3.70)	(3.62)	(3.44)	(3.74)	(3.73)	(3.63)	(3.88)	(3.66)	(3.16)	(3.02)	(2.75)	(2.54)
CAPM alpha	1.32	0.84	0.66	0.60	0.62	0.55	0.58	0.58	0.52	0.59	0.73	0.69
	(2.98)	(3.01)	(2.71)	(3.16)	(3.26)	(2.94)	(3.42)	(3.22)	(2.42)	(2.27)	(2.26)	(1.78)
4-Factor alpha	1.76	1.04	0.74	0.62	0.62	0.53	0.52	0.50	0.41	0.55	1.22	1.15
	(4.70)	(5.52)	(4.96)	(5.66)	(5.47)	(5.02)	(5.11)	(4.34)	(3.37)	(3.55)	(3.29)	(3.18)
5-Factor alpha	1.81	0.97	0.57	0.42	0.38	0.25	0.32	0.31	0.29	0.46	1.35	1.42
	(4.20)	(3.83)	(3.15)	(3.13)	(3.12)	(2.13)	(3.44)	(3.00)	(2.44)	(3.15)	(3.35)	(3.85)

Table reports the excess and risk-adjusted returns of decile portfolios formed on β^{DYCI}. 1-10 column represents a zero-net-investment portfolio that is long in portfolio 1 and short in portfolio 10, 1-5 column shorts portfolio 5 instead of portfolio 10. Portfolios are equal-weighted and rebalanced monthly. CAPM alpha uses MKT, 4-Factor alpha uses MKT, SMB, HML, UMD, 5-factor alpha uses MKT, SMB, HML, RMW, CMA, as the systematic factors. Factors are downloaded from Ken French's data library. Financial stocks (SIC codes between 6000 and 7000) are excluded. Time period is 1994-2016. Returns are given in percent per month. T-statistics based on Newey-West standard errors are in parentheses.

Figure 2: Cumulative Returns for Connectedness Beta Portfolios



These firms would then exhibit above average returns in the future, which will appear as "mispricing", though it is difficult to say for certain whether it is the investors or the models that are wrong. Our results are consistent with both the behavioral and the risk-based explanations. We take up this issue in more detail in Section 9.

One worry with trading strategies based on anomalies is that they could be prone to crashes. A long stream of gains could be erased by a sudden extreme loss, which is easy to miss when looking at arithmetic averages. In Figure 2, we plot cumulative returns of our low connectedness, zero connectedness, 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 between the negative and positive connectedness beta stocks (or twenty-eight-fold compared to the market) implies either significant mispricing, or an extremely lucky period. To foreshadow some of our results from Section 8.1, let us point out that this kind of overperformance does not exist in the 1969-1993 period – the last two decades seem to be special. We just do not think this is due to pure luck; financial connectedness has risen considerably in the 1990s and the financial crisis of 2008 has made investors overly cautious about the impact of the financial sector on the rest of the economy. The exponential growth of portfolio 1 in the post crisis period can be viewed as the gradual "correction" of investors' systematic bias against non-financial firms that are more dependent on the finance sector.

5.4 Bivariate Portfolio Returns

Next, we examine bivariate portfolio returns. As we saw in Table 1, firms in different decile portfolios differ in terms of their characteristics, hence we want to make sure that it is the connectedness beta and not some other characteristic that is driving the alphas. The bivariate portfolios are formed by sorting stocks first on the control variable (size, book-to-market, etc.), and then on connectedness betas within those deciles, ending up with 100 portfolios for each pair. For each connectedness beta decile, we average the returns across the control variable and estimate 4-factor alphas.[7] This procedure generates portfolios with roughly the same number of low and high beta stocks, small and large stocks, or "loser" and "winner" stocks and so on.

Table 3 corroborates our previous findings in Table 2. The 1-10 hedge portfolio earns a statistically and economically significant abnormal return in each column. Alphas range from 0.67% per month to 1.29% per month and t-statistics range from 2.20 to 4.42. Controlling for CAPM beta, book-to-market ratio, and leverage has practically no effect on the alpha generated by the connectedness beta strategy. Similarly, the gross profitability (GP) anomaly of Novy-Marx (2013) and the asset growth (ATG) anomaly of Cooper et al. (2008) appear to be distinct from the effect we document here. Sorting stocks first on GP (revenues minus cost of goods sold divided by total assets), or ATG (total assets at time t minus total assets at time t-1 divided by total assets at time t-1) generates roughly the same return as a simple sort on connectedness beta.

The controls that reduce the alphas the most are size and idiosyncratic volatility. Because small firms are generally the ones with high idiosyncratic volatility it is not surprising that these two variables have a similar effect on our results. 1-10 alpha for the size/connectedness beta bivariate portfolio is 0.67% per month, which is roughly half of what we found in the univariate case. It is clear that the anomaly is stronger among small firms, but as the bivariate portfolios have a uniform distribution of size, we believe that the phenomenon is general enough to be of interest to academics and practitioners. Finally, we control for the downside risk factor of Ang et al. (2006a). Downside beta is defined as the slope coefficient from a regression of excess stock returns on the market excess return only on days when the

[7] 5-factor alphas also yield similar results that are available upon request.

Table 3: Bivariate Portfolios

CON. BETA	BETA	SIZE	BTM	MOM	GP	ATG	DEBT	ILLIQ	IVOL	DOWN BETA
Low	1.76	1.14	1.79	1.27	1.77	1.67	1.71	1.34	1.19	1.77
	(5.69)	(3.86)	(5.12)	(4.44)	(4.92)	(4.83)	(4.60)	(3.97)	(5.14)	(5.28)
2	0.92	0.80	1.01	0.98	1.01	1.06	0.93	0.92	0.86	0.93
	(5.33)	(4.30)	(5.20)	(6.16)	(5.13)	(5.82)	(5.50)	(5.02)	(5.27)	(5.44)
3	0.67	0.84	0.74	0.82	0.73	0.70	0.71	0.78	0.76	0.70
	(4.65)	(5.99)	(4.94)	(5.51)	(5.48)	(4.60)	(5.03)	(5.80)	(5.81)	(4.88)
4	0.71	0.72	0.62	0.72	0.63	0.64	0.68	0.75	0.80	0.69
	(5.92)	(5.40)	(5.43)	(5.80)	(5.20)	(6.06)	(5.74)	(5.87)	(5.67)	(5.66)
5	0.64	0.78	0.63	0.67	0.66	0.63	0.60	0.64	0.81	0.58
	(5.96)	(6.56)	(5.68)	(6.92)	(6.29)	(5.36)	(5.15)	(6.23)	(6.33)	(5.60)
6	0.49	0.57	0.51	0.71	0.52	0.60	0.51	0.57	0.59	0.52
	(4.41)	(5.63)	(5.27)	(6.28)	(5.52)	(5.60)	(4.58)	(5.15)	(5.34)	(5.46)
7	0.61	0.74	0.53	0.57	0.52	0.49	0.50	0.62	0.74	0.57
	(6.02)	(6.65)	(4.89)	(5.06)	(5.46)	(4.49)	(5.35)	(5.93)	(6.42)	(6.35)
8	0.43	0.65	0.48	0.58	0.49	0.56	0.47	0.64	0.58	0.46
	(4.30)	(5.07)	(4.49)	(4.92)	(4.42)	(5.04)	(4.14)	(5.31)	(4.98)	(4.04)
9	0.50	0.58	0.44	0.43	0.42	0.43	0.43	0.52	0.46	0.43
	(4.83)	(4.51)	(3.63)	(3.76)	(3.37)	(3.50)	(3.67)	(4.26)	(4.05)	(3.90)
High	0.54	0.47	0.50	0.51	0.53	0.49	0.46	0.50	0.50	0.62
	(4.00)	(3.26)	(3.41)	(3.67)	(3.53)	(3.49)	(2.79)	(3.36)	(3.80)	(4.34)
1-10	1.22	0.67	1.29	0.77	1.24	1.17	1.25	0.84	0.68	1.14
	(4.42)	(2.20)	(3.69)	(2.70)	(3.54)	(3.41)	(3.33)	(2.53)	(3.02)	(3.61)

Each column represents a different control variable which is used for the first sort. 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. 4-factor alphas (MKT, SMB, HML, UMD) are reported. Sorting variables are lagged for 1 month in general, Compustat variables are lagged for an additional 6 months. CON.BETA is β^{DYCI} estimated using Equation 7. BETA is the slope coefficient on MKT, estimated via rolling 60-month time-series regressions of excess stock returns on the market excess return. SIZE is the market value of equity at the end of each month, BTM is the ratio of book value of equity to market value of equity at the end of the fiscal year (lagged 6 months). MOM is the return over the past 12 months skipping the most recent month, GP is revenues minus cost of goods sold normalized by total assets, ATG is the annual percentage change in total assets, DEBT is the sum of long-term debt and debt in current liabilities normalized by total assets, ILLIQ is the monthly average of daily absolute return divided by dollar volume, IVOL is the standard deviation of the residuals from a monthly regression of daily stock returns on MKT, SMB and HML, DOWN BETA is the slope coefficient on MKT from a regression of daily excess stock returns on the market excess return, estimated using only observations on days where MKT is below its mean over the most recent 1-year window. Returns are given in percent per month. T-statistics based on Newey-West standard errors are in parentheses.

market excess return is below its average over the past year. Ang et al. (2006a) argue that investors demand a premium for holding stocks that perform worse in market downturns and it is plausible that financial connectedness also correlates with the downturns. Fortunately, controlling for downside beta has negligible effect on the alpha. We still observe a premium of roughly 1% per month, which is both statistically and economically significant.

6 Stock Level Cross-sectional Regressions

Portfolio analyses have the benefit of being non-parametric, but they do not allow for controlling multiple factors simultaneously. Fama and MacBeth (1973) methodology solves this problem by utilizing periodic cross-sectional regressions, given that one is willing to assume a linear functional form between the stock level variables and the returns. The general regression specification is:

$$r_{i,t+1} = \lambda_{0,t} + \sum_{j=1}^{n} \lambda_{j,t} X_{j,i,t} + \epsilon_{i,t+1} \tag{8}$$

where $r_{i,t+1}$ is the excess return of stock i in month $t+1$, $\lambda_{j,t}$ is the risk premium associated with the risk factor or the characteristic j in month t, and $X_{j,i,t}$ is the risk factor sensitivity or the observed characteristic j of stock i in month t. We perform nested regressions where the risk factor sensitivity is the market beta or the downside beta, the characteristics are market value of equity, book-to-market ratio, past 12-month return, gross profitability, asset growth, debt-to-assets, illiquidity, and idiosyncratic volatility. Our main variable of interest is the connectedness beta estimated using equation 7. Time-series averages of the slope coefficients along with Newey-West t-statistics in parentheses are reported in Table 4.

The first column, the univariate regression of excess returns on connectedness betas reveal a statistically significant and negative relation, consistent with the portfolio analyses from the previous sections. Stocks with lower connectedness betas have higher returns in subsequent months, on average. Adding market beta in column 2 does not change the magnitude or the statistical significance of this relation. Market beta does not appear to be related to average returns by itself; a well-documented result in the asset pricing literature. Next, we add the size, value, and momentum variables, which are the oldest and the most prevalent anomalies. While the connectedness beta coefficients in columns (2)-(5) are somewhat lower than the one in column (1) they are still highly significant (with t-statistics ranging from -2.41 to -2.94). More recently documented anomalies such as gross profitability and asset

Table 4: Fama-MacBeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CON. BETA	-0.305	-0.299	-0.222	-0.220	-0.206	-0.205	-0.200	-0.191	-0.196	-0.200	-0.202
	(-3.06)	(-3.27)	(-2.70)	(-2.94)	(-2.41)	(-2.46)	(-2.48)	(-2.53)	(-2.62)	(-2.78)	(-2.81)
BETA		0.172	0.181	0.174	-0.004	-0.001	0.012	-0.003	0.074	0.042	
		(0.81)	(0.86)	(0.89)	(-0.03)	(-0.01)	(0.08)	(-0.02)	(0.51)	(0.32)	
LNSIZE			-0.340	-0.304	-0.289	-0.284	-0.280	-0.282	-0.186	-0.158	-0.152
			(-5.80)	(-5.09)	(-4.79)	(-4.61)	(-4.58)	(-4.67)	(-3.32)	(-3.39)	(-3.05)
LNBTM				0.089	0.088	0.096	0.069	0.066	0.050	0.072	0.065
				(0.92)	(0.93)	(0.96)	(0.70)	(0.69)	(0.52)	(0.81)	(0.74)
MOM					-0.064	-0.064	-0.065	-0.067	-0.071	-0.065	-0.058
					(-2.05)	(-2.05)	(-2.09)	(-2.22)	(-2.39)	(-2.16)	(-1.85)
GP						0.163	0.127	0.122	0.092	0.104	0.095
						(0.93)	(0.73)	(0.64)	(0.48)	(0.57)	(0.52)
ATG							-0.449	-0.443	-0.418	-0.414	-0.407
							(-7.33)	(-7.19)	(-6.83)	(-6.79)	(-6.42)
DEBT								0.026	-0.089	-0.067	-0.109
								(0.07)	(-0.26)	(-0.20)	(-0.31)
ILLIQ									0.119	0.117	0.116
									(4.36)	(4.51)	(4.39)
IVOL										4.841	5.902
										(1.32)	(1.59)
DOWN BETA											-0.144
											(-0.95)
CONSTANT	1.390	1.166	3.097	2.927	2.844	2.763	2.783	2.824	2.072	1.788	1.897
	(3.67)	(4.23)	(6.22)	(6.04)	(5.86)	(5.44)	(5.49)	(5.33)	(4.11)	(4.00)	(3.86)
Observations	728,836	728,836	728,445	684,057	684,057	684,052	683,902	683,902	683,902	683,843	683,726
R-squared	0.006	0.021	0.030	0.035	0.042	0.045	0.046	0.048	0.054	0.058	0.058

The dependent variable is the excess stock return at time $t+1$, independent variables are measured at time t. Compustat variables are lagged for an additional 6 months and winsorized at the 1^{st} and 99^{th} percentile. CON.BETA is β^{DYCI} estimated using Equation 7. BETA is the slope coefficient on MKT, estimated via rolling 60-month time-series regressions of excess stock returns on the market excess return. LNSIZE is the log of market value of equity at the end of each calendar year, LNBTM is the log of ratio of book value of equity to market value of equity at the end of the fiscal year. MOM is the return over the past 12 months skipping the most recent month, GP is revenues minus cost of goods sold normalized by total assets, ATG is the annual percentage change in total assets, DEBT is the sum of long-term debt and debt in current liabilities normalized by total assets, ILLIQ is the yearly average of daily absolute return divided by dollar volume, IVOL is the standard deviation of the residuals from a monthly regression of daily stock returns on MKT, SMB and HML, DOWN BETA is the slope coefficient on MKT from a regression of daily excess stock returns on the market excess return, estimated using only observations on days where MKT is below its mean over the most recent 1-year window. Cross-sectional regressions are run for each month from 1994 to 2016 (276 months) and time-series averages of slope coefficients are reported. T-statistics based on Newey-West standard errors are in parentheses.

growth (Novy-Marx (2013), Cooper et al. (2008)) also appear to be unrelated to the financial connectedness, as the results in columns (6) and (7) confirm.

Since we interpret connectedness beta as a measure of a firm's dependence on financial institutions, it is likely to be intertwined with the amount of debt a firm carries. Column (8) adds debt (normalized by total assets) to the mix and once again the connectedness beta comes out unscathed. That is not to say however that connectedness beta and debt are unrelated – they are in fact closely related, but we hold off this discussion until we look at the determinants of connectedness beta in Section 7. Column (9) adds the Amihud (2002) illiquidity measure as a response to the common criticism that most anomalies are in fact liquidity premiums in disguise. While the illiquidity variable is highly significant, it turns out that it has no impact on the premium associated with connectedness beta.

Ang et al. (2009) show that idiosyncratic risk is priced in the cross-section and even carries a negative premium. While this finding is challenged by Bali and Cakici (2008), it may still be important to control for idiosyncratic risk because missing risk factors will show up in idiosyncratic risk estimates by construction. Following Ang et al. (2009), our idiosyncratic risk variable is estimated by regressing daily stock returns on the Fama and French (1996) three factors (MKT, SMB, HML) with a rolling one-month window and taking the standard deviation of residuals. As column (10) shows, it too has no impact on the coefficient on connectedness beta. Lastly, we substitute the downside beta measure of Ang et al. (2006a) for the market beta as a measure of market risk. The authors break CAPM beta down into two components – downside beta and upside beta – where only the observations on down or up markets are used for the estimation, respectively. They show that downside premium is robust in the cross-section, whereas the upside premium is not.[8] Like all the other control variables discussed above, downside beta has no influence on our main result that connectedness beta is negatively related to average returns.

7 Determinants of Connectedness Beta

In previous sections we alluded to the idea that firms with negative connectedness betas are likely to be bank-dependent firms and that they may be more heavily discounted by investors. In this section, we present the supporting evidence for this claim. Our tests revolve around taking the connectedness beta of a firm as the dependent variable in a Fama-

[8] Cremers et al. (2015) and Lu and Murray (2018) also propose new measures for tail risks. Because their measures require options data, we are not able to recreate them for this study.

MacBeth regression and finding out which firm-level characteristics are correlated with it.

The main variables of interest among the regressors are the S&P credit rating of the firm and the ratio of its secured debt to total debt. The rationale for using credit rating as a proxy for bank-dependence is that lower the credit quality of a firm the more difficult it will be to raise capital directly, hence the firm will be forced to rely on financial institutions. 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. A higher fraction of secured debt to total debt implies lower credit quality, as investors would require more collateral for taking on more credit risk. In addition, because bank loans are almost always secured this variable also functions as a proxy for the amount of bank financing a firm might be using.

Table 5 presents Fama-MacBeth regressions run separately for the rated and unrated subsamples of firms, where the dependent variable is the connectedness beta of the firm (winsorized at the 1^{st} and 99^{th} percentiles). Taking the rated group first (columns 1 and 2), the coefficient on credit rating is highly significant and negative. This result is very much in line with our priors; we expect non-investment grade firms (higher numerical values on the scale) to find it more difficult to access capital markets and depend more heavily on bank loans and/or 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.

When we examined the portfolio characteristics in Section 5.1, two variables have caught our attention: size and past return. We now get a chance to understand their relation to connectedness beta at the individual firm level. Here, our proxy for size is sales normalized by assets rather than market value of equity because market value of equity and credit rating are highly collinear. We choose ROE as performance measure to check whether stock performance and the accounting performance lead to similar conclusions. We observe a positive coefficient on sales in Column 2, which implies smaller firms having negative connectedness betas; the same pattern observed in Table 1. Positive coefficient on ROE implies that lower operating performance leads to negative connectedness beta which is consistent with the 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

Table 5: **Determinants of Connectedness Beta**

	Rated	Rated	Unrated	Unrated
LNRATING	-0.066	-0.061		
	(-6.62)	(-4.42)		
SEC. DEBT			-0.072	-0.073
			(-6.11)	(-9.00)
BETA		0.049		0.006
		(3.23)		(0.32)
LNBTM		-0.025		-0.006
		(-4.17)		(-0.63)
SALES		0.051		-0.006
		(7.84)		(-0.74)
LNAGE		0.045		0.031
		(10.38)		(6.69)
R&D		-1.064		-0.284
		(-3.97)		(-3.07)
ROE		0.008		0.006
		(2.04)		(2.40)
CONSTANT	0.229	-0.031	0.008	-0.087
	(10.59)	(-1.00)	(0.45)	(-3.65)
Observations	227,457	213,756	378,439	363,346
R-squared	0.008	0.091	0.002	0.081

Table reports Fama-MacBeth regressions of β^{DYCI} on firm characteristics. Cross-sectional regressions are run for each month from 1994 to 2016 (276 months) and time-series averages of slope coefficients are reported. Compustat variables are lagged for 6 months and winsorized at the 1^{st} and 99^{th} percentile. LNRATING is the log of 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 slope coefficient on MKT, estimated via rolling 60-month time-series regressions of excess stock returns on the market excess return, LNBTM is the log of ratio of book value of equity to market value of equity at the end of the fiscal year, SALES is sales normalized by total assets, LNAGE is the log of 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 of equity. Separate regressions are run on the subset of firms which have credit rating data available (Rated), and which do not (Unrated). Firms with zero debt are excluded from all regressions.

that dependence on the financial sector increases in magnitude with the declining success of the firm's business.

Moving onto columns 3 and 4, for unrated firms the relationship between credit quality and connectedness beta is qualitatively similar to rated firms. We observe that higher levels of secured debt are associated with lower (more negative) connectedness betas. If one views secured debt as a rough measure of bank debt, the implication is that higher levels of financial connectedness harm these firms (lead to lower stock returns). For the unrated group the rest of the control variables with the exception of book-to-market ratio and sales are related to connectedness beta in the same way as the rated group. In the case of book-to-market ratio, the negative coefficient observed for the rated group indicates value firms having lower connectedness betas. One reason 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 reason could be that value firms are "fallen angels" and thus have less bargaining power with their banks. For unrated firms, book-to-market ratio appears to hold no explanatory power over connectedness beta, and the same applies to sales (proxy for size) as well. The fact that size and value distinctions do not fully account for the connectedness beta is further evidence that the anomaly observed in this paper is distinct.

To conclude, while we cannot directly observe the amount of debt financing provided by financial institutions, we feel that credit quality can act as a reasonable proxy to pick out firms that are more likely to be dependent on the financial 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. When financial connectedness rises the stock returns of these firms fall. In addition, we observe younger firms with poor past performance and high R&D spending to be more sensitive to financial connectedness. Size and value measures exhibit only partial success in determining the connectedness beta of a firm.

8 Robustness

8.1 Portfolio Composition and Time Periods

Here we provide additional robustness checks and address certain questions that may possibly arise. The first of these is whether our results are sensitive to the starting point of our sample. They are not. We start forming portfolios in 1994 because they neatly coincide with the passage of the Riegle-Neal act, which allowed for interstate banking in the U.S. Our thinking was that the effects of financial connectedness would be more prominent in the subsequent years. Nevertheless, moving the starting point back a few years, or even decades does not invalidate any of our findings.

Another issue is that whether our results are sensitive to the portfolio weighing method (equal-weighted vs. value-weighted). The answer is, partially, yes. Value-weighted portfolios for the full universe of stocks do not yield statistically significant results. However, limiting the universe to the bottom 40 percentile of stocks by market equity yields statistically significant alphas over the full sample for both equal- and value-weighted portfolios. Value weighting using the log of market value of equity instead of the market value itself or excluding the largest 10% of stocks also yield statistically significant alphas over the full sample.[9]

Table 6: Portfolio Composition and Time Periods

Size	Equal-Weighted			Value-Weighted		
Quintiles	**1994-2016**	**1969-2016**	**1969-1993**	**1994-2016**	**1969-2016**	**1969-1993**
1	2.27	1.42	0.40	3.20	1.94	0.44
	(3.70)	(3.41)	(0.97)	(4.08)	(3.73)	(0.91)
2	0.85	0.82	0.53	1.10	0.90	0.44
	(2.03)	(3.01)	(1.88)	(2.34)	(3.03)	(1.48)
3	-0.07	0.22	0.26	0.49	0.48	0.16
	(-0.21)	(0.97)	(1.01)	(1.20)	(1.79)	(0.60)
4	0.16	0.31	0.17	0.24	0.37	0.15
	(0.52)	(1.51)	(0.72)	(0.73)	(1.65)	(0.64)
5	0.16	0.35	0.23	0.10	0.29	0.17
	(0.54)	(1.75)	(1.06)	(0.32)	(1.38)	(0.71)

Portfolios are formed by first sorting stocks on size, and second on β^{DYCI}(dependent sort). 4-factor alphas (MKT, SMB, HML, UMD) of 1-minus-10 decile portfolios are reported. T-statistics based on Newey-West standard errors are in parentheses. Three different time periods and two weighting methods are presented in each column.

Table 6 presents the 4-factor alphas of the connectedness beta sorted 1-minus-10 portfolios for three time periods, five size quintiles, and two weighing methods. The first and the fourth columns covers the exact same time period as in Table 2 and sort stocks first on size, second on connectedness beta (dependent sort). Compared to the full sample, the alpha for the bottom size quintile is much larger (2.27% vs. 1.22% per month). Value-weighted alpha for the bottom size quintile is larger still at 3.20%. Alphas for the second size quintile are smaller (but still statistically significant) compared to the bottom quintile, 0.85% and 1.10% for equal-weighted and value-weighted portfolios respectively. For the next three size quintiles alphas are no longer statistically significant. These results show that like many other anomalies, the abnormal returns earned by low (negative) connectedness beta stocks are concentrated among small stocks. Because small stocks are the ones to be more bank-dependent we think this is inevitable. Also, keep in mind that larger stocks tend to have connectedness betas centered around zero hence have low variation (Table 1).

In the second and fifth columns we move the starting point of our sample to 1969 and obtain a similar pattern; statistically significant alphas for the bottom two size quintiles for both equal and value-weighted portfolios.[10] We have also tried other years for the start of our sample period and found similar results, leading us to conclude that the exact year

[9] These results are available upon request.

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

when portfolios are being formed is inconsequential. That is not to say however, that the abnormal returns are consistent over time. The third and sixth columns show the alphas in the 1969-1993 period, none of which are significant. The impact of financial connectedness on expected returns appears to be a phenomenon of modern times. We consider this to be perfectly normal because the structure of financial markets before the 90s was dramatically different, and "connectedness" was not even a scientific concept to be studied. In the last two decades, globalization, advances in information technology, and consolidation in the financial services industry have made markets much more connected in a structural way and the academic interest in this topic has grown in response. Therefore, it is hard to see the 1969-1993 period as a representative out-of-sample test for the anomaly we discover between 1994 and 2016. We would need to wait for future data to accumulate before we can perform true out-of-sample tests.

Overall, the picture that emerges is that the effect of financial connectedness on expected returns is stronger among small stocks, yet still applies to a *large number* of stocks. Our assessment is that equal-weighting is a better lens to focus the analysis on connectedness beta. In contrast, value-weighting puts extremely heavier weights on a handful of stocks which are less likely to be affected by financial connectedness. Financial connectedness may not be a concern if one were to invest strictly in the large-cap growth segment. However, there are plenty of fund managers and individual investors concentrating on small stocks, hence in our opinion these results are quite relevant in practice. We also think that these results are of potential interest to policy makers. It would not be wise for regulators to pay attention only to issues pertaining to the largest firms in the economy, simply because they make up a larger portion of the economy. The fact that it is the small firms that are negatively affected by financial connectedness and more heavily discounted in the market place requires more attention by policy makers, not less.

8.2 Other Systematic Factors

Connectedness betas used in all the previous sections were estimated by running time-series regressions of excess stock returns on the market return and the DYCI. Based on the evidence in Tables 3 and 4, connectedness beta is orthogonal to the common characteristics that explain the cross-section of returns; However, it is still possible that DYCI is correlated with other systematic factors in the time series. The goal of this section is to investigate alternative specifications for estimating connectedness beta and make sure that a firm's exposure to financial connectedness is distinct from its exposure to other state variables that have been proposed in the recent asset pricing literature. In addition to the excess market return and DYCI, we add three more series (individually) to the time-series regression in equation 7: i) liquidity innovation series from Pastor and Stambaugh (2003), ii) change in market volatility measured by the VXO index as in Ang et al. (2006b), iii) aggregate macroeconomic uncertainty index (1-month ahead horizon) developed by Jurado et al. (2015).

Table 7: Other Systematic Factors

	Quintile Portfolios					**Diff.**
	1	**2**	**3**	**4**	**5**	**1-5**
MKT+DYCI	1.403	0.680	0.571	0.507	0.477	0.926
	(5.18)	(5.56)	(5.68)	(5.11)	(3.69)	(3.39)
MKT+DYCI+PSINNOV	1.377	0.729	0.528	0.520	0.484	0.893
	(5.06)	(6.17)	(5.44)	(5.09)	(3.65)	(3.25)
MKT+DYCI+DTVXO	1.366	0.671	0.607	0.479	0.515	0.850
	(5.11)	(5.21)	(6.17)	(4.77)	(4.01)	(3.14)
MKT+DYCI+UNCM	1.221	0.650	0.587	0.568	0.614	0.607
	(4.83)	(5.49)	(6.12)	(5.62)	(3.97)	(2.25)

This table reports 4-factor alphas (MKT, SMB, HML, UMD) of quintile β^{DYCI} sorted portfolios. Returns are in percent per month, and t-statistics based on Newey-West standard errors are in parentheses. Each row represents a different specification for the β^{DYCI} estimation prior to portfolio formation. Row 1 regresses excess stock returns on the excess market return and DYCI (Equation 7). Rows 2, 3, and 4 add the Pastor and Stambaugh (2003) liquidity factor (innovations), change in the CBOE S&P 100 Volatility Index (VXO), and the macro uncertainty index of Jurado et al. (2015) (1-month horizon) to the list of systematic factors, respectively. Liquidity series is available on WRDS, VXO historical prices are downloaded from CBOE's website, and the uncertainty index is downloaded from Sydney C. Ludvigson's personal website.

Table 7 reports the 4-factor alphas for the connectedness beta sorted portfolios where each row controls for a different state variable in the estimation of connectedness beta. We use quintile portfolios as opposed to decile portfolios used in previous sections to demonstrate further robustness. The first row is identical to the specification used in Table 2, hence acts as the benchmark to evaluate the addition of other factors. The bottom quintile earns an alpha of 1.40% per month compared to the bottom decile alpha of 1.76% in Table 2. The difference between the top and bottom quintiles is around 0.93% and statistically significant with a t-statistic of 3.39.

As the events following Lehman Brothers bankruptcy in 2008 highlighted, liquidity shocks and financial connectedness can be intimately linked. Therefore, it is natural to wonder whether the DYCI captures the same information that is already captured by the liquidity index. This does not seem to be the case. Second row controls for the liquidity factor of Pastor and Stambaugh (2003) and alphas for portfolio 1 and portfolio 1-minus-5 are only 3-4 basis points less than the benchmark case with no liquidity control (first row). An intuitive explanation of why that is could be that connectedness is a slower moving process than liquidity. It is also easy to imagine a setting where connectedness stays high in a period of ample liquidity (e.g., quantitative easing).

Third row adds the monthly change in the VXO index to the list of market-wide factors and the results are qualitatively unchanged. Portfolio 1 still generates an alpha of 1.36% with a t-statistic of 5.11. Finally, we add the macro uncertainty index of Jurado et al. (2015), which has been used to explain the cross-section of returns by Bali et al. (2017). The difference between the bottom and the top quintiles shrinks to 0.61% per month but is still statistically significant at the 5% level. Macroeconomic uncertainty seems to be more closely related to financial connectedness than the other market-wide variables we consider, nevertheless the last row of Table 7 show that they are different enough to be studied separately.

9 Risk vs Mispricing: A Brief Discussion

We end our study of the effects of financial connectedness on non-financial stocks with a discussion on whether the abnormal returns we found reflect risk premiums or mispricings. In our empirical analyses we have followed the methodology that has become somewhat standard in asset pricing. The researcher proposes a new state variable that might affect the investment opportunity set, estimates the sensitivities (betas) of individual stocks to this variable, and tests whether the betas explain the cross-section of returns. According to the ICAPM (Merton, 1973), stocks with positive betas with respect to the state variable (where negative shocks represent undesirable states) should carry a positive risk premium. While the abnormal returns we discover have the correct sign, are economically plausible, and robust, they do not quite fit the ICAPM framework for reasons we explain below.

Assuming that high financial connectedness is undesirable, and investors would want to hedge against it, one should expect stocks that pay off when financial connectedness rises to be more highly priced, hence earn below average returns. We do not observe this to be the case. In Table 2, decile 10 portfolio which is made up of positive connectedness beta stocks earns about the same as decile 5 portfolio where betas are roughly zero. In fact, because betas increase monotonically across the deciles the returns should also decline monotonically according to the linear pricing equation of the ICAPM. Instead what we find is that abnormal returns only accrue to the highest negative beta stocks.

Another discrepancy with the ICAPM is that we fail to find a premium among large stocks (Table 6), whereas according to the theory, the state variables should price all stocks.

The premium associated with negative connectedness beta stocks is distinct from the "size effect," however. Controlling for size, there is still a difference in the average returns of negative and positive connectedness beta stocks. The effect is concentrated among small stocks (below the 40th percentile), which is a typical sign of an anomaly.

A further requirement of a risk-based explanation is that portfolios formed on past realizations of the factor exposure should exhibit similar exposure to the risk factor over the period for which returns are measured. Fama and French (1992), for example, use the full-period post-formation portfolio betas in their cross-sectional tests. In unreported results, we estimated full-period post-formation connectedness betas of the decile portfolios used in Tables 1 and 2, and found betas to be "flat". In other words, portfolios made up of past negative connectedness beta stocks do not exhibit negative exposure to the financial connectedness index in the full sample period. The way to make sense of the abnormal returns in this case is to view the negative connectedness beta stocks as underpriced when they enter the portfolio, which then become correctly priced in subsequent periods.

To sum up, while some readers may think our methodology implies a typical risk-based story, we are more in favor of a mispricing story. Despite the fact that the main variable we work with is a "beta", we take it to be a characteristic of a stock that proxies for financial sector dependence rather than a covariance with a priced factor. Rightly or wrongly, investors discount these stocks more heavily than their common risk factor exposures would suggest.

10 Conclusion

This study makes use of the Diebold and Yilmaz (2014) connectedness framework to analyze possible effects of increased interconnectedness among the financial institutions on asset prices. The main advantage of this econometric approach is that the assumptions of the model are minimal and the only data needed is daily prices. While it is interesting to take an abstract concept like "connectedness" and develop the mathematical tools to quantify it, ultimately it is the effects on the economy that one has to understand. Our paper is an attempt towards that objective.

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 as of 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 non-financial firm stocks 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 annum, 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% per annum. 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, profitability, asset growth. leverage, illiquidity, idiosyncratic volatility and downside beta. Fama-MacBeth regressions of excess stock returns on these characteristics along with connectedness betas confirm that the abnormals are orthogonal to known risk premiums.

We call the existence of these abnormal returns an anomaly because the evidence for a new risk factor is weak. First, stocks with positive connectedness betas do *not* earn below average returns as the ICAPM model would suggest. In fact, alphas of all decile portfolios except for the first two are almost identical. Second, the abnormal returns only exist in the most recent two decades and are concentrated mostly among small stocks. 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: 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. Irrespective of whether these characteristics drive mispricing or reflect their exposure to systemic (contagion, tail, etc.) risk, we foresee that patient and disciplined investors should be able to earn a premium.

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Appendices

A

Figure A.1: U.S. Financial Volatility Connectedness – Conditional vs Unconditional Indices