Seeing the Forest Through the Trees:

Do Investors Underreact to Systemic Events?

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ABSTRACT

We examine whether investors efficiently incorporate the effect of financial sector shocks into the equity prices of non-financial firms. Shocks to the financial sector are complex macroeconomic events affecting many firms to varying degrees. Prices may adjust slowly in response to financial sector shocks if information processing capabilities are constrained. We test this hypothesis by examining the ability of systemic risk shocks to predict future returns of financially constrained firms. We find that in the month following the month of large systemic events, large debt constrained firms exhibit significantly lower returns than unconstrained firms with an average relative risk-adjusted return of -3.5% (-42% annualized). More generally, innovations in systemic risk exhibit significant predictability for returns of constrained firms in excess of unconstrained firms. To identify financially constrained firms we introduce a new classification method using random decision forests, a machine learning technique. This method allows us to extend the measures based on textual analysis of firm filings both in the cross-section and time series using only financial information. Overall, the results provide evidence that the market is slow to incorporate the effects of financial sector shocks into equity prices.

Keywords: financial constraints, systemic risk, machine learning, complexity

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1 Introduction

We provide evidence investors are slow to price the negative effects of systemic events in the financial sector into the equity prices of financially constrained non-financial firms. The slow response creates predictable variation in asset returns. Examining the returns of debt constrained firms relative to unconstrained firms, we find no evidence debt constrained firms experience relatively lower returns in the month of large systemic events. Instead, they exhibit significantly lower relative returns in the month *after* systemic events with a risk-adjusted return difference of -3.5 percentage points (42 percentage points annualized; t-statistic of of -3.25). Importantly, we show that in months of systemic events, average stock returns are dramatically negative: markets broadly incorporate these events into prices, yet there is no significant difference between the returns of constrained and unconstrained firms within the month. It isn't until the following month that constrained firms underperform unconstrained firms. We show this to be true whether we define systemic events in terms of statistical measures or using well known systemic events. More generally, a conditional trading strategy based on shocks to systemic risk in the *previous* month is very profitable, earning an annualized Fama-French 5-factor alpha of 8.52% (t-statistic of 4.30). The evidence is consistent with the market slowly incorporating the effect of these complex macroeconomic events in a predictable way.

Systemic events are naturally complex and travel across networks of financial institutions that are not easily observable.[1] The complexity of the financial system and the network of firm-lender financing relationships makes forecasting the effect of a systemic event on an individual firm extremely difficult. The difficulty in estimating the effect is likely to be even greater for firms with an opaque information environment (i.e., more asymmetry in

[1]Caballero and Simsek (2013) provide a model of financial crises arising from endogenous complexity in the financial institution network. For a survey on estimating systemic risk and the interconnectedness of financial institutions see Bisias et al. (2012).

information). Additionally, we expect firms with more opaque information environments to be more financially constrained (Myers and Majluf (1984)) and for their constraints to tighten during systemic events.[2] In other words, financially constrained firms should be worse off in periods of high systemic risk and this information may be only slowly incorporated into prices.

To test this hypothesis, we need to properly identify each firm's level of financial constraints. We propose a novel method for estimating firm level financial constraints, which allows us to extend our sample of firms both in the cross-section and in the time-series. This is an important contribution of our paper since properly identifying financially constrained firms on a large scale has proven to be a very difficult problem in the literature. A major breakthrough in the measurement of financial constraints came with the use of textual analysis of firms' 10-K filings by Hoberg and Maksimovic (2015) (henceforth, HM) and the related methodologies proposed by Bodnaruk et al. (2015) and Buehlmaier and Whited (2016). By allowing for a more direct identification of firm financial constraints, these methods are a significant improvement over previous methods that rely on linear combinations of a small set of financial variables.[3] The main drawback of the textual analysis method is coverage. For instance, HM require a firm to have a 10-K with an MD&A section in that year. This limits the panel of firms with estimated constraints to those with an MD&A section in the years 1997 onwards. We provide a solution to this issue by employing random decision forests, a machine learning technique, to extend their classifications both in the cross-section and time series.

Random decision forests allow for large scale prediction with extreme flexibility and, therefore, better out-of-sample predictions. Our model employs eleven firm-level financial

[2] A number of papers examine the relative effect of credit supply shocks on less flexible borrowers. See for example Chava and Purnanandam (2011) and Chodorow-Reich (2013).

[3] Recent work by Farre-Mensa and Ljungqvist (2016) has called into question the ability of classification methods based on an index of financial variables or univariate identifiers (paying dividends or having a credit rating) to identify financially constrained firms. They did not analyze the text-based classifications.

variables and an aggregate measure of primary dealer capital (from He et al. (2016)) as financial constraint predictor variables. The financial variables are the union of predictors used in previous work identifying firm-level financial constraints. We train the random decision forests using the HM financial constraint measures as the dependent variables of interest. Random decision forests are much more flexible than linear regression, as they allow for non-linearities and complex interactions between predictors, which we show is important in properly estimating firm financial constraints.

Our method exhibits significant out-of-sample predictive power especially compared to a linear regression model. We show this in two ways. First, we randomly choose 75% of the firms from the HM sample to use as our training sample and test the out-of-sample predictability on the omitted 25% of firms (the test sample). We find an out-of-sample R^2 of 28% when fitting the test data's actual HM debt constraints. For comparison, the *in sample* R^2 from a linear regression with the same set of variables is 11%. Second, we train the algorithm on the years 2002-2015 and show there is significant out of sample predictive power for the years 1997-2001. These results give us comfort in extending the sample in the time series (1973-2016) as well as cross-sectionally (all firms in the COMPUSTAT-CRSP merged data).

After obtaining financial constraint measures for a large panel of firms, we conduct our main analysis examining the ability of investors to efficiently incorporate information into stock prices. First, we run firm-level regressions examining the effect of large systemic events on financially constrained firms. We find that the average contemporaneous return across firms is significantly negative during systemic events. Surprisingly, debt constrained firms do not exhibit lower returns than unconstrained firms contemporaneously. In other words, the prices of debt constrained firms do not *immediately* decline more than unconstrained firms as systemic risk rises. This is surprising considering the evidence that debt constrained firms are worse off due to systemic events or adverse shocks to lenders (Chava and Purnanandam

(2011), Chodorow-Reich (2013), and Lemmon and Roberts (2010).) The lack of a contemporaneous return differential between constrained and unconstrained firms could arise for two reasons: either systemic risk does not affect constrained firms more than unconstrained firms or the market is slow to incorporate an increase in systemic risk into stock prices. To distinguish between these two possibilities, we examine future returns on constrained versus unconstrained firms. Consistent with the slow incorporation of information hypothesis, we find that the returns on debt constrained firms are significantly negative, -5.38% (-64.6% annualized), in the month *following* major systemic events (t-statistic of -5.17) compared to unconstrained firms. This return difference is not explained by exposure to other risk factors. The risk-adjusted relative return is -3.5% (t-statistic of -3.25).

We further examine the slow-movement in prices by examining returns on financial constraint factor portfolios. We find that systemic risk has significant predictive power for the relative returns of a large firm, debt constraint factor at the one-month time horizon. A one-standard deviation increase in systemic risk is associated with a -113 bps relative monthly return of large debt constrained firms over the next month. The R^2 is 4.10% and the coefficient has a t-statistic of -3.49. The results for the small debt constraint factor are marginally significant with a t-statistic of -1.95. We do not find significant results at longer horizons. Investors appear slow to price in the relative effect of systemic risk on constrained firms, but the mis-pricing lasts for less than one month.

Brunnermeier and Sannikov (2014) argue that the effect of financial sector shocks are amplified when financial institutions are constrained. If this is the case, then innovations in systemic risk should matter more when systemic risk is already high (our proxy for financial institutions constraints). We find that the predictability is concentrated in times when the level of systemic risk is high (above the median). We also assess asymmetry in the innovations of systemic risk. We find that most of the predictability arises from positive systemic risk shocks. Conditioning on the sign of the shock, we find a one standard deviation increase in systemic risk is associated with a -153 bps relative monthly return on the large, debt constraint factor.

We next examine whether the predictable underperformance of debt constrained firms is explained by risk exposure. To do this, we create a conditional trading strategy which takes a short position in the large debt constraint factor following a positive systemic risk shock and a long position following a negative systemic risk shock. Controlling for exposures to well known risks, we find the intercepts are extremely statistically and economically significant no matter the asset pricing model employed. The intercept ranges from 60 bps to 75 bps per month across specifications with a t-statistic greater than 3.9 in all specifications. These results provide further evidence that in the wake of a systemic event, the market is slow to update the effect of these events on constrained firms.

Why do constrained firms exhibit a negative return premium in the month after increases in systemic risk? We address three possible explanations. The first, and least plausible, is that changes in systemic risk may be related to changes in investor risk aversion and the risk premium on large, debt constrained firms changes with changes in systemic risk. If this is the case, we would expect the risk premium to increase for large, debt constrained firms as systemic risk increases, not the opposite as we find. Second, the information related to systemic risk may be slow to be incorporated into prices because equity market participants may be constrained in the positions they can take or stocks may be especially illiquid in times of high systemic risk. In other words, as systemic risk increases, there are greater limits to arbitrage. This is unlikely to be driving our results considering the magnitude of the predictability and that the predictability is greater for large firms even though larger firms have highly liquid stocks. We also find our results are unaffected after controlling for firm-level and market-level illiquidity. The third possibility is that investors are slow to react to changes in systemic risk due to limited attention. Our results are consistent with this explanation.[4]

Our paper documents the slow response of financially constrained firms' equity prices to systemic events. Related work by Chava and Hsu (2015) shows returns on financially constrained firms are slow to respond to monetary policy shocks (with significant return differences after a three-day delay). Our work is also related to the significant literature on market under-reaction to firm-specific events, like earnings surprises or share repurchases.[5] Unlike these papers, we are one of the first to show predictable under-reaction to a macroeconomic event in the cross-section of firms.

2 Related Literature

Our work is related to four main strands of the literature: estimating financial constraints, the relationship between the financial sector and firm financing, and the asset pricing implications of both.

A number of papers use indices based on firm financial variables to categorize firms as financially constrained. The most commonly used indices are based on work by Kaplan and Zingales (1997), Whited and Wu (2006) or Hadlock and Pierce (2010). The authors either read through the filings of a sample of firms or use a structural model to uncover constrained firms, then regress constraints on the firms' financial variables to get the coefficients for the index.[6] Another approach is to process a large sample of firm filings' to identify their level of constraints using textual analysis. Hoberg and Maksimovic (2015), Bodnaruk et al. (2015) and Buehlmaier and Whited (2016) use textual analysis of firms' 10-Ks to classify firms as

[4]Another potential explanation is that financial sector shocks are positively correlated and this is driving the negative returns for financially constrained firms in the following month. This is also unlikely to be the case. First, we explicitly control for auto-correlation in systemic risk by using innovations in an ARMA(1,1) process. Second, we should still see a significant return differential contemporaneously in this case, which we do not observe.

[5]Evidence on earnings surprises: Ball and Brown (1968), Bernard and Thomas (1989). Evidence on share repurchases: Ikenberry et al. (1995), Dittmar and Field (2015)

[6]The use of these indices out-of-sample is not necessarily the goal of the authors, but is widely practiced.

financially constrained and provide evidence that their classifications predict behavior in a manner consistent with theory. An innovation of our paper is in extending the classifications of HM using firm financial variables.

The literature on factor return predictability is relatively small with most work concentrated in predicting returns on the momentum factor. Various predictors for the momentum factor have been proposed including the past spread in momentum returns (Huang (2015)), past market returns (Cooper et al. (2005)), high market volatility (Wang and Xu (2015)), and past market illiquidity (Avramov et al. (2016)). Lamont et al. (2001) examine the relationship between returns on financially constrained firms and lagged macroeconomic variables. They examine leading economic indicators, measures of monetary policy, and credit conditions and find little evidence these variables predict returns on financially constrained firms. Related work by Chava and Hsu (2015) finds financially constrained firms returns are more sensitive to monetary policy shocks. They find it takes three days for prices to fully adjust. We show that systemic risk has a large effect on debt constrained firms and there is a significantly slow incorporation of this effect into prices. Our results are inconsistent with a time-varying risk premium and show that complex macroeconomic shocks are difficult for investors to incorporate into prices.

A number of papers examine the impact of financial sector shocks on non-financial firms. Ivashina and Scharfstein (2010) find evidence of a significant decline in bank lending during the recent financial crisis. Chodorow-Reich (2013) finds reduced employment at firms with less credit availability post-Lehman failure. Lemmon and Roberts (2010) show negative shocks to the supply of capital negatively affect firm financing and investment activity. Chava and Purnanandam (2011) show bank-dependent firms experienced relative declines in capital expenditure and profitability in the wake of the 1998 Russian crisis. They also find borrowers from lenders more exposed to the Russian crisis experienced more negative returns during their defined two week crisis period compared to borrowers with lenders less exposed to the crisis. We are interested in how quickly prices respond to systemic events (including the Russian Default Crisis). We show there is a significant time lag between the systemic event and the full incorporation of information into asset prices.

There is significant evidence that financial sector shocks are related to the business cycle.[7] More specific to our context, systemic risk has been associated with future economic downturns (Allen et al. (2012a) and Giglio et al. (2016)). We support these papers by examining the asset pricing implications of systemic risk and documenting the ability of investors to incorporate the effects of systemic risk changes into asset prices. Additionally, our paper is related to the literature on the relationship between firms external financing and macroeconomic conditions.[8] Eisfeldt and Muir (2016) document significant variation in the relative cost of external financing and model firm responses to changes in the relative cost and Belo et al. (2014) document that exposure to variation in aggregate equity issuance costs is priced in the cross-section of firms. Relatedly, a number of papers examine if financing constraints are priced in the cross-section of firms (Lamont et al. (2001); Whited and Wu (2006); Livdan et al. (2009); Li (2011); Buehlmaier and Whited (2016)). We add to this literature by examining the ability of investors to incorporate the effect of financial sector shocks into firm valuations with a focus on financially constrained firms.

Lastly, our work is related to the literature on time-variation in the risk bearing capacity of financial institutions and asset prices.[9] Adrian et al. (2014) and He et al. (2016) find a factor constructed from the leverage of broker-dealers or the equity of primary dealers, respectively, can explain the cross-section of returns. Our goal is not to explain the cross-section of returns, instead we examine return predictability related to shocks to financial

[7]See Christiano et al. (2010), Justiniano et al. (2010), Hall (2011), Shourideh and Zetlin-Jones (2012), and Gilchrist and Zakrajšek (2012).

[8]See Ritter (1984), Lucas and McDonald (1990), Choe et al. (1993), Ivashina and Scharfstein (2010), Campello et al. (2010), Campello et al. (2011), Duchin et al. (2010), Erel et al. (2012), Kahle and Stulz (2013)).

[9]See Duffie (2010) for a partial review of the literature.

institutions. Another strand of literature examines widening of risk arbitrage spreads and potential deviations from fundamental values during financial crises.[10] These spreads are thought to arise due to shocks to arbitrageur capital coupled with strong demand to hedge by other traders or segmented markets. In our setting, there is not a natural counter-party that will keep prices away from fundamentals. Instead, the market appears to be slow in incorporating the information related to systemic risk into prices due to the complexity of the shock.

3 Data and Methods

In this section we describe the data and sources of data used in our analysis. We also describe in detail the construction of the variables of interest.

3.1 Systemic Risk

A number of systemic risk measures have been proposed in the literature. Since our goal is to capture the salient risk underlying financial sector stress, we use factor analysis to extract the first principal component from three well-known measures of systemic risk. We restrict candidate measures to those computed using readily available equity returns from large, systemically important financial firms. From this set of candidate measures we select three measures which have appeared in the recent literature studying systemic risk and its economic implications. Specifically, we extract the first principal component from measures capturing financial sector volatility, financial sector connectedness or contagion risk and financial sector tail risk. We use existent methods to estimate each measure, then perform principal component analysis in order to capture the component of systemic risk that is common among them. In using the first principal component, we capture the commonality

[10] See Mitchell et al. (2007), Mitchell and Pulvino (2012), Henderson et al. (2015), and Weagley (forthcoming)

across existent measures of systemic risk and avoid any idiosyncrasies inherent in individual measures of risk.

We use the measure of Billio et al. (2012) and Kritzman et al. (2011) to measure connectedness. We use a version of the measure from Allen et al. (2012b) known as $CatFin$ to capture tail risk and we use the volatility of a value-weighted portfolio to measure financial sector volatility. Each of these measures is easily computed from the equity returns of large financial firms which we take from the CRSP database. In computing these measures, we restrict the set of returns to those firms with SIC codes between 6000 and 6300 which includes banks and broker dealers but not insurance and real estate based firms.

At the end of each calendar quarter we rank firms based upon their market capitalization. For the connectedness and volatility based measures we use the 20 largest firms as measured by market capitalization at the end of the previous quarter. For the tail risk measure we use the largest 50 firms in order to estimate tail probabilities more accurately. Our financial sector volatility measure ($FinVOL$) is simply computed by measuring the volatility of daily returns each month for the value weighted portfolio of the 20 largest firms as measured at the end of the previous calendar quarter. The time series of the level of each systemic risk measure is plotted in the Appendix (Figure A.1).

After estimating the time series of each measure, we normalize each measure and estimate the first principal component across the three measures. The first principal component is our measure of the level of systemic risk. To avoid lookahead bias, we use rolling windows when estimating the first principal component. Each month we use the past 10 years of data in our estimation. To estimate unanticipated shocks to systemic risk, we fit an ARMA(1,1) model to the time series, again on a rolling window basis, and use the residuals as our main measure of systemic risk, $FinPC1$. In the Appendix, we provide additional details on the construction of each individual systemic risk measure and our main measure, $FinPC1$.

We plot the level of systemic risk and shocks to systemic risk, $FinPC1$ in Figure 3. Panel

A of Table 1 reports summary statistics for $FinPC1$ and unexpected shocks to each of the original systemic risk measures using similar 10 year rolling window ARMA(1,1) residuals. The financial institution return data we use starts in 1963, so we are able to calculate the systemic risk factor on a monthly basis from 1973 through the end of 2016.

3.2 Financial Constraints

We use data from Hoberg and Maksimovic (2015) (HM), obtained from the authors' website, to identify financially constrained firms within our training sample. The majority of papers studying financial constraints use proxies such as cash holdings, dividend payouts and firm size (among many others) to infer whether firms are financially constrained. HM take a more direct approach by analyzing the text of firm 10-K filings to estimate annual measures of firms' financial constraints. By examining the filings, the authors are able to identify firms that report potential delays in investment due to being unable to raise capital.

The HM method assigns a numerical value to each firm in their sample based on its estimated degree of financial constraints. This method of estimating constraints allows the authors to distinguish between debt based and equity based financial constraints. That is, the data has separate constraint scores for each firm for both equity and debt capital markets. While our anlaysis is easily applied to equity constraints, we focus on debt constraints in this paper. In addition, we perform many of our analyses separately on large and small firms. The original financial constraints data does not include financial firms or utilities. We omit these firms as well. For our purposes, the omission of financial firms ensures that we are capturing the relationship between systemic risk and financial constraints for firms outside of the financial sector.

For asset pricing implications, it is important that more constrained firms tend to remain more constrained from year to year, we refer to this as persistence in relative financial constraints. We expect persistence in relative constraints considering the causes of financial constraints (e.g., information asymmetry, moral hazard, etc.) are unlikely to change quickly over time. The persistence in constraints eases concerns that sorting on the previous year's constraint measure, as we will do in our main tests, is uninformative of current constraints.

3.3 Machine Learning Estimates of Constraint Measures

Text-based measures of financial constraints offer the advantage that they directly capture firms' reported inability to raise capital. However, there are some limitations to using text-based measures of constraints. First, available text-based constraint measure data goes back only as far as 1997 (in the case of Hoberg and Maksimovic (2015)), meaning that typical asset pricing tests which use much longer time series of stock returns must be truncated when examining stock returns of financial constrainted firms. Second, text analysis of firms' 10-K filings for the purposes of measuring financial constraints has been limited to those firms that fill out the MD&A section. This introduces the possibility of response bias.[11] While Hoberg and Maksimovic (2015) suggest that their measure does a good job capturing relative measures of financial constraints of those firms which are likely to be constrained, they do acknowledge the fact that unconstrained firms may not fill out the MD&A section and hence a large number of unconstrained firms may not be included in the data since they are likely to not report the MD&A section.

In order to circumvent the limitations of text-based financial constraint measures, we employ statistical machine learning to model the text-based measure of Hoberg and Maksimovic (2015) as a function of accounting variables commonly included as covariates for describing financial constraints. Not only does this allow us to address the two limitations of text-based constraint measures, it also allows us to gain insight into the possible origins of firms' inabilities to raise capital. The text-based method relies on firms mentioning de-

[11] Buehlmaier and Whited (2016) propose a method based upon further analyzing firm 10-Ks in order to expand the cross section of firms for which text-based constraint measures can be estimated.

laying investment due to an inability to raise capital. This does not give us any insight as to why some firms experience such an inability to raise funds. Accounting measures on the other hand can offer some glimpse into the types of variables that affect firms' abilities to easily raise capital. Our machine learning measure begins with the assumption that the text-based measure is accurate. Under this assumption, we model the text-based measure as a very flexible function of a large set of measurable accounting variables and one market-wide variable.

We use a broad set of accounting measures typically used in the literature for estimating financial constraints. To do so, we use all variables listed in Table 2 of Hadlock and Pierce (2010). The list of characteristics is the following: property, plant and equipment (PPE), the ratio of cash flow to PPE, the ratio of cash to PPE, the ratio of capital expenditures to PPE, Tobin's Q, the ratio of debt to total capital, book assets, sales growth, age and size (measured on log scale). The construction of all variables follows those in Hadlock and Pierce (2010). We further include a measure to capture market-wide conditions as they can play an important role in determining whether firms are constrained or not. For this market variable, we use intermediary capital data from He et al. (2016). Table 1 reports summary statistics for the firm level accounting variables used in the paper.

The most recent update of data from Hoberg and Maksimovic (2015) reports annual measures beginning in 1997, running through 2015. We use the entire Compustat annual file of firms within this window, removing any firm for which we cannot measure one or more of the characteristics described above. We calculate the measures for the remaining firms. We then merge this set of firms with the Hoberg and Maksimovic (2015) data, removing any firm for which we do not have the text-based constraint measure. With this set of firms, we fit a random regression forest, where the text-based measure acts as our dependent variable and the characteristics and intermediary capital are our explanatory variables.

We use random regression forests to estimate firm-level financial constraints because they offer a very flexible alternative to linear regression. The machine learning procedure allows for nonlinearities and complex interactions between predictors. In the Appendix, we briefly discuss random forests, their properties and the algorithm with which they fit data. We fit the random forest to firms' text-based constraint measures from Hoberg and Maksimovic (2015) using the set of 11 firm level accounting variables and the intermediary capital factor of He et al. (2016), using a regression forest ensamble of 2000 trees. We then fit the random forest model to the entire set of firms in the Compustat-CRSP merged file from 1973 through 2016 for which all eleven of our firm level characteristics are available. This larger and extended sample represents the set of constraint measures we use to evaluate the market's reaction to systemic risk and it's incorporation of unexpected shocks into the prices of financially constrained firms.

Since random forests are by their very nature a much more complicated technique than linear regression, understanding the relation between individual predictors and the response is not as straight forward as simply looking at a regression coefficient and its standard error. However, the complicated algorithm does allow us to exploit the richer estimation technique in different ways. We do just that in order to understand which firm characteristics appear to be related to financial constraints.

Figure 1 depicts variable importance plots for the random forest estimates. Variable importance plots measure the average importance of each predictor in terms of how much partitions of the variable reduces the sum of squared residuals on average. More specifically, each of the 2000 trees making up the random forest are fit to a randomly selected (with replacement) subsample of observations, meaning that each tree leaves out some data. The left out data allows us to see how each tree performs out of sample, by fitting the tree to the left out data. Variable importance measures how much sum of squared residuals are decreased on average by partitioning each predictor variable. In order to account for variation in errors, the average reduction in sum of squared errors is then normalized by the standard deviation of the error reduction across trees making up the forest. Larger reductions in errors per unit of standard deviation imply more important predictors.

In each panel of Figure 1 we normalize measures of variable importance so that the largest variable importance measure is equal to 1. We sort variables within each panel from most important to least important. As can be seen in the figure, cash holdings and leverage stand out clearly as the two most important predictors of constraints. Age, intermediary capital and cash flow form the next group of most important predictors. It is interesting to note that the primary dealer capital measure of He et al. (2016), the fourth most important predictor, is a market wide variable. This means that market conditions play an important role in determining the optimal fitting model. The majority of empirical financial constraint measures in the literature do not account for market conditions but our analysis shows that for debt constraints, intermediary capital is in important determinant of constraints. This is consistent with the theory of the bank lending channel of debt constraints.[12]

Next, we create partial dependence plots which depict the average fitted values across all trees in the regression forest as functions of each explanatory variable. Partial dependence plots enable us to view the nonlinear relationship between variables and financial constraints, which random forests are especially good at capturing. Table 2 depicts the partial dependence plots of each predictor. In the figures we restrict the range of values over which the dependence is plotted to be between the first and ninety-ninth percentiles of each dependent variable.

As can be clearly seen in the figure, signficant nonlinearities exist. In some figures the nonlinearities are more evident than in others. For example, cash holdings exhibit a highly nonlinear relation with constraints. The increase in debt constraints is very steep once we get below a certain threshold of cash holdings. Consistent with the variable importance plots, cash holdings and leverage have the largest range of average fitted (vertical axis) values

[12]See Shleifer and Vishny (2010) for example.

meaning variation in these two predictors' values is associated with large variation in fitted debt constraints. It is also of note that intermediary capital, our only market wide variable exhibits a clear monotonic relation with debt constraints where higher intermediary capital is associated with lower debt constraints on average. In some cases where the explanatory variable is highly skewed, it is less easy to discern the relationship. Dividends is one clear example of this.

While nonlinearities can easily be seen from the partial dependence figures, one other strength of random forests cannot be deduced from these plots: the ability of random forests to take into account complex interactions between explanatory variables. We display a selected set of variable interaction plots for the debt constraints in Figures A.2 and A.3.

In order to examine the effectiveness of the random forest for estimating firm level constraints, we split the Hoberg and Maksimovic (2015) data into training and test subsets. We fit the model to the training data and examine the out of sample performance of the test data. As a comparison, we also examine the in and out of sample performance of linear regression using the same training and test samples. Table 3 reports the proportion of variation explained by each estimation technique both in sample and out of sample for the debt-based constraint measure from Hoberg and Maksimovic (2015). The in sample performance simply reports the proportion of variation explained by the model using the entire sample. Not surprisingly, the in sample performance of the random tree is far superior to linear regression. The machine learning technique explains over 72% of the in sample variation. Linear regression on the other hand explains 10.88% of the variation in constraints.

We first examine the out of sample performance in the cross section. Evaluating cross sectional out of sample performance is done by holding out a random selection of 25% of the Hoberg and Maksimovic (2015) data. We call this the test data. We then train the random forest and the linear, OLS regression model on the remaining 75% of the data. With the trained models, we then fit the test data and measure the proportion of variation explained out of sample. Again, the random forest substantially outperforms the OLS model explaining nearly 28% of the test sample's variation in debt constraints. The OLS cross-sectional out of sample performance for comparison is 10.71% in debt constraints. The strong out of sample performance of the random forest gives us confidence in using the trained model to expand the cross section of firms for which we can estimate constraints.

We next examine the out of sample performance in the time series by holding out a block of consecutive years from the data to constitute our testing sample. We train the model on all constraint measures from years 2002 through 2015. Out of sample performance is determined by using the data from 1997 through 2001 as the test sample. Again, the random forest performs vastly better than the OLS for fitting debt constraints. The random forest (OLS) explains 23.2% of variation in constraint measures. This suggests that using our random forest with the accounting variables and intermediary capital to estimate constraint measures for firms prior to 1997 will capture cross sectional variation in financial constraints.

Another method for assessing the fit of the random forest is to examine cross-tabulations of predicted and actual constraint measure portfolio assignments for the test samples. Fitting well in the extreme quintiles is important for our return analysis which focuses on the top and bottom 20% of firms in terms of financial constraints. Tables 4 and 5 examine the out of sample performance of our random forest and the OLS estimates in terms of their ability to properly assign testing data to the proper quintiles based upon their constraint measures.

In each cross tab within Tables 4 and 5, a row represents the machine learning quintile assignment. Columns represent HM quintile assignments. The numbers within each cell of a cross tab give the proportion of firms assigned to a given quintile (row) by the machine learning model that come from a given HM quintile (column). Ideally we want large numbers along the diagonal. This would mean that the model does a good job of correctly classifying firms to quintiles. For our purposes, we need to accurately estimate the bottom and top quintiles so we would ideally like to see large percentages in the upper left and lower right cell of each cross tab. Overall, the results of the out of sample cross tabs suggest that the random forest does a good job of assigning firms to be either constrained or unconstrained. Very few unconstrained (constrained) HM firms are assigned to the machine learning constrained (unconstrained) quintile. Most of the firms assigned to the constrained (unconstrained) quintile come from one of the two most (least) constrained HM quintiles with the largest proportion coming from the single most (least) constrained HM quintile. The random forest quintile classifications are drastically superior to the OLS classifications. For example when looking at large debt constrained firms (the set of firms in which our analysis focuses most heavily), 58% of the firms the random forest assigns to the constrained bin are actually from the constrained quintile. The OLS classification only has 47% of those assigned to the constrained quintile actually coming from the constrained quintile. Looking at the unconstrained quintile, the results are more stark. Of the firms the random forest assigns to the unconstrained quintile, 34% actually come from the unconstrained quintile and 21% come from the next least constrained quintile. By comparison the OLS classification does terribly. Of the firms the OLS model assigns to the unconstrained quintile, only 1% are actually from the unconstrained set. Overall, the random forest performs much better than OLS in fitting the constraint measures both in and out of sample.

3.4 Portfolio Formation

Since the constraint measures of Hoberg and Maksimovic (2015) are based upon firms' 10-K filings, they are reported at the annual frequency. We train the random forest on the HM date which is available from 1997 through 2015. We then use the resulting model fit to estimate the firm-year constraint measures of all Compustat firms for which all eleven accounting variables are available in a given year. In order to create portfolios of returns, we use the CRSP-Compustat merged file. The set of firms we examine is those firms for which we have the fitted constraint values from our model intersected with those firms included in the CRSP-Compustat merged database. Our annual fitted constraint values are based upon annual measures of accounting data and the average level of the four quarterly measures of intermediary capital from He et al. (2016). Next we sort the firms in our returns sample into quintiles based upon their fitted constraint values. In order to ensure that information from all given firm-years from the year t are accessible to market participants when we sort, sorts are performed at the end of June in year $t+1$.

At the end of June in each year, we perform independent sorts along size and our constraint measure. We sort firms by size in addition to constraints because size is commonly believed to be related to financial constraints of companies (see for example Hadlock and Pierce (2010)). This also allows us to analyze the returns of constrained firms without the worrying that size is driving any return differentials we find. We categorize all firms at or above the median market capitalization at the end of June to be large and all firms below to be small. We categorize firms within the top 20 percent of debt constraint estimates to be debt constrained. Those in the bottom 20 percent are considered to be unconstrained. Throughout our entire analysis, we do not use any returns from the firms not assigned to either the constrained (top) quintile or the unconstrained (bottom) quintile each month. This way we focus our analysis on only those firms we believe are likely to be constrained (unconstrained) in order to minimize ambiguity about whether the firms we see are constrained or not. In all, we have four groups of firms for which we examine value-weighted monthly returns: small debt constrained, small debt unconstrained, large debt constrained and large debt unconstrained. Since our annual fitted constraint data begins in 1972 and runs through 2015, our portfolios provide monthly returns data from July of 1973 through December of 2016.

Using the portfolios formed by sorting on the fitted constraint measures, we construct factors to capture premia associated with each size-constraint combination. The factors are formed by taking a long position in the portfolio of the most constrained quintile of firms and shorting the least constrained quintile for each of the four size-constraints combinations. Panel B of Table 1 gives summary statistics for each of the four constraint factors we construct from the constraints data. We note that both constraint factors are negatively skewed. Additionally, the factors have slightly positive means over our sample period from July of 1973 through June of 2015.

3.5 Control Data

In addition to the systemic risk and financial constraint measures, we use a number of standard control variables throughout the remainder of the paper. We take data corresponding to Fama and French (1993), Carhart (1997) and Fama and French (2015) from Kenneth French's website. We take the market liquidity measure of Pástor and Stambaugh (2003) from Lubos Pastor's website. The data for the four factor model of Hou et al. (2015) were obtained directly from the authors. Variance risk premium data of Bollerslev et al. (2009) is taken from Hao Zhou's website. Price dividend ratio and earnings to price ratios were taken from Robert Shiller's website. Credit spread, term spread and net expansion data comes from Amit Goyal's website and was originally compiled for Welch and Goyal (2007). We use a number of macroeconomic indicators throughout the paper. Federal funds rates, discount rates and money supply (M2) are all taken from the FRED economic database provided by the Federal Reserve Bank of St. Louis.

4 Results

4.1 Firm-Level Regressions

We begin our analysis by documenting the relative impact of three well-known systemic events on firm-level stock. We examine what we consider the most well known systemic events within the HM data range of 1998 through 2015. These events are the Russian Default of August 1998, Lehman Brothers collapse in September of 2008 and the United States debt downgrade of August 2011. We run a regression of firm stock return in month t (ret_t) on an indicator variable equal to one if there was a systemic event during month t ($SystemicEvent_t$), an indicator variable equal to one if the firm is in the top 20% of firms in terms of financial constraints ($Constrained_t$), and the interaction between the two independent variables. We include only firms in the top 20% (i.e., constrained) and bottom 20% (i.e., unconstrained) in the regression so that we can be confident that the assignment of a firm to one group or the other is accurate. The systemic event indicator is equal to one in the months of August 1998, September 2008 and August 2011. The coefficient on the interaction term gives the relative sensitivity of constrained firms to systemic events compared to unconstrained firms. In certain specifications, we include the Fama-French three (FF3) factors and their interaction with the constrained indicator. Additionally, we run the same regression with the next month's return (ret_{t+1}) as the dependent variable to examine price dynamics over time.

Results are presented in Table 6. In Columns (1) and (2) we examine returns contemporaneous to systemic events. In this specification, the systemic event indicator is equal to one if the month t in which we measure a stock's return is one of the three systemic event months. Unsurprisingly, we find both constrained and unconstrained firms experience sharply negative contemporaneous returns during systemic events which can be seen by the negative and significant systemic event indicator coefficient. The coefficient on the systemic event indicator is -17.2% (t-statistic of -3.57) before controlling for exposure to the FF3 risk factors. From the large negative coefficient on the systemic event indicator, it is clear that the market reacts to systemic shocks. Information from the events is broadly incorporated into equity prices within the month the shock occurs. Even though the systemic event indicator is not significant once we include common risk factors in the analysis, this is only because the market factor absorbs the effect of the event and the market factor has a very large positive coefficient. These results are important because they establish that equity prices negatively react to systemic events. If we see any more nuanced reaction when comparing constrained firms with unconstrained firms, we should expect that it would show up in the month of the shock since we see extreme negative stock returns in the months in which events occur.

Perhaps surprisingly, constrained firms do not perform worse than unconstrained firms in the event months. Examining the coefficient on the interaction between the constraint indicator and contemporaneous systemic event indicator, we would expect a negative coefficient if constrained firms react more to systemic events. However, we see it is insignificant with the sign changing across specifications. This is puzzling considering the documented sensitivity of constrained firms to financial sector shocks.

Next, we re-run the same regression with the systemic event indicator now equal to one if the *previous* month is contained in our set of systemic event months. Results are presented in Columns (3) and (4). We find significant negative loadings on the interaction of the constrained firm indicator with the systemic event indicator. In the month after a systemic event, debt constrained firms experience a relative return of -5.4% with a t-statistic of -5.17. After controlling for the FF3 factors, there is still a significant relative return of -3.5% per month with a t-statistic of -3.25. The coefficient on the systemic event indicator is insignificant indicating there is no predictability for unconstrained firms. In other words, unconstrained firms experience no significant increase or decrease in returns in the months following systemic events. These results are consistent with the market being slow to incorporate the relative effect of the systemic event on debt constrained firms above that of unconstrained firms.[13][14]

These results are consistent with systemic events tightening firms' debt constraints, and the market slowly incorporating the tightening of debt constraints. The firm-level regressions suggest that returns of debt constrained firms are predictable in the wake of an extreme systemic event. We explore this result more deeply in three ways. First, we examine whether changes in systemic risk more generally can predict returns on debt constrained firms. Second, we examine whether this predictability can be explained by exposure to well known risk factors. Finally, we test whether limits to arbitrage are likely to be driving the result.

4.2 Factor Regressions

For our main analysis, we construct financial constraint factors that are long a portfolio of the most constrained firms and short a portfolio of the least constrained firms.[15] A positive return on the factor indicates that constrained firms outperformed unconstrained firms during the period. Creating factors partially controls for variation that is common across constrained and unconstrained firms and isolates price movements associated with financial constraints. We double sort firms by size and constraints to ensure we are not capturing effects due to size. Additionally, double sorting allows us to examine whether small or large constrained firms are relatively more affected by systemic risk.

To formally examine the relationship between financial constraints and systemic risk, we run regressions of financial constraint factor returns on systemic risk. We run current month,

[13]Note that even if systemic events are persistent it is unlikely that the results presented in Table 6 are simply showing that in event months constrained firms perform worse than unconstrained firms. If this were the case, we would see a significant coefficient on the interaction terms of Columns (1) and (2) as well as the interaction terms in Columns (3) and (4). However, even though we do see significantly negative returns in months of events, there is no significant *difference* between the returns of constrained and unconstrained firms in month of events.

[14]Since the difference in returns between constrained and unconstrained firms is significant in the months following systemic events, this indicates that systemic risk is a potential reason for constrained firms to earn a premium as found in Buehlmaier and Whited (2016). If constrained firms are exposed to systemic risk albeit at a lag of one month, investors should demand a premium for holding them.

[15]Top and bottom 20 percent of firms according to constraint measures each June.

one month ahead and two months ahead non-overlapping predictive regressions with the returns on the constraint factors as the dependent variables. Specifically, we run regressions of the form:

$$FC_{t+m} = \alpha + \beta FinPC1_t + \epsilon_t, \qquad m = 0, 1, 2$$

where $FinPC1_t$ denotes shocks to systemic risk and FC_{t+m} is the return on the relevant constraint factor in month $t + m$.

Table 7 presents the results for the small and large debt constraint factors. Consistent with the market being slow to incorporate the effect of systemic risk on debt constrained firms, we find systemic risk displays predictive power for both the small and large debt constraint factors. The small debt constraint factor is borderline significant with a t-statistic of -1.95 and R^2 of 1.25%. There is much stronger predictability for the large debt constraint factor. The coefficient is -0.70 with a t-statistic of -3.49 and an R^2 of 4.10%. An increase in systemic risk is associated with a large negative relative return for large debt constrained firms compared to large debt unconstrained firms. The predictability is relatively short-lived with no predictability in the second month.

We next examine if there is asymmetry in the relationship between systemic risk and the debt constraint factors. In the model of Brunnermeier and Sannikov (2014), shocks become amplified in crises states when financial institutions are constrained. In this vein, we run two sets of tests to examine whether or not changes in systemic risk have greater power to predict the financial constraint factor in high systemic risk states, when financial institutions are more likely to be constrained, compared to low systemic risk states.

First, we cut the sample period into high and low systemic risk states based on the *level* of systemic risk. Months in which the level of systemic risk is above the sample median are considered high systemic risk states and the complement are low systemic risk states. We run regressions of the form:

$$FC_{t+m} = \alpha + \beta_h FinPC1_t^h + \beta_l FinPC1_t^l + \epsilon_t, \tag{1}$$

where $FinPC1_t^h$ is equal to the systemic risk innovation in the high systemic risk state and zero otherwise, and $FinPC1_t^l$ is similarly defined for the low systemic risk state. FC_{t+m} is the return on the financial constraint factor in month $t+m$. If there are asymmetric effects, we would expect the coefficient on the high systemic risk variable to be larger in magnitude and more significant than the coefficient on the low systemic risk variable (i.e., $\beta_h > \beta_l$).

Results are presented in Panel A of Table 8. Examining the one-month ahead returns on the large, debt constraint factor, we see that the predictability is concentrated in the high systemic risk states. The coefficient in the high systemic risk state is -1.02 with a t-statistic of -3.67, while the coefficient in the low systemic risk state is only -0.30 and insignificant. The R^2 improves to 5.19% when we condition on the level. We do not find significantly different predictability across high and low systemic risk states for the small, debt constrained factor, although the coefficient is almost 50% larger in the high systemic risk states. Conditioning on the level of systemic risk improves predictability since shifts in systemic risk matter much more in periods of financial sector stress than in periods of low systemic risk.

Our second test conditions on the sign of the innovation in systemic risk. We create two independent variables in an analogous manner to $FinPC1_t^h$ and $FinPC1_t^l$ except for positive shocks and negative shocks to $FinPC1$. Results are presented in Panel B of Table 8. We see that positive shocks impart much more predictability for future returns. The small, debt constraint factor has a coefficient of -0.8 (t-statistic=-2.46) on positive innovations and a positive and insignificant coefficient of 0.30 on negative innovations. Similarly, for the large, debt constraint factor the coefficient on positive shocks is -0.95 with a t-statistic of -3.15. The coefficient on negative shocks is -0.17 with a t-statisitic of only -0.46. The R^2 is 4.56%.

For interpretation, a one standard deviation increase in systemic risk in month t leads to a -1.53% relative return in large debt constrained firms in month $t+1$ on average (-18.36% annualized). This is significant predictability that is likely due to investors being unable to quickly incorporate the effects of systemic risk due to the complex inter-relationships between firms in the financial sector and their lending relationships with non-financial firms.

4.3 Understanding the Predictability

There are multiple potential explanations for the predictive relationship between systemic risk and returns on the constraint factor. Here, we discuss and test these potential explanations. The results further support the interpretation that the market is slow to incorporate the effect of systemic risk into the stock prices of financially constrained firms.

Conditional Trading Strategy: To assess whether our results are driven by exposure to risk and premia for bearing risk, we implement a trading strategy that conditions on shocks to the previous month's systemic risk levels. If the systemic risk shock is positive, we short the large, debt constraint factor (short the most debt constrained large firms and long the least debt constrained large firms). If the systemic risk shock is negative, we take a long position in the large, debt constraint factor.[16] We employ a number of factor-based asset pricing models to better understand the risk exposure of the strategy and assess the robustness of the predictable performance.

Results are presented in Table 9. This strategy is significantly profitable with an average return of 61 bps per month (7.32% per year) and a t-statistic of 4.09. If exposure to risk is

[16]In the Appendix, we provide results for an additional strategy that goes long the large, debt constraint factor following a positive systemic risk shock and takes no position following negative systemic risk shocks. The magnitude of the intercepts drop slightly, but the results remain statistically very significant. This eases concerns that we are partially capturing a large, debt constraint premium (Buehlmaier and Whited (2016)) since we are only taking a short position in the factor. We also provide results for a reverse strategy: that takes a long position in the financial constraint factor after a negative shock to systemic risk and no position otherwise. We find a positive and significant average return on this strategy consistent with the large, firm debt constraint premium documented by Buehlmaier and Whited (2016).

driving the predictable performance of the strategy, then the intercept term should be equal to zero when the appropriate factor model is employed. We find that the CAPM, Fama-French three-factor model (FF3), FF3 plus a momentum factor, FF3 plus momentum plus the Pastor-Stambaugh liquidity factor, the Fama-French five-factor model, and the Hou, Xue, and Zhang four-factor model cannot explain this underperformance. In fact, the intercept term tends to become more significant as more factors are controlled for and the magnitude varies between 60 bps and 75 bps (per month). The t-statistic on the intercept in the Fama-French five factor model is 4.30 and the Hou, Xue, and Zhang four-factor model intercept has a t-statistic of 4.32. The commonly used asset pricing models cannot explain the predictable variation in returns of large, debt constrained firms following changes in systemic risk. The intercept term likely becomes more significant because the strategy is negatively related to the value and investment factors. Since the conditional trading strategy trades the equity of large firms, it is unlikely that trading costs will eliminate this abnormal performance.

Market Illiquidity: Can illiquidity during periods of high systemic risk help explain the predictability? It is well known that during systemic events limits to arbitrage are high. Financial institution balance sheets are under stress, arbitrageur funding liquidity is low, the risk bearing capacity of market makers is likely to be low, and, therefore, stock liquidity is likely to be lower than normal. It is possible that the lack of liquidity during periods of high systemic risk leads to slower incorporation of information into prices. This channel is unlikely to fully explain the slow-movement of prices though. Previous results indicated the predictability is strongest in large firms, which have relatively more liquid stocks. Also, in unreported results we find that the predictability is not observed in equity constrained firms which likely experience similar illiquidity shocks.

To further examine this issue, we run two tests. First, we re-run our main predictability regression while including a measure of illiquidity using the liquidity factor of Pástor and Stambaugh (2003). We include the market illiquidity factor in month t and its interaction with systemic risk in month t. Specifically, we subtract the factor each month from its maximum over the entire time period. If the predictability is due to illiquidity, then the results should be strongest when illiquidity is highest, i.e., the coefficient on the interaction term should be negative and significant. Results are presented in Panel A of Table 10. We find that the coefficient on systemic risk actually increases and remains significant with a t-statistic of -2.47. Inconsistent with illiquidity causing the slow-movement of prices the coefficient on the interaction term is actually positive and insignificant. Second, we run a similar test using the change in the market liquidity factor between month t and $t+1$ (positive values indicate an increase in liquidity) to see if an increase in liquidity between month t and month $t+1$ allows for a quicker adjustment of prices. We find this has no significant impact on the systemic risk coefficient and the interaction term is insignificant. These results provide further evidence that illiquidity is not driving the slow-movement of prices.

Stock-Level Illiquidity: We further explore whether illiquidity at the stock level can explain the slow response of constrained firms' equity prices to systemic shocks. A plausible explanation for the observed predictability of debt constrained firms' returns is that stocks of constrained firms are less liquid than stocks of unconstrained firms, which causes their prices to adjust slowly to unexpected shocks. In order to investigate illiquidity at the firm level, we return to a setting similar to the panel regressions shown in Table 6. Since these regressions use firm-level data, we can include a firm-level measure of illiquidity as a control variable. We use the Amihud (2002) measure of firm illiquidity using daily returns and volume for each firm over the previous year. To be consistent with our earlier asset pricing results where we form portfolios prior to the first trading day of July in each year, here we calculate the Amihud illiquidity measure using daily data from July of the previous year to June of the current year. We then use this measure to assign an Amihud illiquidity measure to a given firm. This measure is held fixed until the next year when it is re-calculated.

We find that on average, constrained firms do tend to have less liquid stock (the Amihud illiquidity measure tends to be higher for constrained firms than for unconstrained firms). In order to determine whether this is driving our results, we run panel regressions similar to those described in Table 6 with two additional control variables: The variable $illiq_{i,t}$ denotes the Amihud (2002) measure of firm i's illiquidity at time t. We further include the interaction between stock-level illiquidity and the systemic event indicator 1_t^{SE} which indicates that month t is one of the three months we use as well-known systemic event months (08/1998, 09/2008 and 08/2011). When the indicator function indicates a shock in the previous month, this interaction term captures the additional returns that illiquid stocks earn above liquid stocks in the months directly following systemic events. Table 11 shows that the main coefficients of interest are virtually unchanged from the results of Table 6. Specifically, the coefficient on the interaction term $1_t^{SE} \times 1_{i,t}^{C}$ is highly significant and hardly changes with the additional firm-level illiquidity controls. This indicates that firm-level illiquidity is not likely to be driving the slow adjusment of prices we see in constrained firms following systemic shocks.

Persistence of Systemic Shocks: Another potential explanation is that systemic events are persistent so the results we see in months following shocks or well known event months are just continuations of markets efficiently incorporating information into equity prices as conditions continue to worsen. This is unlikely to be the case for two reasons. First, we only see broad price declines in the month of the shock. This can be seen by examining Column (1) of Table 6.[17] In Column (1), a negative and significant coefficient on the Systemic Event indicator shows that in the month of an event, we see significantly negative returns. The coefficients on the Constrained indicator and the Systemic Event interacted with the Constrained indicators are both insignificant. In unreported results we

[17] The same arguement can be made from Column (2) but one must observe that including the market as a contol absorbs the effect of the Systemic Shock indicator.

also run these regressions on only constrained firms and find a significant negative loading on the Systemic Event indicator. These results indicate that in the month of the shock, markets broadly incorporate the shock into prices yet there is no significant difference between the returns of constrained and unconstrained firms.

The second observation is that in Column (3) we see that the Systemic event indicator is not significant meaning that in months following these major systemic events, we do not see negative returns across constrained and unconstrained firms. If months following these well-known events were simply months of worsening health of the financial system, we would expect to see a significant negative coefficient on the Systemic Event indicator when it indicates events in the previous month. This is especially true given that we know from Column (1) that in months of systemic events we see such a negative loading. At the same time, we only see the significant and negative coefficient on the interaction term, Systemic Event interacted with the Constrained indicator, in the months *after* the shock but not the month of the shock. So in months where we are very confident of worsening financial system health, we do not observe any such discrepancy between returns on constrained and unconstrained firms.

Relatedly, it is worth noting that all of the major events we focus on (Russian Default of August 1998, Lehman Brothers collapse in September of 2008 and the United States debt downgrade of August 2011) were well known to market participants approximately two weeks prior to the end of the month in which we define them to exist. Therefore, it is unlikely that the results we observe in months following the events are simply the market observing the unveiling of events' severity as it happens.

Other Macroeconomic Variables: Another partial explanation for our results is that systemic risk is proxying for "bad times" more generally and it is not systemic risk that is driving the decline in prices of financially constrained firms. For example, the balance sheet channel theory would predict that firm financing constraints tighten more during recessions as firm values decline (see Brunnermeier and Oehmke (2013) for a review). Relatedly, Giglio et al. (2016) show that systemic risk is related to future macroeconomic downturns, so the tightening of debt constraints may be indirectly instead of directly related to systemic risk. Even if systemic risk is proxying for these other outcomes, it is unclear why this information would slowly be impacted into prices. A related concern is that in these "bad times" investor risk aversion may change and differentially affect the premium on financially constrained firms. To be consistent with the predictability results, the risk premium on debt constrained firms would have to experience a relative *decrease* during "bad times", which is highly unlikely.

To formally assess if systemic risk is just proxying for other macroeconomic outcomes, we run univariate and bivariate predictive regressions with a number of macroeconomic variables and market predictors. The dependent variable is the return on the large, debt constraint factor. These regressions will assess the predictive power of other macroeconomic variables that may be related to firm financing constraints and help distinguish the effect of systemic risk from the effect of other macroeconomic variables. The results of the univariate predictive regressions are presented under the univariate header of Table 12. The macroeconomic variables considered are: the credit spread, net expansion, term spread, discount rates, federal funds rate, and M2 (money supply). Additionally, we examine market return predictors (volatility risk premium, dividend-yield and earnings-yield) and another financial sector stress variable: the TED spread. Only the TED spread and federal funds rate shocks exhibit any predictive power for the financial constraint factor. The predictability of the federal funds rate shocks is consistent with Chava and Hsu (2015) who find financially constrained firms are more sensitive to federal funds rate shocks. We note however that the predictive power of the Federal funds rate is much weaker in that its univariate r-squared is roughly one sixth that of systemic risk (0.7% and 4.1%, respectively). The TED spread is another measure of turmoil in the financial sector, so its predictive power gives some comfort as to the robustness of our results. Examining the bivariate regressions, the TED spread is no longer significant. The Federal funds rate shocks maintains its predictive power with a t-statistic of -2.47. More importantly, systemic risk remains highly significant with a t-statistic of -2.9 or greater (in absolute terms) in all regressions. The relationship between systemic risk and future returns on the large debt constraint factor does not appear to be driven by other macroeconomic variables. This is likely due to the complex nature of systemic risk shocks.

4.4 Robustness Tests

We run additional tests to ensure the robustness of our results. There may be potential concerns related to the financial constraint classifications such as: investors may have been unable to identify financially constrained firms pre-1997, that our results are being driven by the random forests classifications, or that the random forests classifications exhibit a lookahead bias since we train the data on more recent periods. To eliminate these concerns, we re-run our analysis using just the HM measures of financial constraints. The time period analyzed is 1998-2016 since the HM measures use firm 10-K filings to estimate constraints. Results are presented in Table 13. We find the results are actually stronger in this sample. The R^2 from the univariate predictive regression on the large, debt constraint factor is 6.75%. To assess whether or not the increased predictability is due to using HM measures or due to the time period, we re-run the predictive regressions using random forest classifications during the 1998-2016 period. Results are presented in Table 14. We find the strong performance is due to the time period covered in which there were a number of large systemic events. The R^2 from the univariate predictive regression on the large, debt constraint factor is extremely high at 10.44%. These results ease concerns that extending the sample using the random forest classifications is driving our results.

5 Conclusion

We show that investors are slow to incorporate the effect of changes in systemic risk and systemic events into stock prices. Our main finding is that returns on debt constrained firms' equity are strongly predicted by changes in systemic risk. The predictability is strongest when systemic risk is high or there is an increase in systemic risk. Large capitalization firms exhibit the most predictability, which is inconsistent with limits to arbitrage driving the results. A trading strategy that times the large debt constraint factor based on changes in systemic risk produces an abnormal return of over eight percentage points per year. These results are consistent with investors slowly incorporating the effect of systemic events and changes in systemic risk into stock prices. The slow movement of prices is likely due to investors with limited processing capabilities becoming overwhelmed by these complex events, which require a significant amount of information to be processed and incorporated into the stock prices of a large number of firms..

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Table 1: **Summary Statistics**

Panel A presents summary statistics for systemic risk measures used throughout the paper. Panels B,C and D give summary statistics for returns to traded constraint factors used throughout the paper. Panel B gives summary statistics for our entire sample of fitted constraint measures using random forest estimates to fit constraints. Panel C describes the subsample of factors described in Panel B from 1998 through 2016. This is the same sample for which we are able to construct traded constraint portfolios directly using the Hoberg and Maksimovic (2015) constraint measure. Panel D give summary statistics for the traded factor constructed by sorting directly on the HM measure.

Panel A: Systemic Risk Summary Statistics

	mean	median	standard dev	skewness
FinPC1	0.0883	-0.1250	1.610	4.930
FinCon	0.0048	0.0051	0.043	-0.009
FinVol	0.0021	0.0004	0.008	2.020
CatFin	0.0006	0.0031	0.019	-4.030

Panel B: Constraint Factors Summary Statistics 1973-2016

	mean	median	standard dev	skewness
Large	0.0011	0.0005	0.0401	-0.242
Small	0.0039	0.0040	0.0460	-0.627

Panel C: Constraint Factors Summary Statistics 1998-2016

	mean	median	standard dev	skewness
Large	-0.0017	-0.0005	0.0461	-0.313
Small	0.0024	0.0076	0.0602	-0.611

Panel D: Constraint Factors Summary Statistics HM measure 1998-2016

	mean	median	standard dev	skewness
Large	-0.0019	-0.0007	0.0358	-0.845
Small	0.0045	0.0032	0.0032	-0.540

Table 2: **Firm-Level Summary Statistics**
This table presents summary statistics firm level predictors of financial constraints used in our machine learning based estimator of financial constraints. Each variable is measured at the annual frequency.

Panel A: Financial Variables

	mean	median	standard dev	skewness
Cap. expend.	0.45	0.10	11.76	88.79
Prop. Plant, equip.	950.30	41.68	5752.44	22.73
age	16.27	12.00	13.15	1.50
cash flow/K	-5.11	0.09	177.39	-95.26
cash/K	6.01	0.27	110.39	62.25
dividends/K	0.50	0.00	49.98	236.63
Tobin's Q	236.25	0.72	9972.90	106.65
book assets	1754.09	138.89	12286.61	38.04
leverage	0.36	0.28	0.35	0.63
sales growth	1.34	0.04	69.23	118.12
size	4.79	4.93	2.59	-0.51

Table 3: **Comparison of Random Forests and Ordinary Least Squares Models**
This table reports a comparison of the predictive power of the random decision forests method versus ordinary least squares. We report R^2 measures for our random forest estimator and for linear OLS regressions. In both cases the model being tested includes all of the predictors included in Table 2 as well as the average level of broker dealer leverage quarterly measures in a given year as measured by He et al. (2016). All models are fit using annual measures of financial constraints from Hoberg and Maksimovic (2015) as the dependent variable. The in sample column reports R^2 for the model fit to the entire sample from 1997 through 2015. The column labeled OOS (Cross-Section) reports the R^2 for a randomly selected test sample containing 25% of the data, using a model trained on the remaining 75% of the data that is not included in the test set. Similarly, the OOS (Time Series) column reports R^2 from the out of sample fit on data from 1997 through 2001 when using a model trained on the data from 2002 through 2015.

	In Sample	OOS (Cross-section)	OOS (Time Series)
Random Forests	0.729	0.278	0.232
OLS	0.109	0.107	0.091

Table 4: **Cross-Tabulations of Predicted vs. Actual HM, Test Sample (Cross-Section)**

This table gives cross tabulations (in percentages) of out of sample portfolio assignments by statistical models versus portfolio assignments based upon financial constraints measures from Hoberg and Maksimovic (2015). We first sort fitted values of the test (cross-sectional out of sample) data into quintiles each month. Next we sort the test set observations based upon HM measures of financial constraints each month. We then examine the percentage of fitted quintiles that come from each HM measure quintile. Within each panel, rows represent quintiles of fitted values using a statistical model. Columns represent quintiles of the HM financial constraint measures for the same test (cross-sectional out of sample) set of data. The i, j^{th} cell in each panel therefore represents the percent of firms assigned to the i^{th} quintile by a statistical model that are assigned to the j^{th} quintile of the test data set based upon HM financial constraints which are also the dependent variable being estimated by each statistical model. RaF denotes random forest fitted values and OLS denotes linear ordinary least squares fitted values.

	RaF (All Firms)				
	1	2	3	4	5
1	43	27	17	9	4
2	27	27	22	15	9
3	18	22	24	21	15
4	8	16	22	27	26
5	3	7	15	27	47

	RaF (Large Firms)				
	1	2	3	4	5
1	34	21	22	16	7
2	14	20	24	25	17
3	8	13	26	30	24
4	3	8	20	32	38
5	1	4	11	26	58

	RaF (Small Firms)				
	1	2	3	4	5
1	50	30	13	6	2
2	36	33	20	8	3
3	28	31	22	13	6
4	15	27	26	22	11
5	8	15	23	28	26

	OLS (All Firms)				
	1	2	3	4	5
1	34	27	18	13	8
2	26	22	20	17	14
3	20	20	21	20	19
4	13	17	21	24	25
5	7	13	20	26	34

	OLS (Large Firms)				
	1	2	3	4	5
1	1	33	27	21	19
2	0	20	24	26	28
3	1	15	22	27	35
4	0	10	20	31	40
5	0	6	16	30	47

	OLS (Small Firms)				
	1	**2**	**3**	**4**	**5**
1	54	24	12	8	2
2	46	24	17	11	3
3	38	25	19	13	5
4	29	27	22	15	6
5	23	27	25	17	8

Table 5: **Cross-Tabulations of Predicted vs. Actual HM, Test Sample (Train Last 14 Years; Test First 5 Years)**

This table gives cross tabulations (in percentages) of out of sample portfolio assignments by statistical models versus portfolio assignments based upon financial constraints measures from Hoberg and Maksimovic (2015). We first sort fitted values of the test (1997 through 2001 out of sample) data into quintiles each month. Next we sort the test set observations based upon HM measures of financial constraints each month. We then examine the percentage of fitted quintiles that come from each HM measure quintile. Within each panel, rows represent quintiles of fitted values using a statistical model. Columns represent quintiles of the HM financial constraint measures for the same test (1997 through 2001 out of sample) set of data. The i, j^{th} cell in each panel therefore represents the percent of firms assigned to the i^{th} quintile by a statistical model that are assigned to the j^{th} quintile of the test data set based upon HM financial constraints which are also the dependent variable being estimated by each statistical model. RaF denotes random forest fitted values and OLS denotes linear ordinary least squares fitted values.

	RaF (All Firms)						**RaF (Large Firms)**						**RaF (Small Firms)**				
	1	2	3	4	5		1	2	3	4	5		1	2	3	4	5
1	42	29	16	9	4	1	32	22	22	16	8	1	48	33	13	5	1
2	26	25	23	16	11	2	15	16	25	25	20	2	34	32	21	9	4
3	18	22	22	21	16	3	9	11	22	30	28	3	27	32	23	12	6
4	10	15	22	26	26	4	5	7	18	32	38	4	17	24	27	20	11
5	4	8	17	28	44	5	2	3	10	29	56	5	8	15	30	27	21

	OLS (All Firms)						**OLS (Large Firms)**						**OLS (Small Firms)**				
	1	2	3	4	5		1	2	3	4	5		**1**	**2**	**3**	**4**	**5**
1	35	30	17	11	7	1	0	37	25	20	18	1	57	26	11	5	1
2	26	22	21	17	14	2	0	19	25	27	30	2	46	25	17	10	2
3	20	20	20	20	20	3	0	14	20	28	38	3	39	26	19	13	3
4	13	17	22	25	24	4	0	9	19	31	41	4	28	26	24	17	4
5	6	12	20	27	35	5	0	5	13	31	51	5	18	25	29	22	6

Table 6: **Firm-level Regressions**

This table reports results of regressions demonstrating the relationship between systemic events on the returns of financially constrained firms. We examine two regression specifications. The first regression is as follows:

$$ret_{i,t} = \alpha + \beta_1 1_t^{SE} + \beta_2 1_{i,t}^{C} + \beta_3 1_t^{SE} \times 1_{i,t}^{C} + \gamma_t^{year} + \gamma_{i,t}^{Industry} + \epsilon_{i,t},$$

where 1_t^{SE} is an indicator variable equal to one if there is a large systemic event in the month (the three event months are 08/1998, 09/2008 and 08/2011) and $1_{i,t}^{C}$ is an indicator variable equal to one if the firm is in the top 20% of firms in terms of financial constraints at time t. The second specification controls for the three Fama and French (1993) factors and their differential relation between constrained and unconstrained firms:

$$ret_{i,t} = \alpha + \beta_1 1_t^{SE} + \beta_2 1_{i,t}^{C} + \beta_3 1_t^{SE} \times 1_{i,t}^{C} + \beta_4 Mkt + \beta_5 SMB + \beta_6 HML + \beta_7 Mkt \times 1_{i,t}^{C} + \beta_8 SMB \times 1_{i,t}^{C} + \beta_9 HML \times 1_{i,t}^{C} + \gamma_t^{year} + \gamma_{i,t}^{Industry} + \epsilon_{i,t},$$

We include year and industry fixed effects, γ_t^{year} and $\gamma^{Industry}$ in both regressions. In Column (1), the indicator 1_t^{SE} indicates a shock in the current month. In Column (2), 1_t^{SE} indicates a shock in the previous month. Standard errors are double clustered at the firm and month level.

	contemporaneous event		event previous month	
Intercept	-0.011	0.033	-0.011	0.033
	(-0.25)	(1.22)	(-0.25)	(1.22)
Systemic Event	-0.172	-0.008	-0.039	0.008
	(-3.57)	(-0.87)	(-0.64)	(1.19)
Constrained	0.002	0.001	0.003	0.001
	(1.47)	(0.718)	(1.71)	(0.833)
Systemic Event $\times$ Constrained	0.013	-0.015	-0.054	-0.035
	(1.11)	(-0.97)	(-5.17)	(-3.25)
Mkt		1.030		1.030
		(20.10)		(20.50)
SMB		1.070		1.070
		(8.38)		(8.41)
HML		-0.21		-0.210
		(-1.79)		(-1.76)
Mkt $\times$ Constrained		0.018		0.017
		(0.37)		(0.355)
SMB $\times$ Constrained		-0.272		-0.275
		(-2.17)		(-2.20)
HML $\times$ Constrained		0.794		0.782
		(8.65)		(8.47)
R^2	1.70	10.50	1.36	10.50

Table 7: **Predictive regressions of constraint factors on systemic risk**
This table presents results of predictive regressions of the following form:

$$FC_{t+m} = \alpha + \beta FinPC1_t + \epsilon_t, \qquad m = 0, 1, 2$$

where $FinPC1_t$ denotes shocks to systemic risk as described in Section 3.5. The factor is composed of a long-short portfolio that is long the value weighted portfolio of the top 20% and short the value weighted portfolio of the bottom 20% of firms according to the random forest-fitted constraint measure. The traded factor is rebalanced annually and held from July through June of the following year. The systemic risk factor, $FinPC1_t$ denotes residuals from fitting a rolling window ARMA(1,1) model to systemic risk levels using the previous 10 years of data. One-month (two months) ahead regressions are labeled $m = 1$ ($m = 2$). The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors. Results are reported small and large firms separately.

	$m = 0$		$m = 1$		$m = 2$	
	β	R^2	β	R^2	β	R^2
Panel A: Debt Constraints						
Small Firms Factor	0.23	0.35	-0.44	1.25	-0.21	0.27
	(1.07)		(-1.95)		(-0.91)	
Large Firms Factor	-0.28	0.65	-0.70	4.10	0.05	0.02
	(-1.57)		(-3.49)		(0.27)	

Table 8: **Systemic Factor Asymmetry Regressions Monthly**
This table presents results of predictive regressions of the following form:

$$FC_{t+m} = \alpha + \beta_h FinPC1_t^h + \beta_l FinPC1_t^l + \epsilon_t, \qquad m = 0, 1, 2$$

where $FinPC1_t^h$ denotes the month t random variable that is equal to the systemic risk factor innovations in the high systemic risk months and equal to zero otherwise. Similarly, $FinPC1_t^l$ is equal to the systemic risk factor innovations in the low systemic risk months and zero otherwise. High (low) systemic risk months are those with systemic risk levels above (below) the full sample median. FC_{t+m} denotes month $t+m$ returns to the traded constraint factor. The factor is composed of a long-short portfolio that is long the value weighted portfolio of the top 20% and short the value weighted portfolio of the bottom 20% of firms according to the random forest-fitted constraint measure which is measured at the end of the previous calendar year. The traded factor is rebalanced annually and held from July through June of the following year. The systemic risk factor, $FinPC1_t$ denotes residuals from fitting a rolling window ARMA(1,1) model to systemic risk levels using the previous 10 years of data. One-month (two months) ahead regressions are labeled $m = 1$ ($m = 2$). The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors.

Panel A: High and Low Systemic Risk States

	$m = 0$			$m = 1$			$m = 2$		
	β_h	β_l	R^2	β_h	β_l	R^2	β_h	β_l	R^2
Debt Constraints:									
Small Firms Factor	0.21	0.26	0.36	-0.49	-0.38	1.27	-0.30	-0.09	0.35
	(0.64)	(1.00)		(-1.32)	(-1.75)		(-0.83)	(-0.36)	
Large Firms Factor	-0.14	-0.44	0.83	-1.02	-0.30	5.19	-0.04	0.16	0.10
	(-0.51)	(-2.24)		(-3.67)	(-1.12)		(-0.18)	(0.72)	

Panel B: Positive and Negative Innovations in Systemic Risk

	β_h	β_l	R^2	β_h	β_l	R^2	β_h	β_l	R^2
Debt Constraints:									
Small Firms Factor	0.13	0.45	0.41	-0.8	0.30	1.96	-0.46	0.32	0.63
	(0.41)	(1.02)		(-2.46)	(0.63)		(-1.34)	(0.73)	
Large Firms Factor	-0.49	0.18	0.99	-0.95	-0.17	4.56	-0.04	0.24	0.08
	(-1.94)	(0.47)		(-3.15)	(-0.46)		(-0.18)	(0.59)	

Table 9: **Conditional Trading Strategy: Full Sample Strategy**

This table reports point estimates and t-statistics for the conditional trading strategy exploiting the relationship between shocks to systemic risk and return differentials between constrained and unconstrained firms. Using our systemic risk factor FinPC1, we condition on the previous month's shock to systemic risk. If there is a positive shock to systemic risk then the following month a short position is taken in the top 20% most (debt) constrained large firms and a long position is taken in the 20% least constrained large firms. In months where the previous month does not experience a positive shock (negative or zero shocks occur), this strategy is long constrained firms and short unconstrained firms. Firms' constraint rankings are calculated annually at the end of June using random forest-fitted constraint estimates. Portfolio constituents are updated on an annual basis. The regressions reported in the table are the following:

$$-FC_{t+1}\mathbb{1}_{(FC_t>0)} + FC_{t+1}\mathbb{1}_{(FC_t<=0)} = \alpha + \beta_1 PF^1_{t+1} + ... + \beta_k PF^k_{t+1} + \epsilon_{t+1}, \quad t \in \{2,...,n\}$$

where FC_{t+1} denotes month t+1 returns to the traded constraint factor using large, debt-constrained firms and $\mathbb{1}$ denotes an indicator function. T-statistics are reported in parentheses and are based upon Newey-West standard errors with 12 month lags.

MODEL	α	MRKT	SMB	HML	MOM	Liq (PS)	Profit.	Invest.	I/A	ROE	R^2
Mean	0.0061										0.00
	(4.09)										
CAPM	0.0060	0.0292									0.11
	(3.94)	(0.58)									
FF3	0.0068	-0.0082	0.0200	-0.1965							2.14
	(4.58)	(-0.17)	(0.28)	(-3.18)							
FF3 + MOM	0.0075	-0.0261	0.0256	-0.2260	-0.0817						2.95
	(4.79)	(-0.52)	(0.36)	(-3.89)	(-1.55)						
FF3 + MOM + Liq	0.0075	-0.0261	0.0259	-0.2258	-0.0819	-0.0043					2.95
	(4.85)	(-0.52)	(0.36)	(-3.91)	(-1.56)	(-0.08)					
FF5	0.0071	-0.0113	-0.0175	-0.2175			-0.1277	0.0660			2.70
	(4.30)	(-0.23)	(-0.22)	(-2.17)			(-1.55)	(0.40)			
HXZ	0.0073	-0.0058	0.0002						-0.2092	-0.0288	0.96
	(4.32)	(-0.11)	(0.00)						(-2.15)	(-0.32)	

Table 10: **Liquidity Interaction Tests**

This table reports point estimates and t-statistics regressions meant to examine the predictive power of (il)liquidity and systemic risk on . We run two different regressions meant to capture possible interactions between (il)liquidity effects and predictability of financially constrained firms. The first regression specification is as follows:

$$FC_{t+1} = \alpha + \beta_1 FinPC1_t + \beta_2 ILLIQ_t + \beta_3 FinPC1_t \cdot ILLIQ_t + \epsilon_{t+1},$$

where $ILLIQ_t$ denotes the market illiquidity as measured by $\max Liq - Liq_t$, where $\max Liq$ denotes the maximum level of the Pástor and Stambaugh (2003) market liquidity factor over our sample and Liq_t denotes the level at time t. The interaction term, β_3 measures the additional sensitivity of constrained firms' relative returns in periods following systemic risk shocks, when illiquidity is high at time of the shock. The second regression specification is as follows:

$$FC_{t+1} = \alpha + \beta_1 FinPC1_t + \beta_2 \Delta LIQ_{t+1} + \beta_3 FinPC1_t \cdot \Delta LIQ_{t+1} + \epsilon_{t+1},$$

where FC denotes the financial constraint factor, $FinPC1$ denotes systemic risk shocks and ΔLIQ denotes liquidity shock measured as shocks to the Pástor and Stambaugh (2003) market liquidity factor. The interaction term, β_3 measures the additional sensitivity of constrained firms' relative returns in periods following systemic risk shocks, when liquidity changes in the month following the systemic risk shock. The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors.

Panel A: Illiquidity Level Month t

	β_1	β_2	β_3	R^2
Large Debt-Constrained	-1.33	4.00	2.06	5.17
	(-2.47)	(0.97)	(1.06)	
Small Debt-Constrained	-0.60	3.20	-0.38	1.47
	(-0.75)	(0.60)	(-0.14)	

Panel B: Changes in Liquidity Month t to Month t+1

	β_1	β_2	β_3	R^2
Large Debt-Constrained	-0.71	8.79	-3.03	5.90
	(-3.60)	(2.69)	(-0.88)	
Small Debt-Constrained	-0.46	3.35	-3.48	1.77
	(-2.12)	(0.69)	(-0.81)	

Table 11: **Firm-level Regressions with illiquidity**
This table reports results of regressions demonstrating the relationship between systemic events on the returns of financially constrained firms while controlling for stock-specific illiquidity. We examine two regression specifications. The first regression is as follows:

$$ret_{i,t} = \alpha + \beta_1 1_t^{SE} + \beta_2 1_{i,t}^{C} + \beta_3 1_t^{SE} \times 1_{i,t}^{C} + \beta_4 illiq_{i,t} + \beta_5 1_t^{SE} \times illiq_{i,t} + \gamma_t^{year} + \gamma_{i,t}^{Industry} + \epsilon_{i,t},$$

where 1_t^{SE} is an indicator variable equal to one if there is a large systemic event in the month (the three event months are 08/1998, 09/2008 and 08/2011) and $1_{i,t}^{C}$ is an indicator variable equal to one if the firm is in the top 20% of firms in terms of financial constraints at time t. The variable $illiq_{i,t}$ is 1000 times the Amihud (2002) measure of illiquidity computed using the daily returns of a given firm over the previous year. The second specification controls for the three Fama and French (1993) factors and their differential relation between constrained and unconstrained firms:

$$ret_{i,t} = \alpha + \beta_1 1_t^{SE} + \beta_2 1_{i,t}^{C} + \beta_3 1_t^{SE} \times 1_{i,t}^{C} + \beta_4 illiq_{i,t} + \beta_5 1_t^{SE} \times illiq_{i,t} + \beta_6 Mkt + \beta_7 SMB + \beta_8 HML$$

$$+\beta_9 Mkt \times 1_{i,t}^{C} + \beta_1 0 SMB \times 1_{i,t}^{C} + \beta_1 1 HML \times 1_{i,t}^{C} + \gamma_t^{year} + \gamma_{i,t}^{Industry} + \epsilon_{i,t},$$

We include year and industry fixed effects, γ_t^{year} and $\gamma^{Industry}$ in both regressions. In Column (1), the indicator 1_t^{SE} indicates a shock in the current month. In Column (2), 1_t^{SE} indicates a shock in the previous month. Standard errors are double clustered at the firm and month level.

	Debt Constraints			
	contemporaneous systemic event		systemic event previous month	
Intercept	-0.013	0.006	-0.013	0.006
	(-0.29)	(2.03)	(-0.30)	(2.07)
Systemic Event	-0.172	0.001	-0.038	0.006
	(-3.52)	(0.01)	(-0.62)	(0.69)
Constrained	0.003	0.001	0.004	0.001
	(1.86)	(0.24)	(2.11)	(0.323)
Systemic Event × Constrained	0.013	-0.018	-0.055	-0.032
	(1.02)	(-1.09)	(-5.38)	(-3.19)
Mkt		1.042		1.042
		(21.00)		(21.70)
SMB		1.187		1.188
		(12.60)		(12.60)
HML		-0.36		-0.361
		(-4.12)		(-4.07)
illiq	0.033	0.035	0.033	0.035
	(3.31)	(3.43)	(3.32)	(3.43)
Mkt × Constrained		0.032		0.033
		(0.63)		(0.67)
SMB × Constrained		-0.360		-0.362
		(-3.26)		(-3.27)
HML × Constrained		0.901		0.890
		(10.89)		(10.70)
Systemic Event×illiq	0.217	0.315	-0.10	-0.237
	(0.77)	(1.13)	(-0.36)	(-0.84)
R^2	1.73	11.65	1.35	11.66

Table 12: **Bivariate Predictive Regressions: Large Debt Constraint Factor**
This table presents results of bivariate and univariate predictive regressions using well known market and macroeconomic variables to predict the large firm, debt constraint factor. The univariate regressions are of the following form:

$$FC_{t+1} = \alpha + \beta_M Macro_t + \epsilon_t,$$

where FC_{t+m} denotes month $t+m$ returns to the traded constraint factor. $Macro_t$ denotes a macroeconomic or market variable used in the predictability regressions. The set of macroeconomic and market variables are well known predictors and macroeconomic indicators. VRP denotes the variance risk premium of Bollerslev et al. (2009). d/p and e/p denote aggregate dividend to price ratio and earnings to price ratio. TED denotes the TED spread. Fed Funds and Discount rates denote ARMA(1,1) shocks to the Federal Funds rate and interest rates respectively. M2 denotes ARMA(1,1) shocks to the M2 measure of money supply in billions of dollars. Credit spread denotes the difference between Moody's BAA and AAA corporate bond yeilds. Net Expansion denotes the ratio of 12 month rolling sum of net equity issues by all NYSE listed firms, divided by total market capitalization of the firms. Term Spread denotes the difference between long-term yields on U.S. government bonds and treasury bills. Bivariate regressions take the following form:

$$FC_{t+1} = \alpha + \beta_{SR} FinPC1_t + \beta_M Macro_t + \epsilon_t,$$

where $FinPC1_t$ denotes shocks to systemic risk as described in Section 3.5 and the set of $Macro_t$ variables is the same as in the univariate regression specification. The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors.

	Univariate		Bivariate		
Variable	β_C	R^2	β_{SR}	β_C	R^2
VRP	-0.02	0.86	-0.94	-0.02	7.73
	(-1.17)		(-3.76)	(-1.13)	
d/p	0.59	0.42	-0.69	0.53	4.44
	(1.15)		(-3.49)	-1.06	
e/p	0.6	0.53	-0.7	0.63	4.69
	(1.36)		(-3.56)	-1.45	
TED	-3.29	3.21	-0.83	-1.64	7.78
	(-2.59)		(-2.90)	(-1.26)	
credit spread	-8.35	0.01	-0.7	9.64	4.21
	(-0.20)		(-3.46)	-0.23	
Net Expansion	-64.87	0.28	-0.69	-62.25	4.36
	(-1.24)		(-3.44)	(-1.16)	
Term Spread	35.13	0.18	-0.7	40.84	4.35
	(0.88)		(-3.47)	-1.02	
Discount rates	-0.2	0.09	-0.69	-0.17	4.17
	(-0.72)		(-3.45)	(-0.64)	
Fed Funds	-1.18	0.70	-0.7	-1.25	4.88
	(-2.35)		(-3.51)	(-2.47)	
M2	0	0.02	-0.71	0	4.13
	(-0.28)		(-3.49)	-0.34	

Table 13: **Predictive regressions using Hoberg and Maksimovic (2015) constraint measures**

This table presents results of predictive regressions of the following form:

$$FC^{HM}_{t+m} = \alpha + \beta FinPC1_t + \epsilon_t, \qquad m = 0, 1, 2$$

where FC^{HM}_{t+m} denotes the financial constraint factor based upon the HM measure. The factor is composed of a long-short portfolio that is long the value weighted portfolio of the top 20% and short the value weighted portfolio of the bottom 20% of firms according to the HM measure. The traded factor is rebalanced annually and held from July through June of the following year begining in July of 1998 through December of 2016. $FinPC1_t$ denotes shocks to systemic risk as described in Section 3.5. The systemic risk factor, $FinPC1_t$ denotes residuals from fitting a rolling window ARMA(1,1) model to systemic risk levels using the previous 10 years of data. One-month (two months) ahead regressions are labeled $m = 1$ ($m = 2$). The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors. Results for small and large firms are reported separately.

	$m = 0$		$m = 1$		$m = 2$	
	β	R^2	β	R^2	β	R^2
Small Firms Factor	0.29	0.46	-0.46	1.69	-0.5	1.96
	(1.33)		(-1.66)		(-1.76)	
Large Firms Factor	0.04	0.58	-0.71	6.75	-0.09	0.12
	(0.22)		(-3.15)		(-0.52)	

Table 14: **Predictive regressions of constraint factors on systemic risk: 1998-2016**
This table presents results of predictive regressions of the following form:

$$FC_{t+m} = \alpha + \beta FinPC1_t + \epsilon_t, \qquad m = 0, 1, 2$$

where $FinPC1_t$ denotes shocks to systemic risk as described in Section 3.5. The financial constraint factor is composed of a long-short portfolio that is long the value weighted portfolio of the top 20% and short the value weighted portfolio of the bottom 20% of firms according to the random forest-fitted constraint measure. The traded factor is rebalanced annually and held from July through June of the following year. The regressions in this table use random tree-based FC factor values only over the same set of months for which we are able to create the factors using HM measures: July of 1998 through December of 2016 (see Table 13). The systemic risk factor, $FinPC1_t$ denotes residuals from fitting a rolling window ARMA(1,1) model to systemic risk levels using the previous 10 years of data. One-month (two months) ahead regressions are labeled $m = 1$ ($m = 2$). The regressions and corresponding t-statistics are calculated using ordinary least squares with White (1980) heteroskedasticity-consistent standard errors. Results for small and large firms are reported separately.

	$m = 0$		$m = 1$		$m = 2$	
	β	R^2	β	R^2	β	R^2
Small Firms Factor	0.32	0.46	-0.81	2.89	-0.38	0.64
	(0.81)		(-2.07)		(-0.97)	
Large Firms Factor	-0.27	0.58	-1.17	10.44	-0.04	0.01
	(-0.96)		(-3.98)		(-0.14)	

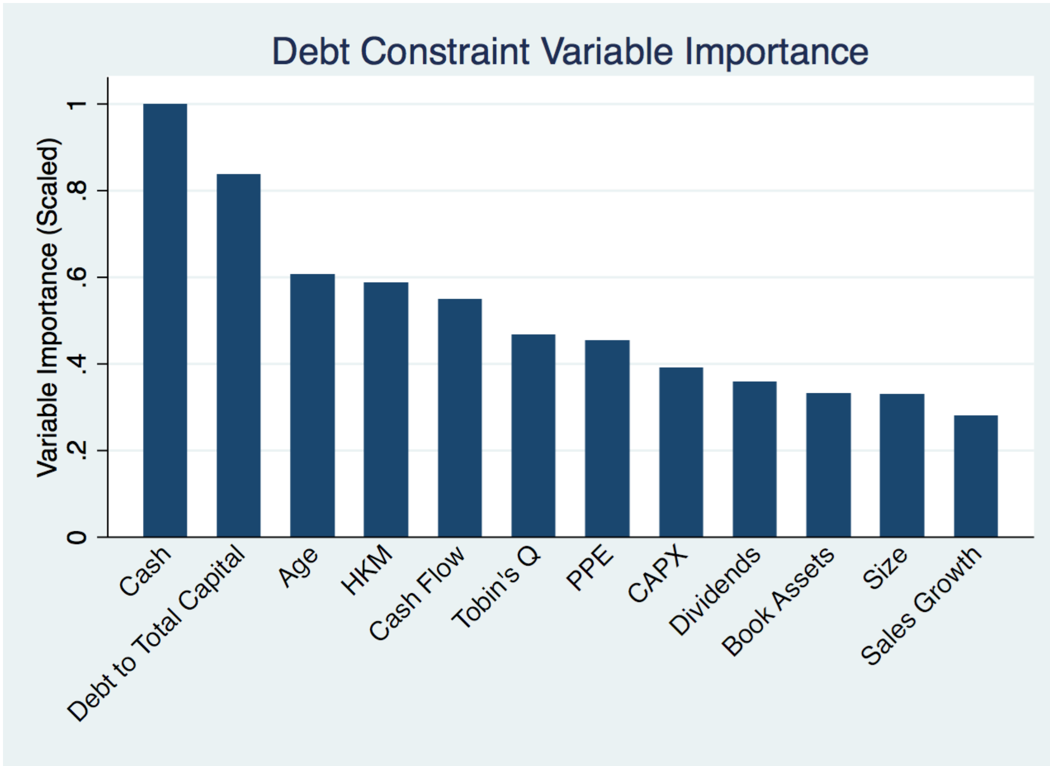

Figure 1: **Financial Constraint Random Forest Predictor Variable Importance**
This Figure depicts the relative importance of each predictor used in our random forest for fitting the model to the Hoberg and Maksimovic (2015) annual financial constraints measures from 1997 through 2015. Variable importance measures the average reduction in residual sum of squares (normalized by variance) for each predictor variable (See Section 3.3 for a more in depth discussion). We normalize the variable importance of each predictor by the importance measure of the predictor with the highest importance (cash holdings).

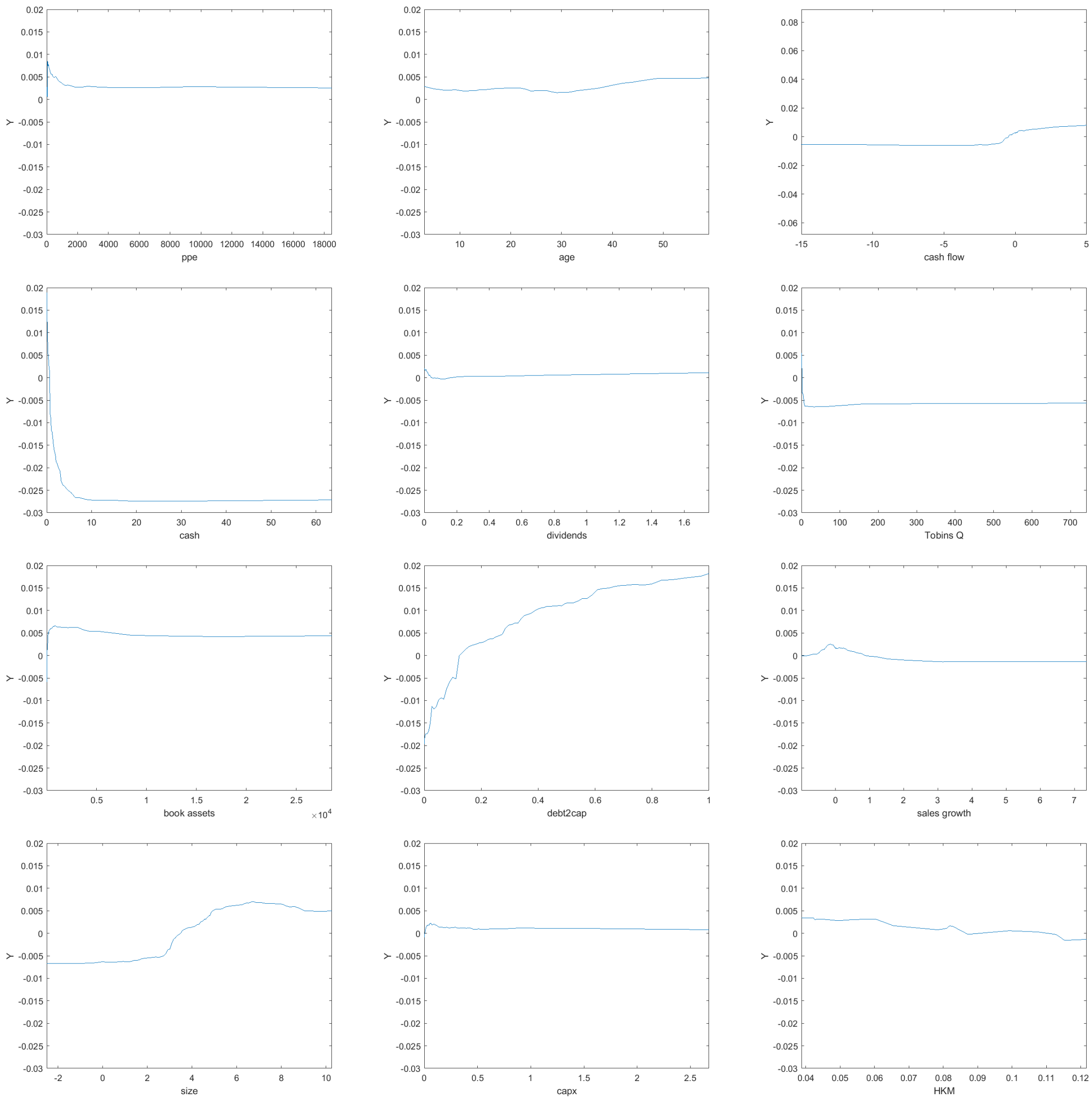

Figure 2: **Debt Constraint Predictor Variables Partial Dependence**
This figure depicts partial dependence plots for each predictor variable used to fit a random forest to the Hoberg and Maksimovic (2015) debt constraint measures from 1997 through 2015. Partial dependence plots show the average fitted value as a function of a particular variable. Here we truncate the support of each variable to be between the first and ninety ninth percentile of observed values in the sample in order to keep the scale of the figure from being distorted by outliers.

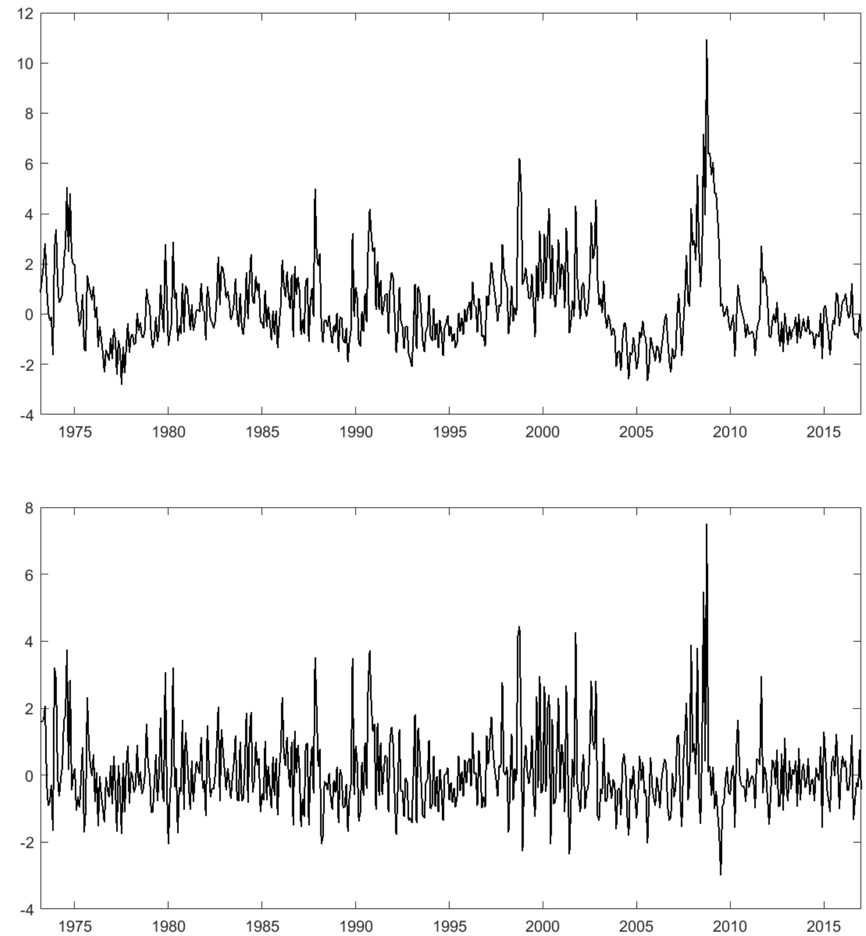

Figure 3: **Systemic Risk.**
The first figure plots the level of systemic risk, $FinPC1$, where the level is computed using the first principal component of $FinCon$, $FinVol$ and $CatFin$ using a 10 year rolling window. The second figure plots innovations in systemic risk. Innovations are calculated as ARMA(1,1) residuals to estimate unexpected shocks to systemic risk. Both innovations and principal components are calculated using a 10 year rolling window of monthly data as described in Section 3.5.

Appendix

A Estimating Systemic Risk

Our measure of systemic risk is based on the first principal component of three different measures (and types) of systemic risk: financial sector volatility, financial sector connectedness or contagion risk and financial sector tail risk. Below we detail the construction of each individual measure of systemic risk and the main systemic risk measure, $FinPC1$.

The measure of connectedness constructed independently in Billio et al. (2012) and Kritzman et al. (2011) is meant to capture the vulnerability of a group of firms to contagion. The more connected a set of firms, the more vulnerable they are to contagion. The measure of financial connectedness and vulnerability to contagion is based upon the fact that when a system is more interconnected, a larger fraction of variation in the system's returns can be explained by fewer orthogonal factors (principal components). We refer to this measure as $FinCon$ which is formally defined by the following:

$$FinCon_t = \frac{\sum_{i=1}^{k} \sigma_{i,t}^2}{\sum_{i=1}^{n} \sigma_{i,t}^2}, \qquad k < n \tag{2}$$

where $\sigma_{i,t}^2$ denotes the variance of the i^{th} eigenvector in month t. We use daily returns within each month to measure variation. The total number of assets in the system is denoted by n. In our empirical analysis, $n = 20$ since we examine returns of the 20 largest financial firms. We set k equal to 5, so that $FinCon$ measures the fraction of total variation in returns explained by the first five principal components. The time series of $FinCon$ levels is shown in the second panel of Figure A.1 in the main text.

We follow Allen et al. (2012b) and their nonparametric $CatFin$ (short for Catastrophic Risk in the Financial Sector) measure to compute a tail risk measure from returns of systemically important financial firms. $CatFin$ is an estimate of the value at risk (VaR) of financial institutions. Our implementation differs slightly from that in Allen et al. (2012b). The original paper computes three variations of the VaR measure and uses the average of the three measures for most of the empirical analysis. We focus only on one of the measures for simplicity. We estimate only the nonparametric version of $CatFin$ in order to avoid any assumptions about parametric distributions of tail returns for the systemically important firms within our sample. Same as with the previous two measures of systemic risk, we focus only on large firms within the SIC code range of 6000 to 6300. However, in order to estimate the nonparametric version of $CatFin$ with reasonable precision, we increase the number of firms with which we estimate the value at risk. We use the largest 50 firms' returns for our $CatFin$ estimate. Each month we collect all daily returns of all 50 firms. The bottom percentile of this set of returns serves as our value at risk estimate of (nonparametric) $CatFin$ for a given month. The time series of $CatFin$ is shown in the final panel of Figure A.1 in the main text.

After constructing the time-series of the individual measures, we perform principal component analysis to extract the common systemic risk component. To estimate the first principal component we first normalize each of the three measures using their mean and standard deviations of monthly returns in the previous 10 years. We denote these normalized values by $FinCon^{norm}$, $FinVol^{norm}$ and $CatFin^{norm}$. Using these normalized systemic risk measures, we extract the first principal component of the factors along with the corresponding linear transformation used to map the three normalized factors to the fist principal component. Using the normalized month t measures, we then use the linear transformation associated with the principal component analysis of the previous ten years of observations, to transform the normalized month t values, $FinCon^{norm}$, $FinVol^{norm}$ and $CatFin^{norm}$ to the first principal component, $FinPC1^{norm}$. This gives our estimate of time t systemic risk. It is important to note that at month t, $FinPC1_t^{norm}$ is computed from observed, month t levels of $FinCon_t$, $FinVol_t$ and $CatFin_t$, which are normalized and transformed to their first principal component using estimated means, standard deviations and linear transformations obtained from the *previous* 10 years of data. This method of re-estimating the principal component each month ensures there is no lookahead bias in our analysis.

Since the main variable of interest throughout our analysis is *unexpected* shocks to systemic risk *levels*, we further estimate the market's expectations about $FinPC1^{norm}$. Following Chang et al. (2013) we assume market participants fit an ARMA(1,1) model to a factor in order to form their expectations about its future values. In order to estimate shocks to $FinPC1^{norm}$ in a real-time manner, we fit an ARMA(1,1) model to the first principal component of $FinCon$, $FinVol$ and $CatFin$ over the previous 10 years (120 months) of observations.

We denote the ARMA(1,1) parameter estimates from the previous 120 months by $\hat{a}_{t-120,t-1}$, $\hat{b}_{t-120,t-1}$ and $\hat{c}_{t-120,t-1}$. We estimate expected systemic risk by fitting the month $t-1$ value of the first principal component extracted from observed values of $FinCon^{norm}$, $FinVol^{norm}$ and $CatFin^{norm}$ from month $t-120$ through month $t-1$,

$$Fin\widehat{PC1}_t^{norm} = \hat{a}_{t-120,t-1} + \hat{b}_{t-120,t-1} Fin\widetilde{PC1}_{t-1}^{norm} + \hat{c}_{t-120,t-1}\widetilde{\epsilon_{t-1}},$$

where $Fin\widetilde{PC1}_{t-1}^{norm}$ denotes the month $t-1$ value of the first principal component extracted from data between month $t-120$ and $t-1$. Similarly, $\widetilde{\epsilon_{t-1}}$ denotes the time $t-1$ residual when fitting the ARMA(1,1) model, $\{\hat{a}_{t-120,t-1}, \hat{b}_{t-120,t-1}, \hat{c}_{t-120,t-1}\}$ to the first principal component, $Fin\widetilde{PC1}^{norm}$ extracted over the same sample period, from month $t-120$ through $t-1$.

We then define *unexpected* shocks to systemic risk, denoted $FinPC1$ throughout the paper, by

$$FinPC1_t = FinPC1_t^{norm} - Fin\widehat{PC1}_t^{norm}.$$

$FinPC1_t$ is our main measure of systemic risk. Importantly, this method of estimating shocks to systemic risk is free of econometrician look ahead bias and is meant to capture market beliefs about systemic risk in real time.

Panel A of Table 1 reports summary statistics for $FinPC1$ and unexpected shocks to each of the original systemic risk measures, $FinCon^{norm}$, $FinVol^{norm}$ and $CatFin^{norm}$ using similar 10 year rolling window ARMA(1,1) residuals. Figure 3 in the main text shows the time series of our $FinPC1$ factor used throughout the paper.

B Random Decision Forests

A random forest is an extension of a regression tree which is a simple yet flexible machine learning method for modeling the relation between a set of explanatory variables and a dependent variable.[18] While the objective of linear regression and regression trees are the same, the methods are very different. Whereas linear regression linearly projects the dependent variable onto the space of explanatory variables in a single step, regression trees iteratively split the data into subgroups based upon explanatory variables, creating the tree branches and leaves that grow as more and more refined splits of the data are implemented. The algorithm begins with all data in a single group which we can think of as the tree trunk. The data is then partitioned into two groups in such a way as to minimize an objective function. Specifically, the data is partitioned into two groups according to the value of one explanatory variable. Those observations whose value of the explanatory variable is above a threshold fall in one group and the remaining observations are assigned to the other group. The average value of explanatory variable values in each group is then computed. These two average values are used as fitted values much the same way that linear projections are used as fitted values in linear regression. However, regression trees allow us to further refine the fit by iteratively partitioning each of the resultant partitions of branches into two new branches. The average value of dependent variables within each of the final partitions can be used as the fitted value for observations in each of these final partitioned groups. The final partition groups are known as the leaves because they are at the end of the branches.

Notice that if we were to take fine enough partitions we could finish with a set of leaves in which each leaf contains only one observation. In this case we would perfectly fit the data. This is obviously not desirable because overfitting the data will not help with out of sample predictions. For this reason, we typically set a minimum number of observations allowed in each leaf or terminal partition. We use a minimum of 5 observations in each leaf (the MATLAB default).

Much the same as linear regression, the objective in partitioning the data is to minimize

[18]See Friedman et al. (2001) for a comprehensive discussion of random forests and regression trees.

the sum of squared errors. At each iteration, partitions are optimally chosen in order to minimize squared errors of all observations. That is, we begin in the tree trunk where the first partition is chosen by looking at all possible partitions of the data along all possible explanatory variables. The partition is chosen that minimizes squared errors between fitted (average within each partition) and actual dependent variables. Once this optimal partition has been accomplished, the next iteration searches over all branches and chooses the single partition from among the entire set of branches to split just one of these branches in such a way that reduces the overall sum of squared errors the most. This process is repeated until the desired number of leaves is attained.

Thus, regression trees offer a very flexible tool for estimating the relation between dependent and explanatory variables. Nonlinear relationships are easily accounted for as are complex interactions between dependent variables. One drawback to regression trees however, is that the algorithm for partitioning the data is "greedy" meaning that it only optimizes over the current set of possible partitions. It does not take into account the effect of the current partition on future partitions since the dynamic nature of the optimization problem is too computationally expensive to solve. As a result regression trees are highly path dependent. The choice of which partition to make first will dramatically affect the resultant branches. This is undesirable when our goal is to predict out of sample values.

In order to address the problems associated with path dependence of regression trees, random forests are essentially a bootstrap sample of regression trees where each tree has its own path dependence. Much like a bootstrap sample, a large number of regression trees are implemented where each tree is fit to a randomly sampled (with replacement) set of observations. Within each tree, at each partition decision, a random subsample of the explanatory variables is chosen and the partition can only be made along values of one of the variables in the subsample. This way the greedy algorithm in each tree within the forest will have its own path dependence. The random forest can then average over all of the decision trees to assign predicted values based upon the entire ensemble of trees in the forest. In our estimation each partition randomly selects four of the twelve explanatory variables along which to partition the data. Once a random forest has been fit to the data, out of sample predictions can be made by using a set of test data which was not a part of the training (in sample) data. The test data can be fed into the pre-trained set of regression trees making up the forest. Fitted values for the test data are assigned based upon the average values within leaves from the training data.

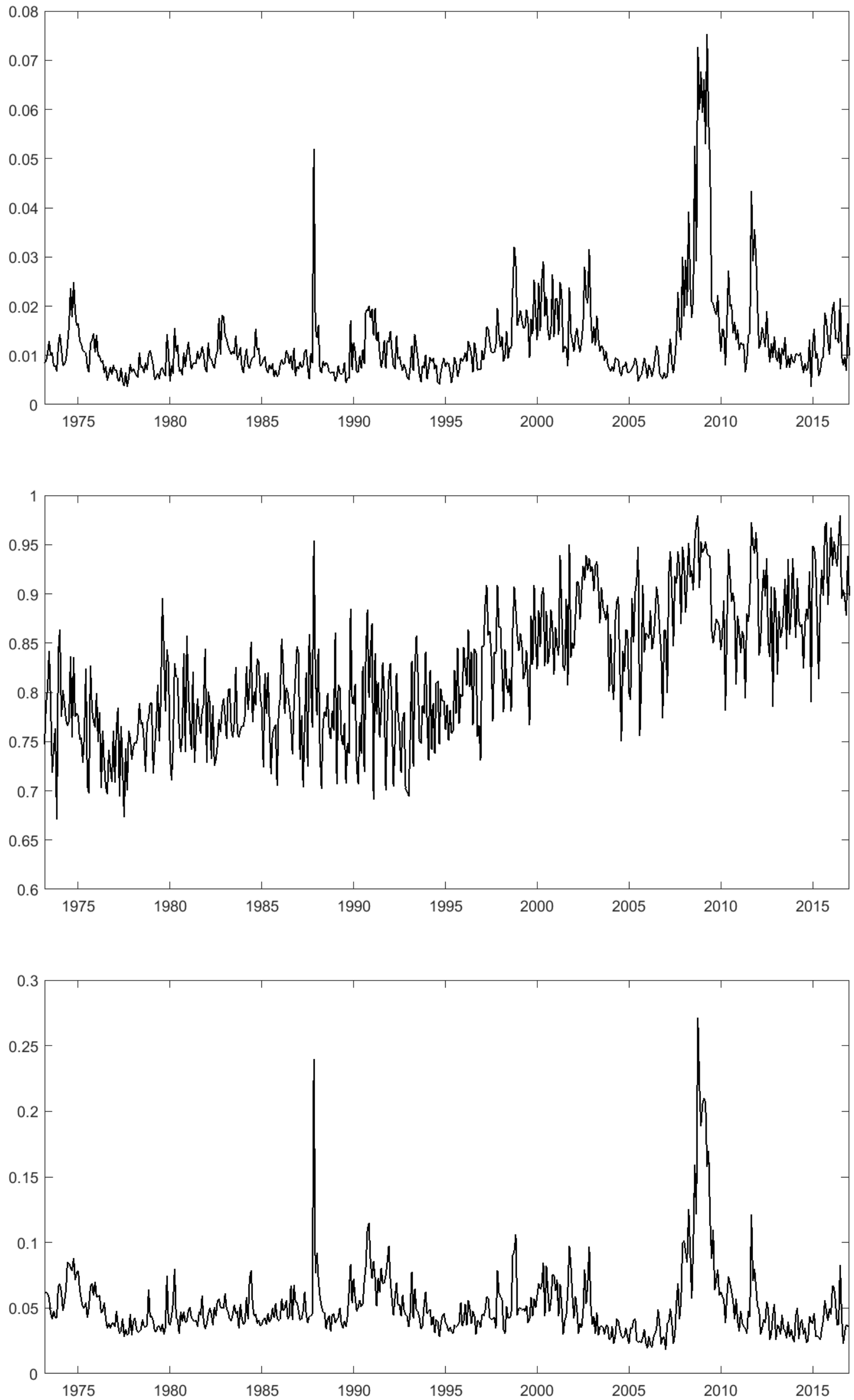

Figure A.1: **Three measures of systemic risk level**
This figure plots three measures of systemic risk levels that we used to extract our measure of systemic risk as described in Section 3.5. The first figure plots the level of $FinCon$. The second plots levels of $FinVOL$ and the third shows levels of $CatFin$.

C Additional Results

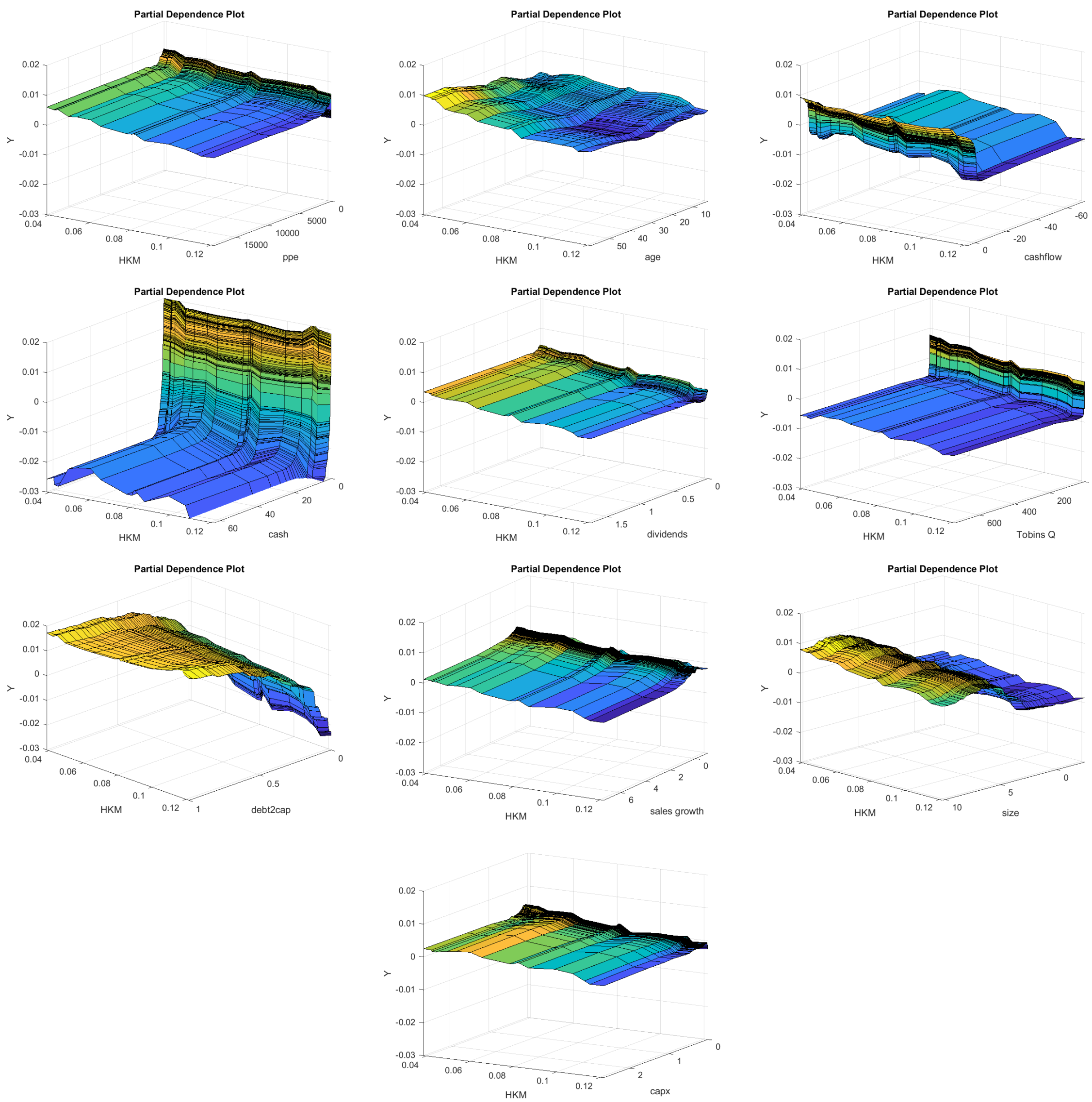

Figure A.2: **Debt Constraint Predictor Variables Interactions**
This Figure depicts a selection of variable interaction plots for the predictors used in fitting the random forest model to firm debt constraints. Each 3 dimensional plot shows the average fitted constraint measure for a given pair of values for two predictors used in the model.

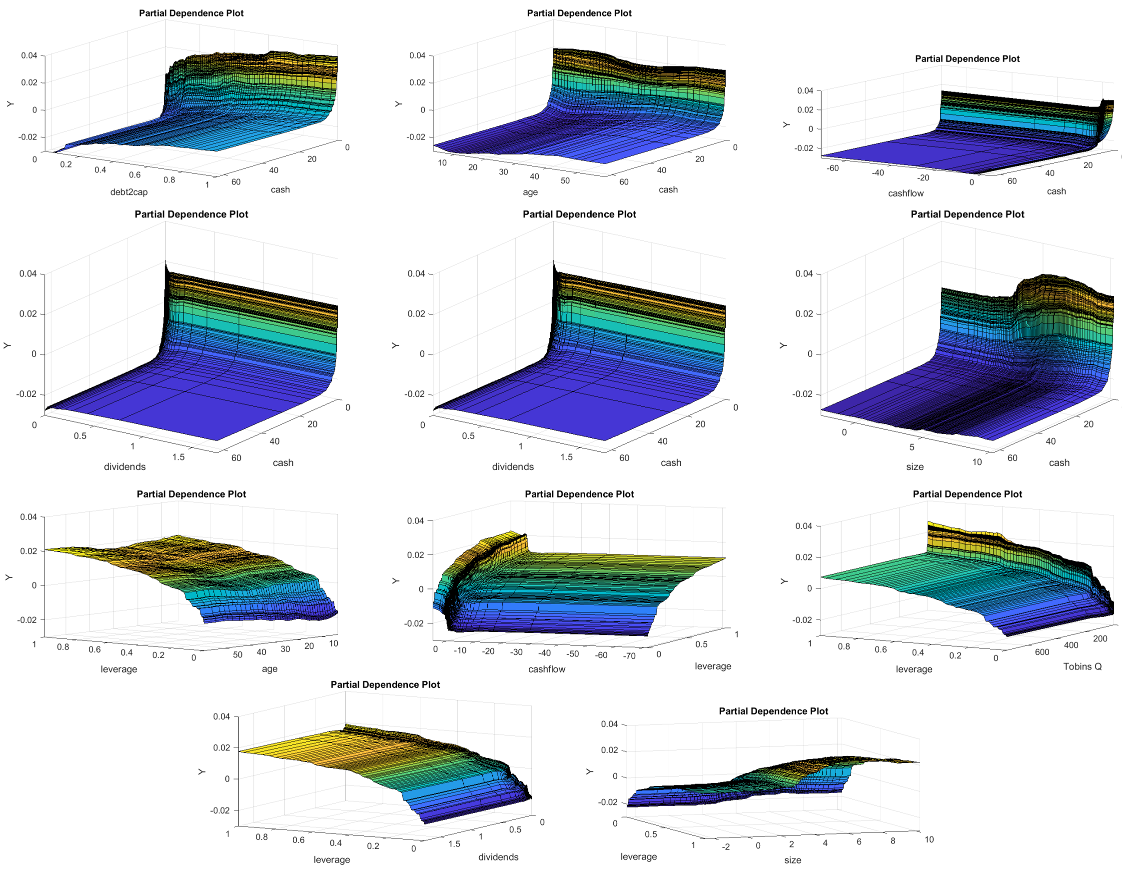

Figure A.3: **Debt Constraint Predictor Variables Interactions Continued**
This Figure depicts a selection of variable interaction plots for the predictors used in fitting the random forest model to firm debt constraints. Each 3 dimensional plot shows the average fitted constraint measure for a given pair of values for two predictors used in the model.

Table A.1: **Conditional Trading Strategy: Time Series Tests**

This table reports point estimates and t-statistics for the conditional trading strategy exploiting the relationship between shocks to systemic risk and return differentials between constrained and unconstrained firms in the subsequent month. Using our systemic risk factor FinPC1, we condition on the previous month's shock to systemic risk. If there is a positive shock to systemic risk then the following month a long position is taken in the top 20% most (debt) constrained large firms and a short position is taken in the 20% least constrained large firms. This table examines returns *only* during the months following positive shocks to $FinPC1$. All other months are excluded from the analysis. A total of 225 months out of 483 in the entire sample are included in the regressions reported here as there are 225 months with positive shocks to $FinPC1$. Firms' constraint rankings are calculated annually at the end of June, before trading on the first trading day of July and are updated on an annual basis. Since we do not rebalance the portfolios after each observed systemic risk shock, the trading strategy can be thought of as a simple unconditional position which is liquidated in months where we did not observe a positive shock in the previous month. The regressions reported in the table are the following:

$$FC_{s+1} = \alpha + \beta_1 PF^1_{s+1} + ... + \beta_k PF^k_{s+1} + \epsilon_{s+1}, \quad s \in \{s_1, s_2, ...s_n\}$$

where $\{s_1, s_2, ...s_n\}$ is the set of all months for which there is a positive shock. FC_{s+1} denotes month $s+1$ returns to the traded constraint factor using large, debt-constrained firms and $PF^1, PF^2, ...PF^k$ denote the pricing factors associated with each pricing model. T-statistics are reported in parentheses and are based upon Newey-West standard errors with 12 month lags.

MODEL	α	MRKT	SMB	HML	MOM	Liq (PS)	Profit.	Invest.	I/A	ROE	R^2
Mean	-0.0055										0.00
	(-2.01)										
CAPM	-0.0054	-0.0138									0.03
	(-1.97)	(-0.12)									
FF3	-0.0088	0.1009	0.1763	0.7764							30.63
	(-3.64)	(1.56)	(1.40)	(5.33)							
FF3 + MOM	-0.0092	0.1082	0.1754	0.7879	0.0566						31.00
	(-4.28)	(1.70)	(1.33)	(6.01)	(0.50)						
FF3 + MOM + Liq	-0.0093	0.1062	0.1732	0.7824	0.5821	0.0338					31.06
	(-4.30)	(1.59)	(1.30)	(6.02)	(0.51)	(0.48)					
FF5	-0.0106	0.1454	0.3823	0.6273			0.5508	0.0965			40.34
	(-4.63)	(2.32)	(4.06)	(4.19)			(4.69)	(0.37)			
HXZ	-0.0114	0.1011	0.3368						0.9291	0.2055	21.86
	(-3.92)	(1.19)	(1.85)						(5.20)	(1.28)	

Table A.2: **Conditional Trading Strategy: Non-Shock Time Series Tests**

This table reports point estimates and t-statistics for the conditional trading strategy that only trades in months which *do not* follow a positive shock. We use our systemic risk factor FinPC1 to condition on the previous month's shock to systemic risk. If there is a negative shock to systemic risk then the following month a long position is taken in the top 20% most (debt) constrained large firms and a short position is taken in the 20% least constrained large firms. Of the 483 months in the entire sample, 258 months follow negative shocks to $FinPC1$. Firms' constraint rankings are calculated annually at the end of June, before trading on the first trading day of July and are updated on an annual basis. Since we do not rebalance the portfolios after each observed systemic risk shock, the trading strategy can be thought of as a simple unconditional position which is liquidated in months where we did not observe a positive shock in the previous month. The regressions reported in the table are the following:

$$FC_{j+1} = \alpha + \beta_1 PF^1_{j+1} + ... + \beta_k PF^k_{j+1} + \epsilon_{j+1}, \quad j \in \{j_1, j_2, ...j_m\}$$

where $\{j_1, j_2, ...j_m\}$ is the set of all months for which there is a negative shock. FC_{j+1} denotes month $j+1$ returns to the traded constraint factor using large, debt-constrained firms and $PF^1, PF^2, ...PF^k$ denote the pricing factors associated with each pricing model. T-statistics are reported in parentheses and are based upon Newey-West standard errors with 12 month lags.

MODEL	α	MRKT	SMB	HML	MOM	Liq (PS)	Profit.	Invest.	I/A	ROE	R^2
Mean	0.0067										0.00
	(3.08)										
CAPM	0.0063	0.0504									0.32
	(2.85)	(0.54)									
FF3	0.0028	0.0846	0.2849	0.5398							16.88
	(1.35)	(0.96)	(2.24)	(2.83)							
FF3 + MOM	0.0031	0.0776	0.2871	0.5280	-0.0215						16.94
	(1.66)	(0.81)	(2.25)	(2.69)	(-0.27)						
FF3 + MOM + Liq	0.0020	0.0921	0.2854	0.5437	-0.0157	0.1530					18.76
	(1.11)	(1.01)	(2.26)	(2.78)	(-0.20)	(1.72)					
FF5	0.0003	0.1532	0.4200	0.3790			0.5588	0.2974			27.03
	(0.17)	(1.89)	(5.09)	(2.54)			(3.92)	(1.90)			
HXZ	0.0003	0.1273	0.3208						0.7491	0.1992	16.45
	(0.12)	(1.53)	(2.70)						(3.74)	(1.26)	