Systemic Default and Return Predictability in the Stock and Bond Markets

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Abstract

Using a structural model of default, we construct a measure of systemic default defined as the probability that many firms default at the same time. Our estimation accounts for correlations in defaults between firms through common exposures to shocks. The systemic default measure spikes during recession periods and is strongly correlated with traditional credit-based macroeconomic measures such as the default spread. Furthermore, our measure predicts future equity and corporate bond index returns, particularly at the one-year horizon, and even after controlling for many traditional return predictors such as the dividend yield, default spread, inflation, and tail risk. These predictability results are robust to out-of-sample tests.

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1 Introduction

As illustrated by a number of academic studies and starkly by the Global Financial Crisis of 2007 – 2009, tail risk and the threat of default can have significant impact on asset prices.[1] In this paper, we construct a novel measure of systemic default, which measures the joint probability of default of many firms. Our measure is constructed largely from accounting variables and historical equity return dynamics, avoiding the mechanical relation with expected future returns embedded in measures based on observed (and contemporaneous) prices. We find that our systemic default measure is high during recessions and exhibits a strong positive correlation with the default spread. Furthermore, it predicts future aggregate returns for both equities and BAA corporate bonds even after controlling for a series of other variables shown in the literature to predict returns. Our results are also robust to running out-of-sample tests.

To construct a measure of systemic default, we generalize the CAPM-style Merton model of Coval, Jurek, and Stafford (2009). Similar to their model, we assume that firms have a value process that follows a Geometric Brownian motion and that shocks to firm value have both a market term and an idiosyncratic term. The market term allows for correlated defaults, which can have significant effects on joint default probabilities as compared to assuming iid firm value processes. Coval, Jurek, and Stafford (2009) then make a homogeneous portfolio assumption, whereby firms have identical parameters. While this assumption is innocuous in their setting as they study portfolios of mortgages (for which a portfolio's components can plausibly be homogeneous), it does not apply to the very heterogeneous set of firms publicly traded in the U.S. Instead, we provide an important generalization that allows us to calculate the probability of at least x% of heterogeneous firms defaulting. Focusing on S&P 500 firms and also all above median market capitalization CRSP firms, our

[1] There is a long literature on the impact of tail risk on prices. Bates (2000), Pan (2002), and Cremers, Driessen, and Maenhout (2008), among others, find that there is a jump risk premium. Defaults are effectively the most extreme tail risks. In addition, the equity literature, including Fama and French (1993, 1996) argue that default risk is priced in equities.

measure of systemic default is then the probability that at least 1%, 2%, or 5% of firms will default in the next year.

Next, we examine the properties of our measure and its relation to macroeconomic conditions. We find that it is high during recessions, particularly during the recent Financial crisis and the early 1980s and 1990s recessions. A one standard deviation increase in our systemic default measure is associated with a roughly 30 basis point increase in the default spread, a commonly used measure of business conditions[2] that is also particularly applicable to default risk. Furthermore, we find a correlation of approximately 60% between our systemic default measure and the default spread. Overall, our results suggest that systemic default is an important measure of macroeconomic conditions.

Examining the relation between our systemic default measure and future equity and corporate bond returns at horizons ranging from one month to five years, we find that our measure has significant power to predict future returns. Predictability is particularly strong at horizons of six months to two years, which is reasonable given that our measure is designed to measure joint default probabilities at one-year horizons. At a one-year horizon, a one standard deviation increase in our measure predicts an increase in future excess CRSP value-weighted returns of 5.0% and an increase in excess Barclays BAA index[3] returns of 5.6%. Furthermore, we also see significant predictability in S&P 500, CRSP equal-weighted, and BAA - AAA returns. Somewhat surprisingly, we find some evidence of predictability in Barclays AAA index and Treasury excess returns.

Controlling for the predictors of equity returns examined by Welch and Goyal (2008), which include standard predictors such as book-to-market, dividend yield, and inflation, along with the Kelly and Jiang (2014) tail risk measure, we continue to find significant predictability with similar economic magnitudes as our univariate results.[4] Finally, we follow

[2]See Fama and French (1989). See Bai (2015) for a recent discussion of the default spread and its drivers.

[3]The Barclays bond indices were the Lehman indices until Lehman's bankruptcy in 2008 and Barclays' subsequent acquisition of some Lehman assets.

[4]In particular, both our measure and Kelly and Jiang's measure predict returns significantly. This is due to the fact that the measures reflect different parts of asset value distributions. Their measure is based on daily equity returns with cut-offs on the order of -3 to -5%, whereas our measure is based on joint defaults,

Welch and Goyal (2008) and run out-of-sample tests to ensure that our results are not simply an in-sample phenomenon. In contrast to many of the predictors considered by Welch and Goyal (2008), who find that most equity return predictors have negative out-of-sample R^2 values, we consistently find positive out-of-sample R^2 values between 0 and 20% for our one-year equity return prediction. Out-of-sample tests are also strong for Barclays BAA index returns. In contrast, out-of-sample tests are poor for Barclays AAA index returns and Treasury excess returns, the two safest classes of securities that we consider. This overturns the surprising in-sample predictability that we had found for these assets. Overall, we argue that our systemic default measure is a robust measure of aggregate macroeconomic conditions that does well in predicting future asset returns of indices exposed to significant default risk.

Our paper is related primarily to three literatures. The first is the literature on structural models of default. Vassalou and Xing (2004) use a Merton (1974) model to calculate distance-to-default at a firm level. We adapt their methodology to calculate some firm-level parameters before constructing our systemic default measure. Our joint default measure builds on Coval, Jurek, and Stafford (2009), who in turn use an extension of the Merton model. We add an important extension that allows for heterogeneity, making the model applicable to firms and not just homogeneous portfolios of mortgages. Other papers have shown the failure of structural models of default to match the level of yield spreads (e.g., Eom, Helwege, and Huang (2004) and Huang and Huang (2012)), but the ability of these models to match relative equity and corporate bond returns and fundamental volatility (e.g., Schaefer and Strebulaev (2008), Bao and Pan (2013), and Huang and Shi (2013)). Due partly to these results, we largely use equity returns as inputs into a Merton-like model in our calculations rather than levels of prices from credit markets.

A second related literature is a literature on calculating tail risk. Kelly and Jiang (2014) use observed daily equity returns to calculate tail risk, using a methodology from Hill (1975).

even more extreme negative events.

As discussed earlier, our measure captures a different part of the distribution and empirically, both our measure and theirs are relevant for predicting future returns. Seo (2014) and Gao and Song (2015) calculate tail risk using CDS and out-of-the-money options, respectively. An important conceptual difference is that we use accounting ratios and observed equity returns to calculate a P-measure joint default rate. While we argue that there are economic reasons to believe that joint default probabilities can predict future returns, the relation is not due to a direct measurement of time-varying risk premia. By matching to market prices of securities that pay-off in tail events, both Seo (2014) and Gao and Song (2015) calculate Q-measure tail events. That is, their measures embed risk premia, potentially including tail risk premia. Though the measurement of Q-measure tail risk is interesting, predictability of returns using such measures is not surprising. Our measure, instead, avoids the direct use of any pricing information from option and credit markets.

Finally, our paper is related to a long literature on aggregate predictability which has largely focused on equities. Early exceptions are Keim and Stambaugh (1986) and Fama and French (1989), who look at the predictability of bond and stock returns using variables such as the dividend yield, default spread, and term spread. More recent papers including Lettau and Ludvigson (2001), Lewellen (2004), and Ang and Bekaert (2007), have examined the robustness of equity return predictors.[5] Welch and Goyal (2008) provide a detailed summary of the literature, in addition to evidence that many equity return predictors are not robust across periods or in out-of-sample tests. Compared to the existing literature, our main contribution is to provide a new economically-founded variable that measures the probability of a significant fraction of firms defaulting together and to show that this variable predicts both equity and corporate bond returns.

The rest of the paper is organized as follows. In Section 2, we discuss how our systemic default measure is computed. In Section 3, we discuss the empirical properties of our measure. Results on predictability are presented in Section 4 and robustness checks and

[5]See also Bakshi and Chen (1994), Kothari and Shanken (1997), Pontiff and Schall (1998), Lamont (1998), Baker and Wurgler (2000), Goyal and Santa-Clara (2003), and Baker and Stein (2004).

out-of-sample tests are presented in Section 5. Section 6 concludes.

2 Measuring Systemic Default

2.1 General set-up

Our primary measure of systemic default is based on calculating the probability that at least x% of S&P 500 firms will default over the next year. Importantly, an average of the default rates of all firms in the sample does not measure the same thing as the probability of many defaults. As illustrated vividly in the Subprime mortgage crisis, the probability of many defaults is much higher in reality than under the assumption of uncorrelated defaults.[6] To do this, we start with the underlying assumption that all firms have a value process that follows a Geometric Brownian Motion

$$\frac{dV_{i,t}}{V_{i,t}} = \mu_i dt + b_{1,i}\sigma_1 dZ^A_{1,t} + ... + b_{N,i}\sigma_N dZ^A_{N,t} + \sigma_i dZ^I_{i,t}, \tag{1}$$

where all of the dZ are independent of each other and the superscript A indicates a common shock while the superscript I indicates an idiosyncratic shock. The firm value process has N shocks that are common across firms, but independent from each other. Each firm can have different loadings on the common shocks and it is through these common shocks that firm defaults are correlated. Very negative common shocks make all firms simultaneously more susceptible to default. In practice, once the firm-level loadings on common shocks are calculated, the N common shocks and the idiosyncratic shock can be aggregated into a single Brownian term as the sum of $N + 1$ independent normal random variables.

[6]Much of the intuition for correlated defaults comes from the literature on pricing tranches in collateralized mortgage obligations. See, for example, Coval, Jurek, and Stafford (2009).

2.2 Calculating asset returns

Our first goal is to calculate firm-level asset returns in order to be able to determine the exposure of each firm's asset returns to aggregate shocks. Unfortunately, asset returns are not easily observable.[7] Thus, we use accounting variables and equity returns to calculate asset returns. Prior to doing this calculation, it is useful to simplify equation (1) to[8]

$$\frac{dV_{i,t}}{V_{i,t}} = \mu_i dt + \sigma_{v,i} dZ_{i,t}, \tag{2}$$
$$\text{where } \sigma_{v,i} = \sqrt{b_{1,i}^2 \sigma_1^2 + ... + b_{N,i}^2 \sigma_N^2 + \sigma_i^2}.$$

Thus, the goal is to calculate a time series of $\Delta \log V_{i,t}$ and a $\sigma_{v,i}$ for each firm. To do this, we adopt a modification of the Vassalou and Xing (2004) methodology. For each firm-month, we start with a dataset that has the last 120 monthly log equity returns for the firm along with start-of-month values of equity market capitalization, face value of debt (measured as DLC + $\frac{1}{2}\times$DLTT), and the one-year Treasury rate associated with each of the 120 months.[9] We use the following iterative procedure that draws from Vassalou and Xing (2004).[10]

1. Start with $\sigma_{E,i}$, the volatility of monthly log equity returns as an initial guess for $\sigma_{v,i}$.

2. Calculate a time series of firm values $V_{i,t}$ for the firm using the standard Merton (1974)

[7] In principle, one could construct firm-level returns by calculating the weighted-average of corporate bond and equity returns as in Hecht (2000). However, not all firms have corporate bonds traded and even for firms with corporate bonds, trading can be sparse, producing noisy estimates of returns. See Doshi, Jacobs, Kumar, and Rabinovich (2015) for a recent example of backing out firm returns from equity returns and a Merton model.

[8] This aggregation of both idiosyncratic and common shocks to a single Brownian term is conceptually similar to calculating the total volatility of a return rather than the systematic and idiosyncratic terms separately.

[9] We require at least 60 months of full data for the calculation.

[10] Our procedure differs from Vassalou and Xing (2004) in that they use daily returns over the past year. Instead, we use monthly returns over a longer history. In addition, we also have a subtle difference in matching to equity returns and directly calculating asset returns using hedge ratios. We find that our calculated survival probabilities (based on all firms, not just S&P 500 firms) have a correlation with the data posted on Maria Vassalou's website of 0.65.

pricing equation

$$E = VN(d_1) - Ke^{-rT}N(d_2). \tag{3}$$

3. Using the current guess of $\sigma_{v,i}$, the time series of $V_{i,t}$ from step (2) and log equity returns, calculate log asset returns from

$$\Delta \log E = \left[\frac{N(d_1)}{N(d_1) - \frac{K}{V}e^{-rT}N(d_2)}\right] \Delta \log V, \tag{4}$$

   where equation (4) follows from the Merton hedge ratio,

$$\frac{\partial \log E}{\partial \log V} = \frac{dE}{dV}\frac{V}{E} = \frac{VN(d_1)}{VN(d_1) - Ke^{-rT}N(d_2)}, \tag{5}$$

   and is essentially a de-leveraging equation.[11]

4. Use the time series of log asset returns from step 3 to calculate a new $\sigma_{v,i}$. If the new $\sigma_{v,i}$ is within 1e-4 of the previous $\sigma_{v,i}$, the process is complete. Otherwise, use this new $\sigma_{v,i}$ in step (2) and repeat.

Once this process is complete, we have two primary sets of outputs. The first is the asset volatility, $\sigma_{v,i}$. The second is for each firm-month, a time series of log asset returns for the

[11] Note that in the de-leveraging equation, we calculate the hedge ratio using firm-level parameters at $t-1$ and log equity returns for the period from $t-1$ to t. Our choice to use hedge ratios stems from empirical evidence that Merton hedge ratios are effective. See, for example, Schaefer and Strebulaev (2008), Bao and Pan (2013), Huang and Shi (2013), and Bao and Hou (2014).

last 120 months. Using this data, we can calculate firm-level survival probabilities as

$$p_{i,t} = N\left[\frac{\log\left(\frac{V_{i,t}}{K_{i,t}}\right) + \left(\mu_i - \frac{1}{2}\sigma_{v,i}^2\right)T}{\sigma_{v,i}\sqrt{T}}\right], \tag{6}$$

where

$$K_{i,t} = DLC_{i,t} + \frac{1}{2}DLTT_{i,t}$$

$$\mu_i = \overline{\Delta \log V_{i,s}} \times 12 + \frac{1}{2}\sigma_{v,i}^2, \text{ and}$$

$V_{i,t}$ is inferred from equation (3).

2.3 Common firm value shocks

With a panel of asset returns calculated above, our next challenge is to calculate common factors. Rather than assuming what the common factors are (e.g., assuming a market factor or a particular multifactor set-up[12]), we use principal components analysis and take the first few principal components of asset returns as common factors. We perform PCA at the end of month t on the subset of firms that belong to the S&P 500. After performing principal components analysis, we extract the first five principal components. Denote these as PC_1 to PC_5.[13] To determine the loadings on the common factors in equation (1), we run the following regression for each firm i in each month t

$$\Delta \log V_{i,s} = b_{0,i} + b_{1,i}PC_{1,s} + ... + b_{5,i}PC_{5,s} + e_{i,s}. \tag{7}$$

The six volatility parameters in equation (1) are determined from the volatilities of the five principal components and the error term, respectively. Keep in mind that the principal components can be expressed using arbitrary units and this does not affect our following

[12]See Fama and French (1996) and Hou, Xue, and Zhang (2015).

[13]Empirically, the first principal component explains an average of 31.5% of the variation while the first five principal components together explain an average of 45.9% of the variation. Our choice of five principal components arises from the fact that by the fifth principal component, the additional explanatory power is only 2.1% on average.

analysis because what is important is $b_{j,i}$ times the volatility of PC_j. If the magnitude of PC_j is scaled up, its volatility is also scaled up, but $b_{j,i}$ will be scaled down correspondingly.

2.4 Calculating the correlated default probability

With all of the parameters in the firm value process in equation (1) calculated, we can calculate the probability of at least x% of firms defaulting by applying a simple insight from Coval, Jurek, and Stafford (2009). Conditional on the realizations of the common shocks, the default probabilities of the firms are independent of each other. Before delving into the details of the calculation, it is useful to take the firm value process in equation (1) and combine the common shocks by again taking advantage of the fact that the sum of independent normal random variables is a normal random variable. Equation (1) can be re-written as

$$\frac{dV_{i,t}}{V_{i,t}} = \mu_i dt + \sigma_i dZ^I_{i,t} + \sigma_{A,i} dZ^A_t, \tag{8}$$
$$\text{where } \sigma_{A,i} = \sqrt{b^2_{1,i}\sigma^2_1 + ... + b^2_{5,i}\sigma^2_5}.$$

Define T as some period in the future and $\tau = T - t$. We know the distribution of log asset value conditional on the realization of Z^A_t has only one source of uncertainty, the idiosyncratic shock.

$$\log V_{i,T}|Z^A_t = \log V_{i,t} + \left(\mu_i - \frac{1}{2}\sigma^2_i - \frac{1}{2}\sigma^2_{A,i}\right)\tau + \sqrt{\tau}\sigma_{A,i}Z^A_t + \sqrt{\tau}\sigma_i Z^I_{i,t} \tag{9}$$

The conditional probability of firm i's survival is

$$P(s_{i,t}|Z^A_t) = N(d_{2,i}), \tag{10}$$
$$\text{where } d_{2,i} = \frac{\log\left(\frac{V_{i,t}}{K_i}\right) + \left(\mu_i - \frac{1}{2}\sigma^2_i - \frac{1}{2}\sigma^2_{A,i}\right)\tau + \sqrt{\tau}\sigma_{A,i}Z^A_t}{\sigma_i\sqrt{\tau}}.$$

The important property that conditioning gives us is that $P(s_{i,t}|Z_t^A)$ is independent of $P(s_{j,t}|Z_t^A)$ for all $i \neq j$. This means that we can calculate the conditional probability of firms i and j both surviving as $P(s_{i,t}|Z_t^A) \times P(s_{j,t}|Z_t^A)$. In principle, this calculation can be done for an arbitrarily large number of firms and all 2^m possibilities can be enumerated, where m is the number of firms. The probability that M or more firms default can then be calculated by adding up the probabilities across all scenarios where at least M firms default. In practice such a direct enumeration is not feasible and we discuss a dimension-reducing enumeration methodology in the Appendix. Consider that even if we were to restrict our estimation to Dow Jones firms, this would require $2^{30} = 1.07 \times 10^9$ possibilities, *conditional* on a realization of Z_t^A. The unconditional probability (as described below) requires an integration over the distribution of Z_t^A, so a reasonable calculation using a 32-point quadrature would require 32 iterations of 1.07×10^9 possibilities. In comparison, our enumeration methodology is able to calculate the unconditional probability for 300 firms (an order of magnitude larger than the Dow Jones index) in a couple of seconds. Coval, Jurek, and Stafford (2009) avoid this enumeration problem by making a homogeneous portfolio assumption. That is, they assume

$$P(s_{i,t}|Z_t^A) = P(s_{j,t}|Z_t^A) \ \forall i, j \tag{11}$$

This makes the conditional probability of joint default follow a binomial distribution, greatly simplifying the calculations. Since Coval, Jurek, and Stafford (2009) focus on providing numerical analysis of representative portfolios of mortgages, it is reasonable to make this assumption in their setting. As we are attempting to estimate the joint default probability of firms, which can be very heterogeneous, this assumption is not appropriate for our setting. In particular, it is not unreasonable to assume that 100 mortgages have the same default probability, conditional on market conditions, especially if the mortgages are loans to households with similar credit scores and in the same region of the country. It is, however, unreasonable to assume that S&P 500 firms all have the same default probability, conditional on market conditions.

Finally, to calculate the unconditional probability of at least M defaults, we can simply integrate over the density function of Z_t^A.

$$\int_{-\infty}^{\infty} P(\text{At least M defaults}|z) f(z) dz, \tag{12}$$

where $f(z)$ is the normal probability density function.

3 Data & Systemic Default Estimates

3.1 Data

To construct our systemic default series, we use equity returns from CRSP and balance sheet information from Compustat. All Compustat data is lagged by three months to allow for reporting delays. The risk-free rate used in our calculation of default probabilities is the one-year Treasury rate from the U.S. Treasury's Constant Maturity Treasury series. The tail risk measure of Kelly and Jiang (2014) is constructed using daily CRSP returns, following the procedure outline in Sections 1 and 2 of their paper. The remaining independent variables are from Amit Goyal's website. This includes AAA and BAA bond yields, which are originally from FRED and Treasury yields originally from Ibbotson's Stocks, Bonds, and Bills Inflation Yearbook along with variables constructed by Welch and Goyal (2008) and extended to more recent periods.

Equity index returns (used as dependent variables) are directly from CRSP. Corporate bond index returns are from Datastream and are Barclays (formerly Lehman) indices. The AAA index is the Barclays United States Aggregate Corporate AAA index (LHIGAAA) and the BAA index is the Barclays United States Aggregate Corporate BAA index (LHIGBAA). The Treasury index is the 10-year Treasury bond series from CRSP.

3.2 Systemic Default Estimates

Using the methods discussed in Section 2, we construct the probability of at least 1%, 2%, or 5% of S&P 500 firms defaulting over the next year. While our base analysis uses all S&P 500 firms with sufficient historical data to estimate firm-level parameters (including loadings on aggregate factors), we also consider the robustness of our results to eliminating financials or using all firms with above median equity market capitalization in CRSP (Section 5.1).[14] In Table 1, we provide summary statistics of our joint default estimates and we plot the time series in Figure 1, along with NBER recession periods.[15]

A striking trend of our joint default estimates is that it spikes during recessions. During the recent Global Financial Crisis, the estimated probability of at least 1% of firms defaulting went above 90%, the largest value in our sample. We see similar, though smaller, spikes during recessions in the mid-1970s, the early 1980s, and the early 1990s. Interestingly, a spike in joint default probability in 2002 followed the Tech bubble in the early 2000s instead of occurring during the recession itself. This peak followed the delisting of Enron and preceded the delisting of Owens Corning, both in 2002.

The mean probabilities of at least 1%, 2%, and 5% of firms defaulting are 20.5%, 7.9%, and 0.8%, respectively. The probability of 5% of firms defaulting hovers around 0 for most of the sample, consistent with this being an extreme and unlikely left-tail event. The probability of 1% or 2% of firms defaulting is not nearly as extreme. In reality, we do sometimes see a significant number of S&P 500 firms default. For example, in 2002, Armstrong Holdings Inc, CNO Financial Group Inc, Enron Corp, Global Crossing Ltd, MCI Inc, Owens Corp, and US Airways Group Inc (Old) were all delisted with delisting codes of 560 (insufficient capital, surplus, and/or equity) or 574 (bankruptcy, declared insolvent). Thus, 2% default is arguably the right balance between having a very unlikely event, but one that is not so unlikely that it almost always has a probability of 0.

[14] Using all CRSP firms introduces defaults from smaller firms that are less likely to significantly impact market conditions. Hence, we restrict to larger firms.

[15] Figure 2 plots joint default probabilities for firms above median equity market capitalization.

An important caveat for our joint default measure is that it is a structural model-based estimate of the joint default of firms based on the firms remaining as standalone companies. The model does not account for government bailouts of firms, nor does it account for distressed firms that are acquired by other firms before default.[16] Thus, we consider our joint default measure an estimate of the probability of x% of firms defaulting absent interventions by the government or other firms. Even more broadly, it is a macroeconomic measure of the general expectation of a default crisis in the near future.

Next, we consider how our measure is related to the default spread, a traditional measure of aggregate default expectations. Defined as the difference between the yields on BAA bonds and AAA bonds, the default spread is meant to capture default expectations by benchmarking a set of moderately risky bonds (BAA) against very safe bonds (AAA). AAA bonds are used instead of Treasuries as part of the gap between BAA and Treasuries can be due to illiquidity or tax reasons.[17] Though it is likely true that there is some difference in liquidity between AAA and BAA bonds, the default spread nevertheless is a proxy for aggregate default expectations.

In Panel A of Table 2, we consider the contemporaneous relation between the default spread and our joint default measure. We find a statistically and economically significant relation. Regressing the default spread on 1% joint default probability, we find an R^2 of 44.5%, implying a correlation of 66.7%. The R^2 for 2% joint default probability is similar at 43.4%. Using 5% joint default probability, we see a smaller R^2 of 22.5%. The smaller correlation with 5% joint default probability arises from the fact that 5% joint default probabilities largely reflect only the worst economic states, whereas the 1% joint default probability and default spread reflect variation in much more moderate economic states. Controlling for

[16]For example, Bear Stearns was delisted in May 2008 (with a delisting code of 231) after being acquired by J.P. Morgan Chase. Though anecdotal evidence suggests that Bear Stearns likely would have defaulted absent this acquisition, we never actually observe a default. See Meier and Servaes (2014) for further discussion of distressed acquisitions.

[17]See Bao, Pan, and Wang (2011) for a discussion of corporate bond illiquidity and Chen (2010) and Feldhutter and Schaefer (2015) for a discussion of the use of BAA-AAA spreads to mitigate tax and liquidity issues.

other known predictors of the default spread[18]), we continue to find a significant relation between the default spread and joint default probability.

In Panels B and C of Table 2, we consider the relation of joint default probability with BAA - Treasury and AAA - Treasury spreads, respectively. We find evidence that the BAA - Treasury spread is related to joint default probabilities, though we lose statistical significance for 1% and 5% joint default probabilities once controls are included. This loss of statistical significance occurs even though the economic significance is comparable to Panel A. It is important to keep in mind that the BAA - Treasury spread reflects both differences in default expectations between BAA and Treasury bonds and also differences in liquidity. The differences in liquidity make the BAA - Treasury spread a noisier measure of aggregate default relative to the default spread, decreasing the statistical significance of any regressor without necessarily affecting the point estimate much. In Panel C, we consider the AAA - Treasury spread, which reflects a strong liquidity component and not much of a default component. Here, we find virtually no relation with our joint default measure.

4 Return Predictability

4.1 Univariate analysis

To examine the predictive power of our systemic default measure, we run a standard return predictability regression

$$r_t = a + bp_{t-1} + \varepsilon_t, \tag{13}$$

where p_{t-1} is our systemic default measure and r_t is the annualized excess return of an index over different holding periods. To account for overlapping returns, we use Hodrick

[18]See Duffee (1998), Collin-Dufresne, Goldstein, and Martin (2001), and Campbell and Taksler (2003).

(1992) standard errors.[19] We normalize our systemic default measure to have zero mean and unit variance to facilitate interpretation. Note that such normalization simply scales the coefficient and has no effect on t-statistics. Though the mean and variance of the joint default series is not known ex-ante, this does not induce a look-ahead bias in the regression. Instead, it is equivalent to an econometrician running the standard predictability regression and normalizing the coefficient ex-post when interpreting economic significance.

In Table 3, we present results on predictability of equity, corporate bond, and Treasury bond index returns using our systemic default measure. We see that 2% joint default predicts excess returns across security markets. In particular, a one standard deviation increase in the systemic default measure predicts an increase in one-year excess returns of 4.99% for the CRSP value-weighted index and 5.60% for the BAA corporate bond index. The strength of predictability tends to be greater for the CRSP equal-weighted index than it is for the S&P 500 or CRSP value-weighted indices, suggesting that high systemic default tends to have a stronger effect on the required return of small firms. This is consistent with investors requiring higher returns for smaller firms in poor economic times because they are more concerned with the effect of macroeconomic conditions on these firms. In addition, previous literature (e.g., Kothari and Shanken (1997) and Pontiff and Schall (1998)) has found predictability to be stronger for equal-weighted than value-weighted indices.

For bonds, we find that predictability is stronger for BAA bonds than AAA bonds and that the difference is statistically significant. While a one standard deviation increase in the systemic default measure predicts an increase in excess one year returns of 5.60% for BAA bonds, it predicts only a 3.11% increase for AAA bonds. The difference is statistically significant. For long-term Treasuries, we find even smaller predictability, with a coefficient of 2.15%. The stronger predictability for lower grade corporates is natural as our predictor variable is a measure of systemic default. If the market is particularly concerned about

[19] See Singleton (2006) and Ang and Bekaert (2007) for a discussion of Hodrick standard errors compared to Hansen and Hodrick (1980) and Newey and West (1987) standard errors. We also consider bootstrap standard errors. Similar to Kelly and Jiang (2014), we find that bootstrap standard errors produce even stronger results than those based on Hodrick standard errors.

default, we would expect an increase in investment in safe assets such as AAA corporates and Treasuries. This would decrease the expected return on safe securities. Hence, the positive predictability for AAA corporates and Treasury bonds is somewhat of a surprise.

In Table 3, we consider three versions of our systemic default measure, 1%, 2%, and 5% joint default. Results are weaker for the 1% measure (Panel A) than the 2% (Panel B), and 5% (Panel C) measures, particularly for equities. This suggests that the predictive power for our systemic default measure arises from relatively rare joint default events. Recall that the mean of 1% joint default is more than 20%, making it unlikely, but not a rare event. In contrast, 2% and 5% joint default have means of 7.9% and 0.8%, making them significantly rarer events.

4.2 Controlling for other predictors

A natural question is whether our systemic default measure is just one of the traditional default measures in disguise.[20] Thus, we run a multivariate regression,

$$r_t = a + bp_{t-1} + cZ_{t-1} + \varepsilon_t, \tag{14}$$

where p_{t-1} is our systemic default measure, Z_{t-1} is a vector of other return predictors, and r_t is an annualized index excess return over different holding periods. As other return predictors, we consider the variables from Welch and Goyal (2008) and also the tail risk measure from Kelly and Jiang (2014).

We present results for the S&P 500, the CRSP value-weighted index, and the CRSP equal-weighted index in Panels A, B, and C of Table 4, respectively. We focus on 2% joint default probability as it strikes a reasonable balance between having events that are far enough in the left tail, but not so far in the left tail as to have zero probability most of the time. Systemic default is consistently a predictor of equity returns at one-to-two-

[20]For example, in the cross-sectional equity return literature, Jackson and Johnson (2006) argue that momentum and postevent drift are both manifestations of persistence in returns following news.

year horizons even after controlling for 13 other traditional equity return predictors. A one standard deviation increase in the systemic default measure predicts an increase in future one-year excess returns of 5.32%, 5.76%, and 7.95% for S&P 500, CRSP value-weighted, and CRSP equal-weighted returns, respectively. Compared to the previously discussed univariate results, we see hardly any change in the economic impact of systemic default.

The 13 controls largely fall into four groups and we discuss the most significant controls in turn. Book-to-Market, Earnings Price Ratio, and Dividend Payout Ratio are variables that have been linked in the cross-sectional literature as predicting relative returns either due to measuring investor sentiment (e.g., Lakonishok, Shleifer, and Vishny (1994)) or measuring firm fundamentals (e.g., Fama and French (1992)). In the time series, Fama and French (1988) find that both Dividend Price Ratio and Earnings Price Ratio positively predict future equity returns. Kothari and Shanken (1997) and Pontiff and Schall (1998) find that Book-to-Market positively predicts future equity returns. In univariate analysis, we find positive and significant predictability for equity returns for all three variables. When included in a multivariate regression in Table 4, we see that Book-to-Market is significant, but of the wrong sign in most specifications, while Earnings Price Ratio tends to be positive and significant, and Dividend Price Ratio insignificant.

Turning to interest rate-related variables, we see that the Term Spread positively predicts equity returns. As argued in Fama and French (1989), the Term Spread is a measure of the term premium, the required premium for holding long-term (interest rate sensitive) securities. If we think of pricing equity using a dividend discount model, the duration of equity securities is much closer to long-term bonds than Treasury bills.

Next, we find that net equity expansion, a measure of equity issuance, positively predicts equity returns in a multivariate regression framework. This provides seemingly contradictory evidence to Baker and Wurgler (2000), who find that when there is more equity issuance (relative to debt issuance), the equity market tends to do poorly afterwards. However, we find that this inconsistency is due to the multivariate regression framework. In univariate regressions, net equity expansion negatively predicts future equity returns.

Finally, we find that the Kelly and Jiang (2014) tail risk measure is a positive predictor of excess equity returns. Initially, it may seem somewhat surprising that both their measure and ours are significant predictors of equity returns as both measures are designed to measure tail events. While the measures draw from roughly similar concepts, what they measure is different. The Kelly and Jiang (2014) measure uses daily returns to measure tail risk. The tail threshold in their estimates are often on the order of -3 to -5% (for individual firm daily returns), significant negative events, but not on the order of multiple large firms defaulting. Thus, the significance of both measures draws from the fact that the two measures are estimates of different parts of the left tail.

In Table 5, we turn to multivariate regression analysis of bond return predictability. We continue to see that our systemic default measure predicts bond returns. A one standard deviation increase in the systemic default measure predicts an increase in one-year BAA excess returns of 6.18%. We also see similar predictability for AAA and Treasury bond excess returns. This is somewhat surprising in light of their low exposure to default risk. In Section 5.2 below, we provide some evidence that suggests that predictability in these low default securities is only an in-sample phenomenon.

Among the control variables, we see strong significance in the Dividend Price Ratio, the Long Term Yield, and the Term Spread. As with equities, the Dividend Price Ratio is surprisingly negative. Both the Long Term Yield and the Term Spread positively predict bond returns. These are both natural as we would expect there to be a term premium embedded in long-term bond returns. When this premium is higher, the required return on bonds is higher.

5 Out-of-Sample Tests & Other Considerations

5.1 Alternative systemic default measures

For most of the paper, we have presented results where our systemic default measure is constructed using all S&P 500 firms. The only restriction other than S&P 500 membership at the time of construction is that firms have enough historical data to allow for calculation of firm-level parameters (as described in Section 2.2) and common firm value shocks (Section 2.3). Though the use of S&P 500 firms is natural as the default of the largest firms in the U.S. economy is a plausible ex-ante indication of trouble in financial markets, we consider two alternative choices here. First, while it was clearly illustrated in the Global Financial Crisis that the health of financial firms is extremely important for the economy, one might be concerned about the use of a structural model in estimating the default probability of financial firms. Hence, we also consider results with financial firms omitted. Second, one might be concerned that defaults of non-S&P 500 firms are also relevant to aggregate economic conditions. Hence, we also construct our joint default measure using all firms above the median equity market capitalization in CRSP.[21]

Multivariate results using the alternative joint default measures are presented in Table 6. For brevity, only the joint default coefficients from the multivariate regressions using 2% joint default are reported, and the coefficients of the controls are omitted in the tables. In Panel A, we present results on a measure using S&P 500 firms, but omitting financials. We see that at a one-year horizon, our systemic default measure has predictive power across indices with particularly strong predictive power for the CRSP equal-weighted index. A one standard deviation increase in our measure is associated with an increase in future 12-month excess returns of 8.56% in the CRSP equal-weighted index. We also see strong results for corporate bonds, as a one standard deviation increase in our measure predicts an increase in excess returns of 3.29 and 3.90% in AAA and BAA excess returns, respectively. For the

[21] An alternative would be to use S&P 1500 firms, but the S&P 1500 index was not launched until 1995, whereas our joint default series starts 20 years earlier.

corporate bond indices, we see predictability for horizons from one month all the way to 36 months. We also see evidence of predictability for Treasury bonds as a one standard deviation increase in our systemic default measure predicts a 2.50% increase in Treasury bond excess returns. Furthermore, we also see evidence of predictability at six month and 24 month horizons for most indices.

In Panels B and C, we consider firms that are above the median for CRSP equity market capitalization with and without financials. We continue to find evidence of significant predictability, particularly at the 12-month horizon. Overall, we find considerable evidence that joint default predicts future returns across different asset classes.

5.2 Out-of-sample tests

Though our evidence to this point suggests that systemic default is a powerful macroeconomic variable that predicts index returns across security classes, Welch and Goyal (2008) argue that findings of in-sample predictability should be interpreted with some skepticism. Instead, they argue that it is important to test the out-of-sample performance of return predictors before concluding that there is predictability.[22] Welch and Goyal (2008) show strong evidence that equity return predictability is an in-sample phenomenon for many traditional return predictors. For example, they find out-of-sample $\bar{R}^2$ values of -1.93% and -20.79% for dividend yield when using the full history of data and only 1977 – 2006, respectively. The interpretation of their out-of-sample $\bar{R}^2$ is that if the predictor performs worse than simply setting forecasts to the sample mean, $\bar{R}^2$ is negative. Hence, their evidence suggests that particularly in the later part of their sample, dividend yield is not a useful predictor of equity returns. They find a similar pattern for a series of other predictors, including earnings yield, book-to-market, and investment-capital ratio.

We use only the data available to time t and run the predicative regressions of the market index returns on the joint default risk measures as in the main univariate test. Then we

[22] We refer readers to Section 2 of Welch and Goyal (2008) for details of the empirical tests.

construct the out-of-sample forecast of the market index returns for the next month. To allow enough observations in forming the initial estimates, we require at least 240 historical observations. The out-of-sample R^2 is calculated as $\bar{R}^2 = 1 - \sum_t (\hat{r}_{t+1|t} - r_{t+1})^2 / \sum_t (\bar{r}_t - r_{t+1})^2$, where $\hat{r}_{t+1|t}$ is the index return forecast using data up until t, and $\bar{r}_t$ is the historical average return until t. Further we conduct the out-of-sample predictive power test using the method proposed in Clark and McCracken (2001), following Welch and Goyal (2008) and Kelly and Jiang (2014).

In Table 7, we present out-of-sample test results for our systemic default measure. Focusing on our 2% joint default measure, we see that our predictability results for AAA corporate bond and Treasury bond returns are only in-sample phenomena. Across horizons, $\bar{R}^2$ values are negative, indicating that predictive regression underperform sample means. However, we find that our measure has positive and statistically significant out-of-sample predictive power for equity indices, and especially for BAA corporate bond returns.

The poor out-of-sample performance for AAA corporate bonds and Treasury bonds overturns a somewhat surprising in-sample result on predictability. AAA corporates and Treasuries have little exposure to default risk, making it surprising that a measure designed to capture joint default should predict their returns. In addition, flight-to-safety phenomena documented in the literature suggest that, if anything, expected returns to safe assets such as AAA bonds and Treasuries should decline in poor economic states as investors flee to these safe assets.[23] In contrast, expected returns on riskier assets should rise. Thus, the significant out-of-sample results for equities and BAA corporates along with the insignificant out-of-sample results for low default assets supports the argument that our measure is an important macroeconomic measure of default.

[23] See Baele, Bekaert, and Inghelbrecht (2010) for a discussion of flight-to-safety and how it affects Treasury and equity returns.

6 Conclusion

In this paper, we build on a CAPM-like Merton model from Coval, Jurek, and Stafford (2009) to construct an systemic default measure. The measure is based on calculating the probability of many joint defaults. As illustrated vividly in the recent Subprime mortgage crisis, it is important to account for correlations in shocks when calculating the probability of joint defaults, and following Coval, Jurek, and Stafford (2009), we model this as exposure to common factors. To apply the joint default methodology, we generalize the model to avoid making a homogeneous portfolio assumption, whereby all firms have the same parameters. While this is a reasonable simplification for studying portfolios of mortgages, it is not suitable for studying a very heterogeneous set of firms. We devise a numerical procedure that allows for firm heterogeneity, but avoids enumerating all possible combinations of defaults and survivals. This makes an estimation of joint default over a large set of firms feasible.

Our systemic default measure shows significant correlation with the business cycle, peaking during NBER recessions and remaining fairly low during quiet periods. We find that our measure robustly predicts future equity and BAA corporate bond returns, particularly for a one-year horizon. This predictability is robust to a series of controls, including the controls in Welch and Goyal (2008) and the tail risk measure of Kelly and Jiang (2014). We surprisingly find some evidence of in-sample predictability for AAA corporate bonds and Treasuries, but the results are not robust to the out-of-sample tests advocated by Welch and Goyal (2008). Overall, we find that systemic default is an important macroeconomic variable that is able to explain expected returns in securities exposed to default risk.

Tables & Figures

Table 1: **Summary Statistics for Joint Default Estimates**

Variable	Mean	Std. Dev.	Skewness	Min.	Max.
1%	0.205	0.231	1.196	0	0.908
2%	0.079	0.136	2.452	0	0.733
5%	0.008	0.027	6.328	0	0.288
N = 496					

This table reports summary statistics for 1%, 2% and 5% joint default probabilities estimated using S&P 500 firms.

Table 2: **Systemic Default and the Default Spread**

			Panel A: BAA-AAA Yield Spread				
	1%	2%	5%		1%	2%	5%
Joint Default	0.315***	0.311***	0.224***		0.120***	0.122***	0.0711***
	(7.53)	(7.78)	(5.72)		(3.21)	(3.82)	(2.96)
Market Leverage				-0.139***	-0.114***	-0.117***	-0.134***
				(-3.21)	(-2.74)	(-2.92)	(-3.23)
Market Volatility				0.354***	0.293***	0.296***	0.327***
				(9.64)	(7.31)	(7.80)	(8.78)
Idiosyncratic Volatility				-0.277***	-0.249***	-0.255***	-0.272***
				(-6.50)	(-6.04)	(-6.39)	(-6.68)
3M Treasury Yield				0.429***	0.311***	0.326***	0.401***
				(8.33)	(5.21)	(6.06)	(8.03)
Term Spread				0.264***	0.211***	0.215***	0.251***
				(7.13)	(5.50)	(5.91)	(7.04)
P/E Ratio				0.0757**	0.0718**	0.0657*	0.0644*
				(1.98)	(1.97)	(1.84)	(1.76)
Industrial Production				-0.0932***	-0.0696***	-0.0645***	-0.0788***
				(-5.22)	(-4.24)	(-4.04)	(-4.77)
Constant	1.115***	1.115***	1.115***	1.116***	1.116***	1.116***	1.116***
	(25.00)	(24.85)	(20.17)	(37.34)	(39.04)	(40.14)	(39.11)
Observations	489	489	489	487	487	487	487
Adjusted R^2	0.445	0.434	0.225	0.671	0.700	0.707	0.687
			Panel B: BAA-Long Treasury Yield Spread				
	1%	2%	5%		1%	2%	5%
Joint Default	0.316***	0.351***	0.285***		0.101	0.133**	0.0416
	(4.32)	(5.33)	(4.99)		(1.55)	(2.40)	(1.03)
Market Leverage				-0.174**	-0.152**	-0.150**	-0.170**
				(-2.40)	(-2.11)	(-2.13)	(-2.37)
Market Volatility				0.539***	0.487***	0.475***	0.523***
				(8.84)	(7.02)	(7.21)	(8.11)
Idiosyncratic Volatility				-0.250***	-0.227***	-0.226***	-0.247***
				(-3.48)	(-3.12)	(-3.20)	(-3.45)
3M Treasury Yield				0.299***	0.200*	0.187**	0.283***
				(3.45)	(1.91)	(1.98)	(3.23)
Term Spread				0.171***	0.126*	0.117*	0.163***
				(2.75)	(1.88)	(1.84)	(2.62)
P/E Ratio				0.0367	0.0335	0.0259	0.0302
				(0.60)	(0.55)	(0.43)	(0.49)
Industrial Production				-0.140***	-0.120***	-0.109***	-0.131***
				(-4.78)	(-4.30)	(-3.98)	(-4.70)
Constant	1.837***	1.837***	1.837***	1.836***	1.835***	1.835***	1.836***
	(23.37)	(24.67)	(23.02)	(36.14)	(35.97)	(36.84)	(36.25)
Observations	489	489	489	487	487	487	487
Adjusted R^2	0.211	0.260	0.171	0.567	0.576	0.587	0.569
			Panel C: AAA-Long Treasury Yield Spread				
	1%	2%	5%		1%	2%	5%
Joint Default	0.00149	0.0401	0.0606*		-0.0190	0.0108	-0.0295
	(0.03)	(0.94)	(1.78)		(-0.48)	(0.31)	(-1.19)
Market Leverage				-0.0344	-0.0384	-0.0325	-0.0367
				(-0.78)	(-0.88)	(-0.74)	(-0.84)

Market Volatility				0.185***	0.194***	0.179***	0.196***
				(4.94)	(4.61)	(4.34)	(4.99)
Idiosyncratic Volatility				0.0268	0.0225	0.0288	0.0248
				(0.61)	(0.51)	(0.65)	(0.57)
3M Treasury Yield				-0.130**	-0.111*	-0.139**	-0.118**
				(-2.46)	(-1.76)	(-2.36)	(-2.23)
Term Spread				-0.0931**	-0.0846**	-0.0975**	-0.0874**
				(-2.45)	(-2.08)	(-2.44)	(-2.31)
P/E Ratio				-0.0389	-0.0383	-0.0398	-0.0343
				(-1.03)	(-1.02)	(-1.05)	(-0.91)
Industrial Production				-0.0467**	-0.0504***	-0.0441**	-0.0526***
				(-2.54)	(-2.85)	(-2.49)	(-2.98)
Constant	0.722***	0.722***	0.722***	0.720***	0.720***	0.720***	0.720***
	(14.91)	(14.99)	(15.19)	(23.21)	(23.41)	(23.17)	(23.47)
Observations	489	489	489	487	487	487	487
Adjusted R^2	-0.002	0.008	0.022	0.438	0.438	0.437	0.441

The table reports results from the following regressions: $CS_t = \alpha + \beta p_t + \gamma Z_t + \varepsilon_t$. The dependent variables are the levels of BAA-AAA, BAA-Long Treasury and AAA-Long Treasury yield spreads. p_t represents the estimated 1%, 2% and 5% joint default probabilities. Z_t represents a vector of control variables: Market leverage is total liabilities divided by the sum of total liabilities and the market value of corporate equity in the non-financial corporate sector; Market Volatility is the six-month moving average of monthly realized market volatility estimated from daily returns; Idiosyncratic volatility is the six-month moving average of the average idiosyncratic realized stock return volatility estimated from daily returns; Term spread is the 10-year minus 3-month treasury yields; Price-earning ratio is the price-earning ratio of the S&P 500 index; Industrial production is the growth rate of the industrial production index. All independent variables are normalized to unit standard deviation, so reported coefficients are scaled to be interpreted as the percentage yield spread change from a one-standard-deviation increase in the independent variable. Test statistics are calculated using Hodrick's (1992) standard error correction for overlapping data with lag length equal to the number of months in each horizon. 1%, 5% and 10% statistical significance are indicated by ***, **, and * respectively.

Table 3: **Univariate Return Predictability**

Panel A: 1% Joint Default Probabilities						
	1 M	6 M	12 M	24 M	36 M	60 M
S&P 500	0.56	2.23	2.74	2.24	1.93	2.44
t-stat	(0.23)	(1.06)	(1.31)	(1.13)	(0.96)	(0.98)
Adjusted R^2	-0.002	0.007	0.022	0.028	0.026	0.031
CRSP Value-weighted	0.72	2.60	3.15	2.65	2.38	2.99
t-stat	(0.29)	(1.20)	(1.50)	(1.41)	(1.31)	(1.40)
Adjusted R^2	-0.002	0.009	0.029	0.042	0.045	0.059
CRSP Equal-weighted	-10.56***	2.48	4.48	4.14*	3.19	3.70
t-stat	(-3.31)	(0.82)	(1.60)	(1.75)	(1.45)	(1.42)
Adjusted R^2	0.020	0.003	0.031	0.062	0.054	0.059
AAA	2.61**	2.19**	2.39**	2.58***	2.63***	2.82**
t-stat	(2.28)	(2.21)	(2.29)	(2.60)	(2.75)	(2.48)
Adjusted R^2	0.008	0.035	0.071	0.141	0.193	0.179
BAA	3.56***	4.19***	4.66***	4.46***	4.11***	4.41***
t-stat	(3.04)	(3.67)	(3.96)	(4.31)	(4.25)	(3.83)
Adjusted R^2	0.00	0.101	0.193	0.308	0.354	0.320
BAA - AAA	0.95	2.00***	2.27***	1.89***	1.48***	1.58***
t-stat	(1.56)	(3.66)	(4.60)	(4.84)	(4.34)	(3.95)
Adjusted R^2	0.003	0.092	0.220	0.320	0.326	0.303
Treasury Bonds	2.39*	1.67	1.65	1.98**	2.12**	2.32**
t-stat	(1.95)	(1.61)	(1.58)	(2.12)	(2.51)	(2.34)
Adjusted R^2	0.006	0.017	0.032	0.089	0.157	0.154
Panel B: 2% Joint Default Probabilities						
	1 M	6 M	12 M	24 M	36 M	60 M
S&P 500	2.02	4.44**	4.46**	3.04*	2.44	2.63
t-stat	(0.84)	(2.17)	(2.26)	(1.71)	(1.39)	(1.23)
Adjusted R^2	-0.001	0.033	0.063	0.054	0.043	0.038
CRSP Value-weighted	2.20	4.88**	4.99**	3.43**	2.81*	3.04
t-stat	(0.88)	(2.31)	(2.52)	(2.03)	(1.76)	(1.64)
Adjusted R^2	-0.000	0.037	0.076	0.072	0.066	0.063
CRSP Equal-weighted	-10.97***	4.98*	7.01***	5.35**	3.90**	4.03*
t-stat	(-3.44)	(1.69)	(2.67)	(2.53)	(2.04)	(1.81)
Adjusted R^2	0.021	0.018	0.081	0.106	0.084	0.073
AAA	3.61***	3.22***	3.11***	2.65***	2.75***	2.70***
t-stat	(3.17)	(3.40)	(3.24)	(3.02)	(3.42)	(2.83)
Adjusted R^2	0.018	0.079	0.122	0.152	0.218	0.170
BAA	4.63***	5.60***	5.60***	4.52***	4.15***	4.07***
t-stat	(3.98)	(5.26)	(5.35)	(5.00)	(5.08)	(4.06)
Adjusted R^2	0.029	0.181	0.281	0.321	0.371	0.283

	1 M	6 M	12 M	24 M	36 M	60 M
BAA - AAA	1.02*	2.38***	2.49***	1.86***	1.40***	1.37***
t-stat	(1.66)	(4.53)	(5.46)	(5.23)	(4.48)	(3.66)
Adjusted R^2	0.004	0.130	0.266	0.318	0.300	0.234
Treasury Bonds	3.15***	2.44**	2.15**	1.99**	2.22***	2.23***
t-stat	(2.58)	(2.42)	(2.20)	(2.35)	(3.10)	(2.67)
Adjusted R^2	0.011	0.039	0.057	0.092	0.178	0.147

Panel C: 5% Joint Default Probabilities

	1 M	6 M	12 M	24 M	36 M	60 M
S&P 500	5.37**	7.38***	5.40***	3.22**	2.29*	1.95
t-stat	(2.23)	(4.11)	(3.43)	(2.48)	(1.92)	(1.38)
Adjusted R^2	0.008	0.095	0.094	0.061	0.038	0.020
CRSP Value-weighted	5.70**	7.95***	5.98***	3.63***	2.72**	2.36*
t-stat	(2.29)	(4.28)	(3.77)	(2.93)	(2.47)	(1.88)
Adjusted R^2	0.003	0.102	0.110	0.082	0.063	0.038
CRSP Equal-weighted	-7.97**	10.10***	9.34***	6.50***	5.00***	4.75***
t-stat	(-2.49)	(3.88)	(4.50)	(4.35)	(3.95)	(3.26)
Adjusted R^2	0.010	0.082	0.145	0.159	0.142	0.104
AAA	2.82**	2.52***	2.02**	1.38**	1.63***	1.11
t-stat	(2.46)	(2.89)	(2.48)	(2.00)	(2.74)	(1.58)
Adjusted R^2	0.010	0.048	0.051	0.040	0.077	0.027
BAA	3.97***	5.36***	4.38***	2.89***	2.71***	2.01**
t-stat	(3.40)	(5.60)	(4.86)	(3.78)	(4.12)	(2.50)
Adjusted R^2	0.021	0.166	0.172	0.131	0.160	0.069
BAA - AAA	1.15*	2.84***	2.36***	1.51***	1.08***	0.91***
t-stat	(1.88)	(6.26)	(6.23)	(5.14)	(4.48)	(3.20)
Adjusted R^2	0.005	0.187	0.240	0.209	0.180	0.104
Treasury Bonds	2.67**	1.53	1.12	0.89	1.36**	0.91
t-stat	(2.18)	(1.64)	(1.36)	(1.33)	(2.57)	(1.49)
Adjusted R^2	0.007	0.014	0.014	0.017	0.067	0.023
Controls	N	N	N	N	N	N
Observations	496	496	490	478	466	454

The table reports results from univariate monthly predictive regressions using S&P 500, CRSP value-weighted, CRSP equal-weighted, BAA corporate bond, and long-term Treasury index excess returns and BAA-AAA corporate bond returns over one-month, six-month and one-year to five-year horizons. Panels A to C adopt 1%, 2%, and 5% joint default probabilities as the predictor variables, respectively. Predictor variables are normalized to have unit standard deviation, so reported coefficients are scaled to interpreted as the percentage change in annualized expected market returns from a one-standard-deviation increase in the predictor variable. Test-statistics are calculated using Hodrick's (1992) standard error correction for overlapping data with lag length equal to the number of months in each horizon. 1%, 5% and 10% statistical significance are indicated by ***, **, and * respectively.

Table 4: **Equity Return Predictability**

Panel A: S&P 500 Returns						
	1 M	6 M	12 M	24 M	36 M	60 M
2% joint default	3.33	4.13*	5.32**	3.39**	2.26*	1.20
	(0.95)	(1.66)	(2.54)	(2.00)	(1.67)	(0.66)
Book-to-Market	-44.05***	-30.48***	-20.66***	-18.49***	-26.90***	-29.47***
	(-3.49)	(-3.42)	(-2.68)	(-2.80)	(-4.86)	(-4.15)
Default Return Spread	7.06***	2.05**	0.56	0.17	-0.14	-0.14
	(2.62)	(2.10)	(0.87)	(0.37)	(-0.37)	(-0.28)
Default Yield Spread	4.05	4.35	1.06	-0.84	1.18	0.66
	(0.93)	(1.46)	(0.42)	(-0.41)	(0.72)	(0.31)
Dividend Payout Ratio	3.87	4.88	4.66**	4.37**	2.32*	1.96
	(0.89)	(1.62)	(1.97)	(2.47)	(1.75)	(1.12)
Dividend Price Ratio	25.61*	10.68	1.62	4.48	13.20**	21.59***
	(1.72)	(1.02)	(0.18)	(0.60)	(2.14)	(2.74)
Earnings Price Ratio	29.10***	26.54***	25.25***	18.59***	16.86***	11.06*
	(2.89)	(3.57)	(3.94)	(3.50)	(3.93)	(1.91)
Inflation	-3.35	-1.46	-3.65***	-1.75**	-0.48	-0.55
	(-1.02)	(-0.94)	(-3.29)	(-2.04)	(-0.68)	(-0.61)
Long Term Return	7.16***	2.83**	1.12	0.38	0.62	0.15
	(2.65)	(2.56)	(1.52)	(0.75)	(1.53)	(0.28)
Long Term Yield	-12.20**	-8.40**	-4.28	-2.16	-1.96	-0.89
	(-2.40)	(-2.28)	(-1.33)	(-0.78)	(-0.81)	(-0.28)
Net Equity Expansion	4.22	5.62**	3.99**	2.85*	4.00***	3.97**
	(1.42)	(2.54)	(2.06)	(1.73)	(2.92)	(2.31)
Stock Variance	-8.72***	-0.48	0.60	1.12	-0.01	-0.13
	(-3.15)	(-0.35)	(0.62)	(1.56)	(-0.01)	(-0.18)
Term Spread	3.05	2.21	3.69*	3.98**	4.67***	3.58**
	(0.95)	(0.98)	(1.94)	(2.56)	(3.73)	(2.09)
KJ Tail Risk	-0.74	6.05**	7.02***	4.89**	2.36	0.74
	(-0.15)	(1.97)	(2.80)	(2.41)	(1.48)	(0.36)
Observations	496	496	490	478	466	454
Adjusted R^2	0.071	0.237	0.384	0.433	0.575	0.486
Panel B: CRSP Value-weighted Returns						
2% joint default	2.95	4.22*	5.76***	3.78**	2.80**	1.85
	(0.82)	(1.65)	(2.79)	(2.40)	(2.34)	(1.14)
Book-to-Market	-43.78***	-29.15***	-18.71**	-15.58**	-23.29***	-23.49***
	(-3.37)	(-3.18)	(-2.46)	(-2.57)	(-4.84)	(-3.83)
Default Return Spread	7.31***	2.15**	0.65	0.15	-0.02	-0.09
	(2.63)	(2.13)	(1.02)	(0.35)	(-0.05)	(-0.21)
Default Yield Spread	4.92	4.81	1.31	-0.84	1.09	0.20
	(1.09)	(1.57)	(0.53)	(-0.44)	(0.76)	(0.11)

Dividend Payout Ratio	4.10	4.87	4.88**	4.37***	2.03*	2.14
	(0.91)	(1.56)	(2.08)	(2.62)	(1.70)	(1.33)
Dividend Price Ratio	25.56*	10.28	0.07	3.63	11.79**	17.86***
	(1.66)	(0.95)	(0.01)	(0.53)	(2.19)	(2.62)
Earnings Price Ratio	30.30***	26.91***	25.80***	17.72***	15.96***	10.11**
	(2.92)	(3.51)	(4.07)	(3.60)	(4.23)	(1.98)
Inflation	-3.47	-1.35	-3.42***	-1.54*	-0.18	-0.19
	(-1.03)	(-0.84)	(-3.09)	(-1.93)	(-0.29)	(-0.24)
Long Term Return	7.69***	3.04***	1.15	0.23	0.52	-0.03
	(2.76)	(2.66)	(1.57)	(0.46)	(1.42)	(-0.06)
Long Term Yield	-13.49***	-9.58**	-5.14	-3.64	-3.71*	-2.54
	(-2.58)	(-2.52)	(-1.62)	(-1.44)	(-1.77)	(-0.94)
Net Equity Expansion	4.78	6.14***	4.38**	3.09**	3.92***	3.76**
	(1.56)	(2.69)	(2.30)	(2.05)	(3.28)	(2.53)
Stock Variance	-8.49***	0.01	0.87	1.30*	0.09	0.19
	(-2.97)	(0.01)	(0.89)	(1.93)	(0.18)	(0.29)
Term Spread	3.28	2.44	4.10**	3.98***	4.73***	3.52**
	(0.99)	(1.04)	(2.18)	(2.77)	(4.29)	(2.33)
KJ Tail Risk	0.07	6.96**	7.75***	5.32***	2.75*	1.32
	(0.01)	(2.19)	(3.12)	(2.83)	(1.93)	(0.71)
Observations	496	496	492	480	468	456
Adjusted R^2	0.074	0.247	0.409	0.464	0.602	0.474
Panel C: CRSP Equal-weighted Returns						
2% joint default	-15.16***	2.13	7.95***	7.23***	6.81***	6.89***
	(-3.67)	(0.63)	(2.98)	(4.23)	(4.19)	(3.32)
Book-to-Market	2.43	-18.80	-1.78	9.51	2.76	10.21
	(0.16)	(-1.55)	(-0.18)	(1.48)	(0.43)	(1.29)
Default Return Spread	17.46***	6.55***	2.77***	1.36***	1.27***	1.07*
	(5.49)	(4.74)	(3.24)	(2.69)	(2.75)	(1.78)
Default Yield Spread	16.35***	12.65***	4.79	0.04	0.66	-1.90
	(3.17)	(3.10)	(1.50)	(0.02)	(0.34)	(-0.77)
Dividend Payout Ratio	10.76**	5.60	5.77*	5.16***	1.21	2.59
	(2.09)	(1.35)	(1.87)	(2.78)	(0.73)	(1.27)
Dividend Price Ratio	-6.80	12.09	-6.50	-10.44	-4.21	-7.37
	(-0.39)	(0.84)	(-0.57)	(-1.41)	(-0.58)	(-0.83)
Earnings Price Ratio	4.34	16.06	16.22**	5.03	3.00	-2.89
	(0.37)	(1.58)	(2.00)	(0.95)	(0.59)	(-0.43)
Inflation	-5.93	-1.55	-3.02**	-0.46	1.19	2.04*
	(-1.53)	(-0.71)	(-2.08)	(-0.51)	(1.42)	(1.94)
Long Term Return	9.05***	5.51***	2.43**	0.90	1.14**	0.68
	(2.84)	(3.55)	(2.47)	(1.60)	(2.26)	(1.09)
Long Term Yield	-3.76	-19.20***	-12.99***	-9.56***	-9.30***	-7.69**
	(-0.63)	(-3.82)	(-3.22)	(-3.53)	(-3.30)	(-2.22)

Net Equity Expansion	-0.92	9.70***	7.13***	4.25***	3.51**	2.06
	(-0.26)	(3.22)	(2.93)	(2.64)	(2.20)	(1.07)
Stock Variance	-28.92***	-3.97**	-0.17	1.18	0.37	1.31
	(-8.85)	(-2.07)	(-0.13)	(1.55)	(0.54)	(1.56)
Term Spread	6.41*	2.24	5.38**	3.85**	3.43**	2.10
	(1.70)	(0.72)	(2.22)	(2.47)	(2.30)	(1.07)
KJ Tail Risk	-12.76**	5.89	6.70**	6.06***	3.38*	2.57
	(-2.20)	(1.39)	(2.08)	(2.93)	(1.74)	(1.05)
Observations	496	496	490	478	466	454
Adjusted R^2	0.271	0.304	0.437	0.577	0.519	0.426

The table reports results from multivariate monthly predictive regressions using S&P 500, CRSP value-weighted, and CRSP equal-weighted market index returns over one-month, six-month and one-year to five-year horizons. The predictor variables are the 2% joint default probability, predictors studied in survey by Welch and Goyal (2008), and the tail risk measure (Kelly and Jiang, 2014). Predictor variables are normalized to have unit standard deviation, so reported coefficients are scaled to interpreted as the percentage change in annualized expected market returns from a one-standard-deviation increase in the predictor variable. Test statistics are calculated using Hodrick's (1992) standard error correction for overlapping data with lag length equal to the number of months in each horizon. 1%, 5% and 10% statistical significance are indicated by ***, **, and * respectively.

Table 5: **Bond Return Predictability**

	1 M	6 M	12 M	24 M	36 M	60 M
Panel A: AAA Excess Returns						
2% joint default	6.01***	5.98***	5.25***	3.54***	3.22***	2.48***
	(3.65)	(5.89)	(6.34)	(4.61)	(5.25)	(3.70)
Book-to-Market	10.13*	11.04***	8.16***	0.72	-1.93	-4.04
	(1.71)	(3.04)	(2.69)	(0.25)	(-0.80)	(-1.54)
Default Return Spread	0.81	-0.35	-0.27	-0.27	-0.25	-0.25
	(0.64)	(-0.83)	(-0.98)	(-1.29)	(-1.48)	(-1.27)
Default Yield Spread	-5.35***	-3.98***	-2.55**	0.56	0.81	1.80**
	(-2.60)	(-3.26)	(-2.57)	(0.61)	(1.11)	(2.27)
Dividend Payout Ratio	2.92	3.48***	3.26***	0.84	0.68	-0.29
	(1.42)	(2.80)	(3.41)	(1.02)	(1.09)	(-0.42)
Dividend Price Ratio	-22.28***	-24.05***	-21.78***	-10.66***	-6.83**	-3.04
	(-3.18)	(-5.60)	(-6.17)	(-3.21)	(-2.50)	(-1.02)
Earnings Price Ratio	9.73**	7.90***	7.72***	2.97	2.01	-0.63
	(2.05)	(2.61)	(3.06)	(1.25)	(1.05)	(-0.29)
Inflation	-2.10	-1.13*	-1.28***	-0.36	0.03	0.00
	(-1.36)	(-1.72)	(-2.78)	(-0.92)	(0.10)	(0.01)
Long Term Return	3.37***	0.46	0.62**	0.05	0.21	-0.13
	(2.65)	(0.97)	(1.99)	(0.23)	(1.10)	(-0.65)
Long Term Yield	7.50***	8.61***	8.78***	6.94***	6.47***	7.43***
	(3.14)	(5.73)	(6.96)	(5.70)	(6.07)	(6.32)
Net Equity Expansion	-2.05	-2.34***	-1.68**	-0.44	-0.55	-0.24
	(-1.47)	(-2.61)	(-2.22)	(-0.61)	(-0.91)	(-0.37)
Stock Variance	4.24***	0.71	0.46	0.08	0.00	-0.09
	(3.26)	(1.23)	(1.13)	(0.26)	(0.01)	(-0.31)
Term Spread	5.67***	5.82***	5.07***	2.24***	1.15**	-0.41
	(3.77)	(6.29)	(6.73)	(3.20)	(2.05)	(-0.65)
KJ Tail Risk	4.93**	3.59***	2.79***	0.36	-0.68	-1.57**
	(2.13)	(2.83)	(2.78)	(0.39)	(-0.93)	(-2.00)
Observations	496	496	490	478	466	454
Adjusted R^2	0.092	0.388	0.566	0.567	0.662	0.685
Panel B: BAA Excess Returns						
2% joint default	4.86***	6.09***	6.18***	4.33***	3.74***	2.85***
	(2.95)	(5.37)	(6.73)	(4.95)	(4.89)	(3.18)
Book-to-Market	5.25	6.26	4.36	-0.49	-3.15	-4.35
	(0.89)	(1.54)	(1.31)	(-0.15)	(-1.04)	(-1.24)
Default Return Spread	4.81***	0.32	-0.31	-0.48**	-0.38*	-0.51**
	(3.79)	(0.68)	(-1.03)	(-1.96)	(-1.84)	(-1.99)
Default Yield Spread	-0.93	-0.08	0.58	2.28**	2.30**	2.92***
	(-0.45)	(-0.06)	(0.53)	(2.17)	(2.52)	(2.76)

Dividend Payout Ratio	6.55***	5.07***	3.22***	0.41	0.17	-0.65
	(3.20)	(3.65)	(3.01)	(0.42)	(0.22)	(-0.71)
Dividend Price Ratio	-21.08***	-19.93***	-17.51***	-7.52**	-4.18	-0.44
	(-3.01)	(-4.15)	(-4.49)	(-1.99)	(-1.23)	(-0.11)
Earnings Price Ratio	14.06***	10.57***	8.92***	2.49	1.89	-1.55
	(2.97)	(3.13)	(3.20)	(0.92)	(0.79)	(-0.54)
Inflation	-3.02*	-2.43***	-1.81***	-0.15	0.37	0.41
	(-1.96)	(-3.31)	(-3.54)	(-0.34)	(0.96)	(0.92)
Long Term Return	5.71***	0.80	0.45	-0.03	0.13	-0.36
	(4.49)	(1.51)	(1.30)	(-0.12)	(0.58)	(-1.32)
Long Term Yield	5.23**	5.29***	5.71***	4.63***	4.39***	5.63***
	(2.19)	(3.16)	(4.11)	(3.35)	(3.30)	(3.59)
Net Equity Expansion	0.32	0.11	-0.32	-0.28	-0.63	-0.63
	(0.23)	(0.11)	(-0.39)	(-0.34)	(-0.83)	(-0.74)
Stock Variance	1.87	1.41**	1.17**	0.45	0.07	0.00
	(1.44)	(2.18)	(2.58)	(1.17)	(0.22)	(0.01)
Term Spread	5.00***	5.14***	5.21***	2.48***	1.06	-0.95
	(3.33)	(4.97)	(6.24)	(3.11)	(1.51)	(-1.14)
KJ Tail Risk	5.38**	4.31***	3.13***	0.06	-1.09	-2.24**
	(2.32)	(3.04)	(2.81)	(0.06)	(-1.20)	(-2.16)
Observations	496	496	490	478	466	454
Adjusted R^2	0.138	0.432	0.620	0.579	0.622	0.602
Panel C: BAA-AAA Return Spreads						
2% joint default	-1.15	0.11	0.93**	0.80**	0.52*	0.37
	(-1.43)	(0.22)	(2.44)	(2.57)	(1.85)	(1.07)
Book-to-Market	-4.88*	-4.78***	-3.80***	-1.21	-1.22	-0.31
	(-1.69)	(-2.73)	(-2.78)	(-1.09)	(-1.18)	(-0.25)
Default Return Spread	4.00***	0.67***	-0.05	-0.21**	-0.13*	-0.26**
	(6.45)	(3.18)	(-0.34)	(-2.19)	(-1.65)	(-2.51)
Default Yield Spread	4.42***	3.91***	3.13***	1.71***	1.49***	1.11***
	(4.40)	(6.64)	(6.90)	(4.63)	(4.42)	(2.68)
Dividend Payout Ratio	3.63***	1.60***	-0.04	-0.43	-0.51*	-0.36
	(3.62)	(2.67)	(-0.10)	(-1.22)	(-1.75)	(-0.99)
Dividend Price Ratio	1.20	4.12**	4.27***	3.14**	2.66**	2.61*
	(0.35)	(1.99)	(2.66)	(2.40)	(2.23)	(1.81)
Earnings Price Ratio	4.32*	2.67*	1.21	-0.47	-0.12	-0.92
	(1.87)	(1.83)	(1.05)	(-0.50)	(-0.14)	(-0.83)
Inflation	-0.92	-1.29***	-0.53**	0.21	0.34**	0.41**
	(-1.22)	(-4.02)	(-2.42)	(1.26)	(2.36)	(2.29)
Long Term Return	2.35***	0.34	-0.17	-0.09	-0.07	-0.23**
	(3.78)	(1.44)	(-1.12)	(-0.82)	(-0.83)	(-2.09)
Long Term Yield	-2.27*	-3.32***	-3.07***	-2.32***	-2.08***	-1.80***
	(-1.95)	(-4.59)	(-5.38)	(-4.90)	(-4.57)	(-3.25)

Net Equity Expansion	2.37***	2.45***	1.36***	0.16	-0.08	-0.40
	(3.47)	(5.67)	(3.97)	(0.57)	(-0.31)	(-1.28)
Stock Variance	-2.37***	0.70**	0.71***	0.37**	0.07	0.09
	(-3.73)	(2.48)	(3.67)	(2.52)	(0.55)	(0.62)
Term Spread	-0.66	-0.68	0.13	0.25	-0.10	-0.54*
	(-0.90)	(-1.53)	(0.39)	(0.89)	(-0.38)	(-1.67)
KJ Tail Risk	0.45	0.71	0.34	-0.30	-0.42	-0.67
	(0.40)	(1.16)	(0.73)	(-0.79)	(-1.20)	(-1.59)
Observations	496	496	490	478	466	454
Adjusted R^2	0.237	0.552	0.658	0.639	0.618	0.536
Panel D: Treasury Bonds						
2% joint default	5.59***	5.11***	4.16***	3.04***	2.85***	2.29***
	(3.13)	(4.41)	(4.33)	(3.60)	(4.49)	(3.34)
Book-to-Market	14.09**	12.44***	7.99**	-0.85	-3.13	-5.20*
	(2.19)	(3.00)	(2.27)	(-0.27)	(-1.25)	(-1.88)
Default Return Spread	1.07	-0.57	-0.32	-0.16	-0.15	-0.08
	(0.78)	(-1.21)	(-1.04)	(-0.70)	(-0.89)	(-0.42)
Default Yield Spread	-5.96***	-4.39***	-2.91**	0.03	0.35	1.34*
	(-2.67)	(-3.15)	(-2.53)	(0.03)	(0.45)	(1.65)
Dividend Payout Ratio	1.40	2.56*	2.92***	0.84	0.60	-0.26
	(0.63)	(1.81)	(2.64)	(0.93)	(0.94)	(-0.37)
Dividend Price Ratio	-22.03***	-24.12***	-20.88***	-9.22**	-4.62	-1.73
	(-2.90)	(-4.91)	(-5.09)	(-2.52)	(-1.63)	(-0.55)
Earnings Price Ratio	5.47	6.25*	7.14**	4.04	2.49	1.03
	(1.06)	(1.80)	(2.43)	(1.54)	(1.25)	(0.47)
Inflation	-1.69	0.05	-0.35	-0.17	0.04	-0.16
	(-1.01)	(0.07)	(-0.68)	(-0.40)	(0.12)	(-0.46)
Long Term Return	2.66*	0.24	0.62*	-0.11	-0.07	-0.30
	(1.93)	(0.46)	(1.75)	(-0.42)	(-0.39)	(-1.44)
Long Term Yield	7.58***	8.95***	8.77***	6.21***	4.80***	5.45***
	(2.93)	(5.21)	(5.98)	(4.62)	(4.35)	(4.38)
Net Equity Expansion	-3.47**	-3.70***	-2.61***	-0.78	-0.82	-0.56
	(-2.28)	(-3.59)	(-2.97)	(-0.98)	(-1.31)	(-0.83)
Stock Variance	4.04***	0.81	0.26	0.01	-0.19	-0.23
	(2.86)	(1.25)	(0.56)	(0.02)	(-0.72)	(-0.80)
Term Spread	5.11***	5.69***	4.91***	1.98**	0.81	-0.36
	(3.13)	(5.38)	(5.62)	(2.57)	(1.40)	(-0.56)
KJ Tail Risk	5.39**	3.95***	2.81**	0.56	-0.31	-0.95
	(2.14)	(2.73)	(2.43)	(0.55)	(-0.41)	(-1.20)
Observations	496	496	490	478	466	454
Adjusted R^2	0.067	0.321	0.457	0.447	0.561	0.585

The table reports results from multivariate monthly predictive regressions using AAA corporate bond, BAA corporate bond, and long term Treasury index excess returns and BAA-AAA corporate bond returns over one-month, six-month and one-year to five-year horizons.

The predictor variables are the 2% joint default probability, predictors studied in survey by Welch and Goyal (2008), and the tail risk measure (Kelly and Jiang, 2014). Predictor variables are normalized to have unit standard deviation, so reported coefficients are scaled to interpreted as the percentage change in annualized expected market returns from a one-standard-deviation increase in the predictor variable. Test statistics are calculated using Hodrick's (1992) standard error correction for overlapping data with lag length equal to the number of months in each horizon. 1%, 5% and 10% statistical significance are indicated by ***, **, and * respectively.

Table 6: **Alternative Default Measures**

Panel A: S&P 500 With only Non-Financials	1 M	6 M	12 M	24 M	36 M	60 M
S&P 500	5.85**	5.45***	4.74***	2.14	0.95	-0.34
t-stat	(2.08)	(2.74)	(2.81)	(1.53)	(0.84)	(-0.23)
Adjusted R^2	0.077	0.260	0.394	0.421	0.562	0.482
CRSP Value-weighted	5.93**	5.81***	5.27***	2.58**	1.67*	0.38
t-stat	(2.05)	(2.84)	(3.18)	(1.98)	(1.67)	(0.29)
Adjusted R^2	0.080	0.272	0.422	0.453	0.588	0.463
CRSP Equal-weighted	-5.32	6.74**	8.54***	6.59***	6.68***	5.89***
t-stat	(-1.58)	(2.48)	(4.13)	(4.99)	(5.49)	(3.62)
Adjusted R^2	0.255	0.328	0.474	0.602	0.575	0.439
AAA	4.59***	3.56***	3.29***	2.17***	1.94***	0.98
t-stat	(3.46)	(4.13)	(4.48)	(3.25)	(3.54)	(1.63)
Adjusted R^2	0.089	0.332	0.505	0.516	0.603	0.636
BAA	4.14***	4.26***	3.90***	2.75***	2.36***	1.23
t-stat	(3.13)	(4.57)	(4.83)	(3.61)	(3.54)	(1.58)
Adjusted R^2	0.140	0.409	0.562	0.529	0.570	0.557
BAA - AAA	-0.45	0.70*	0.61**	0.58**	0.42*	0.25
t-stat	(-0.69)	(1.77)	(1.97)	(2.28)	(1.85)	(0.88)
Adjusted R^2	0.235	0.559	0.653	0.635	0.618	0.534
Treasury Bonds	3.50**	2.47**	2.50***	1.84**	1.64***	0.78
t-stat	(2.43)	(2.52)	(3.04)	(2.56)	(2.93)	(1.27)
Adjusted R^2	0.059	0.269	0.414	0.405	0.497	0.527

Panel B: CRSP Above Median-size Firms (with Financials)	1 M	6 M	12 M	24 M	36 M	60 M
S&P 500	3.67	4.32*	5.27***	3.61**	2.47**	2.29
t-stat	(1.10)	(1.94)	(2.93)	(2.56)	(2.25)	(1.62)
Adjusted R^2	0.071	0.240	0.388	0.441	0.580	0.497
CRSP Value-weighted	3.41	4.35*	5.64***	3.81***	2.61***	2.51**
t-stat	(1.00)	(1.90)	(3.16)	(2.89)	(2.64)	(1.97)
Adjusted R^2	0.074	0.250	0.412	0.469	0.601	0.485
CRSP Equal-weighted	-17.68***	0.91	6.43***	5.47***	4.11***	4.51***
t-stat	(-4.55)	(0.30)	(2.73)	(3.59)	(2.82)	(2.58)
Adjusted R^2	0.281	0.303	0.424	0.544	0.449	0.375
AAA	6.37***	6.42***	5.53***	3.04***	2.51***	2.09***
t-stat	(4.09)	(7.35)	(8.23)	(4.53)	(4.62)	(3.70)
Adjusted R^2	0.097	0.422	0.601	0.545	0.619	0.671
BAA	5.25***	6.45***	6.21***	3.69***	2.97***	2.45***
t-stat	(3.37)	(6.49)	(8.10)	(4.77)	(4.49)	(3.29)
Adjusted R^2	0.141	0.456	0.638	0.552	0.582	0.590

BAA - AAA	-1.12	0.04	0.68**	0.65**	0.46**	0.36
t-stat	(-1.46)	(0.08)	(2.02)	(2.38)	(1.96)	(1.25)
Adjusted R^2	0.237	0.552	0.652	0.632	0.616	0.536
Treasury Bonds	6.28***	5.62***	4.53***	2.53***	2.08***	1.92***
t-stat	(3.72)	(5.58)	(5.69)	(3.43)	(3.72)	(3.36)
Adjusted R^2	0.073	0.348	0.487	0.424	0.507	0.569

Panel C: CRSP Above Median-size Firms (with Only Non-Financials)						
	1 M	6 M	12 M	24 M	36 M	60 M
S& P 500	8.73***	6.73***	5.78***	2.77**	1.50	0.82
t-stat	(3.15)	(3.55)	(3.62)	(2.00)	(1.30)	(0.56)
Adjusted R^2	0.087	0.279	0.419	0.435	0.569	0.485
CRSP Value-weighted	8.70***	6.74***	5.81***	2.91**	1.90*	1.23
t-stat	(3.04)	(3.45)	(3.66)	(2.26)	(1.87)	(0.95)
Adjusted R^2	0.089	0.286	0.436	0.461	0.593	0.470
CRSP Equal-weighted	-6.67**	6.55**	7.15***	5.17***	5.82***	5.66***
t-stat	(-2.00)	(2.49)	(3.45)	(3.70)	(4.47)	(3.51)
Adjusted R^2	0.257	0.327	0.450	0.559	0.535	0.430
AAA	5.03***	3.31***	3.04***	2.37***	1.56***	0.86
t-stat	(3.83)	(3.90)	(4.14)	(3.54)	(2.66)	(1.38)
Adjusted R^2	0.093	0.323	0.492	0.531	0.577	0.632
BAA	5.67***	4.81***	4.36***	3.34***	2.22***	1.25
t-stat	(4.35)	(5.43)	(5.76)	(4.58)	(3.21)	(1.58)
Adjusted R^2	0.153	0.430	0.586	0.570	0.561	0.557
BAA - AAA	0.64	1.50***	1.32***	0.98***	0.66***	0.39
t-stat	(1.00)	(4.09)	(4.90)	(4.31)	(3.02)	(1.42)
Adjusted R^2	0.235	0.588	0.694	0.674	0.646	0.541
Treasury Bonds	2.84**	1.72*	1.84**	1.55**	0.75	0.20
t-stat	(1.98)	(1.79)	(2.21)	(2.08)	(1.23)	(0.32)
Adjusted R^2	0.055	0.254	0.390	0.389	0.443	0.515
Controls	Y	Y	Y	Y	Y	Y
Observations	496	496	490	478	466	454

The table reports results from multivariate monthly predictive regressions using S&P 500, CRSP value-weighted, CRSP equal-weighted, AAA corporate bond, BAA corporate bond, and long-term Treasury index excess returns and BAA-AAA corporate bond returns over one-month, six-month and one-year to five-year horizons, using alternative systemic default measures. Panel A to C use the 2% joint default probability estimated from S&P 500 with only non-financials, CRSP above median-size firms with financials and with only non-financials, respectively. All predictive regressions control for predictors studied in survey by Welch and Goyal (2008), and the tail risk measure (Kelly and Jiang, 2014). Predictor variables are normalized to have unit standard deviation, so reported coefficients are scaled to interpreted as the percentage change in annualized expected market returns from a one-standard-deviation increase in the predictor variable. Test statistics are calculated using Hodrick's (1992) standard error correction for overlapping data with lag length equal to the number of months in each horizon. 1%, 5% and 10% statistical significance are indicated by ***, **, and * respectively.

Table 7: **Out-of-sample Tests (%)**

	1M	6M	12M	24M	36M	60M
1% Joint Default Probabilities						
S&P 500	-1.1	-5.7*	-5.0	-2.4	-0.8	1.0*
CRSP Value-weighted	-1.0	-4.9*	-3.7	-0.8	0.8*	3.8*
CRSP Equal-weighted	0.1*	-0.7	1.5*	3.1*	-0.7	2.4*
AAA	-6.4	-21.1	-37.4*	-82.3*	-100.2*	-137.7*
BAA	-1.3*	2.0*	7.7*	2.5*	-1.0*	1.9*
BAA-AAA	0.0	11.1*	26.5*	35.8*	37.5*	37.5*
Treasury Bonds	-2.3	-6.7	-14.7*	-50.1*	-62.2*	-101.5*
2% Joint Default Probabilities						
S&P 500	-0.9	-3.4	1.8*	0.6*	0.5*	1.6*
CRSP Value-weighted	-0.8	-2.6	0.6*	2.5*	2.3*	4.2*
CRSP Equal-weighted	0.4*	1.0*	5.3*	8.4*	3.9*	6.5*
AAA	-6.2	-23.6	-33.0*	-40.9*	-41.9*	-52.0*
BAA	1.0*	13.1*	23.5*	29.0*	28.0*	28.4*
BAA-AAA	-0.1	16.0*	32.6*	36.9*	35.0*	30.1*
Treasury Bonds	-2.1	-9.8	-16.4	-29.7*	-29.4*	-43.8*
5% Joint Default Probabilities						
S&P 500	-0.1	5.3*	5.4*	5.0*	2.7*	2.2*
CRSP Value-weighted	0.1	5.8*	6.3*	6.9*	4.1*	3.9*
CRSP Equal-weighted	-0.7*	9.7*	12.8*	16.8*	9.0*	11.6*
AAA	-5.1	-14.5*	-15.0*	-10.1*	-6.6*	-1.9*
BAA	2.0*	26.5*	25.7*	23.5*	22.7*	17.2*
BAA-AAA	-0.7	24.5*	31.3*	26.4*	22.2*	14.9*
Treasury Bonds	-1.9	-9.4*	-10.4*	-11.5	-9.6*	-5.1*

The table reports the out-of-sample forecasting $\bar{R}^2$ in percent from predictive regressions using S&P 500, CRSP value-weighted, CRSP equal-weighted, AAA corporate bond, BAA corporate bond, and long-term Treasury index excess returns and BAA-AAA corporate bond returns over one-month, six-month and one-year to five-year horizons. Panels A to C use 1%, 2%, and 5% joint default probabilities as the predictor variables. In each month t (beginning at $t = 240$ to allow for a sufficiently large initial estimation period), we estimate rolling univariate forecasting regressions of monthly index returns on the estimated joint default series. Predictive coefficient estimates only use data through date t, and are then used to forecast returns at $t + 1$. A negative $\bar{R}^2$ implies that the predictor performs worse than setting forecasts equal to the sample mean. An asterisk(*) beside an estimate denotes that it is statistically significant at the 5% level or better based on the Clark and McCracken (2001) ENC-NEW test of out-of-sample predictability.

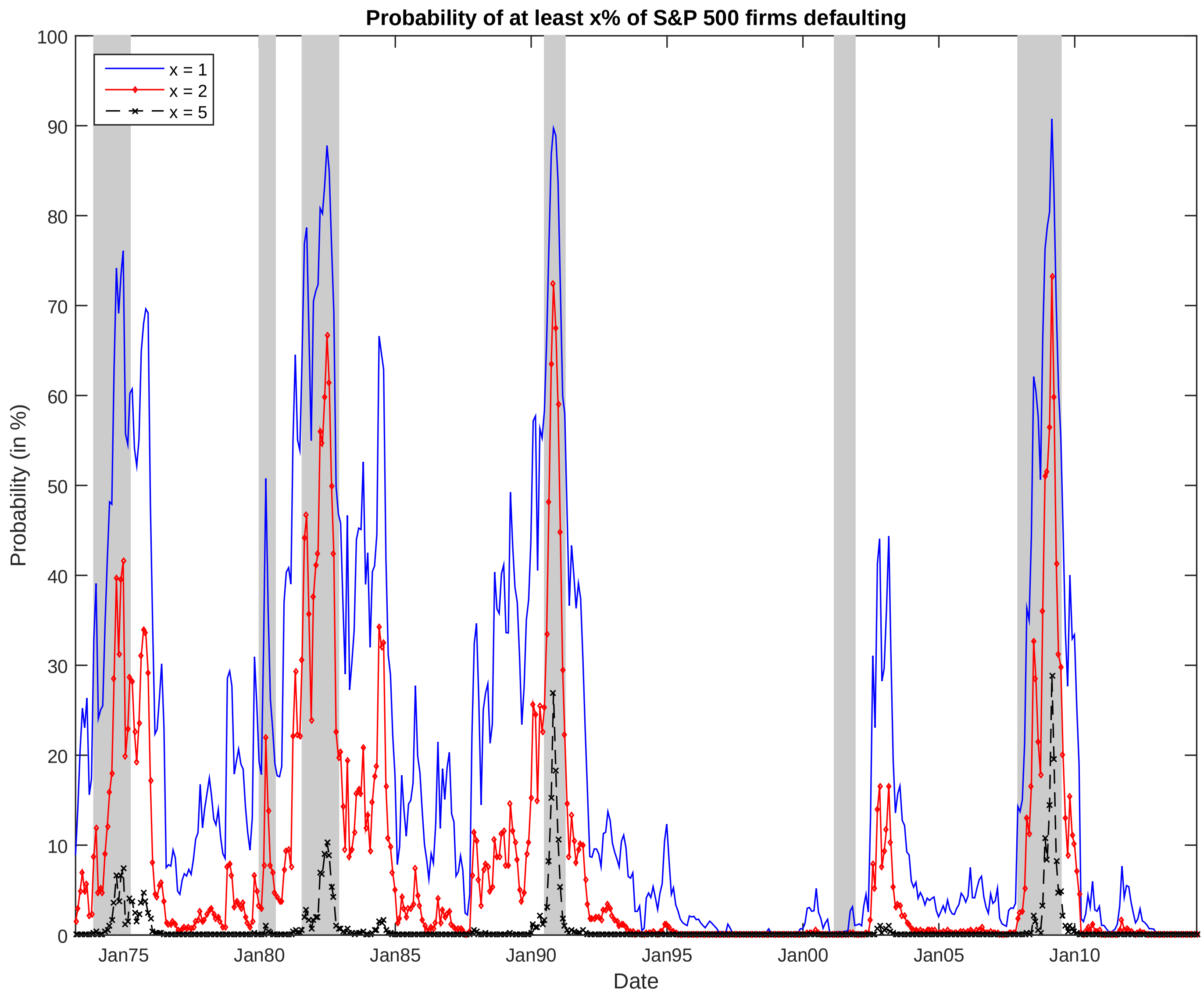

Figure 1: Estimated probabilities of at least x% of S&P 500 firms defaulting in the next year. Gray shaded areas are NBER recessions.

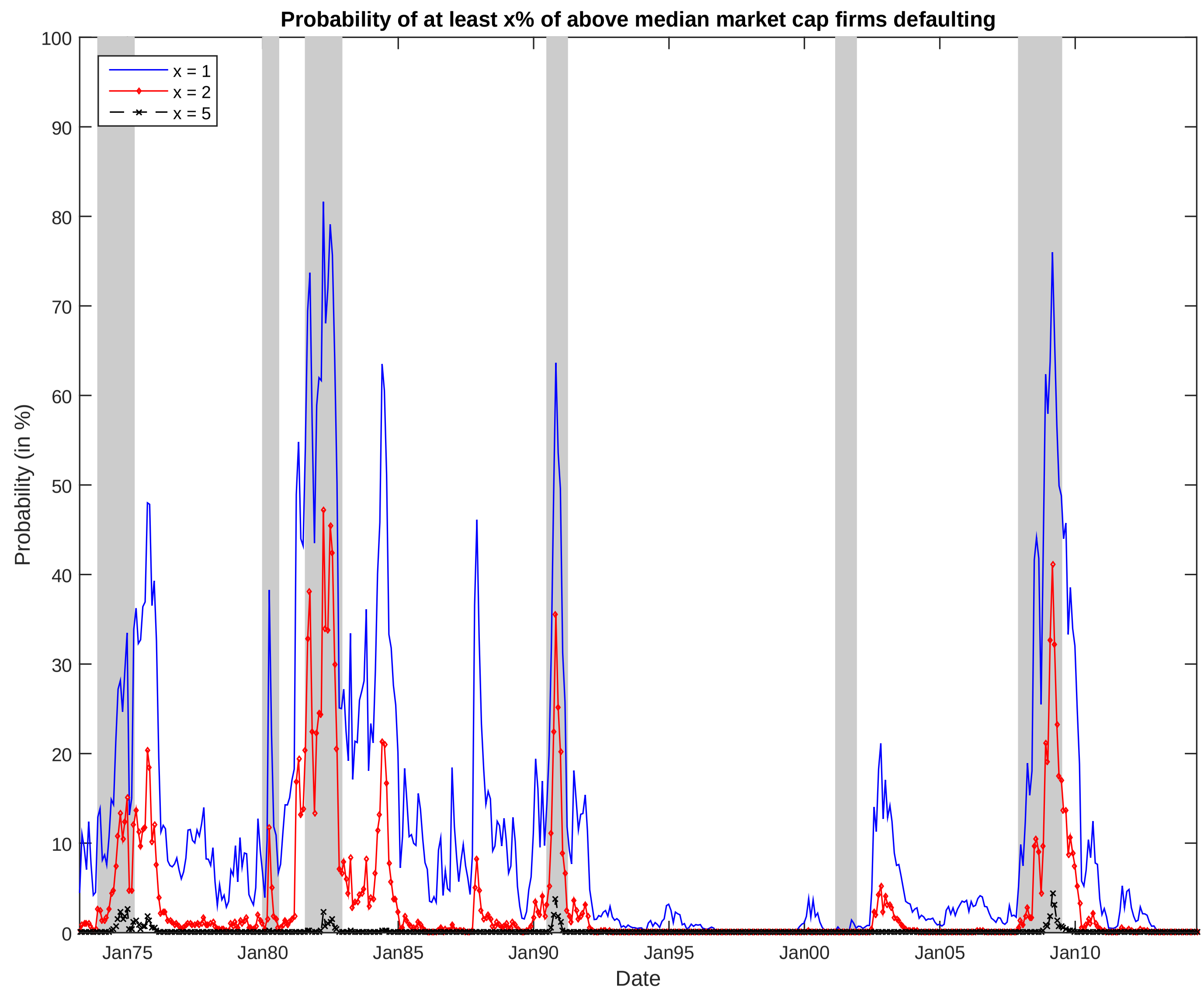

Figure 2: Estimated probabilities of at least x% of above median market cap firms defaulting in the next year. Median market cap is across all CRSP common equities for a particular month. Gray shaded areas are NBER recessions.

Appendix

A Calculating Joint Default

Given k firms with independent defaults, it is in principle possible to calculate probabilities for all 2^k possible outcomes and to use the 2^k possible outcomes to determine the probability that at least x% of the firms default. In practice, such an enumeration is computationally infeasible for large k. Instead, we take advantage of the fact that we are only counting the number of firms that default and propose a numerical solution that we describe below using an example where $k = 16$.

Step 1: For reach firm, create a vector with the survival and default probabilities, where p_i represents the survival probability of firm i.

$$\begin{pmatrix} p_1 \\ 1 - p_1 \end{pmatrix}, \ldots, \begin{pmatrix} p_{16} \\ 1 - p_{16} \end{pmatrix}$$

Step 2: Pair each of the 16 firms and multiply their vectors

$$\begin{pmatrix} p_1 \\ 1 - p_1 \end{pmatrix} \begin{pmatrix} p_2 & 1 - p_2 \end{pmatrix} = \begin{pmatrix} p_1 p_2 & p_1(1 - p_2) \\ p_2(1 - p_1) & (1 - p_1)(1 - p_2) \end{pmatrix}$$

Transform the matrix into a vector that stacks the probabilities of 0, 1, and 2 defaults for each pair.

$$\begin{pmatrix} p_1 p_2 \\ p_1(1 - p_2) + p_2(1 - p_1) \\ (1 - p_1)(1 - p_2) \end{pmatrix}$$

There are now eight such vectors.

Step 3: Pair the remaining eight vectors into pairs and perform vector multiplication again

$$\begin{pmatrix} p_1 p_2 \\ p_1(1-p_2) + p_2(1-p_1) \\ (1-p_1)(1-p_2) \end{pmatrix} \begin{pmatrix} p_3 p_4 & p_3(1-p_4) + p_4(1-p_3) & (1-p_3)(1-p_4) \end{pmatrix}$$

Step 4: Repeat until there is only one remaining vector. Such a vector will be 17×1 and contain the probabilities of 0, 1, ..., 16 defaults.

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