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# DEFAULT RISK: FROM A PERSPECTIVE OF MEASUREMENT ERRORS

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**Abstract**

In this paper, we set up our default probability model to examine the determinants of corporate credit default by taking simultaneous consideration of both firm-specific characteristics as well as macroeconomic variables. The main effort of this study is to reexamine firm default risk from the perspective of measurement error by representing the first treatment of a wide class of nonlinear models with discrete variables using instruments. We found measurement error has great impact on the risk of default. In addition, this relation found to be crucially dependent on credit cycles and firm financial status.

**JEL classification:** G20, G21, G28.

**Keywords:** Measurement error, Default risk, Risk premium, Credit risk, Equity returns.

## 1. Introduction

Is default risk mostly driven by idiosyncratic risk or by systematic factors, or both? This has been a long-unsolved question. On one hand, firm-specific characteristics should be determinants of the firm's default. On the other hand, from a macroeconomic perspective, macroeconomic developments may also play an important role in explaining the dynamic evolution of credit risk over time. The deterioration of economic conditions was then mirrored, with some lag, by an increase in default, as well as by the amount of credit overdue.

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Under this framework, we set up our default probability model to examine the determinants of corporate credit default by taking simultaneous consideration of both firm-specific characteristics as well as macroeconomic variables.

In order to achieve such objectives, we evaluated simultaneously the effects of corporate credit risk to understand how idiosyncratic and systematic risk factors influence firms' default. Using an extensive dataset, we showed that default probabilities are influenced by several firm-specific characteristics. When time-effect controls or macroeconomic variables are also taken into consideration, the results improve substantially. Hence, though the firms' financial situation has a central role in explaining default probabilities, we contributed to the default risk literature by documenting that macroeconomic conditions are also very important when assessing default probabilities over time. The main idea is that most risk is built up during economic expansion, when banks apply looser credit standards. However, most of this risk materializes only when the economy hits a downturn. High default rates during recessions are just a materialization of the risk that is built up during economic upturns, most notably when strong economic growth is accompanied by the creation of unsustainable financial imbalances (Yang and Wei, 2012)

The main purpose and contribution of this paper are that we reexamined misclassification of default probabilities using measurement error approach (Hu, 2007). This paper represents the first treatment of a wide class of nonclassical, nonlinear errors-in-variables models with discrete variables using instruments. We modeled the measurement error as an endogenous variable and found that measurement error attributes to both firm-specific variables and macroeconomic variations.

In order to estimate the effect of measurement error of default, we split our whole sample into constraint and unconstraint firms. As returns to distressed stocks are particularly low when the implied volatility of the S&P 500 index increases. This implies that distressed stocks are vulnerable to increases in market-wide risk or risk aversion, but it does not help to explain the low returns to these stocks. Indeed, previous work (e.g., Hand, Holthausen, & Leftwich, 1992; Dichev & Piotroski, 2001) documents considerable abnormal price declines following economic downturn. Relative to this body of work, however, we uncovered substantial cross-section differences in stock return responses to economic downturn. The considerable stock return drop following economic downturn is apparent among low-quality stocks, whereas high-quality firms often realize positive returns. It is the differential response of high and low credit risk stocks to economic downturn that generates cross-sectional return variation. During economic downturn, low-quality firms experience substantial deterioration in their operating and financial performance and are sold by institutional investors leading to considerable price drops. The deteriorating fundamental performance is unanticipated by the market as evidenced by the large negative earnings surprises and analyst forecast revisions. In contrast, average returns do not differ across credit risk groups in periods of stable or improving credit conditions, which account for about 90% of the

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sample observations. After classifying firms into financially constraint versus unconstraint firms, we found a positive relationship between returns and default risk after correcting default measure error for unconstraint firm.

Probability of bankruptcy is a natural proxy for firm distress, and there is well-developed literature on bankruptcy prediction that provides powerful measures of Ex-ante bankruptcy risk (see Altman (1993) for a review). Evidence that bankruptcy risk is systematic would support a distress factor explanation for the stock returns. Existing evidence on the relation of bankruptcy risk to systematic risk is mostly circumstantial and often contradictory. Lang and Stulz (1992) and Danis and Denis (1995) demonstrate that bankruptcy risk is related to aggregate factors, which implies that bankruptcy risk could be positively related to systematic risk. Shumway (1996) finds that NYSE and AMEX firms with high risk of exchange delisting for performance reasons earn higher than average returns, suggesting that the risk of default is systematic. However, Opler and Titman (1994) and Asquith, Gertner, and Sharfstein (1994) find that bankruptcy risk is unrelated to systematic risk. Interestingly, Altman (1993) finds that the bonds of the most distressed firms (defined as high-yielding bonds) earn lower than average subsequent returns, consistent with bankruptcy risk being negatively related to systematic risk. Wilson (1998), who developed the Credit Portfolio View (McKinsey’s credit risk model), was one of the first authors to emphasize that the role macroeconomic variables could have explanatory power on credit defaults. Moreover, in a period of economic slowdown, loan demand is expected to remain subdued. This may suggest that banks apply tighter standards on loan approval after a period in which non-performing loans increase significantly. Bangla et al. (2002) also had a crucial role in demonstrating the importance of macroeconomic developments in credit risk. Allen and Saunders (2003) provide a survey of cyclical effects in existing credit risk models. Other authors who tried to consider business cycle conditions in credit risk models include Lis et al. (2000), Nickell et al. (2000), Kent and D’Arcy (2001), Lowe (2002), Berger and Udall (2003), Carling et al. (2002, 2004), Nozawa (2017) or Jimenez and Saurian (2006). Danis and Denis (1995) show that default risk is related to macroeconomic factors and that it varies with the business cycle. However, none of these studies tested the simultaneous effect of both micro and macro variables on default risk.

Fama and French (1996) argue that the SMB and HML factors of the model can proxy for financial distress. SMB and HML appear to contain important priced information, unrelated to default risk. Opler and Titman (1994) and Asquith, Gertner, and Sharfstein (1994), on the other hand, find that bankruptcy is related to idiosyncratic factors and therefore does not represent systematic risk. Daniel, Grinblatt, Titman, Wermers (1997), and Doshi et al. (2019) suggest that the credit risk effect in the cross-section of return is unrelated to the size, book-to-market, and momentum effect. They show the relation between bankruptcy risk and book-to-market is not monotonic: distressed firms generally have high book-to-market, but the most distressed firms have lower book-to-market. Thus, a return premium related to bankruptcy risk cannot fully explain the book-to-market effect even if distress was rewarded by higher returns. Several studies suggest that the effects of firm size and book-to-market, probably the two most powerful predictors of stock returns, could be related to some sort of a firm distress risk factor. For example, Chan and Chen (1991) find that "marginal" firms, or inefficient firms with high leverage and cash flow problems, seem to drive the small firm effect. Fama and French (1992) conjecture that the book-to-market effect might be due to the risk of distress. Chan, Chen, and Hsieh (1985) show that much of the size effect is explained by a default factor, computed as the difference between high-grade and low-grade bond returns. Fama and French (1993) and Chen, Roll, Ross (1986), and Eisdorfer et al. (2019) find that a similarly defined default factor is significant in explaining stock returns. Fama and French (1992) and Roll (1995) find that the size effect, strong in the 1960s and 1970s, has virtually disappeared since 1980. Although the disappearance of the size effect is somewhat of a puzzle, pre-1980 evidence suggests that there is no reliable relation between bankruptcy risk and returns that could explain the size effect in earlier years. Most of these results are based on credit rating as a proxy for firm default risk and therefore ignore the gap between the market measure (credit rating) and the endogenous generated true value of default.

The remainder of the paper is organized as follows, Section 2 discusses data specification. Section 3 describes research methodology and empirical findings. I conclude in Section 4 with a summary of main results.

## 2. Data Specification

The sample consists of all industrial firms available simultaneously on the NYSE, AMEX, and NASDAQ Center for Research in Security Prices (CRSP) tapes and the COMPUSTAT annual industrial and research tapes for the period from 1985 to 2016. The sample is restricted to post-1980 years because post-1980 years likely offer a more powerful setting for an investigation of bankruptcy risk as compared to previous years. Specification checks reveal that the CRSP-COMPUSTAT matched sample contains substantially more firms after 1980, which increases statistical power. More importantly, the enlargement of the sample comes from mostly younger, smaller, and otherwise marginal firms, which are likely to have higher Ex-ante bankruptcy risk. This conjecture is corroborated by the fact that Ex-post bankruptcy risk (proxies by bankruptcy and performance delisting) is considerably higher after 1980 in our sample. Data in Altman (1993) also show that the rate of insolvency and business failure has dramatically increased since the‘80s.

We extract quarterly returns on all NYSE, AMEX, and NASDAQ stocks listed in the CRSP database, subject to the requirement that, at the beginning of each quarter, the

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stock price be at least $1. While this is done to ensure that the empirical findings are not driven by low priced and extremely illiquid stocks, we find that our results are robust to these stocks.

Throughout the paper, we use delisted returns whenever appropriate. This is important because a number of stocks delist due to financial distress. We choose stocks that are rated by Standard & Poor's over the January 1985 through December 2016 period. The beginning of our sample is determined by the first time firm ratings by Standard & Poor's became available on the COMPUSTAT tapes. The S&P issuer rating used here is an essential component of our analysis. Note that Standard & Poor's assigns this rating to a firm, not a bond. As defined by S & P, this issuer rating is based on the overall quality of the firm's outstanding debt, either public or private. Before 1998, the issuer rating represents a select subsample of company bonds. After 1998, it represents all company debt.

For the empirical analysis that follows, we transformed the S&P rating into conventional numerical scores. In particular, AAA takes on the value 1 and D takes on the value 22.[1] Thus a higher numerical score corresponds to a lower credit rating or higher credit risk. Numerical ratings at or below 10 (BBB-or better) are considered investment-grade, and ratings of 11 or higher (BB+ or worse) are labeled high-yield or non-investment grade. The equally-weighted average rating in our sample is 8.21 (approximately BBB, the investment-grade threshold) and the median is 8.5 (BBB).

We merge these data sets with firm-level quarterly data from COMPUSTAT, as well as CRSP. This gives us about 2,023 bankruptcies and 981,533 quarterly observations. We use the market value of assets. These measures are more sensitive to new information about firm prospects. We lag all ratios by one quarter. This adjustment ensures that the data are available at the beginning of each period in which bankruptcy is measured. In order to further limit the influence of outliers, we winsorize the market-to-book ratio and all other variables in our model at the $5^{th}$ and $95^{th}$ percentiles of their pooled distributions across all firm-months. That is, we replace any observation below the $5^{th}$ percentile with the $5^{th}$ percentile, and any observation above the $95^{th}$ percentile with the $95^{th}$ percentile.

Table 1 summarizes the properties of bankruptcies. It lists the total number of firms' bankruptcies for every year of our sample period. The number of average firms is computed by averaging over the numbers of firms across all quarters of the year. The second column shows the number of firms in the CRSP database in each year. The third column shows the number of bankruptcies, and the fourth column shows the corresponding percentage of firms that went bankrupt in each year. The bankruptcy rate is high during the 1980s, with a peak of 1.39% in 1989. It remained high through

[1] The entire spectrum of ratings is as follows. AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22.

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the economic slowdown of the early 1990s, but declined in the late 1990s during a period of economic expansion and then increased again in the early 2000s, due to the economic downturn. The bankruptcies rose dramatically during economic crisis with a peak in 2008 and then fell in the 2010s.

Some of these changes are probably due to the changes in the law governing corporate bankruptcy in the 1980s and related financial innovations, such as the development of below-investment grade public debt in the 1980s and the advent of prepackaged bankruptcy filings in the early 1990s (Tashjian, Lease, &McConnell, 1996). Changes in the corporate capital structure (Bernanke &Campbell, 1998) and the riskiness of corporate activities (Campbell et al., 2001) are also likely to have played a role, and one purpose of our investigation is to quantify the time-series effects of these changes.

**Table 1:** Number of Bankruptcies per Year

| Year | All firms | Bankruptcies | % of Bankruptcies |
|---|---|---|---|
| 1985 | 4821 | 66 | 1.37 |
| 1986 | 5396 | 69 | 1.28 |
| 1987 | 5705 | 60 | 1.05 |
| 1988 | 5772 | 73 | 1.26 |
| 1989 | 5888 | 82 | 1.39 |
| 1990 | 6148 | 73 | 1.19 |
| 1991 | 6528 | 69 | 1.06 |
| 1992 | 6796 | 66 | 0.97 |
| 1993 | 8083 | 42 | 0.52 |
| 1994 | 8776 | 35 | 0.40 |
| 1995 | 9197 | 32 | 0.35 |
| 1996 | 9723 | 41 | 0.42 |
| 1997 | 10001 | 55 | 0.55 |
| 1998 | 10025 | 62 | 0.62 |
| 1999 | 10352 | 69 | 0.67 |
| 2000 | 10352 | 58 | 0.56 |
| 2001 | 9922 | 72 | 0.73 |
| 2002 | 9419 | 83 | 0.88 |
| 2003 | 9024 | 71 | 0.79 |
| 2004 | 8912 | 51 | 0.57 |
| 2005 | 8814 | 48 | 0.54 |
| 2006 | 8846 | 42 | 0.47 |
| 2007 | 8798 | 59 | 0.67 |
| 2008 | 8503 | 98 | 1.15 |
| 2009 | 8132 | 82 | 1.01 |
| 2010 | 8131 | 80 | 0.98 |
| 2011 | 8175 | 71 | 0.87 |
| 2012 | 8508 | 60 | 0.71 |
| 2013 | 8525 | 52 | 0.61 |
| 2014 | 8580 | 34 | 0.40 |
| 2015 | 8396 | 32 | 0.38 |
| 2016 | 7976 | 16 | 0.20 |

***Notes:*** This table lists the total number of active firms, bankruptcies for every year of our sample period. The number of active firms is computed by averaging over the number of active firms across all months of the year.

Table 2 summarizes the properties of our main explanatory variables, which documents the statistic characteristics of the stocks in different categories: all firms, active firms, and bankruptcies. This table includes the following variables: net income over market value of total assets (ROA), total liabilities over market value of total assets (leverage), log of excess return over t-bill three-month return (logExret), log of firm's market value of firm's total assets (size), stock of cash and short-term investments over the market value of total assets (liquidity), market-to-book ratio of the firm (MB), GDP, S&P 500 index volatility and five-year treasury bond yield. Panel A reports summary statistics for all firm-quarter observations. Panel B and Panel C report summary statistics for active firms and bankruptcies groups. Summary statistics are reported for those observations for which values of all variables are available.

In interpreting these distributions, it is important to keep in mind that we weighed every firm-quarter equally. This has two important consequences. First, the distributions are dominated by the behavior of relatively small companies; value-weighted distributions look quite different. Second, the distributions reflect the influence of both cross-sectional and time-series variations. In Panel A, the mean level of ROA is almost exactly zero (in fact, very slightly negative). This is lower than the median level of ROA, which is positive at 0.7% per quarter because the distribution of profitability is negatively skewed. All these measures of profitability are strikingly low, reflecting the prevalence of small, unprofitable listed companies in recent years. The average value of logExret is -0.048 or -4.8% per quarter. This extremely low number reflects both the underperformance of small stocks during the latter part of our sample period (the value-weighted mean is almost exactly zero), and the fact that we are reporting a geometric average excess return rather than an arithmetic average. The difference is substantial because individual stock returns are extremely volatile.

Panel B of Table 2 reports the summary statistics for active firms. The patterns are similar to those in Panel A but some effects are stronger. For example, leverage and liquidity status are better, and ROA and returns are higher compared to all firms. A comparison of active firms and bankrupt firms reveals that bankrupt firms have intuitive differences from the rest of the sample. In quarters immediately preceding a bankruptcy filing, their debts are extremely high relative to their assets (average leverage is almost 80%, and median leverage exceeds 85%). They have experienced extremely negative returns over the past quarter (the mean is -13.7% over a quarter, while the median is -17% over a quarter). Bankrupt firms also tend to be relatively small, and they have only about half as much cash and short-term investments as non-bankrupt firms. The market-to-book ratio of bankrupt firms has a lower mean and a much higher standard deviation than the market-to-book ratio for non-bankrupt firms, as the stock market often anticipates bankruptcy driving down the market value of equity and the market-to-book ratio. These two forces can differ across firms, generating a wide spread in the market-to-book ratio for bankrupt firms.

Table 3 summarizes the firms' characteristics for firms with different rating categories. In particular, we split the sample into 10 groups, sorted by highest rating to lowest rating firms. Group 1 represents firms that have the top 10 percentile with the highest rating, while group 10 represents the firms that have the bottom 10 percentile with the lowest rating. It is immediately apparent that firms with good credit rating have higher return, better profitability, and higher market-to-book ratio compared to low rating

**Table 2:** Summary Statistics

| | Size | LogRet | ROA | Leverage | Liquidity | Sigma | M/B | GDP | S&P500 Volatilities | Five Year Bond-Yield |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: All Firms | | | | | |
| MIN | 1.556 | -0.548 | -0.099 | 0.023 | 0.001 | 0.126 | 0.726 | 1095.900 | 11.566 | 0.953 |
| MAX | 9.744 | 0.405 | 0.027 | 0.914 | 0.394 | 1.129 | 9.129 | 3906.400 | 33.578 | 8.797 |
| MEAN | 5.427 | -0.048 | -0.007 | 0.407 | 0.091 | 0.539 | 2.200 | 2500.195 | 20.349 | 4.544 |
| STD | 2.311 | 0.228 | 0.031 | 0.286 | 0.107 | 0.392 | 2.092 | 1016.296 | 6.901 | 2.405 |
| Obs | 981533 | | | | | | | | | |
| | | | | | Panel B: Active Firms | | | | | |
| MIN | 1.665 | -0.348 | -0.099 | 0.023 | 0.001 | 0.126 | 0.926 | 1095.900 | 11.566 | 0.953 |
| MAX | 9.744 | 0.405 | 0.027 | 0.815 | 0.394 | 1.102 | 9.129 | 3906.400 | 33.578 | 8.797 |
| MEAN | 5.439 | -0.036 | -0.003 | 0.305 | 0.098 | 0.488 | 2.397 | 2500.438 | 20.328 | 4.547 |
| STD | 2.321 | 0.227 | 0.031 | 0.210 | 0.107 | 0.312 | 2.087 | 1020.374 | 6.902 | 2.416 |
| Obs | 958865 | | | | | | | | | |
| | | | | | Panel C: Bankruptcies | | | | | |
| MIN | 1.556 | -0.548 | -0.099 | 0.093 | 0.001 | 0.226 | 0.726 | 1095.900 | 11.566 | 0.953 |
| MAX | 9.315 | 0.305 | 0.027 | 0.914 | 0.394 | 1.129 | 8.129 | 3906.400 | 33.578 | 8.797 |
| MEAN | 4.910 | -0.137 | -0.020 | 0.793 | 0.048 | 0.628 | 1.324 | 2489.906 | 21.265 | 4.424 |
| STD | 1.720 | 0.368 | 0.037 | 0.368 | 0.134 | 0.395 | 4.280 | 825.468 | 6.816 | 1.893 |
| Obs | 226688 | | | | | | | | | |

***Notes:*** This table includes the following variables: net income over market value of total assets (ROA), total liabilities over market value of total assets (Leverage), log of gross excess return over value-weighted S&P 500 return (LogExret), log of firm's market equity over the total valuation of S&P 500 (Size), square root of the sum of squared firm stock returns over a 3-month period (Sigma) quarterly, stock of cash and short-term investments over the market value of total assets (Liquidity), Market-to-book ratio of the firm (MB). Market value of total assets is calculated by adding the market value of firm equity to its total liabilities. Panel A reports summary statistics for all firm-quarter observations, Panels B and C report summary statistics for the bankruptcy and failure groups. There are a total of 981,533 observations, of which 2,023 are bankruptcy.

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Firms. High rating firms also have better liquidity condition compared to low rating firms reflected by holding more cash and short-term investments. In terms of financial risk measured by the use of debt, those low rating firms borrow more than double than those of high rating firms. As discussed above, low rating firms have higher financial leverage compared to high rating firms.

**Table 3:** Summary Statistics

| Group | LogRet | ROA | Leverage | Liquidity | MB |
|---|---|---|---|---|---|
| 1 | 0.325 | 0.020 | 0.251 | 0.252 | 5.728 |
| 2 | 0.215 | 0.016 | 0.086 | 0.251 | 6.478 |
| 3 | 0.123 | 0.013 | 0.128 | 0.166 | 5.636 |
| 4 | 0.027 | 0.012 | 0.235 | 0.162 | 3.537 |
| 5 | -0.028 | -0.001 | 0.369 | 0.131 | 3.526 |
| 6 | -0.064 | -0.014 | 0.458 | 0.096 | 2.412 |
| 7 | -0.121 | -0.003 | 0.312 | 0.087 | 1.642 |
| 8 | -0.129 | -0.032 | 0.623 | 0.104 | 1.808 |
| 9 | -0.261 | -0.040 | 0.652 | 0.102 | 2.662 |
| 10 | -0.387 | -0.055 | 0.581 | 0.088 | 2.323 |

***Notes:*** All firms are assigned quarterly into decile portfolios based on their probability of bankruptcy. Portfolio 1 contains the firms with the lowest probability of bankruptcy and portfolio 10 contains the firms with the highest probability of bankruptcy. This table presents a three-year window of average quarterly variables, conditional on probability of bankruptcy at the time of portfolio assignment.

## 3. Methodology and Empirical Findings

### *3.1 Model of Default Probability*

If credit default risk is mostly driven by idiosyncratic or systematic factors (or both)? On one hand, firm-specific characteristics should determine firm's default on bank loans. On the other hand, from a macroeconomic perspective, the bankruptcy rate increased in the early 1970s, and then rose dramatically during the 1980s. It remained high till 1990s when the economic slowdown. Then it fell in the late 1990s to levels only slightly above those that prevailed in the 1970s. There was a steady decline in default frequencies until 2000, accompanied by positive economic developments. It therefore appears that macroeconomic developments may also have an important role in explaining the evolution of a firm's credit risk over time. The deterioration of economic conditions was then mirrored (with some lag) by an increase in observed default frequencies. Under this setup, the main purpose of this section is to empirically examine the determinants of corporate credit default, taking simultaneously into account firm-specific characteristics, as well as macroeconomic variables.

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In order to achieve this objective, we need to understand how idiosyncratic and systematic risk factors influence the default probability. Although we use quarterly data, we do not try to predict the event that bankruptcy will occur during the next quarter. Over such a short horizon, it may not be very useful information if it is relevant only in the extremely short run. We explore time-series variation in the number of bankruptcies and ask how much of this variation is explained by changes over time in the variables that predict bankruptcy at firm level. We thus extend our study by explicitly considering how the optimal specification varies with the horizon of the forecast.

A common approach in credit risk literature is to use discrete choice models, which can be used to empirically examine credit risk drivers, assessing their relative importance in determining whether firms default on their credit liabilities. Following Shumway (2001) and Chava and Jarrow (2004), we estimate the probabilities of bankruptcy over the next period using a logit model. We assume that the marginal probability of bankruptcy over the next period follows a logistic distribution and is given by:

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1+\exp\left(-\alpha-\beta x_{i,t-1}\right)}, \tag{1}$$

In equation (1), $Y_{it}$ is an indicator that equals one if the firm goes bankrupt in quarter$t$, and $x_{i,t-1}$ is a vector of the explanatory variables known at the end of the previous quarter. A higher level of $\alpha + \beta x_{i,t-1}$ implies a higher probability of bankruptcy.

We then ask what happens as we try to predict bankruptcies further into the future. We extended the time series variables and estimate the conditional probability of bankruptcy in 2, 3, and 4 quarters. We allow the coefficients on the variables to vary with the horizon of the prediction. In particular, we assume that the probability of bankruptcy in the$j$ quarters, conditional on survival in the date set for $j-1$quarter, is given by

$$P_{t-1}\left(Y_{i,t-1+j} = 1 \middle| Y_{i,t-2+j} = 0\right) = \frac{1}{1+\exp\left(-\alpha_j-\beta_j x_{i,t-1}\right)}, \tag{2}$$

Under this modeling framework, the default event of firm $i$ in period $t$ as a ramdom variable $Y_{it}$can be modeled such that:

$$Y_{it} = \begin{cases} 1 & if\ firm\ i\ defaults\ in\ t \\ 0 & otherwise \end{cases} \tag{3}$$

The time-discrete hazard rate can be defined as:

$$\theta_{it} = \Pr\left(Y_{it} = 1\right) \tag{4}$$

We will consider two vectors of explanatory variables. The first vector is a set of firm-specific variables, which shall account for idiosyncratic risk ($Z_{it}$). This vector will include contemporaneous and lagged variables regarding several dimensions of the firm's financial situations, such as size, profitability, leverage, and liquidity. The second vector comprises a set of aggregate time-varying regressors, which intend to account for systematic risk ($X_t$). These may include variables such as GDP growth, interest rates, equity prices (and their volatility), and bond spreads.

We want to estimate a linear panel model such as:

$$\theta_{it}(X_t, W_{it}) = \Pr(Y_{it} = 1 | X_t, W_{it}) = F\big(\tilde{\alpha} + \tilde{\gamma}X_t + \tilde{\delta}W_{it}\big). \quad (5)$$

The model to be estimated will depend on the assumption made on the error distribution function $F(.)$. Assuming a logistic distribution function $\Theta(.)$ yields a logit model such that:

$$\theta_{it}(X_t, W_{it}) = \Theta\big(\tilde{\alpha} + \tilde{\gamma}X_t + \tilde{\delta}W_{it}\big). \quad (6)$$

Discrete choice models may provide an interesting assessment of the determinants of firm default, helping to determine whether or not a firm with given characteristics is likely to default. However, it would also be important to focus on the time dimension of default, understanding not only if a firm will default, but also when will that eventually occur.

From this starting point, we made several numbers of contributions to the model specification of corporate bankruptcies. First of all, we added sector dummies to our specifications. The results for these sector dummies suggest that there may be some differences in default risk drivers across different sectors. Overall, the coefficients associated with firms' financial ratios remain robust. Secondly, there are several concerns about the use of accounting models in estimating the default risk of equities. Accounting models use information derived from financial statements, which is inherently backward-looking as financial statements aim to report a firm's past performance, rather than its future prospects. In contrast, Merton's (1974) model uses the market value of a firm's equity in calculating its default risk. It also estimates its market value of debt, rather than using the book value of debt. Market prices reflect the investor's expectations about a firm's future performance. As a result, they contain forward-looking information about ongoing concern, which fits better in calculating the likelihood that a firm may default in the future. In addition and most importantly, accounting models do not take into account the volatility of a firm's assets in estimating its risk of default. Campbell et al. (2001) demonstrate that firm-level volatility has trended upward since the mid-1970s. Furthermore, using data from 1995 to 1999, Campbell and Taksler (2003) show that firm-level volatility and credit ratings can explain equally well the cross- sectional variation in corporate bond yields. Clearly, the volatility of a firm's assets provides crucial information about the firm's probability to default. Moreover, we increase the horizon at which we are trying to predict future default. Consistent with our expectations, we find that volatility becomes more important at long horizons relative to other explaining variables, which implies that our most persistent forecasting variables become relatively more important as we predict further into the future.

To construct this model, we first use a set of individual firm level explanatory variables. The measure of profitability is constructed using net income to total assets ratio, where the equity component of total assets are measured at the market value by adding the book value of liabilities to the market value of equities. Profitability with market value of total assets has stronger explanatory power, compared to the variable with book value of liabilities, perhaps because market prices can rapidly incorporate future market information about the firm's prospects and thus more accurately reflect intangible assets of the firm. Leverage is constructed using total liabilities relative to the total market value of assets. Again, we us the market-valued of this variable, which is defined as total liabilities divided by the sum of market equity and book liabilities. We found this measure performs better than the traditional book-valued variable. Liquidity is measured by a ratio of a company's cash and short-term assets to the market value of its assets. Excess return (Return) is quarterly log excess return on each firm's equity relative to the three-month T-bill return. Volatility is the standard deviation of each firm's daily stock return over the past three months. The size variable is measured as the log of firm's market value of total assets.

In constructing these variables, we adjust the book value of equity to eliminate outliers, following the procedure suggested by Cohen, Polk, and Vuolteenaho (2003). In particular, we add 10% of the difference between market and book equity to the total book value, thereby increasing book values that are extremely small and probably mismeasured. We replace these negative values with small positive values of $1 to ensure that the market-to-book ratios for these firms are in the right tail, not the left tail, of the distribution. All the characteristics are lagged by a quarter, relative to the quarter in which the dependent variable is measured. We align each company's fiscal year appropriately with the calendar year, converting COMPUSTAT fiscal year data to a calendar basis, and then lag accounting data by one quarter. This adjustment ensures that the accounting data are available at the beginning of the quarter over which default is measured.

Empirical results are reported in Table 4. On average, firms in default are less profitable, have lower liquidity ratios, and are more dependent on external funding sources. Return on assets displays a negative coefficient, suggesting that firms with stronger profitability have lower default, as expected; more profitable firms should have a more solid financial situation and thus lower default probabilities. Firm size exhibits a negative coefficient, which indicates that larger firms are, in general, more financially

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healthy and show lower default probability compared to small firms. The liquidity ratio has a negative

**Table 4:** Default Model with Firm-Specific Variables

| | Lag 1 | Lag 2 | Lag 3 | Lag 4 |
|---|---|---|---|---|
| Size | -0.069 | -0.059 | -0.070 | -0.096 |
| | (0.033)** | (0.023)** | (0.036)* | (0.085) |
| LogRet | -0.137 | -0.131 | -0.120 | -0.115 |
| | (0.029)*** | (0.036)*** | (0.044)*** | (0.068)* |
| Leverage | 9.387 | 8.328 | 7.402 | 5.649 |
| | (0.024)*** | (0.035)*** | (0.054)*** | (0.031)*** |
| ROA | -16.397 | -17.053 | -25.655 | -28.489 |
| | (0.202)*** | (0.403)** | (0.104)*** | (0.206)*** |
| Sigma | 1.365 | 1.418 | 1.532 | 1.215 |
| | (0.012)*** | (0.023)*** | (0.058)*** | (0.076)*** |
| Liquidity | -3.534 | -3.655 | -2.699 | -2.756 |
| | (0.065)*** | (0.085)*** | (1.365)** | (1.582)* |
| Sector Dummy | YES | YES | YES | YES |
| Intercept | -3.886 | -4.828 | -5.771 | -3.645 |
| R-square | 0.318 | 0.339 | 0.332 | 0.328 |

***Notes:*** This table reports results from logit regressions of the bankruptcy on predictor variables. The data re constructed such that all of the predictor variables are observable at the beginning of the month over which bankruptcy is measured. We report the predictive power for lags of 1, 2, 3, and 4 quarters. The standard error is reported in parentheses. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

impact on default probabilities, implying that firms facing stronger liquidity constraints may have higher pressure in paying their debt commitments, which is consistent with the results obtained by Bunn and Redwood (2003) and Benito et al. (2004). The coefficient on leverage ratio, defined as a firm’s long-term debt to market value of total assets, is positive and significant, suggesting that firms under financial pressure are more likely to default. Finally, the coefficient on log-returns is negative related to default, which is consistent with Campbell, et al. (2008) that firms with lower returns are more likely to default.

Given the fact that firm-specific data is usually available with a considerable lag, it becomes crucial to assess whether a firm is likely to be stressed in the future by evaluating how the firm’s past performance affects its default probability, which could help to predict future defaults. Departing from the baseline specification presented above, in Table 4, we present some additional regressions, using all firm-specific variables lagged two, three, and four quarters, respectively. When all firm variables are lagged by two, three, and four quarters, the results are mainly robust. Most of the

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coefficients on a firm's characteristics preserve the same signs. There seems to be an increase in the marginal effect of profitability on credit risk, and conversely, a decrease in the relative importance of the leverage ratio. Hence, sustained poor profitability ratios over time indicate a strong sign of a firm's distress, yielding possibly high future default. When variables are lagged by more than four quarters, which is not reported, there is a clear decrease in the model's quality. Most variables are no longer significant and the Pseudo-R2 decreases considerably, suggesting that the firm's recent performance is much more relevant to explain default than its historical background.

**Table 5:** Default Model with Firm-Specific and Macroeconomic Variables

| | Current | Lag 1 | Lag 2 | Lag 4 |
|---|---|---|---|---|
| Size | -0.089 | -0.066 | -0.074 | -0.082 |
| | (0.035)*** | (0.032)** | (0.037)** | (0.048)* |
| LogRet | -0.193 | -0.182 | -0.165 | -0.148 |
| | (0.058)*** | (0.042)*** | (0.083)** | (0.089)* |
| Leverage | 9.819 | 8.734 | 4.767 | 3.896 |
| | (0.024)*** | (0.065)*** | (2.356)** | (2.061)** |
| ROA | -22.194 | -24.996 | -26.737 | -25.853 |
| | (0.207)*** | (0.268)*** | (0.109)*** | (0.312)*** |
| sigma | 1.432 | 1.587 | 1.321 | 1.215 |
| | (0.011)*** | (0.026)*** | (0.638)** | (0.549)** |
| Liquidity | -3.604 | -3.397 | -3.232 | -2.815 |
| | (0.165)*** | (1.686)** | (1.665)** | (1.215)** |
| GDP | -0.236 | -0.242 | -0.158 | 0.106 |
| | (0.012)*** | (0.033)*** | (0.073)** | (0.125) |
| | 0.085 | 0.063 | 0.052 | 0.036 |
| S&P500 Volatility | (0.022)*** | (0.013)*** | (0.021)** | (0.017)** |
| | 0.060 | 0.064 | 0.075 | 0.083 |
| 5 Year Bond Yield | (0.029)** | (0.030)** | (0.041)* | (0.090) |
| Sector Dummy | YES | YES | YES | YES |
| Intercept | -3.251 | -3.168 | -2.815 | -3.889 |
| R-square | 0.421 | 0.436 | 0.429 | 0.458 |

***Notes:*** This table reports results from logit regressions of the bankruptcy on predictor Variables both firm-specific variables and Macroeconomic Variables. The data are constructed such that all of the predictor variables are observable at the beginning of the month over which bankruptcy is measured. We report the predictive power for lags of 1, 2, 3, and 4 quarters. The standard error is reported in parentheses. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

After assessing firm's characteristics that may contribute to the understanding of why some firms default, now we try to assess the role of macroeconomic factors simultaneously with firm's specific characteristics. We considered a relatively large set of macroeconomic variables, including GDP, private consumption, gross fixed capital formation, the coincident economic activity indicator, exports, employment, loan growth, an exchange rate index, the yield curve slope, ten-year bond yields, banks interest rates applied on loans to firms, and stock market prices variation. Some of these variables did not prove to be significant. From all of the variables considered, the most important variables are GDP, S&P 500 stock return volatilities, and five-year bond yield. The empirical results are presented in Table 5. The GDP has a negative contemporaneous impact on default probabilities, in agreement with what was discussed previously. The effects of GDP on default fade as horizon increases beyond one year. S&P 500 return volatility, which usually reflects stock market aggregate risk level, is associated with higher default probabilities. Five-year bond yield is positively related to the default probability, suggesting cyclical movement between default and bond market returns.

The cyclical component of GDP displays a leading indicator with the cycle of credit overdue. The negative correlation with default implies that a strong development in stock market prices, reflected in a broad-based improvement in firms' financial conditions, is usually associated with a lower default probability, as what we expected. This result implies that a period of robust economic growth is usually followed by an increase in default with an average lag of one year. This result confirms the hypothesis that in periods of economic growth there may be some tendency towards excessive risk-taking, which materializes in an increase of credit overdue when the economy hits a downturn. According to our results, these imbalances start to be gradually reflected in new credit overdue with a lag of at least one year. Then, the growth of credit risk in default is progressively reflected in an increase of the non-performing loans to reach its peak (that is when credit risk fully materializes) and the cycle of GDP is at its trough, resulting in a negative contemporaneous correlation between these two variables.

Government bond yield, as a leading variable, is statistically significant and displays a positive correlation with the cyclical component of default. It suggests that an increase in default is often preceded by an interest rate increase. As discussed above, this result may be associated, on one hand, with the increase of interest rates during periods of stronger and prolonged economic growth, which implies a higher debt service, which may put some constraint on firms with financial pressure. On the other hand, when interest rates increase significantly, adverse selection problems may become more severe, resulting a higher default rates.

When the variables considered are lagged by more than one year together with the firm-specific variables, the results are relatively disappointing—none of them remains statistically significant. Hence, even if at an aggregate level, it seems to be clear that significant imbalances are created in a period of strong economic growth, after controlling for firm-specific characteristics. As the horizon increases, the coefficients, significance levels, and overall fit of the logit regression decline as one would expect.

The results discussed above show that there are some important links between default risk and macroeconomic developments. In fact, periods of strong economic growth are sometimes followed by an increase in default rates, possibly as a consequence of imbalances generated in those periods. When micro information is used to assess the determinants of loan default, it becomes clearer that the firm's financial situation is relevant to determine whether they will default. However, when time-effect

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controls or macroeconomic variables are also considered, the results improve considerably.

The results obtained allow us to conclude that macroeconomic dynamics have an important additional and independent contribution in explaining why firms default. The main idea is that most risk is built up during upturns when banks apply looser credit standards. However, most of the risk materializes only when the economy hits a downturn. High default rates during recessions are just a materialization of the risk that is built up during expansions, most notably when strong economic growth is accompanied by the creation of unsustainable financial imbalances. The important finding of this study is that though the firm's financial situation has a central role in explaining default probabilities, macroeconomic conditions are also very important when assessing default probabilities over time.

The incremental information provided by the inclusion of the macroeconomic variables can be confirmed by the significant increase in the R-square of the model. These results allow us to conclude that macroeconomic dynamics have an important additional (and independent) contribution in explaining why firms default. The t-values of all tests are computed from Newey and West's (1987) standard errors. In particular, they are corrected for White's (1980) heteroscedasticity and serial correlation up to the number of lags that are statistically significant at the five percent level.

### *3.2 Model of Measurement Error and Empirical Findings*

In this Section, we will construct our default model under the measurement error framework by Hu (2008, 2017). Measurement error is the difference between a measured quantity and its true value, the latent variable. It includes random error and systematic error. Measurement error can be defined as random variation, of some distributional form, that produces a difference between observed and true values. Random error is caused by any factors that randomly affect the measurement of the variable across the sample. The important thing about random error is that it does not have any consistent effects across the entire sample. Because of this, random error is sometimes considered noise. Systematic error is caused by any factors that systematically affect the measurement of the variable across the sample.

Unlike random error, systematic errors tend to be consistently positive or negative—because of this, systematic error is sometimes considered to be biased in measurement. Measurement error adds noise to predictions, increases uncertainty in parameter estimates, and makes it more difficult to discover new phenomena or to distinguish among competing theories. A common view is that any study finding an effect under noisy conditions provides evidence that the underlying effect is particularly strong and robust. Yet, statistical significance conveys very little information when

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measurements are noisy. In noisy research settings, poor measurements can contribute to exaggerated estimates of effect size. It is possible, therefore, that statistical significance is achieved in the presence of measurement error, and the associated effects would have been insignificant without noise. This is known as the statistical significance filter and can be a severe upward bias in the magnitude of effects (Hu, 2007).

Measurement error models describe the relationship between latent variables, which are not observed in the data, and their measurements. Researchers only observe the measurements, instead of the latent variables in the data. The goal is to identify the distribution of the latent variables and also the distribution of the measurement errors, which are defined as the difference between the latent variables and their observable measurements. In general, the parameter of interest is the joint distribution of the latent variables and their measurements, which can be used to describe the relationship between observables and unobservables in economic models.

In this paper, we start with a general framework, where a measurement can be simply an observed variable with informative support. The measurement error distribution contains the information about a mapping from the distribution of the latent variables to the observed measurements. We start with a definition of measurement. Let $\theta$ denote an observed random variable and $\theta^*$be a latent random variable of interest. We define a measurement of $\theta^*$ as follows:

Definition 1. A random variable $\theta$ with support $\vartheta$ is called a measurement of a latent random variable $\theta^*$ with support $\vartheta^*$ if

$$cardinality\ (\vartheta) \geq (\vartheta^*) \tag{7}$$

When $\theta$ is continuous, the support condition is not restrictive, whether $\theta^*$is discrete or continuous. When $\theta$ is discrete, the support condition implies that the number of possible values of one measurement is larger than or equal to that of the latent variable. In addition, the possible values in $\vartheta^*$are unknown and usually normalized to be the same as those of one measurement.

In a random sample, we observe measurement $\theta$, while the variable of interest $\theta^*$ is unobserved. The measurement error is defined as the difference $\theta - \theta^*$. We can identify the distribution function $f_\theta$ of measurement $\theta$ directly from the sample, but our main interest is to identify the distribution of the latent variable $f_{\theta^*}$, together with the measurement error distribution described by $f_{\theta|\theta^*}$. The observed measurement and the latent variable are associated as follows: for all $\vartheta \in \theta$

$$f_\theta(\vartheta) = \sum_{\vartheta^* \in \theta^*} f_{\theta|\theta^*(\vartheta|\vartheta^*)} f_{\theta^*}(\vartheta^*), \tag{8}$$

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When $\theta^*$is discrete with support $\vartheta^* = \{\vartheta_1^*, \vartheta_2^*, \dots, \vartheta_K^*\}$ and $f_{\theta^*}(x\vartheta^*) = \Pr(\theta^* = \vartheta^*)$ is the probability mass function of $\theta^*$ and $f_{\theta|\theta^*}(\vartheta|\vartheta^*) = \Pr(\theta = \vartheta|\theta^* = \vartheta^*)$. This general framework can be used to describe a wide range of economic relationships between observables and unobservables in the sense that the latent variable $\theta^*$ can be interpreted as unobserved heterogeneity, fixed effects, random coefficients, or latent types in mixture models, etc.

For simplicity, we start with the discrete case and define

$$\overrightarrow{P_\theta} = [f_\theta(\vartheta_1), f_\theta(\vartheta_2), \dots, f_\theta(\vartheta_L)]^T \quad (9)$$

$$\overrightarrow{P_{\theta^*}} = [f_{\theta^*}(\vartheta_1^*), f_{\theta^*}(\vartheta_2^*), \dots, f_{\theta^*}(\vartheta_L^*)]^T \quad (10)$$

$$M_{\theta|\theta^*} = [f_{\theta|\theta^*}(\vartheta_l|\vartheta_k^*)]_{l=1,2,\dots,L;k=1,2,\dots,K^*} \quad (11)$$

The notation $M^T$ stands for the transpose of M. Note that $\overrightarrow{P_\theta}, \overrightarrow{P_{\theta^*}}, and\ M_{\theta|\theta^*}$ contain the same information as distributions $f_\theta, f_{\theta^*}$, and $f_{\theta|\theta^*}$, respectively.

The matrix $M_{\theta|\theta^*}$ describes the linear transformation from $R^K$, a vector space containing$\overrightarrow{P_{\theta^*}}, to\ R^L$ , a vector space containing $\overrightarrow{P_\theta}$. Suppose that the measurement error distribution is known. The identification of the latent distribution $\vec{P}_{\theta^*}^a\ and\ \vec{P}_{\theta^*}^b$ are observationally equivalent, i.e.,

$$\vec{P}_\theta \ = M_{\theta|\theta^*}\vec{P}_{\theta^*}^a = M_{\theta|\theta^*}\vec{P}_{\vartheta^*}^b, \quad (12)$$

Then, the two distributions are the same, i.e., $\vec{P}_{\theta^*}^a = \vec{P}_{\vartheta^*}^b. Let\ h = \vec{P}_{\theta^*}^a - \vec{P}_{\vartheta^*}^b$. The identification of $f_{\theta^*}$ then requires that $M_{\theta|\theta^*}h = 0\ implies\ h = 0\ for\ any\ h \in R^K$. This is a necessary rank condition for the nonparametric identification of the latent distribution.

We find that returns to distressed stocks are particularly low when the implied volatility of the S&P 500 index increases. This implies that distressed stocks are vulnerable to increases in market-wide risk or risk aversion. Indeed, previous work (e.g., Hand, Holthausen, & Leftwich, 1992; Dichev & Piotroski, 2001) documents considerable abnormal price declines following economic downturn. Relative to this body of work, however, we uncover substantial cross-section differences in responses to economic downturn. The considerable stock return drop following economic downturn is apparent among low-quality stocks, whereas high-quality firms often realize positive returns.

To examine the asymmetry, we separate the sample into constrained and unconstrained firms. Firms that are financially constrained may not be able to adjust their leverage, even if its fundamental risk receives an exogenous shock.

Korajczyk and Levy (2003) find that constrained firms adjust slowly to time their issues, while unconstrained firms do not, which is consistent with having a more important endogeneity effect when firms are financially constrained. On the other hand, firms that are financially unconstrained have more flexibility, and their leverage ratios are more sensitive to exogenous shocks in their fundamental risks. Given the evidence from the credit channel literature that firms with differential access to financial markets have different debt issue patterns, we split our sample into two categories that we will refer to as financially constrained if the firm does not have sufficient cash to undertake investment opportunities and if it faces severe agency costs when accessing financial markets. Empirically, we use a high retention rate combined with the existence of investment opportunities to identify financially constrained firms. Since dividends and security repurchase compete with investment for funds, firms that have investment opportunities and face relatively high costs of external finance should choose to retain net income for investment. Therefore, the specific criteria for a firm to be labeled financially constrained are: (1) the firm does not have a net repurchase of debt or equity and does not pay dividends, and (2) the firm's Tobin's Q, defined as the sum of the market value of equity and the book value of debt, divided by the book value of assets, at the end of the quarter should be greater than one. A firm is labeled as financially unconstrained if it does not meet these two criteria. In total, we classify 565 firms as financially constrained and 5,059 as financially unconstrained. Only eight of the financially constrained firms have investment-grade bonds rated by S&P; four have a rating of BBB, four have a rating of AA, and the rest have speculative-grade debt or no rating at all. It is worth noting that although this classification is persistent, firms do switch classifications; approximately one-third of firms that re-enter the sample switch classification.

In order to test the difference of the effect of independent variables for default risk, we conduct the marginal effect on default risk for both firm-specific characteristics as well as macroeconomic variables. In particular, the marginal effects of each of the independent variables are calculated for all data observations. Table 6 reports the average marginal effect for each of the independent variables on default probability. Compared to unconstraint firms, constraint firms are more sensitive to a firm's profitability, which is measured by ROA. Financial constraint firms are more sensitive to a firm's liquidity and leverage compared to unconstraint firms. Constraint firms that have more cash and lower leverage are less likely to default compared to unconstraint firms. From a macroeconomic perspective, constraint firms rely more on aggregate movements of the economy: marginal effects of GDP for constraint firms are

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**Table 6:** Marginal Effects

| | Constraint | Unconstraint |
|---|---|---|
| Marginal effect of Size | -0.016 | -0.012 |
| | (0.0358) | (0.0218) |
| Marginal effect of Return | -0.031 | -0.002 |
| | (0.0642) | (0.0135) |
| Marginal effect of Leverage | 0.0215 | 0.028 |
| | (0.0585) | (0.0522) |
| Margain effect of ROA | -0.1882 | -0.0879 |
| | (0.0672) | (0.0467) |
| Marginal effect of Liquidity | -0.079 | -0.032 |
| | (0.0431) | (0.0858) |
| Marginal effect of GDP | -0.036 | -0.005 |
| | (0.0282) | (0.0212) |
| Marginal effect of Stock Market Volatility | 0.058 | 0.012 |
| | (0.0513) | (0.0349) |
| Marginal effect of 5 Year Bond Yield | 0.0322 | 0.0321 |
| | (0.0412) | (0.0328) |

***Notes:*** This table reports the marginal effect of firm-specific and Macroeconomic Variables on firm default probability. We split whole sample into constraint firms and unconstraint firms.

higher compared to unconstraint firms, indicating that when the economy is good, constraint firms are less likely to default. However, when stock market volatility is high or when the market in general accumulates more systematic risk, constraint firms are more likely to default compared to unconstraint firms. But there is no significant different marginal effect on five-year bond yield between constraint firms versus unconstraint firms, which is probably because constraint firms have limited access to the debt market. In general, marginal effects for both firm-specific variables and macroeconomic variables are stronger for financially constraint firms than that of unconstraint firms which is consistent with the previous discussion. All of these variables display relatively high marginal effects on default probabilities. In fact, these marginal effects are considerably stronger than those obtained for firm-specific variables, showing that macroeconomic conditions are very important in explaining default probabilities.

The above results provide strong evidence that suggests the fundamental performance of the low rated stocks is substantially worse than that of the high rated stocks during economic downturn. The deteriorating fundamental performance of low rated stocks around a downturn is consistent with the severe decline in their returns. Consequently, a natural question to ask is what are factors that affect measurement error?

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Table 7 conducts and reports the empirical results of the measurement error model, in which we adopted previously tested firm-specific and macroeconomic variables. In Table 7, the second

**Table 7:** Measurement Error

| | All | Constraint | Unconstraint |
|---|---|---|---|
| Size | -0.451 | -0.182 | -1.539 |
| | (0.245)* | (0.137) | (0.647)** |
| LogRet | -0.328 | -0.088 | -1.302 |
| | (0.062)*** | (0.042)** | (0.568)** |
| Leverage | 1.131 | 0.769 | 0.426 |
| | (0.031)*** | (0.079)*** | (0.041)*** |
| Roa | -0.353 | -0.321 | -0.162 |
| | (0.158)** | (0.152)** | (0.096)* |
| Liquidity | -0.362 | -0.371 | -0.258 |
| | (0.112)*** | (0.036)*** | (0.089)*** |
| GDP | -2.526 | -2.610 | -1.980 |
| | (1.115)** | (1.021)*** | (1.012)** |
| S&P 500 Volatility | 3.157 | 2.862 | 1.021 |
| | (0.251)*** | (0.218)*** | (0.076)*** |
| 5 Year Bond Yield | 0.082 | 0.053 | 0.091 |
| | (0.036)** | (0.025)** | (0.045)** |
| Sector Dummy | YES | YES | YES |
| Intercept | 3.360 | 2.253 | 1.962 |
| R-square | 0.360 | 0.381 | 0.435 |

***Notes:*** This table reports the results for measurement errors. Independent variables Reported including Size, LogRet, Leverage, ROA, Liquidity, GDP, S & P 500 Volatility and 5 Year Bond Yield. The standard error is reported in parentheses. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

column reports the results for all firms. The third and fourth columns report the results for constraint and unconstraint firms, respectively. First of all, for macroeconomic variables, the coefficients have the same sign for both constraint firms and unconstraint firms, which is consistent with all firms. In particular, GDP is negatively associated with measurement error. It implies that during economic downturn, measurement error is high and constraint firms are more sensitive to GDP. Measurement error is high in a volatile market for both constraint firms and unconstraint firms. This coefficient shows a higher magnitude for constraint firms, implying that constraint firms are more sensitive to market volatility. Five-year bond yield is also positively associated with measurement error, as expected and discussed in the previous session. Constraint firms have higher coefficients, indicating higher sensitivity to the bond market.

These results provide important empirical insight for measurement error and the cause of market mispricing. When the deteriorating performance of high credit risk stocks is not anticipated by the market as evidenced by analyst forecast revisions and earnings surprises, the gap between the market value of default risk and its intrinsic endogenous value is created, the so-called measurement error. Moreover, analyst forecast revisions and earnings surprises are negative and much larger in absolute values for low rated stocks for up to a year after the economic downturn. Institutions reduce their holdings of the low rated stocks due to economic downturn possibly due to their fiduciary responsibilities. One reason why analysts and institutions are surprised by the poor fundamental performance of the low rated stocks may be due to the fact that financial distress itself may prompt suppliers, customers, creditors, and employees to abandon these firms in larger than expected numbers around economic downturn. Given the significantly higher illiquidity of low rated stocks, the institutional selling activity following the negative surprises among high credit risk stocks may be the cause of the substantial market misprice. The returns of high credit risk firms continue to be negative following economic downturn, possibly because the rapid deterioration in fundamental performance is unanticipated by the market. This process is exacerbated by the much larger illiquidity of high credit risk stocks and the institutional selling, which resulted in extreme low return. This market noise exacerbated the measurement error between the unobservable true default probability and biased market measure—the credit rating.

## 3. Conclusion

When the market is not perfectly efficient, firms with low default risk realize higher returns than firms with high default risk. This credit risk effect on the cross-section of stock returns becomes a puzzle because investors appear to pay a premium for bearing credit risk. Our main contribution of the study is we attempt to detangle the puzzle from the perspective of measurement error by representing the first treatment of a wide class of nonlinear models with discrete variables using instruments. Empirical results showed measurement error has great impact on degree of firm default risk. During economic downturn, low quality firms experience substantial deterioration in their operating and financial performance and are sold by institutional investors leading to considerable price drops. The deteriorating fundamental performance is unanticipated by the market as evidenced by the large negative earnings surprises and analyst forecast revisions. In contrast, average returns do not differ across credit risk groups in periods of stable or improving credit conditions. Secondly, this study provides a thorough examination on the determinants of default risk, both at an aggregate macroeconomic perspective and a firm-specific level. On one hand, we model how systematic factors revolute aggregate default rates. On the other hand, we examined how firms' specific characteristics affect their default probabilities.

We explore the links between default risk and measurement error at both firm level as well as macroeconomic developments at an aggregate level. The empirical results confirm the hypothesis that in periods of economic growth, which are sometimes accompanied by strong credit growth, there may be some tendency towards excessive risk-taking. However, the imbalances created in such periods only become apparent when the economic growth slows down. In examining the determinants of credit risk at an aggregate level, we simultaneously incorporate firm-specific effects. The results obtained suggest that default probabilities are influenced by several firm-specific characteristics, such as their financial structure, profitability, and liquidity. Lagged information on the firm's financial situation over a short period also seems to be important in explaining why some firms default on their loan commitments. When macroeconomic variables are taken into account together with the firm-specific characteristics, the results of the models improve considerably, which implies that macroeconomic dynamics have an important additional (and independent) contribution in explaining why firms default. The empirical results of this study provide important insights to the existing literature that even though the determinants of loan default at the micro level are ultimately driven by the firm's specific financial situation, there are important relationships between the overall macroeconomic conditions and default rates, which should be assessed from a financial stability perspective.

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