Credit Market Frictions and the Linkage Between Micro and Macro Uncertainty

Abstract

This paper proposes a quantitative general equilibrium model with credit market frictions to explain the observed stylized facts of micro uncertainty (dispersion of realized firm-level outcomes) and macro uncertainty (volatility of aggregate economic variables). They are conceptually different but strongly comove and countercyclical. An increase in the dispersion of firm-level idiosyncratic shocks leads to more firms in the left tail of the distribution to default, which reduces the total net worth of the corporate sector. As a result, leverage increases, it magnifies the shock amplification mechanism of credit market frictions. Hence, the economy becomes more sensitive to aggregate shocks when micro uncertainty is high and the economy is more volatile. Consistent with the model predictions, I find that in the data, micro uncertainty, based on the dispersion of firm-level stock returns and sales growth, positively predicts future credit spreads.

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1 Introduction

Uncertainty shocks have been demonstrated as an important driving force that affect business cycles, asset prices and firm investment decisions. Various measures of uncertainty used in the literature exhibit a common countercyclical pattern. In this paper, I focus on two different types of uncertainty. I define micro uncertainty as the cross-sectional dispersion of firm-level outcomes, such as the cross-sectional dispersion of stock returns and sales growth. I define macro uncertainty as the standard deviation of the time series of aggregate variables, such as the volatility of stock market returns or GDP growth rates. These two types of uncertainty are conceptually different, but they are positively correlated and both countercyclical in the data. The comovement and countercyclical nature of micro and macro uncertainty strongly affects the decision making of economic agents, therefore it is important to understand the mechanism which drives the dynamics of these two types of uncertainty.

Many recent studies take both fluctuations in micro and macro uncertainty as uncertainty shocks without further distinguishing them. However, they are disparate measures; the first one captures the cross-sectional dispersion and the second one measures the time-series volatility. More importantly, these two types of uncertainty have different implications and effects on the aggregate economy. In this paper, I distinguish micro and macro uncertainty, then I show that their comovement and countercyclical nature originate from the fluctuations in micro uncertainty.

I present a general equilibrium model with credit market frictions to quantitatively account for the comovement between micro and macro uncertainty, as well as their countercyclicality. In a frictionless economy, an increase in micro uncertainty typically does not affect aggregate quantities. However, in my model with credit market frictions, an increase in micro uncertainty can endogenously drive up macro uncertainty. In my model economy, firms experience shocks to the magnitude of idiosyncratic productivity shocks, or equivalently, shocks to micro uncertainty. There are many entrepreneurs, who are firm owners, borrow from creditors to finance investment projects. Each entrepreneur receives cash flows by operating a firm. When the cross-sectional dispersion of idiosyncratic shocks are high, the cash flows received by entrepreneurs become more dispersed, more firms at the left tail will receive very low cash flows, which make them more likely to default on prenegotiated debt. The deadweight loss associated with default shrinks the entrepreneurs' net worth. Therefore,

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2See the review by Bloom (2014).

3Similar setup can be found in Christiano et al. (2014).
the leverage of the economy increases and the shock amplification effects of credit frictions get more stronger. As a result, the economy is more sensitive to aggregate shocks when micro uncertainty is high, hence the economy becomes more volatile. The micro uncertainty in this economy endogenously drives macro uncertainty to be time-varying, thus micro and macro uncertainty are positively correlated. They are both countercyclical because high micro uncertainty leads to more default and more deadweight loss, thus output drops.

My model of credit market frictions builds on the framework of Bernanke, Gertler, and Gilchrist (1999). However, I introduce endogenous growth and recursive preferences to enhance the shock amplification effects of the credit frictions. This is because the standard financial accelerator model, as of Bernanke et al. (1999), cannot quantitatively match the co-movement between micro and macro uncertainty, and their countercyclicality. Even though the shock amplification mechanism exists, the magnitude is not strong enough. As a result, the co-movement between micro and macro uncertainty is positive but small when compare to the data. Endogenous growth and recursive preferences can resolve this quantitative difficulty in this type of model through long-run risks mechanism. Endogenous growth introduces more persistent fluctuations in future expected growth rates. Recursive preferences allow agents to prefer early resolution of uncertainty, which make them care about the fluctuations in future expected growth rates. Following the intuition of the long-run risks literature, these two elements will make asset price to be more responsive upon aggregate shocks. This will further introduce much more fluctuations to the default behavior of the borrowers as well, because their debt paying ability depends on the asset prices. As default is more responsive to aggregate shocks, so are the deadweight loss, leverage and associated shock amplification effects. Therefore, the shock amplification effects get magnified, and the co-movement between micro and macro uncertainty is stronger.

Endogenous growth allows fluctuations in micro uncertainty to have impact on the growth rates of the economy, which helps the long-run risks channel. The endogenous growth rates of my model economy depend on the aggregate capital. When cross-sectional dispersion of idiosyncratic shocks are high, more firms on the left tail will receive very low cash flows, which make them more likely to default. Hence, creditors would like to cut lending and aggregate investment drops, this will reduce future capital stock. As a result, an increase in micro uncertainty will decrease the growth rates of the economy. More importantly, by affecting the growth rates, fluctuations in micro uncertainty will also affect the risk premia introduced by long-run risks mechanism. This risk premium channel allows credit spread to increase more when facing heightened micro uncertainty, thus default of firms is much more severe and the shock amplification effects of credit market frictions get magnified. In comparison to an economy with exogenous growth, the growth rates of the aggregate economy and also
the long-run risks mechanism are not affected by the variations in micro uncertainty.

This model not only successfully replicates the dynamics of micro and macro uncertainty but also provides rich empirical predictions. In the model, when micro uncertainty increases, more firms are likely to default, thus credit spread should increase. In the data, I find that micro uncertainty measures, based on the dispersion of stock returns and sales growth, positively predict future credit spreads. Additionally, high default risks should predict higher future market returns. I test this prediction in the data by using nonperforming loans to total loans as a proxy for the loan default rate, and I find that it significantly predicts future market excess returns. I also show that the model can quantitatively rationalize the credit spread and return predictability.

Related literature There is a large body of literature studying the impact of uncertainty shocks on business cycles. Bloom (2009) documents that various measures of uncertainty are countercyclical. He argues that uncertainty shocks have strong real option effects. When uncertainty is high, investment opportunities deteriorates, firms freeze investment and hiring, they “wait and see” until heightened uncertainty is resolved. Bloom et al. (2018) put this mechanism into a general equilibrium framework. Christiano, Motto, and Rostagno (2014) build a New Keynesian DSGE model with financial frictions, and perform a structural estimation. They find that uncertainty shocks, or risk shocks, which propagate through financial frictions, account for large fluctuations in GDP and other macroeconomic variables. Gilchrist, Sim, and Zakrajšek (2014) build a model allowing uncertainty shocks to affect the economy through both of the two channels: the financial frictions and the real option effect. They find that uncertainty shocks affect the economy more via financial frictions. Gabaix (2011) argues that business cycle fluctuations can originate from idiosyncratic shocks at the firm level because of the fat-tailed firm size distribution. Other papers explore uncertainty shocks as a driving force for business cycles, e.g., Arellano, Bai, and Kehoe (2016), Bachmann and Bayer (2014). Basu and Bundick (2017), Bianchi, Ilut, and Schneider (2017). This paper also relates to the literature focusing on the role of financial frictions on business cycles. My paper complements this literature by explaining why micro and macro uncertainty comove rather than focusing on the business cycle implications of uncertainty shock.

This paper explores the interplay between risk premia and credit market frictions. Similar to my paper, Gomes and Schmid (forthcoming) show that the endogenous movements in leverage and default provide amplification effects, which are crucial to explain the risk premia in equity and corporate bond markets. Bhamra, Kuehn, and Strebulaev (2009) study equity

\footnote{Christiano et al. (2014) is also based on Bernanke et al. (1999) as in my paper. However, as I discussed extensively in Section 4.5, without endogenous growth and recursive preferences, Christiano et al. (2014) or Bernanke et al. (1999) cannot quantitatively match the comovement between micro and macro uncertainty.}
premium and credit spread in a unified framework, emphasizing the importance of both first and second moment fluctuations in consumption growth. Chen (2010) shows that the risk premium channel introduced by long-run risks can help to resolve the credit spread puzzle and the under-leverage puzzle. Brunnermeier and Sannikov (2014), He and Krishnamurthy (2013), and other papers show that credit market frictions can provide non-linear shock amplification effects. Gomes, Yaron, and Zhang (2003) show that financial frictions can help to explain equity premium. These papers abstract from the joint dynamics of micro and macro uncertainty. My paper focuses on how micro and macro uncertainty are linked by risk premia and credit market frictions.

This paper connects to a large body of literature focusing on the connection between uncertainty and financial frictions. Elenev, Landvoigt, and Van Nieuwerburgh (2018) presents an economy where dispersion of idiosyncratic shock affects the economy also through credit market frictions. Their paper focuses on macro-prudential policy. Alfaro, Bloom, and Lin (2018) show that the real and financial frictions can amplify the impact of uncertainty shock. Dou (2017) argues that the impact of uncertainty shock on asset prices and business cycles depends on the risk sharing conditions. My paper shows how micro and macro uncertainty is linked through financial frictions.

The paper also relates to the long-run risks literature, initiated by Bansal and Yaron (2004), where long-run risks affects the risk premia. Kung and Schmid (2015) also explore the importance of endogenous growth, they show that endogenous growth, driven by innovation, can help to explain the equity premium. Croce et al. (2012) study the asset pricing implications of fiscal uncertainty. My paper also explores the implication of long-run risks by showing that endogenous growth and recursive preferences can strengthen the shock amplification effects of financial frictions. This mechanism helps the model to generate a strong comovement between micro and macro uncertainty.

Another strand of literature tries to study mechanism behind the countercyclical uncertainty. Bachmann and Moscarini (2012) argue the costs of experimenting new prices of firms are lower in recessions, thus firm-level outcomes become more dispersed. Decker et al. (2016) argue that firms optimally access to less markets to reduce costs in economic downturns, which decreases risk diversification and makes firm-level outcome more volatile. My paper complements to this literature by explaining the comovement between micro and macro uncertainty quantitatively through financial frictions.

A closely related literature study the dynamics of Knightian uncertainty through learning. Kozeniauskas, Orlik, and Veldkamp (2016) show that when aggregate volatility is high and agents have to form beliefs about the aggregate economic conditions given noisy signal, then micro-level disagreement will also be high. Ilut, Kehrig, and Schneider (2018) argue
that agents are ambiguity averse, so that they respond more to bad news, this asymmetric behavior results in countercyclical uncertainty qualitatively. Benhabib, Liu, and Wang (2016) show that information acquisition allows the feedback between micro and macro uncertainty go either ways. The uncertainty concepts in this literature are Knightian uncertainty, where the agents have to form beliefs about the true distribution of the micro or aggregate-level shocks. However, in my paper, both micro and macro uncertainty are defined on realized outcomes. Agents know the true distribution of shocks, there is no Knightian uncertainty in my model economy. Additionally, the economic mechanism of my paper is credit market frictions rather than learning.

This work also connects to a large body of literature studying on the implications of uncertainty shocks on asset prices. Herskovic et al. (2016) show that shocks to the common idiosyncratic volatility factor is priced in the cross-section. Ai and Kiku (2016) show that micro uncertainty increases the value of growth options, such that option-intensive firms earn lower returns. Bansal et al. (2014) argue that high aggregate volatility pushes up discount rates which drive down asset prices. Whereas my paper proposes an general equilibrium model to explain the comovement between micro and macro uncertainty. My paper can also help to explain why idiosyncratic risk increases with market risk, as documented in Bartram, Brown, and Stulz (2016).

The rest of the paper is structured as follows: In Section 2, I describe the uncertainty measures and discuss the their link to credit frictions. In Section 3, I present the model setup. Section 4 presents the quantitative results, and discusses the mechanism of the model. Section 5 concludes.

2 Empirical Facts

In order to study the economic linkage between micro and macro uncertainty, I construct the corresponding measures of uncertainty and then present the empirical facts. Firstly, I show that micro and macro uncertainty are strongly correlated and countercyclical. Then I show these two uncertainty measures comove with credit spread. Finally, I show that micro uncertainty is a robust predictor for future credit spread.

2.1 Data

The sample starts from January 1 of 1963 and ends in December 31 of 2016. Daily stock returns are from CRSP. Quarterly firm balance sheet data is obtained from Compustat. Monthly corporate bond yield is obtained from St. Louis Fed, Moody’s seasoned BAA
and AAA corporate bond yield, from 1963 January until 2016 December. VIX index is from Chicago Board Option Exchange (CBOE), the sample starts from January of 1990 and ends in December 2016. It is the implied volatility on S&P 500 stock market index of the next 30 days. The macro uncertainty measure of Jurado, Ludvigson, and Ng (2015) is downloaded from Sydney Ludvigson’s website. Annual industry level TFP is from NBER-CES Manufacturing Industry Database from 1958 until 2011. Return predictors, such as earning to price ratio, long term yield on government bonds, net equity issuance, etc., are from Amit Goyal’s website (Welch and Goyal (2007)). All macroeconomic quantities, such as GDP, consumption and investment, are obtained from Bureau of Economic Analysis, from 1963Q1: until 2016:Q4.

2.2 Uncertainty Measures

Micro uncertainty As in Bloom (2014), various measures of micro and macro uncertainty strongly correlate each other. However, if there are common components driving firm-level outcomes, e.g., business cycle conditions, the fluctuations of the common components can mechanically lead to a positive correlation between micro and macro uncertainty. For example, if a fraction of firms react positively, and other firms react negatively, to one common component, the dispersion of firm-level outcomes will increase when the common component increases. In order to mitigate this effect, I remove the common components when constructing the micro uncertainty measure. It allows me to illustrate the correlation between micro and macro uncertainty which are not driven by the common components.

I construct micro uncertainty measure, based on stock returns, using CRSP daily return data, from 1963 until 2016. The micro uncertainty measure is constructed from the following two-step procedure. Firstly, I compute the idiosyncratic component of stock returns. It is constructed within every month $m$ by estimating a factor model using all available daily observations in that month. I take a linear structure model given by

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i'F_t + \varepsilon_{it},$$

(1)

where $t$ denotes an observation made at day $t$ in a given month $m$, and $F_t$ is a set of factors considered in this regression, I specify $F_t$ as the Fama-French five-factor model (Fama and French (2015)). Alternatively, I also use the first ten principal components of the cross section of stock returns within month $m$, the results remain quantitatively similar. The

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5I use the S&P 500 constitutes, the results remain quantitatively similar if I use all firms in CRSP if sufficiently amount of factors are controlled for.

6As robustness, I also used the first fifteen principal components, the results remain quantitatively similar, all results are available upon request.
idiosyncratic stock return is the residual $\varepsilon_{it}$ from regression (1).

In the second step, I define micro uncertainty as the cross-section standard deviation of idiosyncratic stock returns ($ICSV$)

$$ICSV_t = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} (\varepsilon_{i,t} - \bar{\varepsilon}_t)^2},$$

where $\bar{\varepsilon}_t$ is the mean of idiosyncratic returns of all stock at day $t$, and $N_t$ is the total number of stocks at day $t$. To construct the monthly measure of ICSV, I take the average of the daily ICSV measure over $D_m$ days in a given month $m$,

$$ICSV_m = \frac{1}{D_m} \sum_{t=1}^{D_m} ICSV_t.$$

By observing equation (1), it becomes more clear how the common components can drive the correlation between micro and macro uncertainty. Suppose there are two firms, one firm has positive loadings, $\beta_i'$, on all the factors, while the other firm has negative loadings. When the common factors, $F_t$, become more volatile, the factors can reach more extreme realizations, then the returns of two firms become more dispersed because the common factors driving them moving to different directions.\footnote{As argued by Bartram et al. (2016), it is not clear why idiosyncratic risk $\sigma(\varepsilon_{it})$ correlates with aggregate risk $\sigma(\beta_i'F_t)$. My paper can also be extended to explain the question raised by Bartram et al. (2016).} By removing the common components from the firm stock returns, the information contained in the residuals is only idiosyncratic.\footnote{The way I construct the idiosyncratic component of returns is similar to Herskovic et al. (2016). Their common idiosyncratic volatility measure captures the time series variations of the average idiosyncratic volatility of all firms. However, in my study, ICSV measure captures the cross-section variations of the idiosyncratic return component.}

Additionally, I use interquartile range (IQR) of firms-level year-on-year sales growth rates as another micro uncertainty measure. It is denoted as $IQR(\Delta Sales)$. Every quarter, I compute the interquartile range of year-on-year sales growth of all firms in Compustat. The year-on-year sales growth is the current firm sales denominated by the sales four quarters ago. Following Bloom (2009), I only take firms with more than 150 quarters of data in Compustat quarterly accounts.

Finally, I also consider the cross-section standard deviation of TFP constructed from the NBER-CES Manufacturing Industry Database. It is denoted as $CSV(TFP)$. The data is at annual frequency with industry identified at 4 digit SIC code level.
**Macro uncertainty** For macro uncertainty, I use three measures. The first one is the VIX index, which represents the market expectation of S&P 500 index return volatility of the next 30 days. It is widely used as a measure for macro uncertainty, as in Bloom (2009, 2014). The second one is the standard deviation of the daily S&P 500 index returns. The third one is the macro uncertainty measure from Jurado, Ludvigson, and Ng (2015), which captures the one-period ahead expected uncertainty.

Figure 1 shows the time series graph of uncertain measures and credit spread. The credit spread is the difference between BAA and AAA corporate bond yield. The shaded areas indicate NBER recessions. As we can notice that both micro and macro uncertainty rise sharply during recessions. The correlation between micro and macro uncertainty measures is also strong outside the recessions. Additionally, credit spread fluctuates with both micro and macro uncertainty measures. Due to data availability, the sample of VIX index only starts from January of 1990.

Table 1 shows that the selected micro and macro uncertainty measures are highly correlated: $ICSV^{FF}$, $IQR(\Delta Sales)$ and $CSV(TFP)$ strongly correlate with macro uncertainty measures, such VIX index, volatility of S&P 500 index return, and the JLN index from Jurado et al. (2015). All uncertainty measures are countercyclical, i.e., they all negatively correlate with GDP growth rate. We can also observe that credit spread strongly correlates with all uncertainty measures.

### 2.3 Credit Spread and Micro Uncertainty

As shown in the previous section that credit spread strongly correlates with micro and macro uncertainty. This section presents that micro uncertainty predict future credit spreads. As shown in Table 2, I use ICSV measures constructed from Section 2.2 to predict future credit spreads. The cumulative credit spread between period $t$ and $t + h$ is defined as the holding period return of a portfolio, which is long in BAA bond index and short in AAA bond index, from period $t$ until period $t + h$. The predictive regressions are performed at monthly frequency, with horizon $h = 1, 2, 3, 6, 12$ months. In Panel A of Table 2, one standard deviation increase of ICSV leads to 1.2 basis points increase of credit spread in the following month, which translates into 14 basis points per annum.\(^9\) It is economically and statistically significant, since average credit spread is around 80 basis points per annum. In the lower panel, where I control for earning to price ratio, term spread, net equity issuance and inflation. As we can see that the predictive power of ICSV on credit spread is still statistically significant.

The persistence of the regressor may lead to imprecise inference on the estimator, therefore

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\(^9\)The standard deviation of ICSV is 2%, which I use in the calibration.
Figure 1: Uncertainty measures and credit spread

This figure shows monthly time series plots of uncertainty measures, and credit spread. All measures are in percentage numbers. For macro uncertainty, I plot two measures in this figure, which are the VIX index, and $JLN$ index from Jurado et al. (2015). The VIX index is a measure of the expected volatility of the next 30-day variance of S&P 500 index returns. For micro uncertainty, I use $ICSV^{FF}$, which is the cross-section standard deviation of residuals from the Fama French five-factor model, detailed construction is in Section 2.2. Credit spread ($Baa - Aaa$) is the spread between BAA and AAA corporate bond yield. Gray bars are NBER recessions. The VIX index is rescaled by multiplying with 0.01. $JLN$ is rescaled by multiplying with 2.
I perform Bonferroni test proposed by Campbell and Yogo (2006), which takes into account the persistence of the predictor when calculating the finite-sample properties of the test statistics. The results are shown in Appendix 6.1. The slope coefficients of \textit{ICSV} for different horizons are always significantly positive if the persistence of \textit{ICSV} is taken into account.

In the Appendix 6.1, I also use the interquartile range of year-on-year firm sales growth to predict future credit spread, the results remain economically and statistically significant.

To summarize, micro and macro uncertainty measures are strongly correlated, and both are countercyclical. Additionally, micro uncertainty predicts future credit spread. These empirical results guide me to build up a quantitative general equilibrium model with credit market frictions to understand the dynamics of micro and macro uncertainty.

3 Model

In this section, I present a general equilibrium model with credit frictions, à la Bernanke, Gertler, and Gilchrist (1999), to reconcile the empirical findings. There are three types of agents in the economy, households, creditors and entrepreneurs. Entrepreneurs operate firms and borrow loans from creditors. In the model economy, there are two types of goods, consumption and capital goods. They are produced by final goods producers and capital goods producers, respectively. I start by describing the household’s problem, then I present the production sectors, and the creditors and entrepreneurs’ problem.

3.1 Household

Time is discrete and infinite. There is a continuum of identical households in this economy. Each household consists of two types of family members: workers and entrepreneurs. Workers supply labor and return wages to the household. Each entrepreneur operates a firm and transfers earnings back to the household. Thus, the household effectively owns the firm that its entrepreneur operates. Within the family, there is perfect consumption insurance, such that consumption decisions are made altogether by the household head of the family within the same household. The structure of the household follows the big family concept of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). As it will become more clear later, this allows borrowing and lending under a representative household framework.

The composition of the family members is always fixed at any time, with \( f \) fraction of members being workers and \( 1 - f \) fraction being entrepreneurs. A family member can switch between these two occupations. With probability \( \lambda \) the entrepreneurs continue operating...
firms. With probability $1 - \lambda$, entrepreneurs have to liquidate their net worth and transfer it to the household, then they become workers. The same amount of workers will randomly become entrepreneurs, keeping the composition of workers and entrepreneurs fixed. The transfers paid to the households can be interpreted as dividend. It will become clear in Section 3.4 that a finite horizon for entrepreneurs will create borrowing incentives for entrepreneurs. This is to rule out the case that entrepreneurs can accumulate enough net worth to do all investment by self-financing, which eliminates borrowing in this economy.

The households are equipped with recursive preference as in Epstein and Zin (1989):

$$U_t = \left\{ (1 - \beta)C_t^{1-\frac{1}{\psi}} + \beta(E_t[U_{t+1}^{1-\gamma}])^{1-\frac{1}{\psi}} \right\}^{\frac{1}{1-\gamma}}, \quad (2)$$

where $\beta$ is the time discount rate, $\gamma$ is the relative risk aversion, and $\psi$ is the intertemporal elasticity of substitution. Let $C_t$ denote the household’s consumption.

Households can only save through a risk free asset, $B^f_t$. Its gross return is $R^f_t$, which denotes the return from period $t - 1$ to $t$. The risk free asset is traded among households themselves. Workers submit wages $W_tL_t$ and entrepreneurs transfer $\Pi_t$ amount of fund to household each period when liquidation happens. To keep the problem simple, I assume households does not value leisure in their utility, thus the workers in the household supply labor inelastically.

The household chooses consumption, labor supply, corporate bond and risk free asset to maximize its utility subject to the following budget constraint,

$$C_t + B^f_{t+1} = R^f_tB^f_t + W_tL_t + \Pi_t. \quad (3)$$

Let $M_{t,t+1}$ denote the stochastic discount factor implied by the household’s optimization problem, $M_{t,t+1} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left( \frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]} \right)^{\frac{1}{\psi}-\gamma}$. The optimal choice of risk free asset reads,

$$E_t [M_{t,t+1} R^f_{t+1}] = 1. \quad (4)$$

3.2 Final Goods Producers

There is a continuum of islands, indexed by $j$, where $j \in [0, 1]$. On each island, there is a representative firm. All firms on different islands are producing final consumption goods with an identical constant returns to scale Cobb-Douglas technology. Labor is perfectly mobile across firms and islands, while capital is island specific. Each firm $j$ produces final output
\( Y^j_t \) using the following production function

\[
Y^j_t = \bar{A}_t (\omega^j_t K^j_t)^\alpha (L^j_t)^{1-\alpha},
\]

where \( \alpha \) is the capital share, \( \bar{A}_t \) is the aggregate productivity shock, \( K^j_t \) denotes the amount of capital used by firm, \( L^j_t \) is labor input.

The idiosyncratic shock \( \omega^j_t \) affects the efficiency units of capital on island \( j \), where there is an entrepreneur operating the representative firm on that island. The idiosyncratic shock transforms capital \( K^j_t \) into efficiency units \( \omega^j_t K^j_t \). It will become clear in Section 3.4 that this idiosyncratic shock to efficiency units of capital is equivalent to a shock that affects the cash flows paid to the entrepreneurs. The shock \( \omega^j_t \) is a random variable drawn from a log normal distribution, it is independent across time and across islands, it has mean of unity and standard deviation of \( v_t \). I allow \( v_t \) to be time varying, it is essentially the same as the risk shock concept in Christiano, Motto, and Rostagno (2014). It controls the cross-sectional dispersion of idiosyncratic shock \( \omega^j_t \). I assume the dispersion of idiosyncratic shock in period \( t+1 \), \( v_t \), is observed at the end of period \( t \), such that every agent in this economy knows the distribution of idiosyncratic shocks at the beginning of period \( t+1 \) before making choices.\(^{10}\) I call the shock to standard deviation of idiosyncratic shock, \( v_t \), the dispersion shock. The log of \( v_t \) follows an AR(1) process. I use \( F_t(\cdot) \) to denote the cumulative density function, and \( f_t(\cdot) \) as the probability density function of the idiosyncratic shock at period \( t \). The idiosyncratic shock can also be interpreted as the technology used by entrepreneurs for operating capital, it captures how efficient the entrepreneurs at running business.\(^{11}\)

Since labor is perfectly mobile, the wage rate is identical across all firms in this economy. Firms are maximizing their profits at time \( t \) by choosing labor \( L^j_t \),

\[
\max_{L^j_t} \ Y^j_t - W_t L^j_t.
\]

The optimality condition reads

\[
\frac{\omega^j_t K^j_t}{L^j_t} = \left[ \frac{W_t}{\bar{A}_t(1-\alpha)} \right]^{1/\alpha},
\]

which means that the efficiency unit of capital to labor ratio is the same across all islands. Firms \( j \)'s profits on island \( j \) is then given by \( Y^j_t - W_t L_t = \omega^j_t MPK_t \cdot K^j_t \), where \( MPK_t \equiv

\(^{10}\)This is typical timing assumption in uncertainty shock literature, see Bloom (2009), Bloom et al. (2018), Christiano, Motto, and Rostagno (2014).

\(^{11}\)A similar setup can be seen Christiano, Motto, and Rostagno (2014), Carlstrom, Fuerst, and Paustian (2016), etc.
\[ \alpha \bar{A}_t \left[ \frac{(1-\alpha)\bar{A}_t}{W_t} \right]^{1/\alpha - 1} \] is the marginal product of effective capital.

**Endogenous growth** Additionally, following the argument of learning by doing as in Romer (1990), I assume the aggregate productivity is augmented by the aggregate stock of capital \( K_t \),

\[
\bar{A}_t = A_t K_t^{1-\alpha},
\] (5)

where the log of \( A_t \) follows an AR(1) process. There are two effects introduced by endogenous growth. The first one is that together with recursive preference, the model could deliver a sizable equity premium, also a low and smooth risk free rate, as in Bansal and Yaron (2004). The second effect is that it facilitates the amplification of aggregate shocks through credit frictions, which helps the model to quantitatively match the strong correlation between micro and macro uncertainty, it will be discussed more extensively in Section 4.5.

### 3.3 Capital Goods Producers

At the end of period \( t \), capital goods producers purchase \( I_t \) amount of consumption goods and transform them into \( \Lambda \left( \frac{I_t}{K_t} \right) \) amount of new capital goods. They also repair depreciated capital. Then they sell both the newly produced and repaired capital at price \( q_t \). I assume all markets visited by capital goods producers are perfectly competitive, therefore capital price \( q_t \) is the same for all agents in this economy. The production technology of the capital goods producers is constant returns to scale, which resembles the adjustment cost function as in Jermann (1998).\(^{12}\) The capital producers’ optimization problem is

\[
\max_{I_t} \quad q_t \Lambda \left( \frac{I_t}{K_t} \right) K_t - I_t,
\]

where \( I_t \) and \( K_t \) are the aggregate investment and capital stock of the economy in period \( t \). The optimality condition with respect to investment gives the marginal \( q \), which is the price of capital in this economy,

\[
q_t = \left[ \Lambda' \left( \frac{I_t}{K_t} \right) \right]^{-1}.
\]

\(^{12}\)The specification is \( \Lambda \left( \frac{I_t}{K_t} \right) = \frac{\alpha_1}{1-1/\xi} \left( \frac{I_t}{K_t} \right)^{1-1/\xi} + \alpha_2 \), \( \xi \) is the elasticity parameter.
By repairing depreciated capital and supplying newly produced capital, the evolution of aggregate capital is given by

$$K_{t+1} = (1 - \delta)K_t + \Lambda \left( \frac{I_t}{K_t} \right) K_t,$$

where $\delta$ is the capital depreciation rate. Note that the capital goods producers are the only agents cumulating capital.

### 3.4 Entrepreneurs and Creditors

Entrepreneurs are the only agent in this economy who has access to risky projects, therefore they are the marginal investors of equity. On each island $j$, there is an entrepreneur indexed by $j$, who operates the representative $j$ on this island. At the end of each period $t$, entrepreneurs $j$ holds certain amount of net worth $N^j_t$. She decides the amount of capital that she wants to carry into period $t + 1$, and purchases capital $K^j_{t+1}$ from the perfectly competitive capital goods market, at the market price $q_t$. She uses her net worth $N^j_t$ and externally borrowed loan $B^j_{t+1}$ to finance the purchases. Therefore her budget constraint at the end of period $t$ is

$$q_t K^j_{t+1} = N^j_t + B^j_{t+1}.$$  \hspace{1cm} (6)

Note that the entrepreneurs do not borrow from their own household.

After purchasing capital, entrepreneur $j$ operates the firm on island $j$ to make production. At the end of period $t + 1$, she receives profits from this firm, $\omega^j_{t+1} MPK_{t+1} \cdot K^j_{t+1}$. Indeed, since there is only one entrepreneur on island $j$, the shock to this island is effectively also a shock to entrepreneur $j$. Following Bernanke et al. (1999) and Gertler and Kiyotaki (2010), I assume that after the production taken place in period $t + 1$, the undepreciated capital held by the entrepreneur, $\omega^j_{t+1}(1 - \delta)K^j_{t+1}$, must be liquidated in capital goods market, at competitive price $q_{t+1}$, and all new capital has to be purchased in the next period from the capital goods producer. Therefore the total amount of capital gain for entrepreneur $j$ in period $t + 1$ is $\omega^j_{t+1}[MPK_{t+1} + q_{t+1}(1 - \delta)]K^j_{t+1}$.

To simplify notation, I define

$$R^j_k = \frac{MPK_{t+1} + q_{t+1}(1 - \delta)}{q_t},$$  \hspace{1cm} (7)

as the aggregate capital return on capital. Therefore the capital gain, or the cash flow, paid to entrepreneur $j$ by operating capital in period $t + 1$ is $\omega^j_{t+1} R^j_k q_t K^j_{t+1}$. It is clear now that the idiosyncratic shock to the efficiency units of capital, $\omega^j_{t+1}$, is equivalent to a shock to
the capital gains, or the cash flows, paid to the entrepreneurs.

The creditor and the debt contract There is a representative creditor in this economy, she takes the stochastic discount factor implied by the households as given. At the end of period $t$, every entrepreneur can enter a debt contract with the creditor in this economy. The debt contract specifies the amount of debt $B^j_{t+1}$ that the entrepreneur borrows, and the negotiated loan rate $Z^j_{t+1}$. Note that the loan rate $Z^j_{t+1}$ is a pre-specified rate for the loans. The realization of idiosyncratic shock is only known to the entrepreneurs. The creditor can only observe the realization of idiosyncratic shocks at the expense of monitoring costs, $\eta\omega^j_{t+1}R^k_{t+1}q_tK^j_{t+1}$. As discussed in Townsend (1979), it is optimal that the costly monitoring only happens if the borrower cannot honor the debt. When monitoring happens, the borrowers report their true states to the creditor.

After repaying the debt obligations in period $t+1$, the net worth of entrepreneur $j$ becomes

$$N^j_{t+1} = \omega^j_{t+1}R^k_{t+1}q_tK^j_{t+1} - Z^j_{t+1}B^j_{t+1},$$

where $N^j_{t+1}$ is the net worth in period $t+1$ after debt repayment. When an entrepreneur experiences a sufficiently low idiosyncratic shock, $\omega^j_{t+1} \leq \bar{\omega}^j_{t+1}$, such that the net worth is not enough to repay the debt obligations, she declares default. The cut-off value of default for idiosyncratic shock $\bar{\omega}^j_{t+1}$ can be determined by

$$\bar{\omega}^j_{t+1}q_tR^k_{t+1}K^j_{t+1} = Z^j_{t+1}B^j_{t+1}.$$

Note that the cutoff $\bar{\omega}^j_{t+1}$ is known in period $t+1$, it is contingent on the aggregate capital return $R^k_{t+1}$. The value of debt to the creditor is given by:

$$B^j_{t+1} = E_tM_{t,t+1}\left\{ (1 - \eta)R^k_{t+1}q_tK^j_{t+1}\int_{0}^{\bar{\omega}^j_{t+1}} \omega dF_t(\omega) + Z^j_{t+1}B^j_{t+1}\left[1 - F_t(\bar{\omega}^j_{t+1})\right]\right\}. \quad (10)$$

The non-arbitrage condition states that the creditor can lend the money to entrepreneurs, such that the discounted payoff of tomorrow, from making loans, should yield the same value as if the creditor hold $B^j_{t+1}$ amount of money today. The first term on the right

\[13\] One can also think there is a creditor living in each household, she takes the stochastic discount factor implied by the household as given. The creditor makes loan decisions separately. Because of no arbitrage condition of the bond pricing, the creditor makes no profits and transfers no money back to the household which she belongs to.
hand side represents the revenues collected from defaulted entrepreneurs, the second term is the debt repayment from the entrepreneurs with $\omega_{t+1}^j \geq \bar{\omega}_{t+1}$. The first term is net of creditors’ monitoring costs, which is $\eta$ fraction of the remaining asset value of the defaulted entrepreneurs.

**Entrepreneur’s optimization problem**  At the end of each period, after the default decision is made, $1 - \lambda$ fraction of non-default entrepreneurs are liquidated, and transfer their net worth to the household. These transfers deliver utility to the entrepreneurs, because this amount of money is finally consumed by the household which the entrepreneurs belong to. Since the household makes the consumption decision for all members within the same household, the entrepreneur should also value their net worth using the same stochastic discount factor as the household. Let $V_t^j$ denote the value function of entrepreneur $j$, the Bellman equation reads,

$$V_t^j(N_t^j) = \max_{K_{t+1}^j, \omega_{t+1}^j} E_t M_{t,t+1} \int_{\omega_{t+1}^j}^{\infty} \left[ \{\lambda V_{t+1}^j(N_{t+1}^j) + (1 - \lambda)N_{t+1}^j\} \right] dF_t(\omega), \quad (11)$$

subject to flow budget constraint (6) and (8), additionally the creditor’s valuation of debt (10) has to be respected. Note that the integral starts from $\omega_{t+1}^j$, it means that the entrepreneur only value net worth if no default happens. If default happens, all the remaining value is collected by creditor, the entrepreneur no longer value the business and the remaining net worth is zero. The first term on the right hand side indicates that with probability $\lambda$ entrepreneur $j$ continues to operate the capital, therefore she receives the continuation value $V_{t+1}^j(N_{t+1}^j)$. The second term represents that conditional on being liquidated with probability $1 - \lambda$, she transfers the remaining net worth $N_{t+1}^j$ to the household. The liquidation assumption makes the entrepreneurs less patient than the households, hence the entrepreneurs always borrow from the households.

By taking prices as given, the objective function (11), and constraints (6), (8) (10) are all linear, therefore the value function $V_t^j$ must be a linear function of the state variable, net worth $N_t^j$. I conjecture $V_t^j(N_t^j) = \mu_t^j N_t^j$, where $\mu_t^j$ is the marginal value of net worth for entrepreneur $j$.

I rewrite the optimization problem of the entrepreneur by plug in equation (6), (8) and (9). By observing that all equation is homogeneous of degree one with respect to net worth, I normalize all quantities by state variable $N_t^j$ and define leverage of entrepreneur $j$ as $\phi_t^j \equiv q_t K_{t+1}^j / N_t^j$. The entrepreneur $j$’s optimization problem can be written as

\[14\text{See discussions in Carlstrom et al. (2016) and Ai et al. (2017).}\]
\[ \mu_t^j = \max_{\phi_t^j, \bar{\omega}_t+1} \left\{ E_t \left[ M_{t,t+1} \int_{\bar{\omega}_t+1}^\infty \left( \lambda \mu_t^j + (1 - \lambda) \right) \left( \omega - \bar{\omega}_t+1 \right) R_t^{k+1} \phi_t^j dF_t(\omega) \right] \right\} \]  \hspace{1cm} (12) \\
\text{s.t.} \quad \phi_t^j - 1 = E_t M_{t,t+1} \left\{ R_{t+1}^k \phi_t^j \left[ \Gamma_t(\bar{\omega}_t+1) - \eta G_t(\bar{\omega}_t+1) \right] \right\}, \hspace{1cm} (13)

where

\[ \Gamma_t(\bar{\omega}_t+1) \equiv \int_0^{\bar{\omega}_t+1} \omega dF_t(\omega) + \bar{\omega}_t+1 \int_{\bar{\omega}_t+1}^\infty dF_t(\omega) = \left[ 1 - F_t(\bar{\omega}_t+1) \right] \bar{\omega}_t+1 + G_t(\bar{\omega}_t+1), \]

\[ G_t(\bar{\omega}_t+1) \equiv \int_0^{\bar{\omega}_t+1} \omega dF_t(\omega). \]

Here, \( \Gamma_t(\bar{\omega}_t+1) \) represents the expected share of earnings received by creditors, and \( 1 - \Gamma_t(\bar{\omega}_t+1) \) is the expected share of earnings received by entrepreneurs.

Let the variables without subscript \( j \) be the aggregate quantities, the evolution of entrepreneurs’ aggregate net worth is

\[ N_{t+1} = \lambda(1 - \Gamma_t(\bar{\omega}_t+1)) R_{t+1}^k q_t K_{t+1} + (1 - \lambda[1 - F_t(\bar{\omega}_t+1)])[\chi q_t K_{t+1}]. \]  \hspace{1cm} (14)

The first term on the right hand side is the total net worth of the entrepreneurs who survived liquidation and default. The second term on the right hand side represents the net worth of entrepreneurs who experience default or liquidation. The defaulted and liquidated entrepreneurs are replaced by equal mass of new entering entrepreneurs, carrying \( \chi q_t K_{t+1} \) amount of initial net worth. The new entering entrepreneurs are funded by the households which they belong to. Here \( \chi \) is a rescaling parameter.

### 3.5 Competitive Equilibrium

A competitive equilibrium is a set of quantities for households \( \{C_t, B_t^f, L_t\}_{t=0}^\infty \), quantities for entrepreneurs \( \{N_t^j, K_t^j, B_t^j\}_{t=0}^\infty \), quantities for creditors \( \{B_t^j\}_{t=0}^\infty \) and prices \( \{q_t, Z_t, R_t^k, R_t^f\}_{t=0}^\infty \), such that given prices, these quantities solve households, creditors and entrepreneurs’ optimization problems, firms maximize their profits, and markets clear. The market clearing
conditions are

\[ K_t = \int_0^1 K_t^j \, dj \]  
\[ B_t = \int_0^1 B_t^j \, dj \]  
\[ L_t = \int_0^1 L_t^j \, dj \]  
\[ N_t = \int_0^1 N_t^j \, dj \]  
\[ \int_0^1 Y_t^j \, dj - D_t = C_t + I_t, \]

(19)
together with equation (14), where \( D_t = \eta G_t(\bar{\omega}_{t+1}) R_{t+1}^k q_t K_{t+1} \) is the monitoring costs, and \( j \in [0,1] \). Equation (15) shows that the supply of capital from capital goods producer equals to the demand of the entrepreneurs. Equation (16) says the bond demand by creditors equals the supply from entrepreneurs. I assume inelastic labor supply, therefore the aggregate equilibrium labor in equation (17) is always one. Equation (18) implies the net worth of all entrepreneurs sum up to aggregate net worth \( N_t \). In equation (19), the aggregate output less the monitoring cost equals the aggregate consumption and investment.

### 3.6 Equilibrium Asset Pricing

Since the conditions faced by all entrepreneurs are ex-ante identical, and the optimization problem characterized by equation (12) and (13) are independent of size, therefore all entrepreneurs will choose the same leverage ratio \( \phi_t = \phi_t \). Additionally, when creditor offers the debt contract, she does not know the idiosyncratic shock received by each entrepreneur, therefore she offers the same loan rate \( Z_{t+1}^j = Z_{t+1} \) to all entrepreneurs, and also the same cut-off for default, \( \bar{\omega}_{t+1}^j = \bar{\omega}_{t+1} \) for any entrepreneur \( j \). Indeed, the creditor holds a fully diversified portfolio of bonds by providing loans to entrepreneurs with different idiosyncratic shocks. If the optimal \( \bar{\omega}_{t+1}^j \) and \( \phi_t^j \) are the same across entrepreneurs, so is the marginal value of net worth \( \mu_t^j = \mu_t \) for any entrepreneur \( j \).

By dropping the subscript \( j \) and solve for the optimization problem of entrepreneurs characterized by equation (12) and (13), the optimality conditions of entrepreneurs read

\[ E_t \left[ \tilde{M}_{t,t+1} \{ (1 - \Gamma_t(\bar{\omega}_{t+1})) R_{t+1}^k \phi_t \} \right] = 1, \]  
\[ E_t \left[ \tilde{M}_{t,t+1} \Gamma_t(\bar{\omega}_{t+1}) \right] = E_t [ M_{t,t+1}(\Gamma_t(\bar{\omega}_{t+1}) - \eta G_t(\bar{\omega}_{t+1})) ], \]

(20)  
(21)
where
\[ \tilde{M}_{t,t+1} = M_{t,t+1} \frac{\lambda \mu_{t+1} + 1 - \lambda}{\mu_t}, \]  
(22)
is the pricing kernel of entrepreneurs. It is the pricing kernel of the household, \( M_{t,t+1} \), augmented by the intertemporal change of entrepreneur’s marginal value of net worth. The numerator of the augmenting term, \( \lambda \mu_{t+1} + 1 - \lambda \), is the ex-post marginal value of net worth in period \( t + 1 \). With probability \( \lambda \), entrepreneurs can receive continuation value. With probability \( 1 - \lambda \), the net worth is liquidated and transferred to the household. The denominator \( \mu_t \) is the ex-ante marginal value of net worth in period \( t \).

Entrepreneurs are the only investors of equity in this economy, therefore their pricing kernel will price equity returns. The equity in this economy is the net worth held by the entrepreneurs, which is asset less debt. Therefore the aggregate return on equity is defined as
\[ R^E_t = \frac{\int_0^1 N^j_{t+1}dj}{\int_0^1 N^j_t dj} = (1 - \Gamma_t(\bar{\omega}_{t+1})) \frac{R^k_t q_t K_{t+1}}{N_t} = (1 - \Gamma_t(\bar{\omega}_{t+1})) R^k_t \phi_t. \]  
(23)
Recall that \( 1 - \Gamma_t(\bar{\omega}_{t+1}) \) denotes the share of capital gains that goes to entrepreneurs, therefore the equity return in this economy is a levered return of the entrepreneurs’ claim on capital return. The leverage is defined as asset to equity ratio, \( \phi_t \). I can rewrite equation (20) to obtain the pricing equation of aggregate equity returns,
\[ E_t [\tilde{M}_{t,t+1} R^E_{t+1}] = 1. \]  
(24)
The equity return of firm \( j \) from period \( t \) to \( t + 1 \) is given by
\[ R^E_{t+1} = \frac{N^j_{t+1}}{N^j_t} = \frac{\omega^j_{t+1} q_t R^k_{t+1} K^j_{t+1} - Z^j_{t+1} B^j_{t+1}}{N^j_{t+1}} = (\omega^j_{t+1} - \bar{\omega}_{t+1}) R^k_{t+1} \phi_t, \]  
if \( \omega^j_{t+1} > \bar{\omega}_{t+1} \),
\[ R^E_{t+1} = 0, \]  
if \( \omega^j_{t+1} \leq \bar{\omega}_{t+1} \).

The above derivations take into account the equation for default threshold, as in equation (9). Note that the dispersion of equity returns not only depends on idiosyncratic shock, but also on aggregate conditions, such as aggregate capital return \( R^k_t \), default rate, etc.

For other asset classes in this economy, the risk free asset and debt, are priced by household’s stochastic discount factor, as in equation (4) and (10).

### 3.7 Uncertainty Measures in the Model

The model is solved and simulated at monthly frequency, in order to compare the moments from the data and the model, I construct micro and macro uncertainty measures based on
monthly data for both the empirical data and the model simulated data.

**Micro uncertainty**  In the model, I construct micro uncertainty measure as in Section 2.2, which is defined as the cross-section standard deviations of equity return residuals of factor regressions. By only looking at the dispersion of residuals, this micro uncertainty measure mitigates the effects from aggregate fluctuations of common factors. Using model simulated monthly data, I firstly obtain residuals from 36-month non-overlapping rolling window regressions,

$$
R_{t}^{E,j} - R_{t}^{f} = \alpha^{j} + \beta^{j}(R_{t}^{E} - R_{t}^{f}) + \varepsilon_{t}^{j},
$$

where $R_{t}^{E,j} - R_{t}^{f}$ is the individual firm excess equity return, and $R_{t}^{E} - R_{t}^{f}$ is the market factor in the model.

After I obtain the residuals, for each month $t$, I calculate the cross-section standard deviation of these residuals computed from rolling regressions, then I compute the micro uncertainty of the model,

$$
ICSV_{t} = \sqrt{\frac{1}{N_{t}} \sum_{i=1}^{N_{t}} (\varepsilon_{t}^{j} - \bar{\varepsilon}_{t})^{2}}.
$$

For the empirical counterpart, I use the same procedure. Instead of regressing individual firm excess stock returns on only the market factor, I regress individual firm excess returns on Fama-French five-factor model. Because there is only one common component in the model, but there are several well established common factors in the data.

**Macro uncertainty**  Macro uncertainty is defined as the volatility of the aggregate equity returns $\sigma(R_{t}^{E})$ at annual frequency. It is computed as the standard deviation of 12 month aggregate equity returns within a year.

4 Quantitative Analysis

In this section I show the quantitative results of the model. First, the parameter choices are described. Second, I show the performance of the model in terms of matching the moments of macroeconomic quantities and asset prices. Afterwards I show that the model can quantitatively explain the comovement between micro and macro uncertainty, and their countercyclicality observed in the data. Then the mechanism of credit frictions and endogenous growth in this model is discussed extensively. Finally I show that empirical predictions of the model are supported by the data.
4.1 Calibration

The model is calibrated at the monthly frequency. The choice of parameters and the corresponding moments are shown in Table 3. There are three blocks of parameters. The first block contains the household’s preference parameters. The relative risk aversion is set to $\gamma = 6$, and the intertemporal elasticity of substitution $\psi$ is set to 1.4, in line with the long-run risks literature, as in Bansal and Yaron (2004). The second block contains the parameters related to production and entrepreneurs. Capital share $\alpha$ is set to 0.33, and depreciation rate is 7% per annum. These parameters are in line with the RBC literature. The capital adjustment cost parameter $\xi$ is set to 1.6, in order to match the volatility of investment growth rate. The probability of an entrepreneur to survive from liquidation is set to $\lambda = 0.99$, which implies an average 10-year corporate duration as in Gertler and Kiyotaki (2010). The credit frictions related parameters are set to match (i) steady state investment to output ratio is at 0.18, as in the data, (ii) credit spread, the difference between average $Z$ and $R_f$ is at 0.6%, and (iii) a leverage ratio of $\phi = 2$. This leads to a standard deviation of the idiosyncratic productivity shock $\bar{v} = 0.22$, a monitoring cost parameter of $\eta = 0.38$, and a value for the parameter controls the initial net worth of new entering entrepreneurs $\chi = 0.195$.

The last block contains shock parameters. Idiosyncratic shocks to islands are following Christiano et al. (2014), it is specified as a mean preserving spread log $\omega \sim N\left(\frac{\bar{v}^2}{2}, \bar{v}\right)$. The evolution of TFP shocks and the shocks to dispersion $v_t$ are given by

$$\log(A_t) = \rho^A \log(A_{t-1}) + \sigma^A \varepsilon^A_t, \quad \varepsilon^A_t \sim N(0, 1)$$

$$\log(v_t) - \log(\bar{v}) = \rho^v \log(v_{t-1}) - \log(\bar{v}) + \sigma^v \varepsilon^v_t, \quad \varepsilon^v_t \sim N(0, 1).$$

The two shocks $\varepsilon^A_t$ and $\varepsilon^v_t$ are independent from each other. For TFP shocks, $\rho^A$ and $\sigma^A$ are set to match the autocorrelation and volatility of output, respectively. For parameters governing the idiosyncratic shocks, $\rho^v = 0.988$ is roughly in line with Christiano et al. (2014), and $\sigma^v$ is set to match the volatility of ICSV in the data.

4.2 Simulation

In this section, I compare model simulated moments to their data counter part. The model is solved using the third-order perturbation method. I simulate the model at monthly frequency and report the moments of annualized variables. I firstly simulate the model for 3,600 months

\footnote{One may argue that if the volatility of TFP is time-varying and correlates with the dispersion of idiosyncratic shocks, then macro and micro uncertainty are correlated by the correlation structure of the shocks alone. However, in the data, the correlations between volatility of aggregate TFP and various dispersion measures are statistically insignificant.}
and drop the first 600 months to avoid the dependence of initial conditions. Hence 3,000 months are left, which corresponds to 250 years. Then I simulate a panel of 5,000 firms. Table 4 reports moments of the simulated data versus the corresponding moments computed from empirical data.

**Aggregate quantities** The first block of Table 4 reports the moments of macroeconomic quantities, such as volatilities and persistence of output, consumption and investment growth rates. The data simulated by the benchmark model is broadly consistent with the aggregate moments computed from the data.

**Asset prices** The moments of asset prices are listed in the second block of table 4. The equity premium generated by the model is sizable 8.76%, it is roughly in line with the data. This is due to the fact that entrepreneurs are the marginal investors of equity, their pricing kernel prices equity, as in equation (24). Two effects leads to this sizable equity premium. Firstly the entrepreneurs’ pricing kernel is more volatile. We can observe that the entrepreneurs’ pricing kernel, as in equation (22), depends on the marginal value of net worth, which is very volatile in this economy. The reason is that the valuation of net worth depends on the return on capital, as in equation (12), which is very volatile. Secondly, since the model is equipped with endogenous growth and preference for early resolution of uncertainty, the long-run risk channel helps to deliver a high equity premium, as discussed in Bansal and Yaron (2004). The volatility of equity premium is relatively low in comparison to the data. This is extensively discussed in the literature that production based asset pricing models naturally generate very low volatilities in returns.

Credit spread moments are also well matched, both the first and second moments. Default probability in the model is 1.05% in comparison to 2.2% in the data. The volatility of default probability is also in line with the data. In the data, I use non-performing loans to total value of loans as the proxy for loan default rate. It is downloaded from St. Louis Fed. Non-performing loans are defined as loans that bank managers classify as 90-days or more past due or nonaccrual in the call report.

**Dynamics of uncertainty** The last block of Table 4 shows the correlations between micro and macro uncertainty measures, and their cyclical properties.

The micro uncertainty measure $ICSV$ reported in the “Data” and “Benchmark” columns of Table 4 are computed following exactly the same procedure. The only difference is that in the “Data” column, the factors used are the Fama-French five-factors. In the model simulated data, only market factor can be controlled for.
The correlation between micro and macro uncertainty, \( \text{corr}(\sigma(R_t^E), ICSV_t) \), is of 53\%, which is consistent with the data. As a robustness, I compute the conditional variance of the model simulated market excess return \( R_t^E \) using GARCH(2,2) model. The correlation between the conditional variance of \( R_t^E \) and micro uncertainty \( ICSV \) is 0.49.

Additionally, the model successfully generates the countercyclicality of micro and macro uncertainty. Macro uncertainty \( \sigma(R_t^E) \) has a correlation with output growth of -40\%, it matches the data very well. Meanwhile micro uncertainty has a correlation with output growth of -30\%, roughly in line with the data. The correlation between credit spread and macro uncertainty \( \text{corr}(Z_t - R_t^f, \sigma(R_t^E)) \) is a bit higher than in the data.

### 4.2.1 Credit Spread Predictability

In this section I show that this model can replicate the predictability of credit spread as documented in Section 2.3. The micro uncertainty measure based on returns, ICSV, positively predicts future credit spreads.

Table 5 compares the results of credit spread predictive regressions performed on the empirical data (Panel A) and the model simulated data (Panel B). The model does a good job at replicating the predictability of credit spreads using ICSV measure. The slope coefficients increase with respect to horizon, as in the data. The predictability comes from the fact that when entrepreneurs’ cash flows are more dispersed, return dispersion is higher and default is more likely to happen, therefore future credit spread increases.

### 4.3 Impulse Responses

In order to understand the shock propagation in this economy, I show impulse responses in Figure 2. In period one, I introduce two independent contractionary shocks. One is a negative shock to TFP, see the red dotted line. The other one is a positive dispersion shock, see the black solid line. Both of the shock magnitudes are of one standard deviation of the corresponding processes. The left panel shows the dynamics of macroeconomic variables, while the right panel shows the dynamics of variables related to asset prices and default.

Firstly, I briefly discuss the impact of TFP shocks as shown in Figure 2. Focusing on the left panel, upon a negative TFP shock, investment, output and consumption growth drop immediately. Lower aggregate productivity makes more firm less likely to pay back debt, thus more net worth destruction happens and leverage \( \phi \) increases. Focusing on the right panel. Asset price \( q \) decreases when productivity is low. Aggregate return on equity \( r^E \) and capital return \( r^K \) follows the dynamics of the asset price \( q \). As in equation (9), the default threshold \( \omega \) increases if return on capital and asset price fall, because the total value available
This figure plots the impulse responses with respect to a one-standard-deviation negative shock to aggregate productivity and a one-standard-deviation positive shock to dispersion. The y axis is the percentage deviations from the steady state. The black solid lines are with respect to dispersion shock, the red dashed lines are with respect to TFP shock. One period is one month. $\phi$ is the leverage of entrepreneurs, $q$ is the asset price, $r^E$ is the equity return, $\overline{\omega}$ is the default cutoff, $F$ is the default probability and $z - r^f$ is the credit spread. All parameters are calibrated as in Table 3.
to pay back debt is lower. When default threshold $\bar{\omega}$ increases, it pushes up default rate $F$. Creditors charge higher loan rate if more entrepreneurs are likely to default, therefore credit spread $z - r^f$ increases, as shown in the down right panel. By observing equation (9), if credit spread $z - r^f$ demanded by creditor increases, the default threshold should increase even further.

The impact of dispersion shocks works through the debt contract in this model. The return on equity resembles the payoff of an investor buying a European call option. The payoff structure faced by the creditor mimics an investor writing a European put option. When dispersion of idiosyncratic shock increases, the riskiness of assets goes up, which benefits the equity holders at the expense of debt holders. The reason is that equity holders just need to pay back a pre-specified amount of debt obligation, the excess amount of profits are retained. The creditors would like to cut the credit supply and raise the loan rate when uncertainty is high, because more entrepreneurs are likely to default on loans when cash flow dispersion is high.

In this model, the impact on creditors dominates. It means that when micro uncertainty is high, creditors cut credit supply and investment falls, as shown in the left panel of Figure 2. Consumption increases upon a positive innovation in dispersion. This is because, in this model capital is pre-determined and labor is inelastic, thus output growth is not much affected by the dispersion shock directly.\footnote{Output is in fact affected by dispersion shock, but the magnitude is one order smaller than that of the TFP shock.} Investment drops a lot but output stays relatively stable. According to final goods market clearing condition, this implies that consumption has to increase in order to absorb the drop in investment upon dispersion shock. The negative comovement between consumption and investment introduced by uncertainty shock is discussed in Basu and Bundick (2017).

The down left panel of Figure 2 show that when dispersion of idiosyncratic shocks is high, more firms at the left tail are likely to default, thus the aggregate net worth of the corporate sector shrinks and leverage increases. As we will see latter, in Section 4.4, that the increasing leverage plays an important role for amplifying the aggregate shocks. Higher leverage endogenously, introduced by high dispersion, drives up aggregate volatility.

As shown in the right panel of Figure 2, variations in the dispersion of idiosyncratic cash flows introduce much stronger responses in the loan default rate $F$ and the credit spread $z - r^f$ than TFP shock, since it directly controls the fraction of entrepreneurs receive very low cash flows. As in the down right panel in Figure 2, the reaction of credit spread to a one-standard-deviation positive dispersion shock is roughly five times stronger than it to a one-standard-deviation negative TFP shock.

\footnote{Output is in fact affected by dispersion shock, but the magnitude is one order smaller than that of the TFP shock.}
4.4 Credit Frictions and the Dynamics of Uncertainty

This section focuses on the key mechanism about how the model generates a large correlation between micro and macro uncertainty, as well as their countercyclicality.

When the idiosyncratic productivity shocks are more dispersed, more firms at the left tail will receive very low cash flows, they are more likely to default on prenegotiated debt. The deadweight loss associated with default shrinks the net worth of the entrepreneurs. Therefore, the leverage of the economy increases and the shock amplification effects of credit frictions get more stronger. As a result, the credit frictions in this economy ensures that shock amplification effects are higher when micro uncertainty is high, hence the economy becomes more volatile. Additionally, the deadweight loss created by the financial frictions makes the economy take longer time to recover, in comparison to an economy without financial frictions. This sluggish recovery also helps the leverage channel. Through the mechanism discussed above, macro and micro uncertainty are positively correlated. They are both countercyclicical because default happens when micro uncertainty is high, more deadweight loss occurs, output drops.\(^{17}\)

For models with credit frictions as in Bernanke, Gertler, and Gilchrist (1999), in order to generate enough comovement between micro and macro uncertainty, the model should fulfill the following two conditions. First, the magnitude of shock amplification due to credit frictions has to differ between high and low cash flow dispersion states, i.e., the economy should be more responsive to aggregate shocks under high micro level dispersion, thus the economy more volatile. Second, shock amplification due to credit frictions should be quantitatively large. The first condition ensures the model mechanism can make the micro and macro uncertainty comove qualitatively. The second condition is a complement to the first one, which allows the model to match the comovement quantitatively. If the shock amplification effects from the credit frictions are too small, even though the economy exhibits different sensitivities to aggregate shocks under different micro level dispersion states, the volatility of the economy would not change much quantitatively. Therefore, the shock amplification effects from credit frictions have to be sufficiently large.

Endogenous growth strengthens the second condition, which helps the performance of the model quantitatively. It introduces more persistent reactions of the economy, which reinforces the shock amplification effects of credit frictions to be much stronger. Below I firstly show quantitatively that models without endogenous growth cannot jointly match

\(^{17}\)If we introduce stochastic volatility in the TFP process, and let the micro level dispersion to be endogenous, the model will have counterfactual implications. An increase in aggregate volatility of TFP will introduce precautionary saving effects to the households, which will push up investment and asset prices. As a result, borrowers’ asset value is higher and they are less likely to default, credit spread is low when macro uncertainty is high.
the comovement between micro and macro uncertainty, and the moments of macroeconomic quantities. Afterwards, I discuss the importance of endogenous growth.

4.5 Credit Frictions and Endogenous Growth

This section show that endogenous growth discusses why endogenous growth is crucial to replicate the comovement between micro and macro uncertainty, while keeping the dynamics of macroeconomic variables in line with the data.

4.5.1 Models Without Endogenous Growth

In order to show the effects of endogenous growth quantitatively, I simulate an economy without endogenous growth. It is calibrated using the same procedure as the benchmark model, except that the TFP follows an exogenously specified AR(1) process. The results are shown in Table 6. The column “Data” reports the moments computed from empirical data. Column “Benchmark” and “Endo+CRRA” report the moments from the models with endogenous growth, in which the aggregate TFP, $A_t$, is augmented by aggregate capital stock, $A_t = A_t K_t^{1-\alpha}$. The difference is that column “Endo+CRRA” reports the results from a model with endogenous growth, but with constant relative risk aversion (CRRA) preferences, instead of recursive preferences as in “Benchmark”. Column “BGG” is a model with exogenous growth, equipped with CRRA preferences, its TFP follows an exogenous specified AR(1) process. In the exogenous growth model, the correlation between micro and macro uncertainty is around 30%, which is half as it is in the data. The countercyclicality of micro and macro uncertainty is also much lower in comparison to the benchmark model.

4.5.2 The Interaction Between Credit Frictions and Endogenous Growth

In this section, I firstly describe the shock amplification effects of credit frictions, then I show endogenous growth strengthens this effect.

The role of credit frictions The role of financial frictions in lots of macroeconomic models is to provide a channel such that transitory shocks will have a persistent impact on aggregate quantities and prices. For the case of costly state verification as in this paper, the key variable is the asset price.\footnote{For other type of financial frictions, e.g., exogenous or endogenous leverage constraint in Kiyotaki and Moore (1997) or Gertler and Kiyotaki (2010), the asset price also plays an important role in the shock amplification effect. Asset price determines the amount of collateral that can be pledged, therefore if the asset price shrinks upon an adverse shock, less collateral will be available for borrower, then debt financing drops, investment drops, which causes asset price to drop even further. The general equilibrium feed back} It determines the resources available to entrepreneurs to
pay back the debt obligations. Therefore when asset price falls, less asset value is available for entrepreneurs to pay back their debt and more default happens. In the case of default, creditors receive a fraction of the remaining asset value from the borrower instead of the debt payments. However, the collected asset is of less value because of low asset price. As a result, the creditors are also worse off, they cut their credit supply and raise the loan rate to ensure that only entrepreneurs with sufficiently high asset value can participate the debt borrowing. Thus, investment drops due to less credit supply, which causes the asset price (marginal $q$) to drop even further. The falling asset price and default reinforce each other. Hence, if asset price responds more strongly, or persistently, to aggregate shocks, the shock amplification effect will also be stronger. Endogenous growth allows the asset price to respond more persistently to aggregate shocks. It helps to strengthen the shock amplification effects of the credit frictions.

The role of endogenous growth  Endogenous growth allows fluctuations in micro uncertainty to affect the growth rates of the economy, which helps the risk premium channel introduced by long-run risks. Recall that the aggregate productivity of the economy depends on aggregate capital, $\bar{A}_t = A_t K_t^{1-\alpha}$. When cross-sectional dispersion is high, more firms on the left tail of the distribution will receive very low cash flows and default. Thus, creditors would like to cut credit supply and investment drops, as shown in impulse responses (Figure 2). Falling investment will lower down future aggregate capital stock and growth rates. By affecting the growth rates, micro uncertainty will affect the risk premia introduced by long-run risks mechanism. This risk premium channel allows credit spread to increase more when facing heightened micro uncertainty, therefore default is more severe and shock amplification effect is much stronger.

Additionally, endogenous growth offers a channel that makes the aggregate productivity shock to have a stronger and more persistent impact on asset prices. Below I illustrate the channel analytically. I plug in the definition of capital return equation (7) into (20), to obtain the valuation of the asset price,

$$q_t = E_t \left[ \tilde{M}_{t,t+1} \left\{ (1 - \Gamma_t(\bar{\omega}_{t+1})) (MPK_{t+1} + q_{t+1}(1 - \delta)) \phi_t \right\} \right].$$

Iterating forward, $q_t$ can be expressed as the present value of the infinite sum of all future payoffs,

$$q_t = E_t \left[ \sum_{s=1}^{\infty} (1 - \delta)^s \Omega_{t,t+s} \alpha \tilde{A}_{t+s} K_{t+s}^{\alpha-1} \frac{MPK_t}{MPK_t} \right], \quad (25)$$

effect continues such that a transitory shock leads to persistent reactions of the economy.
where $\Omega_{t,t+s} = \prod_{r=1}^{s} \tilde{M}_{t+r-1,t+r}(1 - \Gamma_{t+r-1})\phi_{t+r-1}$ is the effective discount rate of the price of capital, which takes into account the fluctuations in leverage $\phi_t$ and the share that goes to the entrepreneurs $1 - \Gamma_t$. Equation (25) states that the price of capital $q_t$, is the net present value of marginal productivity of capital in all future periods.

In the case of exogenous growth, in which the aggregate productivity is not augmented by capital, $\bar{A}_t = A_t$, the valuation of the asset price is

$$q_t = \mathbb{E}_t \left[ \sum_{s=1}^{\infty} (1 - \delta)^s \Omega_{t,t+s}\alpha A_{t+s} K_{t+s}^{\alpha-1} \right],$$

where $\log(A_t)$ follows an AR(1) process. An increase in TFP directly pushes up marginal productivity of capital by increasing aggregate productivity. I call this the direct effect. The second effect is the general equilibrium effect. When productivity is high, firms invest more, thus future capital stock increases. Note that as long as the marginal product of capital is decreasing with respect to capital, as shown in equation (26), an increase in the future capital stock will reduce the future marginal productivity of capital. As a result, the general equilibrium effect will dampen the direct effect from the aggregate shock.

The dampening effect from general equilibrium exists as long as the TFP process is exogenous, e.g., the productivity with long-run risks specification as in Croce (2014), or a stationary AR(1) process as in the classic RBC literature.

The dampening effect can be mitigated in the case of endogenous growth. If I incorporate the specification of endogenous growth, $\bar{A}_t = A_t K_t^{1-\alpha}$, into equation (25), the valuation of the asset price is

$$q_t = \mathbb{E}_t \left[ \sum_{s=1}^{\infty} (1 - \delta)^s \Omega_{t,t+s}\alpha A_{t+s} \frac{K_{t+s}^\alpha}{MPK_t} \right].$$

As shown in equation (27), it implies that $MPK_t = A_t$. Therefore an increase in future capital stock does not lead to a lower future marginal productivity of capital. Hence there is no general equilibrium effect which dampens the direct effect from aggregate shocks. As a result, the asset price $q_t$ responds more persistently to TFP shocks, and the economy is more sensitive to TFP shocks.

**The role of intertemporal elasticity of substitution** As we know from the long-run risks literature, when investors prefer early resolution of uncertainty, these future cash flow fluctuations will be priced by the investors. This mechanism makes asset price to be more responsive to aggregate productivity shocks.

In order to allow investors to prefer early resolution of uncertainty, IES has to be higher
than the inverse of relative risk aversion, \( \psi > 1/\gamma \). Table 6 column “Endo+CRRA” shows the results of a model in which the household is equipped with constant relative risk aversion (CRRA) preferences. CRRA preferences lead the households to be indifferent between early and late resolution of uncertainty. I achieve this by setting relative risk aversion \( \gamma = 1/\psi = 2 \).

The model generates a small positive correlation between micro and macro uncertainty, at the level of 0.31 in comparison to 0.60 in the data. This is because the household is indifferent between early and late resolution of uncertainty. Even though there is a lot of fluctuations in the future cash flows due to endogenous growth, these fluctuations are not priced by the households. Thus, the asset price \( q \) does not fluctuate much with future cash flows, and the shock amplification effect from the credit frictions is relatively weaker. Additionally, without early resolution of uncertainty, the equity premium is very small, at 1.34%, and the risk free rate is too high, at 5.6%.

### 4.6 Discussion of the Debt Contract

In this section, I discuss why the debt contract adopted in this model is important to produce a countercyclical default rate and credit spread, as well as a positive correlation between micro uncertainty and the credit spread.

The equity holders’ payoff structure resembles that of a European call option. When the volatility of idiosyncratic shocks are higher, the riskiness of the firm’s assets increases, which benefits the equity holders at the expense of the creditors. The creditors would want to lend less given higher default risks associated higher volatility. If the borrowers are the equity holders, upon an increase in cash flow dispersion, the expected equity value increases, which strengthens ability of borrowers for repaying debt. Hence, less default happens and the credit spread decreases.

In this model economy, entrepreneurs are asset holders, their resources can be used to pay back debt obligation is indeed the asset value. When the volatility of idiosyncratic shocks are higher, its impact on creditors dominates and the overall effects, which make the total asset value shrinks. Intuitively, the investment in this economy is directly controlled by the credit supply. When creditors cut credit supply, aggregate investment drops, so is the asset price. The falling asset value increases the likelihood of default, thus the credit spread increases with higher volatility of idiosyncratic shocks. Output drops due to the deadweight loss associated with default. Hence, credit spreads and default rates are countercyclical.

The effect of TFP shocks under this type of contract is extensively discussed in existing literature, as in Bernanke, Gertler, and Gilchrist (1999), Carlstrom, Fuerst, and Paustian (2016), etc. A negative TFP shock drives down entrepreneurs’ net worth, pushes up leverage and default rates, thus credit spread increases. Therefore default rate and credit spread are
countercyclical under TFP shock.

4.7 Empirical Predictions

The model implies that when cash flow dispersion is high, more firms are likely to default on their loans, credit supply and investment drops, and the asset price falls. Therefore default risk should positively predict future stock returns.\footnote{There is mixed empirical evidence regarding whether idiosyncratic risk measures can predict future market returns or not, see e.g., Goyal and Santa-Clara (2003), Bali et al. (2005), Garcia et al. (2014).} Guided by the model, I test whether realized loan default rate can predict future market excess returns or not.

I use nonperforming loans to total loans ratio as the proxy for the loan default rate, which is downloaded from the St. Louis Fed. Nonperforming loans are the loans that banks classify as 90 days or more past due or non-accrual in the call report. I regress market excess returns on lagged loan default rate, at various horizons. Table 7 presents the results. Panel A shows the results from the empirical data, while Panel B shows the results from the model simulated data.

In Panel A, as we can see that the loan default rate positively predicts future excess returns, it is more significant at longer horizons, e.g., 4 quarters or even longer. The model successfully captures the increasing pattern of the slope coefficients.

Robustness I also perform the same predictive regressions, but additionally control for other popular predictors. The results remain robust. Additionally, following Campbell and Yogo (2006), I perform the Benferroni test, which takes into account the persistence of the predictor when calculating the finite sample properties of the estimates. The predictability remains after taking the persistence into account. The results for robustness checks are reported in Appendix 6.1.

5 Conclusion

This paper presents a general equilibrium model with credit market frictions, based on Bernanke et al. (1999), to quantitatively explain the strong positive correlation between micro and macro uncertainty, and their countercyclicality. I assume the cross-sectional standard deviation of idiosyncratic productivity shocks is time-varying, as in Christiano et al. (2014). When the idiosyncratic shock is more dispersed, more firms at the left tail will receive very low cash flows, which makes them more likely to default on prenegotiated debt and net worth shrinks. Therefore, the leverage of the economy increases and the shock amplification effects of the credit frictions get more stronger. As a result, the economy is more
sensitive to aggregate shocks when micro uncertainty is high, macro uncertainty increases. High micro uncertainty states are associated with high default loss, thus output is low, this implies the countercyclical behavior of micro and macro uncertainty. Augmenting the model with endogenous growth and recursive preferences are crucial to quantitatively match the comovement between micro and macro uncertainty, because these two components enhance the shock amplification effects of the credit frictions.

The model has rich empirical predictions on the credit spread and return predictability. Consistent with the model, micro uncertainty, based on the dispersion of equity returns and sales, can predict future credit spreads. Additionally, the loan default rate, measured by nonperforming loans to total loans, positively predicts future excess market returns. The model can quantitatively rationalize the predictability patterns found in the data.
References


Table 1: Correlations of uncertainty with other variables

This table reports the correlations between different uncertainty measures and credit spread, and GDP growth rate. Panel A reports the correlation between micro and macro uncertainty measures. Panel B reports the correlation between uncertainty measures, GDP growth rate and credit spread. For micro uncertainty, I use $ICSV^{FF}$, $IQR(\Delta Sales)$, and $CSV(TFP)$ as proxies. $ICSV^{FF}$ is the cross-section standard deviation of residuals from the Fama French five-factor model. $IQR(\Delta Sales)$ is the interquartile range of firm-level year-on-year sales growth. $CSV(TFP)$ is the cross-section standard deviation of TFP from NBER-CES Manufacturing Industry Database. For macro uncertainty, I use $JLN$, $VIX$ and $Vol(SPX)$ as proxies. $JLN$ is the macro uncertainty measure from Jurado et al. (2015). $VIX$ is the VIX index, which measures the market expectation of the volatility of S&P 500 index returns over the next 30 days. $Vol(SPX)$ is the volatility computed on the realized S&P 500 monthly index returns. $Baa - Aaa$ is the credit spread, defined as the difference between BAA and AAA corporate bond yield. All variables are at annual frequency. If a variable is available at higher frequency, I take the annual average. The sample for $VIX$ starts in 1990 and ends in 2016. For $ICSV^{FF}$, $IQR(\Delta Sales)$, $JLN$ index, $Vol(SPX)$, and $Baa - Aaa$, the sample starts in 1963 and ends in 2016. For $CSV(TFP)$ the sample starts in 1963 and ends in 2011.

Panel A: Correlations between uncertainty measures

<table>
<thead>
<tr>
<th></th>
<th>$JLN$</th>
<th>$VIX$</th>
<th>$Vol(SPX)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IQR(\Delta Sales)$</td>
<td>0.60***</td>
<td>0.65***</td>
<td>0.40**</td>
</tr>
<tr>
<td>$CSV(TFP)$</td>
<td>0.46***</td>
<td>0.61**</td>
<td>0.31**</td>
</tr>
<tr>
<td>$ICSV^{FF}$</td>
<td>0.37**</td>
<td>0.66***</td>
<td>0.60***</td>
</tr>
</tbody>
</table>

Panel B: Correlations with GDP growth rate and credit spread

<table>
<thead>
<tr>
<th></th>
<th>$\Delta GDP$</th>
<th>$Baa - Aaa$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$JLN$</td>
<td>-0.62***</td>
<td>0.80***</td>
</tr>
<tr>
<td>$VIX$</td>
<td>-0.48**</td>
<td>0.64***</td>
</tr>
<tr>
<td>$Vol(SPX)$</td>
<td>-0.43***</td>
<td>0.51***</td>
</tr>
<tr>
<td>$IQR(\Delta Sales)$</td>
<td>-0.11</td>
<td>0.44***</td>
</tr>
<tr>
<td>$CSV(TFP)$</td>
<td>-0.38**</td>
<td>0.38***</td>
</tr>
<tr>
<td>$ICSV^{FF}$</td>
<td>-0.34***</td>
<td>0.31**</td>
</tr>
</tbody>
</table>
Table 2: Predictability of Credit Spread

This table reports the predictability of credit spread using ICSV measure. The sample starts in 1964 and ends in 2016, at monthly frequency. $ICSV^{FF}$ is the cross-section standard deviation of return residuals from Fama French five-factor model, as defined in Section 2.2. $CS_{t \rightarrow t+h} = \sum_{s=1}^{h} (Baa_{t+s} - Aaa_{t+s})$ is the cumulative credit spread. It is the holding period return of a portfolio, which is long in BAA bond and short in AAA bond, from period $t$ until period $t+h$. The credit spread is in percentage, at monthly frequency. 

$E/P$ is earning to price ratio. Term Spread is the difference between long term yield on government bonds and the T-bill. Net Equity Issuance is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total market capitalization of NYSE. Numbers in parentheses are standard errors estimated using Newey-West estimator, allowing for 3 lags.

### Panel A

$$CS_{t \rightarrow t+h} = a + b ICSV_t^{FF} + \varepsilon_{t+h}$$

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>6</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ICSV^{FF}$</td>
<td>0.006***</td>
<td>0.011***</td>
<td>0.017***</td>
<td>0.030***</td>
<td>0.043***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.089</td>
<td>0.090</td>
<td>0.089</td>
<td>0.072</td>
<td>0.042</td>
</tr>
</tbody>
</table>

### Panel B

$$CS_{t \rightarrow t+h} = a + b ICSV_t^{FF} + c X_t + \varepsilon_{t+h}$$

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>6</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ICSV^{FF}$</td>
<td>0.008***</td>
<td>0.017***</td>
<td>0.025***</td>
<td>0.048***</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.010)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>$E/P$</td>
<td>0.000***</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.002***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Term Spread</td>
<td>0.007***</td>
<td>0.014***</td>
<td>0.020***</td>
<td>0.037***</td>
<td>0.050**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Net Equity Issuance</td>
<td>-0.007***</td>
<td>-0.014***</td>
<td>-0.021***</td>
<td>-0.045***</td>
<td>-0.094***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.010)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.003</td>
<td>0.009</td>
<td>0.019</td>
<td>0.065</td>
<td>0.245***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.019)</td>
<td>(0.026)</td>
<td>(0.047)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.366</td>
<td>0.384</td>
<td>0.398</td>
<td>0.417</td>
<td>0.434</td>
</tr>
</tbody>
</table>

numbers in parenthesis are standard errors  
* p < 0.10, ** p < 0.05, *** p < 0.01
Table 3: Benchmark Calibration - Monthly

This table presents the parameters used in the Benchmark model at monthly frequency.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Values</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount rate</td>
<td>$\beta$</td>
<td>0.999</td>
<td>RBC</td>
</tr>
<tr>
<td>Relative risk aversion</td>
<td>$\gamma$</td>
<td>6</td>
<td>LRR</td>
</tr>
<tr>
<td>IES</td>
<td>$\psi$</td>
<td>1.4</td>
<td>LRR</td>
</tr>
<tr>
<td>Capital share in production</td>
<td>$\alpha$</td>
<td>0.33</td>
<td>RBC</td>
</tr>
<tr>
<td>Depreciation rate of capital</td>
<td>$\delta$</td>
<td>0.07/12</td>
<td>RBC</td>
</tr>
<tr>
<td>Investment adjustment cost</td>
<td>$\xi$</td>
<td>1.6</td>
<td>$std(I)$</td>
</tr>
<tr>
<td>Entrepreneur survival rate</td>
<td>$\lambda$</td>
<td>0.99</td>
<td>Gertler and Kiyotaki (2010)</td>
</tr>
<tr>
<td>Monitoring costs</td>
<td>$\eta$</td>
<td>0.38</td>
<td>BGG (1999)</td>
</tr>
<tr>
<td>Equity injection to new entrepreneurs</td>
<td>$\chi$</td>
<td>0.195</td>
<td>BGG (1999)</td>
</tr>
<tr>
<td>Average volatility of idiosyncratic shock</td>
<td>$\bar{v}$</td>
<td>0.22</td>
<td>Leverage</td>
</tr>
<tr>
<td>Persistence of TFP</td>
<td>$\rho^A$</td>
<td>0.998</td>
<td>$\rho(Y)$</td>
</tr>
<tr>
<td>Std of TFP shock</td>
<td>$\sigma^A$</td>
<td>0.007</td>
<td>$std(Y)$</td>
</tr>
<tr>
<td>Persistence of dispersion</td>
<td>$\rho^v$</td>
<td>0.988</td>
<td>Christiano et al. (2014)</td>
</tr>
<tr>
<td>Std of dispersion shock</td>
<td>$\sigma^v$</td>
<td>0.021</td>
<td>$std(ICSV)$</td>
</tr>
</tbody>
</table>
**Table 4: Model Simulations**

This table compares the annual moments of the model simulation and the empirical data (1963-2016). The model is simulated at monthly frequency for 1200 months then time aggregate to annual frequency. The first block reports basic statistics of macroeconomic quantities. The moments in the second block are of asset prices and default rate. The last block reports the correlation between micro and macro uncertainty, and the cyclical properties of uncertainty measures. The micro uncertainty measure is ICSV, it is the cross-section standard deviations of equity return residuals of factor regressions. In the model simulated data, the factor used is the market factor. In the empirical data it is the Fama-French five-factor model. The macro uncertainty is the volatility of aggregate equity returns. Column "Benchmark" reports the moments under calibration specified in Table 3, with both TFP and dispersion shocks.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma(\Delta y))</td>
<td>2.51</td>
<td>2.16</td>
</tr>
<tr>
<td>(\sigma(\Delta c))</td>
<td>2.27</td>
<td>2.21</td>
</tr>
<tr>
<td>(\sigma(\Delta i))</td>
<td>6.53</td>
<td>3.81</td>
</tr>
<tr>
<td>(AC_1(\Delta y))</td>
<td>0.33</td>
<td>0.47</td>
</tr>
<tr>
<td>(AC_1(\Delta c))</td>
<td>0.35</td>
<td>0.44</td>
</tr>
<tr>
<td>(AC_1(\Delta i))</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td>(corr(\Delta y, \Delta c))</td>
<td>0.86</td>
<td>0.97</td>
</tr>
<tr>
<td>(corr(\Delta y, \Delta i))</td>
<td>0.83</td>
<td>0.61</td>
</tr>
<tr>
<td>(corr(\Delta c, \Delta i))</td>
<td>0.66</td>
<td>0.45</td>
</tr>
<tr>
<td>(AC_1(\text{Book Leverage}))</td>
<td>0.86</td>
<td>0.90</td>
</tr>
<tr>
<td>(E[R^E - R^f])%</td>
<td>6.51</td>
<td>8.40</td>
</tr>
<tr>
<td>(\sigma(R^E - R^f)))%</td>
<td>16.66</td>
<td>5.99</td>
</tr>
<tr>
<td>(E[R^f])%</td>
<td>1.17</td>
<td>1.80</td>
</tr>
<tr>
<td>(\sigma(R^f))%</td>
<td>0.89</td>
<td>1.02</td>
</tr>
<tr>
<td>(E[Z - R^f])%</td>
<td>0.96</td>
<td>0.47</td>
</tr>
<tr>
<td>(\sigma(Z - R^f))%</td>
<td>0.44</td>
<td>0.52</td>
</tr>
<tr>
<td>(E[F])%</td>
<td>2.22</td>
<td>1.09</td>
</tr>
<tr>
<td>(\sigma(F))%</td>
<td>1.35</td>
<td>1.42</td>
</tr>
<tr>
<td>(corr(\sigma(R^E), ICSV))</td>
<td>0.60</td>
<td>0.53</td>
</tr>
<tr>
<td>(corr(\Delta y, \sigma(R^E)))</td>
<td>-0.43</td>
<td>-0.40</td>
</tr>
<tr>
<td>(corr(\Delta y, ICSV))</td>
<td>-0.34</td>
<td>-0.30</td>
</tr>
<tr>
<td>(corr(Z - R^f, \sigma(R^E)))</td>
<td>0.51</td>
<td>0.78</td>
</tr>
<tr>
<td>(corr(Z - R^f, ICSV))</td>
<td>0.31</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Table 5: **Credit Spread Predictability**

This table compares the results between credit spread predictive regressions performed on empirical data (Panel A) and the model simulated data (Panel B). The regressions are performed at monthly frequency. $CS_{t \rightarrow t+h}$ denotes the cumulative credit spread from period $t$ to period $t + h$, in percentage numbers. The micro uncertainty measure $ICSV_t$, is the cross-section standard deviations of equity return residuals from factor regressions. In the model simulated data, the factor used is the market factor. In the empirical data it is the Fama French five-factor model. Numbers in parentheses are standard errors estimated using the Newey-West estimator, allowing for 3 lags.

\[
CS_{t \rightarrow t+h} = a + bICSV_t + \epsilon_{t+h}
\]

<table>
<thead>
<tr>
<th>Panels</th>
<th>$h$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>6</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Data</strong></td>
<td>$ICSV^{FF}$</td>
<td>0.006</td>
<td>0.011</td>
<td>0.017</td>
<td>0.03</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>$s.e.$</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.016)</td>
</tr>
<tr>
<td><strong>Panel B: Model</strong></td>
<td>$ICSV$</td>
<td>0.008</td>
<td>0.015</td>
<td>0.021</td>
<td>0.040</td>
<td>0.068</td>
</tr>
<tr>
<td></td>
<td>$s.e.$</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.004)</td>
</tr>
</tbody>
</table>
Table 6: Model Simulations

This table compares the simulated moments of models with endogenous and exogenous growth. The statistics of macro quantities in the data are computed from annualized variables. The micro uncertainty measure is ICSV, it is the cross-section standard deviations of equity return residuals of factor regressions. In the model simulated data, the factor used is the market factor. In the empirical data, the factor model adopted is the Fama-French five-factor model. The macro uncertainty is the volatility of market excess returns, computed using 12 month returns within each year. Moments in column “Data” is the computed from the empirical data. “Benchmark” column is of moments computed from benchmark model. “Endo+CRRA” column presents the moments of a model with endogenous growth and CRRA preferences. “Exo+EZ” Column shows the result from a model with exogenous growth and recursive preferences. “BGG” presents the moments from a model with exogenous growth and CRRA preferences.

<table>
<thead>
<tr>
<th></th>
<th>Endogenous Growth</th>
<th>Exogenous Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Benchmark</td>
</tr>
<tr>
<td>\sigma(\Delta y)</td>
<td>2.51</td>
<td>2.16</td>
</tr>
<tr>
<td>\sigma(\Delta c)</td>
<td>2.27</td>
<td>2.21</td>
</tr>
<tr>
<td>\sigma(\Delta i)</td>
<td>6.53</td>
<td>3.81</td>
</tr>
<tr>
<td>corr(\Delta y, \Delta c)</td>
<td>0.86</td>
<td>0.97</td>
</tr>
<tr>
<td>corr(\Delta y, \Delta i)</td>
<td>0.83</td>
<td>0.61</td>
</tr>
<tr>
<td>corr(\Delta c, \Delta i)</td>
<td>0.66</td>
<td>0.45</td>
</tr>
<tr>
<td>AC₁(Book Leverage)</td>
<td>0.86</td>
<td>0.90</td>
</tr>
<tr>
<td>E[R^E - R^f] %</td>
<td>6.51</td>
<td>8.40</td>
</tr>
<tr>
<td>\sigma(R^E - R^f) %</td>
<td>16.66</td>
<td>5.99</td>
</tr>
<tr>
<td>E[R^f] %</td>
<td>1.17</td>
<td>1.80</td>
</tr>
<tr>
<td>\sigma(R^f) %</td>
<td>0.89</td>
<td>1.02</td>
</tr>
<tr>
<td>E[Z - R^f] %</td>
<td>0.96</td>
<td>0.47</td>
</tr>
<tr>
<td>\sigma(Z - R^f) %</td>
<td>0.44</td>
<td>0.52</td>
</tr>
<tr>
<td>E[F] %</td>
<td>2.22</td>
<td>1.09</td>
</tr>
<tr>
<td>\sigma(F) %</td>
<td>1.35</td>
<td>1.42</td>
</tr>
<tr>
<td>corr(\sigma(R^E), ICSV)</td>
<td>0.60</td>
<td>0.53</td>
</tr>
<tr>
<td>corr(\Delta y, \sigma(R^E))</td>
<td>-0.43</td>
<td>-0.40</td>
</tr>
<tr>
<td>corr(\Delta y, ICSV)</td>
<td>-0.34</td>
<td>-0.30</td>
</tr>
<tr>
<td>corr(Z - R^f, \sigma(R^E))</td>
<td>0.51</td>
<td>0.78</td>
</tr>
<tr>
<td>corr(Z - R^f, ICSV)</td>
<td>0.31</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Table 7: Return Predictability

This table compares the results between return predictive regressions performed on the data (Panel A) and the model (Panel B). The regressions are performed at quarterly frequency. $R_{t\rightarrow t+h}^{ex}$ denotes the cumulative excess market return from period $t$ to $t+h$, in percentage numbers. The regressor is loan default rate, $F$, measured in percentage numbers. In Panel A, the loan default rate is measured by nonperforming total loans to total loans, downloaded from St. Louis Fed, from 1990:Q1 until 2016:Q4. In Panel B, the regressor is measured using the fraction of default loans in the model. Numbers in parentheses are standard errors estimated using Newey-West estimator.

$$R_{t\rightarrow t+h}^{ex} = a + bF_t + \varepsilon_{t+h}$$

**Panel A: Data**

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>4</th>
<th>8</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>0.391</td>
<td>2.210</td>
<td>5.392</td>
<td>8.529</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.508)</td>
<td>(1.212)</td>
<td>(2.070)</td>
<td>(2.450)</td>
</tr>
</tbody>
</table>

**Panel B: Model**

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>4</th>
<th>8</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>3.509</td>
<td>10.257</td>
<td>15.986</td>
<td>19.055</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.445)</td>
<td>(1.033)</td>
<td>(1.511)</td>
<td>(2.035)</td>
</tr>
</tbody>
</table>
6 Appendix

6.1 Robustness of Predictive Regressions

Credit Spread predictability using other micro uncertainty measures Table 8 shows that micro uncertainty measure, computed as the interquartile range of firm sales growth, can also significantly predict future credit spreads. I regress the cumulative difference between BAA and AAA corporate bond indices on the interquartile range of firm sales growth. The predictive regression is performed at quarterly frequency. The results remain significant after controlling for earning to price ratio, term spread, net equity issuance, inflation and GDP growth rate.

Return predictability Table 9 reports return predictability using loan default rates, with popular control variables, including net equity issuance, term spread, inflation, credit spread, consumption to wealth ratio. All these control variables are downloaded from Amit Goyal’s website. Dividend yield is not included because it strongly correlates with default probability, at 53%, which causes multicolinearity problem.

Robustness of predictability The predictors used in this study, ICSV and loan default rate, both have high persistence, therefore in order to take into account the persistence when doing inference on the estimates, I use the Bonferroni test proposed by Campbell and Yogo (2006), which takes into account the persistence when calculating the finite-sample distribution of the estimates. The persistence of $ICSV^{FF}$ and default probability are 0.866 and 0.986, respectively. Table 10 shows that these two variables are robust predictors after taking into account of the persistence, both are significant at the 95% confidence interval.
### Table 8: Credit Spread Predictability - Sales

This table reports predictability of credit spread using dispersion of sales growth. The dispersion of sales growth is measured as interquartile range (IQR) of year-on-year sales growth. The sample starts in 1962:Q2 and ends in 2016:Q4. $CS_{t\rightarrow t+h} = \sum_{s=1}^{h} (Baa_{t+s} - Aaa_{t+s})$ is the cumulative credit spread. It is the holding period return of a portfolio, which is long in BAA bond index and short in AAA bond index, from period $t$ until period $t+h$. The credit spread is in percentage, at quarterly frequency. $IQR(\Delta Sales)$ is the interquartile of firm sales growth. $E/P$ is earning to price ratio. 

*Term Spread* is the difference between long term yield on government bonds and the T-bill. 

*Net Equity Issuance* is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total market capitalization of NYSE. Numbers in parentheses are standard errors estimated using Newey-West estimator allowing for 3 lags.

#### Panel A

$$CS_{t\rightarrow t+h} = a + b IQR(\Delta Sales)_t + \varepsilon_{t+h}$$

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IQR(\Delta Sales)_t$</td>
<td>0.046***</td>
<td>0.236***</td>
<td>0.472***</td>
<td>0.631***</td>
<td>0.774***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.063)</td>
<td>(0.091)</td>
<td>(0.124)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.095</td>
<td>0.185</td>
<td>0.215</td>
<td>0.199</td>
<td>0.180</td>
</tr>
</tbody>
</table>

#### Panel B

$$CS_{t\rightarrow t+h} = a + b IQR(\Delta Sales)_t + c X_t + \varepsilon_{t+h}$$

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IQR(\Delta Sales)$</td>
<td>0.033***</td>
<td>0.164***</td>
<td>0.296***</td>
<td>0.376***</td>
<td>0.470***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.035)</td>
<td>(0.058)</td>
<td>(0.102)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>$E/P$</td>
<td>0.004***</td>
<td>0.011***</td>
<td>0.019***</td>
<td>0.025***</td>
<td>0.034***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Term Spread</td>
<td>0.084***</td>
<td>0.245***</td>
<td>0.155</td>
<td>0.056</td>
<td>0.096</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.082)</td>
<td>(0.168)</td>
<td>(0.244)</td>
<td>(0.289)</td>
</tr>
<tr>
<td>Net Equity Issuance</td>
<td>-0.056***</td>
<td>-0.274***</td>
<td>-0.465***</td>
<td>-0.599***</td>
<td>-0.642***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.065)</td>
<td>(0.110)</td>
<td>(0.150)</td>
<td>(0.201)</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.096**</td>
<td>0.626***</td>
<td>1.336***</td>
<td>2.042***</td>
<td>2.496***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.164)</td>
<td>(0.288)</td>
<td>(0.487)</td>
<td>(0.627)</td>
</tr>
<tr>
<td>GDP Growth</td>
<td>-0.092**</td>
<td>-0.401***</td>
<td>-0.568***</td>
<td>-0.496</td>
<td>-0.303</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.122)</td>
<td>(0.191)</td>
<td>(0.306)</td>
<td>(0.407)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.526</td>
<td>0.615</td>
<td>0.616</td>
<td>0.588</td>
<td>0.542</td>
</tr>
</tbody>
</table>

Numbers in parenthesis are standard errors

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
This table reports the return predictability of default probability after controlling for net equity issuance, term spread, inflation, credit spread, consumption to wealth ratio. The regressions are performed at quarterly frequency. $R_{t+4}^{ex}$ denotes the cumulative market return in excess of risk free rate, from period $t$ to $t+h$, in percentage numbers. The key regressor is the loan default rate, $F$, measured in percentage numbers. Net Equity Issuance is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total market capitalization of NYSE. Term Spread is the difference between long term yield on government bonds and the T-bill. Inflation is the growth rate of CPI. Credit Spread is the difference between yield of BAA and AAA corporate bond. CAY is the consumption to wealth ratio downloaded from Sydney Ludvigson’s website. Numbers in parentheses are standard errors estimated using Newey-West estimator allowing for 3 lags. Numbers in parentheses are standard errors.

$$R_{t+4}^{ex} = a + bF_t + cX_t + \varepsilon_t$$

<table>
<thead>
<tr>
<th>$h$</th>
<th>1</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>1.012</td>
<td>3.190**</td>
<td>5.144***</td>
<td>8.264***</td>
<td>11.850***</td>
</tr>
<tr>
<td></td>
<td>(0.797)</td>
<td>(1.526)</td>
<td>(1.759)</td>
<td>(1.982)</td>
<td>(2.019)</td>
</tr>
<tr>
<td>Net Equity Issuance</td>
<td>0.630</td>
<td>2.939</td>
<td>-0.416</td>
<td>-3.855*</td>
<td>-2.668</td>
</tr>
<tr>
<td></td>
<td>(0.759)</td>
<td>(1.841)</td>
<td>(1.748)</td>
<td>(1.974)</td>
<td>(1.819)</td>
</tr>
<tr>
<td>Term Spread</td>
<td>-0.876</td>
<td>-2.092</td>
<td>4.715*</td>
<td>9.724***</td>
<td>8.503***</td>
</tr>
<tr>
<td></td>
<td>(1.004)</td>
<td>(2.336)</td>
<td>(2.614)</td>
<td>(2.377)</td>
<td>(2.616)</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.018</td>
<td>-4.984</td>
<td>-8.173*</td>
<td>-7.331**</td>
<td>-5.696</td>
</tr>
<tr>
<td></td>
<td>(1.730)</td>
<td>(3.073)</td>
<td>(4.343)</td>
<td>(3.582)</td>
<td>(3.824)</td>
</tr>
<tr>
<td>Credit Spread</td>
<td>-0.082</td>
<td>6.653</td>
<td>-6.676</td>
<td>-20.445**</td>
<td>-11.971</td>
</tr>
<tr>
<td></td>
<td>(3.877)</td>
<td>(7.505)</td>
<td>(9.796)</td>
<td>(9.743)</td>
<td>(10.209)</td>
</tr>
<tr>
<td>CAY</td>
<td>0.250</td>
<td>1.736*</td>
<td>7.385***</td>
<td>12.408***</td>
<td>13.219***</td>
</tr>
<tr>
<td></td>
<td>(0.478)</td>
<td>(1.029)</td>
<td>(1.663)</td>
<td>(1.981)</td>
<td>(2.604)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.045</td>
<td>0.231</td>
<td>0.407</td>
<td>0.616</td>
<td>0.651</td>
</tr>
</tbody>
</table>

Numbers in parenthesis are standard errors
* p < 0.10, ** p < 0.05, *** p < 0.01
Table 10: **Bonferroni Test of Predictability**

This table reports the Bonferroni test of predictability, using the procedure described in Campbell and Yogo (2006). \( CS_{t\to t+h} \) denotes the cumulative credit spread from period \( t \) to \( t+h \), in percentage, at monthly frequency. \( R_{t\to t+h}^{ex} \) denotes the cumulative excess market return from period \( t \) to \( t+h \), in percentage, at quarterly frequency. \( ICSV^{FF} \) is the cross-section standard deviation of return residuals from Fama French five-factor model, as defined in Section 2.2. \( F_t \) is the nonperforming loan to total loan ratio. The table reports the estimate of slope coefficient in the predictive regression, \( b \), and 95% confidence interval based on the Bonferroni test.

**Panel A: Credit Spread Predictability - Monthly**

\[
CS_{t\to t+h} = a + bICSV^{FF}_t + \varepsilon_{t+h}
\]
\[
ICSV^{FF}_t = \mu + \rho ICSV^{FF}_{t-1} + u_t
\]

<table>
<thead>
<tr>
<th>( h )</th>
<th>( b )</th>
<th>95% Conf. Interval</th>
<th>( corr(\varepsilon,u) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.006</td>
<td>[0.005,0.008]</td>
<td>-0.075</td>
</tr>
<tr>
<td>2</td>
<td>0.011</td>
<td>[0.010,0.015]</td>
<td>-0.059</td>
</tr>
<tr>
<td>3</td>
<td>0.017</td>
<td>[0.014,0.022]</td>
<td>-0.043</td>
</tr>
<tr>
<td>6</td>
<td>0.030</td>
<td>[0.023,0.039]</td>
<td>-0.023</td>
</tr>
<tr>
<td>12</td>
<td>0.043</td>
<td>[0.028,0.060]</td>
<td>-0.012</td>
</tr>
</tbody>
</table>

**Panel B: Return Predictability - Quarterly**

\[
R_{t\to t+h}^{ex} = a + bF_t + \varepsilon_{t+h}
\]
\[
F_t = \mu + \rho F_{t-1} + u_t
\]

<table>
<thead>
<tr>
<th>( h )</th>
<th>( b )</th>
<th>95% Conf. Interval</th>
<th>( corr(\varepsilon,u) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.504</td>
<td>[-0.164,1.843]</td>
<td>-0.076</td>
</tr>
<tr>
<td>4</td>
<td>2.619</td>
<td>[2.081,5.891]</td>
<td>-0.151</td>
</tr>
<tr>
<td>8</td>
<td>5.903</td>
<td>[4.812,10.516]</td>
<td>-0.147</td>
</tr>
<tr>
<td>12</td>
<td>9.561</td>
<td>[8.590,15.276]</td>
<td>-0.164</td>
</tr>
<tr>
<td>16</td>
<td>13.455</td>
<td>[12.129,19.508]</td>
<td>-0.157</td>
</tr>
</tbody>
</table>