Idiosyncratic Tail Risk and the Credit Spread Puzzle

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ABSTRACT

This paper studies the asset pricing implications of state-dependent, idiosyncratic labor income tail risk on credit spread. I propose a model featuring incomplete market, heterogeneous households with recursive preference, and a single state variable that drives the time-varying probability of tail events in both labor income and firm cash flow growth. My model produces strong covariation of households' marginal utility and default rates, which helps to account for the stylized fact that the credit spread (1) is on average large and (2) is positively related to labor tail risk. The framework also highlights the quantitative importance of the third moment and its specific pricing mechanism for corporate bonds.

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1 Introduction

This paper studies the asset pricing implication of labor tail risk on corporate bond spreads. Labor income risk from the left tail is associated with infrequent labor market events such as job displacement or wage cut. Historically, labor tail risk and credit spreads are both counter-cyclical and exhibit strong comovement. Figure 1 plots the quarterly time series of Moody's Baa-Aaa credit spread and a proxy for labor tail risk. The figure shows that the two time series move in lockstep and both spike during recessions. The correlation between labor tail risk and credit spread is as high as 0.73. Labor tail risk and default risk are tightly linked since both are likely to be driven by large and negative shocks that hit firms into adverse situations. As figure 1 shows, high labor tail risk is usually accompanied with clustered defaults, especially for the second half sample. This relation can potentially generate large credit spreads as well as the comovement of labor tail risk and credit spreads.

To rationalize the findings, this paper develops a model featuring incomplete market, heterogeneous households with recursive preference, and a single state variable that drives the time-varying probability of tail events in both labor income and firm cash flow growth. The model has three key ingredients. First, households face state-dependent, idiosyncratic tail risk in labor income. Second, the market is incomplete, so that labor risk effectively transfers into consumption risk and drives households' marginal utility. Third, tail risk in firm cash flow is positively related to labor tail risk. Firms make optimal financing decisions based on the trade-off between tax benefits and bankruptcy costs. Default arises endogenously in response to negative shocks from labor risk and cash flow.

The basic intuition is as follows. As the economy contracts, business conditions deteriorate. On the one hand, firms start to lay off workers or managers to reduce costs, which makes the left tail of the cross-sectional distribution of income growth fatter. Ex-post, labor tail risk effectively concentrates among a small fraction of the households for whom the consequences are disastrous. This concentration mechanism makes the households ex-ante more averse to economic downturn. On the other hand, a greater fraction of firms finds their option to default more valuable than paying back creditors, which leads to clustered default. Corporate bonds are bad hedge against labor tail risk, rationalizing a large credit spread. In addition, as more firms are getting closer to default, the bankruptcy probability is more sensitive to negative shocks than in good times. This generates the comovement in credit spread and labor tail risk.

Rather than aggregate, rare disaster type of tail risk, labor tail events considered in this paper are idiosyncratic because they occur almost independently in the cross section. However, during these tail events, households experience large and persistent decline in their labor income. As securities or contracts that can hedge against such risk are rare and inadequate, these large and negative shocks can have a first order effect on household welfare, and, in turn, asset prices. In addition, the probability of these tail events is common economy-wide and state-dependent, which effectively drives households' risk aversion through business cycles.

Idiosyncratic tail risk is of particular importance to corporate bond pricing. Recessions are characterized as a combination of negative first moment (mean) shocks, positive second moment (uncertainty) shocks, and negative third moment (skewness) shocks (Bloom, Guvenen, Salgado, et al. (2016)) in the cross-sectional distribution of firm fundamental growth. In other words, during recessions, risk not only concentrates on a subset of households, but also on a subset of firms. As stock is a call option on asset, risk from the left tail is largely absorbed by debt holders. In this regard, the comovement of labor tail risk and firm cash flow tail risk will induce a significant impact on credit risk premium but not on equity.

The paper proceeds as follows. First, I provide new empirical evidence on the relation between labor tail risk and credit spreads. I construct a quarterly labor skewness index as a proxy for labor tail risk, which targets the time series of cross-sectional labor income growth skewness from Guvenen, Ozkan, and Song (2014b). Regression analysis shows that labor tail risk has strong explanatory power on credit spread. Tail risk itself explains as much as 53% of the Baa-Aaa credit spread variation. One standard deviation increase in labor tail risk is associated with a rise of 33 basis in credit spread. After controlling traditional credit risk determinants, the magnitude remains significant at 31 basis points. I also find labor tail risk is highly correlated with the third moment risk of firm fundamentals, but not the second moment, which supports my model assumption.

Then, I build a simple two period model to illustrate three key points of the basic mechanism. First, I show that if the market is incomplete, uninsurable labor tail risk will affect SDF. Higher tail risk concentrates more risk among small fraction of the households, which ex-ante increases the marginal utility in that state. Second, comovement of household tail risk and firm tail risk has no impact on firm asset valuation as the shocks are idiosyncratic. However, it will increase credit risk since it increases the default probability in bad times. The impact on equity premium, on the contrary, is negative, because with option effect, the comovement effectively transfer some risk from equity to bond. Third, I use Taylor expansion and numerical examples to show that taking higher order moments effect into account is quantitatively important in generating a high credit spread. On the household side, Due to the curvature of utility function, the effect of risk concentration induced by negative skewness is an order of magnitude more important than second moment. On the firm side, the consequence of large, negative shocks are absorbed by the debt holders, thus negative skewness also plays a more important role.

Next, I assess the quantitative significance of idiosyncratic tail risk in affecting the credit spread with the full model. The model, whose parameters are calibrated to match the dynamics of the labor skewness index and firm sales growth, is able to (1) generate a large credit spread of 1.03% with cumulative default rate and recovery rate similar to historical average, (2) account for other stylized facts such as low leverage ratio, high and volatile stock returns, etc., and (3) reproduce the strong comovement between labor tail risk and credit spread.

Lastly, I decompose the model implied credit spread to illustrate the quantitative contribution of each model ingredient. The unique pricing channel for corporate bond, i.e., the comovement between labor tail risk and firm cash flow tail risk, contributes 29 basis points, which is about 1/3 of the total credit risk premium. While the negative relation between labor tail risk and firm cash flow growth contributes about 41 basis points of credit risk premium.

Related Literature This paper establishes a link between idiosyncratic tail risk in labor market and credit spread variation, and adds to the empirical literature on the determinants of credit spread variation[1]. This paper is most connected to the strand of literature on the macroeconomic determinants of credit risk. Several articles[2] show that, under reasonable calibration, large and volatile credit spread can be justified by the exposures to macroeconomic risks. While previous work focus on complete market and aggregate risk, my paper studies the impact of idiosyncratic tail risk, which can be easily identified from the data, under an incomplete market setup. I show that after controlling for a long list of aggregate risks, labor tail risk still remains the most robust and significant variable that explains the credit spread fluctuation. The additional explanatory power of idiosyncratic labor risk indicates that it is critical to take an incomplete market view in resolving the credit spread puzzle. Quantitatively, when calibrated to the dynamics of labor income growth skewness, my model can account for equity premium, under leveraged puzzle, and the level and dynamics of credit spread.

This paper is related to the literature of asset pricing with incomplete market. The risk concentration mechanism in my model builds on the seminal work of Mankiw (1986) and Constantinides and Duffie (1996). In their paper, uninsurable idiosyncratic risk is counter-cyclical and concentrates on a small fraction of households, which helps to generate high equity risk premium. Constantinides and Ghosh (2017) introduce Epstein-Zin preference into the incomplete market setting and calibrate their model to CEX data. They show that the skewness of household consumption growth is pro-cyclical and important for asset prices. With a similar setup, Schmidt (2016) propose idiosyncratic tail risk of labor income as a key driver of asset prices. Besides these endowment models, Ai and Bhandari (2017) study an economy featuring idiosyncratic risk, insurance through labor contracts and limited commitment, providing another channel through which idiosyncratic tail risk can affect risk premia. All these work focuses on the stock market, my paper adds to the literature by studying the impact on corporate bonds. Tail risk is tightly linked to bond pricing with respect to the nature of default risk. My paper distinguishes the pricing mechanism on bond from equity, and points out that the comovement of idiosyncratic tail risk in labor income and firm cash flow growth will induce a positive effect on the credit risk premium but a negative effect on the equity risk premium.

This paper is also related to the literature of labor economics. A growing body of empirical evidence shows that there is a substantial amount of idiosyncratic risk in labor income[3] as well as in consumption [4]. In particular, Guvenen et al. (2014b) study a very large data set from the U.S.

[1]See Duffee (1998); Collin-Dufresn, Goldstein, and Martin (2001); Campbell and Taksler (2003), Chen, Lesmond, and Wei (2007), Cremers, Driessen, Maenhout, and Weinbaum (2008), Zhang, Zhou, and Zhu (2009), Ericsson, Jacobs, and Oviedo (2009), Krishnamurthy and Vissing-Jorgensen (2012), Kang and Pflueger (2015), Culp, Nozawa, and Veronesi (2018).

[2]See Hackbarth, Miao, and Morellec (2006), Chen, Collin-Dufresne, and Goldstein (2008), Bhamra, Kuehn, and Strebulaev (2009), Chen (2010).

[3]See Storesletten, Telmer, and Yaron (2004),McKay, Papp, et al. (2011),Guvenen et al. (2014b),Guvenen, Karahan, Ozkan, and Song (2015).

[4]See Deaton and Paxson (1994), Brav, Constantinides, and Geczy (2002), Vissing-Jørgensen (2002), Blundell, Pistaferri, and Preston (2008), Heathcote, Storesletten, and Violante (2014).

Social Security Administration, and find that the left-skewness of shocks to labor income growth is strongly countercyclical. While households can largely smooth out transitory and diffusion type of idiosyncratic risk in their labor income, they are particularly vulnerable to persistent and jump type of risk, which generate sizable costs of business cycles (Krebs (2007), Davis and von Wachter (2011)). On the other hand, Bloom et al. (2016) show that, during recessions, firm fundamentals are featured with a fatter left tail. This paper combines these two empirical facts and tries to study the implications for corporate decision and bond pricing. My paper shows that the third moment effect through the business cycles is strong in shaping the bond price and corporate financing behavior, which adds a another piece of evidence to the importance of relating labor risk to finance.

Lastly, several studies also explore labor and asset prices[5]. In these papers, rigid wages act as operating leverage and amplify risk premia. Bai (2016) considers search and matching frictions in the labor market and exams the relation between unemployment and credit risk. His work also emphasizes tail risk. However, the type of risk and mechanism in my paper is completely different. In Bai (2016)'s paper, market is complete and tail risk takes the form of aggregate rare disaster. While my paper proposes incomplete market and cross-sectional tail events. In the real economy, both channels might be in play. My paper shows that, quantitatively, the incomplete market channel can achieve a first order effect on credit risk premium without any large aggregate consumption decline, which is seldom observed in the data.

2 Empirical Evidence

In this section, I present several empirical facts that motivate my interest in studying the link between idiosyncratic tail risk of labor income and credit risk. First, I provide evidence that the left-tail risk of labor income is counter-cyclical. Next, I investigate the cyclical behavior of firm fundamentals. I show that the first and third moment of firm growth is most correlated with labor income risk. I then regress credit spread on proxies for idiosyncratic tail risk of labor income. In U.S. data, labor tail risk can explain a large proportion of the time variation in credit spread. The result is robust with controls in both level and first-difference regression. Lastly, I will discuss some issues on the mechanism and interpretation.

2.1 Counter-cyclical Idiosyncratic Tail Risk in Labor Market

In this subsection, I investigate the cyclicality of idiosyncratic tail risk in labor market and construct a quarterly proxy for asset pricing study. As labor tail risk is not directly observable in the data, I rely on the cross-sectional skewness of labor income growth to identify the risk. Guvenen et al. (2014b) (henceforth GOS) reports a number of summary statistics for the cross-section of labor income growth based on a nationally representative sample of panel labor income records for 10% males aged 25-60 in the U.S. population from the Social Security Administration. The

[5]See Danthine and Donaldson (2002), Uhlig (2007), Favilukis and Lin (2015), Favilukis, Lin, and Zhao (2017)

statistics are annual and covers 1978 - 2011. They show that the left-skewness of cross-sectional labor income growth is strongly counter-cyclical.

[Insert Figure 2 here]

Figure 2 plots the time series of skewness measure for trailing 1-year labor income growth. The cross-sectional skewness is on average negative and dips during recession, indicating that households face substantial idiosyncratic downside risk. Table 1 computes the sample moments of cross-sectional labor income growth in recession and expansion period. Notably, the left tail expands and the right tail shrinks in economic downturn, Kelley skewness [6] decrease from 0.048 to -0.092 for 1-year labor income growth and from 0.104 to -0.071 for 5-year labor income growth.

[Insert Table 1 here]

In order to explore the asset pricing implication, I need data at higher frequency and longer sample period. To this end, I target 1-year skewness of cross-sectional labor income growth and construct a quarterly skewness index using a large cross-section of macro variables. I use three pass regression filter (3PRF) of Kelly and Pruitt (2015) as my baseline index construction method. As a robustness check, I also use inverse of mean squared errors (IMSE) method. Two methods generate similar results. Details of index construction refer to Appendix A.

Though skewness measure provides a direct proxy for tail risk, it may still subject to interpolation errors. Therefore, I also include initial claims and unemployment rate as additional proxies for left-tail risk in labor market. Initial claims measures the number of jobless claims filed by individuals seeking to receive jobless benefits. It typically rise before the economy enters a recession and decline before the economy starts to recover. Figure 3 plots the time series of these three proxies. Visually, they comove together with initial claims slightly lead unemployment rate and skewness index. Overall, this confirms that tail risk in labor market is strongly counter-cyclical.

[Insert Figure 3 here]

2.2 Cyclicality of Firm Fundamental Risk

Job displacement or wage cut are usually caused by deteriorated business conditions, which also increase the probability of default. In table 2, I compute the statistics of cross-sectional sales growth distribution for expansion and recession period respectively. Comparing average statistics between recession and expansion period, we observe that in economic downturn, the mean and median of sales growth decline considerably, the standard deviation increase a only little bit and the skewness decrease drastically. Kelley skewness for the cross-section of quarterly sales growth rate drops from 0.066 in expansion period to -0.172 in recession period. To summarize, recessions

[6] Kelley skewness is a robust measure of skewness, which is defined as $\frac{(P_{90}-P_{50})-(P_{50}-P_{10})}{P_{90}-P_{10}}$, where P_n is the n^{th} percentile of the distribution.

are characterized by a large negative shock to first and third moment of firm growth, and a small positive shock to second moment.

[Insert Table 2 here]

2.2.1 Comovement with Labor Tail Risk

In rational asset pricing models, comovement with macro risk is of more importance in determining the asset prices. In this regard, I compute the correlation between skewness index and cross-sectional moments of firm fundamental growth. The firm variables are:

Firm sales growth: Data is from Compustat fundamental quarterly. Sales growth is measured as the log difference between sales in quarter t and quarter t-4. I restrict the sample to firms with 10 or more years of data (Result that require firm to have at least 25 years or 1 year data is similar) and quarters with at least 500 firms in the cross section. This result in a quarterly time series from 1975Q4-2013Q4.

Firm gross profit growth: Data is from Compustat fundamental quarterly. Gross profit is calculated as revenue subtract cost of good sold and divided by total asset $(retq - cosq)/atq$. Gross profit growth is measured as the log difference between gross profit in quarter t and quarter t-4. Sample restriction is the same as sales growth. This result in a quarterly time series from 1976Q4-2013Q4.

Firm employment growth: Data is from Compustat fundamental annual. Employment growth is calculated as log difference between Compustat item emp between year t and year t-1. Sample restriction is the same as sales growth. This result in an annual time series from 1964-2013.

The moments I considered in this exercise is first moment (mean or median), second moment (standard deviation or range $(P_{90} - P_{10})$) and third moment (skewness or Kelly skewness), I also report left tail $(P_{90} - P_{10})$ and right tail $(P_{90} - P_{50})$ for reference.

[Insert Table 3 here]

Table 3 reports the result. Correlation of skewness index and first moment is strong, which ranges from 0.48 to 0.56. Correlation of skewness index and second moment is relatively weak, the absolute value of correlations never go beyond 0.1. Interestingly, skewness index also has high correlation with firm fundamental skewness. Low skewness index accompanies the expansion of left tail and shrink of right tail in the cross section of firm fundamental growth. In summary, when households face higher labor tail risk, firms experience low growth and a subset of them performs extremely badly.

2.2.2 Firm Fundamental Risk in the Cross Section

I further explore heterogeneity of firm fundamental risk in the cross section. Previous work documents a substantial variation in corporate bond yield for firms with different characteristics.

For example, it is well known that small size firms have higher bond yield than big firms, and firms with low market-to-book ratio have higher bond yield than firms with high market-to-book ratio. In this exercise, I compare firm fundamental risk across size and market-to-book sorted portfolios to see if the pattern is consistent with the tail risk story. Specifically, for each period t, I compute the cross-sectional mean, standard deviation and skewness of log sales growth within each size/market-to-book sorted firm group. Then, I calculate the time series average of these statistics and their correlation with labor skewness index.

[Insert Table 4 here]

Table 4 shows the result. The second column reports the credit spread for each portfolio, numbers are from KUEHN and Schmid (2014). Credit spread increase monotonically from high market-to-book portfolio to low market-to-book, from large size to small size. Next, we turn to firm fundamental risks of each portfolio. Panel A reports the statistics of market-to-book sorted portfolio, the average growth rate and skewness increase monotonically from low to high group. More importantly, their correlation with labor tail risk decrease from low to high, which indicates that low market-to-book firms are more risky in terms of downside risk. This provides suggesting evidence that labor tail risk also drives the cross-sectional variation of credit spread. The patten of volatility is non-monotone and its correlation with skewness index is negligible. Panel B shows the statistics of size sorted portfolio and has similar pattern: growth rate and skewness increase from high credit spread portfolio to low, and their correlation with skewness index decrease monotonically. Notably, in size sorted portfolio, though volatility decrease monotonically, their correlation with labor tail risk has the opposite pattern as predicted by theory: large firms' volatility is more negatively correlated with labor tail risk, which means in bad times large firms' cash flow are more volatile and their default timing should be more correlated with SDF. With respect to the fact that correlation of volatility and labor tail risk is weak and its pattern is unclear, credit spread is unlikely to be driven by the comovement of time varying volatility of fundamental risk and labor tail risk.

In summary, the analysis conveys two message: First, the time-varying mean and tail risk (skewness) of firm fundamental growth, as well as their correlation with labor tail risk are important for understanding credit spread variation in the cross section. second, the pattern of cross-sectional firm fundamental risk is consistent with the hypothesis that labor tail risk drives the bond risk premia, providing supporting evidence that labor tail risk should also matter for credit spread in aggregate level.

2.3 Labor Tail Risk and Credit Spread

2.3.1 Credit Spread Regression

In baseline regression, I regress Moody's Baa-Aaa credit spread on skewness index (also initial claims and unemployment rate) together with other macro variables for control.

$$\begin{aligned} CS_t &= \beta_0 + \beta_1 S_t + \gamma \mathbf{X}_t + \epsilon_t. \\ \Delta CS_t &= \beta_0 + \beta_1 \Delta S_t + \gamma \Delta \mathbf{X}_t + \epsilon_t. \end{aligned} \tag{1}$$

where S_t is the skewness index and $\mathbf{X}_t$ is a vector of controls. All the independent variables are standardized to have mean 0 and standard deviation of 1. I also include first-difference regression for robustness check. The controls I considered here are

Aggregate stock volatility: CRSP data. Monthly realized stock market volatility estimated from daily returns on the CRSP market index. Aggregate stock market volatility is constructed as a six-month moving average of monthly series.

Idiosyncratic stock volatility: CRSP data. Monthly realized idiosyncratic stock volatility estimated from daily returns on individual as in Goyal and Santa-Clara (2003). The idiosyncratic stock volatility is constructed as a six-month moving average of monthly series.

3 month treasury yield: FRED data.

Term spread: FRED data. Calculated as 10-year treasury yield minus 3-month treasury yield.

Aggregate market leverage: Flow of Fund table B103 data. Aggregate market leverage is calculated as total liability divided by total asset in the non-financial corporate sector.

Cyclical adjusted price to earnings ratio: Data from Robert Shiller's website.

Industrial production growth: FRED data.

Table 5 reports the level regression result. Model (1) shows that skewness index along can explain 53% of the time series fluctuation of credit spread. Initial claims and unemployment rate has similar explanatory power on credit spread. Putting three variables together, they explain about 65% of the credit spread fluctuation. Controlling for other variables, the effect of labor market risk is still there. Particularly, adding skewness index to the existing controls help improve the adjusted R square from 0.61 to 0.70 and the coefficient of skewness is significant with a -7.05 t-statistics. An interesting observation is that after adding skewness index into the regression, it drives out the explanation power of industrial production growth, the coefficient on industrial production growth even turn from negative to positive. In terms of economic magnitude, 1 standard deviation increase in tail risk (decrease in skewness index) is associated with 33 basis point increase in credit spread. The magnitude remain stable after controls for other macro variables.

[Insert Table 5 here]

Table 6 reports the first difference regression, which tells a similar story: the change in labor tail risk can explain the change in credit spread and contain additional information to existing controls, although the coefficient of skewness index is only significant at 10% level (initial claims and unemployment rate become insignificant in this case).

[Insert Table 6 here]

2.3.2 Labor Tail Risk and Liquidity

Literature documents that part of corporate bond premium can be attributed to liquidity. For example, Longstaff, Mithal, and Neis (2005) estimate that default component represents about 51% to 83% of the credit spreads for different rated bonds and the nondefault components are strongly related to bond liquidity. Bao, Pan, and Wang (2011) documents a strong relation between liquidity and credit spread both in cross section and aggregate level. Default risk and liquidity frictions can also interact with each other, which leads to a default-liquidity spiral (He and Milbradt (2014), Chen, Cui, He, and Milbradt (2017)).

In this section, I add liquidity into credit spread regression for two purposes. First, I would like to make sure that liquidity does not drive out the explanatory power of labor tail risk. Second, I could look at the interactions between liquidity and labor tail risk. To this end, I run the regression for level and change of credit spreads:

$$\begin{aligned} CS_t &= \beta_0 + \beta_1 S_t + \beta_2 N_t + \beta_3 S_t N_t + \epsilon_t. \\ \Delta CS_t &= \beta_0 + \beta_1 \Delta S_t + \beta_2 \Delta N_t + \beta_3 \Delta S_t \Delta N_t + \epsilon_t. \end{aligned} \tag{2}$$

where S_t is skewness index, N_t is a proxy for liquidity and $S_t N_t$ captures the interaction. A direct measure of corporate bond liquidity is usually obtained from TRACE data. However, this liquidity measure begins at 2002. The sample period is too short for my quarterly time series exercise. Therefore, I prefer to use market liquidity measure of Hu, Pan, and Wang (2013), which dates back to 1987Q1 as it uses Treasury data.

Table 7 reports regression result. We make two observations: First, after controlling for liquidity, the coefficient of skewness index remain significant in both level and change regression. Adding liquidity helps increase R squared by 5% in level regression and 18% in change regression. Thus, liquidity adds little in explaining the time series level of credit spread but do contribute to explain the change of credit spread. Second, the interaction term is negative and significant in both regression, which mean when labor tail risk and illiquidity are both high, their relation with credit spread is stronger. In the data, correlation of skewness index and liquidity is as high as -0.71, the correlation of change is about -0.22. These evidence points to a risk-liquidity spiral story: when labor tail risk increases, everyone wants to reduce their corporate bond holding, which reduces secondary bond market liquidity, and higher illiquidity discount the bond value and makes firm more likely to default, which further increase investors' incentive to sell off their bond holdings.

2.3.3 Robustness

In this subsection, I show the robustness of labor skewness and credit spread relation. Skewness index is essentially a linear combination of macro variables. Therefore, it is impossible for the skewness index to capture information beyond these macro variables. However, we can still check whether skewness index is a good combination of individual macro variables such that it better explain the time variation of credit spread.

To this end, I run a horse race of univariate regression of credit spread on skewness index (3PRF and IMSE), 97 macro variables and the 8 macro controls used in baseline regressions. Figure 6 plots the R^2 of each regression. The R^2s are sorted in descending order. The red bar represents R^2 from the 3PRF skewness index regression and the blue bar represents R^2 from the IMSE skewness index. The results shows that in the level regression, 3PRF skewness index archives the highest R^2, followed by capacity utilization and unemployment measure, and then IMSE skewness index. In the change regression, 3PRF skewness index ranks the third and IMSE skewness index ranks the fifth, the champion and runner-up are production price index and purchasing managers' index respectively.

[Insert Figure 6 here]

In addition, I construct indices from the same 97 macro variables but random weights to see the chance that a randomly constructed index outperform the skewness index. Specifically, I draw the weights from a uniform distribution on [-1,1] and construct a index $\sum_{i=1}^{97} w_i v_i$. I then regress the credit spread on this index to get the univariate R^2. I do this 100,000 times and plot the empirical distribution of R^2 in figure 7. The red line and blue line show the univariate regression R^2 from 3PRF skewness index and IMSE skewness index respectively. The 3PRF skewness index and IMSE skewness index both locate somewhere around the right tail of the distribution. Only 0.096% and 4.8% of simulated indices outperform 3PRF skewness index and IMSE skewness index in the level regression. 1.96% and 2.15% of simulated indices outperform 3PRF skewness index and IMSE skewness index in the change regression. To summarize, these evidence show that the skewness index is a good combination of information that explains the fluctuation of credit spread.

[Insert Figure 7 here]

In unreported tables, I also add proxies for skewness of firm fundamental into the baseline regression. When not controlling for labor income skewness, firm fundamental skewness do show some explanatory power on time variation of credit spread. However, the explanatory power is subsumed by labor income skewness after the inclusion of skewness index. This indicate that the labor income channel (through the credit risk channel) should play a more important role than the firm skewness channel (through physical default probability).

2.4 Discussion

2.4.1 Labor Income and Consumption

In standard consumption-based asset pricing models, prices are determined by households' marginal rates of substitution, which is related to consumption risk. Ideally, I should look at idiosyncratic tail risk in consumption. However, long sample and high quality individual consumption data is not available. Because of the sample size, it is also difficult to accurately identify higher moments from survey-based consumption data, such as the Consumer Expenditure Survey (CEX) or the Panel Study of Income Dynamics (PSID). Therefore, I prefer to identify tail risk from labor income growth moments reported by Guvenen et al. (2014b), which has longer sample and is potentially more accurate.

There is a large literature in labor economics that studies the impact of labor income shock on consumption. The general view is that households can largely smooth out transitory shocks of labor income, but can only partially insure against persistent shocks. Blundell et al. (2008) combines information from PSID and CEX to estimate a partial insurance model. In their estimation, 22.45% of permanent shocks to male earnings are transmitted to consumption [7]. Higher moment risk such as long spells of job displacement should be more uninsurable for workers. Unemployment benefits only pays about half of the previous wage and is usually capped at average earnings of that state. In addition, displaced workers usually experience substantial wage reductions even if they find a new job. In a macroeconomic model with incomplete markets, higher moment risk generate far more welfare costs than second-moment risk (Krebs (2007)).

Idiosyncratic tail risk in labor income can also affect asset prices through risk sharing. Ai and Bhandari (2017) studies an economy where capital owners, who is the marginal investor, provide insurance to workers using long-term contract. However, due to limited commitment, tail risk in labor productivity is not insured. In bad times, the prospect of less risk sharing in the future translate to lower consumption share of capital owners through optimal contract. Tail risk of labor productivity essentially makes marginal investors' consumption more volatile.

2.4.2 The Marginal Investor

According to Fed's Flow of Funds, life insurance companies are the largest domestic holder of U.S. corporate bonds. Mutual funds are the second largest domestic holder, followed by households (including hedge funds), private pension funds, and state & local government retirement funds. Potentially, the marginal investors are the wealthy families.

Cross-sectional skewness in GOS focus on growth not level. Households in the left tail is not necessary poor. To alleviate the concern that labor tail risk is not prevalent among wealthy households, I plot the skewness of cross-sectional 1-year labor income growth within recent labor income groups. Specifically, households are first sorted by recent labor income at time t, which is measured as the average labor income of past five years, assigned to 100 groups, and then the

[7] My calibration use the same labor-consumption transition rate

relevant statistics is computed within groups from t to $t+1$. Figure 4 shows the result, the left panel shows the third moment measure and the right panel shows the Kelley skewness. The third moment measure exhibit U shape pattern and Kelly skewness decrease from low income to high income. Overall, the average skewness in labor income growth appear to be more negative among wealthy households.

[Insert Figure 4 here]

Figure 5 shows the time-variation of skewness within different income groups. The skewness of different income group track each other closely. The time series correlation between the overall skewness and each income group skewness is mostly above 0.8. This indicate that the overall skewness is a good candidate for measuring the common idiosyncratic tail risk fluctuation.

[Insert Figure 5 here]

While I emphasize the role of wealthy marginal investors, it is not saying that idiosyncratic tail risk for less wealthy workers is negligible for asset prices. It can still affect bond premium through risk sharing as in Ai and Bhandari (2017). I do not model the specific channel in my calibration exercise. Instead, I take a more tractable framework as in Constantinides and Duffie (1996) to exam the impact of uninsurable tail risk on corporate bond premium.

Corporate bond is mostly hold by institutional investor. Among these institutions, mutual funds, money market funds and exchange-traded funds actively trade corporate bond and their decisions are potentially influenced by capital inflow or outflow. Though it is outside of my model, as in my model, there is no heterogeneity in institutions and all assets must be held by investors in equilibrium, I still would like to exam whether there is withdraw of funds during high tail risk period, leading to price pressure on corporate bond.

To this end, I run regression of fund holdings on tail risk. Specifically, I collect data from Federal Reserve flow of funds table L.213. I divide the amount of corporate bond held by mutual funds, money market funds and exchange-traded funds by the total amount outstanding to compute the percentage holding. I also detrend the holding level and compute the first difference, which is a fund flow measure. Table 8 shows the regression result of fund percentage holding on tail risk. We can see that high tail risk is associated with a low level of fund holding and bad shock to tail risk is associated with outflow of capital from these funds. This suggest that indeed during high tail risk period, these funds are subject to withdrawal of capital, which may further lead to price pressure on the asset.

2.4.3 Equity premium and Bond premium

Idiosyncratic tail risk is an economy-wide macro risk, so it affects credit spread as well as equity returns. Indeed, my asset pricing model can account for both equity premium and bond premium. Schmidt (2016) study labor tail risk and its implication on equity return, while my paper mainly focus on corporate bond premium. Tail risk governs risk premia in general, however, the mechanism through which it affect equity return and bond return is a bit different. As we know, equity is a call option on firm asset, so equity holder is not sensitive to tail risk of firm assets. However, bond holder is particularly sensitive to negative and jump type of risk. In fact, empirical evidence shows that downside risk is the strongest predictor of future bond returns in the cross section(Bai, Bali, and Wen (2018)). In the data, third moment of firm growth is highly correlated with tail risk in labor market, corporate bond will be very sensitive to this macro condition. While with option effect and time-varying asset tail risk, equity will be less exposed to labor tail risk, comparing to the case without modeling debt financing.

Massive layoffs and bankruptcy filling are both costly decisions for firms. They are the last resort when firms are really in bad shape and have no other options. Bond premium should be naturally more related to labor tail risk than equity because they are all about large and negative shock to firms instead of day-to-day small fluctuations. In appendix B, I run the stock return predictability regression. Overall, tail risk in labor market exhibit mild stock return predictability power in sample, comparing to the traditional predictor such as PD ratio, and a robust out-of-sample predictability.

3 Asset Pricing Model

In this section, I build a consumption-based model to quantitatively asses the importance of idiosyncratic tail risk in explaining the level and dynamics of credit spread. I will first use a simple two period model and some numerical example to illustrate: (1) the mechanism through which labor tail risk affect asset prices; (2) firm asset idiosyncratic tail risk has positive effect on bond premium but negative effect on equity premium; (3) the importance of third moment in generating high credit spread. I then describe the full quantitative model setup. The model consists of two building blocks: households with uninsurable idiosyncratic tail risk which determine the stochastic discount factor and a cross-section of firms that optimally make financing and default decisions. Next, I will discuss the model parameters and calibrate them to data. Lastly, I report the model moments and compare the quantitative effect of each model ingredient by shutting down some of the channels.

3.1 Qualitative Model

3.1.1 Two Period Economy

It is a two period endowment economy populated by a continuum of households index with i.

In period 0, all households are endowed with 1 unit of consumption goods. In period 1, there are two aggregate states, each will happen with probability $\frac{1}{2}$: (1) In good state, all households get 1 unit of endowment. (2) In bad state, household i will have endowment $\exp(\xi_i(p))$, with $E(\exp(\xi_i(p))) = 1$, where $\xi_i(p)$ is i.i.d in the cross section and mean preserving. The second and higher order moments of the distribution are driven by p.

Households have log utility:

$$\ln(C_{0,i}) + \ln(C_{1,i}),$$

where $C_{t,i}$ is the consumption of household i at period t. For any financial asset, it should satisfy the Euler equation:

$$E_0\left[\frac{C_{0,i}}{C_{1,i}}R\right] = 1. \tag{3}$$

Every household is marginal investor. Thus, this equation should hold for every household i, whose SDF is $M_i = \frac{C_{0,i}}{C_{1,i}}$.

3.1.2 Price of Risk

Note that in period 1, both states have 1 unit of aggregate endowment. In other words, there is no aggregate risk in this economy. If the market is complete, households can trade contracts at period 0 to insure against the idiosyncratic shock in bad state. As everyone is perfectly insured, we can use aggregate consumption to compute the common SDF. The state price in both states are zero ($q_g = 1$, $q_b = 1$).

However, if the market is incomplete, idiosyncratic shock would matter. In this example, I take the extreme case, where households have no risk sharing so they have to consume their own endowment. As in the Euler equation 3, asset return R has no exposure to $\xi_i(p)$, I can integrate out idiosyncratic shocks to compute the common SDF. The state price is $q_g = 1$ and $q_b(p) = E\left(\frac{1}{\exp(\xi_i(p))}\right)$.

As a numerical example, I set $\xi_i(p)$ to be a compensated Poisson jump $\xi_i(p) = -d_c J_i - \zeta(p)$, with jump intensity p, where $\zeta(p)$ is a compensation term to make it mean zero. d_c is the jump size when a tail event occurs. I set it to be 0.8. Figure 8 plots the state price q_b with respect to p in complete and incomplete market cases. I also add a log normal case where I specify $\xi_i(p) = \sigma(p)\epsilon_i - \frac{1}{2}\sigma(p)^2$. $\sigma(p)$ is adjusted some that the cross-sectional variance of household endowment in log normal case is the same as in tail risk case.

[Insert Figure 8 here]

I make three observation from the figure. First, Idiosyncratic risk matters in incomplete market. The state price $q_b(p)$ remain flat at 1 for the complete market case. For the incomplete market cases, state prices are greater than 1, which indicate that household are averse to idiosyncratic risk. Second, Tail event probability p serves as a state variable, higher p is associated with larger state price q_b and higher marginal utility. Third, the quantitative effect is stronger with tail risk than log normal risk as the state price of tail risk case is always greater than log normal case.

To understand the last point better, I take Taylor expansion of $q_b(p)$. Denote $\bar{\xi} = E(\xi_i(p))$, we have

$$q_b(p) = \frac{1}{\exp(\bar{\xi})} + \underbrace{\frac{2}{\exp(3\bar{\xi})}E(\xi_i(p) - \bar{\xi})^2}_{\text{2nd moment effect}} \underbrace{- \frac{6}{\exp(4\bar{\xi})}E(\xi_i(p) - \bar{\xi})^3 + \cdots}_{\text{higher moment effects}}$$

The coefficient on n^{th} moment takes the form of $(-1)^n \frac{n!}{\exp((n+1)\bar{\xi})}$, thus, the higher moment effects are important. In particular, the third moment effect is positive if skewness is negative, which is exactly what I want to capture from labor income skewness.

3.1.3 Price of Securities

In this section I will use the SDF to price a firm and discuss the asset pricing implications. Suppose firm's asset liquidation value at period 1 is V_j. The firm has a exogenous debt level B. Firm defaults if the liquidation value is lower than B. Thus in period 1, debt holders have payoff $\min(V_j, B)$ and equity holders have payoff: $\max(V_j - B, 0)$.

The liquidation value V_j has the following dynamics: In good state, it takes form of $V_j^g = \exp(\xi_j(\bar{p}))$; in bad state $V_j^b = \exp(\xi_j(\bar{p} + \phi_1 p))$, with $E\exp(\xi_j(\bar{p} + \phi_1 p)) = 1$. In this setup, firm asset does not have exposure to aggregate shock, the key difference between good and bad state is the idiosyncratic tail risk. In particular, ϕ_1 determines the comovement of asset tail risk and household tail risk.

Denote v_a, v_b, v_e as asset value, bond value and equity value at period 0 respectively. The asset value can be computed as

$$\begin{aligned}
v_a &= \frac{1}{2} q_g E\left(V_j^g\right) + \frac{1}{2} q_b E\left(V_j^b\right) \\
&= \frac{1}{2} q_g E\left(\exp(\xi_j(\bar{p}))\right) + \frac{1}{2} q_b E\left(\exp(\xi_j(\bar{p} + \phi_1 p))\right) \\
&= \frac{1}{2} q_g + \frac{1}{2} q_b,
\end{aligned}$$

which is the same as if there is no idiosyncratic risk. Since shocks to liquidation value is idiosyncratic and mean zero, it does not affect the unlevered asset risk premium. However, the time-varying higher moment will positively affect bond risk premium and negatively affect equity through default. Denote ξ_D ($\exp(\xi_D) = B$) as the default threshold, the default probability in each state is:

$$\begin{aligned}
P_D^g &= \int_{-\infty}^{\xi_D} d\xi_j(\bar{p}), \\
P_D^b &= \int_{-\infty}^{\xi_D} d\xi_j(\bar{p} + \phi_1 p).
\end{aligned}$$

As the comovement in higher order moments of idiosyncratic risk ϕ_1 increases, default probability in bad state P_D^b increases and $Cov(SDF, P_D^b)$ increase, which in turn drives up credit risk premium. With the relation $v_e = v_a - v_b$, we know equity premium will decrease as ϕ_1 increases. This indicate asset idiosyncratic risk has an option effect that transfer risk from equity to bond.

To numerically illustrate the effect, I keep the endowment jump size d_c to be 0.8 and fix jump intensity p to be 0.3. I specify firm tail risk to be $\xi_j(\bar{p} + \phi_1 p) = -0.8J_j - \zeta(\bar{p} + \phi_1 p)$, with jump intensity $\bar{p} + \phi_1 p$. I set $\bar{p}$ to be 0.1 and jump size of firm to be 0.8. I look at the change of asset, bond, equity risk premium $E(r) - r_f$ by varying comovement parameter ϕ_1.

[Insert Figure 9 here]

As figure 9 shows, when higher moment comovement ϕ_1 increases: (1) asset risk premium remains at zero because asset tail risk is idiosyncratic shock. (2) Credit risk premium increases since the default in bad times increases which increase $Cov(SDF, P_D^b)$. (3) Equity risk premium decreases and is negative. Because of the option effect, equity actually serves as a hedge to household tail risk.

To compare the second moment effect and higher moments effect, I also add a log normal case where I specify $\xi_j(\bar{p} + \phi_1 p) = \sigma(\bar{p} + \phi_1 p)\epsilon_j - \frac{1}{2}\sigma(\bar{p} + \phi_1 p)^2$ adjusted $\sigma(\bar{p} + \phi_1 p)$ to have the same cross-sectional variance as tail risk. Figure 10 plots the credit risk premium and the covariance between SDF and default. Because tail risk contain more downside risk and large, negative shocks are all absorbed by debt holders, credit risk premium and $Cov(SDF, P_D^b)$ are always much higher in tail risk case than log normal case. This emphasize the importance of taking into account higher moment comovement in calibration. In addition, the comovement of firm second moment with labor tail risk is not supported in the data as shown in section 2.2.

[Insert Figure 10 here]

To focus on the different implication of tail risk on equity and bond, my model use some simplification assumption that produces counterfactual, negative equity premium. In the data, since the expected growth of cash flow is negatively related to labor tail risk, which will be taken in account in full model calibration, the equity premium is also positive.

To summarize, this qualitative model illustrate that: (1) idiosyncratic labor tail risk can affect SDF if the market is incomplete. (2) It is quantitatively important to take higher order moments effect into consideration. (3) comovement in tail risk have no effect on asset risk premium, positive effect on bond and negative effect on equity.

3.2 The Full Model setup

3.2.1 Household

The stochastic discount factor is derived from an exchange economy with a single nondurable consumption good. The economy is populated by a continuum of households with mass 1. Households have identical recursive preferences and try to maximize their life-time utility by choosing consumptions and savings:

$$U_{i,t} = [(1-\beta)C_{i,t}^{1-1/\psi} + \beta(E_t U_{t+1}^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}}]^{\frac{1}{1-1/\psi}}$$

where $C_{i,t}$ is household i's consumption. ψ is the elasticity of intertemporal substitution and γ is risk aversion. From Epstein and Zin (1991), the SDF of each household is given by

$$M_{i,t+1} = \exp[\theta \log \beta - \frac{\theta}{\psi}\Delta c_{i,t+1} + (\theta - 1)r_{i,c,t+1}]$$

where $\theta = \frac{1-\gamma}{1-1/\psi}$

The aggregate consumption process C_t (with log consumption denoted as c_t) follows:

$$\Delta c_{t+1} = \mu + \phi_c x_{t+1} + \sigma_{t+1}\varepsilon_{c,t+1}$$

where x_t is a state variable. Later we will see that this state variable drives both the predictive component of aggregate consumption growth and the economy-wide conditional probability of idiosyncratic tail event. $\phi_c > 0$ is the loading of consumption growth on predictive component. $\varepsilon_{c,t+1}$ is an i.i.d normal shock to the aggregate consumption growth and σ_t drives stochastic volatility.

In addition to aggregate shock, households are also subject to state-dependent, idiosyncratic tail risk, which is modeled as a Possion jump with time varying jump intensity. Specifically, their log consumption growth is modeled as

$$\Delta c_{i,t+1} = \Delta c_{t+1} + d_c J_{i,t+1} - \xi(x_{t+1})$$

where $J_{i,t}$ follows a Poisson distribution with jump intensity $\lambda_0 + \lambda_1 x_t$. The size of consumption decline when a tail event occurs is denoted as d_c, which follows a normal distribution with mean μ_d and standard deviation σ_d. State variable x_t has mean 0 and standard deviation 1. It determines the conditional probability of tail event. In calibration, the coefficient λ_1 is negative, which reflect the fact that labor tail risk is counter-cyclical. $\xi(x_t)$ is an adjustment term which compensate Poisson process $d_c J_{i,t}$. Specifically:

$$\xi(x_t) = (e^{\mu_d + \frac{1}{2}\sigma_d^2} - 1)(\lambda_0 + \lambda_1 x_t)$$

3.2.2 State Variable Evolution

State variable evolution follows an AR(1) process with time-varying volatility:

$$x_{t+1} = \rho_x x_t + \sigma_t \varepsilon_{x,t+1}$$
$$\sigma_{t+1}^2 = (1-\rho_\sigma) + \rho_\sigma \sigma_t^2 + \sigma_t \varepsilon_{\sigma,t+1}$$

where $E[x_t] = 0$, $E[\sigma_t^2] = 1$ and the σ_t^2 follow a square-root process. The covariance matrix for the shocks is:

$$E_t[\varepsilon_{t+1}\varepsilon_{t+1}'] = \begin{bmatrix} \sigma_c^2 & 0 & 0 \\ 0 & \sigma_x^2 & \varphi_{x,\sigma}\sigma_x\sigma_\sigma \\ 0 & \varphi_{x,\sigma}\sigma_x\sigma_\sigma & \sigma_\sigma^2 \end{bmatrix}$$

The innovation to x_t and σ_t^2 is allowed to be correlated. The correlation coefficient $\varphi_{x,\sigma}$ is calibrated to be negative, which reflect the fact that when tail risk is high (low x_t), the volatility of shock to tail risk also tend to be high.

There are two reasons to introduce the additional complexity of stochastic volatility. The first reason is to match time series property of labor skewness, which exhibit substantial heteroscedasticity. Second, though the mechanism does not change, quantitatively, I need stochastic volatility to generate large enough risk premium.

The state variable evolution resembles long-run risk in Bansal and Yaron (2004). however, they differ in two key aspect. First, state variable x_t is far less persistent in my model than long-run risk[8]. Second, the mechanism to drive risk premium is completely different. This point will be clear later in my calibration, the predictive consumption growth contribute very little to the total risk premium.

3.2.3 Firm Problem

There is a cross section of firms in this economy. Denote $E_{j,t}$ as the cash flow of firm j at time t ($e_{j,t}$ as the logarithm of it), the log cash flow growth rate of a typical firm follows:

$$\Delta e_{j,t+1} = \mu_e + \phi_e x_{t+1} + \sigma_{t+1}\sigma_e \varepsilon_{c,t+1} + \varepsilon_{j,t+1} + d_e J_{j,t+1} - \xi_e(x_{t+1})$$

The form of cash flow process is motivated by the empirical facts. First, Firm cash flow growth is exposed to state variable x_t and consumption shocks $\varepsilon_{c,t}$. As expected cash flow growth is negatively related to labor tail risk, I set $\phi_e > 0$. Second, the idiosyncratic volatility is not correlated with labor tail risk, thus the normal shock $\varepsilon_{j,t}$ have i.i.d distribution $N(0, \sigma_{id}^2)$ through business cycle. Lastly, firm tail risk is modeled as Poisson jump $J_{j,t+1}$ with jump size d_e. Since in the data, labor tail risk and firm tail risk is highly correlated, the time-varying jump intensity takes the form of $\lambda_{e,0} + \lambda_{e,1}x_t$. $\lambda_{e,1} < 0$ ensures the jump probability of labor income and firm cash flow comoves. The last term $\xi_e(x_t)$ is to compensate for jump and Jansen's inequality effect from normal shock. Specifically:

$$\xi_e(x_t) = \frac{1}{2}\sigma_e^2\sigma_{t+1}^2 + \frac{1}{2}\sigma_{id}^2 + (e^{d_e} - 1)(\lambda_{e,0} + \lambda_{e,1}x_t)$$

Firm optimally chooses leverage and default to maximize its equity value $V_{j,t}$:

$$V_{j,t} = \max\{0, \max_{I_{j,t}}\{D_{j,t} + E_t[M_{t,t+1}V_{j,t+1}]\}\}$$

$$s.t. \quad B_{j,t+1} = (1-\kappa)B_{j,t} + I_{j,t}$$

$$D_{j,t} = (1-\tau)E_{j,t} - ((1-\tau)c + \kappa)B_{j,t} + P_{j,t}I_{j,t}$$

where $D_{j,t}$ is the dividend and $I_{j,t}$ is the new debt issuance. The first max in the objective function reflect that firm will choose to default whenever the equity value become less than zero. The second max means firm optimally choose debt issuance. Finite-maturity debt is modeled via sinking funds provisions with existing book value of debt denoted as $B_{j,t}$. For each period, a fraction of κ is retired. In this case, the average maturity of debt is $\frac{1}{\kappa}$. After taxes, debt repayment and refinancing, the rest of cash flow goes to equity holders as dividend. c is the coupon rate, $P_{j,t}$ is the price of corporate bond. Note that interest is tax deductible, so effectively, firm only need to repay $(1-\tau)c$. This

[8] In my calibration, the quarterly autocorrelation ρ_x is 0.88. In long-run risk, its about 0.96.

provides incentive for firms to use leverage.

The market price of debt should satisfy the Euler equation:

$$P_{j,t} = E_t\{M_{t,t+1}[(1 - \mathbb{I}_{V_{j,t+1}=0})(c + \kappa + (1-\kappa)P_{j,t+1}) + \mathbb{I}_{V_{j,t+1}=0}\frac{(1-\alpha_t)W_{j,t+1}}{B_{j,t+1}}]\}$$

$\mathbb{I}_{V_{j,t+1}=0}$ is a default indicator. $W_{j,t+1}$ is cash flow value of the firm, which equals the present value of unlevered cash flow:

$$W_{j,t} = E_t\left[\sum_{s=t}^{\infty} M_{t,s}E_{j,s}\right]$$

Essentially, if the firm does not default, bond holders can get coupon payment, κ fraction of principle repayment and $(1-\kappa)$ of next period bond value. If firm defaults, the bond holders can only claim $1-\alpha$ fraction of firm cash flow value, where α is the fraction of loss incurred during bankruptcy. Bankruptcy cost will be reflected in the bond price, which, in turn, affect equity value. Thus, firm will choose leverage based trade-off between tax shield and bankruptcy cost.

3.3 Model solution

First, I need to solve the SDF. Every household is marginal investor in this economy and they value assets using their private SDF. However, since households are ex-ante the same and financial asset does not expose to idiosyncratic labor income shocks, there will be a common SDF to price all the assets in market.

The solution technique is similar to Constantinides and Ghosh (2017). Specifically, conjecture that autarky is an equilibrium. Let $P_{i,c,t}$ be household i's private valuation of his wealth portfolio. $z_{i,c,t} = \log(P_{i,c,t}) - \log(C_{i,t})$ is the log price to consumption ratio. Then the log return on wealth portfolio can be written as

$$r_{i,c,t+1} = \log(e^{z_{i,c,t+1}} + 1) - z_{i,c,t} + \Delta c_{i,t+1}$$

Conjecture that log price to consumption ratio is a function of only aggregate state variables, or put it in another way, the log price to consumption ratio is common among all households $z_{i,c,t+1} = z_{c,t+1}$, then, according to the Euler equation

$$E\{\exp[\theta \log\beta + (1-\gamma)\Delta c_{i,t+1} + \theta(\log(e^{z_{c,t+1}} + 1) - z_{i,c,t})]\} = 1$$

Time t log price to consumption ratio of households i can be computed as

$$\exp(z_{i,c,t}) = E\{\exp[\theta\log\beta + (1-\gamma)\Delta c_{i,t+1} + \theta\log(e^{z_{c,t+1}} + 1)]\}$$

Observe that after integrating out $\varepsilon_{c,t+1}$, $\varepsilon_{x,t+1}$, $\varepsilon_{\sigma,t+1}$ and $J_{i,t+1}$, $z_{i,c,t}$ is a function of only aggregate state variables. This proves that log price to consumption ratio is common among all the households.

The private SDF can be written as:

$$M_{i,t+1} = \exp[\theta \log \beta - \frac{\theta}{\psi} \Delta c_{i,t+1} + (\theta - 1) r_{i,c,t+1}]$$

The only component that is unique for household i is the idiosyncratic tail shock $J_{i,t+1}$. Since no asset is exposed to this shock, I can integrate it out to get a common SDF. As all households have the same valuation of assets, they do not have the incentive to trade. This proves that autarky is an equilibrium.

I solve firm problem by value function iteration. Because equity value and bond value is jointly determined, I iterate the equity maximization equation and bond equation simultaneously. Details of computation steps can be found in appendix C.

3.4 Benchmark calibration

Table 9 provides a summary of the calibration parameters. I set elasticity of inter-temporal substitution to be 2 and risk aversion to be 11, which is broadly consistent with the literature. Subjective discount factor β is calibrated to match risk-free rate. Mean μ_c and volatility σ_c of aggregate consumption is calibrated to match an annual consumption growth rate of 2% and volatility of 2.5%. The loading on state variable ϕ_c in aggregate consumption is calibrated such that condition on idiosyncratic tail event does not occur, the consumption process for individual household is i.i.d.

[Insert Table 9 here]

Parameters for individual household's consumption dynamics are largely borrowed from Schmidt (2016). In his paper, state variable dynamics parameters, namely, persistence of x_t and σ_t^2, correlation and volatility of shocks, are obtained by estimating a VAR model to fit the dynamics of labor income growth skewness. Parameters for consumption jump intensity and jump size are obtained by estimating a parametric labor income model to match the GOS moments. Aggregate dynamics are discretized into 25 state, as it is an AR1 with time varying volatility, I use the moment matching method in Farmer and Toda (2017). See details in appendix D.

I estimate the parameters for conditional probability of firm cash flow jump using Compustat data of sales growth. Details of the estimation is relegated to appendix E. Estimation shows that average quarterly jump probability is about 3%, and 1 standard deviation increase in aggregate state x_t is associated with 2% decrease in jump probability. Whenever a jump occurs, the log cash flow drops by 40%. I truncate the jump intensity to make it greater or equal to zero.

I calibrate ϕ_e and σ_e to broadly match the equity premium. Bankruptcy cost α is set to be 0.5 to target the historical recovery rate. To study the five year debt, κ is set to be 0.05 so that the average maturity of bond is 20 quarters. I adjust the coupon rate to be get a reasonable leverage ratio, and also adjust the idiosyncratic volatility to target the 5-year cumulative default rate around 2%.

3.5 Calibration Results

3.5.1 Benchmark Calibration

I simulate a cross section of 5000 firms with 10000 time periods sample to compute the model implied asset pricing moments. Table 10 shows the unconditional moments generated by the model and corresponding sample moments in the data. The benchmark calibration matches the data moments quite well. The model generates a credit spread as high as 1.03% with reasonable 5-year cumulative default of 2.02 % and recovery rate of 43.15%, which are quite close to data counterpart. The numbers of equity premium, equity volatility and risk-free rate are also in a reasonable range. In this sense, my model is able to simultaneously account for the credit spread puzzle and equity premium puzzle. The leverage ratio is bit lower than the data counterpart which resolves the under-leverage puzzle. In my model, the time-varying labor tail risk makes default cost to be large. Therefore, firms choose a low leverage ratios.

[Insert Table 10 here]

To investigate the dynamics of firm financing and default decision, I plot the conditional moments in Figure 11, the x axis is the value of x_t, the y axis is the value of σ_t^2, and the z axis is the value of conditional moments. The 25 bars represent 25 discretized aggregate state. As high tail risk (low x_t) is usually associated with high volatility of shocks (high σ_t), the grids are not evenly spaced. The market leverage is counter-cyclical. As tail risk become higher, the market value of firm decreases. Since it is costly for firm to deleverage, the market leverage increase substantially in bad times. The 5-year cumulative default rate is also strongly counter-cyclical, from about 0.12 in the worst state and near 0 in the best state. The recovery rate is some how constant during the business cycle (In the best two state there is no default so the recovery rate show up as 0). In this sense, credit spread is largely generated by counter-cyclical risk premia and counter-cyclical default rate in my model. Cyclicality of recovery rate does not play much role here.

[Insert Figure 11 here]

In figure 12, I plot the conditional default rate and conditional covariance between default and SDF with respect to state variable x_t. We make two observations: first, default probability is a decreasing function of x_t, which means when labor tail risk is high, firm is more likely to default. Thus, in the right sub-figure, covariance bewteen default probability and SDF is always positive. This contributes to generate the level of credit spread. Second, as x_t become lower, the default probability become more sensitive to change of x_t. This reflect the fact that when labor tail risk is high, firms are already close to default, a negative shock will increase the default probability a lot. Thus, in the right sub-figure, covariance is a decreasing function of x_t. This contributes to generate the comovement between labor tail risk and credit spread.

[Insert Figure 12 here]

My model can also simultaneously account for the stock return predictability and credit spread dynamics. Table 11 reports time series regression results in data and model. Panel A reports the result of credit spread regression. In the model, skewness index also has high explanatory power on the dynamics of credit spread. The magnitude of comovement is somehow stronger in the model than what we observe in data. 1 standard deviation increase in skewness is associated with 51 basis point decrease in credit spread for the median case. But the data estimate is still within the range of 90% confidence interval. The stronger relationship is probably caused by the fact that, in my model, the only macro risk that drives the credit spread is labor tail risk. Panel B reports the result of stock return predictability regression. Overall, the data indicate that high skewness index predicts a lower stock return in the future. My model also generate stock return predictability. The median coefficient is close to the data estimates and r squared also increase with predictive horizon.

[Insert Figure 11 here]

3.5.2 Credit Spread Decomposition

The model features idiosyncratic tail risk on household side and firm side, predictive component in aggregate consumption growth, and time-varying volatility on aggregate state. In this subsection, I assess how much of the bond premium can be attributed to each channel. Specifically, I shut down some of the channels and recalibrate the model to see how the model performs. I set $d_e = 0$ to shut down cash flow jumps on firm side, set $\sigma_t = 1$ to shut down time-varying volatility on aggregate state, set $\mu_d = 0$ and $\sigma_d = 0$ to shut down idiosyncratic tail risk on household side, and set $\phi_c = 0$ to shut down the predictive component in aggregate consumption growth. I keep other parameters the same and adjust the idiosyncratic volatility σ_{id} and default loss α to keep the cumulative default and recovery rate as in benchmark calibration.

[Insert Table 12 here]

Table 12 shows the decomposition of credit spread. In model (1), firm cash flow jump is shut down. The credit spread decrease about 29 bps comparing to benchmark calibration, almost 1/3 of the total credit risk premium. This shows that time-varying tail risk of firm cash flow is very important in generating the high credit spread. The conditional probability of jump rises substantially in bad times. This contributes a lot to counter-cyclical default rate and in turn generate high credit spread. Notably, since the cash flow jump is purely idiosyncratic, the unleveled equity premium does not change, but levered equity premium increase a little bit through the option effect. This indicates that cash flow jump shifts some of the risk premium from equity side to bond side. Equity is a call option on firm asset, so equity holders are not very sensitive to downside risk. Bond holders are just the opposite. Intuitively, in bad times the firm is more likely to experience jump type of shock and default, this type of shock is largely absorbed by bond holder, which makes the bond very risky.

As I mentioned previously, introducing time-varying volatility on aggregate state x_t is just for quantitative purpose. This point is clear in model (2). If I shut down this channel, credit drops another 26 bps. The unlevered equity premium also decrease. Since, skewness index in the data is not very persistent, without time-varying volatility channel, the risk premia in general will be low.

In model (3), I keep the time-varying volatility and shut down the idiosyncratic tail risk on household side. In this case, idiosyncratic risk channel is shut down, but predictive consumption growth channel is still in play. Compared to model (1), credit spread decreases about 41 bps, which can be attributed to the negative relation between labor tail risk and firm cash flow growth. We also observe that unlevered premium drop significantly. That means idiosyncratic tail risk of household plays a very important role in generating high risk premium. Though the state variable dynamics is similar to long-run risk in Bansal and Yaron (2004), the mechanism here is quite different.

Model (4) only keeps i.i.d business cycle risk. In this case, the credit spread is about 23 bps, which is approximately the expected default loss. In this regard, the co-movement of idiosyncratic tail risk on household side and firm fundamentals can explain nearly 80% of observed credit spread.

4 Conclusion

In this paper, I show that idiosyncratic tail risk is a potential key determinants of the credit spreads. Empirically, the skewness of cross-sectional labor income growth is highly correlated with the mean and skewness of firm growth. Labor tail risk can explain a large fraction of credit spread fluctuation. 1 standard deviation increase in tail risk is associated with about 33 basis point increase in credit spread. I develop a endowment-based model with a single process that drives both the time variation of idiosyncratic tail risk on household side and firm asset. The model, whose parameters are disciplined by the data, can quantitatively account for the level and dynamics of credit spread.

Figure 1. Corporate Default, Credit Spread and Tail Risk.

This figure plots the quarterly time series of idiosyncratic tail risk in labor market, Moody's Baa-Aaa credit spread (both are normalized to have mean 0 and variance 1) and corporate bond default rate of all rated firms. The solid line is the proxy for idiosyncratic tail risk in labor market (negative of skewness index constructed from cross-sectional distribution of labor income growth rates), the dashed line is Moody's Baa-Aaa credit spread and the blue bars are corporate bond default rate of all rated firms (data from Moody's (2018)). The sample spans 1960Q1-2013Q4.

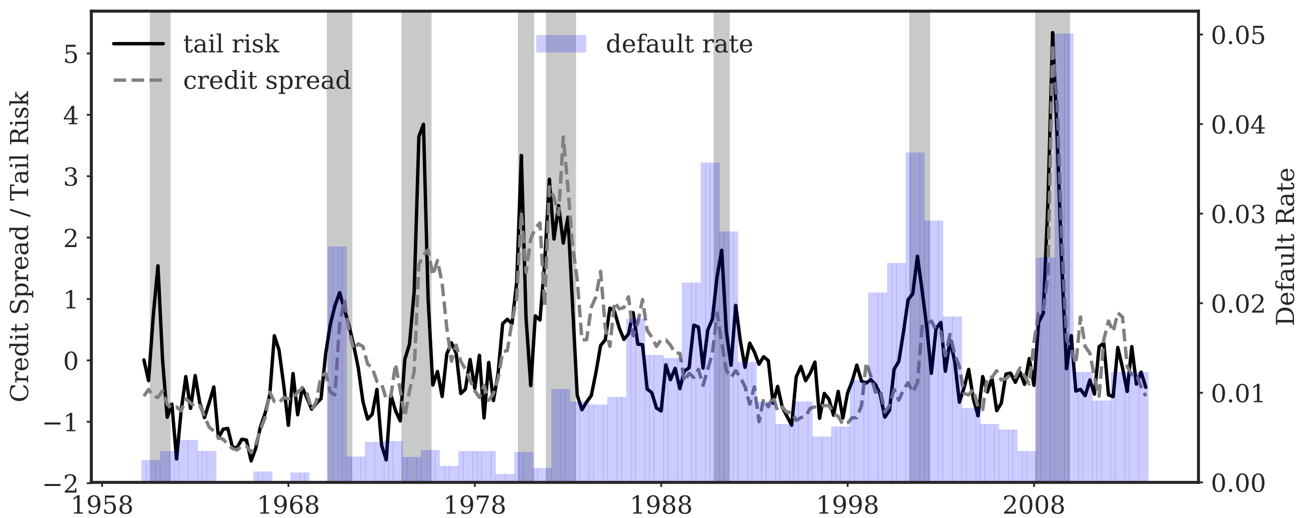

Figure 2. Skewness of Cross-sectional Labor Income Growth

This figure shows annual time series of cross-sectional 1-year trailing labor income growth skewness. The shaded area is the recession period. The sample spans 1978-2010.

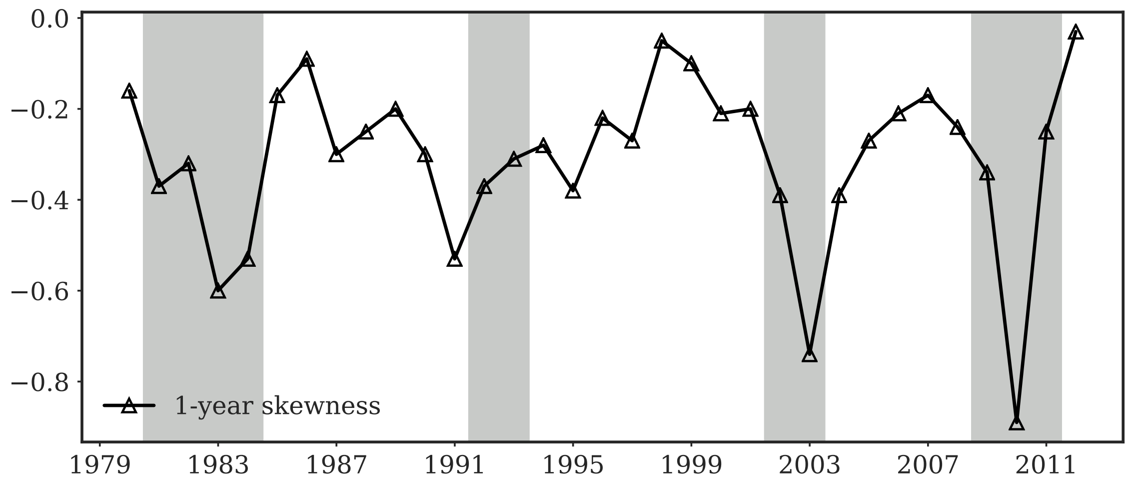

Figure 3. Tail Risk in Labor Market.

This figure shows the time series of proxies for labor market tail risk. The solid black line is the negative of skewness index, the solid gray line is the initial claim and the dashed black line is the unemployment rate. The sample of skewness index and unemployment rate spans 1960Q1-2013Q4, and the sample of initial claims spans 1967Q1-2013Q4.

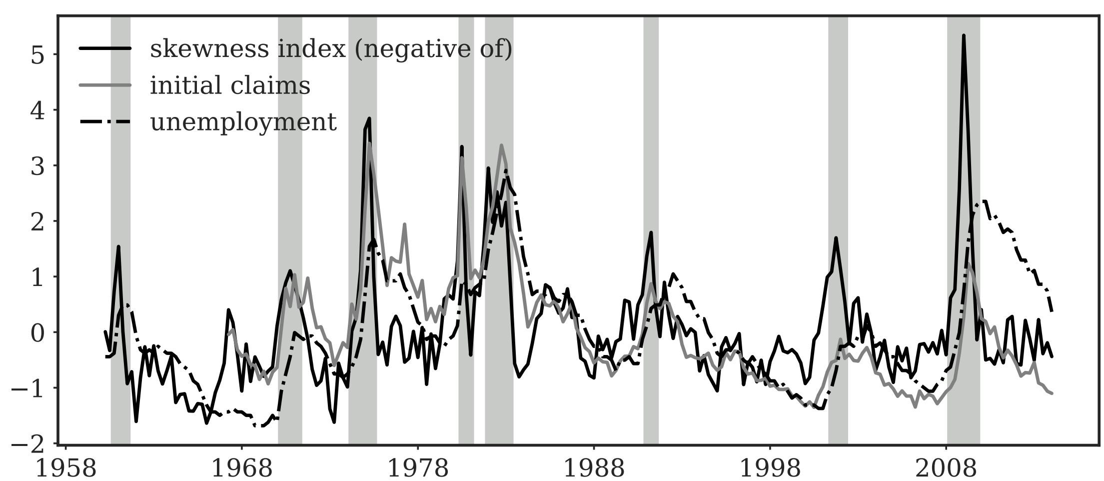

Figure 4. Skewness: by Recent Labor Income Percentile

This figure shows the cross-sectional skewness (kelly skewness) of 1-year labor income growth by recent labor income percentile. An individual's recent labor income rank is based on his past 5-year average labor income. The figure reports the mean skewness of sample from 1981 to 2012.

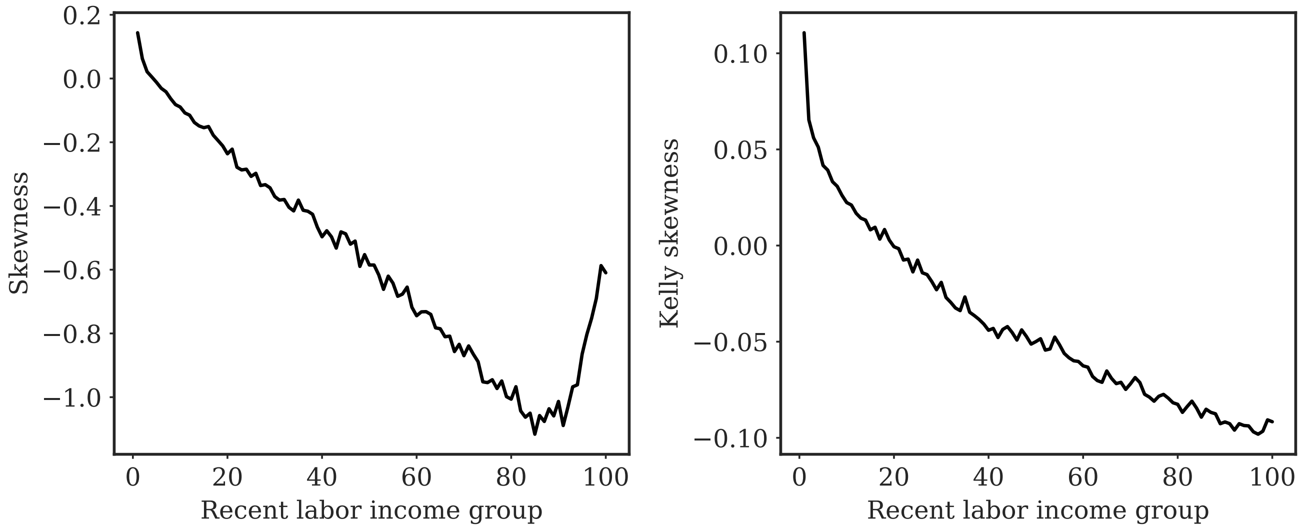

Figure 5. Skewness: Selected Labor Income Percentile Time Series.

This figure shows the time series of cross-sectional 1-year labor income growth skewness of selected recent labor income percentile (P10, P50 P90, and P95). An individual's recent labor income rank is based on his past 5-year average labor income. The sample spans 1981 to 2012.

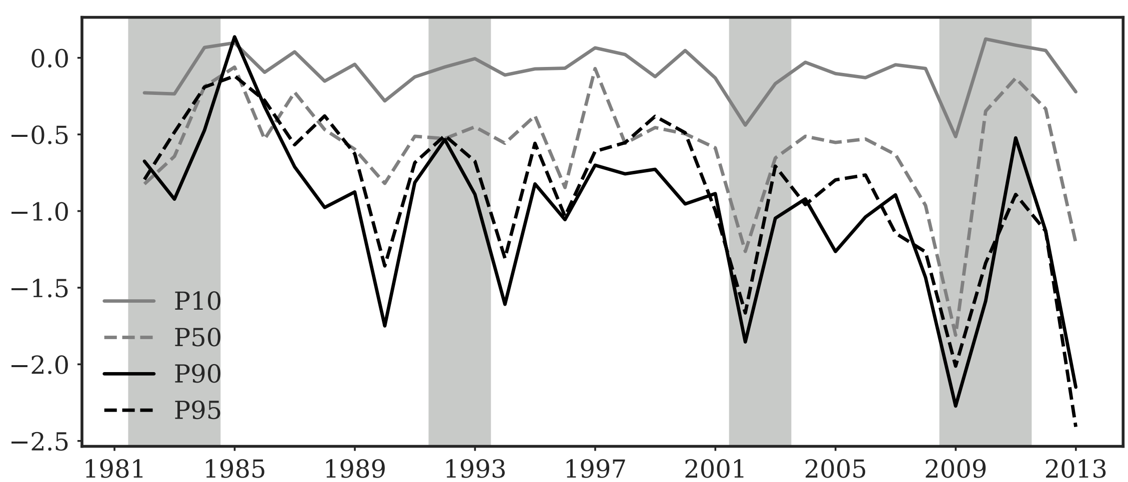

Figure 6. A Horse Race of Univariate Regression R^2.

This figure shows the univariate regression R^2 of credit spread on skewness index (constructed using 3PRF or IMSE) as well as on 97 macro variables and 8 control variables. The R^2 are sorted in descending order, the red bar and blue bar show the univariate regression R^2 from 3PRF skewness index and IMSE skewness index respectively and the rest of the variable are displayed with light blue bars. The sample spans 1960Q1-2013Q4.

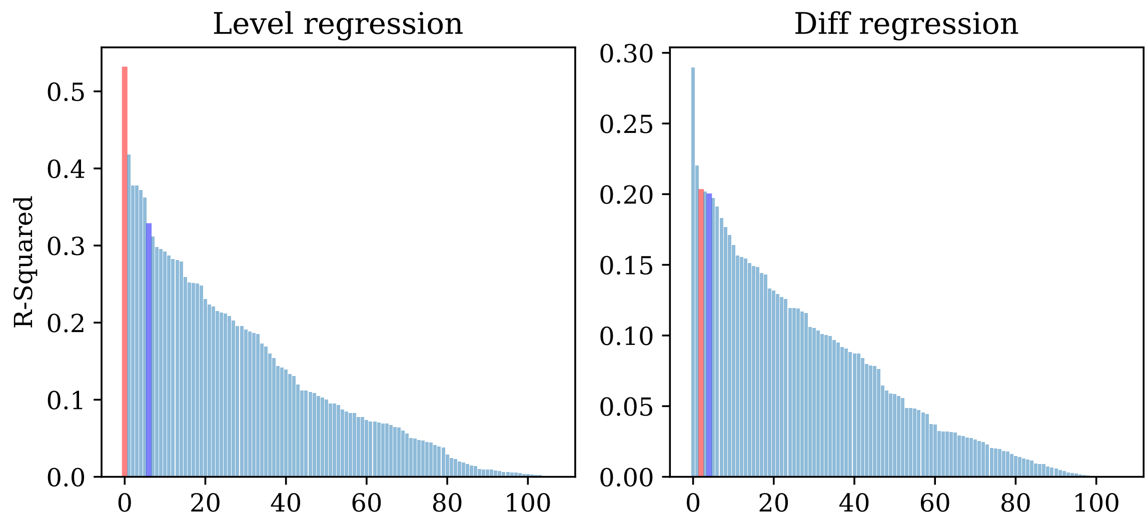

Figure 7. Distribution of Simulated Univariate Regression R^2.

This figure shows the empirical distribution of univariate regression R^2 of credit spread on simulated indices. The indices are constructed using 97 macro variables and random weights which are drawn from a uniform distribution on [-1,1]. The red line and blue line show the univariate regression R^2 from 3PRF skewness index and IMSE skewness index respectively. The sample spans 1960Q1-2013Q4.

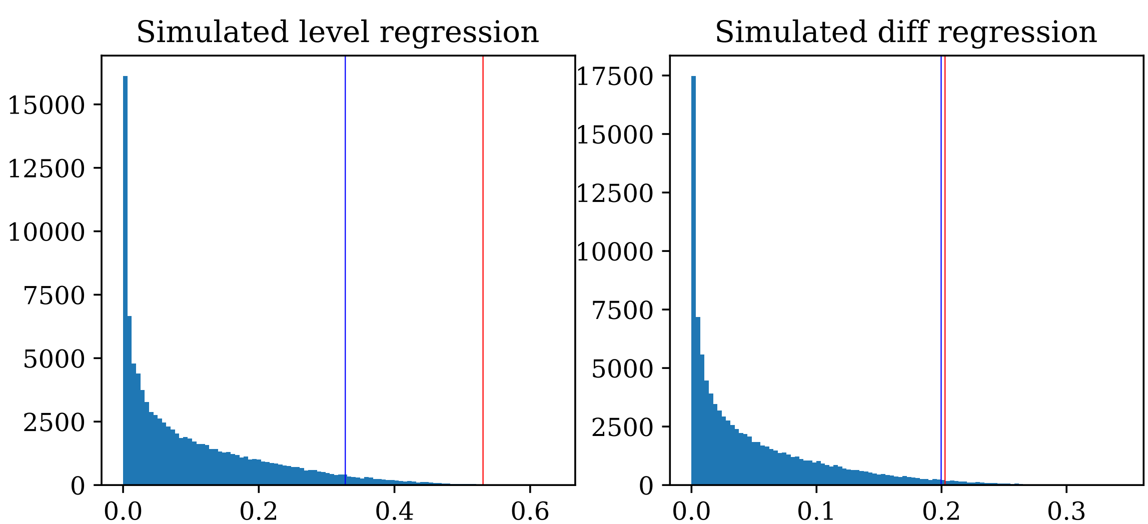

Figure 8. Qualitative Model: State Prices

This figure plots the state price q_b with respect to the parameter p in three cases (complete market, incomplete market with tail risk and in complete market with log normal risk). p drives the second and higher moments of idiosyncratic shocks. The parameter for log normal risk is adjusted to have the same cross-sectional variance of endowment as the tail risk case.

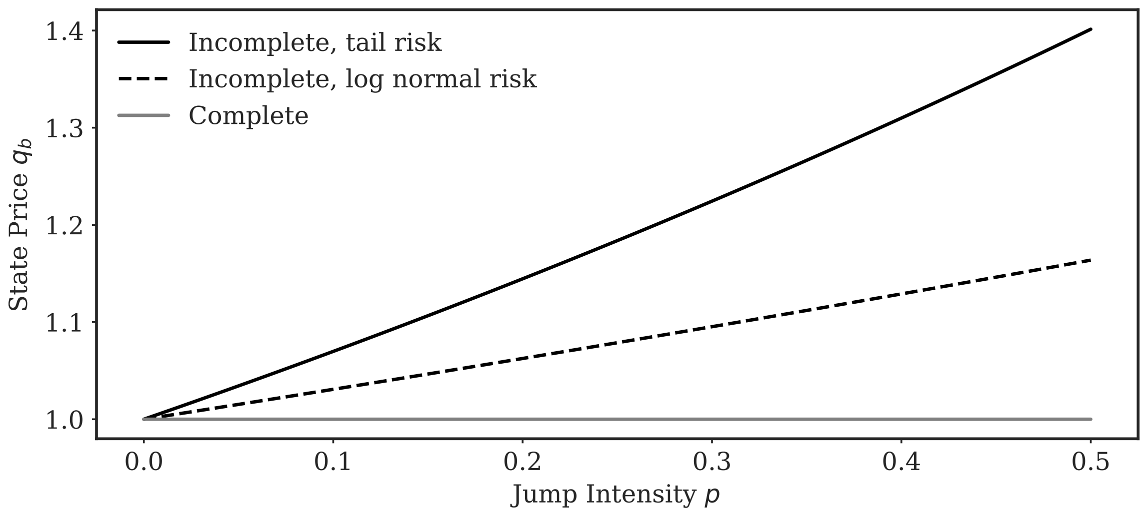

Figure 9. Qualitative Model: Risk Premium

This figure plots the risk premium $E(r) - r_f$ with respect to parameter ϕ_1 for asset, bond and equity in the two period model. ϕ_1 drive the higher moment comovement between household tail risk and firm tail risk.

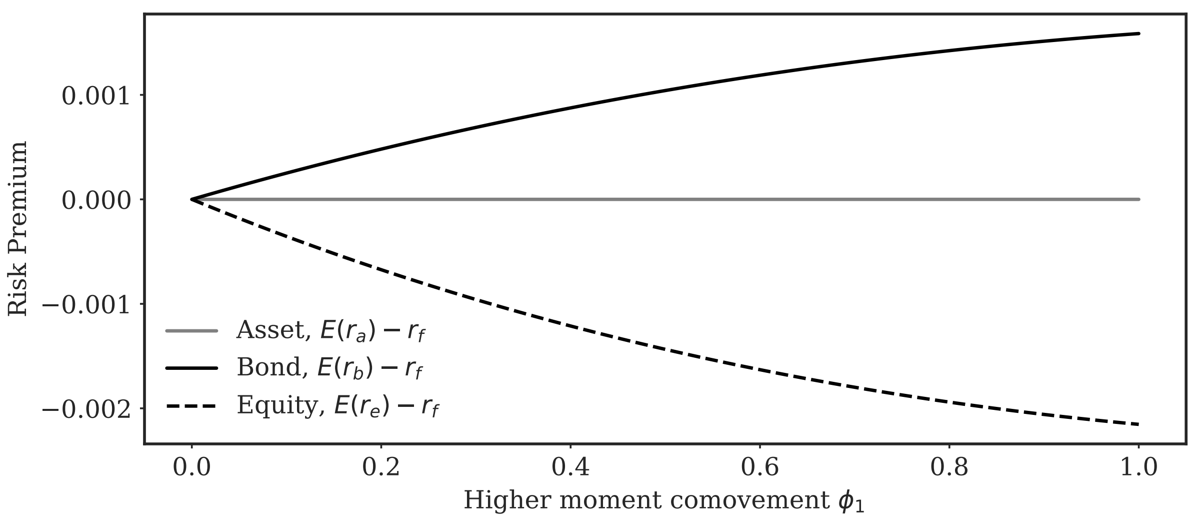

Figure 10. Qualitative Model: Credit Risk

This figure plots the credit risk premium and covariance between SDF and default with respect to the parameter phi_1 in tail risk and log normal risk cases. ϕ_1 drive the higher moment comovement between household tail risk and firm tail risk. The parameter for log normal risk is adjusted to have the same cross-sectional variance of endowment as the tail risk case.

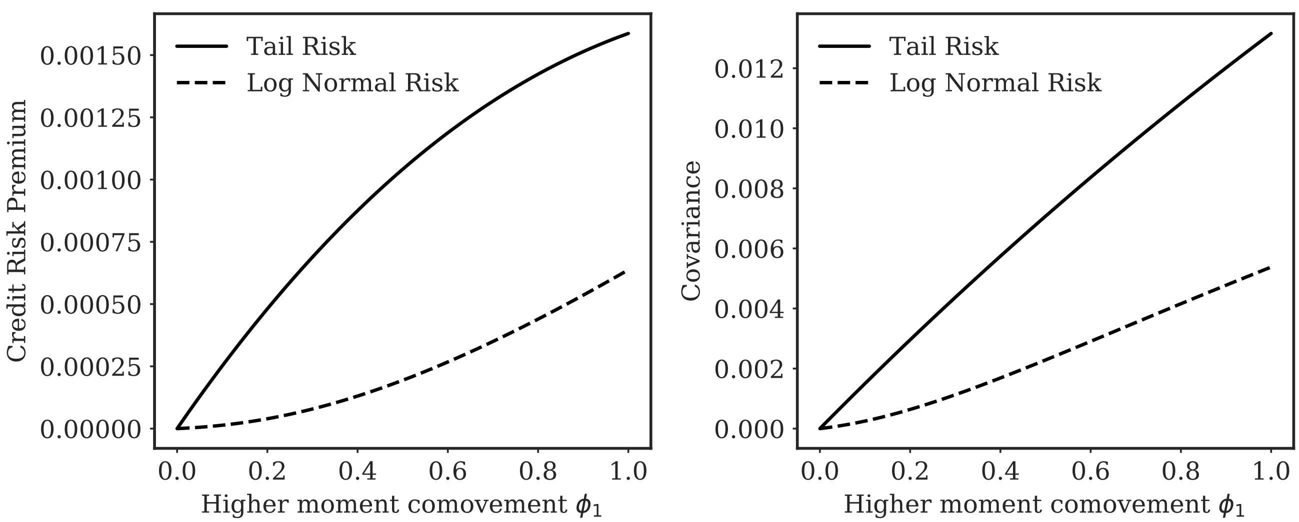

Figure 11. Benchmark Calibration: Conditional Moments

This figure plots the conditional statistics of simulated data in each state. The x axis is the value of x_t, the y axis is the value of σ_t^2 and the z axis is the average value in each state (credit spread, leverage ratio, recovery rate, cumulative default rate, recovery rate).

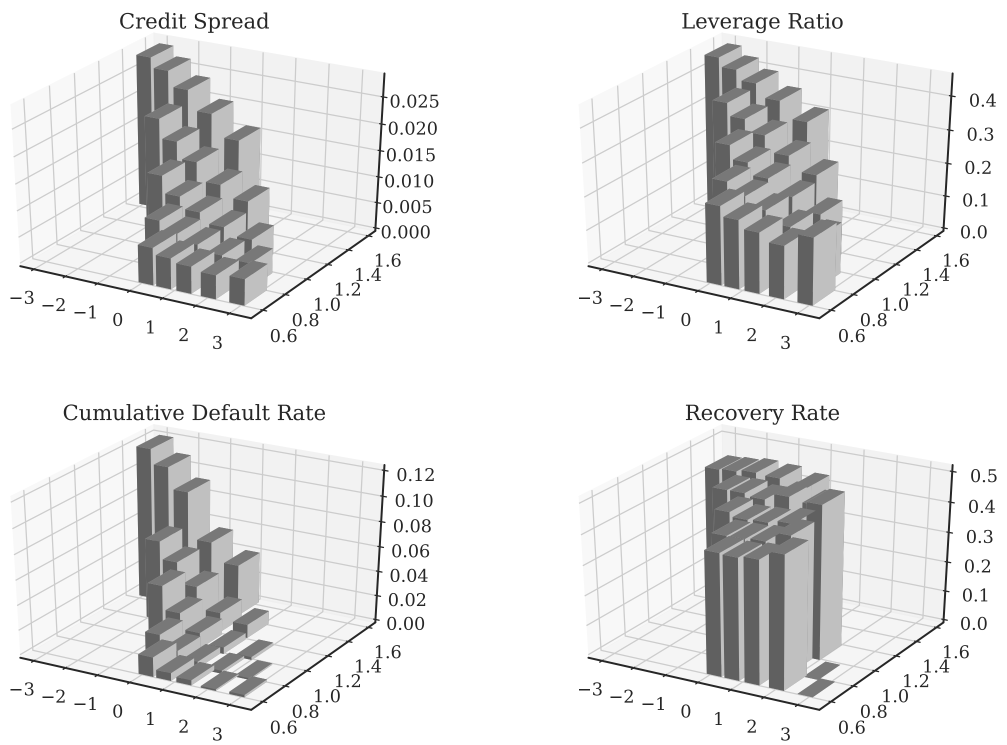

Figure 12. Conditional Default Rate and Covariance with SDF

This figure plots the cumulative default rate and $Cov_t(M_{t+1}, \mathbb{I}_{V_{j,t+1}=0})$ conditional on state variable x_t. I fit a polynomial on simulated result for display purpose.

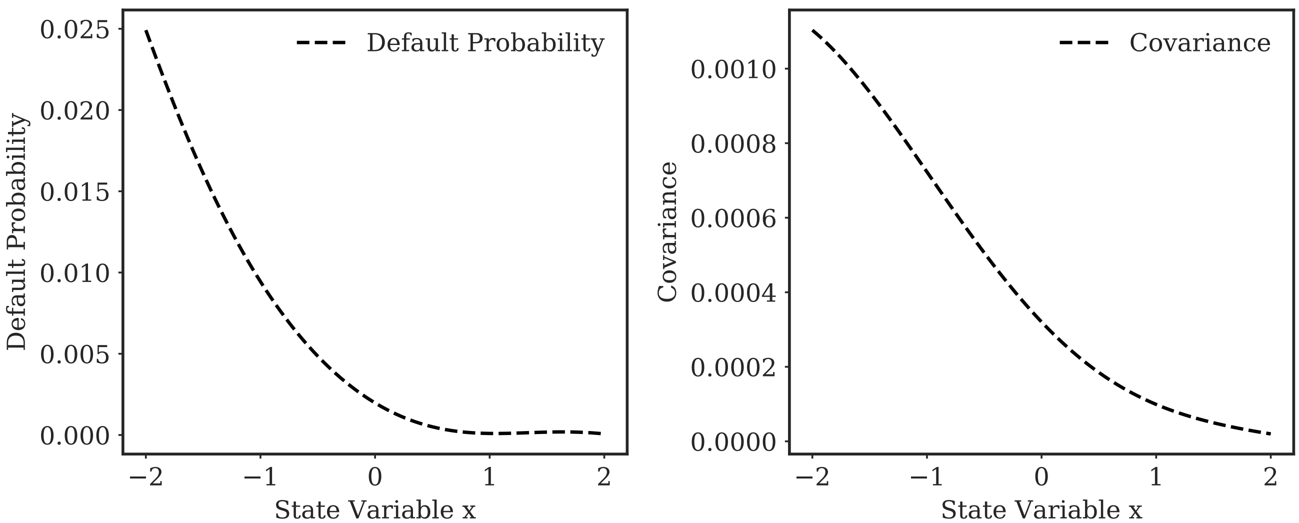

Table 1. Summary Statistics of Labor Income Growth Distribution.

This table reports the statistics from the cross-section of 1-year and 5-year log labor income growth, which are based on the 1978-2011 annual data series from GOS. The second column reports the average statistics over the whole sample period, third column is based on expansion period, forth column recession period and the last column reports the difference between the recession and expansion. Recession has the same definition as in GOS.

1-year log labor income growth				
	All	Expansion	Recession	R-E
Median	2.02	2.42	1.22	-1.20
10th Percentile	-43.45	-40.76	-48.83	-8.07
90th Percentile	47.44	49.87	42.57	-7.29
90-10 Percentile Spread	90.89	90.63	91.40	0.78
Left tail	45.47	43.18	50.05	6.87
Right tail	45.41	47.44	41.35	-6.09
Kelley's Skewness	0.11	4.79	-9.24	-14.03
Mean	1.92	3.28	-0.80	-4.08
Std	53.21	52.95	53.73	0.77
Skewness	-30.70	-22.82	-46.45	-23.64
5-year log labor income growth				
	All	Expansion	Recession	R-E
Median	10.32	13.31	7.48	-5.83
10th Percentile	-63.08	-53.19	-69.40	-16.20
90th Percentile	84.81	95.29	74.19	-21.10
90-10 Percentile Spread	147.88	148.49	143.59	-4.90
Left tail	73.39	66.50	76.88	10.37
Right tail	74.49	81.98	66.72	-15.27
Kelley's Skewness	0.77	10.43	-7.07	-17.50
Mean	10.58	16.94	5.10	-11.84
Std	72.86	73.00	71.50	-1.50
Skewness	-23.59	-5.40	-38.00	-32.60

Table 2. Summary Statistics of Sales Growth Distribution.

This table reports the statistics from the cross-section of quarterly log sales growth (the log difference of quarterly sales this year and sales at the same quarter of last year), which are computed from the 1978-2014 quarterly data in Compustat. The second column reports the average statistics over the whole sample period, third column is based on expansion period, forth column recession period and the last column reports the difference between the recession and expansion. The statistics is classified to be in recession if at least 3 quarters over which the growth rate is computed is in recession quarters defined by NBER.

Quarterly log sales growth				
	All	Expansion	Recession	R-E
Median	7.30	8.12	-2.70	-10.82
10th Percentile	-22.37	-20.60	-43.79	-23.20
25th Percentile	-3.86	-2.67	-18.23	-15.57
75th Percentile	19.77	20.63	9.43	-11.20
90th Percentile	39.89	41.03	26.14	-14.89
90-10 Percentile Spread	62.26	61.62	69.93	8.31
50-10 Percentile Spread	29.66	28.72	41.09	12.37
50-25 Percentile Spread	11.15	10.79	15.53	4.74
90-50 Percentile Spread	32.59	32.90	28.84	-4.06
75-25 Percentile Spread	12.47	12.50	12.13	-0.37
Kelley's Skewness	4.75	6.56	-17.15	-23.70
Mean	8.01	9.15	-5.70	-14.84
Std	24.09	23.88	26.68	2.80
Skewness	8.00	12.53	-46.77	-59.30
Kurtosis	3.33	3.34	3.25	-0.08

Table 3. Correlation of Skewness Index and Fundamental Moments.

This table shows the correlation of skewness index and firm fundamental moments. Firm fundamental (sales growth, gross profit growth, employment growth) moments are calculated using cross-sectional data from Compustat. Sales growth and gross profit are in quarterly frequency (1975Q4-2013Q4 and 1976Q4-2013Q4 respectively). Employment is in annual frequency (1964-2013).

vairiable	**mean**	**std**	**skewness**	**median**	**range**	**left tail**	**right tail**	**kelly**
Sales growth	0.48	0.03	0.47	0.42	0.00	-0.24	0.23	0.52
Gross profit	0.56	-0.05	0.46	0.58	-0.06	-0.23	0.14	0.42
Employment	0.50	-0.09	0.48	0.45	-0.11	-0.34	0.19	0.49

Table 4. Fundamental Risk in the Cross Section.

This table shows the firm fundamental risk within market-to-book and size sorted portfolio. The second column shows the corporate bond yield of each portfolio (numbers are from KUEHN and Schmid (2014)). The rest columns shows statistics of fundamental risks. I first compute the cross-sectional mean, volatility and skewness of sales growth within each group, and report the time series average (numbers in percentage) and their correlation with skewness index in labor market. The sample covers 1975Q4-2013Q4.

		growth rate		volatility		skewness	
Portfolio	Credit Spread	mean	corr	mean	corr	mean	corr
Panel A: Market-to-Book Sort							
1(Low)	315	3.0	0.50	21.1	0.01	-4.1	0.52
2	204	6.6	0.40	17.8	0.02	3.3	0.46
3	139	7.9	0.48	17.8	-0.14	5.7	0.46
4	90	9.7	0.49	18.5	-0.09	7.5	0.49
5(High)	53	13.3	0.44	24.7	0.03	9.6	0.36
Panel B: Size Sort							
1(Small)	371	6.3	0.54	24.7	0.02	0.7	0.55
2	201	9.8	0.44	18.3	-0.03	9.9	0.52
3	114	10.1	0.45	16.1	-0.18	12.0	0.45
4	71	9.3	0.46	15.1	-0.13	10.3	0.38
5(Large)	44	8.6	0.35	13.1	-0.18	12.5	0.34

Table 5. Credit Spread Regression: Level.

This table shows the results of the regression

$$CS_t = \beta_0 + \beta_1 S_t + \gamma \mathbf{X}_t + \epsilon_t.$$

The dependent variable is credit spread. S_t is the skewness index and $\mathbf{X}_t$ is a vector of controls, including market volatility, idiosyncratic volatility, 3 month t-bill rate, term spread, aggregate market leverage, cyclical adjusted price to s ratio, growth of industrial production and unemployment rate. All independent variables are standardized to have mean 0 and standard deviation of 1. For each regression, the table reports OLS estimates (numbers are in percentage) and Newey-West t-statistics with 4 lags. The sample spans 1960Q1-2013Q4.

	Baa-Aaa Credit Spread							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.03	1.09	1.03	1.06	1.03	1.03	1.05	1.03
	(27.26)	(24.45)	(22.25)	(34.69)	(30.96)	(38.69)	(31.20)	(35.79)
skewness index	-0.33			-0.22		-0.31		
	-(7.71)			-(3.29)		-(7.05)		
Initial Claims		0.30		0.09			0.19	
		(7.53)		(1.63)			(3.21)	
Unemployment			0.28	0.13				0.20
			(5.51)	(3.98)				(4.35)
Volatility					0.19	0.16	0.19	0.16
					(3.05)	(3.31)	(3.24)	(3.34)
IVOL					0.01	-0.07	-0.05	0.01
					(0.11)	-(1.10)	-(0.62)	(0.22)
Treasury yield					0.10	0.06	0.02	0.12
					(1.34)	(1.08)	(0.37)	(2.06)
Term spread					0.12	0.06	0.03	0.03
					(1.75)	(1.32)	(0.58)	(0.69)
Leverage					-0.03	-0.06	-0.09	0.01
					-(0.59)	-(1.49)	-(1.39)	(0.29)
CAPE					-0.18	-0.11	-0.09	-0.06
					-(3.36)	-(2.40)	-(1.38)	-(0.93)
IPG					-0.08	0.13	-0.07	-0.09
					-(2.60)	(4.37)	-(1.93)	-(3.23)
Observation	216	188	216	188	216	216	188	216
R^2	0.53	0.44	0.38	0.65	0.61	0.70	0.61	0.68

Table 6. Credit Spread Regression: Change.

This table shows the results of the regression

$$\Delta CS_t = \beta_0 + \beta_1 \Delta S_t + \gamma \Delta \mathbf{X}_t + \epsilon_t.$$

The dependent variable is change in credit spread. ΔS_t is change in skewness index and $\Delta \mathbf{X}_t$ is a vector of controls, including change in market volatility, idiosyncratic volatility, 3 month t-bill rate, term spread, aggregate market leverage, cyclical adjusted price to s ratio, growth of industrial production and unemployment rate. For each regression, the table reports OLS estimates (numbers are in percentage) and Newey-West t-statistics with 4 lags. The sample spans 1960Q1-2013Q4.

	Baa-Aaa Credit Spread							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.03)	(0.10)	-(0.09)	-(0.12)	-(0.06)	(0.00)	(0.02)	-(0.06)
skewness index	-0.15			-0.15		-0.12		
	-(2.80)			-(2.20)		-(1.97)		
Initial Claims		0.20		-0.02			0.08	
		(3.86)		-(0.23)			(1.38)	
Unemployment			0.29	0.21				0.12
			(2.72)	(1.56)				(1.07)
Volatility					0.09	0.06	0.10	0.09
					(1.76)	(1.90)	(1.58)	(1.76)
IVOL					0.10	0.10	0.09	0.09
					(2.39)	(2.42)	(1.90)	(2.09)
Treasury yield					-0.42	-0.39	-0.40	-0.39
					-(3.58)	-(3.60)	-(3.28)	-(3.06)
Term spread					-0.17	-0.16	-0.18	-0.17
					-(2.76)	-(2.83)	-(3.08)	-(2.76)
Leverage					0.04	0.07	0.05	0.06
					(0.45)	(1.04)	(0.56)	(0.78)
CAPE					-0.04	0.00	-0.03	-0.03
					-(0.50)	(0.03)	-(0.35)	-(0.33)
IPG					-0.01	0.04	-0.01	-0.01
					-(0.84)	(1.13)	-(0.34)	-(0.82)
Observation	215	187	215	187	215	215	187	215
R^2	0.20	0.09	0.07	0.24	0.33	0.39	0.34	0.34

Table 7. Tail Risk and Liquidity.

This table shows the results of the regression

$$CS_t = \beta_0 + \beta_1 S_t + \beta_2 N_t + \beta_3 S_t N_t + \epsilon_t.$$

The dependent variable is credit spread. S_t is the skewness index and N_t is a market wide liquidity measure from Hu et al. (2013). β_3 captures the interaction effect of tail risk and liquidity. (1)-(3) shows the level regression and (4)-(6) shows the first difference regression. All independent variables are standardized to have mean 0 and standard deviation of 1. For each regression, the table reports OLS estimates (numbers are in percentage) and Newey-West t-statistics with 4 lags. The sample covers 1987Q1-2013Q4.

	Baa-Aaa Credit Spread					
	Level			Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.98	0.97	0.95	-0.01	0.00	-0.01
	(22.56)	(22.11)	(22.26)	-(0.24)	-(0.17)	-(1.05)
Skewness index	-0.33	-0.24	-0.17	-0.24	-0.13	-0.12
	-(4.35)	-(3.34)	-(2.26)	-(2.61)	-(2.66)	-(2.40)
Noise bp		0.12	0.07		0.19	0.18
		(2.37)	(1.40)		(6.02)	(7.36)
Skewness×Noise			-0.04			-0.04
			-(2.65)			-(2.77)
Observation	108	108	108	107	107	107
R^2	0.56	0.61	0.64	0.36	0.54	0.58

Table 8. Fund Percentage Holding.

This table shows the regression results of the fund percentage holding on tail risk proxies. The dependent variable is the total percentage corporate bond holding by money market funds, mutual funds and exchange-traded funds. (1)-(3) shows the level regression and (4)-(6) shows the first difference regression. For the level variable, I remove the linear trend of the raw data and use the residual as dependent variable. All independent variables are standardized to have mean 0 and standard deviation of 1. The sample covers 1987Q1-2013Q4.

	Fund Percentage Holding					
	Level			Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Skewness index	0.81			0.07		
	(6.47)			(2.22)		
Initial Claim		-0.76			-0.11	
		-(6.84)			-(1.63)	
Unemployment			-0.74			-0.09
			-(5.81)			-(0.90)
Observation	216	188	216	215	187	215
R2	0.16	0.20	0.13	0.02	0.01	0.00

Table 9. Summary of Calibration Parameters.

This table summarize the parameters of benchmark calibration.

Parameter	Value	Description
γ	11	Risk aversion coefficient
ψ	2	Intertemporal elasticity of substitution
δ	0.9745	Rate of time preference
λ_0	0.0065	Average idiosyncratic jump intensity
λ_1	-0.0026	Sensitivity to x_t
μ_d	-0.18	mean of consumption decline in a idiosyncratic tail event
σ_d	0.115	std of consumption decline in a idiosyncratic tail event
ρ_x	0.8847	Persistence of x_t
ρ_σ	0.9446	Persistence of σ_t^2
σ_x	$\sqrt{1-\rho_x^2}$	Standard deviation of shock to x_t
σ_σ	0.1674	Standard deviation of shock to σ_t^2
σ_σ	-0.66	Correlation of shocks to x_t and σ_t^2
μ_c	0.005	Average growth rate of consumption
ϕ_c	0.000414	Loading of consumption growth on x_t
σ_c	0.0125	Standard deviation of shock to consumption growth
μ_e	0.005/4	Average growth rate of firm cash flow
ϕ_e	0.0225	Loading of cash flow growth on x_t
σ_e	0.0125	Standard deviation of systematic shock to cash flow growth
σ_{id}	0.105	Standard deviation of idiosyncratic shock to cash flow growth
$\lambda_{e,0}$	0.03	unconditional probability of cash flow jump
$\lambda_{e,1}$	-0.02	Sensitivity of cash flow jump probability to x_t
d_e	-0.4	Cash flow decline given a idiosyncratic firm tail event
c	0.02	Coupon rate of bond
τ	0.14	Corporate tax rate
α	0.5	Bankruptcy cost
κ	0.05	Inverse debt maturity ($\frac{1}{\kappa}$ as average bond maturity)

Table 10. Benchmark Calibration: Unconditional Moments.

This table reports unconditional moments generated by the benchmark calibration. Sample moments of equity premium and risk-free rates are from Bansal, Kiku, and Yaron (2012), Credit spread data are from Huang and Huang (2012), Historical default rates are from Ou, Chiu, and Metz (2011). All numbers are in percentage expect for price to dividend ratio.

Moments	Data	Model
Credit spread	1.03	1.03
Cum. default rate	2.06	2.02
Recovery rate	44.57	43.15
Leverage ratio	28.2	24.1
Equity premium	7.09	7.16
Volatility of equity premium	20.28	21.65
Log price to dividend ratio	3.36	3.95
Risk-free rate	0.57	0.86
Volatility of risk-free rate	2.86	1.87

Table 11. Model: Predictability.

This table reports predictive regression results in data and model. For credit spread, I run univariate regression of credit spread on contemporaneous skewness index. For equity return, I regress future (1 quarter, 1 year, 3 year and 5 year) CRSP value weighted stock return on skewness index. The sample period covers 1960Q1-2013Q4. To compute the model counter-part. I simulate the model 1000 times with the same sample size as data and run the corresponding regression. I report the simulation median as well as percentile values.

Credit Spread							
	Data		Model				
	Estimate		Median	2.5%	5.0%	95.0%	97.5%
skewness index	-0.33	-(7.71)	-0.51	-0.73	-0.72	-0.24	-0.24
R^2	0.528		0.739	0.587	0.627	0.857	0.861
Stock Return							
Forecasting 1 quarter return							
skewness index	-2.76	-(0.80)	-2.64	-8.02	-7.65	2.83	3.82
R^2	0.003		0.005	0.000	0.000	0.024	0.030
Forecasting 1 year return							
skewness index	-3.80	-(2.61)	-2.31	-7.12	-6.55	2.65	3.35
R^2	0.049		0.016	0.000	0.001	0.084	0.116
Forecasting 3 year return							
skewness index	-1.47	-(2.03)	-2.07	-5.29	-4.70	1.42	2.48
R^2	0.024		0.036	0.000	0.001	0.190	0.233
Forecasting 5 year return							
skewness index	-2.24	-(4.35)	-1.59	-4.14	-3.99	1.28	1.80
R^2	0.111		0.042	0.000	0.001	0.246	0.318

Table 12. Decomposition of Credit Spread.

This table shows the decomposition of credit spread generated by the benchmark calibration by shutting down some of the channels. For all cases, I recalibrate idiosyncratic volatility and default loss to match the cumulative default rate and recovery rate to the benchmark case.

	Benchmark	(1)	(2)	(3)	(4)
Credit spread	1.03	0.74	0.48	0.33	0.23
Unlevered equity premium	4.39	4.39	3.27	2.31	0.97
Levered equity premium	7.16	7.39	6.04	5.16	2.73
Firm: cash flow jump	Y	N	N	N	N
Time varying volatility of x	Y	Y	N	Y	N
Household: tail risk	Y	Y	Y	N	N
Aggregate consumption: loading on x	Y	Y	Y	Y	N

A Skewness Index Construction

This sections list the details in constructing the skewness index. I use a structural labor income model to construct the index as in Schmidt (2016). Specifically, assume quarterly log labor income follows

$$
\begin{gathered}
w_t^i = \underbrace{\alpha_i + \beta_i age_t^i}_{\text{profile heterogeneity}} + \underbrace{\epsilon_t^i}_{\text{transitory shock}} + \underbrace{\xi_t^i}_{\text{permanent component}} \\
\xi_t^i = \xi_{t-1}^i + \eta_t^i \\
E[(\eta_t^i)^3 | y_{t-1}] = a + b' y_{t-1}
\end{gathered}
\tag{4}
$$

where ξ_t^i is permanent component of labor income, which follows a random walk. The third moment of the shock to permanent component follows a linear structure on lagged macro variables, which captures the conditional ex-ante risk faced by households. α_i and β_i allows for heterogeneity in income levels and growth rates and ϵ_t^i is a state independent transitory shock. Denote $w_{A,t}^i = \log(W_{A,t}^i)$ as the log annual wage, where $W_{A,t}^i$ is a trailing four quarter moving average of quarterly labor income and can be observed every four quarters. It can be proved that the skewness of cross-sectional annual labor income growth can be expressed as

$$
E((w_{A,t}^i - w_{A,t-4}^i - E(w_{A,t}^i - w_{A,t-4}^i | \mathcal{F}_{t-1}))^3 | \mathcal{F}_{t-1}) \approx c + b' \phi(L) y_{t-1} \tag{5}
$$

where $\phi(L) = \frac{1}{4}^3 + \frac{1}{2}^3 L + \frac{3}{4}^3 L^2 + L^3 + \frac{3}{4}^3 L^4 + \frac{1}{2}^3 L^5 + \frac{1}{4}^3 L^6$ is a lag operator on macro variables.

The macro variables considered here are 97 monthly variables from global insight, data from 1960-2013 can be find in Wu and Xia (2016). I list the variable details in the Appendix table 13. I aggregate the monthly variable to quarterly variable by taking the end quarter value for level variables and taking the log sum for change variables. Since the number of macro variables is greater than the time series, I use three-pass regression filter (3PRF) method (Kelly and Pruitt (2015)) or forecast combination method to estimate the model. The 3PRF can extract the relevant information from noisy predicting variables and optimally combine them, while the forecast combination method takes the inverse of mean-squared error(IMSE) as weights and combine the univariate forecast. Due to the efficiency of 3PRF, I treat 3PRF method as benchmark in constructing the skewness index. As our main focus is the time series fluctuation of skewness, I demean both the dependent variable and independent variables and estimate the coefficient b, therefore, the constructed skewness index has mean 0 but capture the time variation of skewness.

Table 14 shows the goodness of fit for different constructions. We can see that the 3PRF method achieve an R^2 of 70% in fitting the annual time series of skewness. The R^2 drops to 52% when I switch to IMSE method. For the sub-set of macro variables, real activity has the highest explanatory power for skewness, followed by employment and real inventory. The aggregate consumption explains only 29.6% of skewness, which indicates that the information contained in the cross-sectional skewness of labor income growth is largely orthogonal to aggregate consumption. The correlation of skewness indices constructed by 3PRF and IMSE is as high as 0.92.

[Insert Table 14 here]

Figure 13 plots the constructed skewness indices with top 5 highest R^2. We can see that the indices move in lockstep even before 1978, where our first annual skewness data point is available. This means the skewness indices are not just capturing spurious information by over-fitting the data, but contain useful information in terms of the idiosyncratic jump risk. We can also observe that the skewness index is highly pro-cyclical and always has a significant drop during NBER recession period.

[Insert Figure 13 here]

B Stock Return Predictability

In this section, I exam the predictive power of idiosyncratic tail risk on future equity premium. The literature has documented a large set of macro or financial variables that can predict future stock returns. Welch and Goyal (2007) provide a comprehensive study of the existing equity premium predictor. I treat the predictors in their study as controls or benchmark, and run in-sample and out-of-sample regression to look at the stock return predictability of labor tail risk.

Table 15 shows the in-sample regression result. I regress 1-year ahead CRSP value-weighted market return on proxies for tail risk (skewness index, initial claims and unemployment) as well as other controls. (1)-(3) shows the univariate regression. The coefficients of all three proxies are significant at 5% level and their magnitude is similar. One standard deviation increase in tail risk is associated with about 4% increase in next year's equity return. However, after controlling for other predictors, the coefficient become insignificant as shown in (5)-(7).

Table 16 reports the out-of-sample regression r squared. The out-of-sample r squared (oos R^2) is defined as:

$$R^2_{oos} = 1 - \frac{\sum(y_t - \hat{y}_{t,model})^2}{\sum(y_t - \hat{y}_{t,mean})^2}$$

where $\hat{y}_{t,model}$ is the predicted value from OLS model and $\hat{y}_{t,mean}$ is the predicted value from historical mean model. Since skewness index is constructed using the whole sample which is subject to look ahead bias, I only use unemployment and initial claims in this exercise. Comparing to other variables, unemployment has the most robust out-of-sample performance. Its oos R^2 is positive for all predictive horizons and reaches nearly 40% for 5 year horizon. The performance of initial claims is a bit weaker but still better than most of the other variables. Overall, tail risk in labor market do exhibit robust stock return predictability.

C Computation Detail

This section shows the detailed steps of solving the firm problem. Firm value $V_{j,t}$ is a function of aggregate state variable x_t, σ_t, bond level $B_{j,t}$ and $E_{j,t}$. Denote (x_t, σ_t) as ω_t, then we write $V_{j,t}(\omega_t, B_{j,t}, E_{j,t})$. By inspecting the firm problem, we can see that if a issuance plan $\{I_{j,t}(\omega_t, B_{j,t}, E_{j,t})\}$, which is a collection of contingent action from period t to ∞, is feasible for $(\omega_t, B_{j,t}, E_{j,t})$ with firm value $\tilde{V}$, the issuance plan $\{\frac{E'_{j,t}}{E_{j,t}} I_{j,t}(\omega_t, \frac{E'_{j,t}}{E_{j,t}} B_{j,t}, E'_{j,t})\}$ is also feasible for $(\omega_t, \frac{E'_{j,t}}{E_{j,t}} B_{j,t}, E'_{j,t})$ with corresponding firm value $\frac{E'_{j,t}}{E_{j,t}} \tilde{V}$. Thus, if issuance plan $\{I^*_{j,t}(\omega_t, B_{j,t}, E_{j,t})\}$ maximize firm value in state $(\omega_t, B_{j,t}, E_{j,t})$, then $\{\frac{E'_{j,t}}{E_{j,t}} I^*_{j,t}(\omega_t, \frac{E'_{j,t}}{E_{j,t}} B_{j,t}, E'_{j,t})\}$ also maximize firm value in state $(\omega_t, \frac{E'_{j,t}}{E_{j,t}} B_{j,t}, E'_{j,t})$. This means firm value is homogeneous of degree one in term of $E_{j,t}$. Therefore, we can scale all the firm variable by $E_{j,t}$ to simplify the representation. For ease of notation, I omit the subscript j for the following analysis. Define:

$$b_{t+1} = \frac{B_{t+1}}{E_t}, \qquad v_t = \frac{V_t}{E_t}, \qquad d_t = \frac{D_t}{E_t}, \qquad i_t = \frac{I_t}{E_t}, \qquad w_t = \frac{W_t}{E_t},$$

Divide the both side of equity function by E_t:

$$v(b_t e^{-\Delta e_t}, \omega_t) = max\{0, d_t + E_t[M_{t,t+1} e^{\Delta e_{t+1}} v(b_{t+1} e^{-\Delta e_{t+1}}, \omega_{t+1})]\} \tag{6}$$

the value function is $v(b_t, e^{\Delta e_t}, \omega_t)$. The state variable we need to track is b_t, Δe_t and aggregate state ω_t. Or more specifically $v(b_t, \varepsilon_{c,t}, \varepsilon_{j,t}, J_{j,t}, \omega_t)$.

The bond price should satisfy:

$$P_t = E_t\{M_{t,t+1}[(1 - \mathbb{I}_{v_{t+1}=0})(c + \kappa + (1-\kappa)P_{t+1}) + \mathbb{I}_{v_{t+1}=0} e^{\Delta e_{t+1}} \frac{(1-\alpha_t) w_{t+1}}{b_{t+1}}]\} \tag{7}$$

where w_t is the cum dividend value of the unleveled firm. The optimization problem is subject to the constraint

$$b_{t+1} = (1-\kappa) b_t e^{-\Delta e_t} + i_t$$
$$d_t = (1-\tau) - ((1-\tau)c + \kappa) b_t e^{-\Delta e_t} + P_t i_t$$

since the bond price depend on the next period bond choice of the firm, the bond price $P_t(\omega_t, b_{t+1})$ is a function of aggregate state and choice variable b_{t+1}

I use value function iteration to solve the model. Price to consumption ratio can be found by iterating the function:

$$pc_t = E\{\exp[\theta \log \beta + (1-\gamma)\Delta c_{i,t+1} + \theta \log(pc_{t+1} + 1)]\}$$

Thus, we can get the functional form of SDF M_{t+1}. The cum dividend unlevered price to cash flow ratio w_t can be found by iterating the function:

$$w_t = 1 - \tau + E[M_{t+1} w_{t+1} \Delta E_{t+1}]$$

The firm problem can be solved by iterating equation 6 and equation 7 simultaneously.

D Discretizing the Aggregate State

The aggregate state is a AR(1) process with time varying volatility, and shocks to x_t and σ_t are correlated. Directly apply Gauss-Hermite quadrature will be too costly. To facilitate the computation, I discretized the aggregate process into a Markov process. The basic strategy is to transform the original system into two orthogonal process, use the moment matching method proposed by Farmer and Toda (2017) to discretize the process into a Markov chain and then reconstruct the original state variables.

Specifically, rewrite the aggregate state evolution into a VAR system

$$\begin{bmatrix} \sigma_{t+1}^2 \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} 1-\rho_\sigma \\ 0 \end{bmatrix} + \begin{bmatrix} \rho_\sigma & 0 \\ 0 & \rho_x \end{bmatrix} \begin{bmatrix} \sigma_t^2 \\ x_t \end{bmatrix} + \sigma_t \begin{bmatrix} \varepsilon_{\sigma,t+1} \\ \varepsilon_{x,t+1} \end{bmatrix}$$

The innovation has a correlation structure

$$E_t[\varepsilon_{t+1}\varepsilon_{t+1}'] = \begin{bmatrix} \sigma_x^2 & \varphi_{x,\sigma}\sigma_x\sigma_\sigma \\ \varphi_{x,\sigma}\sigma_x\sigma_\sigma & \sigma_\sigma^2 \end{bmatrix}$$

We can decompose the covariance matrix of innovation as CC', where C is a lower triangular martix. Denote the state vector $[\sigma_t^2, x_t]'$ as X_t. Demean the state vector X_t and multiply both sides by C^{-1}, I transform the original state variable into $y_t = C^{-1}(X_t - \mu)$. The first element of y_t is just a linear transformation of σ_t^2 and the second element is a linear combination of x_t and σ_t^2 so that the innovations to these two elements are orthogonal to each other. The problem becomes

$$y_{t+1} = Ay_t + \sigma_t\eta_{t+1}$$

Where $A = C^{-1}\Phi C$ and $\eta_{t+1} = C^{-1}\varepsilon_{t+1}$. Using the moment matching method proposed by Farmer and Toda (2017), I can first discretize the volatility component and then conditional on the volatility component, dicretize the second component. The original state variables are just $X_t = \mu + Cy_t$

E Estimation of Cash Flow Parameters

E.1 Firm cash flow process

I use a parametric model to characterize the labor income and firm cash flow process. Specifically, assume firm's quarterly cash flow process follows

$$E_t^i = \xi_{E,t}^i + \alpha_{E,i} + \beta_{E,i}x_t + \epsilon_{E,t}^i$$
$$\xi_{E,t}^i = \xi_{E,t-1}^i + \eta_{E,t}^i$$

Where $\xi_{E,t}^i$ is permanent component of firm earnings and $\alpha_{E,i}$ captures firm fix effect and heterogeneity in exposure to aggregate variables. Quarterly observations of firm fundamentals is available in Compustat. In order to eliminate potential seasonality effect in data, I use the quarter over quarter growth rate to compute target moments.

E.2 Estimation Method

This section list the detailed step in estimating the jump intensity with respect to the labor income process and firm cash flow process. Assume the permanent shock η_t is a mixture of jump and Gaussian process

$$\eta_t = (J_{g,t} - E_t[J_{g,t}]) + (J_{b,t} - E_t[J_{b,t}]) + N(0, \sigma_n^2)$$

$J_{g,t}$ and $J_{b,t}$ are compound Poisson jump process with time varying intensities. The jump intensity for $J_{g,t}$ is $\lambda_{0,g} + \lambda_{1,g} x_t$, the jump intensity for $J_{b,t}$ is $\lambda_{0,b} - \lambda_{1,b} x_t$ the size of a jump follow a normal distribution $N(\mu_{s,g}, \sigma_{s,g}^2)$ for positive jumps and $N(\mu_{s,b}, \sigma_{s,b}^2)$ for negative jumps.

The model tries to match the sample moments in the data. I minimize the scaled deviation of theoretical moments and sample moments. Define

$$F_n(\theta) = \frac{m(\theta) - \hat{m}_n}{|\hat{m}_n|}$$

The objective function is

$$\min_\theta F_n(\theta)' W F_n(\theta)$$

where W is an identity matrix.

The distribution of log growth rate is just the convolutions of several Poisson distributions and normal distributions. I can use the characteristic function of log growth rate distribution and compute the density function through fractional fast Fourier transformation. The cash flow growth process has a transitory shock component and permanent shock component. The characteristic function of transitory shock $\epsilon_t - \epsilon_{t-4}$ is $\varphi_\epsilon(\omega) = \exp[-\sigma_\epsilon^2 \omega^2]$. The characteristic function of permanent shock $\Delta\eta_t$ is

$$\begin{aligned}\log(\varphi_{\Delta\eta_t}(\omega)) = {} & (\lambda_{0g} + \lambda_1 x_t)(\exp(i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) - 1) + (\lambda_{0b} - \lambda_1 x_t)(\exp(-i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) - 1) \\ & - \frac{1}{2}\omega^2\sigma_n^2 - (\lambda_{0g} + \lambda_1 x_t) i\mu_s\omega + (\lambda_{0b} - \lambda_1 x_t) i\mu_s\omega\end{aligned}$$

We can calculate the characteristic function of cash flow growth process $\varphi(\omega) = E[\exp\{i\omega(w_{A,t} - w_{A,t-k})\}]$ analytically as

$$\log\varphi(\omega) = \sum_{j=0}^{k+2}[h(\rho(j)\omega, x_{t-j})] - \sigma_\epsilon^2\omega^2 - \frac{1}{2}\sigma_\beta^2\omega^2$$

where

$$
\begin{aligned}
h(\omega, x_t) = {} & (\lambda_{0g} + \lambda_1 x_t)(\exp(i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) - 1) + (\lambda_{0b} - \lambda_1 x_t)(\exp(-i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) - 1) \\
& - \frac{1}{2}\omega^2\sigma_n^2 - (\lambda_{0g} + \lambda_1 x_t)i\mu_s\omega + (\lambda_{0b} - \lambda_1 x_t)i\mu_s\omega
\end{aligned}
$$

Standardize $w_{A,t} - w_{A,t-k}$ to have mean 0 and standard deviation of 1

$$
\varphi_s(\omega) = \varphi_s(\frac{\omega}{\sigma_A})\exp(-i\omega\frac{\mu_A}{\sigma_A})
$$

The density function of the standardized growth is

$$
f(x) = \frac{1}{\pi} \cdot Real[\int_0^\infty [\varphi_s(\omega)e^{-i\omega x}]d\omega]
$$

I use trapezoid rule and fractional fast Fourier Transform to approximate the integration as a sum over the equally-spaced grid $[0, \bar{\Omega}]$, the grid for x is $[-\bar{X}, \bar{X}]$. Here I chose $2^{10} = 1024$ grid points and $\bar{\Omega} = 20$ and $\bar{X} = 9$. Then, use the Simpson's rule, I numerically integrate density function to get conditional CDF. The target quantiles are calculated using quadratic interpolation. To calculate the mean function, use

$$
\frac{\partial\varphi(\omega)}{\partial\omega} = (\sum_{j=0}^{k+2}[h'(\rho(j)\omega, x_{t-j})\rho(j)] - 2\sigma_\epsilon^2\omega - \sigma_\beta^2\omega)\varphi(\omega)
$$

where

$$
\begin{aligned}
h'(\omega, x_t) = {} & (\lambda_{0g} + \lambda_1 x_t)(i\mu_s - \sigma_s^2\omega)\exp(i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) + (\lambda_{0b} - \lambda_1 x_t)(-i\mu_s - \sigma_s^2\omega)\exp(-i\mu_s\omega \\
& - \frac{1}{2}\sigma_s^2\omega^2) - \omega\sigma_n^2 - (\lambda_{0g} + \lambda_1 x_t)i\mu_s + (\lambda_{0b} - \lambda_1 x_t)i\mu_s
\end{aligned}
$$

set $\omega = 0$ to get the mean. To calculate the second moment function, use

$$
\frac{\partial^2\varphi(\omega)}{\partial\omega^2} = (\sum_{j=0}^{k+2}[h''(\rho(j)\omega, x_{t-j})\rho(j)^2] - 2\sigma_\epsilon^2 - \sigma_\beta^2)\varphi(\omega) + \frac{\varphi'(\omega)^2}{\varphi(\omega)}
$$

where

$$
\begin{aligned}
h''(\omega, x_t) = {} & (\lambda_{0g} + \lambda_1 x_t)(-\sigma_s^2)\exp(i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) \\
& + (\lambda_{0b} - \lambda_1 x_t)(-\sigma_s^2)\exp(-i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) \\
& + (\lambda_{0g} + \lambda_1 x_t)(i\mu_s - \sigma_s^2\omega)^2\exp(i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) \\
& + (\lambda_{0b} - \lambda_1 x_t)(-i\mu_s - \sigma_s^2\omega)^2\exp(-i\mu_s\omega - \frac{1}{2}\sigma_s^2\omega^2) - \sigma_n^2
\end{aligned}
$$

set $\omega = 0$ to get the second moment

E.3 Estimation Results

My firm cash flow model tries to match the sample moment computed from quarterly sales growth data. The target moments are: left-tail measure ($P_{50} - P_{10}, P_{50} - P_{25}$), right tail measure ($P_{90} - P_{50}, P_{75} - P_{50}$), and skewness in expansion, recession and difference; average range ($P_{90} - P_{10}$), standard deviation and kurtosis in whole sample.

Table 17 reports the estimation result. The average conditional probability of negative cash flow jump is 3%. Ones standard deviation increase in skewness index is associated with about 2% decrease in jump intensity. The lower bound of jump intensity is set to be 0. Once a negative jump occurs, the cash flow drops about 40%.

Figure 13. Skewness Index.

This figure shows the fitted time series of quarterly skewness index (normalized to have mean 0 and variance 1). The figure plots the fitted time series with top 5 highest R^2. The variables and method are all variables by 3PRF, all variables by IMSE, real activity variables by IMSE, employment variables by IMSE, and real inventory variables by IMSE. The shaded area denotes the NBER recession period. The sample spans 1960Q1-2013Q4.

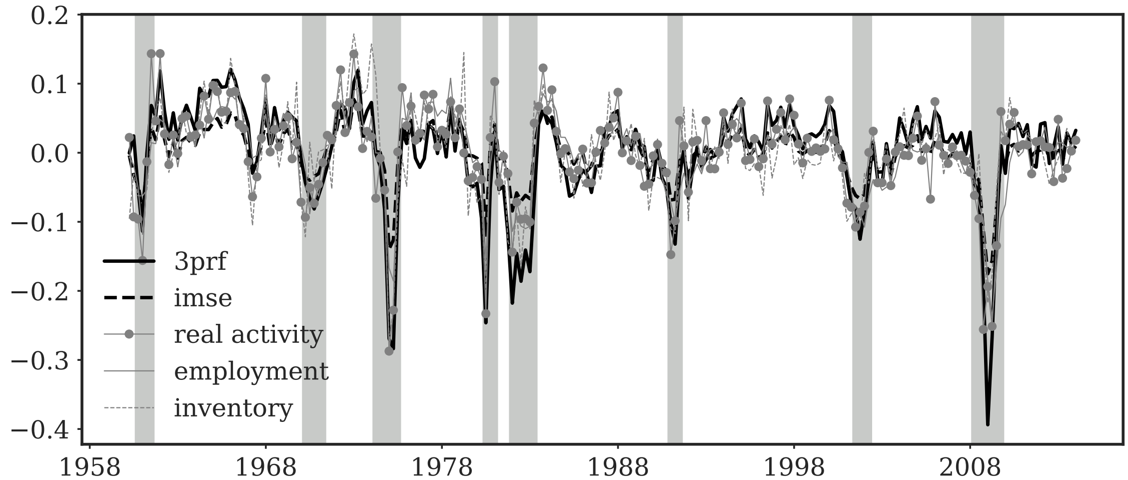

Table 13. Macro Variable List.

This table lists the mnemonics, short names and transformations for the 97 macroeconomic series used in the paper. All series are from the Global Insights Basic Economics Database. Slow-moving variables are marked with *.

No.	Mnemonic	Short name	Transformation
		Real output and income	
1	IPS11.M*	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL	Δln
2	IPS299.M*	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS	Δln
3	IPS12.M*	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS	Δln
4	IPS13.M*	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	Δln
5	IPS18.M*	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	Δln
6	IPS25.M*	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	Δln
7	IPS32.M*	INDUSTRIAL PRODUCTION INDEX - MATERIALS	Δln
8	IPS34.M*	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	Δln
9	IPS38.M*	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	Δln
10	IPS43.M*	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	Δln
11	IPS311.M*	INDUSTRIAL PRODUCTION INDEX - OIL & GAS WELL DRILLING & MANUFACTURED HOMES	Δln
12	IPS307.M*	INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES	Δln
13	IPS10.M*	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	Δln
14	UTL11.M*	CAPACITY UTILIZATION - MANUFACTURING (SIC)	
15	PMI.M*	PURCHASING MANAGERS' INDEX (SA)	
16	PMP.M*	NAPM PRODUCTION INDEX (PERCENT)	
17	PI001.M*	PERSONAL INCOME, BIL$, SAAR	Δln
18	A0M051.M*	PERS INCOME LESS TRSF PMT (AR BIL. CHAIN 2009 $),SA-US	Δln
		Employment and hours	
19	LHEM.M*	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)	Δln
20	LHNAG.M*	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	Δln
21	LHUR.M*	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS and OVER (%,SA)	
22	LHU680.M*	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	
23	LHU5.M*	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	
24	LHU14.M*	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	
25	LHU15.M*	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	
26	LHU26.M*	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	
27	CES001.M*	EMPLOYEES, NONFARM - TOTAL NONFARM	Δln
28	CES002.M*	EMPLOYEES, NONFARM - TOTAL PRIVATE	Δln
29	CES003.M*	EMPLOYEES, NONFARM - GOODS-PRODUCING	Δln
30	CES006.M*	EMPLOYEES, NONFARM - MINING	Δln
31	CES011.M*	EMPLOYEES, NONFARM - CONSTRUCTION	Δln
32	CES015.M*	EMPLOYEES, NONFARM - MFG	Δln
33	CES017.M*	EMPLOYEES, NONFARM - DURABLE GOODS	Δln
34	CES033.M*	EMPLOYEES, NONFARM - NONDURABLE GOODS	Δln
35	CES046.M*	EMPLOYEES, NONFARM - SERVICE-PROVIDING	Δln
36	CES048.M*	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES	Δln
37	CES049.M*	EMPLOYEES, NONFARM - WHOLESALE TRADE	Δln
38	CES053.M*	EMPLOYEES, NONFARM - RETAIL TRADE	Δln
39	CES140.M*	EMPLOYEES, NONFARM - GOVERNMENT	Δln
40	CES154.M*	AVG WKLY HOURS, PROD WRKRS, NONFARM - MFG	
41	CES155.M*	AVG WKLY OVERTIME HOURS, PROD WRKRS, NONFARM - MFG	
42	PMEMP.M*	NAPM EMPLOYMENT INDEX (PERCENT)	
		Consumption	
43	PI031.M*	PERSONAL CONSUMPTION EXPENDITURES, BIL$, SAAR	Δln
44	PI032.M*	PERSONAL CONSUMPTION EXPENDITURES - DURABLE GOODS, BIL$, SAAR	Δln
45	PI033.M*	PERSONAL CONSUMPTION EXPENDITURES - NONDURABLE GOODS, BIL$, SAAR	Δln
46	PI034.M*	PERSONAL CONSUMPTION EXPENDITURES - SERVICES, BIL$, SAAR	Δln

Table 13. Macro Variable List: Continued.

This table lists the mnemonics, short names and transformations for the 97 macroeconomic series used in the paper. All series are from the Global Insights Basic Economics Database. Slow-moving variables are marked with *.

No.	Mnemonic	Short name	Transformation
		Housing starts and sales	
47	HSFR.M	HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA	ln
48	HSNE.M	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	ln
49	HSMW.M	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	ln
50	HSSOU.M	HOUSING STARTS:SOUTH (THOUS.U.)S.A.	ln
51	HSWST.M	HOUSING STARTS:WEST (THOUS.U.)S.A.	ln
52	HS6BR.M	HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,NSA)	ln
53	HMOB.M	MOBILE HOMES: MANUFACTURERS' SHIPMENTS (THOUS.OF UNITS,SAAR)	ln
		Real inventories, orders and un lled orders	
54	PMNV.M	NAPM INVENTORIES INDEX (PERCENT)	
55	PMNO.M	NAPM NEW ORDERS INDEX (PERCENT)	
56	PMDEL.M	NAPM VENDOR DELIVERIES INDEX (PERCENT)	
57	MOCMQ.M	NEW ORDERS (NET) - CONSUMER GOODS and MATERIALS, 1996 $ (BCI)	Δln
58	MSONDQ.M	NEW ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 $ (BCI)	Δln
		Stock prices	
59	FSPCOM.M	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	Δln
60	FSPIN.M	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)	Δln
		Exchange rates	
61	EXRUK.M	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	Δln
62	EXRCAN.M	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	Δln
		Interest rates	
63	FYFF.M	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	
64	FYGM3.M	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	
65	FYGM6.M	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	
66	FYGT1.M	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	
67	FYGT5.M	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	
68	FYGT10.M	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	
69	FYGM3.M-FYFF.M	SPREAD: FYGM3.M-FYFF.M	
70	FYGM6.M-FYFF.M	SPREAD: FYGM6.M-FYFF.M	
71	FYGT1.M-FYFF.M	SPREAD: FYGT1.M-FYFF.M	
72	FYGT5.M-FYFF.M	SPREAD: FYGT5.M-FYFF.M	
73	FYGT10.M-FYFF.M	SPREAD: FYGT10.M-FYFF.M	
		Money and credit quantity aggregates	
74	ALCIBL00.M	COML&IND LOANS OUTST IN 2009 $,SA-US	Δln
75	CCINRV.M	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	Δln
76	FM1.M	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	Δln
77	FM2.M	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,SA),	Δln
78	MBASE.M	REVISED MONETARY BASE-ADJUSTED-(FED RESERVE BANK-SAINT LOUIS),SA-US	Δln
79	MNY2.M	M2 - MONEY SUPPLY - M1 + SAVINGS DEPOSITS, SMALL TIME DEPOSITS, & MMMFS [H6],SA-US	Δln
		Price indexes	
80	PMCP.M	NAPM COMMODITY PRICES INDEX (PERCENT)	
81	PWFSA.M*	PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)	Δln
82	PWFCSA.M*	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)	Δln
83	PWIMSA.M*	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)	Δln
84	PWCMSA.M*	PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)	Δln
85	PUNEW.M*	CPI-U: ALL ITEMS (82-84=100,SA)	Δln
86	PU83.M*	CPI-U: APPAREL & UPKEEP (82-84=100,SA)	Δln
87	PU84.M*	CPI-U: TRANSPORTATION (82-84=100,SA)	Δln
88	PU85.M*	CPI-U: MEDICAL CARE (82-84=100,SA)	Δln
89	PUC.M*	CPI-U: COMMODITIES (82-84=100,SA)	Δln
90	PUCD.M*	CPI-U: DURABLES (82-84=100,SA)	Δln
91	PUS.M*	CPI-U: SERVICES (82-84=100,SA)	Δln
92	PUXF.M*	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)	Δln
93	PUXHS.M*	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)	Δln
94	PUXM.M*	CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)	Δln
		Average hourly earnings	
95	CES277.M*	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION	Δln
96	CES278.M*	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG	Δln
		Miscellaneous	
97	U0M083.M	BUSINESS CYCLE INDICATORS,CONSUMER EXPECTATIONS,NSA	

Table 14. Skewness Index: Goodness of Fit.

This table shows the goodness of fit of different method in constructing the skewness index. The first column shows the variable set. Except for the benchmark 3PRF (3 pass regression filter) case, all the other construction use IMSE (inverse mean square error) method. The third column shows the regression R-squared and the forth column shows the correlation between constructed skewness index with the benchmark case (All variable 3PRF). The target is 1-year labor income growth skewness from 1978-2010, the constructed skewness index spans 1960Q1-2013Q4.

Category	**Var Num.**	R^2	**Corr.**
All Variables (3PRF)	97	70.03%	1
All Variables (IMSE)	97	51.76%	0.92
Real output and income	18	62.83%	0.85
Employment and hours	24	60.24%	0.87
Real inventories, orders, and unfilled orders	5	55.74%	0.81
Consumption	4	29.57%	0.34
Money and credit quantity aggregates	6	25.50%	0.47
Stock indices	2	24.00%	0.12
Price indices	15	23.91%	0.21
Exchange rates	2	20.52%	0.21
Average hourly earnings	2	17.76%	0.17
Consumer expectation	1	13.92%	0.52
Interest rates	11	1.35%	0.21
Housing starts and sales	7	8.33%	0.38

Table 15. Stock Return Predictability: in-sample.

This table shows the results of in-sample stock return predictability regression

$$r_{e,t+1\to t+4} - r_f = \beta_0 + \beta_1 S_t + \gamma \mathbf{X}_t + \epsilon_t.$$

The regression use time t variable to forecast 1-year ahead stock return. S_t is the skewness index and $\mathbf{X}_t$ is a vector of controls, including dividend payout ratio, long term yield, dividend price ratio, treasury-bill rate, book to market ratio, default yield spread, net equity expansion, term spread, stock variance, inflation, long term return and default return spread. All independent variables are standardized to have mean 0 and standard deviation of 1. For each regression, the table reports OLS estimates (numbers in percentage) and Newey-West t-statistics with 4 lags. The sample spans 1960Q1-2013Q4.

	1-year stock return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
skewness index	-3.80				-2.97		
	-(2.61)				-(1.43)		
Initial Claims		4.03				4.33	
		(2.12)				(1.26)	
Unemployment			4.45				0.84
			(2.80)				(0.42)
Controls	N	N	N	Y	Y	Y	Y
Observation	216	188	216	216	216	188	216
R2	0.049	0.052	0.068	0.236	0.258	0.253	0.244

Table 16. Stock Return Predictability: out-of-sample.

This table shows the out-of-sample r squared (oos R^2) of stock return predictability regression. I leave the first 10 year data as training period. I report the oos R^2 for forecasting period of 1 quarter, 1 year, 3 year and 5 year. The last column shows the sample period.

Variables	1 quarter return	1 year return	3 year return	5 year return	sample period
Unemployment	0.52%	5.93%	20.50%	38.21%	1960Q1-2012Q4
Initial claims	-0.67%	-1.44%	7.07%	15.44%	1967Q1-2012Q4
Dividend payout ratio	-8.85%	-2.16%	-5.03%	-12.02%	1960Q1-2012Q4
Long term yield	-4.21%	-4.62%	5.02%	8.32%	1960Q1-2012Q4
Dividend yield	-2.91%	-0.51%	8.98%	18.69%	1960Q1-2012Q4
Dividend Price ratio	-3.09%	-0.15%	9.79%	21.00%	1960Q1-2012Q4
Treasury-bill rate	-3.23%	-5.07%	-1.25%	-5.02%	1960Q1-2012Q4
Earning price ratio	-8.34%	-1.53%	6.88%	10.19%	1960Q1-2012Q4
Book to market	-5.72%	-1.56%	0.11%	5.73%	1960Q1-2012Q4
Default yield spread	-2.19%	1.18%	1.86%	13.96%	1960Q1-2012Q4
Net equity expansion	-3.10%	-4.65%	-1.82%	-1.37%	1960Q1-2012Q4
Term spread	-1.54%	0.02%	8.52%	8.74%	1960Q1-2012Q4
Stock variance	-17.94%	-18.85%	-18.03%	-15.40%	1960Q1-2012Q4
Inflation	-2.95%	-3.17%	-1.81%	-5.22%	1960Q1-2012Q4
Long term return	-1.85%	-0.25%	-1.33%	-0.94%	1960Q1-2012Q4
Defualt return spread	-1.43%	-1.66%	-1.29%	-4.97%	1960Q1-2012Q4

Table 17. Estimated Cash Flow Growth Process Parameters.

This table reports sales growth process parameters estimated by minimizing a weighted sum of squared errors between the sample moments and model implied moments. The target moments are computed from Compustat quarterly 1978-2014.

Parameters	Value	Description
$\lambda_{0,g}$	4.73%	Average quarterly intensity of positive jump
$\lambda_{0,b}$	3.25%	Average quarterly intensity of negative jump
$\lambda_{1,g}$	0.76%	Sensitivity of positive jump intensity to skewness index
$\lambda_{1,b}$	1.99%	Sensitivity of negative jump intensity to skewness index
$\mu_{s,g}$	34.80%	Average change in log sales given a positive jump
$\sigma_{s,g}$	0.02%	Standard deviation of positive jump
$\mu_{s,b}$	38.62%	Average change in log sales given a negative jump
$\sigma_{s,b}$	0.02%	Standard deviation of negative jump
σ_n	2.13%	Standard deviation of permanent shock
σ_ϵ	9.18%	Standard deviation of temporary shock

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