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Federal Reserve Board

Abstract

Using U.S. data from 1926 to 2015, I show that financial skewness—a measure comparing cross-sectional upside and downside risks of the distribution of stock market returns of financial firms—is a powerful predictor of business cycle fluctuations. I then show that shocks to financial skewness are important drivers of business cycles, identifying these shocks using both vector autoregressions and a dynamic stochastic general equilibrium model. Financial skewness appears to reflect the exposure of financial firms to the economic performance of their borrowers.

Key Words: Cross-Sectional Skewness, Business Cycle Fluctuations, Financial Channel.

JEL Classification: C32, E32, E37, E44.

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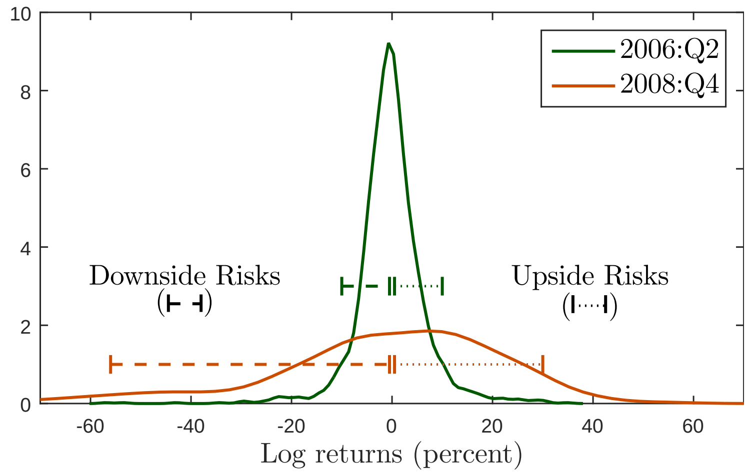
1 Introduction

Historically, economists have been engaged in both predicting and understanding the origins of business cycle fluctuations. Recently, much of this literature has analyzed how fluctuations in uncertainty about economic variables affect business cycles.[1] However, the focus on uncertainty overlooks the role of tail risks, as both downside and upside risks increase uncertainty while generally leading to divergent economic outcomes. Moreover, there is still little evidence on how the interplay between these tail risks contribute to the prediction and explanation of business cycles. In this paper, I show evidence that a measure of cross-sectional skewness—i.e., the balance between cross-sectional upside and downside risks—not only has a powerful predictive ability on economic activity, but also seems to be an important source of cyclical fluctuations for the US economy.

Figure 1: Cross-Sectional Distribution of Stock Market Returns of Financial Firms

(a) Probability Density Function



(b) Cross-Sectional Moments

	2006:Q2	2008Q4
Median	0%	0%
Dispersion	20%	86%
Skewness	0%	-27%

I demean the cross-sectional distributions of stock market returns and then I calculate skewness by $\left[(r_t^{95} - r_t^{50}) - (r_t^{50} - r_t^{5})\right]$, dispersion by $(r_t^{95} - r_t^{5})$, upside risks by $(r_t^{95} - r_t^{50})$, and downside risks by $(r_t^{50} - r_t^{5})$, where r_t^{p} is the p$^{\text{th}}$ percentile of the distribution of log-returns at time t.

I define *financial skewness* as a measure comparing cross-sectional upside and downside risks of the distribution of log-returns of financial firms. Specifically, I calculate it by $\left[(r_t^{95}-r_t^{50})-(r_t^{50}-r_t^{5})\right]$, where r_t^{p} is the p^{th} percentile of the distribution of log-returns at time t, $(r_t^{95}-r_t^{50})$ measures upside risks, and $(r_t^{50}-r_t^{5})$ measures downside risks. Thus, if financial skewness is negative, the balance of cross-sectional risks is tilted to the downside, while if financial skewness is positive, risks are tilted to the upside. Figure 1 shows the distribution of log-returns of financial firms for 2006:Q2 and 2008:Q4. It documents that financial skewness

[1] See Bloom (2014) for a literature review on this topic.

became markedly negative from 2006:Q2 to 2008:Q4, as the increase in downside risks was substantially larger than the increase in upside risks.

The relationship between financial skewness and the business cycle appears to be robust across time as well as quantitatively powerful. First, I document that financial skewness closely tracks business cycles over the period 1926 to 2015 (Figure 2), with correlations higher than those associated with most other variables. Second, I present evidence showing that financial skewness has a strong predictive power on several measures of economic activity. Using in-sample and out-of-sample regressions for the 1973 to 2015 sample, I show that financial skewness generally performs better than many well-known indicators of economic conditions, such as bond spreads (e.g., Gilchrist and Zakrajsek (2012)), measures of aggregate uncertainty (e.g., Jurado et al. (2015), and Ludvigson et al. (2015)) and other moments from the cross-sectional distribution of returns. Finally, I show that these results are not dependent on specific events, such as the Great Recession, as financial skewness performs well in both recessions and expansions.

Figure 2: Financial Skewness and the Business Cycle

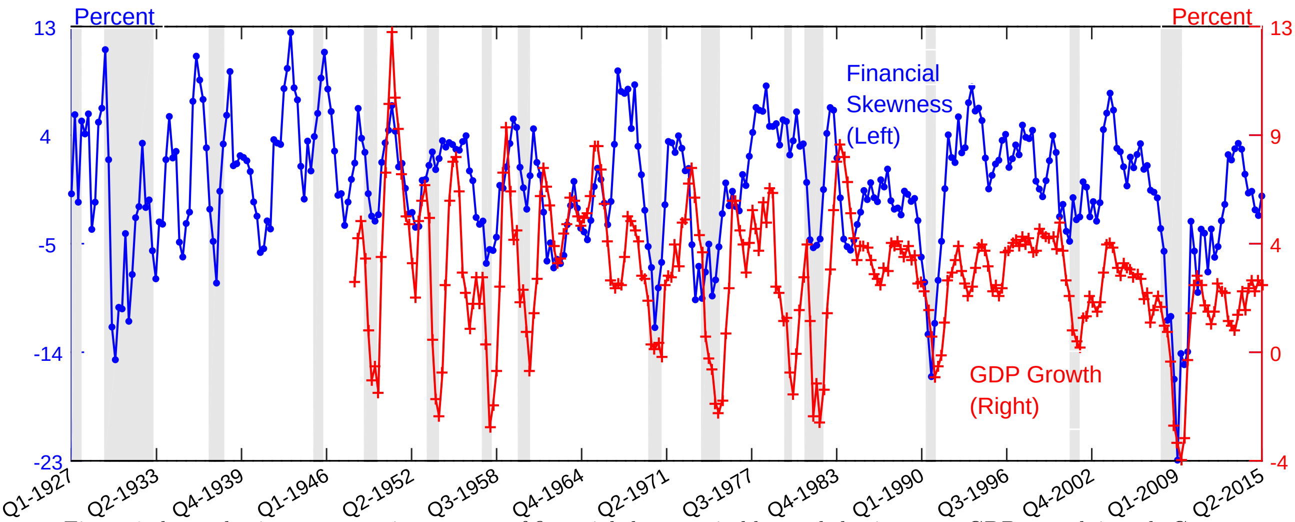


Figure 2 shows the 4-quarter moving average of financial skewness in blue and the 4-quarter GDP growth in red. Gray areas represent periods classified as recessions by the NBER.

I argue that this tight relationship between financial skewness and the business cycle reflects the exposure of financial firms to the economic performance of their borrowers. This hypothesis is based on three arguments. First, financial firms focus on specific loan markets they expect to boost their equity returns. Second, stock markets evaluate these exposures of financial firms to specific markets by pricing higher equity valuations for those firms financing borrowers with higher expected profits. Then, as economic shocks (e.g. technology innovations and policy surprises) impact different nonfinancial firms differently, the cross-section of stock returns of financial firms signals how the distribution of profitability of their borrowers reacts to these shocks. Third, because financial firms also diversify idiosyncratic risks across loan markets, financial firms' stock returns signal risks related to investment projects most impactful to the macroeconomy.

I provide three pieces of empirical evidence to support this hypothesis that financial skewness signals the economic performance of their borrowers. First, I show that cross-sectional distributions of stock market returns of financial firms have less dispersion and thinner tails than those of nonfinancial firms. This result is consistent with financial firms being exposed to specifically chosen loan markets while achieving some diversification across markets. Second, I show that variables associated with asset quality of financial firms, such as banks' asset returns, account for 76% of the fluctuations in financial skewness. Moreover, since these variables are released after the end of the quarter, results indicate that financial skewness anticipates financial firms' asset quality. Third, I document that financial skewness also leads credit market conditions, such as loan growth. This last result points to stock markets timely pricing credit market fundamentals, especially for a submarket for which financial firms are expected to have a comparative advantage in sorting borrower quality.

I then investigate the quantitative role of shocks to financial skewness in explaining business cycles. For this, I use two complementary approaches: a dynamic stochastic general equilibrium (DSGE) model and Bayesian vector autoregressions (BVARs). The DSGE model rationalizes the hypothesis that financial firms are exposed to specific loan markets, embeds a financial accelerator channel, and allows cross-sectional risks to be subject to skewness shocks, thus modeling heterogeneous effects of macroeconomic shocks. The BVARs have more flexible identifications of skewness shocks and their transmission channels. Both the DSGE model and BVARs estimate that financial skewness shocks are important business cycle drivers, have sizable economic effects, and account for most of the fluctuations in financial skewness, displacing many other shocks studied in the literature including cross-sectional dispersion ones.[2]

Finally, I provide evidence that an important transmission channel of financial skewness shocks is consistent with models of financial frictions. I support this argument with three results. First, both the DSGE model and BVARs estimate that when cross-sectional risks are exogenously tilted to the downside, nonfinancial firms receive less credit, face higher lending interest rates, have lower equity values, invest less, and produce less. Second, I document that the effects on economic activity from skewness shocks are amplified when lending rates respond more to these shocks.[3] Third, I show that the response of many macroeconomic

[2]Bachmann and Bayer (2014) and Zeke (2016) use calibrated theoretical models to provide different arguments on why dispersion shocks should not be viewed as important business cycle drivers.

[3]See Caldara et al. (2016) for related evidence using uncertainty measures focused on second moments, such as dispersion and volatility.

variables to skewness shocks in the BVARs are consistent with analogous responses from the DSGE model with financial frictions used in this paper.

Differently from most of the literature studying the sources of business cycle fluctuations, this paper argues that cross-sectional tail risks are important drivers of these fluctuations. In one branch of this literature, many business cycle theories advocate that idiosyncratic risk—i.e., the cross-sectional idiosyncratic component of firms' behavior—is an important driver of aggregate fluctuations.[4] However, these papers overlook the aggregate effects from shocks to cross-sectional upside and downside risks, with most them focusing on dispersion shocks. In another branch of this literature, many papers analyze the relationship between tail risks and the macroeconomy, although they focus on aggregate tail risks.[5] This paper shows evidence that cross-sectional skewness—i.e. the balance between upside and downside cross-sectional risks—is an important source of aggregate fluctuations.[6]

Lastly, this paper has several contributions to the literature studying the predictive ability of financial indicators on economic conditions. First, it shows that financial skewness is a powerful predictor of economic activity, performing better than many influential financial indicators cited in the literature.[7] Second, this paper provides evidence that stock markets can be an effective barometer of economic fundamentals. This argument is supported by the predictive ability of financial skewness on economic activity and by the data corroborating the interpretation that financial skewness reflects the economic health of its borrowers. This argument also challenges the hypothesis that bond markets are more accurate than stock markets about economic fundamentals.[8] Third, this paper provides evidence of a measure of cross-sectional idiosyncratic risk that performs well in both predicting and driving economic fluctuations. Despite the importance of idiosyncratic risk in business cycle theories, empirical measures of it have had little influence on the research seeking to predict these same aggregate fluctuations.

[4]These papers argue that shocks to idiosyncratic risk have economic effects through several channels: wait-and-see effects from capital adjustment frictions (Bloom et al. (2012)); financial frictions (Arellano et al. (2012), Christiano et al. (2014), Gilchrist et al. (2014), and Chugh (2016)); search frictions in the labor market (Schaal (2017)); agency problems in the management of the firm (Panousi and Papanikolaou (2012)); granular effects (Gabaix (2011)); and network effects (Acemoglu et al. (2012)).

[5]For instance, see Barro (2006), Gabaix (2012), and Gorio (2012).

[6]Kelly and Jiang (2014) show some evidence on the relationship between cross-sectional downside risks economic activity, although the focus of their analysis is on asset pricing. Other papers document that high-order moments of the cross-sectional distribution of many economic variables seem to co-move with the economic cycle, such as firm sales, profit, and employment (Bloom et al. (2016)); household income (Guvenen et al. (2014)); and price changes (Luo and Vallenas (2017)).

[7]For literature reviews on this topic, see Stock and Watson (2003) and Ng and Wright (2013).

[8]See Philippon (2009), Gilchrist and Zakrajsek (2012), and Lopez-Salido et al. (2017) for different versions of this argument.

2 Financial Skewness and Business Cycles

In this section, I describe the cross-sectional distribution measures used in this paper (Section 2.1), and document that financial skewness stands out not only as a close tracker of business cycles (Section 2.2), but also as a powerful predictor of economic activity (Section 2.3).

2.1 Cross-Sectional Distribution Measures

I use U.S. stock market returns from the CRSP database for the period from 1926:Q1 to 2015:Q2. I define $R_t^{i,s}$ as the stock market *gross return* of firm i at sector s and quarter t, $r_t^{i,s} = \log(R_t^{i,s})$ as the log-return of firm i at quarter t, and $r_t^{p,s}$ as the p^{th} percentile of the distribution of log-returns within sector s at quarter t. Then, I calculate sectoral cross-sectional measures of mean, dispersion, skewness, left kurtosis, and right kurtosis as follows:

$$\text{mean: } M(1)_t^s = \frac{100}{N_{s,t}}\left(\sum_{i\in s} R_t^{i,s} - 1\right), \quad \text{for } s \in \{\text{fin}, \text{nfin}\}, \tag{1}$$

$$\text{dispersion: } M(2)_t^s = r_t^{95,s} - r_t^{5,s}, \quad \text{for } s \in \{\text{fin}, \text{nfin}\}, \tag{2}$$

$$\text{skewness: } M(3)_t^s = (r_t^{95,s} - r_t^{50,s}) - (r_t^{50,s} - r_t^{5,s}), \quad \text{for } s \in \{\text{fin}, \text{nfin}\}, \tag{3}$$

$$\text{left kurtosis: } M(4)_t^s = (r_t^{45,s} - r_t^{25,s}) - (r_t^{25,s} - r_t^{5,s}), \quad \text{for } s \in \{\text{fin}, \text{nfin}\}, \tag{4}$$

$$\text{right kurtosis: } M(5)_t^s = (r_t^{95,s} - r_t^{75,s}) - (r_t^{75,s} - r_t^{55,s}), \quad \text{for } s \in \{\text{fin}, \text{nfin}\}, \tag{5}$$

where $N_{s,t}$ is the number of firms in sector s at quarter t and "fin" and "nfin" represent financial and nonfinancial sectors of the U.S. economy, respectively.[9] Notice that the intuition for left kurtosis (equation (4)) and right kurtosis (equation (5)) is analogous to the one for skewness, with the difference being that these kurtoses measures compare upside and downside risks within each distribution tail using the 25^{th} and 75^{th} quartiles as their reference returns.

I also calculate cross-sectional distribution measures weighted by firm size. To do so, for each time t, sector s, and return $R_t^{i,s}$, I artificially augment the sample by repeating return $R_t^{i,s}$ proportionally to its market capitalization share in its sector s at quarter t. Then, I apply the same formulas (1)-(5). Throughout this paper, unless otherwise noted, I refer to unweighted measures. Thus, I refer to unweighted $\text{M}(3)_t^{\text{fin}}$ as financial skewness, unweighted $\text{M}(3)_t^{\text{nfin}}$ as nonfinancial skewness, and analogously for other distribution measures.[10]

[9] The classification between financial and nonfinancial sectors is according to the NAICS codes. When NAICS codes are not available, I use SIC codes. For details, see Appendix A.1.

[10] I use raw realized returns to calculate measures (1)-(5), instead of residuals of regressions on market factors, such as Fama-French (1993). I choose this procedure because market returns themselves may be determined by the distribution of idiosyncratic risks (e.g., Ferreira (2016)). Thus, if the goal is to measure aggregate effects from time-varying idiosyncratic risk, one may be excluding important information through these factor regressions. Alternatively, I control for aggregate factors, such as market returns and volatility, by including direct measures of them in the regressions of this paper.

2.2 Financial Skewness Tracks Business Cycles

Table 1 documents the correlations between financial and nonfinancial skewness and measures of economic activity for the period 1926–2015. Two results emerge. First, correlations are higher for financial skewness relative to the nonfinancial skewness, regardless of the activity measure and sample period. Second, correlations are higher for the 1985–2015 period relative to the full sample, regardless of the activity and skewness measures. Notably, the correlation between financial skewness and GDP growth in the 1985–2015 period is 0.71.

Table 1: Correlations between Cross-Sectional Skewness and the Business Cycle

Sample	Expansion Indicator		GDP Growth	
	Financial Skewness	Nonfinancial Skewness	Financial Skewness	Nonfinancial Skewness
1926*–2015	0.34	0.31	0.40	0.36
1986–2015	0.59	0.49	0.71	0.42

I use 4-quarter moving averages of unweighted skewness, 4-quarter GDP growth, and an expansion indicator from the NBER classification. *For GDP growth, the larger sample ranges from 1947 to 2015.

I then measure the co-movement between all distribution measures (1)-(5) and the business cycle by estimating logit regressions on the NBER expansion indicator. This dependent variable not only encompasses a wide set of information about the economic cycle, but also is available for the whole sample period for which the distribution measures are calculated: 1926 to 2015. Thus, we can interpret the results from these logit regressions as being robust to specific historical periods, such as the Great Depression, the Great Moderation, and the Great Recession. As control variables, I include the spread between Moody's Baa and Aaa corporate rates (Baa-Aaa spread) and the lagged NBER expansion indicator. Finally, I standardize the series of all regressors to ensure comparability between the estimated coefficients. Table 2 displays regression estimates.

These logit regressions show that financial skewness is one of the variables most correlated with the business cycle and that this correlation is quantitatively relevant. These conclusions come from four results. First, financial skewness adds more explanatory power (pseudo R^2) to the benchmark regression with only lagged NBER-indicator than most other variables (columns (1)-(7) of Tables 2a-2b). Second, the correlation of financial skewness and the cycle is robust to the inclusion of other variables, with its coefficient retaining an intuitive sign and being statistically significant (regressions (8)-(9) of Table 2a). Third, within the universe of the largest specifications (columns (9)-(10) of Tables 2a-2b), the coefficient of financial skewness is the second largest, only lower than the one associated with the weighted nonfinancial mean. Finally, declines in financial skewness imply considerable increases in recession probabilities. For instance, when the economy is expanding, a drop of two standard

Table 2: Logit Regressions on NBER Expansion Indicator, 1926–2015

(a) Financial Distribution Measures

Variables	Regressions with Unweighted Distribution Measures (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Weighted (10)
Constant	-1.26***	-1.55***	-1.11***	-1.36***	-1.24***	-1.35***	-1.22***	-1.73***	-1.77***	-1.77***
Expansion lag	4.12	4.55	3.93	4.38	4.11	4.23	4.04	5.02	5.05	4.95
Mean		1.17***						1.33***	1.23**	1.50***
Dispersion			-0.34					-0.44	-0.68	-0.47
Skewness				1.17***				1.71**	1.68**	0.90*
Left kurtosis					0.43			-0.92*	-0.98*	-0.42
Right kurtosis						0.20		-0.69	-0.64	-0.79
Baa-Aaa							-0.24**		0.23	0.10
Pseudo R^2	0.53	0.58	0.54	0.57	0.54	0.53	0.55	0.62	0.63	0.62

(b) Nonfinancial Distribution Measures

Variables	Regressions with Unweighted Distribution Measures (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Weighted (10)
Constant	-1.26***	-1.55***	-1.24***	-1.27***	-1.29***	-1.25***	-1.22***	-1.54***	-1.54***	-1.75***
Expansion lag	4.12	4.58	4.09	4.37	4.20	4.24	4.04	4.76	4.78	4.99
Mean		1.30***						1.05**	1.17*	1.85***
Dispersion			-0.09					-1.03	-0.84	-1.57**
Skewness				1.06***				-0.43	-0.47	-0.13
Left kurtosis					0.40			0.15	0.30	-1.27
Right kurtosis						0.79**		1.44	1.38	0.62
Baa-Aaa							-0.24**		-0.13	-0.02
Pseudo R^2	0.53	0.59	0.53	0.57	0.54	0.55	0.55	0.61	0.61	0.62

Distribution measures are included in the regression as they are calculated in equations (1)-(5). All regressors are standardized, except the lagged expansion indicator. I include two lags of the expansion indicator because it has a lower AIC score. For all other regressors, I include its contemporaneous and one lagged values. The coefficients reported are the sum of all coefficients associated with a particular regressor. Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

deviations in financial skewness sustained over the previous and current quarters implies a 52% probability of recession in the current quarter.[11]

2.3 Financial Skewness is a Powerful Predictor of Business Cycles

The following features are common to all regressions in this section: (i) I restrict the sample to the period 1973:Q1-2015:Q2, as some of the best-performing competing variables are not available before this period; (ii) I standardize all regressors, thus enabling the comparison between regression coefficients; and (iii) for a variable Y_t, I forecast $Y_{t+h|t-1}$ at time t, where

$$Y_{t+h|t-1} = \begin{cases} \frac{400}{h+1} \ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right), & \text{if } Y_t \text{ is nonstationary,} \\ Y_{t+h}, & \text{if } Y_t \text{ is stationary.} \end{cases}$$

[11] For this computation, I use the estimates of specification (9) and assume that (i) financial skewness equals to minus 2, (ii) expansion lag is 1, and (iii) all remaining regressors are at their historical mean values.

Thus, for instance, I forecast the mean annualized real GDP growth h quarters ahead, while I forecast the level of the unemployment rate h quarters ahead. Finally, I consider several competing variables to financial skewness. Besides financial and nonfinancial distribution measures (1)-(5), I use (i) financial uncertainty (Ludvigson et al. (2016)), proxying for aggregate uncertainty from financial markets; (ii) GZ-spread (Gilchrist and Zakrajsek (2012)), representing the large literature on corporate credit spreads; (iii) term spread, measured by the difference between the 10-year Treasury constant maturity and the three-month Treasury bill rates; and (iv) the real fed funds rates, measuring the current monetary policy stance. For short, I refer to variables (i)-(iv) as *economic predictors.*

2.3.1 In-Sample Predictive Regressions on Economic Activity

In this section, the general form of the in-sample regressions is

$$\underbrace{Y_{t+h|t-1}}_{\text{economic activity measure}} = \alpha + \underbrace{\sum_{i=1}^{p} \rho_i Y_{t-i|t-i-1}}_{\text{lagged forecasted variable}} + \underbrace{\sum_{k=1}^{5}\sum_{j=0}^{q} \beta_j^k M(k)_{t-j}}_{\text{distribution measures}} + \underbrace{\sum_{j=0}^{q} \gamma_{\mathbf{j}} \mathbf{z_{t-j}}}_{\text{economic predictors}} + e_{t+h}. \quad (6)$$

I focus on predictions for four quarters ahead ($h = 4$). Also, I make $p = 4$ because of the relatively high Akaike information criterion (AIC) of this specification and $q = 1$ to keep the model parsimonious. I calculate the elasticities of regressor variables by summing the coefficients of each regressor's contemporaneous and lagged values. Thus, if a regressor X_t has an elasticity of $C\%$ on dependent variable $Y_{t+h|t-1}$, a decrease of one standard deviation in X_t lasting periods t and $t-1$ should decrease $Y_{t+h|t-1}$ by $C\%$. Lastly, I compute standard errors using Hodrick (1992).

Table 3 reports the results of regression (6) on GDP growth, with financial skewness having a large explanatory power as well as a high elasticity on GDP growth. Table 3 focuses on unweighted distribution measures, with Table 3a showing the results of distribution measures of the financial firms' returns.[12] In Table 3a, column (1) represents the benchmark model only with lags of GDP growth ($\beta_j^k = \gamma_j = 0,\ \forall j, k$), while columns (2)-(10) represent models adding one variable at a time to the benchmark model. Comparing these 10 regressions, we see that financial skewness not only improves the benchmark's in-sample fit (R^2) by one of the largest amounts—20 percentage points—but also has the largest elasticity on GDP growth: a decline of one standard deviation of financial skewness lasting two consecutive quarters leads to a drop of 1.2% in the mean GDP growth over the next four quarters.

[12]Results for weighted measures are shown in Table 12 of Appendix A.3, with weighted financial skewness performing only slightly worse than nonweighted financial skewness.

Table 3: In-Sample GDP Forecast Regressions, Four Quarters Ahead, 1973–2015

(a) Financial Firms, Unweighted Distribution Measures

	Regressions Specifications											
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean		1.19***									0.73*	
Dispersion			-0.15*								1.07**	
Skewness				1.20***							1.60**	1.00***
Left kurtosis					0.71**						0.26	
Right kurtosis						0.46**					-1.06***	
Uncertainty							-0.46**					0.24
Real fed funds								-0.44				0.18
Term spread									0.92***			1.03***
GZ spread										-0.55**		-0.49
R^2	0.08	0.29	0.11	0.28	0.17	0.11	0.19	0.12	0.28	0.23	0.40	0.54

(b) Nonfinancial Firms, Unweighted Distribution Measures

	Regressions Specifications											
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean		1.11***									1.40***	0.57**
Dispersion			-0.15								0.01	
Skewness				0.61***							-1.98**	
Left kurtosis					0.38***						1.16	
Right kurtosis						0.43***					1.02	
Uncertainty							-0.46**					0.10
Real fed funds								-0.44				0.06
Term spread									0.92***			0.96***
GZ spread										-0.55**		-0.67
R^2	0.08	0.24	0.09	0.15	0.13	0.12	0.19	0.12	0.28	0.23	0.26	0.47

This table reports the results from regressions (6) on average GDP growth four quarters ahead ($h = 4$), with p equal to 4 because of the relatively low AIC of this specification, and q equal to 1 to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core inflation from the personal consumption expenditures. The elasticities of regressor variables reported above are calculated by summing the contemporaneous and lagged coefficients of each regressor, $\left\{\beta^k = \sum_{j=0}^{q} \beta_j^k\right\}_{k=1}^{5}$ and $\gamma = \sum_{j=0}^{q} \gamma_{\mathbf{j}}$. Coefficients of lagged GDP growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

I then show that the predictive ability of financial skewness is robust to the inclusion of other regressors. To avoid having an excessively large number of regressors, I proceed in two steps. First, I include all financial distribution measures in one regression (column (11) in Table 3a). The results show that financial skewness is statistically significant and has the highest elasticity on GDP growth, 1.6%. Then, I include financial skewness in a regression with all economic predictors (column (12) in Table 3a). Financial skewness remains statistically significant and has one of the largest elasticities, 1%—a number somewhat smaller than the ones from regressions (4) and (11).

Financial skewness also explains future GDP growth better than nonfinancial distribution measures. Regressions (2)-(6) of Table 3b add one nonfinancial distribution measure at a time to the benchmark model, regression (1). The R^2s and elasticities from these regressions are lower than those from the analogous regression with financial skewness (regression (4) of Table 3a). Turning to the regressions with all nonfinancial measures (column (11)) and all economic predictors (column (12)), even the nonfinancial measure with the largest and intuitive elasticities—the mean—has these elasticities being lower that those associated with financial skewness in analogous regressions (columns (11)-(12) of Table 3b relative to column (11)-(12) of Table 3a).

Table 3 shows that the economic predictors' regression estimates are broadly consistent with results from other papers. In regressions (7)-(10), the coefficients of most variables are statistically significant and with expected signs. For instance, a lower GDP growth is preceded by higher financial uncertainty, lower term-spreads, and higher corporate spreads. However, the coefficients of many of these variables, such as financial uncertainty and GZ-spread, either lose their statistical significance or have unintuitive signs in the larger specifications (12) of Tables 3a-3b. The only economic predictor with statistical significance in these larger regressions is term-spread. Moreover, the magnitude of the elasticity of term-spread is similar to the one of financial skewness.

Studying additional measures of economic activity, we learn that the predictive ability of financial skewness goes beyond GDP growth. Table 4 reports the results for the following variables: GDP, personal consumption expenditures, private fixed investment, total hours worked, and unemployment rate. Table 4b focuses on the results of regressions that use financial skewness as a predictor variable. Row (a) shows estimates from benchmark regressions only with lagged predicted variables, while rows (b) and (c) show the results for regressions that add financial skewness to the benchmark. These first three rows document that financial skewness adds about 10% to 25% of explanation power to future economic activity and has statistically and economically significant elasticities, such as 3.9% on investment. Rows (d) through (i) present the results of regressions adding both financial skewness and economic predictors to benchmark regressions. In all of these regressions, financial skewness remains statistically significant and has one of the largest elasticities, with these elasticities being of sizable magnitudes.

Finally, financial skewness also performs better than other distribution measures across many activity indicators. Given the large literature on dispersion measures, I focus on results comparing dispersion and skewness measures. Table 4b shows the results of financial skewness, Table 4c of financial dispersion, Table 4e of nonfinancial skewness, and Table 4f of nonfinancial dispersion. By comparing these tables, we first notice that financial skewness is the distribution measure that adds the most explanatory power to predicted variables (row

Table 4: In-Sample Forecast Regressions, Macro Variables, Four Quarters Ahead, 1973–2015

(a) Notation			(b) Variable = Financial Skewness					(c) Variable = Financial Dispersion				
			GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
(a)	Benchmark	R^2	0.08	0.22	0.21	0.17	0.54	0.08	0.22	0.21	0.17	0.54
(b)	Bivariate	Variable	1.20***	0.64***	3.89***	1.67***	-0.75***	-0.15*	0.13**	-0.77***	-0.72***	0.51***
(c)		R^2	0.28	0.31	0.39	0.41	0.67	0.11	0.25	0.26	0.26	0.62
(d)	Multivariate	Variable	1.00***	0.71***	2.72***	0.89**	-0.59***	-0.29	-0.18	-0.91	-0.35	0.43**
(e)		Uncertainty	0.24	0.26	0.50	-0.13	0.07	0.23	0.25	0.53	-0.12	-0.03**
(f)		Real fed funds	0.18	0.36**	-0.83	-0.45	0.15	0.07	0.25	-1.14	-0.52	0.14
(g)		Term spread	1.03***	0.84***	2.76***	0.87***	-0.36***	1.04***	0.83***	2.83***	0.89***	-0.46***
(h)		GZ spread	-0.49	-0.25	-1.86	-0.94**	0.12**	-0.84**	-0.48*	-2.81**	-1.28**	0.34***
(i)		R^2	0.54	0.54	0.67	0.70	0.77	0.46	0.48	0.61	0.66	0.75

(d) Notation			(e) Variable = Nonfinancial Skewness					(f) Variable = Nonfinancial Dispersion				
			GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
(a)	Benchmark	R^2	0.08	0.22	0.21	0.17	0.54	0.08	0.22	0.21	0.17	0.54
(b)	Bivariate	Variable	0.61***	0.21***	2.11***	1.08***	-0.35***	-0.15	0.06	-0.62	-0.81***	-0.07
(c)		R^2	0.15	0.25	0.28	0.28	0.57	0.09	0.23	0.23	0.25	0.54
(d)	Multivariate	Variable	0.21	0.07**	0.79	0.38	-0.17	0.60**	0.47	1.90***	0.31**	-0.43***
(e)		Uncertainty	0.06	0.16	0.07	-0.31	0.17**	-0.06	0.05	-0.37	-0.36	0.27*
(f)		Real fed funds	0.02	0.21	-1.22	-0.54	0.24	-0.21	0.06	-2.01*	-0.72	0.40
(g)		Term spread	0.98***	0.78***	2.68***	0.86***	-0.39***	0.88***	0.74***	2.33***	0.76***	-0.21*
(h)		GZ spread	-0.74	-0.46	-2.42	-1.09*	0.29**	-1.21***	-0.80**	-3.99***	-1.44***	0.56***
(i)		R^2	0.45	0.48	0.61	0.66	0.72	0.49	0.50	0.65	0.67	0.74

This table reports the results from regressions (6) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$, $p = 4$ because of the relatively low AIC of this specification, and $q = 1$ to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core inflation from the personal consumption expenditures. The elasticities of regressor variables reported above are calculated by summing the contemporaneous and lagged coefficients of each regressor, $\left\{\beta^k = \sum_{j=0}^{q} \beta_j^k\right\}_{k=1}^{5}$ and $\gamma = \sum_{j=0}^{q} \gamma_{\mathbf{j}}$. Coefficients of lagged predicted variables are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

(c) of all tables). Then, we see that financial skewness also has the largest elasticities, both among the bivariate regressions (row (b) of all tables) and among the multivariate regressions (row (d) of all tables). In short, results from this section point to a powerful predictive ability of financial skewness on a broad range of measures of economic activity.

2.3.2 Out-of-Sample Predictive Regressions on GDP Growth

I then turn to a more stringent evaluation of the predictive ability of financial skewness by calculating out-of-sample forecasts of GDP growth. To focus on the performance of predictor variable X_t, I only include lags of GDP growth as additional regressors:

$$GDP^{X_t}_{t+h|t-1} = \alpha + \sum_{i=1}^{p} \rho_i GDP_{t-i|t-i-1} + \sum_{j=0}^{q} \theta_j X_{t-j} + u_{t+h}. \tag{7}$$

The details of the forecasts and their performance evaluation are as follows. I extend the list of predictor variables X_t beyond the ones in Section 2.3.1 by including Moody's Baa corporate yields minus 10-year Treasury yields (Baa-10y), Moody's Baa yields minus Moody's Aaa yields (Baa-Aaa), and macroeconomic uncertainty (Jurado et al. (2016)). I also use forecasts from regression (7) that only include lags of GDP growth ($\theta_j = 0,\ \forall j$), referring to these forecasts as GDP-AR. I determine the number of lags of GDP growth (p) and predictor variable X_t (q) by choosing the specification with the minimum AIC at each forecasting period. I use an expanding window of data with jump-off date 1986:Q1. I also add Consensus predictions to the list of forecasts to evaluate predictions from regressions (7) against forecasts that use a potentially wider information set.[13] Finally, I document the performance of different variables by computing ratios of root mean squared forecast errors (RMSFEs). I use financial skewness as the benchmark variable and refer to these ratios as relative root mean squared forecast error (R-RMSFE) of variable X_t. Values below 1 indicate that financial skewness performs better than variable X_t.

Figure 3 shows the R-RMSFEs from these forecasts, with financial skewness outperforming almost all variables. Figures 3a-3c focus on a set of selected predictor variables, providing R-RMSFEs for the full sample, recessions, and expansions. On the full sample (Figure 3a), R-RMSFEs are below 1 and statistically significant (estimates with circles) for almost all variables and horizons ($h = 2, 4, 6$).[14] Moreover, the magnitudes by which financial skewness

[13] Given that Consensus forecasts are released on the 10$^{\text{th}}$ of every month, I average forecasts from the last month of the quarter with those from the month right after the end of quarter. For performance evaluation, I compare the times series of Consensus forecasts directly against realized GDP growth data.

[14] To calculate statistical significance, I use the Diebold-Mariano test (Diebold and Mariano (1995)) on the difference between the RMSFE of the predictor variable and the RMSFE of financial skewness. I com-

Figure 3: Out-of-Sample Forecasts of GDP Growth, R-RMSFEs

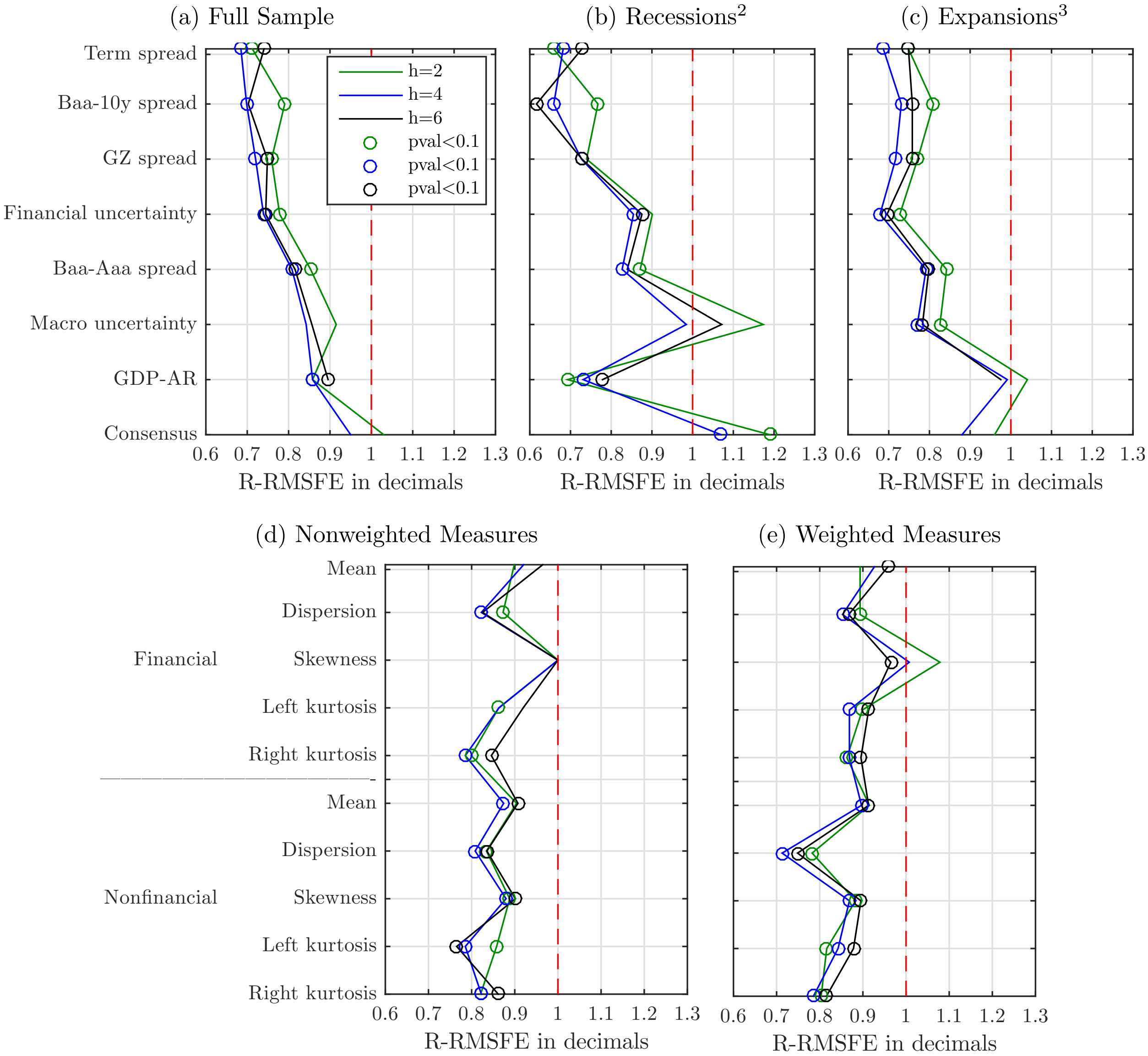


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis that the predictor variable and financial skewness have equal predictive power. Circles represent significance levels of at least 10 percent. [2]Recession R-RMSFEs are computed using forecast errors from forecasts estimated during a quarter classified by the NBER as a recession. [3]Expansion R-RMSFEs are analogous to recession R-RMSFEs.

outperforms other variables range from 8% to 32% of improvement. R-RMSFEs from expansions and recessions for selected variables (Figures 3b and 3c) yield results broadly similar to those from the full sample, with statistical significance slightly more frequent in expansions. Finally, Figures 3d and 3e show that financial skewness also outperforms almost all of the re-

pute this heteroskedasticity-autocorrelation (HAC) robust test by using the result from Kiefer and Vogelsang (2002). These authors show that using Bartlett kernel HAC standard errors without truncation yields the test distribution from Kiefer et al. (2000). Abadir and Paruolo (2002) provide critical values for this distribution.

Figure 4: Forecasts of GDP Growth Four Quarters Ahead, Rolling 20-Quarter R-RMSFEs

(a) R-RMSFE of Macro Uncertainty (b) R-RMSFE of Term-Spread

(c) R-RMSFE of GZ-Spread (d) R-RMSFE of Consensus

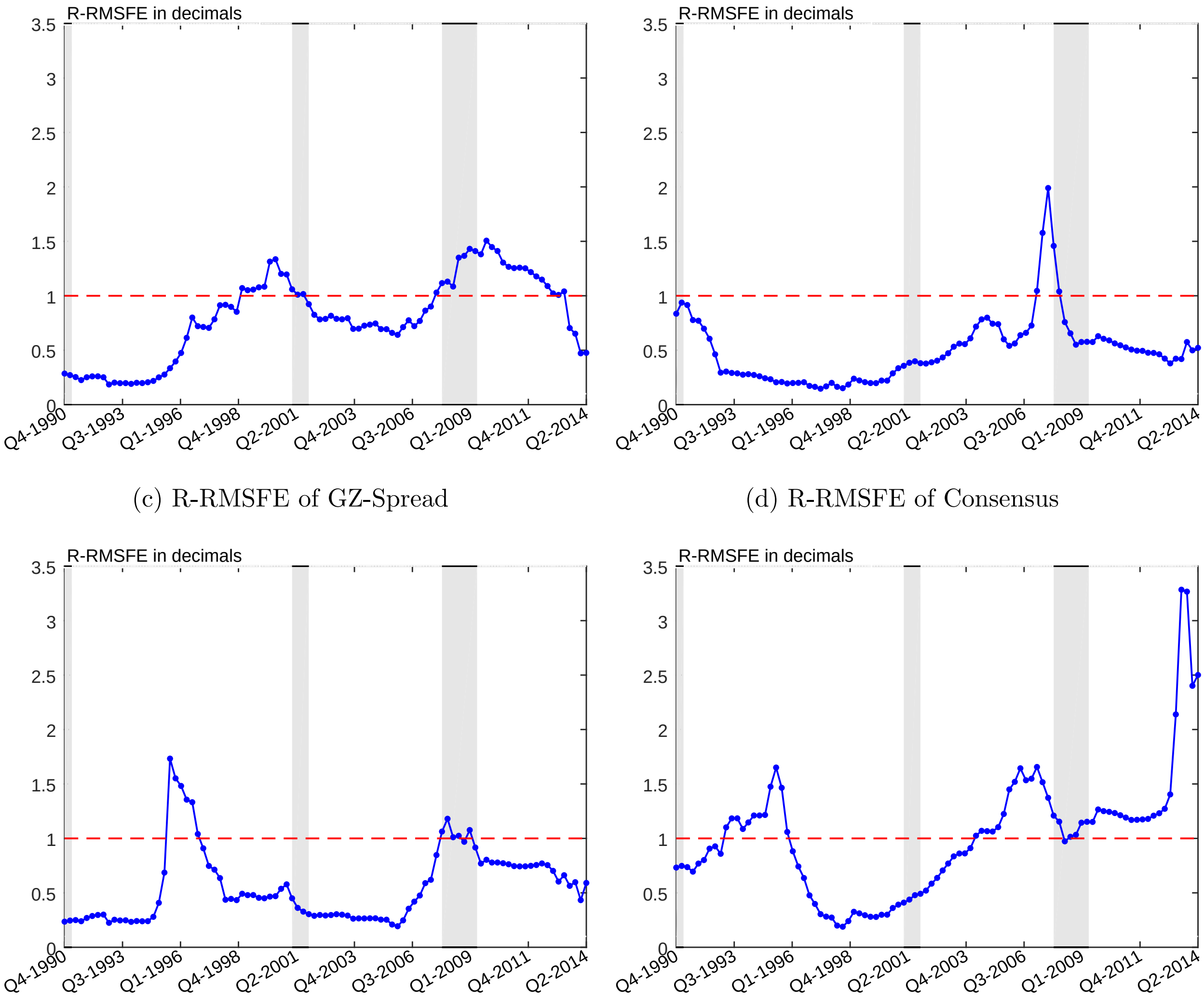


Figure 4 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) of variable X_t. At every quarter, I compute the R-RMSFE over the current and past 19 quarters. Rolling 20-quarter R-RMSFEs are reported in decimals.

maining distribution variables, either weighted or unweighted.

For the few variables for which the performance comparison with financial skewness is less straightforward, results still support the powerful predictive ability of financial skewness. For instance, financial skewness performs as well as Consensus in the full sample and for the forecast horizons available ($h = 2, 4$). Results are similar for expansions. In contrast, Consensus statistically outperforms financial skewness in recessions, especially for predictions for two quarters ahead. These results document that forecasts of financial skewness are most often comparable with those using a wide information set, even though forecasts of financial skewness come from a very simple model. The few other variables that outperform financial skewness do not achieve statistical significance (e.g., weighted financial skewness) and/or are statistically outperformed in one state of the cycle (e.g., macro uncertainty and GDP-AR).

Finally, I show that financial skewness has powerful predictive ability within the majority of the sample period. Figure 4 displays 20-quarter rolling R-RMSFEs for GDP growth four quarters ahead ($h = 4$), focusing on some well-known predictor variables: macro uncertainty (Figure 4a), term spread (Figure 4b), GZ spread (Figure 4c), and Consensus (Figure 4d). For most of the sample, Figures 4a-4c show that the rolling R-RMSFE stays below 1, indicating that the forecasts using financial skewness have a lower RMSFE than those from alternative variables. Although Figures 4a-4c point to some short-lived spikes to values higher than 1, these figures show that financial skewness performs better than the competing variables in many periods other than the Great Recession. Finally, Figure 4d shows financial skewness and Consensus alternating in outperforming each other, with financial skewness generally performing better in the first half of the sample.

3 Interpreting the Relationship between Financial Skewness and the Business Cycle

In this section, I provide evidence supporting the hypothesis that the tight relationship between financial skewness and the business cycle originates from the exposure of financial firms to the economic performance of their borrowers.

3.1 Financial Sector Diversifies Cross-Sectional Risks

The hypothesis above relies on the argument that financial firms focus on specific loan markets they expect to boost their equity returns, while diversifying idiosyncratic risks across markets. In turn, this partial diversification allows financial firms' stock returns to signal risks related to investment projects most impactful to the macroeconomy. I support this argument by showing that cross-sectional distributions of stock market returns of financial firms are less dispersed than those of nonfinancial firms, as well as less concentrated in the tails.

Table 5 reports time series averages of moments of cross-sectional distributions of stock market returns. Specifically, it reports these averages for returns of financial and nonfinancial firms during the periods 1926-2015 and 1947-2015. We see that in both sample periods returns are less dispersed (row (b), columns (3) and (6)) and less concentrated in the tails (rows (d)-(e), columns (3) and (6)) for financial firms relative to nonfinancial ones, while mean returns

Table 5: Time Series Averages of Distribution Measures (in percent)

		Sample 1926 - 2015			Sample 1947 - 2015		
		Financial	Nonfinancial	Difference	Financial	Nonfinancial	Difference
		(1)	(2)	(3) = (1) - (2)	(4)	(5)	(6) = (4) - (5)
(a)	Mean	3.3	3.7	-0.5	2.9	3.4	-0.5
(b)	Dispersion	36.5	49.2	-12.7***	35.8	58.8	-23.0***
(c)	Skewness	-0.4	-0.1	-0.3	-1.1	-2.0	0.9*
(d)	Left Kurtosis	-7.1	-9.0	1.9***	-7.9	-12.1	4.3***
(e)	Right Kurtosis	7.2	9.1	-1.9***	7.0	11.0	-4.0***

Time series averages reported in Table 5 are computed from unweighted distribution measures. Statistical significance tests the null hypothesis that cross-sectional moments are the same for returns from financial and nonfinancial firms, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01. Results are similar if computed for weighted distribution measures.

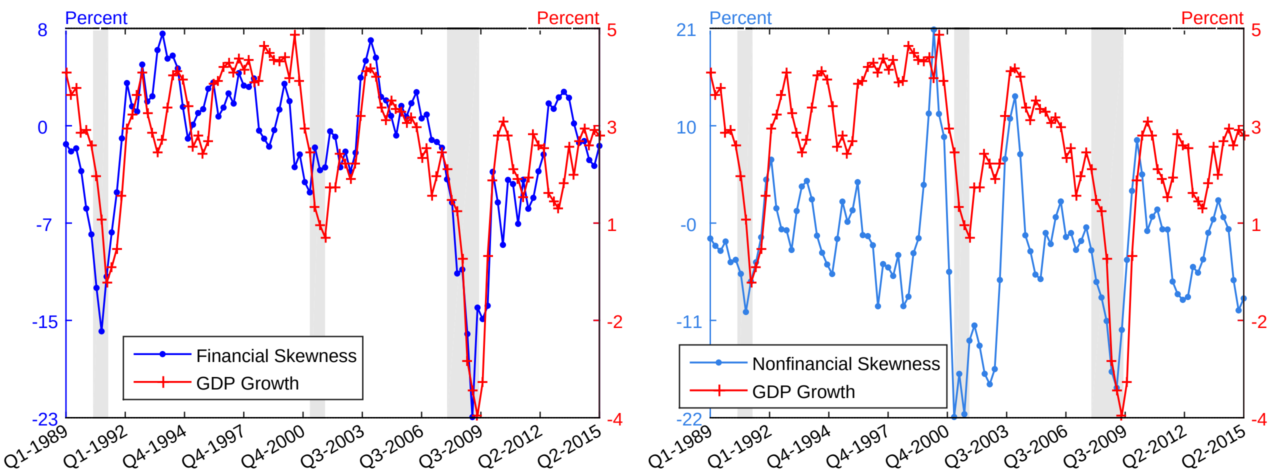
across financial firms are not statistically different from those across nonfinancial firms (row (a), columns (3) and (6)).

In Figures 5a and 5b, I illustrate how this partial diversification of risks allows financial skewness to better signal economic activity relative to its nonfinancial counterpart. These figures show the evolution of GDP growth and financial and nonfinancial skewness in the past three recessions. While financial skewness follows GDP growth very closely (Figure 5a), nonfinancial skewness is noisier and has peaks and troughs disproportional to the cyclical variation of GDP around the early 2000s recession (Figure 5b).[15]

Figure 5: Cross-Sectional Skewness and Last Three Recessions

(a) Financial Skewness

(b) Nonfinancial Skewness



Figures 5a and 5b show 4-quarter GDP growth and 4-quarter moving average of financial skewness (dark blue) and nonfinancial skewness (light blue). Gray areas represent periods classified as recessions by the NBER.

[15]These large increases and decreases in nonfinancial skewness around the early 2000s are present not only in the nonweighted nonfinancial skewness, but also in its weighted version and in the nonfinancial skewness measures calculated by Bloom et al. (2016).

One criticism about the results above is that they rely on the distribution of equity returns, while the hypothesis of the paper could be interpreted as more closely related to asset returns. However, combining results from Table 5 with the fact that financial firms are generally more leveraged than nonfinancial ones tells us that asset returns should also be less dispersed across financial firms relative to nonfinancial ones.

3.2 Financial Skewness Signals Financial Firms' Asset Quality

I then argue that financial skewness captures stock markets' views about the quality of financial firms' assets. If this hypothesis is correct, variables measuring the quality of financial firms' assets should then account for a considerable amount of the variation in financial skewness. Indeed, I show that 76% of the evolution of financial skewness in a recent sample is accounted for by two variables: return on average assets for banks (ROA) and changes in banks' lending standards.[16] Moreover, these two variables are released between one and one and a half months after the end of the quarter, indicating that financial skewness also anticipates information contained in these two variables.

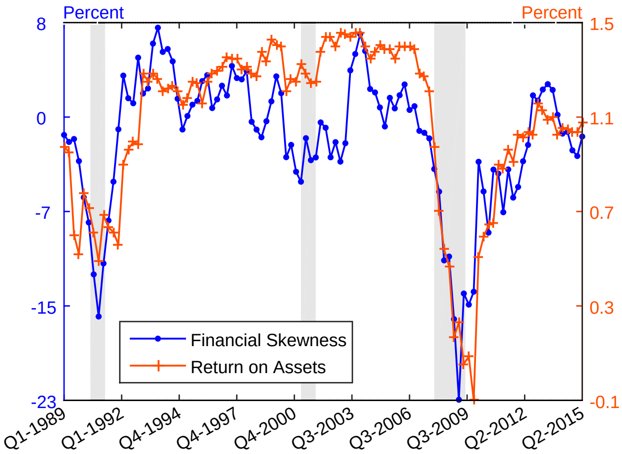
Figure 6 and Table 6 describe the key results from this section. Figures 6a and 6b display the series of ROA and changes in banks' lending standards to small firms (LSSF), respectively. These figures show a moderate amount of co-movement between these variables and the four-quarter moving average of financial skewness. Table 6a then measures these co-movements with simple univariate regressions. It shows that ROA explain 64% of the variation in financial skewness, while LSSF explains 41%. Changes in lending standards to medium and large firms (LSMLF) explain 34% of financial skewness, somewhat less than LSSF and consistent with financial firms providing more information about nonfinancial firms with less access to capital markets. Finally, the first column of Table 6b shows that a regression with ROA and LSSF explains 76% of the variation in financial skewness. This result is also shown in Figure 6c, where the fitted values of this last regression are plotted against financial skewness.

One concern about the results above is that ROA and LSSF may explain a large share of the variation in financial skewness mostly because they co-move with aggregate macroeconomic and financial conditions. To shed light on this issue, I add the following variables in the regressions on financial skewness: the Chicago Fed's Adjusted Financial Condition Index (AFCI), excess bond premium (EBP), VIX and Consensus forecasts for GDP growth for the

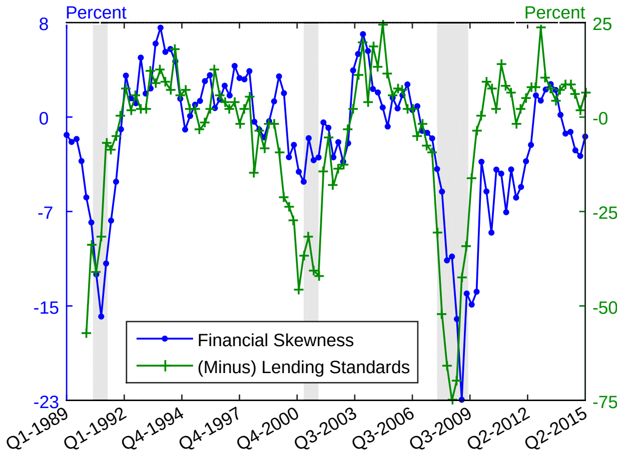
[16] More precisely, the variable is the net percentage of domestic banks tightening standards for commercial and industrial loans. The interpretation of banks' lending standards as being informative about financial firms' assets is based on the results of Basset et al. (2014). After accounting for endogenous responses to aggregate macro and financial conditions, the authors argue that changes in banks' lending standards reflect issues such as reassessments of the riskiness of certain loans and changes in business strategies.

Figure 6: Financial Skewness and Banks' Asset Quality

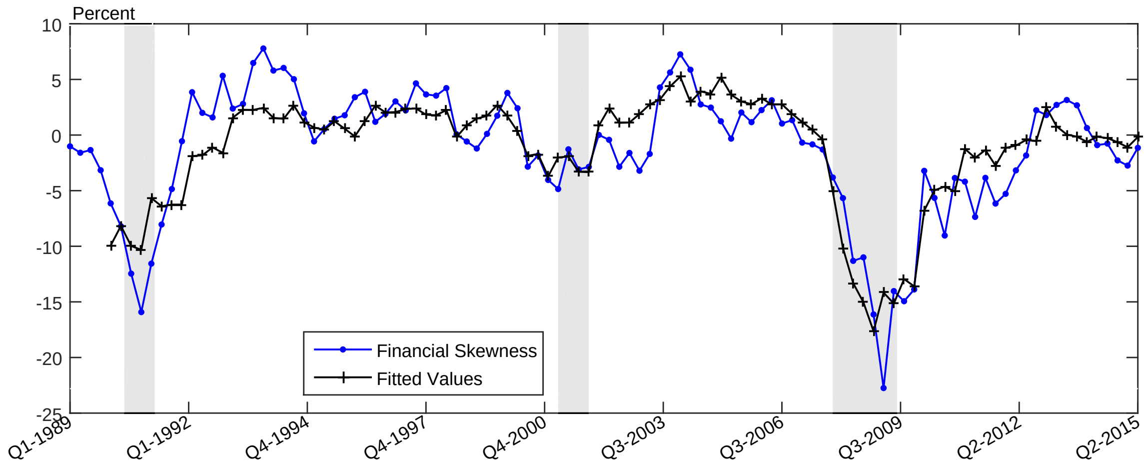
(a) Banks' Return on Assets



(b) Changes in Lending Standards for Small Firms



(c) Fitted Values from Banks' Return on Assets and Change in Lending Standards for Small Firms



All figures show the 4-quarter moving average of financial skewness in blue. Figure 6a plots in red the return on average assets for banks (ROA). Figure 6b plots in green the negative of the changes in banks' lending standards to small firms (LSSF). Figure 6c plots in black the fitted values of a regression using only the contemporaneous values of ROA and LSSF on the 4-quarter average of financial skewness.

current quarter and for the next four quarters ahead.[17] Table 6b provides the estimates, with all coefficients reflecting the fact that regressors are standardized within the sample. These estimates show that variables proxying macro and financial conditions add little explanatory power to a regression using ROA and LSSF. Moreover, Table 6b also shows that the coefficients of these macro and financial indicators are smaller than those from ROA and LSSF. Although

[17] Chicago Fed's Adjusted Financial Condition Index (AFCI) uses a large set of financial variables while purging out the influence of business cycle conditions (Brave and Butters (2011)). Excess bond premium (EBP) reflects liquidity risks and shifts in risk bearing capacity by financial firms (Gilchrist and Zakrajek (2012)) and credit market sentiment associated with credit booms and busts (Lopez-Salido et al. (2017)). VIX reflects not only uncertainty about the stock market, but also risk appetite (Bekaert et al. (2013)).

Table 6: Regressions on Financial Skewness

(a) Univariate Regressions

	ROA	LSSF	LSLMF	AFCI	EBP	VIX	Term Spread	$\text{GDP}^{\text{Consensus}}_{t\|t-1}$	$\text{GDP}^{\text{Consensus}}_{t+4\|t-1}$
	4.6***	-3.6***	-3.3***	-3.8***	-3.4***	-3.5***	-0.4	3.8***	3.6***
R^2	0.64	0.41	0.34	0.44	0.36	0.39	0.01	0.44	0.41

(b) Multivariate Regressions

		Variable:	AFCI	EBP	VIX	Term Spread	$\text{GDP}^{\text{Consensus}}_{t\|t-1}$	$\text{GDP}^{\text{Consensus}}_{t+4\|t-1}$
ROA	3.7***		3.5***	3.6***	3.5***	4.0***	3.4***	3.5***
LSSF	-2.1***		-1.6***	-1.6***	-1.4***	-1.9***	-1.8***	-1.9***
Variable			-0.8*	-0.7*	-1.3***	0.6**	0.8**	0.4
R^2	0.76		0.76	0.76	0.79	0.76	0.77	0.76

Regressions described in Tables 6a and 6b share the following features: sample period 1990Q1-2015Q2, standardized regressors within this sample, and 4-quarter moving average of financial skewness as the dependent variable. Table 6a describes the results from univariate regressions using contemporaneous column variables. The first column of Table 6b displays the results of a regression using contemporaneous values of ROA and LSSF. The remaining columns of Table 6b use as regressors the contemporaneous values of ROA, LSSF and the column variable. Statistical significance tests the null hypothesis that the coefficient associated to a regressor is zero, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01.

these results are consistent with macro and financial conditions accounting for some variation in financial skewness, they point to ROA and LSSF as being more prominent drivers.

3.3 Financial Skewness Anticipates Credit Market Conditions

Finally, if financial skewness anticipates economic activity because it signals the quality of projects being financed by the financial sector, it should then also anticipate future credit market conditions. Indeed, financial skewness not only leads several credit variables, but it also performs particularly well in explaining future loan growth, a market in which financial firms are expected to have comparative advantage in sorting borrower quality.

The empirical strategy of this section is similar to the one used in Section 2.3.1. I use regression specifications (6) with the following dependent variables at four quarters ahead (h=4): loan growth, debt growth, loan spread, GZ spread, and Baa-10y spread. I report results in Table 7 not only for financial skewness, but also for nonfinancial dispersion, given the relevance of the latter in the literature of time-varying uncertainty.[18] Row (a) reports estimates from benchmark regressions using only lagged predicted variables as regressors. Rows (b) and (c) report estimates from regressions with a distribution measure added to the benchmark regressions. Finally, rows (d) through (i) report estimates from regressions with a

[18] I report results for financial dispersion and nonfinancial skewness in Table 13 of Appendix A.3. The results for these measures have less clear patterns than those reported here.

Table 7: In-Sample Forecast Regressions, Credit Variables, Four Quarters Ahead, 1973–2015

(a) Notation	(b) Variable = Financial Skewness					(c) Variable = Nonfinancial Dispersion				
	Loans (%)	Debt (%)	Loan Sp (bp)	GZ Sp (bp)	Baa-10y (bp)	Loans (%)	Debt (%)	Loan Sp (bp)	GZ Sp (bp)	Baa-10y (bp)
Benchmark										
(a) R^2	0.57	0.40	0.88	0.84	0.78	0.57	0.40	0.88	0.84	0.78
Bivariate										
(b) Variable	2.93***	0.11	-7.95***	-11.18***	-17.69***	-1.85***	-0.82***	3.53*	7.01***	6.77***
(c) R^2	0.73	0.40	0.89	0.86	0.82	0.66	0.46	0.88	0.89	0.82
Multivariate										
(d) Variable	1.73**	-0.52	-6.66***	-7.79***	-12.87***	-0.16	-0.77***	-3.65	7.79***	3.07***
(e) Uncertainty	-0.35	0.51	4.64**	6.72***	6.27**	-0.62	0.80	9.33***	3.74***	7.16**
(f) Real fed funds	-0.59	0.53	-7.83	-4.12**	-3.15***	-0.89**	0.89	-8.57*	-4.67*	-2.39***
(g) Term spread	0.21	0.25	1.96	-0.76	-0.88**	0.14	0.41	0.33	-1.52	-1.28**
(h) GZ spread	-1.41	-1.56***				-1.92*	-0.95			
(i) R^2	0.79	0.55	0.91	0.88	0.86	0.76	0.57	0.90	0.90	0.86

This table reports the results from regression (6) on loan growth, debt growth, loan spread, GZ spread, and Baa-10y spread. Loan and debt are taken from the Flow of Funds, nonfinancial business balance sheet. Loan spread is from the Survey of Terms of Business Lending of the Federal Reserve. Loan, GZ, and Baa-10y spreads are used in levels. I use $h = 4$, $p = 4$ because of the relatively low AIC of this specification, and $q = 1$ to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core inflation from the personal consumption expenditures. Uncertainty refers to the financial uncertainty calculated by Ludvigson et al. (2016). The elasticities of regressor variables reported above are calculated by summing the contemporaneous and lagged coefficients of each regressor, $\left\{\beta^k = \sum_{j=0}^{q} \beta_j^k\right\}_{k=1}^{5}$ and $\gamma = \sum_{j=0}^{q} \gamma_{\mathrm{j}}$. Elasticities on loan and debt growth is expressed in percentage, while on spreads is in basis points. Coefficients of lagged predicted variables are ommitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

distribution measure and all control variables.

Table 7b describes the estimates from the regressions using financial skewness. The best results are achieved for loan growth. Financial skewness adds 16% of explanatory power to the benchmark regression and has an elasticity of 1.7% in the regression with all controls, meaning that a decline of one standard deviation of financial skewness lasting two consecutive quarters anticipates a drop of 1.7% in mean loan growth over then next four quarters. Although financial skewness does not add much explanatory power to loan, GZ, and Baa-10y spreads, it has significant elasticities on these variables in the presence of all controls. Finally, financial skewness neither adds explanatory power to debt growth nor has a significant effect on it.

Relative to financial skewness (Table 7b), nonfinancial dispersion (Table 7c) is equally or more informative about debt market variables, while being equally or less informative about loan market variables. To see this, first notice that nonfinancial dispersion adds 6% of explanatory power to the benchmark regression on debt growth and has a statistically significant elasticity of 0.8% in the analogous regression with all controls. This result contrasts with the poor performance of financial skewness on debt growth. Second, nonfinancial dispersion has an explanatory power to corporate spreads (GZ and Baa-10y) similar to financial skewness, while having a smaller coefficient on Baa-10y. Finally, nonfinancial dispersion has insignificant coefficients on both loan growth and loan spreads in the regressions with all controls.

4 Identifying Financial Skewness Shocks

In this section, I identify financial skewness shocks by estimating BVARs and a new Keynesian DSGE model with the financial accelerator channel (Bernanke et al. (1999)). The choice for this DSGE model is because of its explicit predictions for the endogenous behavior of the cross-sectional distribution of returns (Ferreira (2016)), its success in explaining the co-movement between macro and financial variables with cross-sectional shocks (Christiano et al. (2014)), and its wide use among academics and policymakers. Both the DSGE model and BVARs find that financial skewness shocks are important sources of business cycles.

4.1 DSGE Model with Financial Accelerator Channel and Cross-Sectional Skewness Shocks

Entrepreneurs and Skewness Shocks. There is a unit measure of entrepreneurs. At the end of period t, entrepreneur i with amount of equity N^i_{t+1} gets a loan (B^i_{t+1}, Z^i_{t+1}) from a mutual fund, where B^i_{t+1} is the loan amount and Z^i_{t+1} is the interest rate. With loan B^i_{t+1} and equity N^i_{t+1}, entrepreneur i purchases physical capital $\overline{K}^i_{t+1}$ with unit price Q_t in competitive markets. He then totals an amount of assets of $Q_t\overline{K}^i_{t+1} = N^i_{t+1} + B^i_{t+1}$. In the beginning of period $t+1$, entrepreneur i draws an exogenous idiosyncratic return ω_{t+1} only observable by him, which transforms $\overline{K}^i_{t+1}$ into $\omega_{t+1}\overline{K}^i_{t+1}$ efficient units of physical capital. I interpret each entrepreneur as the aggregate of a financial firm and its debtors. In this interpretation, ω_{t+1} measures the idiosyncratic risk of specific loan markets to which a financial firm is exposed.

To allow for both cross-sectional dispersion and skewness shocks, I model ω_t as i.i.d. across entrepreneurs and following a time-varying mixture of two lognormal distributions:

$$\omega_t \sim F_t(\omega_t; m^1_t, s^1_t, m^2_t, s^2_t, p^1_t) = \begin{cases} p^1_t \cdot & \Phi\left[(\log(\omega_t) - m^1_t)/s^1_t\right] \\ +(1-p^1_t)\cdot & \Phi\left[(\log(\omega_t) - m^2_t)/s^2_t\right] \end{cases}, \tag{8}$$

where F_t is the cumulative distribution function (cdf) of ω_t, Φ is the cdf of a standard normal, and $m^1_t, s^1_t, m^2_t, s^2_t$ and p^1_t are time-varying exogenous parameters. This approach is particularly useful because it encompasses the lognormal distribution, often used in the literature.

To focus the analysis on dispersion and skewness shocks, I make two normalizations on the mixture F_t. First, I re-parametrize it by picking m^2_t and p^1_t such that $\mathbb{E}_t(\omega_t) = \int_0^\infty \omega dF_t(\omega) = 1$

Figure 7: Distribution of Idiosyncratic Asset Returns of the DSGE Model

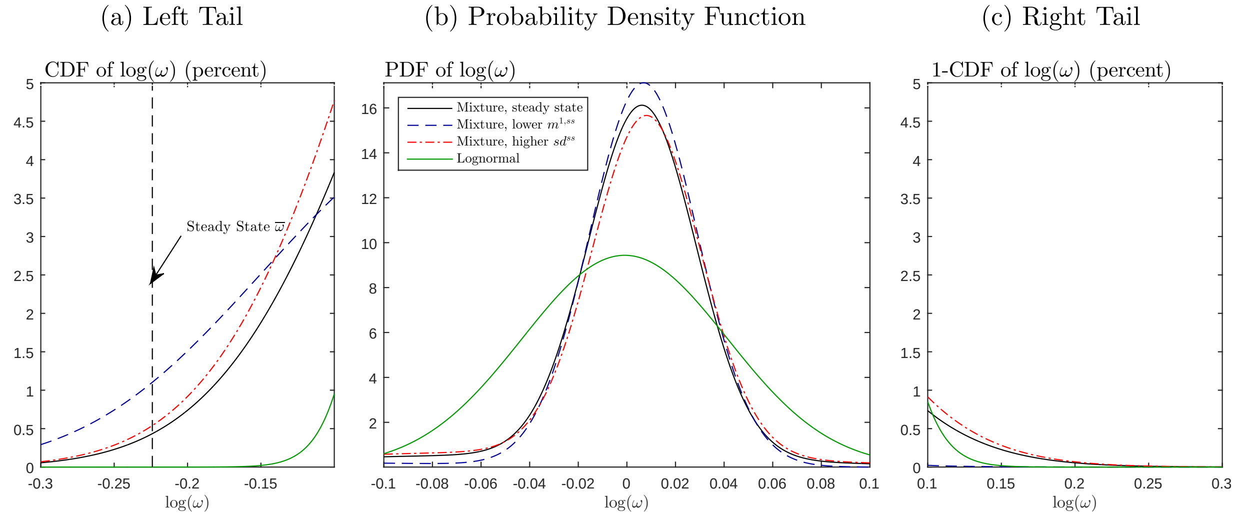


Figure 7a plots cumulative distribution functions (CDFs) of log(ω) under different assumptions. Analogously, Figure 7b plots probability density functions (PDFs) of log(ω) and Figure 7c plots complementary cumulative functions (1-CDFs) of log(ω). The black lines (Mixture, steady-state) plot the CDF/PDF/(1-CDF) of log(ω) when ω follows the steady-state distribution $F^{ss} = F(\cdot; m^{1,ss}, s^{1,ss}, sd^{ss}, s^{2,ss})$. The blue lines (Mixture, lower $m^{1,ss}$) plot the CDF/PDF/(1-CDF) of log(ω) when ω follows the distribution $F(\cdot; \widetilde{m}^{1,ss}, s^{1,ss}, sd^{ss}, s^{2,ss})$, where $\widetilde{m}^{1,ss} < m^{1,ss}$. The red lines (Mixture, higher sd^{ss}) plot the CDF/PDF/(1-CDF) of log(ω) when ω follows the distribution $F(\cdot; m^{1,ss}, s^{1,ss}, \widetilde{sd}^{ss}, s^{2,ss})$, where $\widetilde{sd}^{1,ss} > sd^{ss}$. The green lines (Lognormal) plot the CDF/PDF/(1-CDF) of log(ω) when ω follows a lognormal distribution with the same mean and standard deviation of F^{ss}.

and $\mathrm{Std}_t(\omega_t) = \int_0^\infty (\omega - \mathbb{E}_t(\omega_t))^2 \, dF_t(\omega) = sd_t$, for any given vector (m_t^1, s_t^1, s_t^2). Second, I fix the s_t^1 and s_t^2 at their steady-state levels. In this way, sd_t measures the second moment of F_t, while a lower/higher m_t^1 makes F_t more negatively/positively skewed, as shown by the variations of F_t (blue and red lines) around its steady state F^{ss} (black line) in Figures 7a-7c. I then model sd_t and m_t^1 as first-order autoregressions (AR(1)) and name them cross-sectional dispersion and skewness shocks.[19]

During period $t+1$ and with $\omega_{t+1}\overline{K}_{t+1}^i$ efficient units of physical capital, entrepreneur i earns rate of return $\omega_{t+1}R_{t+1}^c$ on its purchased capital. To do so, first, he determines capital utilization u_{t+1} by maximizing profits from renting capital services $\omega_{t+1}\overline{K}_{t+1}^i R_{t+1}^k u_{t+1}$ to intermediate firms net of utilization costs $\omega_{t+1}\overline{K}_{t+1}^i P_{t+1} a(u_{t+1})$, where R_{t+1}^k is the nominal rental rate of capital, $a(u_{t+1})$ is a cost function,[20] and P_{t+1} is the nominal price level. Then, after goods production takes place, entrepreneur i receives the depreciated capital back from intermediate firms and sells it to households. Thus, $\omega_{t+1}R_{t+1}^c = \omega_{t+1}\frac{R_{t+1}^k u_{t+1} - P_{t+1}a(u_{t+1}) + (1-\delta)Q_{t+1}}{Q_t}$.

[19]Besides the wanted focus on dispersion and skewness shocks, I excluded kurtosis shocks from the DSGE model because of the empirical results discussed in Section 2, which show strong evidence of skewness dominating kurtoses measures in their association with the business cycle.

[20]Cost function $a(\cdot)$ is defined by $a(u_t) = \Upsilon^{-t}\frac{r^{k,ss}}{\sigma^a}\left[\exp\left(\sigma^a(u_t - 1)\right) - 1\right]$, where σ^a measures the curvature in the cost of adjustment of capital utilization, and Υ is explained later.

Loan Markets. At the end of period t, mutual funds compete in the loan market for entrepreneurs with equity level N^i_{t+1} by choosing loan terms (B^i_{t+1}, Z^i_{t+1}), where interest rate Z^i_{t+1} may vary with $(t+1)$'s state of nature. It is then easier to determine loan terms with the following change of variables: leverage $L^i_{t+1} = (Q_t\overline{K}^i_{t+1})/N^i_{t+1}$ and threshold $\overline{\omega}^i_{t+1}$, such that $Z^i_{t+1}B^i_{t+1} = \overline{\omega}^i_{t+1}R^c_{t+1}Q_t\overline{K}^i_{t+1}$ and $\overline{\omega}^i_{t+1}$ may also vary with $(t+1)$'s state of nature. Threshold $\overline{\omega}^i_{t+1}$ determines whether entrepreneur i is able to pay his debt. If $\omega_{t+1} \geq \overline{\omega}^i_{t+1}$, then entrepreneur i pays his lender the amount owed, $Z^i_{t+1}B^i_{t+1}$, and keeps the rest of his assets. Otherwise, entrepreneur i declares bankruptcy, and the lender seizes all remaining assets net of a proportional auditing cost: $(1-\mu)\,\omega_{t+1}R^c_{t+1}Q_t\overline{K}^i_{t+1}$, with $\mu \in (0,1)$.

Because entrepreneurs are risk neutral and only care about their equity holdings, mutual funds compete by seeking loan contracts that maximize entrepreneurs' expected earnings:

$$\mathbb{E}_t\left(\int_{\overline{\omega}^i_{t+1}}^{\infty}\left(\omega-\overline{\omega}^i_{t+1}\right)dF_{t+1}(\omega)\frac{R^c_{t+1}Q_t\overline{K}^i_{t+1}}{N^i_{t+1}}\right) = \mathbb{E}_t\left[\left(1-\Gamma_{t+1}(\overline{\omega}^i_{t+1})\right)R^c_{t+1}L^i_{t+1}\right], \tag{9}$$

where $G_{t+1}(\overline{\omega}^i_{t+1}) = \int_0^{\overline{\omega}^i_{t+1}}\omega dF_{t+1}(\omega)$ and $\Gamma_{t+1}(\overline{\omega}^i_{t+1}) = (1-F_{t+1}(\overline{\omega}^i_{t+1}))\overline{\omega}^i_{t+1} + G_{t+1}(\overline{\omega}^i_{t+1})$.

In order to finance their loans, mutual funds can only issue noncontingent debt to households at the riskless interest rate R_{t+1}. As a result, in every contract between mutual funds and entrepreneurs with equity level N^i_{t+1}, revenues in each state of nature of period $t+1$ must be greater than or equal to the amount owed to households:

$$(1-F_{t+1}(\overline{\omega}^i_{t+1}))B^i_{t+1}Z^i_{t+1} + (1-\mu)G^f_{t+1}(\overline{\omega}^i_{t+1})R^c_{t+1}Q_t\overline{K}^i_{t+1} \geq R_{t+1}B^i_{t+1}. \tag{10}$$

We then normalize equation (10) by N^i_{t+1} and impose equality because competition in loan markets drives profits to zero. Finally, we determine loan contracts by choosing $(L^i_{t+1}, \overline{\omega}^i_{t+1})$ that maximizes (9) subject to the renormalized equation (10). Notice that this maximization does not depend on the level of equity N^i_{t+1} and, therefore, nor does its solution, thus allowing us to drop the i superscript. In turn, this solution implies that all entrepreneurs have the same market leverage, L_{t+1}, and face the same market threshold, $\overline{\omega}_{t+1}$.

At the end of period $t+1$, two additional events finally determine the entrepreneurial equity used to apply for new loans in the next period. First, a mass of (1-γ_{t+1}) entrepreneurs is randomly selected to transfer all of their assets to households, where γ_{t+1} is a white noise shock. Second, all entrepreneurs receive a lump-sum transfer of W^e_{t+1} from households. Then, we have the following law of motion for aggregate equity:

$$N_{t+2} = \gamma_{t+1}\left[1-\Gamma_{t+1}(\overline{\omega}_{t+1})\right]R^c_{t+1}Q_t\overline{K}_{t+1} + W^e_{t+1}, \text{ where } N_{t+2} = \int N^i_{t+2}\,di \text{ and } \overline{K}_{t+1} = \int \overline{K}^i_{t+1}\,di.$$

Cross-Sectional Distribution of Equity Returns. As shown by Ferreira (2016), we can calculate model counterparts of empirical measures (1) – (5). To do so, define the *gross realized equity return* of entrepreneur i at period t by X_t^i, such that

$$X_t^i = \begin{cases} \frac{\omega_t R_t^c Q_{t-1}\overline{K}_t^i - Z_t^i B_t^i}{N_t^i}, & \text{if } \omega_t R_t^c Q_{t-1}\overline{K}_t^i \geq Z_t^i B_t^i \\ 0, & \text{otherwise} \end{cases} = \begin{cases} [\omega_t - \overline{\omega}_t] R_t^c L_t, & \text{if } \omega_t \geq \overline{\omega}_t \\ 0, & \text{otherwise.} \end{cases}$$

For instance, cross-sectional skewness of the model can be calculated as $(\widetilde{x}_t^{95} - \widetilde{x}_t^{50}) - (\widetilde{x}_t^{50} - \widetilde{x}_t^{5})$, where $\widetilde{x}_t^v = \log(\widetilde{\omega}_t^v - \overline{\omega}_t)$ and $\widetilde{\omega}_t^v$ is the v^{th} percentile of distribution $F_t(\cdot|\omega_t > \overline{\omega}_t)$. The use of $F_t(\cdot|\omega_t > \overline{\omega}_t)$ is to match the fact that empirical measures (1) – (5) only use returns of non-bankrupt firms (i.e., strictly positive returns). Finally, cross-sectional distribution moments from the model are endogenous variables, as $\overline{\omega}_t$ is an endogenous variable.

Goods Production. A representative final goods producer uses technology $Y_t = \left[\int_0^1 Y_{jt}^{1/\lambda_t^f} dj\right]^{\lambda_t^f}$, and intermediate goods Y_{jt}, for $j \in [0,1]$, to produce a homogeneous good Y_t. Cost-push shock λ_t^f follows an AR(1) process. Intermediate producers' production function is $Y_{jt} = \epsilon_t K_{jt}^{\alpha}(z_t H_{jt})^{(1-\alpha)} - \phi z_t^*$, if $\epsilon_t K_{jt}^{\alpha}(z_t H_{jt})^{(1-\alpha)} > \phi z_t^*$. Otherwise, Y_{jt} equals zero. These producers rent capital services K_{jt} and hire homogenous labor H_{jt} in competitive markets. Additionally, ϵ_t represents an AR(1) productivity shock, z_t a permanent productivity shock with an AR(1) growth rate, and ϕ a fixed cost.[21] Shock z_t^* is explained below.

Intermediate producers monopolistically set their prices P_{jt} subject to Calvo-style frictions. Each period, a randomly selected fraction $(1 - \xi_p)$ of these producers chooses their optimal price, while the remaining ξ_p fraction follows an indexation rule $P_{j,t} = \widetilde{\Pi}_t P_{j,t-1}$, where $\widetilde{\Pi}_t = (\Pi_t^{tar})^{\iota_p} (\Pi_{t-1})^{1-\iota_p}$, Π_t^{tar} is an AR(1) inflation trend, $\Pi_{t-1} = P_{t-1}/P_{t-2}$, and $P_t = \left[\int_0^1 P_{jt}^{1/(1-\lambda_t^f)} dj\right]^{1-\lambda_t^f}$.

Final goods Y_t can be transformed by competitive firms into either investment goods, I_t, consumption goods, C_t, or government expenditures, G_t. Although Y_t is transformed into C_t and G_t with a one-to-one mapping, Y_t is transformed into $\Upsilon^t \zeta_t^q$ units of I_t, where $\Upsilon > 1$ and ζ_t^q is an AR(1) shock. Thus, P_t is the unit price of Y_t, C_t, and G_t, while $P_t/(\Upsilon^t \zeta_t^q)$ is the price of I_t. Finally, we also define $z_t^* = z_t \Upsilon^{\alpha/(1-\alpha)}$, $\mu_{z,t}$ as an AR(1) process for the growth rate of z_t, $\mu_{z,t}^*$ as an AR(1) process for the growth rate of z_t^*, μ_z^{ss} as the steady state of $\mu_{z,t}$ and $\mu_z^{*,ss}$ as the steady state of $\mu_{z,t}^*$.

Households. There is a large number of identical households, each able to supply all types of differentiated labor services h_{it}, for $i \in [0,1]$. At each period, members of each household

[21] The value of ϕ is chosen to ensure zero profits in steady state for intermediate producers.

pool their incomes, thus insuring against idiosyncratic income risk. Households choose their consumption C_t, investment I_t, savings B_{t+1}, and end-of-period-t physical capital $\overline{K}_{t+1}$, facing competitive markets. Underlying households' choices are the following preferences:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \zeta_t^c \left(\log\left(C_t - b\,C_{t-1}\right) - \psi_0 \int_0^1 \frac{h_{it}^{1+\psi_l}}{1+\psi_l} di \right), \tag{11}$$

where ζ_t^c is an AR(1) preference shock. I describe the labor supply decision below.[22]

After final goods are produced in each period t, households build physical capital $\overline{K}_{t+1}$ and sell it to entrepreneurs at unit price Q_t. To build $\overline{K}_{t+1}$, households purchase investment goods and the existing physical capital from entrepreneurs, $(1-\delta)\overline{K}_t$, where δ is the depreciation rate. The production function of capital is $\overline{K}_{t+1} = (1-\delta)\overline{K}_t + (1 - S(\zeta_t^i I_t/I_{t-1}))I_t$, where $S(\cdot)$ is an increasing and convex cost function with $S(1) = 0$, $S'(1) = 0$ $S''(1) = \chi > 0$, and ζ_t^i is an investment efficiency shock. Because it takes one unit of depreciated capital, $(1-\delta)\overline{K}_t$, to produce one unit of a new one, $\overline{K}_{t+1}$, the unit price of $(1-\delta)\overline{K}_t$ is also Q_t.

Finally, the households' budget constraint is

$$P_t C_t + B_{t+1} + (P_t/(\Upsilon^t \zeta_t^q))I_t \leq R_t B_t + \int_0^1 W_{it} h_{it}\, di + Q_t \overline{K}_{t+1} - Q_t(1-\delta)\overline{K}_t + D_t$$

where R_t is the risk-free interest rate paid on households savings, W_{it} is the nominal hourly wage for differentiated labor service h_{it}, and D_t represents all lump-sum transfers to and from households. The households' problem is then to choose C_t, B_{t+1}, I_t, and $\overline{K}_{t+1}$, maximizing (11) subject to the capital production function and to the budget constraint.

Labor Supply. A representative labor aggregator purchases differentiated labor services h_{it}, for $i \in [0,1]$, to produce homogeneous labor H_t. The labor aggregator uses technology $H_t = \left[\int_0^1 h_{it}^{1/\lambda^w} di\right]^{\lambda^w}$ and sells H_t to intermediate firms at price $W_t = \left[\int_0^1 W_{it}^{1/(1-\lambda^w)} di\right]^{1-\lambda^w}$. Unions then represent household members supplying the same type of differentiated labor h_{it} by monopolistically selling h_{it} to the labor aggregator. However, unions are subject to a Calvo-style friction. In each period, a randomly selected fraction $(1-\xi_w)$ of these unions chooses the optimal wage from the point of view of households. The remaining unions readjust their wages according to the rule $W_{it} = \widetilde{\Pi}_{w,t} W_{it-1}$, where $\widetilde{\Pi}_{w,t} = \left(\Pi_t^{tar}\right)^{\iota_w} \left(\Pi_{t-1}\right)^{1-\iota_w} \left(\mu_{z,t}^*\right)^{\theta} \left(\mu_z^{*,ss}\right)^{1-\theta}$.

[22] I choose ψ_0 such that $h_{it} = 1$ for all i at steady state.

Government and Resource Constraint. The central bank sets its policy rate R_t according to

$$\frac{R_t}{R^{ss}} = \left(\frac{R_{t-1}}{R^{ss}}\right)^{\rho_r} \left[\mathbb{E}_t \left(\frac{\Pi_{t+1}}{\Pi_t^{tar}}\right)^{\alpha_\pi} \left(\frac{\Pi_t^{tar}}{\Pi^{ss}}\right) \left(\frac{\Delta GDP_t}{\mu_z^{*,ss}}\right)^{\alpha_y}\right]^{(1-\rho_r)} \zeta_t^{mp},$$

where ΔGDP_t is the quarterly growth of GDP and ζ_t^{mp} is a monetary policy shock. Fiscal policy is represented by G_t following an AR(1) and by an equal amount of lump-sum taxes on the household. For simplicity, I assume that all auditing and capital utilization costs are rebated as lump-sum transfers to the household. This assumption captures the idea that these costs represent services provided by a negligible set of specialized agents who bring those earnings to the realm of the consumption smoothing decision. Therefore, I have the following resource constraint: $Y_t = C_t + I_t/(\Upsilon^t \zeta_t^q) + G_t$.

News Shocks. I allow for anticipated and unanticipated components on shocks to dispersion, sd_t, skewness, m_t^1, and monetary policy, ζ_t^{mp}. I then model these shocks as

$$\widehat{\zeta}_t = \rho_\zeta \, \widehat{\zeta}_{t-1} + \sum_{i=0}^{4} \xi_{i,t-i}^\zeta, \qquad \rho_{\zeta,\xi}^{|i-j|} = \frac{\mathbb{E}(\xi_{i,t}^\zeta \xi_{j,t}^\zeta)}{\sqrt{\mathbb{E}(\xi_{i,t}^\zeta)\mathbb{E}(\xi_{j,t}^\zeta)}}, \ \ i,j = 0,\ldots,4,$$

where $\widehat{\zeta}_t$ represents shocks ζ_t^{mp}, sd_t and m_t^1 in log-deviation from their means, and $\{\xi_{i,t}^\zeta\}_{i=0}^4$ measure disturbances observed by agents at time period t. I then denote $\xi_{0,t}^\zeta$ as the unanticipated disturbance to $\widehat{\zeta}_t$ and $\{\xi_{i,t-i}^\zeta\}_{i=1}^4$ as the anticipated ones, or news shocks. Disturbances $\{\xi_{i,t-i}^\zeta\}_{i=0}^4$ are i.i.d random variables orthogonal to $\{\widehat{\zeta}_{t-i}\}_{i=1}^\infty$, with zero mean and with $\mathbb{E}(\xi_{0,t}^2) = \sigma_\zeta^2$, $\mathbb{E}(\xi_{1,t}^2) = \ldots \mathbb{E}(\xi_{4,t}^2) = \sigma_{\zeta,\xi}^2$. Parameter $\rho_{\zeta,\xi}$ measures the correlation between $\xi_{i,t}^\zeta$'s.

4.2 DSGE Model: Data, Estimation, Priors, and Posteriors

The estimation of the DSGE model uses 14 financial and macroeconomic quarterly series for the period 1964:Q1–2015:Q2: real GDP, real consumption, real investment, hours worked, real wage, relative investment price, the fed funds rate, core inflation, real total credit, the real nonfinancial equity index, the spread between the Moody's Baa rate and the 10-year Treasury rate (Baa-10y), nonfinancial dispersion, financial skewness, and OIS expectation of the one-year-ahead fed funds rate.[23]

Motivated by a potential change in structural parameters after the Great Recession and

[23] Quantity variables, such as GDP and credit, are transformed to per capita quarterly growth rates. Price variables, such as real wages and relative investment price, are expressed in quarterly growth rates, as well as core inflation. See Appendix A.2 for details about data definitions and transformations. I include nonfinancial dispersion instead of the financial counterpart because of the evidence from Section 3.3 that it predicts debt growth. I then use total credit growth (loan and debt) to measure aggregate effects on credit.

Table 8: Parameters of the DSGE model

(a) Calibrated Parameters

Description	Name	Value	Description	Name	Value
Capital share in production	α	0.32	Steady-state mark-up of intermediate firms	$\lambda^{f,ss}$	1.2
Depreciation rate of capital	δ	0.025	Labor preference	ψ_l	1
Ratio of government expenditures to GDP	G^{ss}/Y^{ss}	0.19	Steady-state mark-up of labor unions	λ^w	1.05
Steady-state survival rate of entrepreneurs	γ^{ss}	0.975	Exogenous transfer to entrepreneurs[1]	w_e	0.005
Persistence of inflation trend	$\rho_{\pi^{tar}}$	0.975	Standard deviation of inflation trend	$\sigma^{\pi^{tar}}$	0.001

(b) Estimated Parameters

Description	Name	Prior distribution Shape	Mean	SD	Posterior distribution Mode	SD
Steady-state productivity growth[2]	$400\log(\mu_z)$	invg2	1.07	0.2	0.82	0.126
Investment-specific trend[2]	$400\log(\Upsilon)$	invg2	0.78	0.2	0.55	0.093
Preference discount rate[2]	$-400\log(\beta)$	invg2	1.06	0.2	0.88	0.124
Steady-state inflation rate[3]	$400\log(\Pi^{ss})$	invg2	2	0.3	1.99	0.324
Weight of GDP growth in wage indexation	θ	beta	0.5	0.15	0.69	0.176
Calvo parameter, intermediate firms	ξ_p	beta	0.5	0.1	0.86	0.005
Persistence of monetary policy rate	ρ_r	beta	0.75	0.1	0.78	0.018
Weight of inflation in policy rate	α_π	invg2	1.7	0.2	2.02	0.147
Weight of GDP growth in policy rate	α_y	beta	0.3	0.1	0.54	0.053
Investment adjustment cost	χ	invg2	11	5	4.21	0.306
Calvo parameter, labor unions	ξ_w	beta	0.75	0.1	0.92	0.011
Habit persistence	b	beta	0.5	0.075	0.89	0.005
Capital utilization cost	σ^a	invg2	2.5	2	2.01	0.713
Weight of inflation trend on inflation indexation	ι_p	beta	0.5	0.15	0.26	0.070
Weight of inflation trend on wage indexation	ι_w	beta	0.5	0.15	0.71	0.078
Auditing cost	μ	beta	0.275	0.05	0.18	0.031
Steady-state mixture probability of lognormals[4]	$p^{1,ss}$	beta	0.5	0.2	0.13	0.005
Steady-state location parameter of mixture[4]	$m^{1,ss}$	normal	0	0.2	-0.05	0.003
Steady-state scale parameter of mixture[4]	$s^{1,ss}$	invg2	0.2	0.1	0.10	0.004
Steady-state scale parameter of mixture[4,5]	$\alpha^{s^{2,ss}}$	beta	0.5	0.2	0.23	0.018
Shock autocorrelation: mark-up, intermediate firms	ρ_{λ_f}	beta	0.5	0.2	0.03	0.045
Shock autocorrelation: preference	ρ_{ζ_c}	beta	0.5	0.2	0.27	0.073
Shock autocorrelation: investment price	ρ_{ζ_q}	beta	0.5	0.2	0.998	0.002
Shock autocorrelation: investment efficiency	ρ_{ζ_i}	beta	0.5	0.2	0.98	0.002
Shock autocorrelation: government expeditures	ρ_{gov}	beta	0.5	0.2	0.95	0.014
Shock autocorrelation: transitory TFP	ρ_ϵ	beta	0.5	0.2	0.96	0.012
Shock autocorrelation: permanent TFP	ρ_{μ^*}	beta	0.5	0.2	0.25	0.063
Shock autocorrelation: cross-sectional dispersion	ρ_{sd}	beta	0.5	0.2	0.68	0.040
Shock autocorrelation: anticipated cross-sectional dispersion	$\rho_{sd,\xi}$	beta	0.5	0.2	0.53	0.163
Shock autocorrelation: cross-sectional skewness	ρ_{m1}	beta	0.5	0.08	0.90	0.006
Shock autocorrelation: anticipated cross-sectional skewness	$\rho_{m1,\xi}$	beta	0.5	0.2	0.23	0.049
Shock autocorrelation: anticipated monetary policy	$\rho_{mp,\xi}$	beta	0.5	0.2	0.83	0.044
Shock standard deviation: mark-up, intermediate firms	σ_λ	invg2	0.002	0.0033	0.103	0.0035
Shock standard deviation: preference	σ_c	invg2	0.002	0.0033	0.030	0.0014
Shock standard deviation: investment price	σ_q	invg2	0.002	0.0033	0.005	0.0002
Shock standard deviation: investment efficiency	σ_i	invg2	0.002	0.0033	0.388	0.0055
Shock standard deviation: government expeditures	σ_g	invg2	0.002	0.0033	0.029	0.0015
Shock standard deviation: transitory TFP	σ_ϵ	invg2	0.002	0.0033	0.008	0.0004
Shock standard deviation: permanent TFP	σ_{μ^*}	invg2	0.002	0.0033	0.015	0.0017
Shock standard deviation: cross-sectional dispersion	σ_{sd}	invg2	0.002	0.0033	0.037	0.0022
Shock standard deviation: anticipated cross-sectional dispersion	$\sigma_{sd,\xi}$	invg2	0.001	0.0012	0.0003	0.0002
Shock standard deviation: cross-sectional skewness	σ_{m1}	invg2	0.002	0.0033	0.046	0.0036
Shock standard deviation: anticipated cross-sectional skewness	$\sigma_{m1,\xi}$	invg2	0.001	0.0012	0.037	0.0010
Shock standard deviation: monetary policy	σ_{mp}	invg2	0.002	0.0033	0.001	0.0001
Shock standard deviation: anticipated monetary policy	$\sigma_{mp,\xi}$	invg2	0.001	0.0012	0.001	0.0001
Shock standard deviation: equity	$\sigma_{\gamma,e}$	invg2	0.002	0.0033	0.033	0.0017
Measurement error: dispersion	$\sigma_{disp,obs}$	invg2	0.005	0.01	0.003	0.0032
Measurement error: skewness	$\sigma_{skew,obs}$	invg2	0.005	0.01	0.015	0.0020
Measurement error: equity proportion[6]	Γ	invg2	1	0.5	0.23	0.007
Measurement error: equity[6]	σ_{eq}	invg2	0.001	0.05	0.092	0.0053
Measurement error: real wages	$\sigma_{w,obs}$	invg2	0.001	0.05	0.006	0.0004

All shock autocorrelations and standard deviations are estimated in 2 steps, as described in Section 4.2. Remaining parameters are fixed at the mode found in the estimation with the 1964-2006 sample (1st step). "invg2" is the inverse gamma distribution, type 2. [1]Steady-state $W^{e,ss}$ is calibrated as a percentage w_e of the steady-state capital stock K^{ss} (normalized by its growth trend). [2]These parameters are only estimated in the 2nd stage, while being fixed at their sample means during the 1st stage. [3]It is only estimated in the 1st step, being fixed at 2 in the 2nd step. [4]Although I renormalize F_t from $(m_t^1, s^{1,ss}, m_t^2, s^{2,ss}, p_t^1)$ to $(m_t^1, s^{1,ss}, sd_t, s^{2,ss})$, I pin down the steady state of F^{ss} by estimating $(m^{1,ss}, s^{1,ss}, s^{2,ss}, p^{1,ss})$, where $m^{2,ss}$ is such that $\int \omega dF^{ss}(\omega) = 1$. [5]To achieve identification, I estimate $s^{2,ss}$ as a percentage $\alpha^{s^{2,ss}}$ of $s^{1,ss}$. [6]I assume that observed equity growth is Γ times model equity growth plus a measurement error.

Table 9: Data Averages and Steady State Moments from the Model

Description	Model	Data
Consumption GDP ratio	0.55	0.55
Investment GDP ratio	0.26	0.25
Capital GDP ratio	9.03	10.9[a]
Inflation (APR)	2	3.41
Monetary policy interest rate	4	5.29
Leverage of entrepreneurs	5	1.7-15.3[b]

[a]From Christiano et al (2014). [b]These are aggregate measures, where the lower bond is for nonfinancial businesses and the upper bound is for the domestic financial sector. Source: Financial Accounts, Federal Reserve Board.

by the adoption of a more explicit guidance about future policy rates by the Fed, I use a two-step estimation procedure. In the first step, I estimate model parameters using data for the period 1964:Q1–2006:Q4, excluding OIS-rates and imposing a white noise structure on monetary policy shocks ζ_t^{mp}. I calibrate some model parameters, postulate priors for the remaining parameters, and then maximize the log-posterior of the model. In the second step, I re-estimate the persistence and standard deviation of all shocks, using data for the period 2002:Q1–2015:Q2, including OIS-rates and allowing for anticipated and unanticipated monetary policy shocks. Additionally, in the second estimation step, I (i) fix at the first-step mode all parameters not re-estimated in the second step, (ii) center the prior of re-estimated parameters on the first-step mode, (iii) choose the standard deviation of the prior of re-estimated parameters to be the standard deviation of the first-step posterior, and (iv) impose a zero auto-correlation ρ_{mp} for monetary policy shocks.[24] The focus of this two-step procedure on the persistence and size of economic shocks lowers the number of parameters estimated twice and is consistent with the evidence provided by Stock and Watson (2012). They argue that the 2008 recession was the result of large versions of shocks already experienced and that the response of macro variables was in line with historical standards.

Table 8 documents calibrated values as well as prior and posterior distributions of all parameters. Most estimated parameters are within the range of estimates reported in the literature. However, the parameters determining the steady-state distribution of idiosyncratic asset returns F^{ss} pin down a distribution markedly different from the lognormal case, which is largely assumed in the financial frictions literature. Figure 7 reports F^{ss} (black line) and a lognormal distribution with identical mean and standard deviation (green line). We then see that the tails of F^{ss} are much fatter than the ones of the lognormal distribution, especially the left one. Finally, Table 9 documents the steady state of several model variables, showing

[24]The reason for having an overlapping period between the samples used by the two estimation steps is to dilute the influence of a particular break-date. Additionally, I include measurement errors in real wage growth, equity growth, cross-sectional dispersion, and cross-sectional skewness.

that they are close to most of their data counterparts.[25]

4.3 The Primacy of Skewness Shocks in The DSGE Model

Skewness shocks are the most important driver of economic fluctuations in the DSGE model, as shown in the variance decomposition of Table 10. It shows that skewness shocks, anticipated and non-anticipated, account for 48% of fluctuations in GDP growth and similarly large numbers for other endogenous variables, such as 60% for investment growth, 41% for credit growth, and 66% for Baa-10y spread. We also see that the anticipated portion of shocks to skewness account for the majority of their explanatory power. Shocks to TFP, investment cost, equity, and monetary policy have moderate explanatory power for business cycles. In contrast, dispersion shocks become essentially irrelevant. Finally, the skewness measure is mostly exogenous, while dispersion is mostly endogenous.

Table 10: Variance Decomposition from the DSGE Model[1] (Percent)

	Shocks								
	Inv-Cost	TFP	Equity	MP	MP-News	Disp	Disp-News	Skew	Skew-News
Variables	ζ_t^i	ϵ_t, μ_t^*	γ_t	$\xi_{0,t}^{mp}$	$\{\xi_{i,t-i}^{mp}\}_{i=1}^4$	$\xi_{0,t}^{sd}$	$\{\xi_{i,t-i}^{sd}\}_{i=1}^4$	$\xi_{0,t}^{m^1}$	$\{\xi_{i,t-i}^{m^1}\}_{i=1}^4$
GDP[2]	12	18	1	0	15	0	0	7	41
Consumption[2]	26	17	2	0	13	0	0	5	32
Investment[2]	11	10	2	0	16	0	0	9	51
Credit[2]	33	7	9	0	7	0	0	6	35
Equity[2,3]	18	0	1	0	1	0	0	1	4
Baa-10y	29	0	2	0	2	0	0	16	50
Dispersion	53	1	3	0	3	11	4	4	19
Skewness	1	0	0	0	0	5	2	19	74

[1]Percentages do not add to 100 because remaining shocks account for the residual. [2]Variables used in four quarter growth. [3]Measurement error accounts for a large variability of this variable.

Figure 8 shows that skewness shocks are important economic drivers regardless of the state of the cycle. It shows both the data of GDP growth, investment growth, credit growth, and Baa-10y spread (in red) and how these variables would have evolved if only skewness shocks had impulsed the economy (in blue). The difference between the blue and red series is accounted for by the contribution of all the other shocks used in the estimation. We then see that skewness shocks were major contributors to all expansions and recessions throughout the period 1964–2015. We also see that variations in credit spreads are largely explained by skewness shocks and that these shocks account for low frequency movements in credit growth.

[25]Appendix A.4 also documents that the marginal likelihood of this DSGE model is close to the one from a BVAR with the same time series and sample period.

Figure 8: Shock Decomposition, 1964–2015

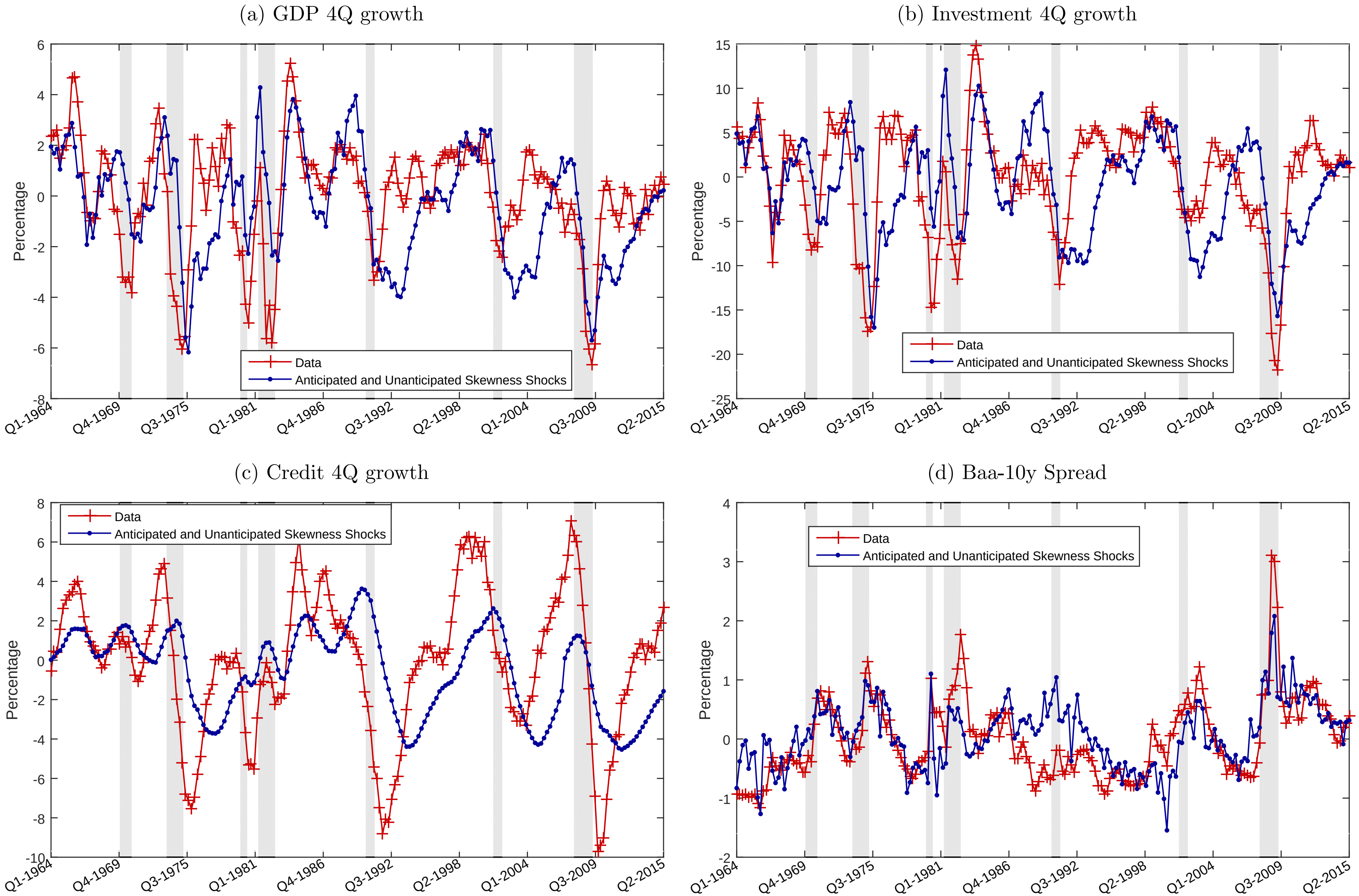
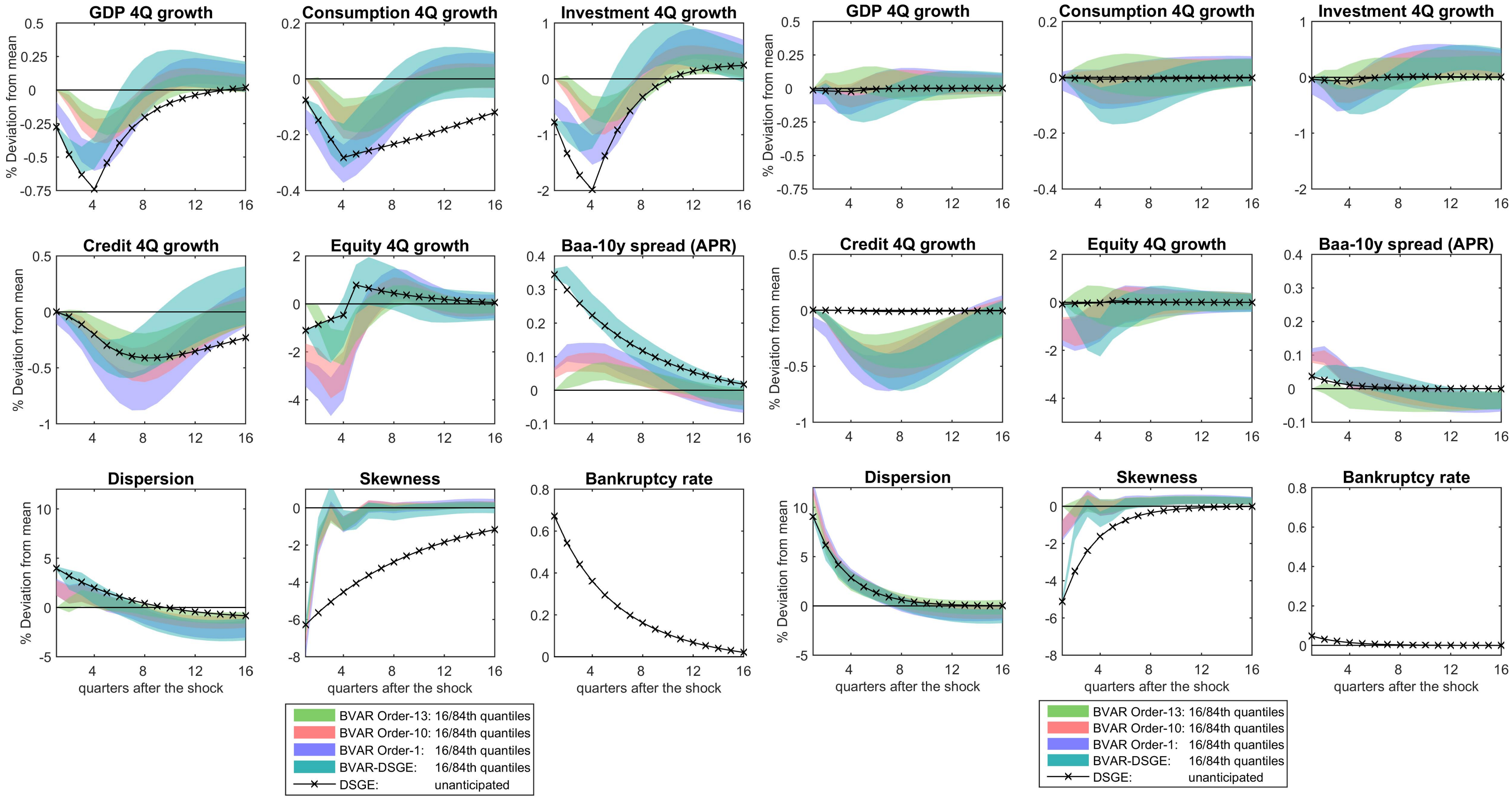


Figure 9: Impulse Response Functions from BVARs and DSGE model

(a) Skewness Shocks

(b) Dispersion Shocks



Impulse response functions (IRFs) in Figure 9 shed light on the reason skewness shocks are important drivers of business cycle fluctuations. Essentially, when cross-sectional skewness is exogenously lower, endogenous variables respond with co-movements generally observed over the cycle (black lines in Figure 9a): higher credit spreads and dispersion, and then lower credit, equity, investment, consumption, and GDP growth. Similarly to Christiano et al. (2014), most other shocks do not generate this entire set of co-movements, and thus are not able to account for large shares of business cycle fluctuations.[26] The exception to this argument in this paper are dispersion shocks, shown in Figure 9b.

The question then becomes why skewness shocks are more related to the business cycle than dispersion ones. The answer comes from comparing Figures 9a and 9b. Although IRFs to skewness and dispersion shocks follow qualitatively similar dynamics, skewness shocks cause much stronger effects to endogenous variables. A one standard deviation exogenous drop in skewness increases the Baa-10y spread by 35 basis points and dispersion by about 4.5% at their peaks, while it decreases credit growth by 0.4%, equity growth by 1%, investment growth by 2%, consumption growth by 0.3%, and GDP growth by 0.8% at their troughs. In contrast, these variables barely react to a one standard deviation exogenous increase in dispersion, with the exception of dispersion itself.

Skewness shocks have stronger effects on the economy than dispersion shocks because of two factors. First, entrepreneurial bankruptcy is more reactive to changes in skewness than to changes in dispersion. To see this argument at its simplest form, I ignore general equilibrium effects and (i) decrease by one standard deviation the steady-state value of the skewness parameter from $m^{1,ss}$ to $\widetilde{m}^{1,ss}$, (ii) keep fixed the threshold $\overline{\omega}^{ss}$ at its steady-state level as well as all the other parameters of F^{ss}, and (iii) graph the change in entrepreneurial bankruptcy (i.e., from $\mathrm{F}(\overline{\omega}^{ss}; m^{1,ss}, \cdot)$ to $\mathrm{F}(\overline{\omega}^{ss}; \widetilde{m}^{1,ss}, \cdot)$). I also implement an analogous exercise to steady-state cross-sectional dispersion sd^{ss}. Figure 7a displays these exercises. The comparison of the increase in bankruptcy due to changes in skewness and dispersion reveals a much higher elasticity to changes in skewness. The second factor is that skewness shocks m_t^1 are much more persistent than dispersion ones sd_t, as seen in Table 8b.

In general equilibrium, these two factors then increase the effects of skewness shocks, relative to dispersion ones, by amplifying the channel through which both of these shocks affect the economy. More specifically, there is a larger and more persistent increase in the mass of entrepreneurs with low asset returns and, in turn, higher and more persistent bankruptcy

[26] I report the IRFs of other shocks, including anticipated skewness shocks, in Appendix A.3. There we see that shocks such as investment efficiency have difficulty in matching co-movements of not only credit outstanding and credit spreads (as in Christiano et al. (2014)), but also of the series of cross-section dispersion and skewness.

losses (IRFs in lower right of Figures 9a and 9b); mutual funds magnify their decreases in the amount of credit and their increases in loan interest rates to compensate for these higher losses; equity drops more; and investment and GDP contract more decisively, which then lead to several other larger general equilibrium effects described by Figures 9a and 9b.

4.4 Identification of Shocks in the BVARs

In addition to estimating a DSGE model, I also identify financial skewness shocks using BVARs. The goal of using different frameworks is to reach robust conclusions about the importance of skewness shocks to business cycles as well as about the transmission of these shocks through the economy. I use the same data as in the estimation of the DSGE model (Section 4.2), except that I exclude OIS rates because they only start at 2002.[27]

In the BVARs, I identify unanticipated skewness shocks with four strategies: three different recursive orderings and one identification strategy based on the DSGE model. I define *Order-13* as the recursive ordering placing skewness last in the BVAR, thus allowing the remaining variables to react to a skewness shock only with one quarter of lag. I define *Order-10* as the ordering placing skewness before equity growth, Baa-10y spread, and dispersion, thus allowing these variables to react contemporaneously to a skewness shock, while only letting the remaining variables react to the shock with one quarter of lag. I also define *Order-1* as the ordering placing skewness as the first variable, thus allowing all remaining variables to react contemporaneously to a skewness shock.

The strategy for identifying skewness shocks based on the DSGE model is named *BVAR-DSGE* and it works as follows. I build a vector of contemporaneous responses of all BVAR variables to a skewness shock.[28] Then, I pin down the magnitude of the responses in this vector by using the contemporaneous responses of the same variables to an unanticipated skewness shock estimated by the DSGE model. For completeness, I also identify dispersion shocks using analogous recursive and *BVAR-DSGE* strategies.

The reason for using the *BVAR-DSGE* identification is to provide a cleaner comparison between the DSGE model and the BVARs. To see this, notice that the economic analysis of a shock in either the DSGE model or the BVARs may be divided in two components: the economic effects of the shock at the time period of its arrival (impulse), and the propagation of the impulse through the economy over time (propagation mechanism). Thus, when we compare, for instance, the IRFs to skewness shocks from the DSGE model with those from

[27] I use the BVAR with Minnesota prior and optimal shrinkage from Giannone et al. (2015).

[28] Uhlig (2005) shows that a sufficient condition to exactly identify a shock is to pin down a vector of contemporaneous responses of all BVAR variables to the desired shock.

recursive identifications, we compare not only different impulses, but also different propagation mechanisms. Alternatively, when we compare IRFs to skewness shocks from the DSGE model with those from the *BVAR-DSGE* identification, we focus only on the differences in propagation mechanisms.

4.5 DSGE Model and BVARs: The Prominence of Skewness Shocks

Skewness shocks have sizable and long-lasting economic effects, account for a relevant share of business cycles, and explain the majority of the fluctuations in financial skewness. I reach these conclusions by focusing on results from IRFs and variance decompositions that are robust across the DSGE model and the many identifications used in the BVARs.

More precisely, the conclusions above originate from three results. First, IRFs (Figure 9a) to unanticipated skewness shocks have a considerable effect on GDP growth, decreasing it for at least six quarters and by 0.3-0.8% at the troughs. Moreover, results for other measures of economic activity, such as consumption and investment, show similarly strong effects. Second, variance decompositions of GDP growth (Tables 10 and 11a) show that unanticipated skewness shocks account for 5-20% of the fluctuations in this variable, with shares for investment and consumption being of similar magnitudes. Third, variance decompositions of financial skewness show that it is largely an exogenous variable. Skewness shocks (anticipated and unanticipated) are responsible for almost all of the variance of financial skewness in the DSGE model (Table 10) and unanticipated skewness shocks explain between 54% to 74% in the BVAR's recursive identifications.

Table 11: Variance Decompositions from BVARs (Percent)

(a) Skewness Shocks

	Identifications			
Variables	Order-1	Order-10	Order-13	BVAR-DSGE
GDP[1]	20	7	5	9
Consumption[1]	19	6	4	6
Investment[1]	20	7	4	7
Credit[1]	20	9	5	5
Equity[1]	21	14	4	3
Baa-10y	16	8	4	39
Dispersion	13	7	3	8
Skewness	74	63	54	22

(b) Dispersion Shocks

	Identifications			
Variables	Order-1	Order-10	Order-13	BVAR-DSGE
GDP[1]	3	2	2	3
Consumption[1]	3	2	2	3
Investment[1]	5	3	2	4
Credit[1]	14	9	7	12
Equity[1]	4	3	2	3
Baa-10y	10	8	4	5
Dispersion	48	43	35	27
Skewness	6	5	2	31

[1]Variables used in 4 quarter growth.

In contrast, dispersion shocks have almost negligible economic effects, account for a very small share of business cycles, and explain only a modest share of the fluctuations in the observed dispersion measure. All of these conclusions are also robust across the DSGE model and the many identifications used in the BVARs. I reach these conclusions with the following three results: (i) IRFs to dispersions shocks are not different from zero (Figure 9b), (ii) the contribution of dispersion shocks to fluctuations in GDP, investment and consumption are 0-5% (Tables 10 and 11b), and (iii) dispersion shocks account for less than half of the fluctuations in the observed dispersion measure (Tables 10 and 11b).

4.6 The Transmission of Skewness Shocks

I then provide evidence that financial frictions is an important transmission channel of financial skewness shocks.

4.6.1 The Larger The Response of Credit Spreads, The Larger The Macro Effects

I do so by first showing that the larger the effect of skewness shocks on credit spreads, the larger the effect on economic activity. This result comes from looking at the IRFs in Figure 9a in the following progression of identification strategies: Order-13, Order-10, Order-1, BVAR-DSGE, and DSGE. First, we observe that the response of Baa-10y spread to skewness shocks is increasing in this progression of identifications, with the IRF peak increasing from 6 basis points to 35 basis points. Then, we observe an increasing response of economic activity in this progression of IRFs, with the trough of GDP growth decreasing from negative 0.3% to negative 0.8%. Investment and consumption growth also follow similar patterns.

Although the results above are consistent with financial frictions being a powerful amplifier of skewness shocks, they do not rule out other transmission channels for these shocks. For instance, the IRF of the Order-13 identification (Figure 9a) shows skewness shocks decreasing GDP growth by 0.3% while credit spreads only increase by 6 basis points, a result consistent with a nonfinancial transmission channel such as capital frictions (Ehouarne et al. (2015)).

4.6.2 Financial Accelerator Is Channel Mostly Consistent with The BVAR

I then provide further support for the importance of financial frictions in transmitting skewness shocks by showing evidence consistent with the financial accelerator channel of the DSGE model: After unexpected decreases in financial skewness, credit conditions tend to quickly tighten (lower credit and equity growth, and higher credit spreads), with investment and GDP contracting in the following quarters.

I provide the evidence above by comparing the IRFs to unanticipated skewness shocks estimated by the DSGE model with the IRFs identified by the BVAR-DSGE procedure.

Intuitively, this exercise compares the transmission of a specific financial skewness shock in two different model economies: one agnostically maximizing its data fit through a BVAR, and another that also maximizes its data fit while being restricted to have a financial accelerator channel. This comparison (Figure 9a) shows that IRFs of measures of economic activity (GDP, consumption, and investment) under the BVAR-DSGE identification are similar to those from the DSGE model, with the latter being somewhat larger. This comparison also shows that IRFs from the DSGE model for most financial variables (credit, equity, Baa-10y spread, and dispersion) often lie inside the probability intervals of the BVAR-DSGE IRFs.

Although the comparison of IRFs above provides support for the financial accelerator channel of financial skewness shocks, it also shows one limitation of this model. While it takes approximately only 3 quarters for financial skewness to return to its level prior to the shock in the BVAR-DSGE, it takes more than 16 quarters in the DSGE model. This discrepancy suggests that the DSGE model lacks an internal mechanism that can transmit skewness shocks throughout the economy for many periods after the shock dissipates.

5 Conclusion

In this paper, I argue that *financial skewness*—the cross-sectional skewness of the distribution of stock market returns of financial firms—is an empirical measure with considerable potential to both predict and explain business cycle fluctuations. I support this argument with three main results. First, using data from 1926 to 2015, I show that financial skewness not only closely track business cycles, but also predicts economic activity better than well-known indicators. Second, I provide evidence supporting the hypothesis that the predictive ability of financial skewness originates from the exposure of financial firms to the economic performance of their borrowers. Third, I show that shocks to financial skewness are important drivers of business cycles using both BVARs and a DSGE model.

This paper points to two avenues of future research. First, one investigating how high-order moments of asset prices may shed light on understanding business cycle fluctuations. Second, a research path in which the financial sector not only is the origin of shocks to the economy (e.g., the 1929 and 2008 financial crises), but also is well placed to efficiently signal shocks from other sectors. Thus, papers investigating these issues on additional asset prices, such as bonds, and theoretical models microfounding the signaling power of financial firms are important examples of tasks for future research.

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A Appendix

A.1 Classification: Financial and Nonfinancial Sectors

This section is reproduced from Ferreira (2016). In order to classify the firms as financial or non-financial, I use all the information available in the sample. On the one hand, CRSP provides the most recent U.S. Census classification, NAICS, and an older one, SIC. On the other hand, there is an SIC code for all firms, while the NAICS is available only for some. To avoid an outdated classification procedure of an ever-changing financial sector, I place an emphasis on the NAICS classification. Moreover, since this study focuses on private financial firms, I look for those with the following three-digit NAICS classifications: 522 (Credit Intermediation and Related Activities), 523 (Securities, Commodity Contracts, and Other Financial Investments and Related Activities), 524 (Insurance Carriers and Related Activities), and 525 (Funds, Trusts, and Other Financial Vehicles). With these issues in mind, I adopt the following classification procedure:

(a) for those firms with a NAICS code available, I classify:

  (a1) as financial those with codes 522, 523, 524, or 525;

  (a2) as nonfinancial those with codes other than those above;

(b) for those firms without a NAICS code, I use information from the U.S. Census website about bridging the two classifications to find the SIC codes associated with the 3-digit NAICS codes 522, 523, 524, or 525. Then, I follow procedures (a1) and (a2).

A.2 Data Used by BVAR and DSGE Models

1. Core inflation is calculated using the price index of personal consumption expenditures (PCE) that excludes food and energy.
2. Real GDP is calculated by deflating nominal GDP by the implicit GDP price index and by the population over 15 years old.
3. Real consumption is the sum of nominal PCE in services and non-durables, deflated by the PCE price index and by the population over 15 years old.
4. Real investment is the sum of nominal PCE in durables and nominal business investment, deflated by the business investment price index and by the population over 15 years old.
5. Real wage is measured by the hourly compensation of all employees in non-farm business, deflated by the core PCE price index.
6. Relative investment price is calculated as the ratio between the business investment price index and the core PCE price index.

7. Real credit is sum of loans (depository institutions loans nec, other loans and advances and total mortgages) and debt (commercial paper, municipal securities, corporate bonds) from the financial accounts (liabilities of nonfinancial businesses) published by the Board of Governors of the Federal Reserve System. It is then normalized by the core PCE price index and by the population over 15 years old.
8. Nonfinancial equity index is the cumulative weighted return of all nonfinancial firms, normalized by the core PCE price index and by the population over 15 years old.
9. Hours worked is measured by the aggregate weekly hours of production and non-supervisory employees in all private industries, divided by the population over 15 years old.
10. Fed funds rate is the average of the daily rates over the quarter.
11. Baa-10y spread is measured by the spread between the Moody's Baa rate and the 10-year Treasury rate.
12. Nonfinancial dispersion is calculated as described in Section 2.
13. Financial skewness are calculated as described in Section 2.

I then take the growth rates of variables (2)-(8), while keeping variables (9)-(13) at their quarterly levels. Finally, I demean these variables as follows: (i) for the period 1964-1985, I divide the variable by its mean within this subsample; (ii) for the period 1986-2015, I divide the variable by its mean within this subsample; and (iii) I splice the demeaned series from (i) and (ii). This demeaning procedure is done to account for the evidence that long-run growth for the United States has decreased since the 1960s and for the evidence of a structure break around 1985 due to the Great Moderation. Given that I include inflation trend in the dynamic stochastic general equilibrium (DSGE) model, I exclude inflation, fed funds, and OIS rates from this demeaning process.

A.3 Additional Results

Table 12: In-Sample GDP Forecast Regressions, Four Quarters Ahead, 1973–2015

(a) Financial Firms, Weighted Distribution Measures

	Regressions Specifications											
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean		1.01***									0.51**	
Dispersion			-0.42*								-0.15	
Skewness				1.11***							1.17***	0.92***
Left kurtosis					0.63						-0.38	
Right kurtosis						0.39***					-0.28***	
Uncertainty							-0.46**					0.08
Real fed funds								-0.44				0.02
Term spread									0.92***			1.04***
GZ spread										-0.55**		-0.50
R^2	0.08	0.23	0.13	0.26	0.13	0.11	0.19	0.12	0.28	0.23	0.32	0.53

(b) Nonfinancial Firms, Weighted Distribution Measures

	Regressions Specifications											
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean		0.94***									0.89***	0.61*
Dispersion			-0.30								-0.41	
Skewness				0.50**							-0.91	
Left kurtosis					0.47**						0.37	
Right kurtosis						0.51**					0.82	
Uncertainty							-0.46**					0.12
Real fed funds								-0.44				-0.01
Term spread									0.92***			0.98***
GZ spread										-0.55**		-0.69
R^2	0.08	0.21	0.11	0.12	0.12	0.12	0.19	0.12	0.28	0.23	0.26	0.49

This table reports the results from regression (6) on average GDP growth four quarters ahead ($h = 4$), with $p = 4$ because of the relatively low AIC of this specification, and $q = 1$ to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core inflation from the personal consumption expenditures. The elasticities of regressor variables reported above are calculated by summing the contemporaneous and lagged coefficients of each regressor, $\left\{\beta^k = \sum_{j=0}^{q} \beta_j^k\right\}_{k=1}^{5}$ and $\gamma = \sum_{j=0}^{q} \gamma_{\mathbf{j}}$. Coefficients of lagged GDP growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

Table 13: In-Sample Forecast Regressions, Credit Variables, Four Quarters Ahead, 1973–2015

(a) Notation			(b) Variable = Financial Dispersion					(c) Variable = Nonfinancial Skewness				
			Loans	Debt	Loan Sp(bp)	GZ Sp(bp)	Baa-10Y(bp)	Loans	Debt	Loan Sp(bp)	GZ Sp(bp)	Baa-10Y(bp)
(1)	Benchmark	R^2	0.57	0.40	0.88	0.84	0.78	0.57	0.40	0.88	0.84	0.78
(2)	Bivariate	Variable	-2.35***	0.18*	4.69***	-0.85***	6.99***	1.74***	0.29	-4.06*	-16.83***	-18.63***
(3)		R^2	0.69	0.41	0.89	0.88	0.82	0.64	0.40	0.88	0.87	0.83
(4)	Multivariate	Variable	-2.12*	0.69*	1.95	-4.89***	2.52***	0.35	-0.37	-2.21	-15.98***	-15.57***
(5)		Uncertainty	0.44*	0.28	5.79***	9.06***	6.66*	-0.68	0.65	6.20***	8.36***	8.57***
(6)		Real fed funds	-0.32	0.49	-8.87*	-1.41*	-2.67***	-0.88*	0.55	-5.53	-5.29**	-3.08***
(7)		Term spread	0.51	0.14	0.14	0.78	-1.74***	0.16	0.26	2.23	-2.04	-1.90**
(8)		GZ spread	-1.97**	-1.47***				-1.84	-1.56***			
(9)		R^2	0.81	0.56	0.90	0.89	0.86	0.76	0.55	0.90	0.89	0.87

This table reports the results from regression 6 on loan growth, debt growth, loan spread, GZ spread, and Baa-10y spread. Loan and debt are taken from the Flow of Funds, nonfinancial business balance sheet, levels. Loan spread is from the Survey of Terms of Business Lending of the Federal Reserve. Loan, GZ, and Baa-10y spreads are used in levels. I use $h = 4$, $p = 4$ because of the relatively low AIC of this specification, and $q = 1$ to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core inflation from the personal consumption expenditures. Uncertainty refers to the financial uncertainty calculated by Ludvigson et al. (2016). The elasticities of regressor variables reported above are calculated by summing the contemporaneous and lagged coefficients of each regressor, $\left\{\beta^k = \sum_{j=0}^{q} \beta_j^k\right\}_{k=1}^{5}$ and $\gamma = \sum_{j=0}^{q} \gamma_\mathbf{j}$. Elasticities on loan and debt growth is expressed in percentage, while on spreads is in basis points. Coefficients of lagged predicted variables are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that all coefficients associated to a regressor equal to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05, and 0.01.

A.4 The DSGE Model Is Statistically Comparable to BVAR

The first column of Table 14 shows that the marginal likelihood of the DSGE model from Section 4 is close to the one from a BVAR using the same time series and sample period (2002–2015). However, the second and third columns of Table 14 show that if we exclude OIS rates from the estimation of the DSGE model and focus on either the entire sample (1964–2015) or the pre-Great-Recession era (1964–2006), the marginal likelihood of the DSGE model becomes considerably lower than those from BVARs with identical data.

Table 14: Marginal Likelihood (Log Points)

Sample	2002-2015	1964-2006	1964-2015
DSGE[a]	2178	6154[b]	7374[b]
BVAR[c]	2158	6368	7672

[a]It is computed by the Modified Harmonic Mean method from a Markov Chain Monte Carlo with 2 blocks, each with 300,000 draws. [b] In these estimations, I use standard Bayesian methods without the two-step procedure used for the baseline model and exclude the OIS rates from the estimation. [c]It uses the exact same data as the DSGE model and it is computed from a BVAR with Minnesota prior and optimal shrinkage, as in Giannone et al (2015).

These results from Table 14 support the choice of Section 4's DSGE model and its estimation procedure as a reasonable starting point to study the transmission of skewness shocks through financial frictions. This argument is based on the fact that the performance of the DSGE model, relative to a BVAR, is best exactly when there is more evidence that financial frictions contributed to a cyclical downturn of the U.S. economy.

Figure 10: Impulse Response Functions