Stock Market Cross-Section Skewness and Business Cycle Fluctuations*

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Abstract

Using U.S. data from 1926 to 2015, I document that the cross-section skewness of the distribution of financial firms' returns, i.e., financial skewness, closely tracks business cycles and predicts economic activity better than well-known bond spreads, uncertainty measures, and other cross-section moments. I also find that financial skewness anticipates financial firms' asset quality and credit market conditions, such as banks' asset returns and loan growth. Finally, I identify financial skewness shocks using vector autoregressions and a dynamic stochastic general equilibrium model and show that these shocks are important drivers of business cycles, while dispersion shocks become unimportant. This paper's results are consistent with capital markets uncovering information about economic fundamentals through a channel not much explored by the macro-finance literature. Financial firms diversify away uninformative idiosyncratic risks through their asset portfolio choice, retain cleaner exposures to the overall quality of projects undertaken in the economy, and then signal the quality distribution of these projects through stock markets.

KEY WORDS: Cross-Section Skewness, Business Cycle Fluctuations, Financial Channel.

JEL CLASSIFICATION: C32, E32, E37, E44.

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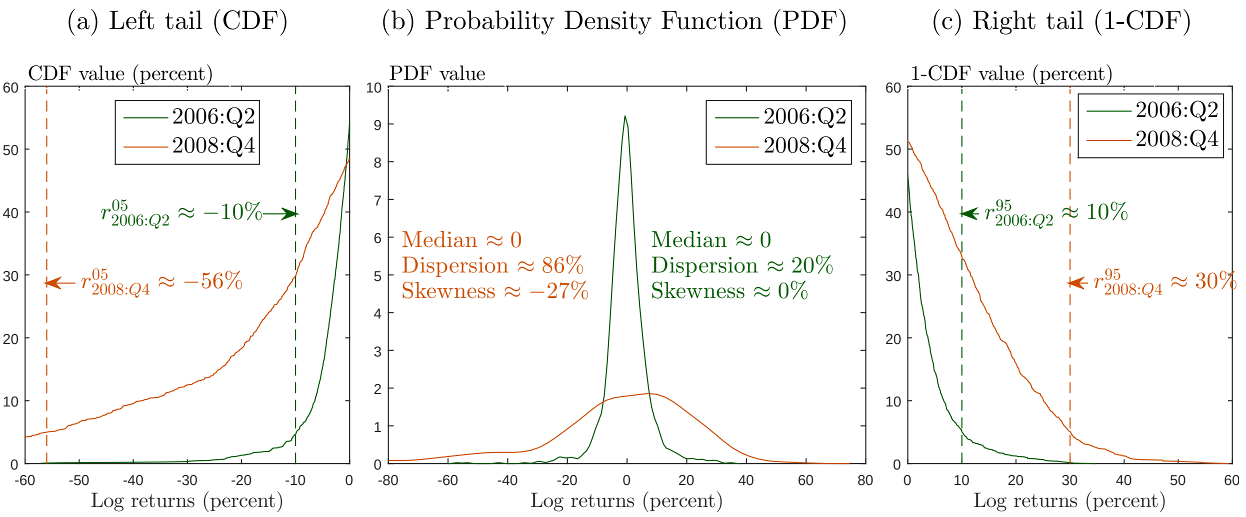
1 Introduction

Economists are constantly engaged in both predicting and understanding the causes of business cycle fluctuations. In this paper, I show that financial firms reveal information with powerful predictive ability on economic activity through the skewness of their cross-section distribution of stock market returns. Moreover, I show that shocks to cross-section skewness are an important source of business cycle fluctuations, displacing dispersion shocks.

Figure 1 shows the distribution of log-returns of financial firms for 2006:Q2 and 2008:Q4. I measure cross-section skewness by $[(r_t^{95} - r_t^{50}) - (r_t^{50} - r_t^{5})]$, where r_t^p is the p^{th} percentile of the distribution of log-returns at time t. This skewness measure compares distribution upside $(r_t^{95} - r_t^{50})$ and downside $(r_t^{50} - r_t^{5})$ risks by subtracting the sizes of two equally probable tails. I refer to this skewness measure as *financial skewness*. For comparison, I also measure cross-section dispersion by $(r_t^{95} - r_t^{5})$, referring to it as financial dispersion. Figure 1 not only documents that financial dispersion increased from 2006:Q2 to 2008:Q4, but also that financial skewness became markedly negative, as the increase in left tail $(r_t^{50} - r_t^{5})$ was substantially larger than the increase in the right tail $(r_t^{95} - r_t^{50})$.

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



Dispersion is calculated by $(r_t^{95} - r_t^{5})$, while skewness is calculated by $\left[(r_t^{95} - r_t^{50}) - (r_t^{50} - r_t^{5})\right]$, where r_t^p is the p$^{\text{th}}$ distribution percentile at time t. Figure 1a shows the cumulative distribution function (CDF). Figure 1b shows the probability density function (PDF). Figure 1c shows the complementary cumulative function (1-CDF).

However, the relationship between financial skewness and the business cycle goes beyond the Great Recession, as intuitively seen in Figure 2. I show that this relationship is quantitatively powerful and robust over time. First, I document that financial skewness closely tracks business cycles from 1926 to 2015, with partial correlations for this whole period higher than those associated with most other variables. Second, I show that financial skewness has a substantial predictive ability on several measures of economic activity. Using in-sample and out-of-sample regressions for the 1973–2015 period, I show that financial skewness generally performs better than many well-known 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 cross-section distribution of returns. Moreover, a regression model with financial skewness performs, on average, as well as Consensus forecasts. Finally, these results are not dependent on specific events, such as the Great Recession, as financial skewness performs well both in recessions and expansions.

Figure 2: Financial Skewness and the Business Cycle

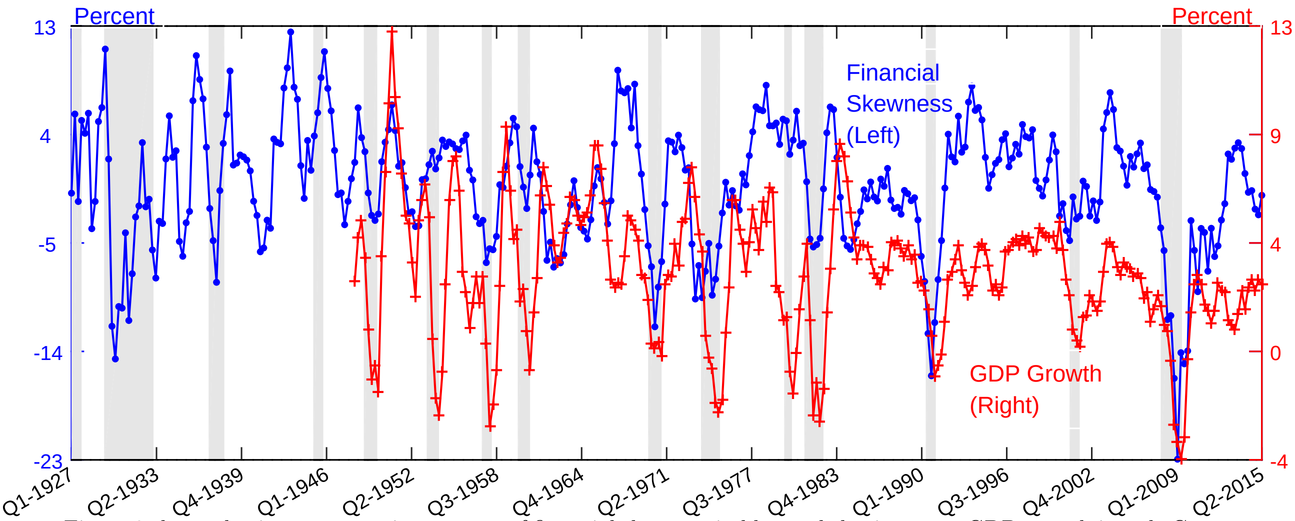


Figure 2 shows the 4-quarter moving average of financial skewness in blue and the 4-quarter GDP growth in red. Gray areas represent periods classified as recessions by the NBER.

I then investigate the economic reasoning for financial skewness' strong performance in anticipating economic activity. This paper's hypothesis is that stock markets uncover economic fundamentals to which financial firms are exposed, such as borrowers' quality. This hypothesis is based on the interpretation that financial firms choose their asset portfolio diversifying risks across different markets, while remaining exposed to markets they expect to boost their equity returns. This partial diversification eliminates uninformative idiosyncratic risks while retaining a cleaner exposure to the overall quality of projects undertaken in the economy. Stock markets price these exposures with higher equity valuations for financial firms with assets of higher expected profits. Then, as economic shocks impact different firms differently, the cross-section of stock returns reveals information about the distribution of quality of projects to which both financial firms and the whole economy are exposed.

To support this hypothesis that financial skewness uncovers economic fundamentals, I provide three pieces of empirical evidence. First, I show that financial firms hold smaller cross-section risks relative to nonfinancial firms, consistent with financial firms achieving partial diversification and remaining exposed to strategically chosen markets. Second, I show that variables associated with the quality of the assets of financial firms account for a sizable variance share of financial skewness. Moreover, since these variables are released after the end of the quarter, results indicate that financial skewness anticipates financial firms' asset quality. Finally, I document that financial skewness also anticipates credit market conditions, performing particularly well for loan growth. This last result points to stock markets timely pricing credit market fundamentals, especially for a submarket in which financial firms should have comparative advantage in sorting borrower quality.

I then provide a structural analysis of the relationship between financial skewness and the business cycle. To do so, I use two frameworks: a Dynamic Stochastic General Equilibrium (DSGE) model and Bayesian Vector Autoregressions (BVARs). The DSGE model rationalizes the idea that the relationship between financial firms and their borrowers achieve some diversification of cross-section risks, while not totally eliminating them. The model has a financial accelerator channel (Bernanke et al. (1999)), and allows cross-section risks to be subject to dispersion and skewness shocks, thus capturing the fact that macroeconomic shocks may impact different firms differently. Lastly, I use BVARs to identify dispersion and skewness shocks for two reasons: BVARs are a flexible model of transmission channel of shocks (Del Negro et al. (2006)) and its use makes the structural analysis robust to a specific DSGE model.

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. In contrast, cross-section dispersion shocks have little influence on the cycle, have small economic effects, and account for the minority of the fluctuations in cross-section dispersion. These results corroborate findings that cross-section dispersion shocks cease to be major drivers of business cycles when we expand the data targeted by benchmark DSGE models (e.g., Bachmann and Bayer (2014)). Moreover, these same results point to skewness shocks as the major source of idiosyncratic risk driving business cycles.

I then study the transmission of financial skewness shocks through the economy, showing evidence of an important financial channel. First, I show that not only measures of economic activity respond to skewness shocks, but also credit growth, equity, and credit spreads. Second, I document that impulse response functions (IRFs) of economic activity to skewness shocks are amplified when credit spreads respond more to these shocks. These results are consistent with related evidence (Caldara et al. (2016)) and with financial frictions being one of the main channels of transmission of idiosyncratic risk shocks (Gilchrist et al. (2014)). Third, I show that the IRFs from the DSGE model are broadly consistent with those from the BVAR. The exception is the IRF of financial skewness, which is substantially more persistent in the DSGE model. These results corroborate the importance of a financial channel while pointing to a lack of amplification mechanism of the financial accelerator model, as it relies on a counterfactually large shock persistence.[1]

This paper contributes to the large literature on the predictive ability of financial indicators.[2] Moreover, it contributes to the debate about which capital market most effectively signals economic fundamentals. Bond spreads have emerged as one of the main barometers of business cycle conditions after the Great Recession motivated by their significant performance in predicting economic activity.[3] In turn, this performance has corroborated the argument that bond markets could be more accurate than stock markets in providing information about economic fundamentals.[4] I challenge this argument by showing a quantitatively strong relationship between stock markets and the business cycle, and by providing evidence that financial firms are well placed to uncover economic fundamentals.

This paper also contributes to the literature documenting how uncertainty measures associated with tail risks not only fluctuate with business cycles, but also help explain these cycles. Building on the large research on measures of uncertainty and volatility,[5] this paper adds evidence to the empirical regularity that high-order moments of the cross-section distribution of economic variables co-move with the economic cycle.[6] Then, the paper shows that cross-section skewness shocks are important business cycle drivers, displacing dispersion shocks, and complementing the literature on macroeconomic tail risks (Barro (2006), Gabaix (2012), and Gorio (2012)).

Finally, this paper helps bridge the gap between studies attempting to explain business cycles and studies attempting to predict business cycles. On one hand, the literature studying the cross-section idiosyncratic component of firms behavior—for short, idiosyncratic risk—points to its importance in driving aggregate fluctuations through several channels.[7] On the

[1]This result adds another item to the list of challenges faced by macro-finance DSGE models (Adrian et al. (2012), Linde et al. (2016))

[2]For literature reviews on the predictive ability of financial indicators, see Stock and Watson (2003) and Ng and Wright (2013).

[3]For an evaluation of the predictive ability of corporate spreads on economic activity, see Faust et al. (2013) for the United State and Gilchrist and Mojon (2016) for the euro area.

[4]See Philippon (2009) and Lopez-Salido et al. (2017) for examples of this argument.

[5]See Bloom (2014) and Datta et al. (2017) for literature reviews.

[6]Among these variables are firm sales, profit, and employment (Bloom et al. (2016)); household income (Guvenen et al. (2014)); firm productivity (Kehrig (2015)); and price changes (Luo and Vallenas (2017)).

[7]These channels include: wait-and-see effects from capital adjustment frictions (Bloom et al. (2012)), financial frictions (Arellano et al. (2012) 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)).

other hand, empirical measures of idiosyncratic risk have had little influence on the research attempting to predict these same aggregate fluctuations. To the best of my knowledge, this paper is the first to provide evidence of a measure of idiosyncratic risk that performs well in predicting economic fluctuations.

2 Financial Skewness and Business Cycles

In this section, I describe the cross-section distribution measures used throughout 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 powerful predictor of economic activity (Section 2.3).

2.1 Cross-Section 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-section measures of mean, dispersion, skewness, left kurtosis, and right kurtosis as follows:

$$\begin{aligned}
\text{Mean: } M(1)_t^s &= \tfrac{100}{N_{s,t}}\left(\textstyle\sum_{i\in s} R_t^{i,s} - 1\right), && \text{for } s \in \{\text{fin}, \text{nfin}\} && (1)\\
\text{Dispersion: } M(2)_t^s &= r_t^{95,s} - r_t^{5,s}, && \text{for } s \in \{\text{fin}, \text{nfin}\} && (2)\\
\text{Skewness: } M(3)_t^s &= (r_t^{95,s} - r_t^{50,s}) - (r_t^{50,s} - r_t^{5,s}), && \text{for } s \in \{\text{fin}, \text{nfin}\} && (3)\\
\text{Left kurtosis: } M(4)_t^s &= (r_t^{45,s} - r_t^{25,s}) - (r_t^{25,s} - r_t^{5,s}), && \text{for } s \in \{\text{fin}, \text{nfin}\} && (4)\\
\text{Right kurtosis: } M(5)_t^s &= (r_t^{95,s} - r_t^{75,s}) - (r_t^{75,s} - r_t^{55,s}), && \text{for } s \in \{\text{fin}, \text{nfin}\}, && (5)
\end{aligned}$$

where $N_{s,t}$ is the number of firms in sector s at quarter t and "fin" and "nfin" represent the financial and nonfinancial sectors of the U.S. economy.[8] I also calculate cross-section 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 $\mathrm{M}(3)_t^{\text{fin}}$ as financial skewness, unweighted $\mathrm{M}(3)_t^{\text{nfin}}$ as nonfinancial skewness, and analogously for other distribution measures.[9] Finally, the intuition for left kurtosis (equation

[8]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.

[9] Notice that I use raw realized returns to calculate measures (1)-(5) instead of residuals of regressions on market factors, such as Fama-French (1993). The reason is that although one may express $R_t^{i,s}$ as a

(4)) and right kurtosis (equation (5)) is analogous to the one for skewness. The difference is that these kurtoses measures compare the size of upside and downside risks within each distribution tail (right or left), with the 25^{th} and 75^{th} quartiles as their reference returns.

2.2 Financial Skewness Tracks the Business Cycle: 1926–2015

Table 1 documents the correlations between financial and nonfinancial skewness and measures of economic activity. After noticing a reasonable range of correlations (from 0.31 to 0.71), two patterns emerge. First, correlations are higher for financial skewness relative to the nonfinancial one, 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-Section Skewness and the Business Cycle

	Expansion Indicator		GDP Growth	
Sample	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

In Table 1, I use 4-quarter moving averages of unweighted skewness, 4-quarter GDP growth, and an expansion indicator based on 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 lagged NBER expansion indicator. Finally, I standardize the series of all regressors to ensure comparability between the estimated coefficients. Table 2 displays regression estimates.

function of market returns and an idiosyncratic component, market returns themselves may be determined by the distribution of idiosyncratic components (Ferreira (2016)). Thus, if the goal is to measure 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.

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.

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), financial skewness' coefficient is the second to 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 2 standard deviations in financial skewness sustained over the previous and current quarters imply a probability of recession of

52% in the current quarter.[10]

2.3 Financial Skewness Predicts the Business Cycle: 1973–2015

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, (iii) for a variable Y_t, I forecast $Y_{t+h|t-1}$ at time t, where

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

Thus, for instance, I forecast the mean annualized real GDP growth h quarters ahead, while I forecast just the level of 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 $Y_{t+h|t-1}$, it means that 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

[10] For this computation, I use the estimates of specification (9) and assume that all other regressors are at their historical mean values.

standard errors using Hodrick (1992).

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 $\gamma = \sum_{j=0}^{q} \gamma_{\mathrm{j}}$. 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 3 reports the results of regressions (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.[11] 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

[11] Results for weighted measures are shown in Table 12 of Appendix A.3. They are in line with those discussed here, with the unweighted financial skewness performing better than its weighted counterpart.

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.

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 largest and intuitive elasticities—the mean—has these elasticities being lower that those associated with financial skewness in analogous regressions ((11)-(12) of Table 3b relative to (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 financial skewness' predictive ability 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

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 $\gamma = \sum_{j=0}^{q} \gamma_j$. 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.

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 (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 financial skewness' predictive ability by calculating out-of-sample forecasts of GDP growth. To focus on the performance of predictor variable X_t, I only include GDP growth lags 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 add to this list of forecasts estimates from regressions (7) using only 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 1986Q1. I also add Consensus predictions to the list of forecasts. I do so to evaluate regression predictions (7) against forecasts that use a wide information set.[12] Finally, I document the performance

[12]Given that Consensus forecasts are released at the 10^{th} of every month, I average forecasts from the last

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 ($h = 2, 4, 6$).[13] Moreover, the magnitudes by which financial skewness 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 is slightly more frequent in expansions. Finally, Figures 3d and 3e show that financial skewness also outperforms almost all of the remaining distribution variables, either weighted or unweighted.

For the few variables for which the performance comparison with financial skewness is less straightforward, results still support financial skewness' powerful predictive ability. 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 financial skewness' forecasts are most often comparable with those using a wide information set, even though financial skewness' forecasts come from a very simple model. The few other variables that outperform financial skewness do not achieve statistical significance (e.g. weighted financial skewness). Moreover, some are even statistically outperformed in one state of cycle (macro uncertainty and GDP-AR).

Finally, I show that financial skewness has powerful predictive ability within most 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.

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.

[13] 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 compute 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 3: Out-of-Sample Forecasts of GDP Growth, R-RMSFEs

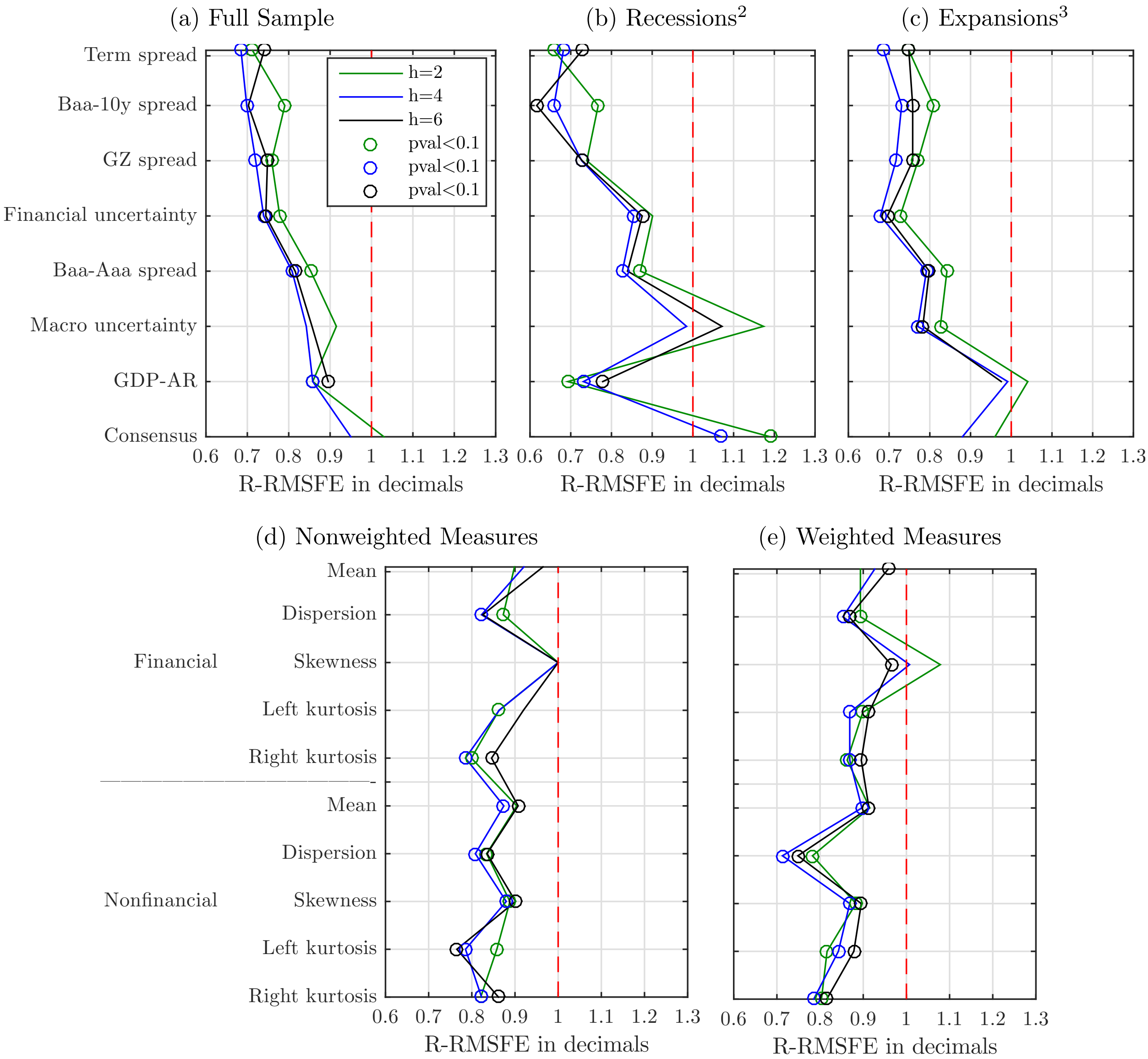
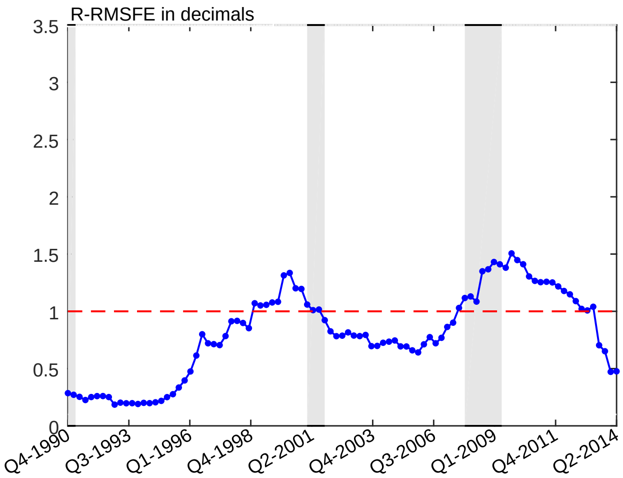


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis 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.

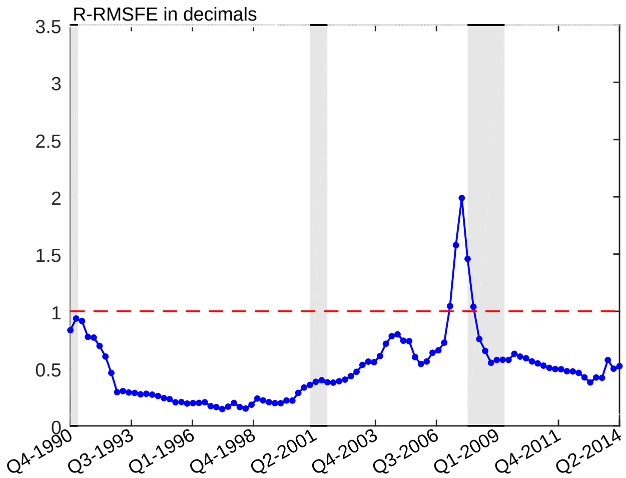
Although Figures 4a-4c point to some short-lived spikes to values higher than 1, these figures show that financial skewness performs better than the competing variables in many periods other than the Great Recession. Finally, Figure 4d shows financial skewness and Consensus alternating in outperforming each other, with financial skewness generally performing better in the first half of the sample.

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

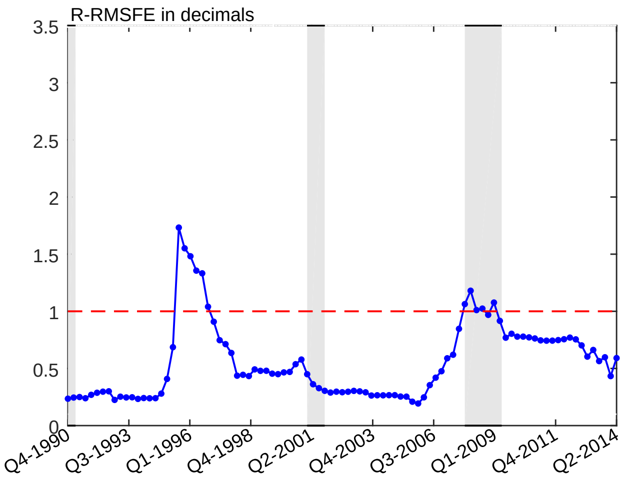
(a) R-RMSFE of Macro Uncertainty



(b) R-RMSFE of Term-Spread



(c) R-RMSFE of GZ-Spread



(d) R-RMSFE of Consensus

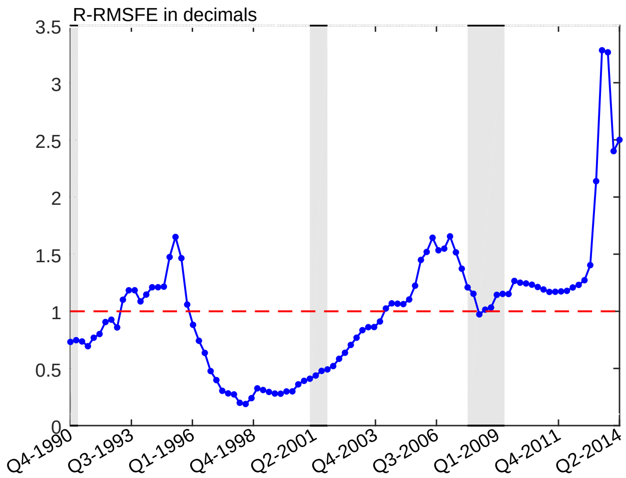


Figure 4 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) of variable X_t. At every quarter, I compute the R-RMSFE over the current and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

3 Interpreting Financial Skewness' Predictive Ability

In this section, I provide evidence supporting the hypothesis that financial skewness' predictive ability on business cycles originates from the fact that financial firms uncover economic fundamentals, such as borrower's quality.

3.1 Financial Sector Diversifies Away Some Cross-Section Risks

The hypothesis above relies on the idea that, when choosing its credit portfolio, financial firms diversify away uninformative idiosyncratic risks while remaining exposed to the overall quality of projects undertaken in the economy. I support this idea of financial firms achieving partial diversification by showing that not only cross-section distributions of stock market returns of financial firms are less dispersed than those of nonfinancial firms, but they are also less concentrated in the tails.

Table 5 reports times series averages of moments of cross-section 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 across financial firms are not statistically different from the ones across nonfinancial firms (row (a), columns (3) and (6)).

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***

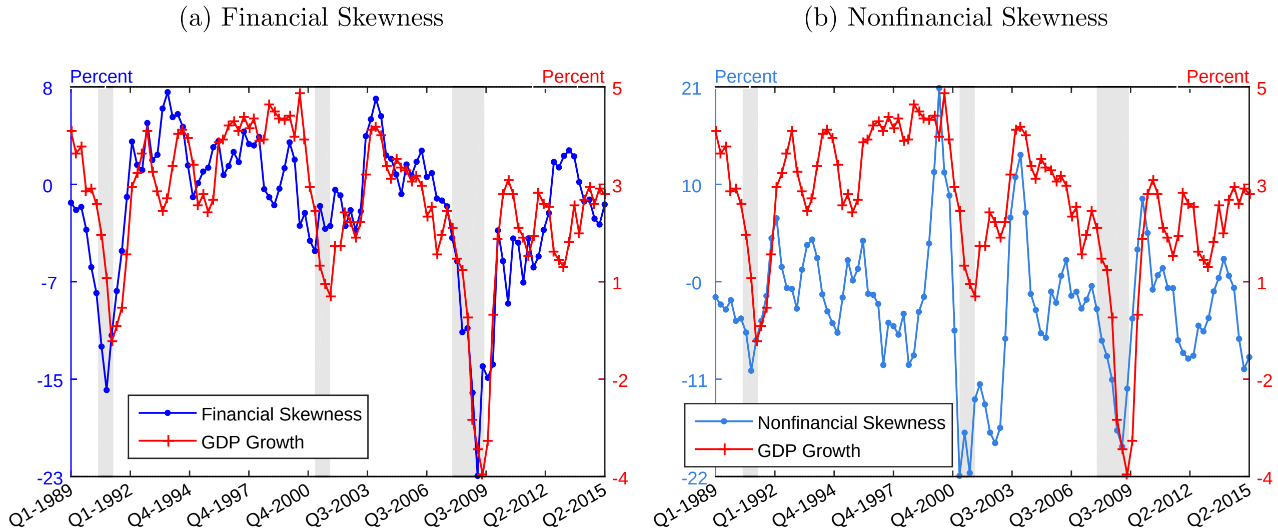
Time series averages reported in Table 5 are computed from unweighted distribution measures. Results are very similar if computed for weighted distribution measures.

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 last three recessions. While financial skewness follows very closely GDP growth (Figure 5a), nonfinancial skewness is noisier and has peaks and troughs disproportional to the cyclical variation of GDP around the early 2000's recession (Figure 5b).[14]

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

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

Figure 5: Cross-Section Skewness and Last Three Recessions



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.

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

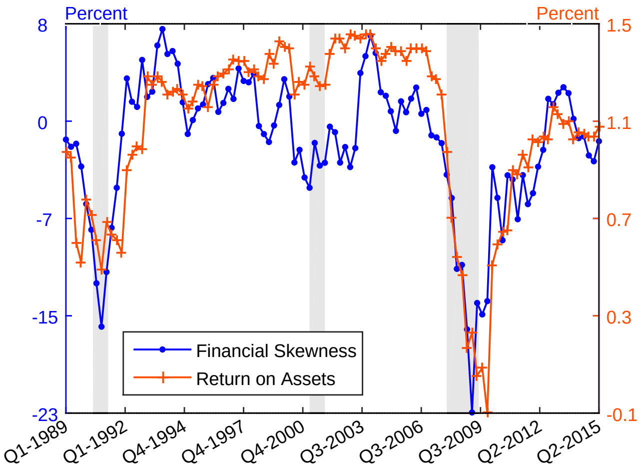
After showing that financial firms achieve some asset diversification, I argue that financial skewness captures stock markets' views about the quality of financial firms' assets. If this hypothesis is correct, variables measuring the quality of financial firms' assets should then account for a considerable amount of variation in financial skewness. Indeed, I show that 76% of the evolution of financial skewness in a recent sample is accounted by two variables: return on average assets for banks (ROA) and changes in banks' lending standards.[15] 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.

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 riskness of certain loans and changes in business strategies.

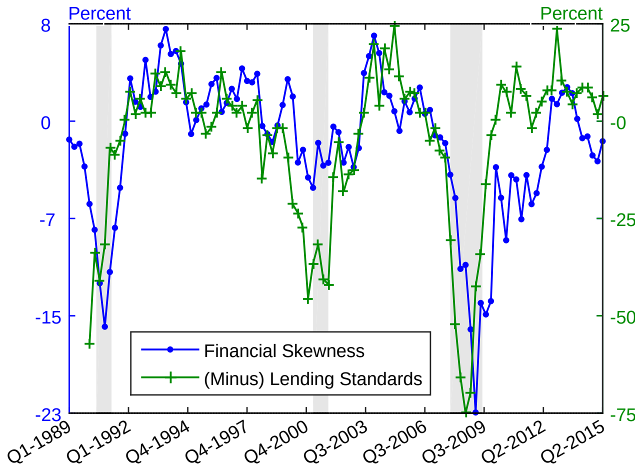
[15]More precisely, the variable is the net percentage of domestic banks tightening standards for commercial and industrial loans.

Figure 6: Financial Skewness and Banks' Asset Quality

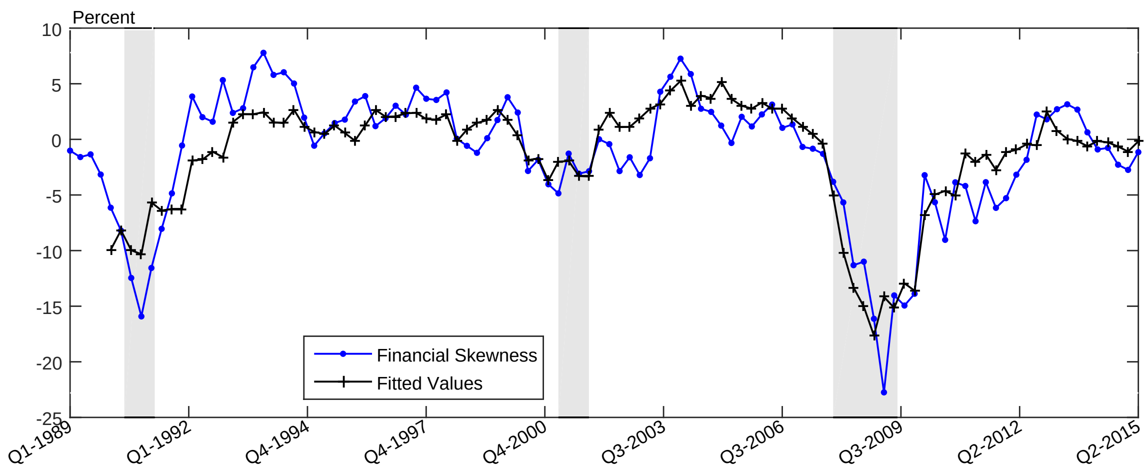
(a) Banks' Return on Assets



(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.

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 comovement between these variables and the 4-quarter moving average of financial skewness. Table 6a then measures these comovements 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 most information about firms with less access to capital markets.

Finally, the first column of Table 6b shows that a regression with ROA and LSSF explain 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 the time series of financial skewness.

Table 6: Regressions on Financial Skewness

(a) Univariate Regressions

	ROA	LSSF	LSLMF	AFCI	EBP	VIX	Term Spread	$\text{GDP}^{\text{Consensus}}_{t\mid t-1}$	$\text{GDP}^{\text{Consensus}}_{t+4\mid t-1}$
	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	$\text{GDP}^{\text{Consensus}}_{t\mid t-1}$	$\text{GDP}^{\text{Consensus}}_{t+4\mid t-1}$
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 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.

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 comove with aggregate macroeconomic and financial conditions. To shed light on this issue, I add the following variables in the regressions on financial skewness: Chicago's Fed financial condition index (AFCI), Excess Bond Premium (EBP), VIX and Consensus forecasts for GDP growth for the current quarter and for the next 4 quarters ahead.[16] 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 and have coefficients smaller than those from ROA and LSSF. Although 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.

[16] Chicago's Fed financial condition index (AFCI) use 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)).

3.3 Financial Skewness Anticipates Credit Market Conditions

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

The empirical strategy of this section is the same as the one from Section 2.3.1. Specifically, 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. For comparison, I report results in Table 7 using two distribution measures as regressors: financial skewness and nonfinancial dispersion[17]. Row (a) reports estimates from benchmark regressions with only lagged predicted variables. 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 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 1 standard deviation of financial skewness lasting 2 consecutive quarters anticipates a drop of 1.7% in mean loan growth over then next 4 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.

Given the relevance of nonfinancial dispersion in the literature of time-varying uncertainty, I display its results in Table 7c. Relative to financial skewness (Table 7b), nonfinancial dispersion is particularly informative about future debt growth. It adds 6% of explanatory power to the benchmark regression and has a statistically significant elasticity of 0.8%. This result contrasts with financial skewness' poor performance in regressions on debt growth. Regarding the remaining dependent variables, nonfinancial dispersion has a performance similar to financial skewness on corporate spreads (GZ and Baa-10y), while it does worse on loan spreads. With these last results highlighting the relatively better performance of financial skewness on loan market variables, it reinforces the idea that financial firms uncover economy's risks through its credit intermediation activity.

[17] I report results for financial dispersion and nonfinancial skewness in Table 13 of Appendix A.3. The results for these measures fall broadly in between 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 $\gamma = \sum_{j=0}^{q} \gamma_{\mathbf{j}}$. Elasticities on loan and debt growth is expressed in percentage, while on spreads is in basis points. Coefficients of lagged predicted variables are 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.

4 Identifying Financial Skewness Shocks

In this section, I identify financial skewness shocks by estimating BVARs and a new Keynesian DSGE model with financial accelerator channel. The choice for this DSGE model is because of its explicit predictions for the endogenous behavior of the cross-section distribution of returns (Ferreira (2016)), its success in explaining the co-movement between macro and financial variables with cross-section shocks (Christiano et al. (2014)), and its wide use among academics and policy-makers. Both the DSGE model and BVARs find that financial skewness shocks are important sources of business cycles, while dispersion shocks are not.

4.1 DSGE Model with Financial Accelerator Channel and Cross-Section 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} then measures the risk of idiosyncratic loan markets to which a financial firm chooses to be strategically exposed.

To allow for both cross-section 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 Φ is the cumulative distribution function of a standard normal. 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 $\mathbb{E}_t(\omega_t) = \int_0^\infty \omega dF_t(\omega) = 1$ and $\text{Std}_t(\omega_t) = \int_0^\infty (\omega - \mathbb{E}_t(\omega_t))^2 dF_t(\omega) = sd_t$, for any given vector (m^1_t, s^1_t, s^2_t). Second, I fix the s^1_t and s^2_t at their steady-state levels. In this way, sd_t measures the second moment of F_t, while a lower/higher m^1_t makes F_t more negatively/positively skewed, as shown by the variations of F_t around its steady state F^{ss} in Figures 7a-7c. I then model sd_t and m^1_t as first-order autoregressions (AR(1)) and name them cross-section dispersion and skewness shocks.[18]

During period $t+1$ and with $\omega_{t+1}\overline{K}^i_{t+1}$ efficient units of physical capital, entrepreneur i earns rate of return $\omega_{t+1}R^c_{t+1}$ on its purchased capital. To do so, first, he determines capital utilization u_{t+1} by maximizing profits from renting capital services $\omega_{t+1}\overline{K}^i_{t+1}R^k_{t+1}u_{t+1}$ to intermediate firms net of utilization costs $\omega_{t+1}\overline{K}^i_{t+1}P_{t+1}a(u_{t+1})$, where R^k_{t+1} is the nominal rental rate of capital, $a(u_{t+1})$ is a cost function,[19] 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: $\omega_{t+1}R^c_{t+1} = \omega_{t+1}\frac{R^k_{t+1}u_{t+1} - P_{t+1}a(u_{t+1}) + (1-\delta)Q_{t+1}}{Q_t}$.

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

[18] 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.

[19] 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.

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

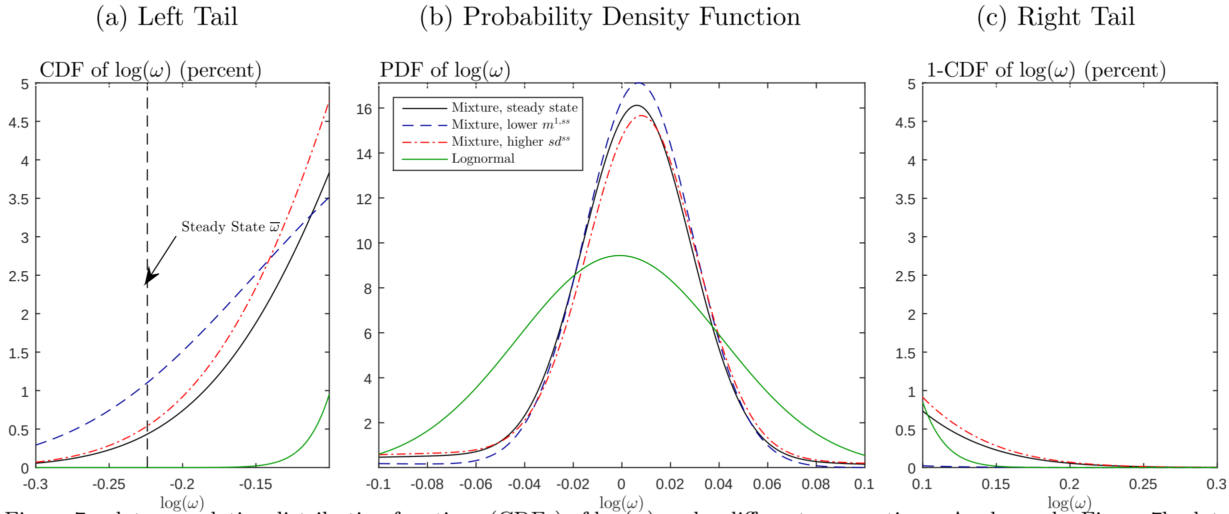


Figure 7a plots cumulative distribution functions (CDFs) of $\log(\omega)$ under different assumptions. Analogously, Figure 7b plots probability density functions (PDFs) of $\log(\omega)$ and Figure 7c plots complementary cumulative functions (1-CDFs) of $\log(\omega)$. The black lines (Mixture, steady-state) plot the CDF/PDF/(1-CDF) of $\log(\omega)$ 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 $\log(\omega)$ 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 $\log(\omega)$ 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 $\log(\omega)$ when ω follows a lognormal distribution with the same mean and standard deviation of F^{ss}.

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-Section 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^i_t, such that

$$X^i_t = \begin{cases} \frac{\omega_t R^c_t Q_{t-1}\overline{K}^i_t - Z^i_t B^i_t}{N^i_t}, & \text{if } \omega_t R^c_t Q_{t-1}\overline{K}^i_t \geq Z^i_t B^i_t \\ 0, & \text{otherwise} \end{cases} = \begin{cases} \left[\omega_t - \overline{\omega}_t\right] R^c_t L_t, & \text{if } \omega_t \geq \overline{\omega}_t \\ 0, & \text{otherwise.} \end{cases}$$

For instance, cross-section skewness of the model can be calculated as $(\widetilde{x}^{95}_t - \widetilde{x}^{50}_t) - (\widetilde{x}^{50}_t - \widetilde{x}^{5}_t)$, where $\widetilde{x}^v_t = \log(\widetilde{\omega}^v_t - \overline{\omega}_t)$ and $\widetilde{\omega}^v_t$ 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-section 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 $Y_t = \left[\int_0^1 Y_{jt}^{1/\lambda^f_t}\, dj\right]^{\lambda^f_t}$, and intermediate goods Y_{jt}, for $j \in [0,1]$, to produce a homogeneous good Y_t. Cost-push shock λ^f_t follows an AR(1) process. Intermediate producers' production function is $Y_{jt} = \epsilon_t K^\alpha_{jt}(z_t H_{jt})^{(1-\alpha)} - \phi z^*_t$, if $\epsilon_t K^\alpha_{jt}(z_t H_{jt})^{(1-\alpha)} > \phi z^*_t$. 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 fix cost.[20] 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 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.[21].

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

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

[20] The value of ϕ is chosen to ensure zero profits in steady state for intermediate producers.
[21] I choose ψ_0 such that $h_{it} = 1$ for all i at steady state.

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 $\widetilde{\Pi}_{w,t} = \left(\Pi_t^{tar}\right)^{\iota_w} \left(\Pi_{t-1}\right)^{1-\iota_w} \left(\mu_{z,t}^*\right)^{\theta} \left(\mu_z^{*,ss}\right)^{1-\theta}$.

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, and skewness, m_t^1, and monetary policy, ζ_t^{mp}. I then model these shocks as

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

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. More specifically, it includes real GDP, real consumption, real investment, hours worked, real wage, relative investment price, fed funds rate, core inflation, real total credit, real nonfinancial equity index, 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.[22] After calibrating some model parameters and postulating priors for the remaining ones, I then maximize the log-posterior of the model.

Motivated by a potential change in structural parameters after the Great Recession and by the adoption of 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}. 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.[23] The focus of this two-step procedure on the persistence and size of economic shocks 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, and 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

[22] 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.

[23] 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-section dispersion, and cross-section skewness.

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

		Prior distribution			Posterior distribution	
Description	Name	Shape	Mean	SD	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-section dispersion	ρ_{sd}	beta	0.5	0.2	0.68	0.040
Shock autocorrelation: anticipated cross-section dispersion	$\rho_{sd,\xi}$	beta	0.5	0.2	0.53	0.163
Shock autocorrelation: cross-section skewness	ρ_{m1}	beta	0.5	0.08	0.90	0.006
Shock autocorrelation: anticipated cross-section 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-section dispersion	σ_{sd}	invg2	0.002	0.0033	0.037	0.0022
Shock standard deviation: anticipated cross-section dispersion	$\sigma_{sd,\xi}$	invg2	0.001	0.0012	0.0003	0.0002
Shock standard deviation: cross-section skewness	σ_{m1}	invg2	0.002	0.0033	0.046	0.0036
Shock standard deviation: anticipated cross-section 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]
Dispersion of equity returns (percent)	62	56
Skewness of equity returns (percent)	-24	-1

[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.

assumed in the financial frictions literature. Figure 7 reports F^{ss} and a lognormal distribution with identical mean and standard deviation. 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 that they are close to most of their data counterparts.[24]

4.3 DSGE Model: The Primacy of Skewness Shocks

Focusing on the economic shocks, the variance decomposition in Table 10 points to skewness shocks as the most important driver of economic fluctuations. 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.

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 hit 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

[24]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 (2002–2015).

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.

the period 1964–2015. We also see that variations in credit spreads are largely explained by skewness shocks.

IRFs in Figure 9a shed light on the reason skewness shocks are important drivers of business cycle fluctuations. Essentially, when cross-section skewness is exogenously lower, endogenous variables respond with co-movements generally observed over the cycle: lower GDP, consumption, investment, credit and equity growth, and then higher credit spreads and dispersion. Moreover, these co-movements hold for both anticipated and unanticipated skewness shocks. Most other shocks, however, do not generate this entire set of co-movements and thus do not account for large shares of business cycle fluctuations.[25] The exception is 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 skewnewss 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 Baa-10y spread by 35 bps 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

[25]For an extensive discussion of this issue, see Christiano et (2014). I also report the IRFs of other shocks, including anticipated skewness shocks, in Appendix A.3.

Figure 8: Shock Decomposition, 1964–2015

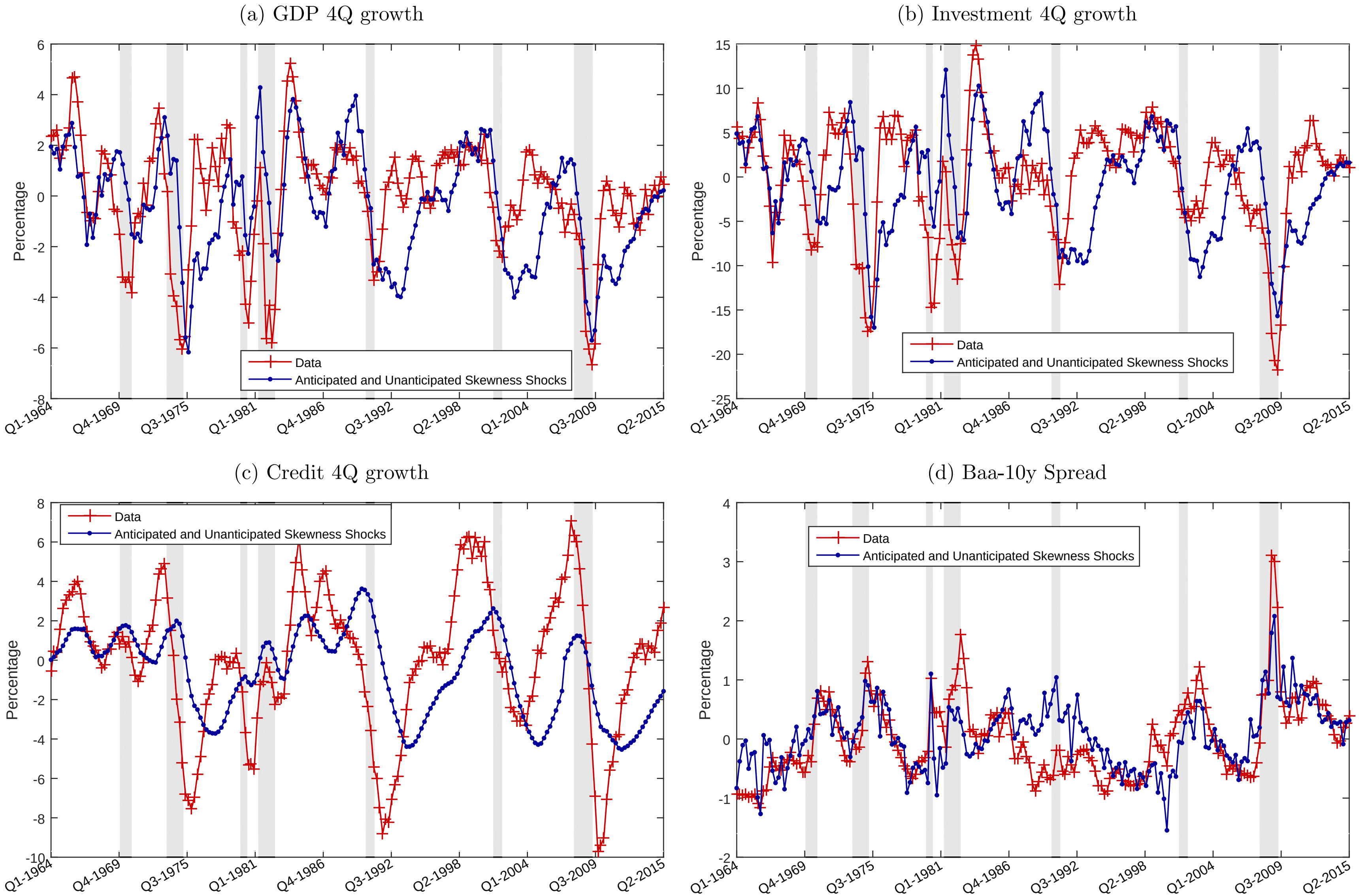
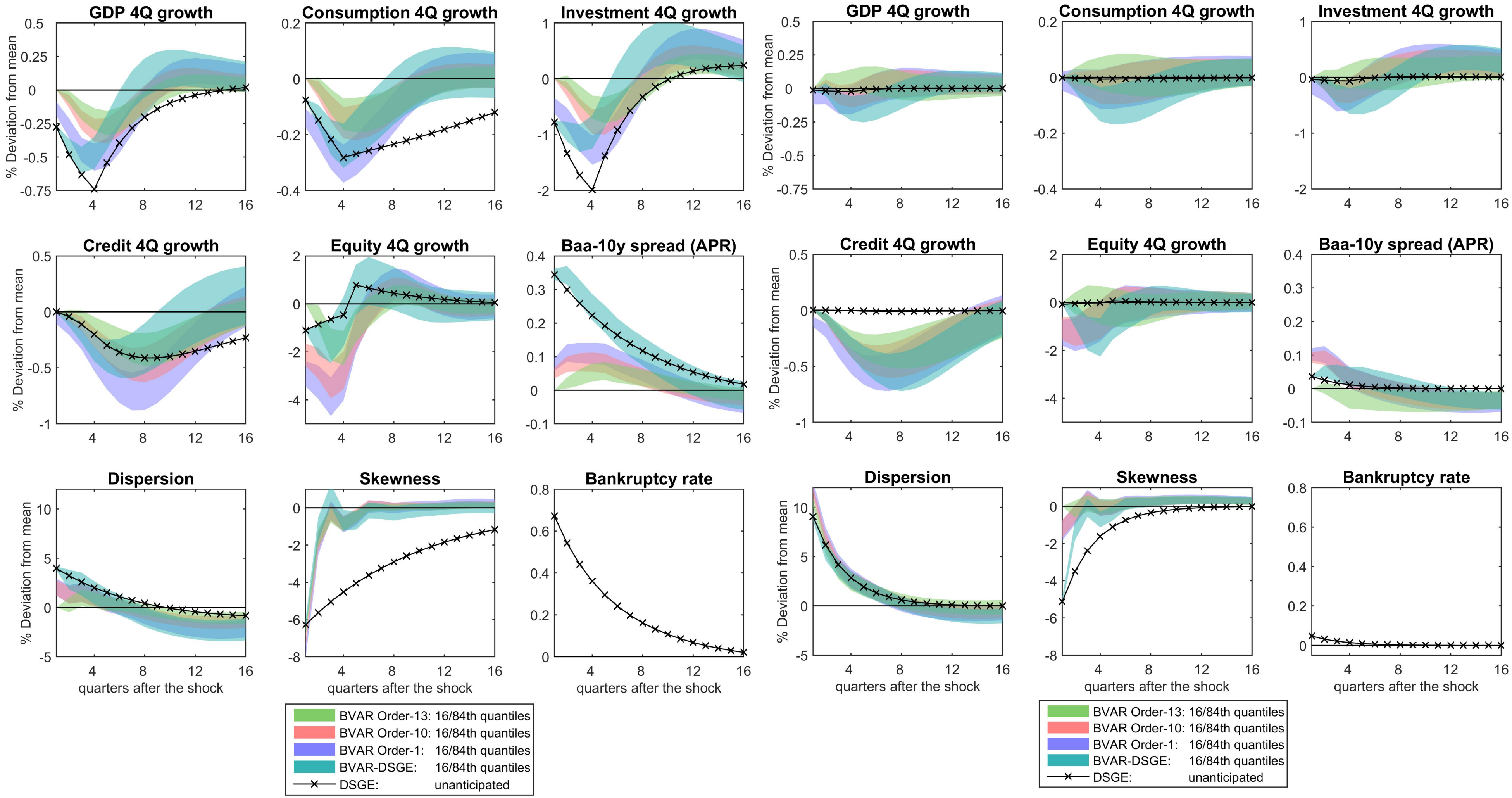


Figure 9: Impulse Response Functions from BVARs and DSGE model

(a) Skewness Shocks

(b) Dispersion Shocks



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

4.4 DSGE Model vs BVAR: Identification of Shocks in BVAR

I then compare results from the DSGE model of Sections 4.1 to 4.3 with those computed using a BVAR.[26] The goal is to reach robust conclusions about the importance of dispersion and skewness shocks, as well as about the transmission of skewness shocks through the economy. I use the same data as the one used in the estimation of the DSGE model (Section 4.2), except that I exclude OIS rates because it only starts at 2002.

In the BVAR, I identify unanticipated skewness and dispersion shocks with four strategies: three different recursive orderings and one identification vector originated from 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. Finally, I define *Order-1* as the ordering placing skewness as the first variable, thus allowing all remaining variables to react contemporaneously to a skewness shock. I also identify dispersion shocks using analogous recursive orderings.

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

Although recursive identifications are easy to interpret and serve as good benchmarks, they do not give a clean comparison between what the DSGE model and BVARs tell us about skewness and dispersion shocks. The reason is that by using recursive identifications in the VAR and comparing results with those from the DSGE model, we not only compare different frameworks, but also different shocks. To see this, first notice that to identify a shock in a BVAR, it is sufficient to pin down a vector of contemporaneous effects on all endogenous variables (Uhlig (2005)). Then, notice that unanticipated skewness and dispersion shocks identified by recursive orderings have different contemporaneous effects from those identified by the DSGE model (Figure 9a). To address this issue, I identify skewness and dispersion shocks using the same contemporaneous effects estimated by the DSGE model. I call this identification strategy *BVAR-DSGE.*

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.

4.5 DSGE Model vs BVAR: Skewness Shocks Are Important, Dispersion Shocks Are Not

Regardless of the identification strategy, unanticipated skewness shocks have sizable and long-lasting economic effects and account for a relevant share of business cycles. Dispersion shocks, however, have almost negligible economic effects and account for very a small share of business cycles. To reach these conclusions, I compare IRFs and variance decompositions calculated with the DSGE model of Sections 4.1-4.3 with those calculated using the BVARs. The different identification strategies (DSGE, BVAR-DSGE, Order-1, Order 10, and Order 13) show that skewness shocks decrease GDP growth for at least six quarters, with growth lower by 0.3-0.8% at its trough (Figure 9a), and account for 4-20% of fluctuations in economic activity (GDP, consumption, and investment in Tables 10 and 11a). Looking at analogous exercises for dispersion shocks, we see an inverted robust conclusion: small-sized IRFs (Figure 9b) on economic activity and near-zero variance decomposition contributions to the same variables (Tables 10 and 11b).

Another result emphasizing the importance of skewness shocks relative to dispersion ones is that financial skewness is largely an exogenous variable across different identification strategies, while dispersion is not. The DSGE model estimates that skewness shocks (anticipated and unanticipated) are responsible for almost all of the variance of financial skewness (Table 10), while the BVAR's recursive identifications point to unanticipated skewness shocks accounting for 54% to 74% of financial skewness' variance (Table 11a). In contrast, the DSGE model estimates that dispersion shocks (anticipated and unanticipated) explain only 15% of the variance of the times series of dispersion, while the BVAR's recursive identifications of unanticipated shocks account for less than half of dispersion's variance.

4.6 DSGE Model vs BVAR: Transmission of Skewness Shocks...

4.6.1 ...Is Larger, the Larger the Response of Credit Spreads

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

4.6.2 ...Needs More Amplification under the Financial Accelerator Channel

I then verify whether the data support the transmission of unanticipated skewness shocks through the financial accelerator channel. I do so by comparing IRFs estimated by the DSGE model (Section 4) with the IRFs identified by the BVAR-DSGE procedure (Section 4.5). The rationale for this exercise has three building blocks. First, I feed the same skewness shock through two different frameworks, thus avoiding the comparison between different types of skewness shocks. Second, the choice of the specific shock is not arbitrary: It is the skewness shock that maximizes the Bayesian likelihood of the DSGE model with financial accelerator channel. Third, the transmission of skewness shocks through the DSGE model also is the one that maximizes the Bayesian likelihood of the model. Thus, in short, the exercise compares the propagation of "financial accelerator skewness shocks" through two different model economies: one agnostically maximizing its data fit through a BVAR and another with a financial accelerator channel that also maximizes its data fit.

The comparison between the IRFs of the DSGE model and the BVAR-DSGE is reported in Figure 9a. It shows broadly similar economic effects, thus providing some support to the relevance of the financial accelerator channel. The similarities start by the IRFs of the measures of economic activity (GDP, consumption, and investment), with responses estimated by the DSGE model modestly larger than those from the BVAR-DSGE. The similarity of IRFs then extends to most financial variables, where the IRFs of the DSGE model for credit, equity, Baa-10y spread, and dispersion often lie inside the probability intervals reported for the BVAR-DSGE IRFs.

However, the response of cross-section skewness to a skewness shock in the BVAR-DSGE is very different from the one in the DSGE model. While it takes approximately only 3 quarters for 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 result shows that in the search for its best fit of the data, the DSGE model estimates a shock persistence that is not corroborated by a more agnostic framework as the BVAR. In turn, this discrepancy suggests that the DSGE model lacks an internal mechanism that can transmit skewness shocks throughout the economy for a period longer than the one in which shock persists.

4.6.3 . . . Does Not Need Large Credit Spread Responses

Finally, I document that skewness shocks do not need to have large effects on credit spreads to have significant economic consequences. To reach this conclusion, I first focus on IRFs from Figure 9a estimated with the Order-13 identification. This figure shows that the effects on GDP, consumption, investment, and credit are economically significant, with GDP growth decreasing 0.3% at its trough. As a matter of comparison, Gilchrist and Zakrajsek (2012) estimate a drop of 0.5% in GDP growth after an excess bond premium shock. However, Figure 9a also shows that credit spreads barely react to an Order-13 skewness shock: By assumption, it does not react contemporaneously and only increases 6 basis points at its IRF peak.

Moreover, Figure 9a also shows that this subdued reaction of credit spreads is not only limited to identification Order-13, but extends to Order-10 and Order-1. Under these latter identifications, skewness shocks cause Baa-10y spread to increase only about 10 basis points, while, for instance, decreasing GDP growth by around 0.5% at its trough. This result suggests the presence of transmission channels for which credit spreads may not be a good indicator, such as capital frictions (Ehouarne et al. (2015)) and other nonfinancial frictions.

5 Conclusion

In this paper, I show that the cross-section skewness of the distribution of stock market returns of financial firms, i.e. *financial skewness*, has a relationship with the business cycle that is quantitatively powerful and robust over time. Financial skewness closely tracks business cycle fluctuations in the 1926–2015 period and, predicts economic activity better than well known bond spreads and other cross-section moments. I then identify financial skewness shocks, showing sizable economic effects transmitted to the economy through a financial channel.

I provide evidence supporting an explanation for the facts above. The hypothesis is that stock markets uncover economic fundamentals to which financial firms are exposed, such as the distribution of quality of projects undertaken in the economy. To the best of my knowledge, both the empirical regularities and the hypothesis explaining them have not been explored before in the macro-finance literature.

This paper suggests an avenue of research exploring the interconnections of the financial sector with other sectors as a way of anticipating and understanding business cycle conditions. This avenue is consistent with results such as in Acemoglu et al. (2012), who report that financial institutions are one of the sectors most interconnected with others. Moreover, this paper suggest that the financial sector may not only be the origin of shocks that propagate throughout the economy (e.g., 1929 and 2008 financial crises), but also be well placed to efficiently signal shocks from other sectors of the economy.

References

[1] Abadir, Karim M., and Paolo Paruolo. "Two mixed normal densities from cointegration analysis." *Econometrica* 65, no. 3 (1997): 671-680.

[2] Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. "The network origins of aggregate fluctuations." *Econometrica* 80, no. 5 (2012): 1977-2016.

[3] Adrian, Tobias, Paolo Colla, and Hyun Song Shin. "Which financial frictions? Parsing the evidence from the financial crisis of 2007 to 2009." NBER Macroeconomics Annual 27, no. 1 (2013): 159-214.

[4] Arellano, Cristina, Yan Bai, and Patrick J. Kehoe. "Financial frictions and fluctuations in volatility." No. w22990. National Bureau of Economic Research, 2016.

[5] Bachmann, Rdiger, and Christian Bayer. "Investment dispersion and the business cycle." *The American Economic Review* 104, no. 4 (2014): 1392-1416.

[6] Barro, Robert J. "Rare disasters and asset markets in the twentieth century." *The Quarterly Journal of Economics* 121, no. 3 (2006): 823-866.

[7] Bassett, William F., Mary Beth Chosak, John C. Driscoll, and Egon Zakrajsek. "Changes in bank lending standards and the macroeconomy." *Journal of Monetary Economics* 62 (2014): 23-40.

[8] Bekaert, Geert, Marie Hoerova, and Marco Lo Duca. "Risk, uncertainty and monetary policy." *Journal of Monetary Economics* 60, no. 7 (2013): 771-788.

[9] Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. "The financial accelerator in a quantitative business cycle framework." *Handbook of Macroeconomics 1* (1999): 1341-1393.

[10] Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. "Really uncertain business cycles." No. w18245. National Bureau of Economic Research, 2012.

[11] Bloom, Nicholas. "Fluctuations in uncertainty." *The Journal of Economic Perspectives* 28, no. 2 (2014): 153-175.

[12] Bloom, Nicholas, Fatih Guvenen, and Sergio Salgado. "Skewed Business Cycles." In 2016 Meeting Papers, no. 1621. Society for Economic Dynamics, 2016.

[13] Brave, Scott A., and R. Andrew Butters. "Monitoring financial stability: A financial conditions index approach." (2011).

[14] Caldara, Dario, Cristina Fuentes-Albero, Simon Gilchrist, and Egon Zakrajek. "The macroeconomic impact of financial and uncertainty shocks." *European Economic Review* 88 (2016): 185-207.

[15] Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. "Risk shocks." *The American Economic Review* 104, no. 1 (2014): 27-65.

[16] Chugh, Sanjay K. "Firm risk and leverage-based business cycles." *Review of Economic Dynamics* 20 (2016): 111-131.

[17] Datta, Deepa, Juan M. Londono, Bo Sun, Daniel Beltran, Thiago T Ferreira, Matteo Iacoviello, Mohammad Jahan-Parvar, Canlin Li, Marius Rodriguez, and John Rogers. "Taxonomy of Global Risk, Uncertainty, and Volatility Measures." No. 1216. International Finance Discussion Papers (2017).

[18] Del Negro, Marco, Frank Schorfheide, Frank Smets, and Rafael Wouters. "On the fit of new Keynesian models." *Journal of Business & Economic Statistics* 25, no. 2 (2007): 123-143.

[19] Diebold, Francis X., and Robert S. Mariano. "Comparing Predictive Accuracy." *Journal of Business & Economic Statistics* 13 (1995): 253-263.

[20] Ehouarne, Cedric, Lars-Alexander Kuehn, and David Schreindorfer. "The Market Price of Capital Misallocation." (2015).

[21] Fama, Eugene F., and Kenneth R. French. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics* 33, no. 1 (1993): 3-56.

[22] Faust, Jon, Simon Gilchrist, Jonathan H. Wright, and Egon Zakrajsek. "Credit spreads as predictors of real-time economic activity: a Bayesian model-averaging approach." *Review of Economics and Statistics* 95, no. 5 (2013): 1501-1519.

[23] Ferreira, Thiago RT. "Financial Volatility and its Economic Effects." Working paper (2016).

[24] Gabaix, Xavier. "The granular origins of aggregate fluctuations." *Econometrica* 79, no. 3 (2011): 733-772.

[25] Gabaix, Xavier. "Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance." *The Quarterly Journal of Economics* (2012): qjs001.

[26] Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri."Prior selection for vector autoregressions." *Review of Economics and Statistics* 97, no. 2 (2015): 436-451.

[27] Gilchrist, Simon, and Egon Zakrajek. "Credit spreads and business cycle fluctuations." *The American Economic Review* 102, no. 4 (2012): 1692-1720.

[28] Gilchrist, Simon, Jae W. Sim, and Egon Zakrajek. “Uncertainty, financial frictions, and investment dynamics.” No. w20038. National Bureau of Economic Research, 2014.

[29] Gilchrist, Simon, and Benoit Mojon. “Credit risk in the euro area.” *The Economic Journal* (2016).

[30] Gourio, Francois. “Disaster risk and business cycles.” *The American Economic Review* 102, no. 6 (2012): 2734-2766.

[31] Guvenen, Fatih, Serdar Ozkan, and Jae Song. “The nature of countercyclical income risk.” *Journal of Political Economy* 122, no. 3 (2014): 621-660.

[32] Hodrick, Robert J. “Dividend yields and expected stock returns: Alternative procedures for inference and measurement.” *Review of Financial Studies* 5, no. 3 (1992): 357-386.

[33] Kehrig, Matthias. “The cyclical nature of the productivity distribution.” (2015).

[34] Kelly, Bryan, and Hao Jiang. “Tail risk and asset prices.” *Review of Financial Studies* 27, no. 10 (2014): 2841-2871.

[35] Kiefer, Nicholas M., Timothy J. Vogelsang, and Helle Bunzel. “Simple robust testing of regression hypotheses.” *Econometrica* 68, no. 3 (2000): 695-714.

[36] Kiefer, Nicholas M., and Timothy J. Vogelsang. “Heteroskedasticity-autocorrelation robust standard errors using the Bartlett kernel without truncation.” *Econometrica* 70, no. 5 (2002): 2093-2095.

[37] Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. “Measuring uncertainty.” *The American Economic Review* 105, no. 3 (2015): 1177-1216.

[38] Linde, Jesper, Frank Smets, and Rafael Wouters. “Challenges for Central Banks’ macro models.” *Handbook of Macroeconomics* 2 (2016): 2185-2262.

[39] Lopez-Salido, David, Jeremy C. Stein, and Egon Zakrajsek. “Credit-market sentiment and the business cycle.” *The Quarterly Journal of Economics* (2017): qjx014.

[40] Ludvigson, Sydney C., Sai Ma, and Serena Ng. “Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?” No. w21803. National Bureau of Economic Research, 2015.

[41] Luo, Shaowen and Daniel Villar Vallenas. “The Skewness of the Price Change Distribution: A New Touchstone for Sticky Price Models.” No. 2017-028. Board of Governors of the Federal Reserve System (US), 2017.

[42] Ng, Serena, and Jonathan H. Wright. “Facts and Challenges from the Recession for Forecasting and Macroeconomic Modeling.” *Journal of Economic Literature* 51, no. 4 (2013): 1120-1154.

[43] Panousi, Vasia, and Dimitris Papanikolaou. "Investment, idiosyncratic risk, and ownership." *The Journal of Finance* 67, no. 3 (2012): 1113-1148.

[44] Philippon, Thomas. "The bond market's q." The *Quarterly Journal of Economics* 124, no. 3 (2009): 1011-1056.

[45] Schaal, Edouard. "Uncertainty and unemployment." *Econometrica* 85, no. 6 (2017): 1675-1721.

[46] Stock, James H., and Mark W. Watson. "Forecasting output and inflation: The role of asset prices." *Journal of Economic Literature* 41, no. 3 (2003): 788-829.

[47] Stock, James H., and Mark W. Watson. "Disentangling the Channels of the 2007-2009 Recession." No. w18094. National Bureau of Economic Research, 2012.

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). Having the above 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. 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 and (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 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

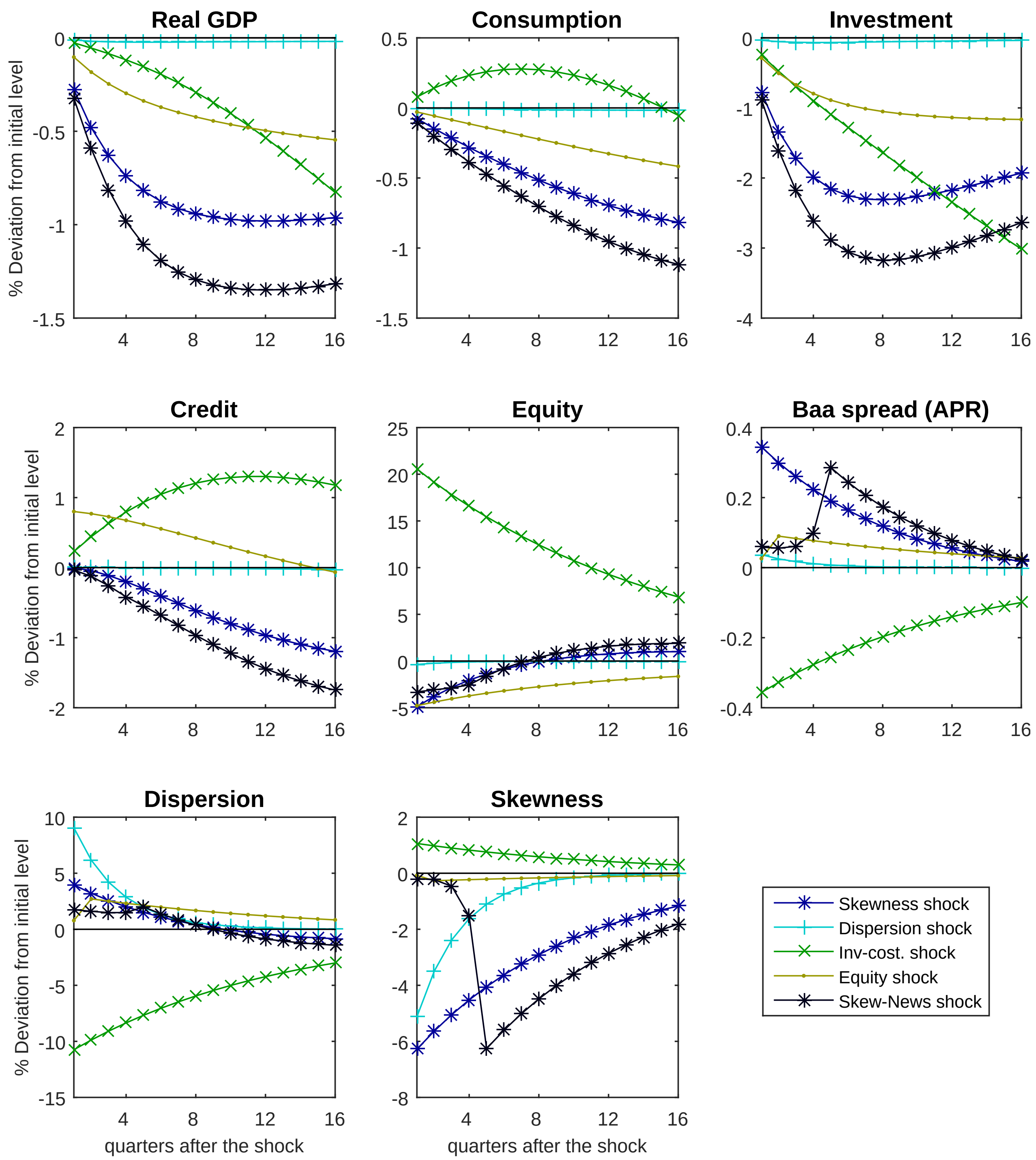
This table reports the results from regression (6) on average GDP growth four quarters ahead ($h = 4$), with $p = 4$ because of the relatively low AIC of this specification, and $q = 1$ to keep the model parsimonious. Real fed funds is measured by the fed funds rate minus the four-quarter change of core 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.

Figure 10: Impulse Response Functions



A.4 DSGE model Is Statistically Comparable to BVAR

Table 14 shows that the marginal likelihood of the DSGE model from Section 4 is close to the one from a BVAR with the same time series and sample period (2002–2015). However, Table 14 also shows that if we exclude OIS rates from the estimation of the DSGE model and focus either on the entire sample (1964–2015) or on 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	1964-2006	2002-2015	1964-2015
DSGE[a]	6154[b]	2178	7374[b]
BVAR[c]	6368	2158	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. [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.