

Stock Market Cross-Sectional Skewness and Business Cycle Fluctuations*

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Abstract

Using U.S. data from 1926 to 2015, I show that financial skewness—a measure comparing cross-sectional upside and downside risks of the distribution of stock market returns of financial firms—is a powerful predictor of business cycle fluctuations and credit activity. I then show that shocks to financial skewness lead to sizable macroeconomic effects through a channel consistent with a financial frictions mechanism. I argue that these results stem from the ability of financial skewness to measure cross-sectional risk on fundamentals faced by the financial sector and their borrowers, such as the quality of borrowers' projects, and the sector's lending capacity.

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

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1 Introduction

Historically, economists have been engaged in understanding the origins of business cycles. Recently, much of this literature has analyzed how fluctuations in uncertainty about economic variables affect macroeconomic performance.¹ In particular, many business cycle theories advocate that idiosyncratic risk—i.e., cross-sectional agent-specific uncertainty—faced by firms and households is an important determinant of macroeconomic fluctuations.² Simultaneously, several papers have documented that the cross-sectional behavior of households and nonfinancial firms indeed tend to follow the business cycle,³ thus providing distinctive evidence against which theories are being tested.⁴

However, there are much fewer analyses about the cross-sectional behavior of financial firms over the cycle, despite the prominence of explanations for the Great Recession involving these firms. From a theoretical perspective, many macroeconomic models focus on a representative financial sector (e.g. Gertler and Kiyotaki (2015)).⁵ Few models analyze the macroeconomic implications of a heterogeneous financial sector, such as Boissay et al (2016) on the effects from moral hazard and asymmetric information in the interbank market, and Martinez-Miera and Repullo (2017) on the effects from search for yield. However, there is little investigation on whether the cross-sectional cyclical behavior of financial firms predicted by theory is consistent with the data.⁶ Moreover, empirical evidence is also limited, with studies on cross-sectional equity volatility focusing on issues related to systemic risk (Giglio et al (2016)).

This paper documents that the relationship between the cross-sectional behavior of financial firms and the business cycle is robust across time and quantitatively powerful. Specifically, I show that *financial skewness*—a variable comparing cross-sectional upside and downside risks of the distribution of stock market returns of financial firms—(i) has a correlation with business cycles over a long time period (1926–2015), (ii) has a powerful predictive ability on

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

²These papers argue that shocks to idiosyncratic risk have economic effects through several channels: wait-and-see effects from capital adjustment frictions (Bloom et al. (2012)); financial frictions (Arellano et al. (2012), Christiano et al. (2014), Gilchrist et al. (2014), and Chugh (2016)); search frictions in the labor market (Schaal (2017)); agency problems in the management of the firm (Panousi and Papanikolaou (2012)); granular effects (Gabaix (2011)); and network effects (Acemoglu et al. (2012)).

³Researchers document that both dispersion (Bloom 2014) and high-order moments of the cross-sectional distribution of many economic variables seem to co-move with the economic cycle, such as nonfinancial firm sales, profit, and employment (Bloom et al. (2016)); household income (Guvenen et al. (2014)); price changes (Luo and Vallenas (2017)); and general stock returns (Kelly and Jiang (2014)).

⁴For instance, see Ilut et al (2017) for theories on employment growth over the cycle.

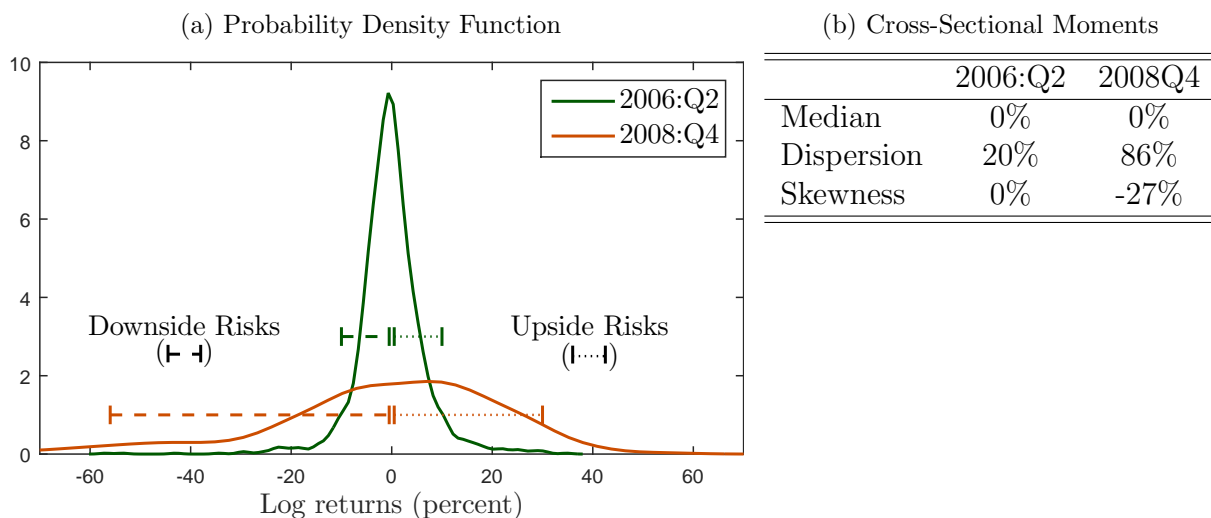
⁵Several other papers follow a similar strategy, such as Gertler and Karadi (2011), Brunnermeier and Sannikov (2014), Christiano and Ikeda (2016), and Ferrante (2018).

⁶Two exceptions are Coimbra and Rey (2017), with predictions for cross-section leverage, and Ferreira (2016), with predictions for cross-sectional dispersion of stock returns.

economic and credit activity, and (iii) its exogenous disturbances lead to sizable aggregate effects through a channel consistent with a financial frictions mechanism. I argue that results (i)-(iii) stem from the ability of financial skewness to measure cross-sectional risk on fundamentals faced by the financial sector and their borrowers, such as the quality of borrowers' projects, and the sector's lending capacity. All told, this paper points to an agenda for business cycle theories in which not only financial firms play an active role, but the cross-sectional distribution of their equity is strongly cyclical and is an important veil for signaling macroeconomic fundamentals.⁷

I define financial skewness as $[(r_t^{95} - r_t^{50}) - (r_t^{50} - r_t^5)]$, where r_t^p is the p^{th} percentile of the distribution of log-returns of financial firms at time t . Intuitively, $(r_t^{95} - r_t^{50})$ measures upside risks, and $(r_t^{50} - r_t^5)$ measures downside risks. Thus, if financial skewness is negative, the balance of cross-sectional risks is tilted to the downside, while if financial skewness is positive, risks are tilted to the upside. Figure 1 illustrates these concepts by displaying the distribution of log-returns of financial firms in 2006:Q2 and 2008:Q4. It shows that financial skewness went from zero in 2006:Q2 to markedly negative in 2008:Q4, as downside risks outgrew upside risks.

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



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

I then document the business cycle properties of financial skewness with four results. First, financial skewness correlates with NBER expansions/recessions over the period 1926 to 2015 (Figure 2) better than most other available variables. Second, financial skewness

⁷This paper is also related to the disaster risk hypothesis (e.g. Barro (2006), Gabaix (2012), and Gorio (2012).)

has a strong predictive power on several measures of economic activity. Using in-sample and out-of-sample regressions for the 1973 to 2015 period, I show that financial skewness generally performs better than many well-known indicators of economic conditions, such as excess bond premium (e.g., Gilchrist and Zakrajsek (2012)), measures of aggregate uncertainty (e.g., Jurado et al. (2015), and Ludvigson et al. (2015)) and other moments from the cross-sectional distribution of returns of financial and nonfinancial firms. Third, previous predictive results are not dependent on specific events, such as the 2008 recession, as financial skewness performs well in both recessions and expansions. Fourth, financial skewness also anticipates credit market conditions, with a relatively stronger predictive ability on loan growth.

Figure 2: Financial Skewness and the Business Cycle

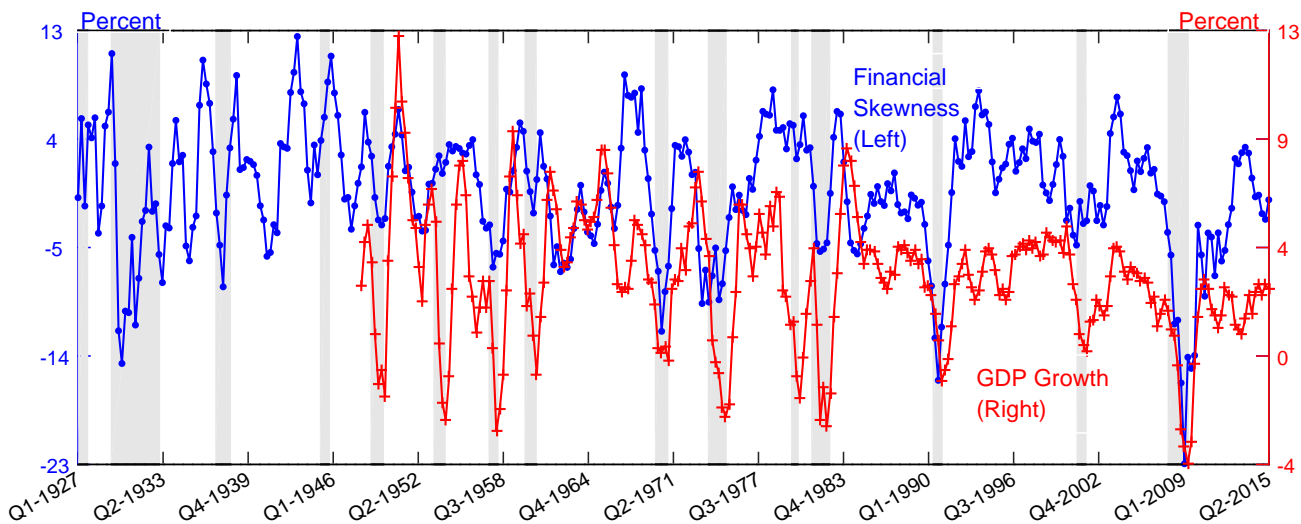


Figure 2 shows the 4-quarter moving average of financial skewness in blue and the 4-quarter GDP growth in red. Gray areas represent periods classified as recessions by the NBER.

The results above bring new evidence to the literature studying the ability of financial indicators to anticipate economic activity.⁸ First, financial skewness’ predictive power oppose the hypothesis that bond markets are more accurate than stock markets about economic fundamentals⁹, pointing, instead, to a direction of possible complementarity between these markets. Second, despite the importance of idiosyncratic risk in business cycle theories, empirical measures of it have had little influence on the research seeking to predict cyclical fluctuations. The results of this paper then help fill this gap in the literature.

I then investigate the quantitative role of financial skewness in both explaining business cycles, and being explained by them. For this, I identify shocks to financial skewness using two complementary approaches: a dynamic stochastic general equilibrium (DSGE) model and Bayesian vector autoregressions (BVARs). The DSGE model embeds a financial accelerator

⁸For literature reviews on this topic, see Stock and Watson (2003) and Ng and Wright (2013).

⁹See Philippon (2009), and Lopez-Salido et al. (2017) for different versions of this argument.

channel a la Bernanke et al. (1999), rationalizes a hypothesis that different financial firms are exposed to different loan markets, and incorporate financial skewness as an endogenous variable. The BVARs allow for more flexible identifications of financial skewness shocks and their transmission channels. In both approaches, I interpret financial skewness shocks not necessarily as exogenous fundamentals per se, but as un-modeled unexpected events leading to skewed heterogeneous effects on, for instance, the productivity of borrowing firms' projects and the lending capacity of financial firms.

The DSGE model and the BVARs agree on their main takeaways. Specifically, they estimate that: (i) financial skewness is largely an exogenous variable, thus mostly explaining business cycles instead of the opposite; (ii) financial skewness shocks are relevant business cycle drivers, displacing other important shocks such as cross-sectional dispersion ones¹⁰; and (iii) financial skewness shocks generate sizable macroeconomic fluctuations with a transmission channel consistent with a financial accelerator mechanism. This last takeaway comes from the specific macroeconomic effects of financial skewness shocks: nonfinancial firms to receive less credit, face higher lending interest rates, have lower equity values, invest less and produce less, with all these effects being amplified when lending rates respond more to skewness shocks.¹¹

Finally, I argue in favor of two hypotheses for financial skewness' predictive and explanatory power on business cycles. In the first, financial skewness reflects shocks that change the cross-sectional risks of investment projects in the economy, i.e. risks faced by the *credit demand*. In this case, financial firms' stocks anticipate business cycles because these firms' lending relationships makes them well interconnected within the economy¹², and their asset diversification purges nonfinancial idiosyncratic risks unrelated to aggregate outcomes. Several of this paper's results are supportive of this hypothesis, among which are: financial skewness has a robust correlation with measures of credit demand's health, such as return on banks' average assets; financial skewness predicts better loan growth than debt growth, suggesting that it is more informative about financial sector's more direct borrowers; financial skewness predicts better economic activity than nonfinancial cross-sectional moments; and cross-sectional distributions of stock returns of financial firms are generally less dispersed and thinner-tailed than those of nonfinancial firms.

An alternative, and likely complementary, hypothesis is that financial skewness captures risks about the lending capacity of the financial sector, or risks faced by the *credit supply*.

¹⁰Bachmann and Bayer (2014) and Zeke (2016) use calibrated theoretical models to provide different arguments on why dispersion shocks should not be viewed as important business cycle drivers.

¹¹See Caldara et al. (2016) for related evidence using uncertainty measures focused on second moments, such as dispersion and volatility.

¹²One of the measures of interconnectivity used by Acemoglu et al. (2012) ranks "monetary authorities and depository credit intermediation" within the five most interconnected sectors.

Under this hypothesis, adverse shocks push financial firms against internal constraints, such as capital and liquidity ones, tilting financial firms' risks to the downside, and causing less lending and lower economic activity. While some of the previous results are also supportive of this hypothesis, such as financial skewness predictive ability on loan growth, I also find that financial skewness correlates with some variables measuring distress faced by financial firms.

2 Cross-Sectional Distribution Measures

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

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

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

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

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

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

where $N_{s,t}$ is the number of firms in sector s at quarter t and “fin” and “nfin” represent financial and nonfinancial sectors of the U.S. economy, respectively.¹³ Notice that the intuition for left kurtosis (equation (4)) and right kurtosis (equation (5)) is analogous to the one for skewness, with the difference being that these kurtoses measures compare upside and downside risks within each distribution tail using the 25th and 75th quartiles as their reference returns.

I also calculate cross-sectional distribution measures weighted by firm size. To do so, for each time t , sector s , and return $R_t^{i,s}$, I artificially augment the sample by repeating return $R_t^{i,s}$ proportionally to its market capitalization share in its sector s at quarter t . Then, I apply the same formulas (1)-(5). Throughout this paper, unless otherwise noted, I refer to unweighted measures. Thus, I refer to unweighted $M(3)_t^{\text{fin}}$ as financial skewness, unweighted $M(3)_t^{\text{nfin}}$ as nonfinancial skewness, and analogously for other distribution measures.¹⁴

¹³The classification between financial and nonfinancial sectors is according to the NAICS codes. When NAICS codes are not available, I use SIC codes. For details about the data, see Appendices A.1 and A.2.

¹⁴I use raw realized returns to calculate measures (1)-(5), instead of residuals of regressions on market factors, such as Fama-French (1993). I choose this procedure because market returns themselves may be determined by the distribution of idiosyncratic risks (e.g., Ferreira (2016)). Thus, if the goal is to measure

Table 1: Time Series Averages of Distribution Measures (in percent)

| | Sample 1926 - 2015 | | | Sample 1947 - 2015 | | |
|--------------------|--------------------|---------------------|-------------------------------|--------------------|---------------------|-------------------------------|
| | Financial (1) | Nonfinancial (2) | Difference (3) = (1) - (2) | Financial (4) | Nonfinancial (5) | Difference (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 1 are computed from unweighted distribution measures. Statistical significance tests the null hypothesis that cross-sectional moments are the same for returns from financial and nonfinancial firms, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01. Results are similar if computed for weighted distribution measures.

Table 1 reports time series averages of moments of cross-sectional distributions of stock market returns. Specifically, it reports these averages for returns of financial and nonfinancial firms during the periods 1926-2015 and 1947-2015. We see that in both sample periods returns are less dispersed (row (b), columns (3) and (6)) and less concentrated in the tails (rows (d)-(e), columns (3) and (6)) for financial firms relative to nonfinancial ones, while mean returns across financial firms are not statistically different from those across nonfinancial firms (row (a), columns (3) and (6)).

3 Financial Skewness and Business Cycles

In this section, I document that financial skewness stands out as a close tracker of business cycles (Section 3.1), and is a powerful predictor of economic activity (Section 3.2).

3.1 Financial Skewness Tracks Business Cycles

Table 2 documents the correlations between financial and nonfinancial skewness and measures of economic activity for the periods 1926–2015 and 1986–2015. Correlations are higher for financial skewness relative to the nonfinancial skewness, regardless of the activity measure and sample period.

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 period 1926 to 2015. Thus, we can interpret the results from these logit

aggregate effects from time-varying idiosyncratic risk, one may be excluding important information through these factor regressions. Alternatively, I control for aggregate factors, such as market returns and volatility, by including direct measures of them in the regressions of this paper.

Table 2: Correlations between Cross-Sectional Skewness and the Business Cycle

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

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

regressions as being robust to specific historical periods, such as the Great Depression, the Great Moderation, and the Great Recession. As control variables, I include the spread between Moody’s Baa and Aaa corporate rates (Baa-Aaa spread) and the lagged NBER expansion indicator. Finally, I standardize the series of all regressors to ensure comparability between the estimated coefficients. Table 3 displays regression estimates.

Table 3: Logit Regressions on NBER Expansion Indicator, 1926–2015

(a) Financial Distribution Measures

| Variables | Regressions with Unweighted Distribution Measures | | | | | | | | | Weighted (10) |
|-----------------------|---|----------|----------|----------|----------|----------|----------|----------|----------|---------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | |
| 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 | | | | | | | | | Weighted (10) |
|-----------------------|---|----------|----------|----------|----------|----------|----------|----------|----------|---------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | |
| 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 3a-3b). 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 3a). Third, within the universe of the largest specifications (columns (9)-(10) of Tables 3a-3b), the coefficient of financial skewness is the second largest, only lower than the one associated with the weighted nonfinancial mean. Finally, declines in financial skewness imply considerable increases in recession probabilities. For instance, when the economy is expanding, a drop of two standard deviations in financial skewness sustained over the previous and current quarters implies a 52% probability of recession in the current quarter.¹⁵

3.2 Financial Skewness is a Powerful Predictor of Business Cycles

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

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

Thus, for instance, I forecast the mean annualized real GDP growth h quarters ahead, while I forecast the level of the unemployment rate h quarters ahead. Finally, I consider several competing variables to financial skewness. Besides financial and nonfinancial distribution measures (1)-(5), I use (i) financial uncertainty (Ludvigson et al. (2016)), proxying for aggregate uncertainty from financial markets; (ii) excess bond premium or EBP (Gilchrist and Zakrajsek (2012)); (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*.

¹⁵For this computation, I use the estimates of specification (9) and assume that (i) financial skewness equals to minus 2, (ii) expansion lag is 1, and (iii) all remaining regressors are at their historical mean values.

3.2.1 In-Sample Predictive Regressions on Economic Activity

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

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

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

Table 4 reports the results of regression (6) on GDP growth, with financial skewness having a large explanatory power as well as a high elasticity on GDP growth. Table 4 focuses on unweighted distribution measures, with Table 4a showing the results of distribution measures of the financial firms' returns.¹⁶ In Table 4a, column (1) represents the benchmark model only with lags of GDP growth ($\beta_j^k = \gamma_j = 0, \forall j, k$), while columns (2)-(10) represent models adding one variable at a time to the benchmark model. Comparing these 10 regressions, we see that financial skewness not only improves the benchmark's in-sample fit (R^2) by one of the largest amounts—20 percentage points—but also has the largest elasticity on GDP growth: a decline of one standard deviation of financial skewness lasting two consecutive quarters leads to a drop of 1.2% in the mean GDP growth over the next four quarters.

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 4a). 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 4a). Financial skewness remains statistically significant and has one of the largest elasticities, 1.15%—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 4b add one nonfinancial distribution measure at a

¹⁶Results for weighted measures are shown in Table 12 of Appendix C, with weighted financial skewness performing only slightly worse than nonweighted financial skewness.

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

(a) Financial Firms, Unweighted Distribution Measures

| Variable | Regressions Specifications | | | | | | | | | | | |
|----------------|----------------------------|---------|--------|---------|--------|--------|---------|-------|---------|----------|----------|---------|
| | (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** | 1.15*** |
| Left kurtosis | | | | | 0.71** | | | | | | 0.26 | |
| Right kurtosis | | | | | | 0.46** | | | | | -1.06*** | |
| Uncertainty | | | | | | | -0.46** | | | | | 0.10 |
| Real fed funds | | | | | | | | -0.44 | | | | 0.39 |
| Term spread | | | | | | | | | 0.92*** | | | 1.02*** |
| EBP | | | | | | | | | | -0.35*** | | -0.10* |
| R ² | 0.08 | 0.29 | 0.11 | 0.28 | 0.17 | 0.11 | 0.19 | 0.12 | 0.28 | 0.20 | 0.40 | 0.51 |

(b) Nonfinancial Firms, Unweighted Distribution Measures

| Variable | Regressions Specifications | | | | | | | | | | | |
|----------------|----------------------------|---------|-------|---------|---------|---------|---------|-------|---------|----------|---------|---------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Mean | | 1.11*** | | | | | | | | | 1.40*** | 0.74*** |
| 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** | | | | | -0.06 |
| Real fed funds | | | | | | | | -0.44 | | | | 0.35 |
| Term spread | | | | | | | | | 0.92*** | | | 0.96*** |
| EBP | | | | | | | | | | -0.35*** | | -0.21 |
| R ² | 0.08 | 0.24 | 0.09 | 0.15 | 0.13 | 0.12 | 0.19 | 0.12 | 0.28 | 0.20 | 0.26 | 0.44 |

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, $\{\beta^k = \sum_{j=0}^q \beta_j^k\}_{k=1}^5$ and $\gamma = \sum_{j=0}^q \gamma_j$. 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.

time to the benchmark model, regression (1). The R²s and elasticities from these regressions are lower than those from the analogous regression with financial skewness (regression (4) of Table 4a). Turning to the regressions with all nonfinancial measures (column (11)) and all economic predictors (column (12)), even the nonfinancial measure with the largest and intuitive elasticities—the mean—has these elasticities being lower than those associated with financial skewness in analogous regressions (columns (11)-(12) of Table 4b relative to column (11)-(12) of Table 4a).

Table 4 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 EBP. However, the coefficients of many of these variables, such as financial uncertainty, either lose their statistical significance or have unintuitive signs in the larger specifications (12) of Tables 4a-4b. The only economic predictor with statistical significance in these larger regressions is term-spread. Moreover, the magnitude of the elasticity of term-spread is similar to the one of financial skewness.

Studying additional measures of economic activity, we learn that the predictive ability of financial skewness goes beyond GDP growth. Table 5 reports the results for the following variables: GDP, personal consumption expenditures, private fixed investment, total hours worked, and unemployment rate. Table 5b focuses on the results of regressions that use financial skewness as a predictor variable. Row (a) shows estimates from benchmark regressions only with lagged predicted variables, while rows (b) and (c) show the results for regressions that add financial skewness to the benchmark. These first three rows document that financial skewness adds about 10% to 25% of explanation power to future economic activity and has statistically and economically significant elasticities, such as 3.9% on investment. Rows (d) through (i) present the results of regressions adding both financial skewness and economic predictors to benchmark regressions. In all of these regressions, financial skewness has the largest elasticities, with these being statistically and economically significant.

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 5b shows the results of financial skewness, Table 5c of financial dispersion, Table 5e of nonfinancial skewness, and Table 5f 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 one of 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.

Table 5: In-Sample Forecast Regressions, Macro Variables, 4 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 | 1.15*** | 0.81*** | 3.15*** | 1.00*** | -0.52*** | -0.01 | -0.09 | 0.26 | 0.33 | 0.24 |
| (e) | | Uncertainty | 0.10 | 0.14 | 0.17 | -0.18 | 0.02 | -0.08 | 0.04 | -0.34 | -0.43 | 0.04* |
| (f) | | Real Fed Funds | 0.39 | 0.45** | 0.07 | 0.04 | 0.06 | 0.38 | 0.42* | -0.06 | -0.01 | 0.00 |
| (g) | | Term Spread | 1.02*** | 0.80*** | 2.88*** | 0.99*** | -0.39*** | 1.01*** | 0.78*** | 2.81*** | 0.95*** | -0.44*** |
| (h) | | EBP | -0.10* | 0.07 | -0.86 | -0.74** | 0.29** | -0.45** | -0.11** | -1.91** | -1.25*** | 0.38*** |
| (i) | | R^2 | 0.51 | 0.52 | 0.64 | 0.67 | 0.78 | 0.39 | 0.44 | 0.55 | 0.62 | 0.74 |

| (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 | 0.46 | 0.26** | 1.47** | 0.54* | -0.10 | 0.11 | 0.07 | 0.39 | -0.15 | -0.44* |
| (e) | | Uncertainty | -0.13 | -0.01 | -0.40 | -0.38 | 0.12* | -0.12 | -0.01 | -0.43 | -0.32 | 0.22 |
| (f) | | Real Fed Funds | 0.35 | 0.40** | -0.06 | 0.02 | 0.06 | 0.37 | 0.41* | -0.01 | 0.06 | 0.08 |
| (g) | | Term Spread | 1.00*** | 0.77*** | 2.86*** | 1.00*** | -0.41*** | 0.99*** | 0.76*** | 2.80*** | 0.98*** | -0.25** |
| (h) | | EBP | -0.23 | -0.05 | -1.08 | -0.82* | 0.43*** | -0.49*** | -0.18** | -1.96** | -1.03*** | 0.66*** |
| (i) | | R^2 | 0.41 | 0.45 | 0.57 | 0.63 | 0.74 | 0.40 | 0.44 | 0.56 | 0.62 | 0.76 |

This table reports the results from regression 6 on GDP, Personal Consumption Expenditures, Private Fixed Investment, total hours worked and unemployment rate. With exception of unemployment rate, all predicted variables are used in growth rates, where $h = 4$, $p = 4$ due to 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 4 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, $\{\beta^k = \sum_{j=0}^q \beta_j^k\}_{k=1}^5$ 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.

3.2.2 Out-of-Sample Predictive Regressions on GDP Growth

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

$$GDP_{t+h|t-1} = \alpha + \sum_{i=1}^p \rho_i GDP_{t-i|t-i-1} + \sum_{j=0}^q \theta_j X_{t-j} + u_{t+h}. \quad (7)$$

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 3.2.1 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), GZ-spread (Gilchrist and Zakrajsek (2012)), and macroeconomic uncertainty (Jurado et al. (2016)). I also use forecasts from regression (7) that only include lags of GDP growth ($\theta_j = 0, \forall j$), referring to these forecasts as GDP-AR. I determine the number of lags of GDP growth (p) and predictor variable X_t (q) by choosing the specification with the minimum AIC at each forecasting period. I use an expanding window of data with jump-off date 1986:Q1. Finally, I document the performance of different variables by computing ratios of root mean squared forecast errors (RMSFEs). I use financial skewness as the benchmark variable and refer to these ratios as relative root mean squared forecast error (R-RMSFE) of variable X_t . Values below 1 indicate that financial skewness performs better than variable X_t .

Figure 3 shows the R-RMSFEs from these forecasts, with financial skewness outperforming almost all variables. Figures 3a-3c focus on a set of selected predictor variables, providing R-RMSFEs for the full sample, recessions, and expansions. On the full sample (Figure 3a), R-RMSFEs are below 1 and statistically significant (estimates with circles) for almost all variables and horizons ($h = 2, 4, 6$).¹⁷ 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 slightly more frequent in expansions. Figures 3d and 3e show that financial skewness also outperforms almost all of the remaining distribution variables, either weighted or unweighted. The variables that outperform financial skewness do not achieve statistical significance (e.g., weighted financial skewness) and/or are statistically outperformed in another state of the cycle (e.g., macro uncertainty and GDP-AR).

¹⁷To 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

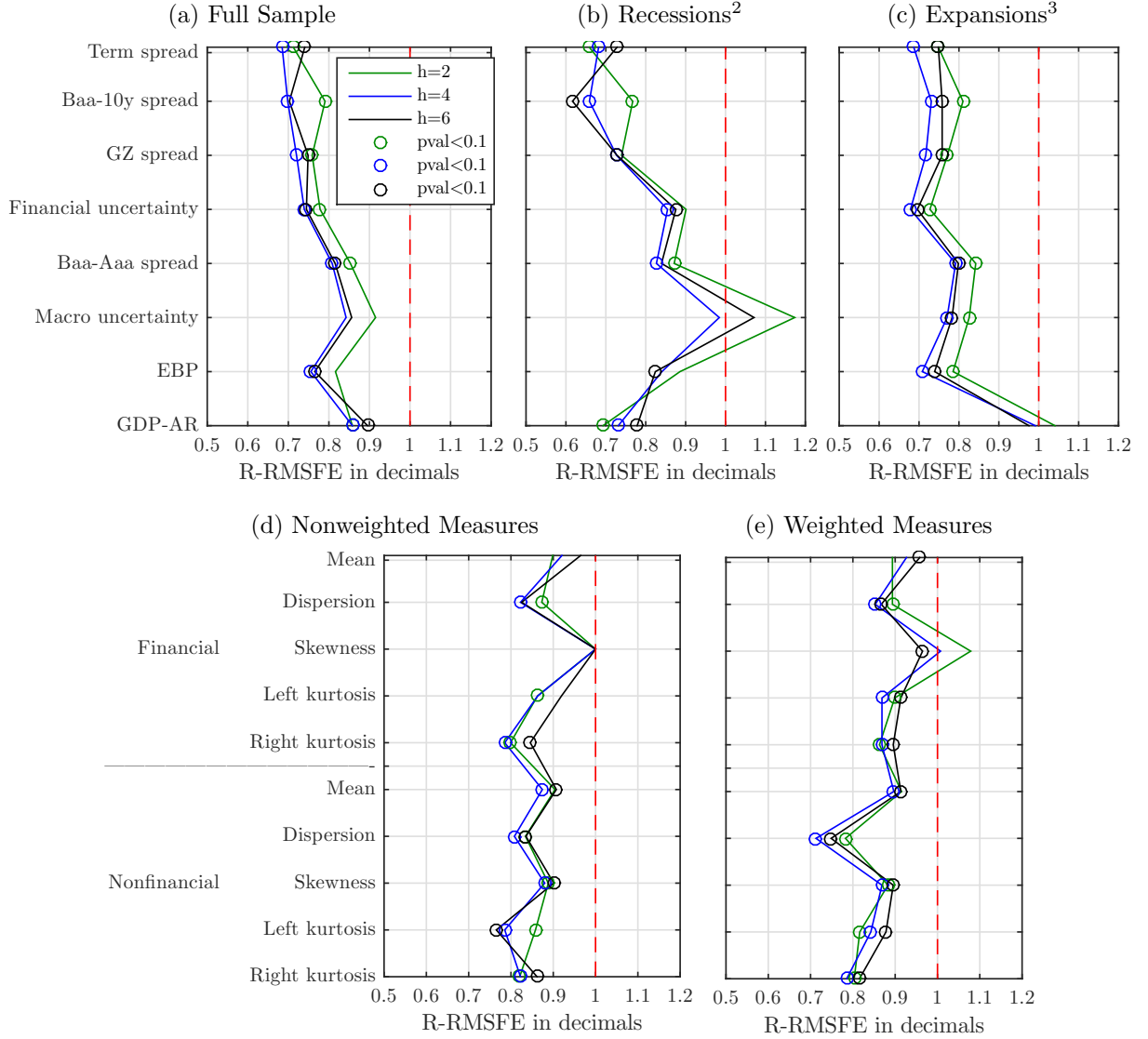


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis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

I also show that financial skewness has powerful predictive ability within the majority of the sample period. Figure 4 displays 20-quarter rolling R-RMSFEs for GDP growth four quarters ahead ($h = 4$), focusing on some well-known predictor variables: macro uncertainty (Figure 4a), term spread (Figure 4b), GZ spread (Figure 4c), and lagged GDP growth (Figure 4d). For most of the sample, Figures 4a-4d show that the rolling R-RMSFE stays below

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

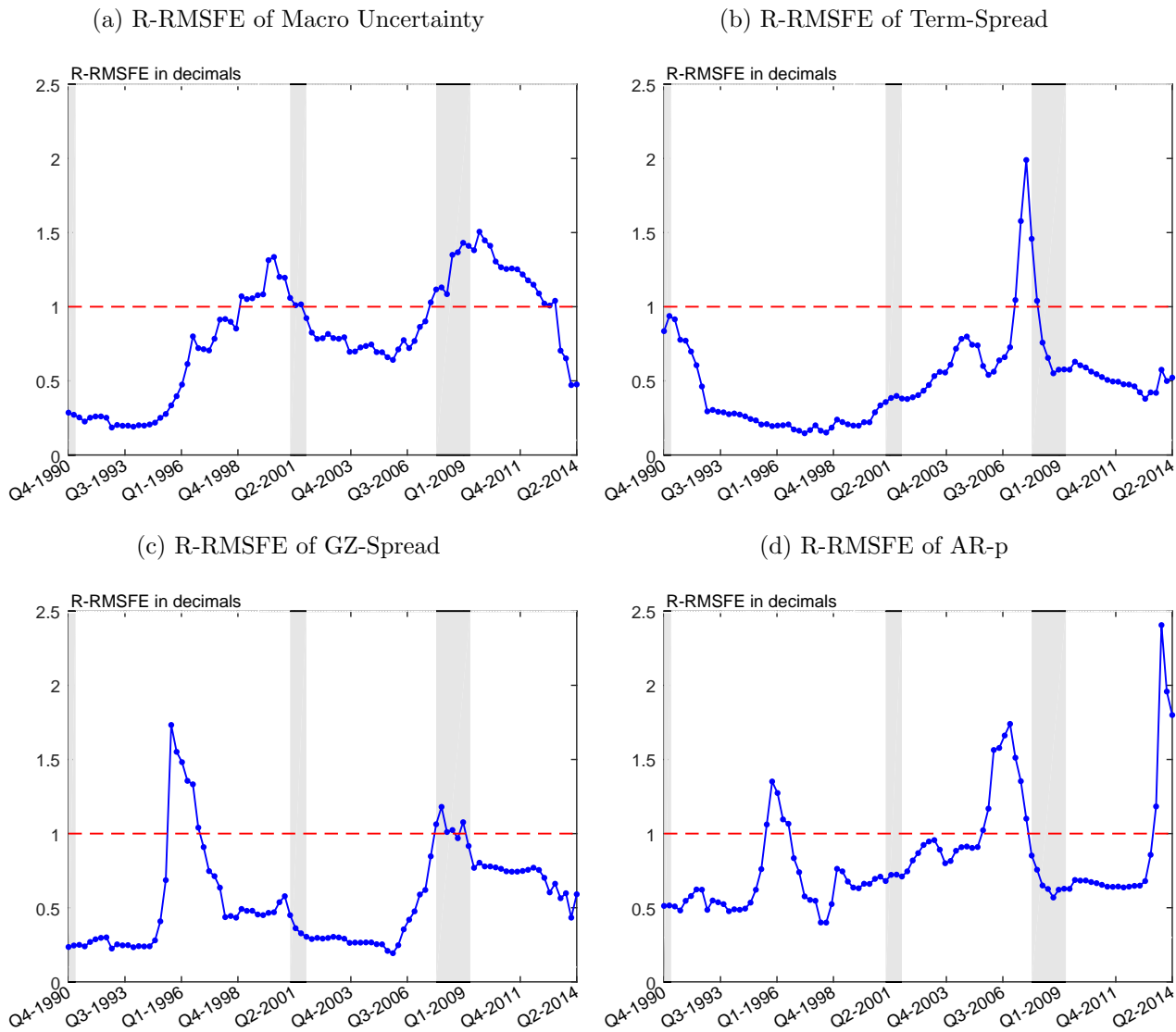


Figure 4 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) of variable X_t . At every quarter, I compute the R-RMSFE over the current and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

1, indicating that the forecasts using financial skewness have a lower RMSFE than those from alternative variables. Although Figures 4a-4d 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.

Appendix C shows results for two robustness exercises. It shows that results are very similar if we use end-of-quarter observations of the financial indicators (Figure 9) and kelly-skewness (Figure 10) instead of financial skewness (the two measures have a 0.95 correlation).

4 Financial Skewness Anticipates Credit Conditions

In this section, I show that financial skewness anticipates many credit variables, performing particularly well for loan growth. I do so by using regressions similar to those from Section 3.

I first focus on in-sample regressions. I use regression specifications (6) with the following dependent variables at four quarters ahead ($h=4$): loan growth, debt growth, loan spread, GZ spread, and Baa-10y spread. I report results in Table 6 not only for financial skewness, but also for nonfinancial dispersion, given the relevance of the latter in the literature of time-varying uncertainty.¹⁸ Row (a) reports estimates from benchmark regressions using only lagged predicted variables as regressors. Rows (b) and (c) report estimates from regressions with a distribution measure added to the benchmark regressions. Finally, rows (d) through (i) report estimates from regressions with a distribution measure and all control variables.

Table 6b describes the estimates from the regressions using financial skewness. The best results are achieved for loan growth. Financial skewness adds 16% of explanatory power to the benchmark regression and has an elasticity of 1.7% in the regression with all controls, meaning that a decline of one standard deviation of financial skewness lasting two consecutive quarters anticipates a drop of 1.7% in mean loan growth over then next four quarters. Although financial skewness does not add much explanatory power to loan, GZ, and Baa-10y spreads, it has significant elasticities on these variables in the presence of all controls. Finally, financial skewness neither adds explanatory power to debt growth nor has a significant effect on it.

Relative to financial skewness (Table 6b), nonfinancial dispersion (Table 6c) is equally or more informative about debt market variables, while being equally or less informative about loan market variables. To see this, first notice that nonfinancial dispersion adds 6% of explanatory power to the benchmark regression on debt growth and has a statistically significant elasticity of -1.1% in the analogous regression with all controls. This result contrasts with the poor performance of financial skewness on debt growth. Second, nonfinancial dispersion has an explanatory power to corporate spreads (GZ and Baa-10y) similar to financial skewness, while having a smaller coefficient on Baa-10y. Finally, nonfinancial dispersion has insignificant coefficients on both loan growth and loan spreads in the regressions with all controls.

Figure 5 reports the results out-of-sample regressions on loan growth, with the details of these forecasts being similar to those of Section 3.2.2. In the full sample (Figure 5a), financial skewness outperforms most other variables with an improvement of around 20%. In recessions (Figure 5b), this performance increases to a range between 20% and 42%, while in expansions (Figure 5c) it decreases to range between 0% and 20%.

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

Table 6: In-Sample Forecast Regressions, Credit Variables, Four Quarters Ahead, 1973 - 2015

| (a) Notation | | (b) Variable = Financial Skewness | | | | | (c) Variable = Nonfinancial Volatility | | | | |
|--------------|-----------------------------|--|--------|----------|-----------|-----------|---|----------|---------|---------|----------|
| | | Loans | Debt | Loan Sp | GZ Sp | Baa-10y | Loans | Debt | Loan Sp | GZ Sp | Baa-10y |
| | | (%) | (%) | (bps) | (bps) | (bps) | (%) | (%) | (bps) | (bps) | (bps) |
| (a) | Benchmark R^2 | 0.57 | 0.40 | 0.88 | 0.84 | 0.78 | 0.57 | 0.40 | 0.88 | 0.84 | 0.78 |
| (b) | Bivariate 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 |
| (d) | Variable | 1.71** | -0.31 | -6.66*** | -7.79*** | -12.87*** | -0.51 | -1.11*** | -3.65 | 7.79*** | 3.07*** |
| (e) | Uncertainty | -0.13 | 0.26 | 4.64** | 6.72*** | 6.27** | -0.27 | 0.67 | 9.33*** | 3.74*** | 7.16** |
| (f) | Multivariate Real Fed Funds | 0.16 | 1.12 | -7.83 | -4.12** | -3.15*** | 0.17 | 1.29* | -8.57* | -4.67* | -2.39*** |
| (g) | Term Spread | 0.55 | 0.32 | 1.96 | -0.76 | -0.88** | 0.56 | 0.47 | 0.33 | -1.52 | -1.28** |
| (h) | EBP | -1.73** | -0.90* | | | | -2.09*** | -0.32 | | | |
| (i) | R^2 | 0.80 | 0.50 | 0.91 | 0.88 | 0.86 | 0.77 | 0.55 | 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, 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 $h = 4$, $p = 4$ due to 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 4 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, $\{\beta^k = \sum_{j=0}^q \beta_j^k\}_{k=1}^5$ and $\gamma = \sum_{j=0}^q \gamma_j$. 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 5: Out-of-Sample Forecasts of Loan Growth, R-RMSFEs

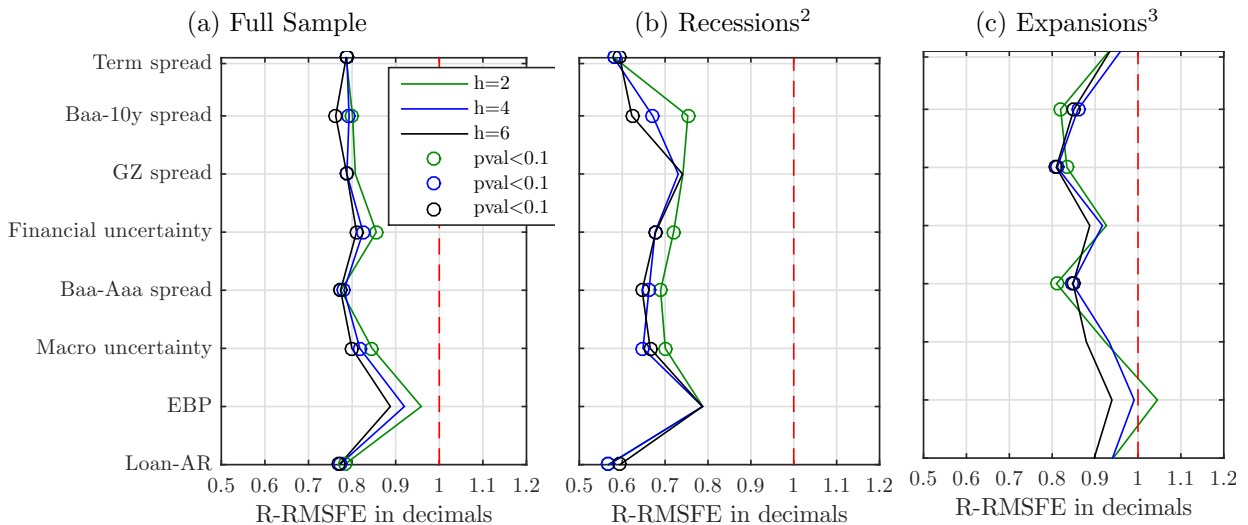


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis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

5 Identifying Financial Skewness Shocks

In this section, I identify financial skewness shocks by estimating BVARs and a new Keynesian DSGE model with the financial accelerator channel (Bernanke et al. (1999)). I choose this DSGE model because of its explicit predictions for the endogenous behavior of the cross-sectional distribution of returns (Ferreira (2016)), and its success in explaining the comovement between macro and financial variables with cross-sectional shocks (Christiano et al. (2014)). Both the DSGE model and BVARs find that financial skewness shocks lead to sizable aggregate effects through a channel consistent with the financial accelerator mechanism.

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

Entrepreneurs and Skewness Shocks. There is a unit measure of entrepreneurs. At the end of period t , entrepreneur i with amount of equity N_{t+1}^i gets a loan (B_{t+1}^i, Z_{t+1}^i) from a mutual fund, where B_{t+1}^i is the loan amount and Z_{t+1}^i is the interest rate. With loan B_{t+1}^i and

Figure 6: Distribution of Idiosyncratic Asset Returns of the DSGE Model

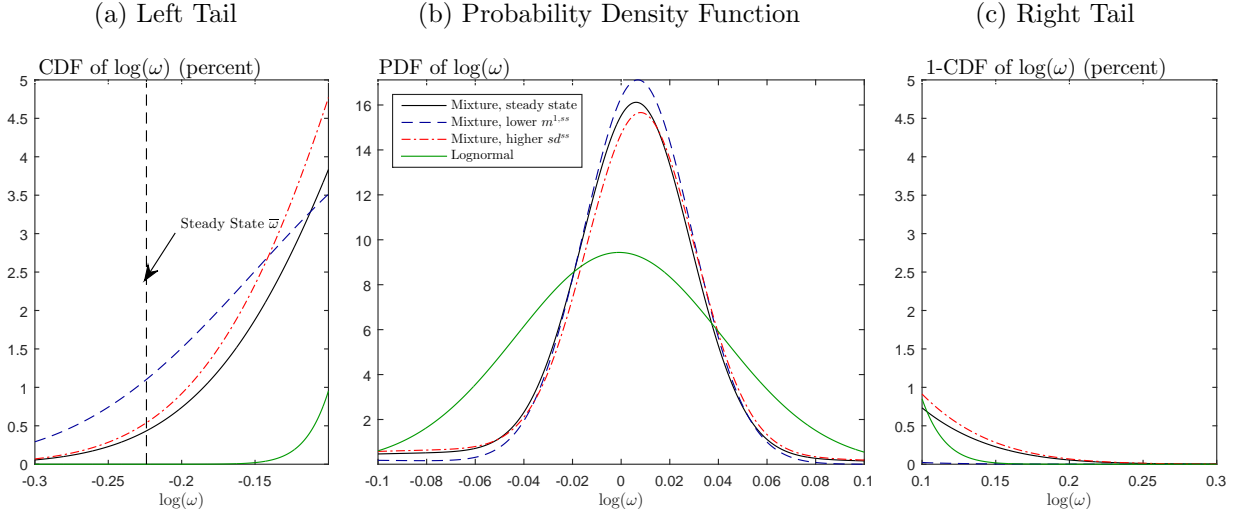


Figure 6a plots cumulative distribution functions (CDFs) of $\log(\omega)$ under different assumptions. Analogously, Figure 6b plots probability density functions (PDFs) of $\log(\omega)$ and Figure 6c plots complementary cumulative functions (1-CDFs) of $\log(\omega)$. The black lines (Mixture, steady-state) 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 $F(\cdot; \tilde{m}^{1,ss}, s^{1,ss}, sd^{ss}, s^{2,ss})$, where $\tilde{m}^{1,ss} < m^{1,ss}$. The red lines (Mixture, higher sd^{ss}) plot the CDF/PDF/(1-CDF) of $\log(\omega)$ when ω follows the distribution $F(\cdot; m^{1,ss}, s^{1,ss}, \tilde{sd}^{ss}, s^{2,ss})$, where $\tilde{sd}^{1,ss} > sd^{ss}$. 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} .

equity N_{t+1}^i , entrepreneur i purchases physical capital \bar{K}_{t+1}^i with unit price Q_t in competitive markets. He then totals an amount of assets of $Q_t \bar{K}_{t+1}^i = N_{t+1}^i + B_{t+1}^i$. In the beginning of period $t+1$, entrepreneur i draws an exogenous idiosyncratic return ω_{t+1} only observable by him, which transforms \bar{K}_{t+1}^i into $\omega_{t+1} \bar{K}_{t+1}^i$ efficient units of physical capital. I interpret each entrepreneur as the aggregate of a financial firm and its debtors. In this interpretation, ω_{t+1} measures the idiosyncratic risk of specific loan markets to which a financial firm is exposed.

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

$$\omega_t \sim F_t(\omega_t; m_t^1, s_t^1, m_t^2, s_t^2, p_t^1) = \begin{cases} p_t^1 \cdot \Phi[(\log(\omega_t) - m_t^1)/s_t^1] \\ + (1 - p_t^1) \cdot \Phi[(\log(\omega_t) - m_t^2)/s_t^2] \end{cases}, \quad (8)$$

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

To focus the analysis on dispersion and skewness shocks, I make two normalizations on the mixture F_t . First, I re-parametrize it by picking m_t^2 and p_t^1 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_t^1, s_t^1, s_t^2) . Second, I fix the s_t^1 and s_t^2 at their steady-state levels. In this way, sd_t measures the second moment

of F_t , while a lower/higher m_t^1 makes F_t more negatively/positively skewed, as shown by the variations of F_t (blue and red lines) around its steady state F^{ss} (black line) in Figures 6a-6c. I then model sd_t and m_t^1 as first-order autoregressions (AR(1)) and name them cross-sectional dispersion and skewness shocks.¹⁹

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

Loan Markets. At the end of period t , mutual funds compete in the loan market for entrepreneurs with equity level N_{t+1}^i by choosing loan terms (B_{t+1}^i, Z_{t+1}^i) , where interest rate Z_{t+1}^i may vary with $(t + 1)$'s state of nature. It is then easier to determine loan terms with the following change of variables: leverage $L_{t+1}^i = (Q_t \bar{K}_{t+1}^i) / N_{t+1}^i$ and threshold $\bar{\omega}_{t+1}^i$, such that $Z_{t+1}^i B_{t+1}^i = \bar{\omega}_{t+1}^i R_{t+1}^c Q_t \bar{K}_{t+1}^i$ and $\bar{\omega}_{t+1}^i$ may also vary with $(t + 1)$'s state of nature. Threshold $\bar{\omega}_{t+1}^i$ determines whether entrepreneur i is able to pay his debt. If $\omega_{t+1} \geq \bar{\omega}_{t+1}^i$, then entrepreneur i pays his lender the amount owed, $Z_{t+1}^i B_{t+1}^i$, 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: $(1 - \mu) \omega_{t+1} R_{t+1}^c Q_t \bar{K}_{t+1}^i$, 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:

$$\mathbb{E}_t \left(\int_{\bar{\omega}_{t+1}^i}^{\infty} (\omega - \bar{\omega}_{t+1}^i) dF_{t+1}(\omega) \frac{R_{t+1}^c Q_t \bar{K}_{t+1}^i}{N_{t+1}^i} \right) = \mathbb{E}_t \left[(1 - \Gamma_{t+1}(\bar{\omega}_{t+1}^i)) R_{t+1}^c L_{t+1}^i \right], \quad (9)$$

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

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_{t+1}^i , revenues in each state of nature of period $t + 1$ must

¹⁹Besides the wanted focus on dispersion and skewness shocks, I excluded kurtosis shocks from the DSGE model because of the empirical results discussed in Section 3, which show strong evidence of skewness dominating kurtosis measures in their association with the business cycle.

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

be greater than or equal to the amount owed to households:

$$(1 - F_{t+1}(\bar{\omega}_{t+1}^i))B_{t+1}^i Z_{t+1}^i + (1 - \mu)G_{t+1}^f(\bar{\omega}_{t+1}^i)R_{t+1}^c Q_t \bar{K}_{t+1}^i \geq R_{t+1} B_{t+1}^i. \quad (10)$$

We then normalize equation (10) by N_{t+1}^i and impose equality because competition in loan markets drives profits to zero. Finally, we determine loan contracts by choosing $(L_{t+1}^i, \bar{\omega}_{t+1}^i)$ that maximizes (9) subject to the renormalized equation (10). Notice that this maximization does not depend on the level of equity N_{t+1}^i 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, $\bar{\omega}_{t+1}$.

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 $(1 - \gamma_{t+1})$ 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_{t+1}^e from households. Then, we have the following law of motion for aggregate equity:

$$N_{t+2} = \gamma_{t+1} [1 - \Gamma_{t+1}(\bar{\omega}_{t+1})] R_{t+1}^c Q_t \bar{K}_{t+1} + W_{t+1}^e, \text{ where } N_{t+2} = \int N_{t+2}^i di \text{ and } \bar{K}_{t+1} = \int \bar{K}_{t+1}^i di.$$

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

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

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

New-Keynesian Features. I also allow for features widely used in New-Keynesian models, such as sticky prices and wages a la Calvo, habit persistence in the consumption of households, adjustment cost in investment growth, and a Taylor rule governing monetary policy. For details on these features of the model, see Appendix B.

News Shocks. I allow for anticipated and unanticipated components on shocks to dispersion,

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

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

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 $\mathbb{E}(\xi_{0,t}^2) = \sigma_\zeta^2$, $\mathbb{E}(\xi_{1,t}^2) = \dots = \mathbb{E}(\xi_{4,t}^2) = \sigma_{\zeta,\xi}^2$. Parameter $\rho_{\zeta,\xi}$ measures the correlation between $\xi_{i,t}^\zeta$'s.

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

The estimation of the DSGE model uses 14 financial and macroeconomic quarterly series for the period 1964:Q1–2015:Q2: real GDP, real consumption, real investment, hours worked, real wage, relative investment price, the fed funds rate, core inflation, real total credit, the real nonfinancial equity index, the spread between the Moody's Baa rate and the 10-year Treasury rate (Baa-10y), nonfinancial dispersion, financial skewness, and OIS expectation of the one-year-ahead fed funds rate.²¹

Motivated by a potential change in structural parameters after the Great Recession and by the adoption of a more explicit guidance about future policy rates by the Fed, I use a two-step estimation procedure. In the first step, I estimate model parameters using data for the period 1964:Q1–2006:Q4, excluding OIS-rates and imposing a white noise structure on monetary policy shocks ζ_t^{mp} . I calibrate some model parameters, postulate priors for the remaining parameters, and then maximize the log-posterior of the model. In the second step, I re-estimate the persistence and standard deviation of all shocks, using data for the period 2002:Q1–2015:Q2, including OIS-rates and allowing for anticipated and unanticipated monetary policy shocks. Additionally, in the second estimation step, I (i) fix at the first-step mode all parameters not re-estimated in the second step, (ii) center the prior of re-estimated parameters on the first-step mode, (iii) choose the standard deviation of the prior of re-estimated parameters to be the standard deviation of the first-step posterior, and (iv) impose a zero auto-correlation ρ_{mp} for monetary policy shocks.²² The focus of this two-step procedure

²¹Quantity 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.3 for details about data definitions and transformations. I include nonfinancial dispersion instead of the financial counterpart because of the evidence from Section 4 that it predicts debt growth. I then use total credit growth (loan and debt) to measure aggregate effects on credit.

²²The reason for having an overlapping period between the samples used by the two estimation steps is

on the persistence and size of economic shocks lowers the number of parameters estimated twice and is consistent with the evidence provided by Stock and Watson (2012). They argue that the 2008 recession was the result of large versions of shocks already experienced and that the response of macro variables was in line with historical standards.

Most estimated parameters are within the range of estimates reported in the literature (see Table 11 in Appendix B). However, the parameters determining the steady-state distribution of idiosyncratic asset returns F^{ss} pin down a distribution markedly different from the lognormal case, which is largely assumed in the financial frictions literature. Figure 6 reports F^{ss} (black line) and a lognormal distribution with identical mean and standard deviation (green line). We then see that the tails of F^{ss} are much fatter than the ones of the lognormal distribution, especially the left one. Finally, Table 7 documents the steady state of several model variables, showing that they are close to most of their data counterparts.²³

Table 7: 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 |

^aFrom Christiano et al (2014). ^bThese are aggregate measures, where the lower bound is for nonfinancial businesses and the upper bound is for the domestic financial sector. Source: Financial Accounts, Federal Reserve Board.

5.3 The Primacy of Skewness Shocks in The DSGE Model

Skewness shocks are the most important driver of economic fluctuations in the DSGE model, as shown in the variance decomposition of Table 8. 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

to dilute the influence of a particular break-date. Additionally, I include measurement errors in real wage growth, equity growth, cross-sectional dispersion, and cross-sectional skewness.

²³Appendix C.1 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.

mostly exogenous, while dispersion is mostly endogenous.

Table 8: Variance Decomposition from the DSGE Model¹ (Percent)

| Variables | Shocks | | | | | | | | |
|--------------------------|-------------|-----------------------|------------|------------------|--------------------------------|------------------|--------------------------------|-------------------|---------------------------------|
| | Inv-Cost | TFP | Equity | MP | MP-News | Disp | Disp-News | Skew | Skew-News |
| | 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 |

¹Percentages do not add to 100 because remaining shocks account for the residual. ²Variables used in four quarter growth.

³Measurement error accounts for a large variability of this variable.

Figure 7 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 impuled the economy (in blue). The difference between the blue and red series is accounted for by the contribution of all the other shocks used in the estimation. We then see that skewness shocks were major contributors to all expansions and recessions throughout the period 1964–2015. We also see that variations in credit spreads are largely explained by skewness shocks and that these shocks account for low frequency movements in credit growth.

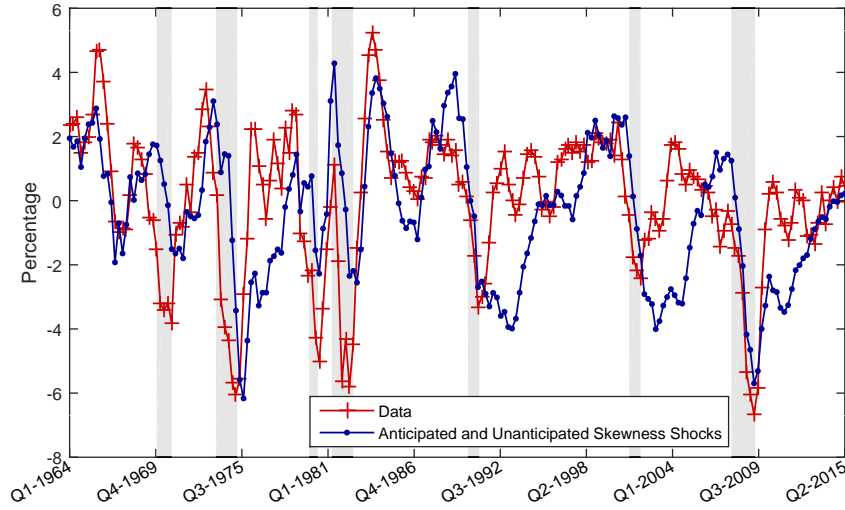
Impulse response functions (IRFs) in Figure 8 shed light on the reason skewness shocks are important drivers of business cycle fluctuations. Essentially, when cross-sectional skewness is exogenously lower, endogenous variables respond with co-movements generally observed over the cycle (black lines in Figure 8a): higher credit spreads and dispersion, and then lower credit, equity, investment, consumption, and GDP growth. Similarly to Christiano et al. (2014), most other shocks do not generate this entire set of co-movements, and thus are not able to account for large shares of business cycle fluctuations.²⁴ The exception to this argument in this paper are dispersion shocks, shown in Figure 8b.

The question then becomes why skewness shocks are more related to the business cycle than dispersion ones. The answer comes from comparing Figures 8a and 8b. Although IRFs to skewness and dispersion shocks follow qualitatively similar dynamics, skewness shocks cause

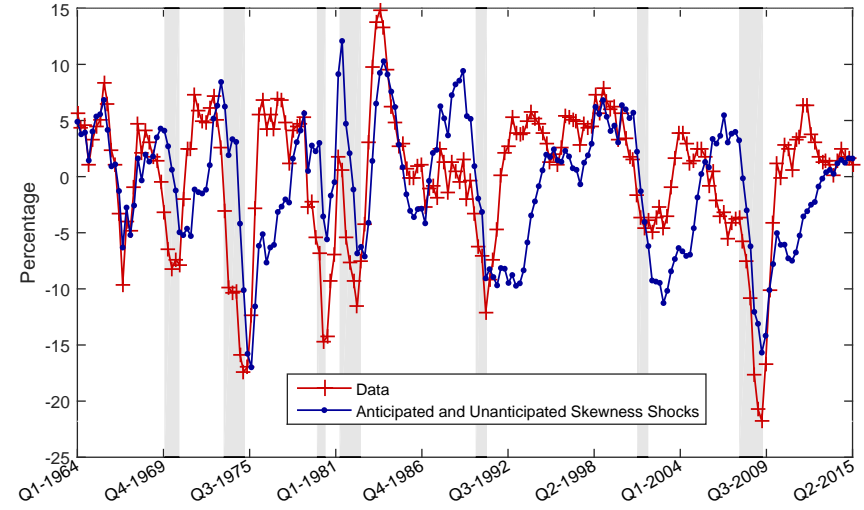
²⁴I report the IRFs of other shocks, including anticipated skewness shocks, in Appendix C. There we see that shocks such as investment efficiency have difficulty in matching co-movements of not only credit outstanding and credit spreads (as in Christiano et al. (2014)), but also of the series of cross-section dispersion and skewness.

Figure 7: Shock Decomposition, 1964–2015

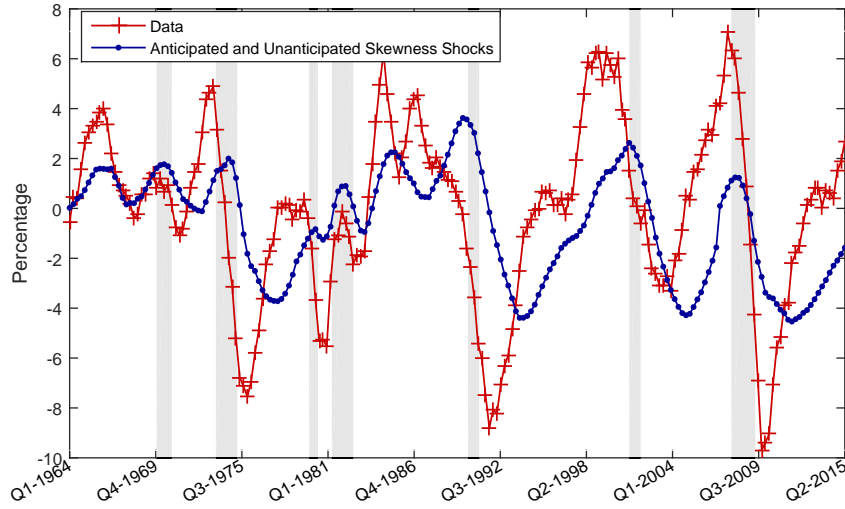
(a) GDP 4Q growth



(b) Investment 4Q growth



(c) Credit 4Q growth



(d) Baa-10y Spread

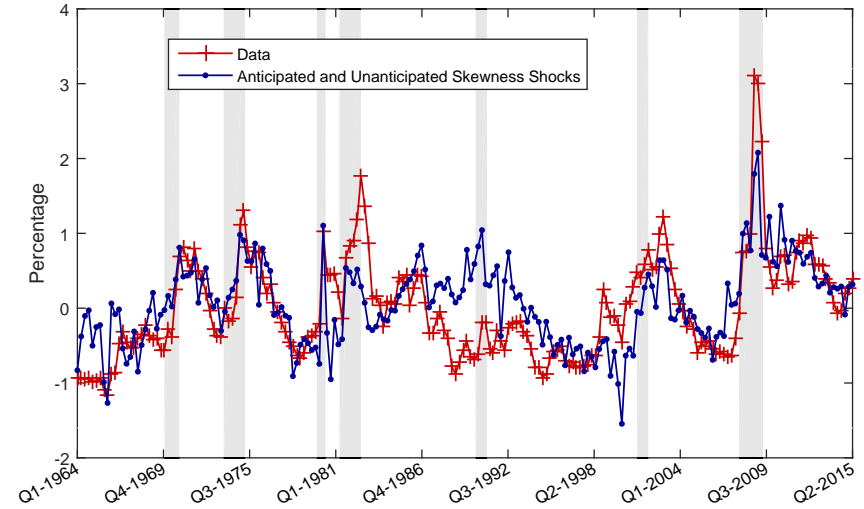
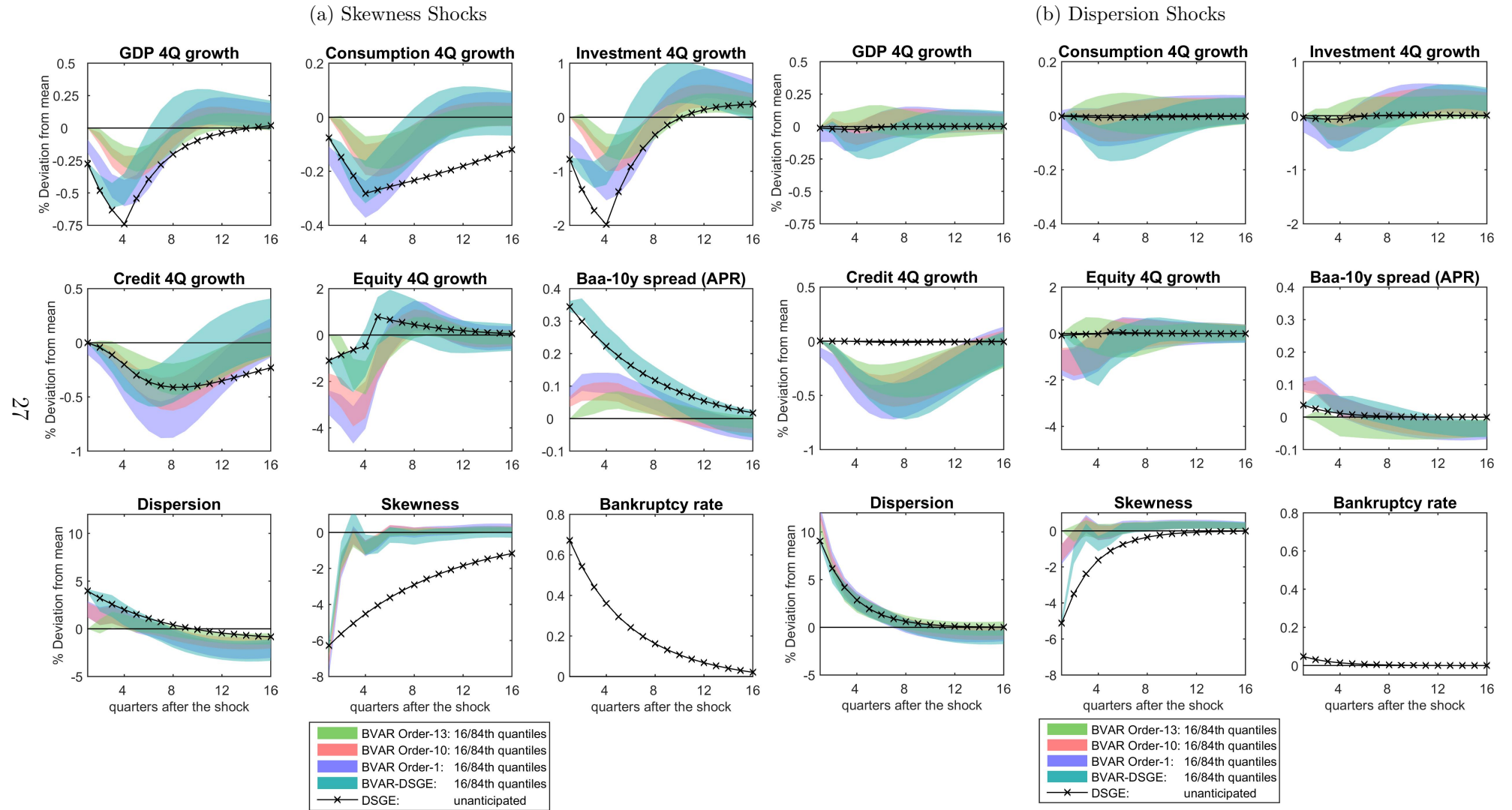


Figure 8: Impulse Response Functions from BVARs and DSGE model



much stronger effects to endogenous variables. A one standard deviation exogenous drop in skewness increases the Baa-10y spread by 35 basis points and dispersion by about 4.5% at their peaks, while it decreases credit growth by 0.4%, equity growth by 1%, investment growth by 2%, consumption growth by 0.3%, and GDP growth by 0.8% at their troughs. In contrast, these variables barely react to a one standard deviation exogenous increase in dispersion, with the exception of dispersion itself.

Skewness shocks have stronger effects on the economy than dispersion shocks because of two factors. First, entrepreneurial bankruptcy is more reactive to changes in skewness than to changes in dispersion. To see this argument at its simplest form, I ignore general equilibrium effects and (i) decrease by one standard deviation the steady-state value of the skewness parameter from $m^{1,ss}$ to $\tilde{m}^{1,ss}$, (ii) keep fixed the threshold $\bar{\omega}^{ss}$ 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 $F(\bar{\omega}^{ss}; m^{1,ss}, \cdot)$ to $F(\bar{\omega}^{ss}; \tilde{m}^{1,ss}, \cdot)$). I also implement an analogous exercise to steady-state cross-sectional dispersion sd^{ss} . Figure 6a 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 11b.

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 (IRFs in lower right of Figures 8a and 8b); mutual funds magnify their decreases in the amount of credit and their increases in loan interest rates to compensate for these higher losses; equity drops more; and investment and GDP contract more decisively, which then lead to several other larger general equilibrium effects described by Figures 8a and 8b.

5.4 Identification of Shocks in the BVARs

In addition to estimating a DSGE model, I also identify financial skewness shocks using BVARs. The goal of using different frameworks is to reach robust conclusions about the importance of skewness shocks to business cycles as well as about the transmission of these shocks through the economy. I use the same data as in the estimation of the DSGE model (Section 5.2), except that I exclude OIS rates because they only start at 2002.²⁵

In the BVARs, I identify unanticipated skewness shocks with four strategies: three different recursive orderings and one identification strategy based on the DSGE model. I define *Order-*

²⁵I use the BVAR with Minnesota prior and optimal shrinkage from Giannone et al. (2015).

13 as the recursive ordering placing skewness last in the BVAR, thus allowing the remaining variables to react to a skewness shock only with one quarter of lag. I define *Order-10* as the ordering placing skewness before equity growth, Baa-10y spread, and dispersion, thus allowing these variables to react contemporaneously to a skewness shock, while only letting the remaining variables react to the shock with one quarter of lag. I also define *Order-1* as the ordering placing skewness as the first variable, thus allowing all remaining variables to react contemporaneously to a skewness shock.

The strategy for identifying skewness shocks based on the DSGE model is named *BVAR-DSGE* and it works as follows. I build a vector of contemporaneous responses of all BVAR variables to a skewness shock.²⁶ Then, I pin down the magnitude of the responses in this vector by using the contemporaneous responses of the same variables to an unanticipated skewness shock estimated by the DSGE model. For completeness, I also identify dispersion shocks using analogous recursive and *BVAR-DSGE* strategies.

The reason for using the *BVAR-DSGE* identification is to provide a cleaner comparison between the DSGE model and the BVARs. To see this, notice that the economic analysis of a shock in either the DSGE model or the BVARs may be divided in two components: the economic effects of the shock at the time period of its arrival (impulse), and the propagation of the impulse through the economy over time (propagation mechanism). Thus, when we compare, for instance, the IRFs to skewness shocks from the DSGE model with those from recursive identifications, we compare not only different impulses, but also different propagation mechanisms. Alternatively, when we compare IRFs to skewness shocks from the DSGE model with those from the *BVAR-DSGE* identification, we focus only on the differences in propagation mechanisms.

5.5 DSGE Model and BVARs: The Prominence of Skewness Shocks

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

More precisely, the conclusions above originate from three results. First, IRFs (Figure 8a) to unanticipated skewness shocks have a considerable effect on GDP growth, decreasing it for at least six quarters and by 0.3-0.8% at the troughs. Moreover, results for other measures of economic activity, such as consumption and investment, show similarly strong effects.

²⁶Uhlig (2005) shows that a sufficient condition to exactly identify a shock is to pin down a vector of contemporaneous responses of all BVAR variables to the desired shock.

Second, variance decompositions of GDP growth (Tables 8 and 9a) show that unanticipated skewness shocks account for 5-20% of the fluctuations in this variable, with shares for investment and consumption being of similar magnitudes. Third, variance decompositions of financial skewness show that it is largely an exogenous variable. Skewness shocks (anticipated and unanticipated) are responsible for almost all of the variance of financial skewness in the DSGE model (Table 8) and unanticipated skewness shocks explain between 54% to 74% in the BVAR's recursive identifications.

Table 9: Variance Decompositions from BVARs (Percent)

| Variables | (a) Skewness Shocks | | | | (b) Dispersion Shocks | | | |
|--------------------------|---------------------|----------|----------|-----------|-----------------------|----------|----------|-----------|
| | Identifications | | | | Identifications | | | |
| | Order-1 | Order-10 | Order-13 | BVAR-DSGE | Order-1 | Order-10 | Order-13 | BVAR-DSGE |
| GDP ¹ | 20 | 7 | 5 | 9 | 3 | 2 | 2 | 3 |
| Consumption ¹ | 19 | 6 | 4 | 6 | 3 | 2 | 2 | 3 |
| Investment ¹ | 20 | 7 | 4 | 7 | 5 | 3 | 2 | 4 |
| Credit ¹ | 20 | 9 | 5 | 5 | 14 | 9 | 7 | 12 |
| Equity ¹ | 21 | 14 | 4 | 3 | 4 | 3 | 2 | 3 |
| Baa-10y | 16 | 8 | 4 | 39 | 10 | 8 | 4 | 5 |
| Dispersion | 13 | 7 | 3 | 8 | 48 | 43 | 35 | 27 |
| Skewness | 74 | 63 | 54 | 22 | 6 | 5 | 2 | 31 |

¹Variables used in 4 quarter growth.

In contrast, dispersion shocks have almost negligible economic effects, account for a very small share of business cycles, and explain only a modest share of the fluctuations in the observed dispersion measure. All of these conclusions are also robust across the DSGE model and the many identifications used in the BVARs. I reach these conclusions with the following three results: (i) IRFs to dispersions shocks are not different from zero (Figure 8b), (ii) the contribution of dispersion shocks to fluctuations in GDP, investment and consumption are 0-5% (Tables 8 and 9b), and (iii) dispersion shocks account for less than half of the fluctuations in the observed dispersion measure (Tables 8 and 9b).

5.6 The Transmission of Skewness Shocks

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

5.6.1 Financial Accelerator Is Channel Mostly Consistent with The BVAR

I first show evidence that the transmission of financial skewness shocks in the BVAR is consistent with the financial accelerator channel of the DSGE model: After unexpected decreases in

financial skewness, credit conditions tend to quickly tighten (lower credit and equity growth, and higher credit spreads), with investment and GDP contracting in the following quarters.

I provide the evidence above by comparing the IRFs to unanticipated skewness shocks estimated by the DSGE model with the IRFs identified by the BVAR-DSGE procedure. Intuitively, this exercise compares the transmission of a specific financial skewness shock in two different model economies: one agnostically maximizing its data fit through a BVAR, and another that also maximizes its data fit while being restricted to have a financial accelerator channel. This comparison (Figure 8a) shows that IRFs of measures of economic activity (GDP, consumption, and investment) under the BVAR-DSGE identification are similar to those from the DSGE model, with the latter being somewhat larger. This comparison also shows that IRFs from the DSGE model for most financial variables (credit, equity, Baa-10y spread, and dispersion) often lie inside the probability intervals of the BVAR-DSGE IRFs.

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

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

I then provide further support for the importance of financial frictions in transmitting skewness shocks by showing that the larger the effect of skewness shocks on credit spreads, the larger the effect on economic activity. This result comes from looking at the IRFs in Figure 8a in the following progression of identification strategies: Order-13, Order-10, Order-1, BVAR-DSGE, and DSGE. First, we observe that the response of Baa-10y spread to skewness shocks is increasing in this progression of identifications, with the IRF peak increasing from 6 basis points to 35 basis points. Then, we observe an increasing response of economic activity in this progression of IRFs, with the trough of GDP growth decreasing from negative 0.3% to negative 0.8%. Investment and consumption growth also follow similar patterns.

Although the results above are consistent with financial frictions being a powerful amplifier of skewness shocks, they do not rule out other transmission channels for these shocks. For instance, the IRF of the Order-13 identification (Figure 8a) shows skewness shocks decreasing GDP growth by 0.3% while credit spreads only increase by 6 basis points, a result consistent with a nonfinancial transmission channel such as capital frictions (Ehouarne et al. (2015)).

6 Interpreting Financial Skewness

This section provides additional evidence on the two hypotheses for financial skewness' predictive and explanatory power on business cycles. As discussed in the Introduction, financial skewness could capture risks faced by the *credit demand*, and/or *credit supply*. I also analyze whether financial skewness could be reflecting past and current macroeconomic conditions, thus implying some reverse causality. I find evidence supporting the credit demand and supply hypotheses, but not the reverse causality argument.

The approach is to measure how much information financial skewness share with variables associated to the hypotheses above. I implement this approach by regressing the following variables on financial skewness. On credit demand conditions, I use variables related to the quality of financial firms' assets: return on average assets for banks (ROA) and changes in banks' lending standards (LSSF).²⁷ On credit supply conditions, I use variables measuring distress faced by financial firms: Chicago Fed's Adjusted Financial Condition Index (AFCI) for general financial conditions, excess bond premium (EBP) for liquidity risks, measures originated from the VIX for uncertainty (UC) and risk aversion (RA), and term-spread for conditions on maturity transformation.²⁸ Finally, on macroeconomic conditions, I use Consensus now-casting of current GDP growth ($\widehat{\text{GDP}}_{t|t-1}$) and lagged 4-quarter GDP growth ($\text{GDP}_{t-1|t-5}$) for current and past conditions, respectively.²⁹ The sample is 1990Q1-2015Q2 and regressors are standardize within the sample.

Table 14 shows the results from the regressions. Four results are worth highlighting. First, the R^2 of most regressors is 20% -30% in univariate regressions (Table 10a), consistent with none of the hypotheses being singlehandedly dominant here. Second, the significance of ROA and LSSF is robust to the inclusion of all other variables (Table 10b), consistent with credit demand conditions being important for financial skewness. Third, among the variables capturing credit supply conditions, only UC and RA are statistically significant in the multivariate regressions (Table 10b), consistent with some evidence for this hypothesis. Fourth, neither $\widehat{\text{GDP}}_{t|t-1}$ nor $\text{GDP}_{t-1|t-5}$ are significant in the multivariate regressions, consistent with a minor role for macro conditions or reverse causality.

²⁷More precisely, the variable is the net percentage of domestic banks tightening standards for commercial and industrial loans. The interpretation of banks' lending standards as being informative about financial firms' assets is based on the results of Basset et al. (2014). After accounting for endogenous responses to aggregate macro and financial conditions, the authors argue that changes in banks' lending standards reflect issues such as reassessments of the riskiness of certain loans and changes in business strategies.

²⁸Chicago Fed's Adjusted Financial Condition Index (AFCI), excess bond premium (EBP), and VIXs decomposition into uncertainty (UC) and risk aversion (RA) are calculated by Brave and Butters (2011), Gilchrist and Zakrajek (2012) and Bekaert et al. (2013), respectively.

²⁹Given that Consensus forecasts are released on the 10th of every month, I average forecasts from the last month of the quarter with those from the month right after the end of quarter.

Table 10: Regressions on Financial Skewness

(a) Univariate Regressions

| | ROA | LSSF | AFCI | EBP | UC | RA | Term Spread | $\widehat{\text{GDP}}_{t t-1}$ | $\text{GDP}_{t-1 t-5}$ |
|-------------|--------|---------|---------|---------|---------|---------|-------------|--------------------------------|------------------------|
| | 4.6*** | -4.7*** | -4.9*** | -4.3*** | -4.4*** | -4.1*** | 0.5 | 4.0*** | 2.7*** |
| \bar{R}^2 | 0.25 | 0.26 | 0.28 | 0.22 | 0.23 | 0.20 | 0.00 | 0.19 | 0.09 |

(b) Multivariate Regressions

| | Variable | | | | | | | |
|-----------------|----------|--------|--------|--------|-------------|--------------------------------|------------------------|---------|
| | AFCI | EBP | UC | RA | Term Spread | $\widehat{\text{GDP}}_{t t-1}$ | $\text{GDP}_{t-1 t-5}$ | |
| ROA | 3.2*** | 2.7*** | 3.1*** | 3.0*** | 2.9*** | 3.8*** | 3.0*** | 4.2*** |
| LSSF | -3.4*** | -2.1* | -2.7** | -2.1** | -2.6*** | -2.9*** | -3.2*** | -3.4*** |
| Variable | -1.9 | -1.0 | -2.1** | -1.6* | 1.2 | 0.4 | -1.4 | |
| \bar{R}^2 | 0.36 | 0.38 | 0.37 | 0.39 | 0.38 | 0.37 | 0.36 | 0.37 |

Regressions described in Tables 10a and 10b share the following features: sample period 1990Q1-2015Q2, standardized regressors within this sample, and financial skewness as the dependent variable. Table 10a describes the results from univariate regressions using only contemporaneous column variables. The first column of Table 10b displays the results of a regression using contemporaneous values of ROA and LSSF. The remaining columns of Table 10b use as regressors the contemporaneous values of ROA, LSSF and the column variable. Statistical significance tests the null hypothesis that the coefficient associated to a regressor is zero, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01.

Appendix C corroborates the conclusions discussed here with additional robustness regressions. Using data at a monthly frequency yields statistically significant coefficients, but with markedly lower R^2 's (Table 14a). Adding a non-linear effect from the measures of credit supply conditions improve their performance, but the increase in R^2 's is only up to 7% and the gain is focused on the 2008 crisis. Substituting UC by financial or macro uncertainty in the Table 10b does not yield statistically significant coefficients. Finally, if we focus on surprises on macroeconomic conditions (Scotti 2016), we find significant coefficients but with an R^2 of only 5% (Table 14a).

7 Conclusion

Using U.S. data from 1926 to 2015, I show that financial skewness—a measure comparing cross-sectional upside and downside risks of the distribution of stock market returns of financial firms—is a powerful predictor of business cycle fluctuations and credit activity. I do so using in-sample and out-of-sample regressions, and comparing the performance of financial skewness with well-known indicators of economic conditions, such as excess bond premium (e.g., Gilchrist and Zakrajsek (2012)), measures of aggregate uncertainty (e.g., Jurado et al. (2015), and Ludvigson et al. (2015)) and other moments from the cross-sectional distribution of returns of financial and nonfinancial firms.

I then show that shocks to financial skewness lead to sizable macroeconomic effects through a channel consistent with a financial frictions mechanism. I identify financial skewness shocks using two complementary approaches: a dynamic stochastic general equilibrium (DSGE) model a la Bernanke et al. (1999) and Bayesian vector autoregressions (BVARs). Finally, I argue that these previous results stem from the ability of financial skewness to measure cross-sectional risk on fundamentals faced by the financial sector and their borrowers, such as the quality of borrowers' projects, and the sector's lending capacity.

Finally, this paper points to three avenues of future research. First, there are additional cross-sectional properties of the behavior of financial firms that remain little explored, such as the cross-sectional distribution of bond spreads and leverage. Second, we should strive to make fluctuations in the cross-sectional distributions of financial firms more endogenous, such as in nonlinear models. Third, there is potential for a research path in which the financial sector not only is the origin of shocks to the economy (e.g., the 1929 and 2008 financial crises), but also is well placed to efficiently signal shocks from other sectors.

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A Appendix: Data Details

A.1 Stock Market Returns Data

I use data from the monthly CRSP database. Then, I aggregate the returns data for quarterly frequency by measuring the change in the average price over one quarter relative to the average price over the previous quarter. Finally, I eliminate returns from stocks with less than 10 years of consecutive non-missing data. Prior to 1947, I use all the data available.

A.2 Classification: Financial and Nonfinancial Sectors

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

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

A.3 Data Used by BVAR and DSGE Models

1. Core inflation is calculated using the price index of personal consumption expenditures (PCE) that excludes food and energy.
2. Real GDP is calculated by deflating nominal GDP by the implicit GDP price index and by the population over 15 years old.
3. Real consumption is the sum of nominal PCE in services and non-durables, deflated by the PCE price index and by the population over 15 years old.

4. Real investment is the sum of nominal PCE in durables and nominal business investment, deflated by the business investment price index and by the population over 15 years old.
5. Real wage is measured by the hourly compensation of all employees in non-farm business, deflated by the core PCE price index.
6. Relative investment price is calculated as the ratio between the business investment price index and the core PCE price index.
7. Real credit is sum of loans (depository institutions loans nec, other loans and advances and total mortgages) and debt (commercial paper, municipal securities, corporate bonds) from the financial accounts (liabilities of nonfinancial businesses) published by the Board of Governors of the Federal Reserve System. It is then normalized by the core PCE price index and by the population over 15 years old.
8. Nonfinancial equity index is the cumulative weighted return of all nonfinancial firms, normalized by the core PCE price index and by the population over 15 years old.
9. Hours worked is measured by the aggregate weekly hours of production and non-supervisory employees in all private industries, divided by the population over 15 years old.
10. Fed funds rate is the average of the daily rates over the quarter.
11. Baa-10y spread is measured by the spread between the Moody's Baa rate and the 10-year Treasury rate.
12. Nonfinancial dispersion is calculated as described in Section 3.
13. Financial skewness are calculated as described in Section 3.

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

B Appendix: DSGE Model Details

Goods Production. A representative final goods producer uses technology $Y_t = \left[\int_0^1 Y_{jt}^{1/\lambda_t^f} dj \right]^{\lambda_t^f}$, and intermediate goods Y_{jt} , for $j \in [0, 1]$, to produce a homogeneous good Y_t . Cost-push shock λ_t^f follows an AR(1) process. Intermediate producers' production function is $Y_{jt} = \epsilon_t K_{jt}^\alpha (z_t H_{jt})^{(1-\alpha)} - \phi z_t^*$, if $\epsilon_t K_{jt}^\alpha (z_t H_{jt})^{(1-\alpha)} > \phi z_t^*$. Otherwise, Y_{jt} equals zero. These producers rent capital services K_{jt} and hire homogenous labor H_{jt} in competitive markets. Additionally, ϵ_t represents an AR(1) productivity shock, z_t a permanent productivity shock with an AR(1) growth rate, and ϕ a fixed cost.³⁰ 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 $P_{j,t} = \tilde{\Pi}_t P_{j,t-1}$, where $\tilde{\Pi}_t = (\Pi_t^{tar})^{\iota_p} (\Pi_{t-1})^{1-\iota_p}$, 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 \bar{K}_{t+1} , facing competitive markets. Underlying households' choices are the following preferences:

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

where ζ_t^c is an AR(1) preference shock. I describe the labor supply decision below.³¹

After final goods are produced in each period t , households build physical capital \bar{K}_{t+1} and sell it to entrepreneurs at unit price Q_t . To build \bar{K}_{t+1} , households purchase investment goods and the existing physical capital from entrepreneurs, $(1 - \delta)\bar{K}_t$, where δ is the depreciation

³⁰The value of ϕ is chosen to ensure zero profits in steady state for intermediate producers.

³¹I choose ψ_0 such that $h_{it} = 1$ for all i at steady state.

rate. The production function of capital is $\bar{K}_{t+1} = (1 - \delta)\bar{K}_t + (1 - S(\zeta_t^i I_t/I_{t-1}))I_t$, 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, $(1 - \delta)\bar{K}_t$, to produce one unit of a new one, \bar{K}_{t+1} , the unit price of $(1 - \delta)\bar{K}_t$ is also Q_t .

Finally, the households' budget constraint is

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

where R_t is the risk-free interest rate paid on households savings, W_{it} is the nominal hourly wage for differentiated labor service h_{it} , and D_t represents all lump-sum transfers to and from households. The households' problem is then to choose C_t , B_{t+1} , I_t , and \bar{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 $W_{it} = \tilde{\Pi}_{w,t} W_{it-1}$, where $\tilde{\Pi}_{w,t} = (\Pi_t^{tar})^{\iota_w} (\Pi_{t-1})^{1-\iota_w} (\mu_{z,t}^*)^\theta (\mu_{z,ss}^*)^{1-\theta}$.

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: $Y_t = C_t + I_t/(\Upsilon^t \zeta_t^q) + G_t$.

Table 11: Parameters of the DSGE model

(a) Calibrated Parameters

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

(b) Estimated Parameters

| Description | Name | Prior distribution | | | Posterior distribution | |
|--|----------------------|--------------------|-------|--------|------------------------|--------|
| | | 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 expenditures | ρ_{gov} | beta | 0.5 | 0.2 | 0.95 | 0.014 |
| Shock autocorrelation: transitory TFP | ρ_ϵ | beta | 0.5 | 0.2 | 0.96 | 0.012 |
| Shock autocorrelation: permanent TFP | ρ_{μ^*} | beta | 0.5 | 0.2 | 0.25 | 0.063 |
| Shock autocorrelation: cross-sectional dispersion | ρ_{sd} | beta | 0.5 | 0.2 | 0.68 | 0.040 |
| Shock autocorrelation: anticipated cross-sectional dispersion | $\rho_{sd,\xi}$ | beta | 0.5 | 0.2 | 0.53 | 0.163 |
| Shock autocorrelation: cross-sectional skewness | ρ_{m1} | beta | 0.5 | 0.08 | 0.90 | 0.006 |
| Shock autocorrelation: anticipated cross-sectional skewness | $\rho_{m1,\xi}$ | beta | 0.5 | 0.2 | 0.23 | 0.049 |
| Shock autocorrelation: anticipated monetary policy | $\rho_{mp,\xi}$ | beta | 0.5 | 0.2 | 0.83 | 0.044 |
| Shock standard deviation: mark-up, intermediate firms | σ_λ | invg2 | 0.002 | 0.0033 | 0.103 | 0.0035 |
| Shock standard deviation: preference | σ_c | invg2 | 0.002 | 0.0033 | 0.030 | 0.0014 |
| Shock standard deviation: investment price | σ_q | invg2 | 0.002 | 0.0033 | 0.005 | 0.0002 |
| Shock standard deviation: investment efficiency | σ_i | invg2 | 0.002 | 0.0033 | 0.388 | 0.0055 |
| Shock standard deviation: government expenditures | σ_g | invg2 | 0.002 | 0.0033 | 0.029 | 0.0015 |
| Shock standard deviation: transitory TFP | σ_ϵ | invg2 | 0.002 | 0.0033 | 0.008 | 0.0004 |
| Shock standard deviation: permanent TFP | σ_{μ^*} | invg2 | 0.002 | 0.0033 | 0.015 | 0.0017 |
| Shock standard deviation: cross-sectional dispersion | σ_{sd} | invg2 | 0.002 | 0.0033 | 0.037 | 0.0022 |
| Shock standard deviation: anticipated cross-sectional dispersion | $\sigma_{sd,\xi}$ | invg2 | 0.001 | 0.0012 | 0.0003 | 0.0002 |
| Shock standard deviation: cross-sectional skewness | σ_{m1} | invg2 | 0.002 | 0.0033 | 0.046 | 0.0036 |
| Shock standard deviation: anticipated cross-sectional skewness | $\sigma_{m1,\xi}$ | invg2 | 0.001 | 0.0012 | 0.037 | 0.0010 |
| Shock standard deviation: monetary policy | σ_{mp} | invg2 | 0.002 | 0.0033 | 0.001 | 0.0001 |
| Shock standard deviation: anticipated monetary policy | $\sigma_{mp,\xi}$ | invg2 | 0.001 | 0.0012 | 0.001 | 0.0001 |
| Shock standard deviation: equity | $\sigma_{\gamma,e}$ | invg2 | 0.002 | 0.0033 | 0.033 | 0.0017 |
| Measurement error: dispersion | $\sigma_{disp,obs}$ | invg2 | 0.005 | 0.01 | 0.003 | 0.0032 |
| Measurement error: skewness | $\sigma_{skew,obs}$ | invg2 | 0.005 | 0.01 | 0.015 | 0.0020 |
| Measurement error: equity proportion ⁶ | Γ | invg2 | 1 | 0.5 | 0.23 | 0.007 |
| Measurement error: equity ⁶ | σ_{eq} | invg2 | 0.001 | 0.05 | 0.092 | 0.0053 |
| Measurement error: real wages | $\sigma_{w,obs}$ | invg2 | 0.001 | 0.05 | 0.006 | 0.0004 |

All shock autocorrelations and standard deviations are estimated in 2 steps, as described in Section 5.2. 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. ¹Steady-state $W^{e,ss}$ is calibrated as a percentage w_e of the steady-state capital stock K^{ss} (normalized by its growth trend). ²These parameters are only estimated in the 2nd stage, while being fixed at their sample means during the 1st stage. ³It is only estimated in the 1st step, being fixed at 2 in the 2nd step. ⁴Although 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 $\int \omega dF^{ss}(\omega) = 1$. ⁵To achieve identification, I estimate $s^{2,ss}$ as a percentage $\alpha^{s^2,ss}$ of $s^{1,ss}$. ⁶I assume that observed equity growth is Γ times model equity growth plus a measurement error.

C Appendix: Additional Results

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

(a) Financial Firms, Weighted Distribution Measures

| Variable | Regressions Specifications | | | | | | | | | | | |
|----------------|----------------------------|---------|--------|---------|------|---------|---------|-------|---------|----------|----------|---------|
| | (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*** | 1.08*** |
| Left kurtosis | | | | | 0.63 | | | | | | -0.38 | |
| Right kurtosis | | | | | | 0.39*** | | | | | -0.28*** | |
| Uncertainty | | | | | | | -0.46** | | | | | -0.07 |
| Real fed funds | | | | | | | | -0.44 | | | | 0.21 |
| Term spread | | | | | | | | | 0.92*** | | | 1.04*** |
| EBP | | | | | | | | | | -0.35*** | | -0.10 |
| R ² | 0.08 | 0.23 | 0.13 | 0.26 | 0.13 | 0.11 | 0.19 | 0.12 | 0.28 | 0.20 | 0.32 | 0.50 |

(b) Nonfinancial Firms, Weighted Distribution Measures

| Variable | Regressions Specifications | | | | | | | | | | | |
|----------------|----------------------------|---------|-------|--------|--------|--------|---------|-------|---------|----------|---------|---------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Mean | | 0.94*** | | | | | | | | | 0.89*** | 0.72** |
| 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** | | | | | -0.07 |
| Real fed funds | | | | | | | | -0.44 | | | | 0.27 |
| Term spread | | | | | | | | | 0.92*** | | | 0.98*** |
| EBP | | | | | | | | | | -0.35*** | | -0.19 |
| R ² | 0.08 | 0.21 | 0.11 | 0.12 | 0.12 | 0.12 | 0.19 | 0.12 | 0.28 | 0.20 | 0.26 | 0.44 |

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, $\{\beta^k = \sum_{j=0}^q \beta_j^k\}_{k=1}^5$ and $\gamma = \sum_{j=0}^q \gamma_j$. 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.

Figure 9: Out-of-Sample Forecasts of GDP Growth, End-of-Quarter, R-RMSFEs

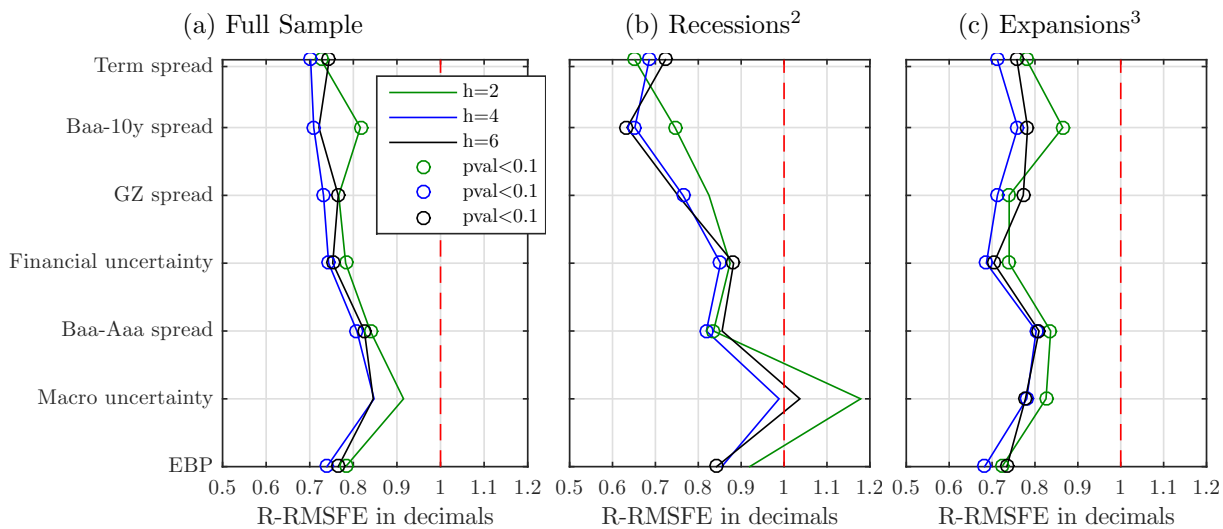


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis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

Figure 10: Out-of-Sample Forecasts of GDP Growth, Kelly Skewness, R-RMSFEs

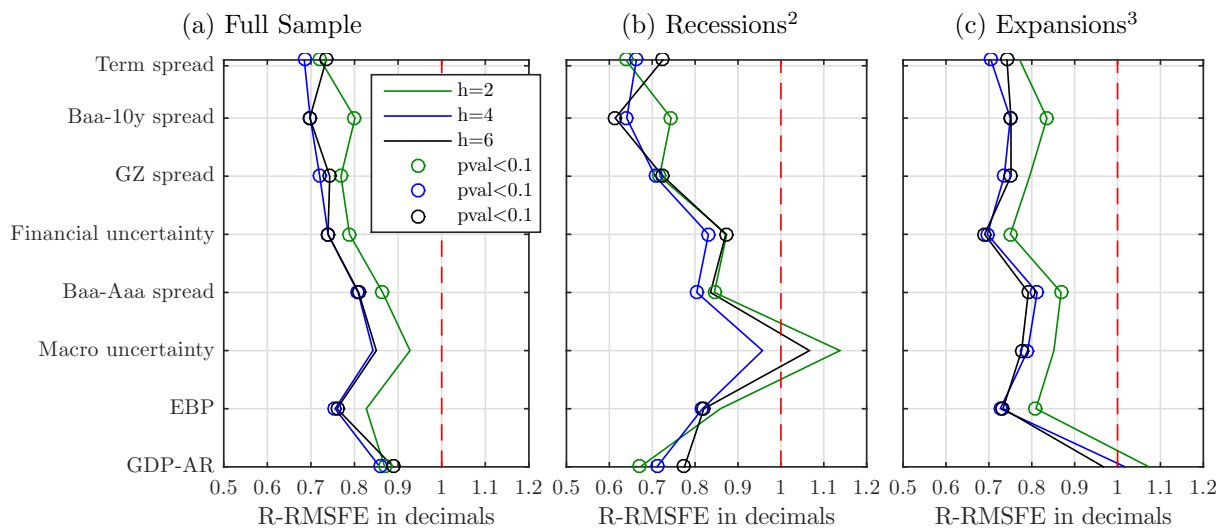


Figure 3 reports the ratio between the root mean squared forecast error (RMSFE) of financial skewness relative to the RMSFE of competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Statistical significance is relative to the null hypothesis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

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 | GZ Sp | Baa-10y | Loans | Debt | Loan Sp | GZ Sp | Baa-10y |
| | | (%) | (%) | (bps) | (bps) | (bps) | (%) | (%) | (bps) | (bps) | (bps) |
| (a) Benchmark | R^2 | 0.57 | 0.40 | 0.88 | 0.84 | 0.78 | 0.57 | 0.40 | 0.88 | 0.84 | 0.78 |
| (b) Bivariate | Variable | -2.35*** | 0.18* | 4.69*** | -0.85*** | 6.99*** | 1.74*** | 0.29 | -4.06* | -16.83*** | -18.63*** |
| (c) | R^2 | 0.69 | 0.41 | 0.89 | 0.88 | 0.82 | 0.64 | 0.40 | 0.88 | 0.87 | 0.83 |
| (d) | Variable | -1.11 | 1.23** | 1.95 | -4.89*** | 2.52*** | 0.29 | -0.09 | -2.21 | -15.98*** | -15.57*** |
| (e) | Uncertainty | -0.08* | -0.04 | 5.79*** | 9.06*** | 6.66* | -0.45 | 0.32 | 6.20*** | 8.36*** | 8.57*** |
| (f) Multivariate | Real Fed Funds | 0.38 | 0.97 | -8.87* | -1.41* | -2.67*** | 0.10 | 1.14 | -5.53 | -5.29** | -3.08*** |
| (g) | Term Spread | 0.71 | 0.16 | 0.14 | 0.78 | -1.74*** | 0.58 | 0.33 | 2.23 | -2.04 | -1.90** |
| (h) | EBP | -1.81** | -1.36** | | | | -2.13** | -0.85 | | | |
| (i) | R^2 | 0.78 | 0.53 | 0.90 | 0.89 | 0.86 | 0.77 | 0.49 | 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 $h = 4$, $p = 4$ due to 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 4 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, $\{\beta^k = \sum_{j=0}^q \beta_j^k\}_{k=1}^5$ and $\gamma = \sum_{j=0}^q \gamma_j$. 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.

Table 14: Regressions on Financial Skewness

(a) Univariate Regressions at a Monthly Frequency

| | AFCI | EBP | UC | RA | Term Spread | Financial Uncertainty | Macro Uncertainty | Macro Surprise |
|-------------|------|------|------|------|-------------|-----------------------|-------------------|----------------|
| | -1.7 | -1.5 | -2.1 | -2.1 | 0.2 | -1.5 | -1.5 | 2.7 |
| \bar{R}^2 | 0.10 | 0.08 | 0.15 | 0.16 | 0.00 | 0.08 | 0.08 | 0.05 |

(b) Multivariate Regressions at a Quarterly Frequency

| | Variable | | | | | | | |
|-------------------------|----------|---------|--------|---------|-------------|-----------------------|-------------------|--|
| | AFCI | EBP | UC | RA | Term Spread | Financial Uncertainty | Macro Uncertainty | |
| ROA | 2.7*** | 2.7*** | 2.6*** | 2.5*** | 3.8*** | 2.9*** | 3.0*** | |
| LSSF | -2.3*** | -3.6*** | -2.2** | -2.9*** | -2.8*** | -2.5** | -3.0*** | |
| Variable | -0.8 | 3.3* | 1.6 | 4.4** | -0.6 | -0.4 | -0.9 | |
| $ \mathbf{Variable} ^2$ | -0.3 | -1.5*** | -2.5** | -4.0*** | 1.4 | -0.6 | 0.1 | |
| \bar{R}^2 | 0.38 | 0.42 | 0.42 | 0.45 | 0.38 | 0.37 | 0.36 | |

Regressions described in Tables 14a and 14b share the following features: standardized regressors within this sample, and financial skewness as the dependent variable. Table 14a describes the results from univariate regressions using only contemporaneous column variables at a monthly frequency with sample 1990M1-2015M6. The regression with the macro surprise index (Scotti 2016) has shorter sample (2003M5-2015M6) due to its unavailability for earlier dates. Table 14b displays the results of regressions using contemporaneous values of ROA, LSSF, and the regressor named in the column. Moreover, I use both the values of the column-regressor (with coefficients in the row “**Variable**”) and the square of the absolute value of the regressor-column (with coefficients in the row $|\mathbf{Variable}|^2$). The sample used for Table 14b is 1990Q1-2015Q2. Statistical significance tests the null hypothesis that the coefficient associated to a regressor is zero, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01.

C.1 The DSGE Model Is Statistically Comparable to BVAR

The first column of Table 15 shows that the marginal likelihood of the DSGE model from Section 5 is close to the one from a BVAR using the same time series and sample period (2002–2015). However, the second and third columns of Table 15 show that if we exclude OIS rates from the estimation of the DSGE model and focus on either the entire sample (1964–2015) or the pre-Great-Recession era (1964–2006), the marginal likelihood of the DSGE model becomes considerably lower than those from BVARs with identical data.

Table 15: Marginal Likelihood (Log Points)

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

^aIt is computed by the Modified Harmonic Mean method from a Markov Chain Monte Carlo with 2 blocks, each with 300,000 draws. ^bIn these estimations, I use standard Bayesian methods without the two-step procedure used for the baseline model and exclude the OIS rates from the estimation. ^cIt 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 15 support the choice of Section 5’s DSGE model and its esti-

mation procedure as a reasonable starting point to study the transmission of skewness shocks through financial frictions. This argument is based on the fact that the performance of the DSGE model, relative to a BVAR, is best exactly when there is more evidence that financial frictions contributed to a cyclical downturn of the U.S. economy.

Figure 11: Impulse Response Functions

