Cross-Sectional Financial Conditions, Business Cycles and The Lending Channel*

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Abstract

I document business cycle properties of the *full* cross-sectional distributions of U.S. stock returns and credit spreads from financial and nonfinancial firms. The skewness of returns of financial firms (SRF) best predicts economic activity, while being a barometer for lending conditions. SRF also affects firm-level investment beyond firms' balance sheets, and adverse SRF shocks lead to macroeconomic downturns with tighter lending conditions in vector autoregressions (VARs). These results are consistent with a lending channel in which cross-sectional financial firms' balance sheets play a prominent role in business cycles. I rationalize this argument with a model that matches the VAR evidence.

Key Words: Cross-Sectional, Skewness, Business Cycles, Lending Channel.

JEL Classification: E32, E37, E44.

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1 Introduction

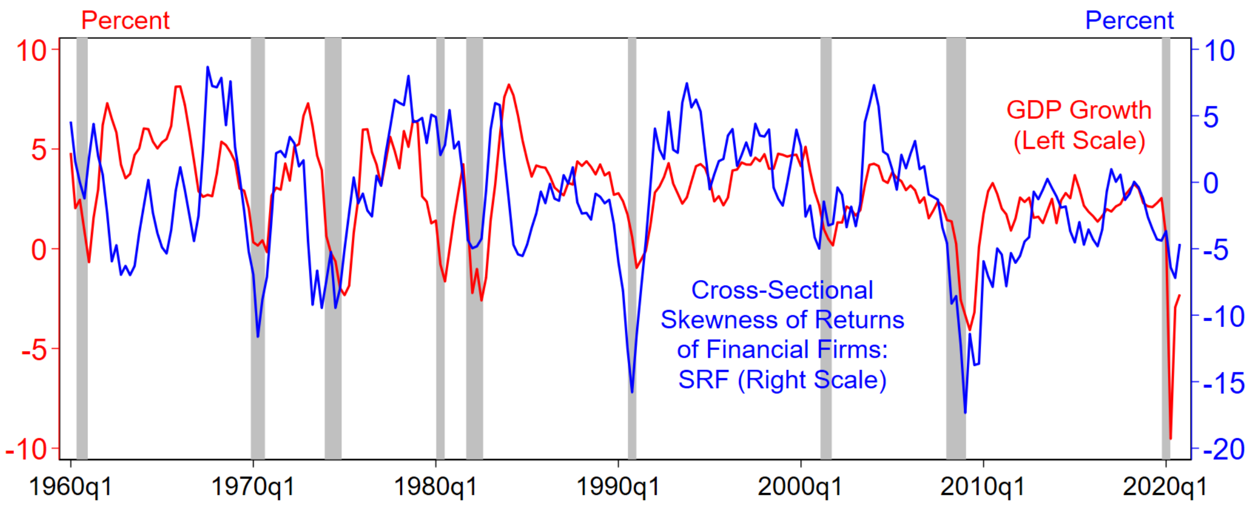
To monitor and understand macroeconomic business cycles, economists have extensively investigated the ability of financial assets to anticipate economic activity given these assets' forward-looking nature.[1] Among many assets, researchers have highlighted the predictive ability of credit spreads (e.g., Gilchrist and Zakrajšek, 2012), arguing that bond markets are more accurate than stock markets about economic fundamentals (e.g., Philippon, 2009) and that investors' sentiment is an important component of bonds' informational content (e.g., López-Salido et al., 2017). In this paper, I revisit this stock versus bonds debate by studying the business cycle properties of the *full cross-sectional distributions* of stock market returns and credit spreads of both financial and nonfinancial firms.

I find that the skewness of returns of financial firms (SRF) stands out as a leading indicator of the cycle, while also being a barometer for conditions in the *lending channel* (Bernanke and Gertler, 1995)—shifts in the supply of intermediated credit beyond what is explained by borrowers' balance sheet conditions. On the economic activity front, SRF outperforms other cross-sectional moments and renowned financial indicators in predicting GDP growth, and performs similarly to professional forecasters. On the lending channel, SRF forecasts loan growth, rather than debt issuance, and correlates with measures of risk-bearing capacity and asset quality of the financial sector. Moreover, SRF affects firm-level investment beyond firms' financial and balance sheet conditions, and adverse SRF shocks lead to macroeconomic downturns with tighter financial and lending conditions in vector autoregressions (VARs). Altogether, these results are consistent with the cross-sectional state of financial firms' balance sheets being an important component of business cycles, not just of financial crises (Boissay et al., 2016). I rationalize this argument using a modified financial accelerator model (Bernanke et al., 1999) that qualitatively matches the VARs and quantifies challenges from the new evidence.

The paper first documents the cyclical properties of the cross-sectional distributions of

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

FIGURE 1
Skewness of the Returns of Financial Firms and the Business Cycle



Note. Figure 1 shows the 4-quarter moving average of cross-sectional skewness of the returns of financial firms (SRF) in blue (see definition in Section 2) and the 4-quarter GDP growth in red. Gray areas represent periods classified as recessions by the National Bureau of Economic Research.

stock returns and credit spreads, adding another facet to the literature showing that cross-sectional uncertainty is an important element of business cycles.[2] Using cross-correlations, in-sample and out-of-sample regressions, I evaluate the cyclicality of cross-sectional moments of financial conditions and identify SRF as the best performer in predicting economic activity. Intuitively, when SRF turns negative, the left tail of the cross-sectional distribution of stock returns becomes larger than the right tail, signaling that economic activity is likely to slowdown (Figure 1). SRF also forecasts economic activity better than renowned financial indicators and measures of uncertainty, such as the excess bond premium (Gilchrist and Zakrajšek, 2012) and macroeconomic uncertainty (Jurado et al., 2015). Moreover, SRF performs comparably to professional forecasters, thus having a realistically relevant performance. The performance of SRF is robust to different definitions of skewness, specific events, such as the 2008 Global Financial Crisis (GFC), and the state of the cycle.

I investigate why SRF is so intrinsically related to economic activity, showing that SRF

[2]Several papers argue that cross-sectional uncertainty have economic effects through different channels: wait-and-see effects from capital adjustment frictions (Bloom et al., 2018); financial frictions (Arellano et al., 2019, 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).

is a barometer for lending channel conditions. To uncover the informational content of SRF, I first test whether it is more informative about loan or debt markets. Relative to the latter (e.g., commercial paper and bonds), loan markets are more associated with nonfinancial firms without access to public capital markets and the risk-bearing capacity of the financial sector (Holmstrom and Tirole, 1997). Indeed, I show that SRF predicts aggregate loan growth, while not predicting debt issuance, thus pointing to SRF as informative about *either* nonfinancial firms reliant on loans *or* credit supply. To shed further light on SRF, I correlate it with variables measuring several hypotheses for SRF's informational content, including that it may signal policy uncertainty (Baker et al., 2016) and expectations about the macroeconomy. I find that measures of risk-bearing capacity (He et al., 2017) and asset quality of the financial sector explain 43 percent of SRF's fluctuations, thus supporting the interpretation that SRF reflects conditions on the lending channel.

To further test the relationship between SRF and the lending channel, I turn to a firm-level analysis. I find that SRF affects firms' investment beyond their balance sheet and financial conditions. Using data on publicly listed U.S. nonfinancial corporations, I assemble a list of firm-level variables important for firms' investment decision, such as measures of default risk (Ottonello and Winberry, 2020), asset liquidity, and credit spreads (Gilchrist et al., 2014). Controlling for these variables, I find that a one-standard deviation decline in SRF reduces investment by about 1 percentage point after four quarters, with effects declining thereafter. These firm-level results corroborate the previous evidence on SRF's relationship with economic activity and its role as barometer for the lending channel.

To complement the previous results with a more general perspective, I use VARs to study the link between economic activity, loan growth, and cross-sectional financial conditions. The estimated impulse response functions (IRFs) show that an adverse SRF shock leads to a quick tightening of financial conditions (fall in the equity index and increase in credit spreads), an increase in the dispersion of returns, a fall in economic (GDP, consumption, investment, and hours) and loan activity, a dip in inflation, and a decline in the fed funds. Importantly, the deterioration of SRF unwinds after only three quarters, while the effects in economic and loan activity persist for at least eight quarters.

Altogether, the empirical results of this paper are consistent with a *cross-sectional lending channel.* An adverse fluctuation in SRF signals a cross-sectional deterioration of financial firms' balance sheets, leading these firms to adopt a more cautious lending strategy, which then reduces loan supply and causes a contraction in economic activity. More broadly, these results point to a lending channel in which the cross-sectional state of financial firms' balance sheets is an important component of business cycles, not just of financial crises. Thus, the paper's results complement the financial stability literature, in which researchers argue that cross-sectional heterogeneity is an important element of banking crises (Boissay et al., 2016), as well as of the risk-taking behavior of the sector (Coimbra and Rey, 2017).

To rationalize this cross-sectional lending channel and quantify challenges from the new evidence, I use a modified financial accelerator model that builds on Christiano et al. (2014). I choose this model because of its success in explaining business cycle co-movements between macro variables, credit activity, and the cross-section of stock returns.[3] Re-interpreting the model to the financial sector, adverse SRF shocks arise from cross-sectional *risk shocks* that deplete the *asset quality* of some financial firms more than others, leading to the cross-sectional deterioration of these firms' balance sheets. These skewed risk shocks are meant to capture heterogenous exposition to aggregate (e.g., Lehman failure) and regional (e.g., Savings and Loans Crisis) shocks. The model's IRFs are qualitatively consistent with those from the VARs. However, the model lacks (i) an amplification mechanism for the risk shock to generate realistically persistent effects after only short-lived fluctuations in SRF, and (ii) a channel through which other shocks may endogenously generate cross-sectional variation in financial firms' asset quality, such as concave policy functions (Ilut et al., 2018).

Related literature. This paper contributes to the literature studying how financial variables anticipate business cycles. Several papers focus on the predictive ability of financial

[3]Despite having stronger amplification of shocks, other benchmark off-the-shelf models of financial frictions, such as Gertler and Karadi (2011) and Gertler and Kiyotaki (2015), focus on representative-agent financial sectors.

conditions of nonfinancial firms, such as credit spreads (Bernanke, 1990, Friedman and Kuttner, 1992, Gertler and Lown, 1999, Gilchrist et al., 2009) and options (Dew-Becker and Giglio, 2021). Additional papers focus on stock-market based measures of financial systemic risk (Allen et al., 2012 and Giglio et al., 2016), and the U.S. treasury yield curve (Estrella and Hardouvelis, 1991). This paper differs from these studies by investigating the *full cross-sectional distributions* of credit spreads and stock returns of *both* financial and nonfinancial firms. Moreover, given SRF's timeliness and forecasting performance relative to renowned variables, SRF may be useful for practitioners monitoring economic activity.

Following the seminal work of Bernanke and Gertler (1995), this paper contributes to the literature investigating the role of the lending channel to business cycles. Using matched bank-firm lending data, Amiti and Weinstein (2018) finds that idiosyncratic shocks to Japanese banks affects investment. Using structural models, Rampini and Viswanathan (2019) and Becard and Gauthier (2022) focus on financial intermediaries' aggregate equity and collateral, respectively, as cyclical drivers. This paper uses almost 50 years of U.S. stock market and firm-level data, as well as a structural model, finding that the cross-sectional state of financial firms is an important unexplored component of business cycles.

Finally, this paper adds to the literature documenting that cross-sectional higher moments, such as skewness, of economic variables fluctuate with the business cycle. For instance, economists have studied individuals' income (Guvenen et al., 2014, Busch et al., 2022); nonfinancial firm sales, profit, and employment (Salgado et al., 2019); and price changes (Luo and Villar, 2021). This paper shows that cross-sectional moments of financial conditions are cyclical. Moreover, with SRF's performance in predicting economic activity, it provides another important metric against which business cycle theories should be tested.

The rest of the paper is organized as follows. Section 2 describes data sources and definitions of cross-sectional moments of financial conditions. Section 3 documents business cycle properties of these moments. Section 4 shows that SRF reflects lending channel conditions. Section 5 finds that SRF affects firm-level investment. Section 6 presents the VAR evidence and the model rationalizing it. Section 7 concludes with implications from the results.

2 Cross-Sectional Financial Conditions

In this section, I describe the data sources and definitions of cross-sectional moments of financial conditions.

2.1 Stock Returns and Credit Spreads Data

I use U.S. stock market returns from the CRSP database for the period 1960–2020. To measure credit spreads, I use data sources and similar methods as Gilchrist and Zakrajšek (2012). I use corporate bond yields quoted in secondary markets from the Lehman/Warga and Merrill Lynch databases for the period 1973–2020. I then obtain credit spreads by gathering each corporate yield and subtracting the U.S. Treasury yield with the exact same maturity using the estimates from Gürkaynak et al. (2007).[4] I provide more details about the data in Appendices A.1 and A.2.

Throughout the paper, I use log-returns and log-credit-spreads when focusing on the cross-sectional distributions of these financial conditions, as well as on the higher moments of these distributions. Specifically, for a given the stock market return $X_{i,t}^{\text{ret}}$ (in percent) of firm i at quarter t, the log-return is $x_{i,t}^{\text{ret}} = 100 \cdot \log(1 + X_{i,t}^{\text{ret}}/100)$. Analogously, I calculate log-credit-spreads as $x_{i,t}^{\text{spd}} = 100 \cdot \log(1 + X_{i,t}^{\text{spd}}/100)$.

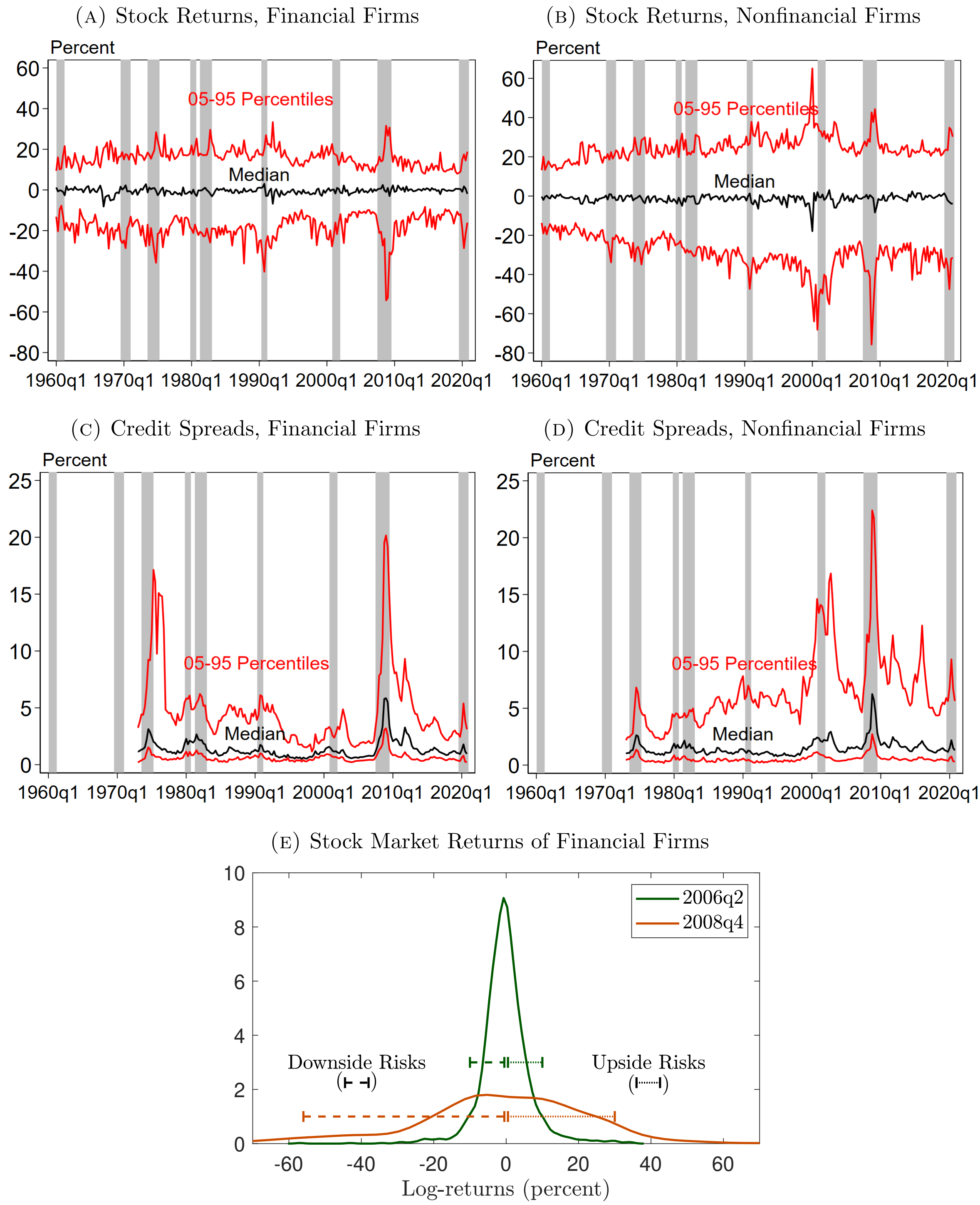
2.2 Cross-Sectional Moments of Financial Conditions

I summarize the times-series and cross-sectional behavior of log-returns and log-credit-spreads in Figure 2. For returns of financial and nonfinancial sectors (Figures 2a-2b), both the upside (95$^{\text{th}}$ percentile) and downside (5$^{\text{th}}$ percentile) tails fluctuate significantly with the business cycle. In contrast, the upside tail of credit spreads has substantially more sizable cyclical fluctuations than the right tail (Figures 2c-2d).

I then calculate cross-sectional mean, dispersion, and skewness for returns and credit

[4] Appendix A.2 shows that the mean cross-sectional credit spreads of nonfinancial firms from this paper has a correlation of 0.96 with the one calculated by Gilchrist and Zakrajšek (2012).

Figure 2
Cross-Sectional Financing Conditions



Note: Figures 2a-2d show the median, 95$^{\text{th}}$, and 5$^{\text{th}}$ percentiles of the cross-sectional distribution of log-returns and log-credit-spreads for the financial and nonfinancial sectors. Figure 2e shows the probability density function of the distribution of returns of financial firms in 2006q2 (green) and 2008q4 (orange).

spreads of firms in the financial ("fin") and nonfinancial ("nfin") sectors as follows:

$$\text{mean: } M(1)_t^{s,m} = \frac{1}{N_t^{s,m}} \left(\sum_{i \in s} X_{i,t}^{s,m} \right), \quad \text{for } s \in \{\text{fin}, \text{nfin}\},\ m \in \{\text{ret}, \text{spd}\}, \tag{1}$$

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

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

where $x_t^{p,s,m}$ is the p$^{\text{th}}$ percentile of log-returns or log-credit-spreads in sector $s \in \{\text{fin}, \text{nfin}\}$. Note that the mean of returns or credit spreads at sector s, $M(1)_t^{s,m}$, is measured on the percentage level to keep the comparison with the rest of the literature. Importantly, I denote $M(3)_t^{\text{fin,ret}}$ as *skewness of the returns of financial firms*—or *SRF*—because of its importance throughout the paper (as illustrated in Figure 1). Additionally, I focus on unweighted cross-sectional moments. SRF empirical performance is then consistent with Kashyap and Stein (2000) result that smaller banks provide large contributions to declines in loan supply.

I focus on the skewness measure (3) because of two reasons. First, it may be interpreted as the balance between cross-sectional upside and downside risks. Using the concept of Values at Risk (VaR), as in Allen et al. (2012), the probability of quarterly returns in sector s (relative to the median) lower than $(x_t^{50,s,ret} - x_t^{5,s,ret})$ is 5%, or the 5% downside VaR is $(x_t^{50,s,ret} - x_t^{5,s,ret})$. Conversely, the 5% upside VaR is $(x_t^{95,s,ret} - x_t^{50,s,ret})$. Thus, SRF can be interpreted as a balance of upside and downside VaRs, with SRF negative when downside risks are larger than upside ones, and vice-versa. Figure 2e illustrates this skewness measure using the distributions of log-returns of financial firms in 2006q2 and 2008q4. The second reason for using measure (3) is that it avoids the sensitivity to outliers found in Pearson's moment-based measure (e.g., Ghysels et al., 2016).[5]

Throughout the paper, I provide several robustness results on the choice of measures for cross-sectional moments, such as skewness.

[5]Using measure (3) also preserves the VaR intuition that is lost in Kelly's skewness measure, $\frac{M(3)_t^{s,m}}{M(2)_t^{s,m}}$.

3 Cross-Sectional Moments and Business Cycles

In this section, I first document which cross-sectional moments lead or lag the business cycle using cross-correlations (Section 3.1). Then, I quantify the ability of different moments to predict economic activity using in-sample (Section 3.2) and pseudo out-of-sample forecasts (Section 3.3). Overall, SRF stands out as a leading indicator of business cycles, with a performance comparable to professional forecasters in predicting medium-run GDP growth.

3.1 Do Moments Lead or Lag the Cycle?

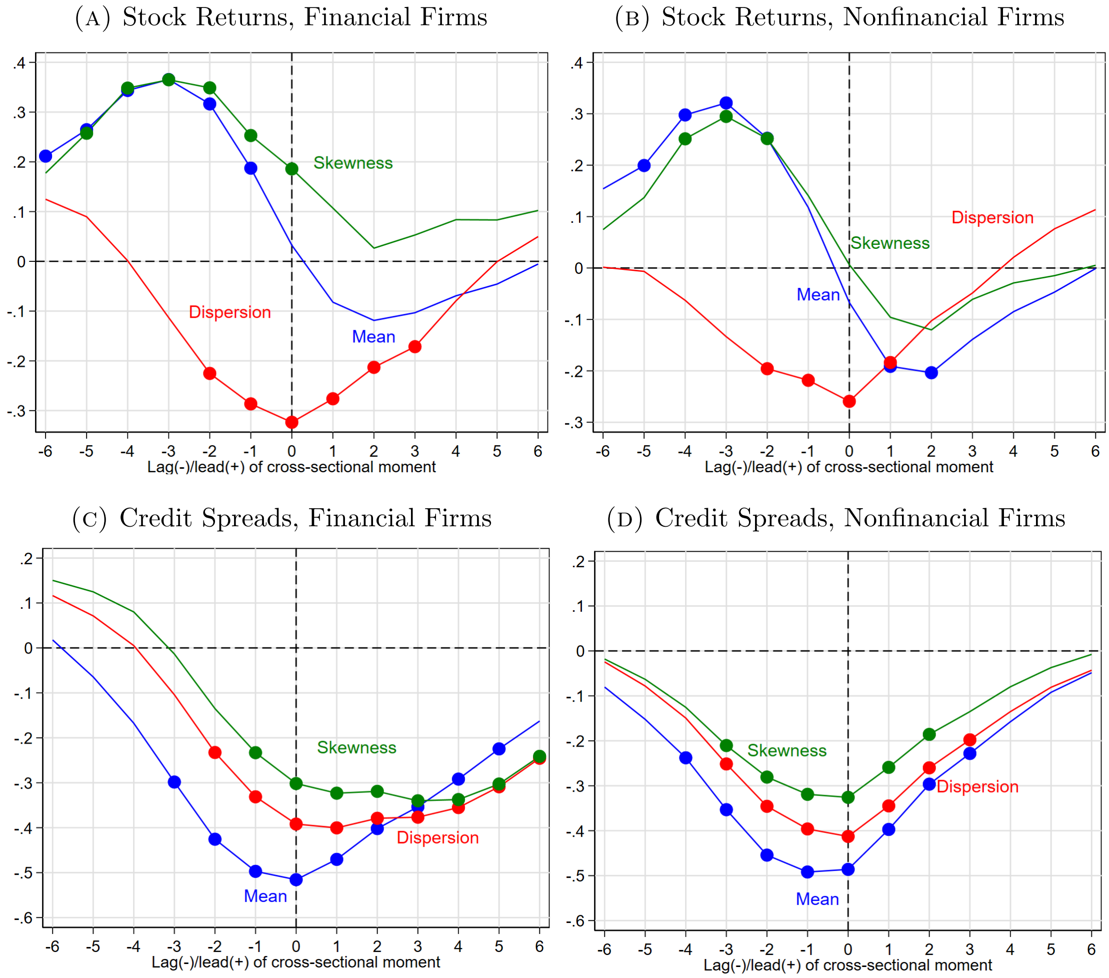
In Figure 3, I provide a descriptive statistic of how different cross-sectional moments of returns and spreads behave over the business cycle. It shows the cross-correlations with 4-quarter GDP growth, with dots denoting correlations that are statistically significant at 1%. I find that the mean and skewness of returns are procyclical, while the dispersion of returns and all cross-sectional moments of spreads are countercyclical. More importantly, the mean and skewness of returns lead the business cycle because their correlations with GDP growth are highest when the cross-sectional measures are lagged (top-left quadrant). In contrast, the dispersion of returns as well as the three moments of credit spreads tend to move contemporaneously with the cycle because their correlations with GDP growth reach their troughs around the zero-lag vertical line. These results are robust to using aggregate consumption or investment, instead of GDP (Figures C.1 and C.2 in Appendix C).

3.2 Do Moments Add Information to Other Financial Indicators?

I evaluate this question considering several prominent financial variables: financial uncertainty (Ludvigson et al., 2015), proxying for aggregate uncertainty in financial markets; excess bond premium or EBP (Gilchrist and Zakrajšek, 2012), measuring investor sentiment in the corporate bond market; term spread, calculated as 10-year Treasury constant maturity rate minus the three-month Treasury bill rate, conveying the slope of the Treasury term structure (Estrella and Hardouvelis, 1991); and the real fed funds rates (fed funds mi-

Figure 3

Cross-Correlations with 4-Quarter GDP Growth



Note: Figure 3 shows the cross-correlations between the 4-quarter GDP growth and the cross-sectional mean, dispersion, and skewness of stock market returns and credit spreads of financial and nonfinancial firms. Correlations are measured either leading (positive x-axis) or lagging (negative x-axis) the cross-sectional moments. Dots denote the correlations that are statistically significant at 1%. The sample is 1973–2020.

nus the 4-quarter change of personal consumption expenditures inflation), measuring the current monetary policy stance. For short, I refer to these variables as *financial indicators.*

Regarding the measure of economic activity, I focus on the mean annualized real GDP growth h quarters ahead. Specifically, for a variable Y_t, I forecast $Y_{t+h|t-1}$ at time t:

$$Y_{t+h|t-1} = \frac{400}{h+1} \ln \left(\frac{Y_{t+h}}{Y_{t-1}} \right). \tag{4}$$

I then use the following general specification for the in-sample regressions:

$$\underbrace{Y_{t+h|t-1}}_{\text{economic activity}} = \underbrace{\beta(k)^{s,m} M(k)_t^{s,m}}_{\text{cross-sectional moment}} + \underbrace{\gamma' \mathbf{F_t}}_{\text{financial indicators}} + \underbrace{\sum_{i=1}^{p} \rho_i Y_{t-i|t-i-1}}_{\text{lagged forecasted variable}} + \alpha + e_{t+h}, \quad (5)$$

where $M(k)_t^{s,m}$ follows the notation of Section 2.2, $\mathbf{F_t}$ encompasses the financial indicators previously discussed, and e_{t+h} is the error. I focus on predictions for four quarters ahead ($h = 4$), and I use four lags of GDP growth ($p = 4$) because of the relatively low Akaike information criterion (AIC) of this specification. The sample period is 1973q1-2020q4, and I standardize all regressors, thus enabling the comparison between their associated coefficients. For the sake of concision, I focus on regressions that include one cross-sectional moment at a time. Lastly, I compute standard errors following Hodrick (1992) because they retain the correct size even in small samples.[6]

The results from these regressions (Table 1) point to mean and skewness of returns performing well in anticipating GDP growth, with SRF standing out as the best performer. Indeed, the third column of Table 1a shows that SRF has highest R^2 and one of the largest statistically significant elasticities: a decline of one standard deviation in SRF anticipates a drop of 0.74% in the mean GDP growth over the next four quarters. The mean return of financial firms and the mean and skewness of returns of nonfinancial firms are also statistically significant. Among the credit spreads, the mean credit spread of nonfinancial firms is the only moment with statistically significant coefficient. These results are consistent with the cross-correlations of Section 3.1, pointing to the first and third moments of the stock returns as leading indicators of business cycles.

Results from Table 1 for the financial indicators are also consistent with those from the literature. For instance, a higher GDP growth is preceded by lower financial uncertainty, higher term-spreads, and lower EBP. However, the coefficients of many of these variables, such as financial uncertainty are not statistically significant in these regressions with many

[6] See Ang and Bekaert (2007) for further discussion.

Table 1
In-Sample GDP Forecast Regressions, 4 Quarters Ahead

(a) Stock Returns: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	0.74***	0.54	0.74***	0.63***	0.24	0.39***
Uncertainty	-0.07	-0.28	-0.07	-0.15	-0.20	-0.20
Real Fed Funds	0.34	0.28	0.35	0.35	0.39	0.31
Term Spread	0.89***	0.86***	0.94***	0.91***	0.96***	0.93***
EBP	-0.44*	-0.71**	-0.32	-0.35	-0.64**	-0.31
R^2	0.37	0.34	0.41	0.37	0.34	0.37

(b) Credit Spreads: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	-0.30	0.08	0.20	-0.75**	-0.43	-0.34
Uncertainty	-0.07	-0.17	-0.19	-0.05	-0.13	-0.14
Real Fed Funds	0.33	0.41	0.44*	0.13	0.25	0.29
Term Spread	0.98***	0.96***	0.94***	0.95***	0.99***	0.99***
EBP	-0.43	-0.58**	-0.61**	-0.08	-0.29	-0.37
R^2	0.34	0.33	0.34	0.38	0.35	0.35

Note: Table 1 reports the results from regression (5) on average GDP growth 4 quarters ahead ($h = 4$), with p equals 4 because of the relatively low AIC of this specification. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess bond premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. Coefficients of lagged GDP growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that the coefficient associated to a regressor equals to zero, where $*$, $**$, and $***$ denote significance levels of 0.1, 0.05 and 0.01, respectively. The sample is 1973–2020.

competing explanatory variables. The best performer among these financial indicators is the term-spread, with an elasticity that is slightly higher than the one for SRF.

In Appendix C, I document that the prominence of SRF in anticipating future economic activity in terms of R^2 and elasticity is robust to many different specifications and measures of economic activity: using multiple cross-sectional moments in the same regression (Table C.1); forecasting personal consumption expenditure, investment, hours worked, and the unemployment rate (Tables C.2–C.5); and using weighted cross-sectional moments (Tables C.6–C.9).

3.3 How Well Do Moments Predict Economic Activity?

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

$$GDP_{t+h|t-1} = \alpha + \sum_{i=1}^{p} \rho_i GDP_{t-i|t-i-1} + \sum_{j=0}^{q} \theta_j X_{t-j} + u_{t+h}, \tag{6}$$

where $GDP_{t+h|t-1}$ follows the notation of equation (4).

The details of the forecasting regressions are as follows. The list of predictor variables X_t goes beyond the financial indicators of Section 3.2 by including the following times series: 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 Zakrajšek, 2012); macro uncertainty (Jurado et al., 2015); a measure of aggregate systemic risk, CATFIN, from Allen et al. (2012); and measures of cross-sectional kurtoses.[7] 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 the jump-off date 1986q1.

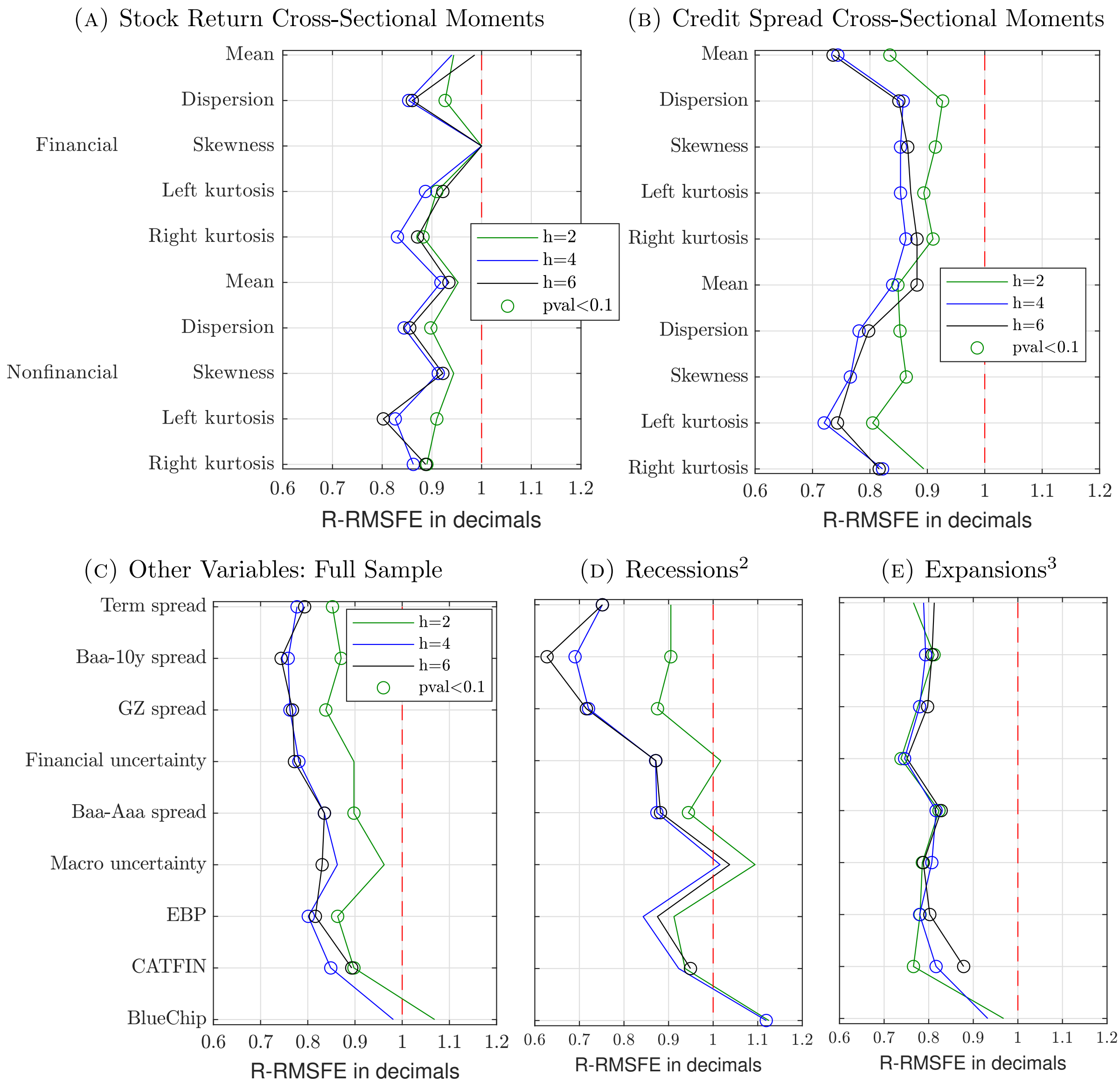
Regarding the forecasting performance evaluation, I benchmark results against SRF. I consider three different horizons (h) for GDP growth: 2, 4, and 6 quarters ahead. I document the performance of different variables by computing ratios of root mean squared forecast errors (RMSFEs), with the one for SRF in the numerator. I refer to these ratios as relative root mean squared forecast error (R-RMSFE) of variable X_t, with values below 1 indicating that SRF performs better than variable X_t. Finally, I also use mean forecasts from the Blue Chip Survey of Professional Forecasters without any regressions.

[7] Following the same notation of cross-sectional moments (1)–(3), I use

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

$$\text{right kurtosis: } M(5)_t^{s,m} = (x_t^{95,s,m} - x_t^{75,s,m}) - (x_t^{75,s,m} - x_t^{55,s,m}), \text{for } s \in \{\text{fin}, \text{nfin}\},\ m \in \{\text{ret}, \text{spd}\}.$$

FIGURE 4
Performance of Out-of-Sample GDP Forecasts Relative to SRF



Note: Figure 4 reports the ratio between the root mean squared forecast error (RMSFE) of regressions (6) using SRF relative to RMSFEs from similar regressions using competing variables. I denote this ratio as the relative root mean squared forecast error (R-RMSFE) and report it in decimals. Blue Chip forecasts are used directly without any regressions. I consider three different horizons (h) for GDP growth: 2, 4, and 6 quarters ahead. Statistical significance is relative to the null hypothesis that the predictor variable and SRF have equal predictive power. Circles represent significance levels of at least 10 percent. [2]Recession R-RMSFEs are computed using forecast errors from forecasts estimated during a quarter classified by the NBER as a recession. [3]Expansion R-RMSFEs are analogous to recession R-RMSFEs. The sample is 1973–2020.

The results from the out-of-sample forecasts point to SRF as the best performer in predicting GDP growth. Figures 4a and 4b show that SRF outperforms almost all cross-sectional distribution measures at statistically significant levels, with R-RMSFEs below 1 for all variables and forecast horizons.[8] Figures 4c–4e also show that SRF outperforms most financial indicators for the full sample, recessions, and expansions, with magnitudes close to 40% of improvement in some cases. The only variable that outperforms SRF, macro uncertainty, does not achieve statistical significance and is statistically outperformed in expansions.

I also document that SRF has a powerful predictive ability within the majority of the sample period. Figure 5 displays 20-quarter rolling R-RMSFEs for GDP growth four quarters ahead, focusing on some prominent predictor variables: macro uncertainty (Figure 5a), term spread (Figure 5b), EBP (Figure 5c), and CATFIN (Figure 5d). For most of the sample, Figures 5a-5d show that the rolling R-RMSFE stays below 1, indicating that the forecasts using SRF have a lower RMSFE than those from alternative variables. Although Figures 5a-5d point to some short-lived spikes to values higher than 1, these figures show that SRF performs better than the competing variables in many periods other than the financially turbulent 2008 recession.

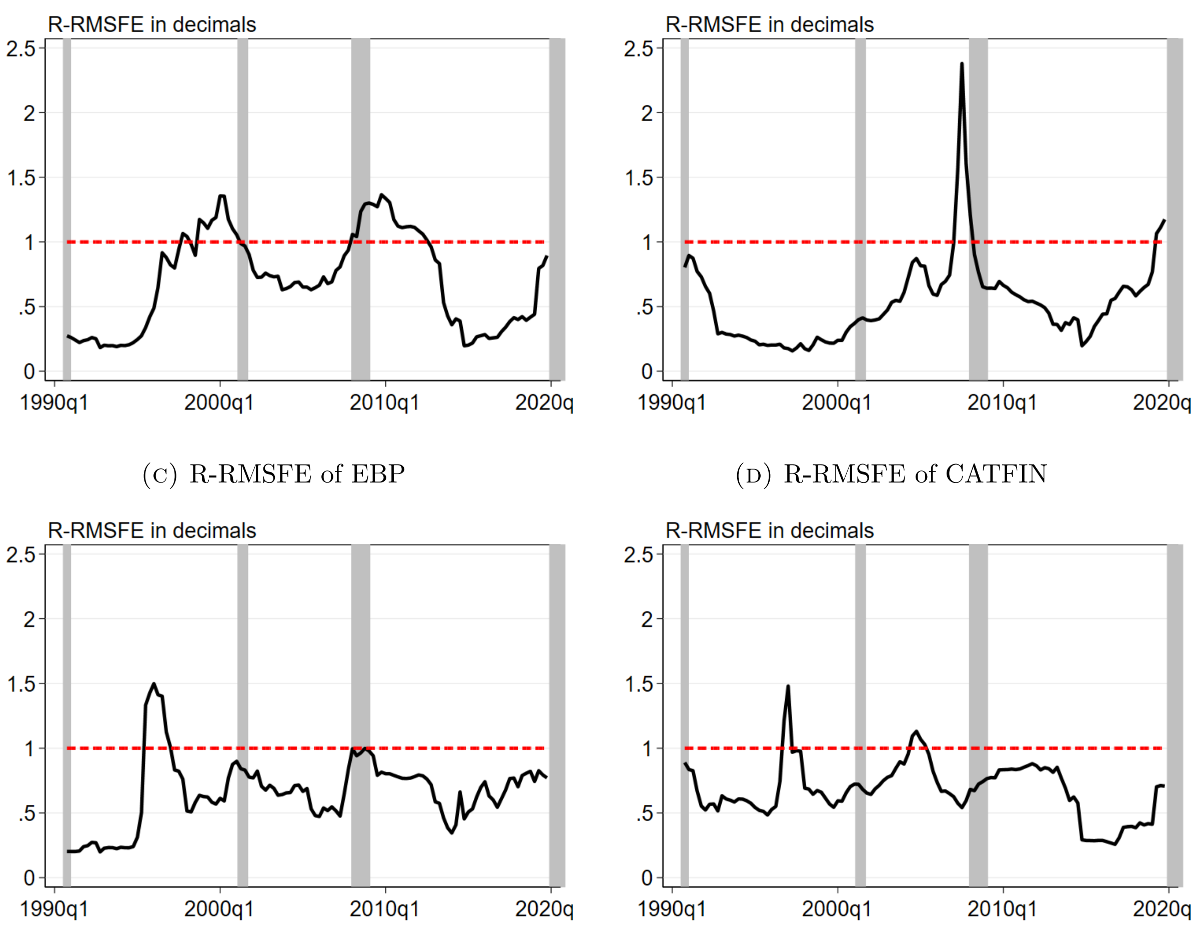
Finally, I find that SRF has a forecasting performance comparable to those from the Blue Chip Survey of Professional Forecasters. Indeed, the last row in Figures 4c–4e shows that SRF has forecasts that are broadly as precise as those from Blue Chip forecasters in the full sample, with SRF performing worse in recessions and slightly better in expansions. This result provides evidence that SRF has a forecasting ability that is realistically significant, as professional forecasters take into account a wide range of data and statistical models as well as human judgment about economic developments.

Appendix C shows that the conclusions discussed above are robust to three different

[8] To calculate statistical significance, I use the Diebold-Mariano test (Diebold and Mariano (2002)) on the difference between the RMSFE of the predictor variable and the RMSFE of SRF. I compute this heteroskedasticity-autocorrelation (HAC) robust test by using the result from Kiefer and Vogelsang (2002), who show that using Bartlett kernel HAC standard errors without truncation yields the test distribution from Kiefer et al. (2000). Abadir and Paruolo (1997) provide critical values for this distribution.

Figure 5

Rolling Performance of Out-of-Sample GDP Forecasts Relative to SRF



(A) R-RMSFE of Macro Uncertainty

(B) R-RMSFE of Term-Spread

(C) R-RMSFE of EBP

(D) R-RMSFE of CATFIN

Note: Figure 5 reports the ratio between the root mean squared forecast error (RMSFE) for predicting GDP growth four quarters ahead when using SRF relative to the RMSFE of competing variables X_t. I denote this ratio as the 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.

ways of calculating cross-sectional moments: (i) using cross-sectional moments weighted by the associated par value of bonds or market capitalization of stocks (Figure C.3); (ii) focusing on normalized—or Kelly—measures of skewness and kurtosis (Figure C.4); and (iii) using the residuals of regressions of the time series of individual stock returns on market-wide returns, thus decomposing individual returns into a systematic correlation with markets and a measure of idiosyncratic component (Figure C.5).[9]

4 SRF as a Barometer of The Lending Channel

In this section, I investigate the reason for the close relationship between SRF and business cycles. I find that SRF provides information about the lending channel (Bernanke and Gertler, 1995): it anticipates fluctuations in loan growth, instead of the more directly-tapped debt markets (Section 4.1), and reflects the risk bearing capacity of the financial sector as well as the quality of its balance sheet (Section 4.2).

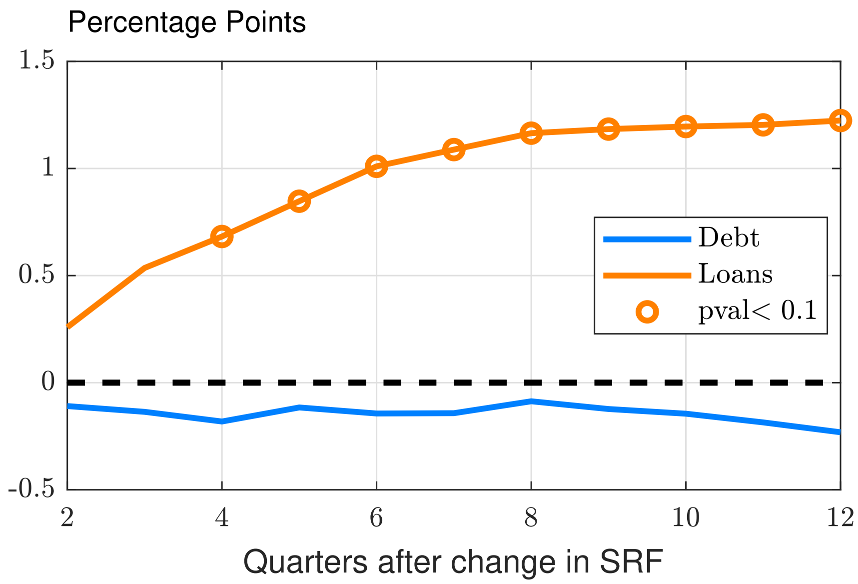
4.1 SRF Forecasts Loan Growth, not Debt Issuance

I start from the hypothesis that SRF anticipates information about credit markets. However, different credit markets may be associated with information about different agents in the economy (Holmstrom and Tirole, 1997). Relative to direct debt markets (e.g., commercial paper and bonds), the loan market is associated with nonfinancial firms that are smaller, younger, and less likely to have access to public debt and equity markets (Saunders et al., 2021). Additionally, credit market dynamics are tied to those intermediating the credit, with the state of banks' balance sheets playing an important role in the availability of loans (Kishan and Opiela, 2000, Hubbard et al., 2002, Chodorow-Reich, 2014).

To shed light on the informational content of SRF, I measure its predictive ability on aggregate loan and debt growth. Using regressions similar to (5), I standardize all regressors and control for the same financial indicators of Section 3.2. I find that SRF anticipates loan growth over a persistent time horizon (Figure 6). For instance, a decline of one standard deviation in SRF anticipates a drop of 1% in the mean loan growth over the next six quarters. In contrast, fluctuations in SRF do not statistically anticipate changes in debt growth. These results are consistent with SRF providing information about *either*

[9] Throughout the paper, I have not implemented transformations on individual stock returns because market-wide returns themselves may be determined by the distribution of idiosyncratic risks (e.g., Ferreira, 2016).

FIGURE 6
Elasticity of Credit Growth to SRF



Note: Figure 6 reports the elasticity of SRF from regressions (5) on average loan and debt growth (h) quarters ahead, with p equals 4 because of the relatively low AIC of this specification. The controls of the regression are the following: financial uncertainty (Ludvigson et al., 2015) measuring aggregate uncertainty in financial markets; excess bond premium (Gilchrist and Zakrajšek, 2012) measuring investor sentiment in the corporate bond market; real fed funds measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures; and term spread as the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. Standard errors are calculated according to Hodrick (1992). Circles represent significance levels of at least 10 percent. The sample is 1973–2020.

nonfinancial firms with greater reliance on loan markets *or* the ability of the financial sector to intermediate funds.

To better identify differing patterns across asset markets and economic sectors, I provide the results for the cross-sectional moments of credit spreads, as well as other moments of stock returns, in Appendix C (Tables C.10 and C.11). I find that credit spreads perform well in anticipating debt growth (Table C.11b), while providing little information about loan growth (Table C.10b). I find that increases in all three cross-sectional moments of credit spreads of nonfinancial firms correlate with lower future debt growth. These results are consistent with nonfinancial spreads forecasting conditions in debt rather than loan markets. Credit spreads of financial firms also anticipate fluctuations on debt growth but with a positive sign, consistent with the deterioration of conditions faced by financial firms, followed by nonfinancial firms switching for direct financing in debt markets (analogously to results from Kashyap et al., 1993 after monetary policy tightenings).

4.2 SRF Signals Intermediaries' Balance Sheet Quality

In this section, I shed light on the informational content of SRF by regressing on it well-known variables associated with the following hypotheses.

- *Risk bearing capacity of the financial sector*: SRF may reflect binding constraints faced by financial firms which may impair their risk bearing and lending capacities. I measure this issue using the intermediary capital risk factor (ICRF) from He et al. (2017), who calculate the equity capital ratio of primary dealer counterparties of the New York Federal Reserve.

- *Quality of financial firms' assets*: market participants may anticipate, through SRF, the quality of assets of financial firms. To evaluate this issue, I use the return on average assets for all U.S. banks (ROA), and the net percentage of domestic banks tightening standards for loans for small (LS-SF) and medium and large firms (LS-LMF). The motivation to use lending standards comes from Bassett et al. (2014), who find that these variables reflect issues such as reassessments of loans' riskiness and changes in business strategies.

- *Current and future macroeconomic conditions:* SRF may suffer from reverse causality, under which it reflects market participants' views about the macroeconomic outlook. I consider this issue using Blue Chip's now-cast of current quarter GDP growth ($\widehat{\text{GDP}}_{t|t-1}$), as well as the forecast of four-quarter-ahead GDP growth ($\widehat{\text{GDP}}_{t+4|t-1}$).

- *Policy uncertainty*: SRF may signal uncertainty about different policy aspects of the economy. I consider this issue by using the economic policy uncertainty (EPU) index from Baker et al. (2016) and its sub-index focused monetary policy (EPU-MP).[10]

[10] I find similar results using the monetary policy uncertainty measure of Husted et al. (2020), as well

TABLE 2

Co-variates of Skewness of Returns of Financial Firms (SRF)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ICRF	0.45***								0.43***	0.37***
ROA		0.50***							0.48***	0.40***
LS-SF			-0.47***							-0.29
LS-LMF				-0.43***						0.08
$\widehat{\text{GDP}}_{t\|t-1}$					0.09**					-0.09
$\widehat{\text{GDP}}_{t+4\|t-1}$						0.05				0.09
EPU							-0.31***			-0.03
EPU-MP								-0.25***		-0.06
R^2	0.24	0.20	0.22	0.19	0.05	0.02	0.10	0.06	0.43	0.47

Note: Table 2 shows the results from univariate regressions of several variables on SRF. Regressions have the sample period from 1990 to 2019. I standardize both the regressors and SRF, and thus omit the constant from the regressions. Variables are named as follows: the intermediary capital risk factor (ICRF) from He et al. (2017); return on average assets for banks (ROA); changes in banks' lending standards for small (LS-SF), and medium and large firms (LS-LMF); Blue Chip's now-casting ($\widehat{\text{GDP}}_{t|t-1}$) and four-quarter-ahead forecast of GDP growth ($\text{GDP}_{t+4|t-1}$); economic policy uncertainty (EPU) from Baker et al. (2016) and its sub-index focused monetary policy (EPU-MP). 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, respectively.

I standardize all variables, including SRF. The sample is 1990–2019 at a quarterly frequency because of data availability. See Appendix A.4 for exact definitions of variables.

The main result from these regressions is that SRF conveys information about the risk bearing capacity of the financial sector as well as the quality of its balance sheet. Table 2 shows that while most variables are statistically significant, only ICRF and ROA are robust to the inclusion of all regressors simultaneously (column 10). The positive coefficients on these variables are also consistent with the discussed hypotheses. Higher ICRF (i.e., higher equity capital ratio) is associated with less distress faced by primary dealers and improving risk-bearing capacity, while higher ROA (i.e., returns on banks' assets) signals better financial firms' balance sheets. Additionally, the relationship between ICRF/ROA and SRF is quantitatively significant, with an elasticity of about 0.4 (in column 10): a rise of one standard deviation in ICRF/ROA is associated with a rise of 0.4 standard deviations in SRF. Finally, these regressors have a sizable explanatory power, with an R^2 of 0.43

as other sub-indexes of policy uncertainty from Baker et al. (2016), such as those focused on fiscal policy, taxes, government spending, regulation, financial regulation, trade policy, and sovereign debt and currency crises.

(column 9). Still, it is important to emphasize that the share of unexplained fluctuations in SRF (57% in column 9) is consistent with it capturing a cross-sectional heterogeneity in the health of financial firms that other measures, by construction, overlook.

The results discussed in this section are robust to two important issues: (i) whether we focus on samples pre and/or post the 2008 GFC, and (ii) whether we focus on the component of each variable that is orthogonal to business cycles. These additional results, as well as details of their implementation, are reported in Appendix C (Table C.12).

5 SRF as a Driver of Firm-Level Investment

In this section, I use firm-level data from nonfinancial corporations to further evaluate the relationship between SRF and the lending channel. I find that SRF predicts firm-level investment beyond what is explained by firms' financial and balance sheet conditions.

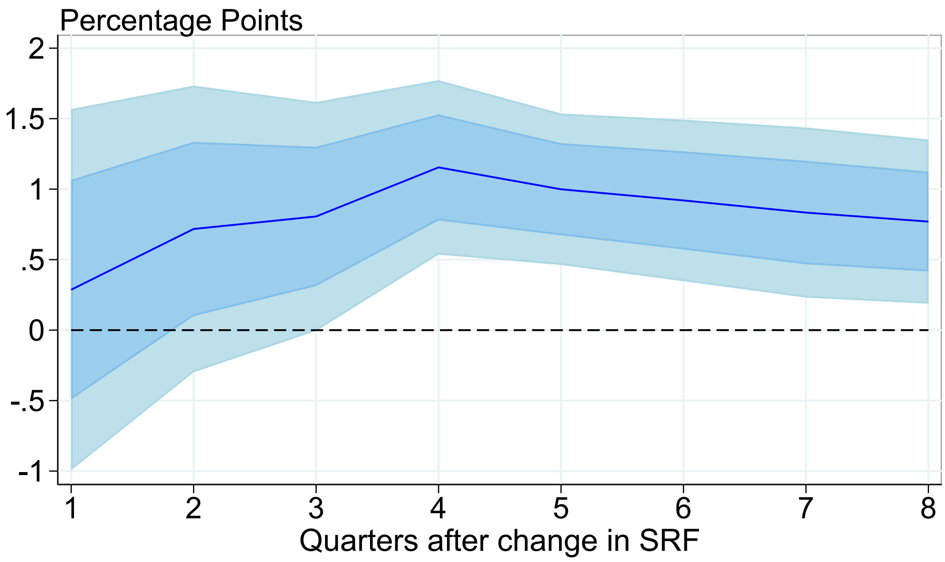
I merge the data on firm-level credit spreads from Lehman/Warga and Merrill Lynch with the quarterly Compustat data on balance sheet information of publicly listed U.S. firms. As in Ottonello and Winberry (2020), I measure firm i investment, $K_{i,t+h|t-1}$, as the change in the book value of tangible capital stock, using the same notation of equation (4). For the balance sheet conditions, I use the following variables: leverage—firm's debt-to-asset ratio—where debt sums short and long-term debts and assets uses the book value measure; distance to default, following the calculation from Gilchrist and Zakrajšek (2012); inflation-adjusted sales growth; and asset liquidity measured by the ratio of cash and liquid assets to total assets (Jeenas, 2019). I also average credit spreads across the same firm's bonds. Appendix A.5 describes in the detail these firm-level variables.

I estimate the effects of SRF on firm-level investment with the following regression:

$$K_{i,t+h|t-1} = \sum_{k=1}^{3} \beta(k) M(k)_t^{fin,ret} + \gamma' \mathbf{F}_t + \eta' \mathbf{Z}_{i,t} + \alpha + \alpha_i + \alpha_{cr} + e_{i,t+h}, \tag{7}$$

where $M(k)_t^{fin,ret}$ for $k \in \{1, 2, 3\}$ denote the first three moments of the cross-sectional dis-

FIGURE 7
Elasticity of Firm-Level Investment to SRF



Note. Figure 7 shows the elasticity of firm-level investment to SRF (solid blue line) calculated in regression (7). Shaded areas report the 68% and 90% error bands. Controls $\mathbf{F}_t$ of the regression are the following: financial uncertainty (Ludvigson et al., 2015) measuring aggregate uncertainty in financial markets; excess bond premium (Gilchrist and Zakrajšek, 2012) measuring investor sentiment in the corporate bond market; real fed funds measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures; and term spread as the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Firm-level controls $\mathbf{Z}_{it}$ of the regression are the following: leverage, measured as the firm's debt-to-asset ratio; distance to default, following the calculation from Gilchrist and Zakrajšek (2012); average credit spread across the firm's bonds; inflation-adjusted sales growth; and the ratio of short-term assets to total assets. Appendix A.5 describes these firm-level variables. The regression also includes firm and credit-rating fixed effects, with OLS estimation and standard errors double clustered in the firm and time dimensions (Cameron et al., 2011). The sample is 1973–2019.

tribution of stock market returns of financial firms; $\mathbf{F}_t$ includes the same financial indicators used in Section 3.2; $\mathbf{Z}_{i,t}$ denotes the variables measuring firm-level financial and balance sheet conditions, described in the previous paragraph; α_i is the firm-fixed effect; α_{cr} is the credit-rating fixed effect; and $e_{i,t+h}$ is the error. The sample is 1973q4–2019q4 and SRF is standardized over this period to facilitate the interpretation of its elasticity on investment, $\beta(3)$. The regression is estimated by ordinary least squares (OLS) with standard errors double clustered in the firm and time dimensions, following Cameron et al. (2011).

I find that SRF anticipates sizable and persistent fluctuations in firm-level investment. Figure 7 shows the elasticity of firm-level investment to SRF, $\beta(3)$, over different horizons. This elasticity is initially not statistically significant for horizons up to three quarters after the change in SRF. However, after four quarters, the elasticity is significant with a magnitude of about 1 percentage point: an increase of one standard deviation of SRF anticipates an increase of about 1 percentage point in the average investment growth. Over longer horizons, this elasticity gradually decreases. This result corroborate the hypothesis that SRF reflects conditions on the lending channel, as SRF affects firm-level investment well beyond the many variables measuring firm-level financial and balance sheet conditions.

In Appendix C, I show that results are robust to using a sample restricted to the period before the 2008 GFC (Figure C.6).

6 SRF and the Cross-Sectional Lending Channel

In this section, I find that macroeconomic fluctuations after SRF shocks are consistent with a lending channel in which the cross-sectional state of financial firms' balance sheets is an important component of business cycles. I first show empirical evidence from VARs (Section 6.1) and then rationalize this argument with a modified financial accelerator model (Section 6.2) that qualitatively matches the VAR evidence (Section 6.3).

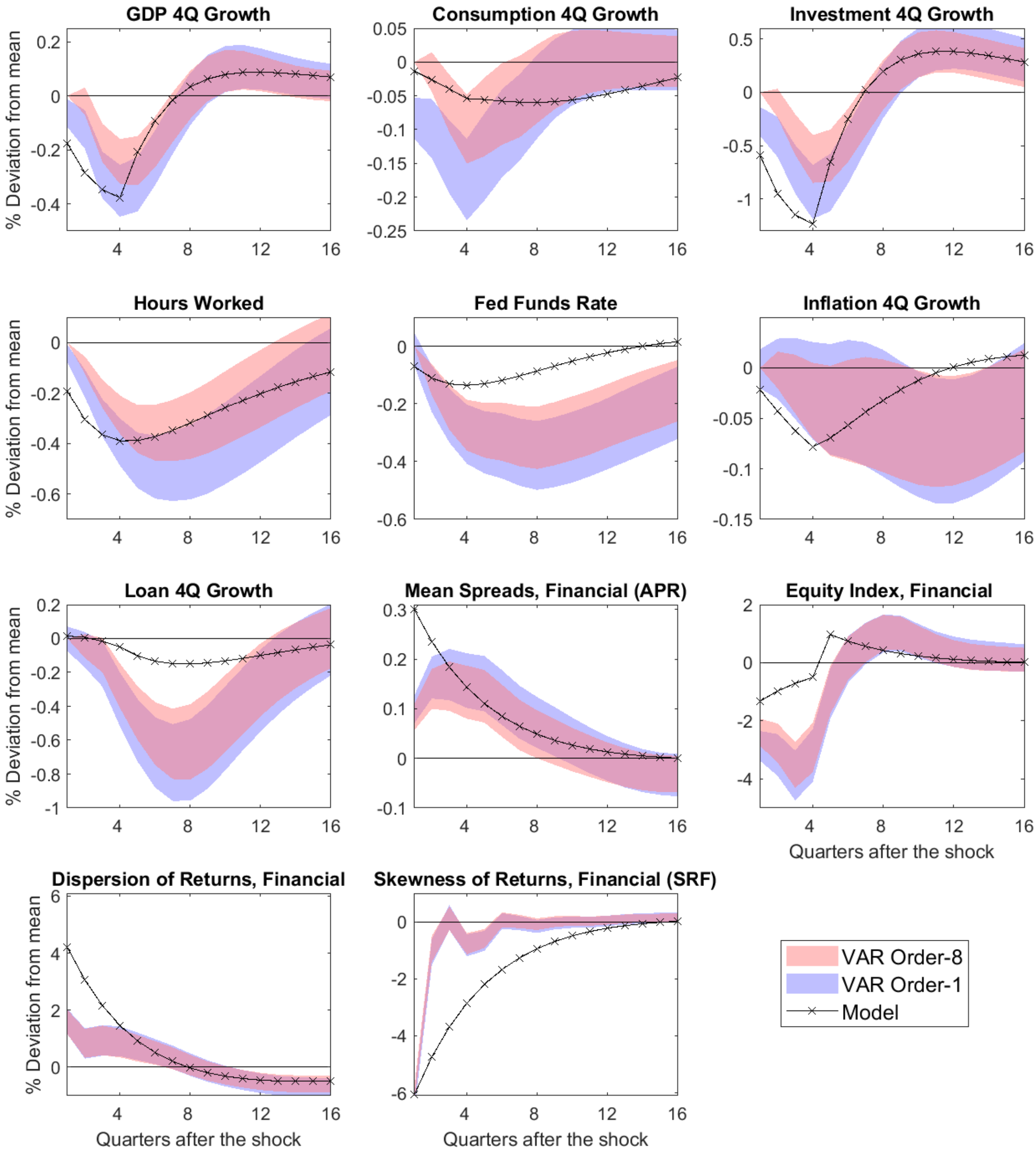
6.1 SRF Shocks Lead to Significant Macroeconomic Effects

To study the link between economic activity, loan growth, and cross-sectional financial conditions, I complement the previous analyses using vector autoregressions (VARs).

I employ a Bayesian VAR with 11 macroeconomic and financial data for the period 1973q1–2019q4 at a quarterly frequency. Specifically, I use real GDP, real consumption, real investment, hours worked, the fed funds rate, core inflation, real loans, real financial equity index, dispersion of returns of financial firms $M(2)_t^{\text{fin,ret}}$, SRF $M(3)_t^{\text{fin,ret}}$, and mean credit spreads of financial firms $M(1)_t^{\text{fin,spd}}$. Quantity variables, such as GDP, consumption, investment and loans are transformed to per capita four-quarter growth rates. Loans are also deflated by core inflation. Hours is in per capita terms and then demeaned. The financial equity index is normalized by the population, deflated by core inflation, and then

Figure 8

Impulse Response Functions from VARs and Model



Note: Figure 8 shows the impulse response functions (IRFs) of VARs with the following variables: real GDP, real consumption, real investment, hours worked, the fed funds rate, core inflation, real loans, mean credit spreads of financial firms $M(1)_t^{\text{fin,spd}}$, real financial equity index, dispersion of returns of financial firms $M(2)_t^{\text{fin,ret}}$, and skewness of returns of financial firms SRF $M(3)_t^{\text{fin,ret}}$. I identify unanticipated SRF shocks with two recursive orderings: *Order-8* places SRF before financial equity index, dispersion of returns, and mean credit spreads; *Order-1* places SRF as the first variable. Shadings indicate 68% probability intervals. Details about VARs are in Section 6.1, with details about the data in Appendix A.6. The IRFs from the model are calculated by finding parameters that minimize the distance between the model's IRFs and those from the VAR. Details about the model are in Section 6.2. The sample is 1973–2019.

used in four-quarter changes. Appendix A.6 describes details about data definitions and transformations. I identify SRF shocks with two recursive orderings. I define *Order-8* as the ordering that places SRF before financial equity index, dispersion of returns, and mean credit spreads. I also define *Order-1* as the ordering that places SRF as the first variable.[11]

The impulse response functions (IRFs) of these VARs show that SRF shocks lead to sizable and persistent economic effects (Figure 8). After unexpected declines in SRF, financial conditions quickly tighten (equity index falls and credit spreads increase), dispersion of returns increases, economic activity falls (GDP, consumption, investment, and hours), lending declines, inflation dips, and monetary policy eases with fed funds policy rate decreasing. All of these co-movements between macroeconomic and financial variables are typical of recessions. However, the VARs reveal a distinct evidence about the relative timing of these variables: the sharp decrease in SRF is followed by a quick rebound, while economic effects persist. For instance, after an SRF shock, GDP growth takes 8 quarters to become positive (similarly for consumption and investment) and loan growth takes 16.

Altogether, the empirical results of this paper are consistent with SRF signaling conditions about a cross-sectional lending channel and, ultimately, the macroeconomy. SRF is associated with the risk-bearing capacity and asset quality of financial firms (Section 4), and predicts both aggregate (Section 3) and firm-level (Section 5) economic activity. The VARs of this section complement these previous results with a more general equilibrium perspective, showing that sudden adverse changes in SRF lead to a quick tightening of financial conditions, which is then followed by a decline in lending and economic activity. Thus, the evidence not only points to SRF as a barometer of the cross-sectional state of financial firms' balance sheets, but also as an important element of business cycles, given its performance in predicting economic activity.

[11] I estimate the VAR with Bayesian methods, a Minnesota prior distribution, and optimal shrinkage from Giannone et al. (2015).

6.2 The Modified Financial Accelerator Model

The model is similar to Christiano et al. (2014), but I modify it in two key features. First, I re-interpret the original model, assuming that the financial friction is between financial firms and households while also supposing a frictionless relationship between nonfinancial firms and their financial firms.[12] These assumptions allow us to focus on the financial firms' cross-sectional distribution of equity returns, especially its skewness, which is what stands out in the empirical analyses of the previous sections. The second modification of the model is that financial firms face a two-regime cross-sectional uncertainty, analogously to Hamilton (1989). Returns on financial firms' *assets* are drawn from a mixture of two normal distributions: a "bad" (lower mean and higher variance) and a "good" one (higher mean and lower variance). Skewness *risk shocks* (Christiano et al., 2014) arise from the worsening of the mean of the "bad" distribution of asset returns, while keeping unchanged both the mean and standard deviation of the overall distribution of asset returns. This two-regime framework allows us to better fit the time series behavior of observed cross-sectional dispersion and skewness of equity returns.

This skewed risk shock is meant to capture asymmetrical cross-sectional changes in the risk bearing capacity of the financial sector, as well as on the quality of assets of the sector. These asymmetrical cross-sectional changes in asset quality may arise from heterogenous exposition to shocks originated in aggregate (e.g., Lehman failure) and regional markets (e.g., Savings and Loans Crisis).[13] Admittedly, the cross-sectional distribution of *asset* returns of financial firms is an *exogenous* object in this model and deserves further study to make it more realistic. Still, as in Christiano et al. (2014) and Ferreira (2016), this assumption makes the distribution of *equity* returns *endogenous* in the model, with skewness risk shocks generating important fluctuations in the model cross-sectional skewness of returns of financial firms (SRF).[14] Finally, the model proposed in this paper is different from those

[12] This assumption is similar to Gertler and Karadi (2011) and Gertler and Kiyotaki (2015), who assume that the financial friction is between the household and the financial sector.

[13] See Sharpe et al. (1995) for a detailed discussion about culprits of the Savings and Loans Crisis, with cross-sectional studies featured prominently.

[14] The property of *exogenous* cross-sectional *asset* returns generating *endogenous* cross-sectional *equity*

based on the disaster risk hypothesis (e.g. Barro, 2006, Gabaix, 2012, and Gourio, 2012). While the latter papers study aggregate tails risks, I focus on cross-sectional tail risks.

The rest of the model include features widely used New-Keynesian models: sticky prices and wages à la Calvo; habit persistence in the consumption of households with these agents owning the capital stock; adjustment cost in investment growth; and a Taylor rule governing monetary policy. Since the model is similar to Christiano et al. (2014), I leave its full description to Appendix B.

6.3 Cross-Sectional Lending Channel: VAR vs Model

To verify whether the model is able to match the IRFs from the VARs (Figure 8), I divide the model parameters in two groups. First, to simplify the analysis, I calibrate several parameters associated with the New-Keynesian block of the model using estimates from Christiano et al. (2014). Second, I search for the remaining parameters that minimize the distance between the IRFs of the model and those from the VARs. These remaining parameters are associated with the habit persistence in consumption, price and wage-setting stickiness, adjustment cost of investment, and the financial accelerator block of the model. I provide more details on about the IRF-matching algorithm in Appendix B.3.

Figure 8 shows that the model IRFs (black line) match qualitatively well the IRFs of the VARs (shaded areas), with some model IRFs being inside the probability intervals of the VAR IRFs. However, the comparison between these IRFs also reveals two important limitations of the financial accelerator model applied to cross-sectional uncertainty shocks: (i) loan growth falls by much less in the model relative to the VARs, and (ii) the model IRF of SRF is significantly more persistent than the one from the VARs. We could increase the effects from the risk shock on loan growth by, for instance, raising the persistence of the risk shock. However, this would only magnify issue (ii).

The results from this section show that although the financial accelerator model helps rationalize the cross-sectional lending channel described in this paper, they also quantify

returns is also discussed in Christiano et al. (2014), while being first derived in Ferreira (2016).

the model's lack of internal amplification mechanism to transmit cross-sectional uncertainty shocks relative to the data.

7 Conclusion

In this paper, I study the business cycle properties of the *full* cross-sectional distributions of U.S. stock returns and credit spreads from financial and nonfinancial firms. Among the moments of these distributions of financial conditions and relative to renowned financial indicators, the skewness of returns of financial firms (SRF) stands out as a leading indicator of the cycle. I then investigate the informational content of SRF, showing evidence that it is a barometer of conditions on the lending channel. Consistent with this view, SRF affects firm-level investment beyond nonfinancial firms' balance sheet conditions, and adverse SRF shocks lead to macroeconomic downturns with tighter financial and lending conditions in vector autoregressions (VARs). Altogether, these results are consistent with a *cross-sectional lending channel*: the cross-sectional state of financial firms' balance sheets is an important component of business cycles. I rationalize this argument using a modified financial accelerator model that qualitatively matches the evidence from the VARs.

The paper leaves for future research at least two important questions. First, it remains to be investigated how economic fundamentals, such as monetary policy, productivity, and regulatory changes, affect the cross-sectional distributions of financial conditions. These distributions may reveal additional channels through which exogenous shocks affect economic activity. Second, while the financial accelerator model provides a first step to rationalize the results presented in this paper, the evidence also points to the necessity of further study on *simultaneously* rationalizing fluctuations in (i) cross-sectional financial conditions, (ii) business, and (iii) financial cycles.

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A Appendix: Data Details

A.1 Stock Market Returns Data

I use all returns from the monthly CRSP database. Then, I use the following procedures:

- 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.
- I eliminate returns from stocks with less than 10 years of consecutive non-missing data.

A.1.1 Classification: Financial and Nonfinancial Sectors

This section is reproduced from Ferreira (2016). In order to classify the firms as financial or nonfinancial, 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 a 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).

Figure A.1
Comparison between GZ spread and Mean Nonfinancial Spreads

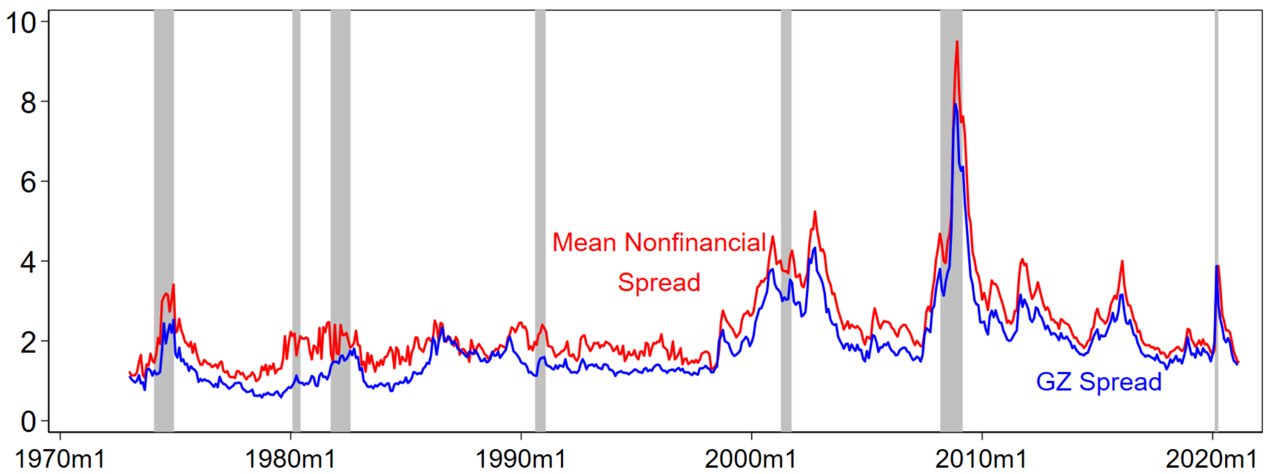


Figure A.1 shows the GZ spread (Gilchrist and Zakrajšek, 2012) in blue and the mean spread of nonfinancial firms in red. Gray areas represent periods classified as recessions by the National Bureau of Economic Research.

A.2 Credit Spreads Data

I start with all corporate yields from Lehman/Warga (1973m1–1998m3) and Merrill Lynch (1997m1–2020m12). Then, I implement the following procedures:

- I drop observations with the following characteristics: putable bonds, bonds with residual maturity of less than 6 months or higher than 30 years, bonds with credit spreads higher than 35% and lower than 0.05%, and observations of bonds with lower than 12 months of consecutive non-missing spread values.

- I merge the two datasets by averaging the yields that are available in both datasets during the intersecting period, and then I append the remaining observations.

I classify bonds as either from financial or nonfinancial firms according to the following methodology. While these databases provide the NAICS classification, NAICS is not available for every firm/bond within the sample. It is then available internal classifications under which one of the sector categories is called "Finance"/"Financial". I then classify bonds as from financial firms as follows. If NAICS is available, I use both NAICS and the internal classification of each dataset. Otherwise, I use only the internal classification.

Figure A.1 compares the mean cross-sectional credit spreads of nonfinancial firms from this paper with the one calculated under the methodology of Gilchrist and Zakrajšek (2012). The figure shows that they are very similar with a correlation of 0.96.

A.3 Data References for Section 3

For convenience, I retrieve many times series through two renown macroeconomic datasets: Saint Louis FRED, and Haver. The latter is available only through subscription, but it is widely used in the academic and policy research community.

1. GDP: Real gross domestic product, real billions of chained 2012 dollars, quarterly, seasonally adjusted annual rate. FRED mnemonic "GDPC1"

2. Consumption: Real personal consumption expenditures, billions of chained 2012 dollars, quarterly, seasonally adjusted annual rate. FRED mnemonic: "PCECC96".

3. Investment: Real private fixed investment, real billions of chained 2012 dollars, quarterly, seasonally adjusted annual rate. Haver mnemonic "FH@USECON".

4. Financial uncertainty: as explained in Ludvigson et al. (2015) with data provided here.

5. Macroeconomic uncertainty: as explained in Jurado et al. (2015) with data provided here.

6. Excess bond premium (EBP): as explained in Gilchrist and Zakrajšek (2012) with data provided here.

7. GZ spread: as explained in Gilchrist and Zakrajšek (2012) with data provided here.

8. Term spread: 10-year Treasury constant maturity rate (Haver mnemonic "FCM10@USECON") minus the three-month Treasury bill rate (Haver mnemonic "FTBS3@USECON").

9. Real fed funds: Fed funds (FRED mnemonic "FEDFUNDS") minus the four-quarter change of personal consumption expenditures: chain-type index 2012=100, quarterly, seasonally adjusted price index (FRED mnemonic "PCECTPI").

10. Baa - 10y: Moody's Seasoned Baa Corporate Bond Yield minus 10-year Treasury yields. FRED mnemonic "BAA10YM".

11. Baa - Aaa: Moody's Seasoned Baa Corporate Bond Yield (FRED mnemonic "BAA") minus Moody's Seasoned Aaa Corporate Bond Yield (FRED mnemonic "AAA").

12. CATFIN: as explained in Allen et al. (2012) with data provided here.

A.4 Data References for Section 4

For convenience, I retrieve many time series through two renowned macroeconomic datasets: Saint Louis FRED and Haver. The latter is available only through subscription, but it is widely used in the academic and policy research community.

1. Loan growth: amount outstanding of loans from the liabilities of nonfinancial businesses. Source: Financial Accounts of the United States, L.102. Haver mnemonic "OL14ABN5@FFUNDS".

2. Debt growth: this is the sum of the amount outstanding of commercial paper and corporate bonds from the liabilities of nonfinancial businesses. Source: Financial Accounts of the United States, L.102. Haver mnemonics: commercial paper is "OL10DPP0@FFUNDS", and corporate bonds is "OL10COF3@FFUNDS".

3. ICRF: intermediary capital risk factor from He et al. (2017). Data link here.

4. ROA: return on average assets for all U.S. Banks. FRED mnemonic "USROA".

5. LS-SF: the net percentage of domestic banks tightening standards for commercial and industrial loans for small firms. FRED mnemonic "DRTSCIS".

6. LS-LMF: the net percentage of domestic banks tightening standards for commercial and industrial loans for large and medium firms. FRED mnemonic "DRTSCILM".

7. $\widehat{\text{GDP}}_{t|t-1}$: Blue Chip's now-cast of current quarter GDP growth. These data are available to the public only through subscription. Given that Blue Chip's forecasts are released on the 10^{th} of every month, I average forecasts from the last month of the quarter with those from the month right after the end of quarter.

8. $\text{GDP}_{t+4|t-1}$: Blue Chip's forecast of four-quarter-ahead GDP growth. These data are available to the public only through subscription. Given that Blue Chip's forecasts are released

on the 10^{th} of every month, I average forecasts from the last month of the quarter with those from the month right after the end of quarter.

9. EPU: economic policy uncertainty from Baker et al. (2016). Data link here.

10. EPU-MP: the sub-index of economic policy uncertainty based on news about monetary policy. Documentation for these sub-indexes is here.

11. Market returns: from the French Fama data library, with link here.

A.5 Data References for Section 5

Firm-level balance sheet data comes from the Compustat database, with definitions below.

1. Investment is based the on net plant, property, and equipment (PPEGTQ). I then calculate its change using equation (4).

2. Leverage is calculated as the ratio of total debt (sum of current debt, DLCQ, and long-term debt DLTTQ) to total assets (ATQ).

3. Inflation adjusted sales is calculated as SALEQ deflated by the CPI. Then, I take the log-change this measure of real sales. Also, CPI is retrieved from Saint Louis FRED (CPI-AUCSL).

4. Asset liquidity is calculated as the ratio between cash and short-term investments (CHEQ) and total assets (ATQ).

For firm-level distance to default, I closely follow Gilchrist and Zakrajšek (2012), and omit the full description. Of note, I also use data from CRSP database for this calculation.

A.6 Data References for Section 6

1. Real GDP is calculated by deflating nominal (FRED mnemonic "GDP") by the implicit GDP price index (FRED mnemonic "GDPDEF") and by the population over 15 years old (United Nations data via Haver[15]).

[15]Total population with Haver mnemonic "C111TB@UNPOP" subtracted by the population lower than 15 with Haver mnemonics "C111AB@UNPOP", "C111BB@UNPOP", and "C111CB@UNPOP".

2. Core inflation is the personal consumption expenditures (PCE) excluding food and energy (Chain-Type Price Index). FRED mnemonic "PCEPILFE".

3. Real consumption is the sum of nominal PCE in services (FRED mnemonic "PCESV") and non-durables (FRED mnemonic "PCND"), deflated by the PCE price index (FRED mnemonic "PCECTPI") and by the population over 15 years old (United Nations data via Haver, see footnote 15).

4. Real investment is the sum of nominal PCE in durables (FRED mnemonic "PCDG") and nominal business investment (Haver mnemonic "F@USECON"), deflated by the business investment price index (Haver mnemonic "JF@USECON") and by the population over 15 years old (United Nations data via Haver, see footnote 15).

5. Hours worked is measured by the aggregate weekly hours of production and nonsupervisory employees in all private industries (FRED mnemonic "AWHI"), divided by the population over 15 years old (United Nations data via Haver, see footnote 15), and normalized relative to the sample average.

6. Real credit is the amount outstanding of loans from the liabilities of nonfinancial businesses. Source: Financial Accounts of the United States, L.102. (Haver mnemonic "OL14ABN5@FFUNDS"). It is then normalized by the core PCE price index (FRED mnemonic "PCEPILFE") and by the population over 15 years old (United Nations data via Haver, see footnote 15).

7. Financial equity index is the cumulative weighted return of all financial firms, normalized by the core PCE price index (FRED mnemonic "PCEPILFE") and by the population over 15 years old (United Nations data via Haver, see footnote 15).

8. Fed funds rate is the average of the daily rates over the quarter. FRED mnemonic "FEDFUNDS".

9. Financial spreads is the $M(1)_t^{fin,spd}$ described in Section 2.

10. Financial equity dispersion is the $M(2)_t^{fin,ret}$ described in Section 2.

11. Financial equity skewness is the $M(3)_t^{fin,ret}$ described in Section 2.

B Appendix: Model Details

B.1 Model: Financial Frictions

As discussed in Section 6.2, I re-interpret the original model. I assume that the financial friction is between financial firms and households while also supposing a frictionless relationship between nonfinancial firms and their financial firms. Mechanically, this assumption entails relabeling the "entrepreneurs" from the original models as financial firms. This is also discussed in footnote 13 of Christiano et al. (2014). For simplicity, I refer to bankers as the financial firms.

Bankers and Cross-Sectional Uncertainty. Bankers directly purchase physical capital using their own equity and loans from households. There is a unit measure of these bankers, with each one of them facing a return on capital $\omega_t \cdot R_t^c$ with two components: an endogenous and aggregate, R_t^c, dependent on the state of economy; and an idiosyncratic, ω_t, capturing specific risks taken by bankers. I model ω_t as exogenous and interpret it as a shock either to the banker's lending capacity or more directly to the quality of its assets.

I model ω_t as i.i.d. across bankers following a time-varying cumulative distribution function (cdf) F_t. Specifically, F_t is a mixture of two lognormal distributions:

$$\omega_t \sim F_t(\omega_t; m_t^1, s_t^1, m_t^2, s_t^2, p_t^1) = \begin{cases} p_t^1 \cdot & \Phi\left[(\log(\omega_t) - m_t^1)/s_t^1\right] \\ +(1-p_t^1)\cdot & \Phi\left[(\log(\omega_t) - m_t^2)/s_t^2\right] \end{cases}, \tag{B.1}$$

where 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 exogenous parameters that may vary over time. This approach is particularly useful because it encompasses the lognormal distribution, often used in the literature.

To focus the analysis on a shock that generates skewness on the distribution of stock returns, I make several normalizations on the mixture F_t. First, I re-parametrize it by picking m_t^2 and p_t^1 such that $\mathbb{E}_t(\omega_t) = 1$ and $\text{Std}_t(\omega_t) = \sqrt{\int_0^\infty (\omega - \mathbb{E}_t(\omega_t))^2 \, dF_t(\omega)} = sd_t$, for any given vector (m_t^1, s_t^1, s_t^2). Thus, the distribution F_t does not *directly* change the mean of the return of capital $\omega_t \cdot R_t^c$ and the standard deviation of F_t is pinned down by sd_t. Second, I fix sd_t, s_t^1, and s_t^2 at steady state levels, with $s^1 > s^2$. Third, I choose the steady state level of m_t^1 with $m^1 < m^2$.

Finally, I model m_t^1 as a first-order autoregression, AR(1): a decrease in m_t^1 leads to a decrease in the cross-sectional skewness of returns.

<u>One Time Period as a Banker.</u> At the end of period t, banker 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 equity N_{t+1}^i, banker i purchases physical capital $\overline{K}_{t+1}^i$ with unit price Q_t in competitive markets. Banker i then totals an amount of assets of $Q_t\overline{K}_{t+1}^i = N_{t+1}^i + B_{t+1}^i$. In the beginning of period $t+1$, banker i draws an exogenous idiosyncratic return ω_{t+1} only observable by him, which transforms $\overline{K}_{t+1}^i$ into $\omega_{t+1}\overline{K}_{t+1}^i$ efficient units of physical capital.

During period $t+1$ and with $\omega_{t+1}\overline{K}_{t+1}^i$ efficient units of physical capital, banker i earns rate of return $\omega_{t+1}R_{t+1}^c$ on this capital. To get this return, the banker first determines capital utilization u_{t+1} by maximizing profits from renting capital services $\omega_{t+1}\overline{K}_{t+1}^i R_{t+1}^k u_{t+1}$ to intermediate firms net of utilization costs $\omega_{t+1}\overline{K}_{t+1}^i P_{t+1} a(u_{t+1})$, where R_{t+1}^k is the nominal rental rate of capital, $a(u_{t+1})$ is a cost function,[16] and P_{t+1} is the nominal price level. Then, after goods production takes place, banker i receives the capital back from intermediate firms depreciated at rate δ and sells it at price Q_{t+1}. Thus, $\omega_{t+1}R_{t+1}^c = \omega_{t+1}\frac{R_{t+1}^k u_{t+1} - P_{t+1}a(u_{t+1}) + (1-\delta)Q_{t+1}}{Q_t}$.

<u>Loan Markets.</u> At the end of period t, mutual funds compete in the loan market for bankers 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 $L_{t+1}^i = (Q_t\overline{K}_{t+1}^i)/N_{t+1}^i$ and threshold $\overline{\omega}_{t+1}^i$, such that $Z_{t+1}^i B_{t+1}^i = \overline{\omega}_{t+1}^i R_{t+1}^c Q_t \overline{K}_{t+1}^i$. Threshold $\overline{\omega}_{t+1}^i$ may vary with $(t+1)$'s state of nature and determines whether banker i is able to pay his debt. If $\omega_{t+1} \geq \overline{\omega}_{t+1}^i$, then banker i pays his lender the amount owed, $Z_{t+1}^i B_{t+1}^i$, and keeps the rest of his assets. Otherwise, banker i declares bankruptcy, and mutual funds seize all remaining assets net of a proportional auditing cost: $(1-\mu)\,\omega_{t+1}R_{t+1}^c Q_t \overline{K}_{t+1}^i$, with $\mu \in (0,1)$.

Because bankers are risk neutral and only care about their equity holdings, mutual funds

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

compete by seeking loan contracts that maximize bankers' expected earnings:

$$\mathbb{E}_t\left(\int_{\overline{\omega}^i_{t+1}}^{\infty}\left(\omega-\overline{\omega}^i_{t+1}\right)dF_{t+1}(\omega)\frac{R^c_{t+1}Q_t\overline{K}^i_{t+1}}{N^i_{t+1}}\right)=\mathbb{E}_t\left[\left(1-\Gamma_{t+1}(\overline{\omega}^i_{t+1})\right)R^c_{t+1}L^i_{t+1}\right], \tag{B.2}$$

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

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

$$(1-F_{t+1}(\overline{\omega}^i_{t+1}))B^i_{t+1}Z^i_{t+1}+(1-\mu)G^f_{t+1}(\overline{\omega}^i_{t+1})R^c_{t+1}Q_t\overline{K}^i_{t+1}\geq R_{t+1}B^i_{t+1}. \tag{B.3}$$

We then normalize equation ($B.3$) by N^i_{t+1} and impose equality because competition in loan markets drives profits to zero. Finally, we determine loan contracts by choosing $(L^i_{t+1},\overline{\omega}^i_{t+1})$ that maximizes (B.2) subject to the renormalized equation (B.3). Notice that this maximization does not depend on the level of equity N^i_{t+1} and, therefore, nor does its solution, thus allowing us to drop the i superscript. In turn, this solution implies that all bankers have the same market leverage, L_{t+1}, and face the same market threshold, $\overline{\omega}_{t+1}$.

Aggregate Financial Variables. At the end of period $t+1$, two additional events finally determine the banker's equity used to apply for new loans in the next period. First, a mass of (1-γ) bankers is randomly selected to transfer all of their assets to households. Second, all bankers receive a lump-sum transfer of W^e from households. Thus, the law of motion for aggregate equity is

$$N_{t+2}=\gamma\left[\int_{\overline{\omega}_{t+1}}^{\infty}\left(\omega-\overline{\omega}_{t+1}\right)dF_{t+1}(\omega)\right]R^c_{t+1}Q_t\overline{K}_{t+1}+W^e,$$

where the first term is the earnings of the bankers able to pay their loans (net of transfers to households), $N_{t+2}=\int N^i_{t+2}di$ and $\overline{K}_{t+1}=\int\overline{K}^i_{t+1}di$. Additionally, the aggregate amount of loans taken to finance capital purchases is $B_{t+1}=Q_t\overline{K}_{t+1}-N_{t+1}$, and loan interest rate is $Z_{t+1}=\overline{\omega}_{t+1}R^c_{t+1}\frac{L_{t+1}}{L_{t+1}-1}$. Model credit spread is relative to the monetary policy interest rate.

Cross-Sectional Distribution of Equity Returns. As shown by Ferreira (2016), we can calculate model counterparts of empirical measures (1) − (3). To do so, define the *gross realized equity return* of banker i at period t by X_t^i, such that

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

Thus, the SRF of the model is $(\widetilde{x}_t^{95} - \widetilde{x}_t^{50}) - (\widetilde{x}_t^{50} - \widetilde{x}_t^{5})$, where $\widetilde{x}_t^{v} = \log(\widetilde{\omega}_t^v - \overline{\omega}_t)$ and $\widetilde{\omega}_t^v$ is the v^{th} percentile of distribution $F_t(\cdot|\omega_t > \overline{\omega}_t)$. The use of $F_t(\cdot|\omega_t > \overline{\omega}_t)$ is to match the fact that empirical measures (1) − (3) only use returns of non-bankrupt firms (i.e., strictly positive returns). Finally, cross-sectional distribution moments from the model are endogenous variables, as $\overline{\omega}_t$ is an endogenous variable.

B.2 Model: Standard Features

Goods Production. A representative final goods producer uses technology $Y_t = \left[\int_0^1 Y_{jt}^{1/\lambda^f} dj\right]^{\lambda^f}$, and intermediate goods Y_{jt}, for $j \in [0, 1]$, to produce a homogeneous good Y_t. Intermediate producers' production function is $Y_{jt} = K_{jt}^{\alpha}(H_{jt})^{(1-\alpha)} - \phi$, if $K_{jt}^{\alpha}(H_{jt})^{(1-\alpha)} > \phi$. Otherwise, Y_{jt} equals zero. Additionally, ϕ represents a fixed cost.[17] These producers rent capital services K_{jt} and hire homogenous labor H_{jt} in competitive markets. 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 with a one-to-one mapping.

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. The remaining ξ_p fraction follows an indexation rule $P_{j,t} = \widetilde{\Pi}_t P_{j,t-1}$, where $\widetilde{\Pi}_t = (\Pi^{ss})^{\iota_p} (\Pi_{t-1})^{1-\iota_p}$, Π_t^{ss} is steady state inflation, $\Pi_{t-1} = P_{t-1}/P_{t-2}$, and $P_t = \left[\int_0^1 P_{jt}^{1/(1-\lambda^f)} dj\right]^{1-\lambda^f}$.

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

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

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\log\left(C_t - b\, C_{t-1}\right) - \psi_0 \int_0^1 \frac{h_{it}^{1+\psi_l}}{1+\psi_l} di \right). \tag{B.4}$$

I describe the labor supply decision in subsection below.[18]

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

Finally, the households' budget constraint is

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

where R_t is the risk-free interest rate paid on households savings, W_{it} is the nominal hourly wage for differentiated labor service h_{it}, and D_t represents all lump-sum transfers to and from households. The households' problem is then to choose C_t, B_{t+1}, I_t, and $\overline{K}_{t+1}$, maximizing (B.4) subject to the capital production function and to the budget constraint.

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

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

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

$$\frac{R_t}{R^{ss}} = \left(\frac{R_{t-1}}{R^{ss}}\right)^{\rho_r} \left[\mathbb{E}_t \left(\frac{\Pi_{t+1}}{\Pi_t^{ss}}\right)^{\alpha_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{\alpha_y}\right]^{(1-\rho_r)}$$

Fiscal policy is represented by expenditure G and 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. Thus, I have the following resource constraint: $Y_t = C_t + I_t + G$.

B.3 Model Parameters and IRF Matching

The values of all parameters are reported in Table B.1. On the estimated variables, I weight the difference between model IRFs and the IRFs from the VAR by the inverse of the variance of the VAR IRFs. Because of the nonlinearity of the IRF-matching objective function, I discretize the grid of possible parameters and evaluate the objective function—sum of the square of the differences between IRFs of the model and VARs—at this grid. I minimize the objective function by blocks of parameters. Step 1: I fix the parameters of Table B.1b at their estimated values by Christiano et al. (2014), and search for optimal parameters of Table B.1c. Step 2: I fix the parameters of Table B.1c at their first-step optimal values, and search for optimal values of parameters of Table B.1b. Step 3: I repeat Step 1, and stop there. Tables B.1b and B.1c reports the upper (UB) and lower (LB) bounds for the estimated parameters, as well as the optimal values (Value).

Table B.1
Model Parameters

(a) Calibrated Parameters

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 bankers	γ^{ss}	0.975
Exogenous transfer to bankers[1]	w_e	0.005
Preference discount rate	$-400\log(\beta)$	1
Steady-state inflation rate	$400\log(\Pi^{ss})$	2
Persistence of monetary policy rate	ρ_r	0.85
Weight of inflation in policy rate	α_π	2.4
Weight of GDP growth in policy rate	α_y	0.36
Capital utilization cost	σ^a	2.54
Weight of inflation trend on inflation indexation	ι_p	0.90
Weight of inflation trend on wage indexation	ι_w	0.49

(b) Estimated Parameters: New Keynesian Block

Description	Name	Value	LB	UB
Habit persistence of Consumption	b	0.80	0.60	0.90
Calvo parameter, intermediate firms	ξ_p	0.80	0.60	0.90
Calvo parameter, labor unions	ξ_w	0.85	0.60	0.90
Investment adjustment cost	χ	4.2	2	11

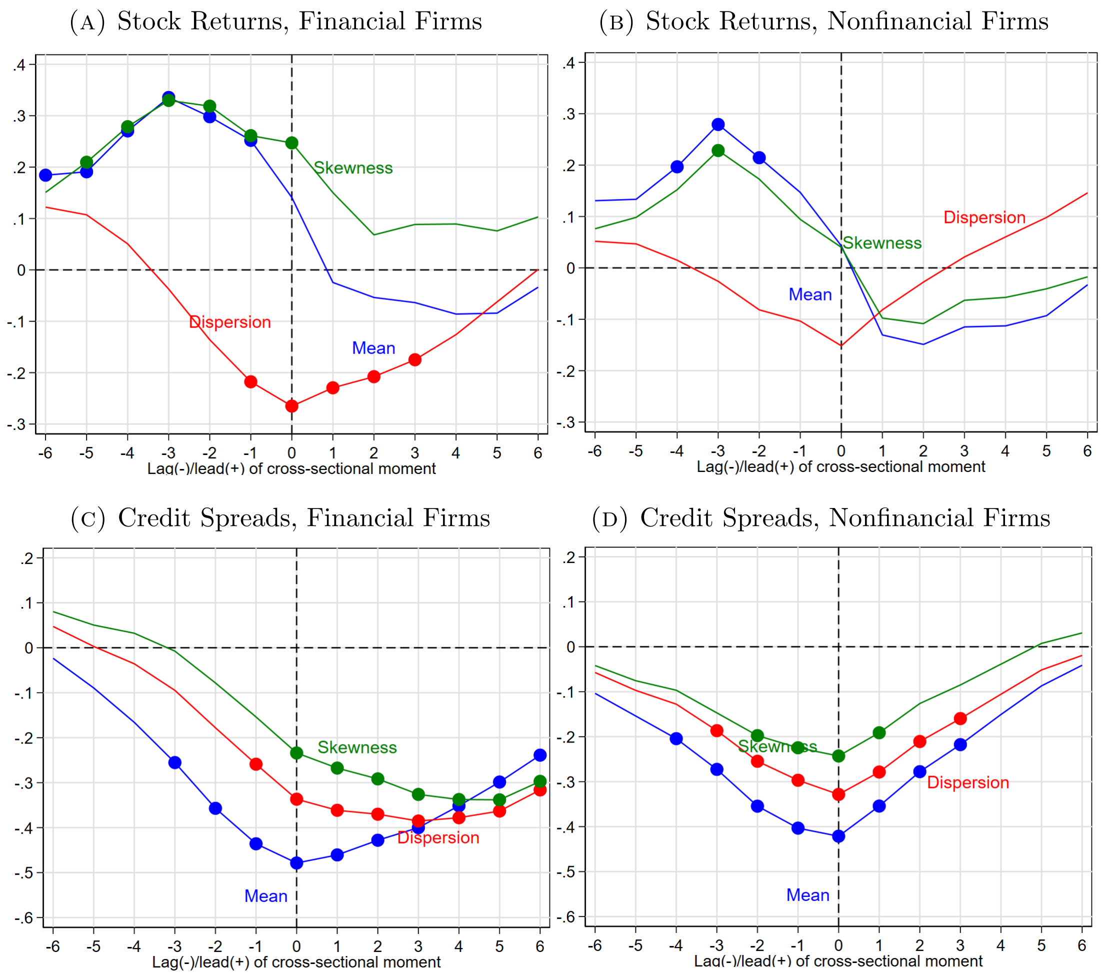
(c) Estimated Parameters: Financial Accelerator Block

Description	Name	Value	LB	UB
Auditing cost	μ	0.16	0.15	0.25
Steady-state mixture probability of lognormals[2]	$p^{1,ss}$	0.15	0.05	0.20
Steady-state location parameter of mixture[2]	$m^{1,ss}$	-0.06	-0.10	-0.02
Steady-state scale parameter of mixture[2]	$s^{1,ss}$	0.06	0.05	0.15
Steady-state scale parameter of mixture[2,3]	$\alpha^{s^2,ss}$	0.25	0.10	0.50
Persistence of AR shock m_t^1	ρ^{m^1}	0.75	0.6	0.9

Note. Table B.1 shows the model parameters and their values. [1]Steady-state $W^{e,ss}$ is calibrated as a percentage w_e of the steady-state capital stock K^{ss}. [2]Although I renormalize F_t from $(m_t^1, s^{1,ss}, m_t^2, s^{2,ss}, p_t^1)$ to $(m_t^1, s^{1,ss}, sd_t, s^{2,ss})$, I pin down the steady state of F^{ss} by estimating $(m^{1,ss}, s^{1,ss}, s^{2,ss}, p^{1,ss})$, where $m^{2,ss}$ is such that $\int \omega dF^{ss}(\omega) = 1$. [3]To achieve identification, I estimate $s^{2,ss}$ as a percentage $\alpha^{s^2,ss}$ of $s^{1,ss}$. LB stands for the lower bound on the parameters for which I run the IRF-matching algorithm, while UB stands for upper bound.

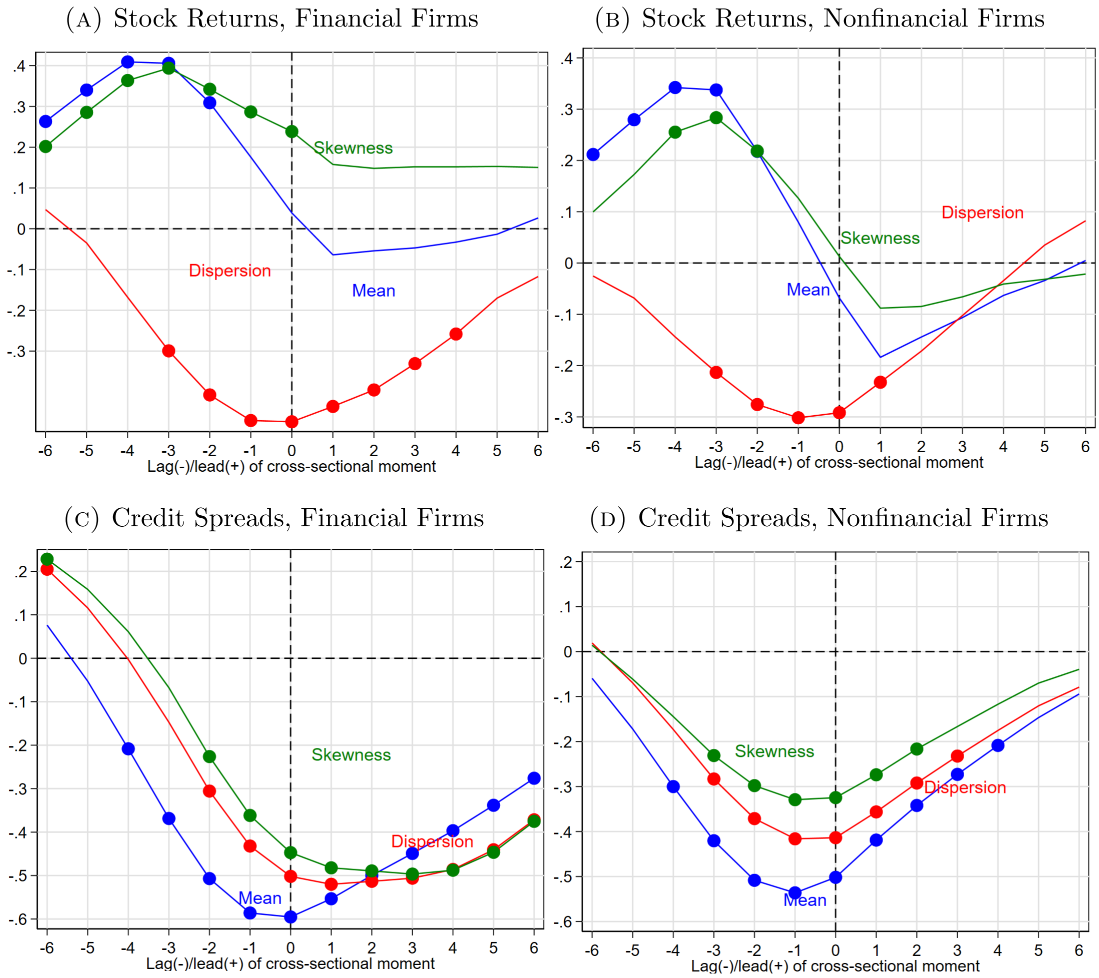
C Appendix: Robustness Results

Figure C.1
Cross-Correlations with 4-Quarter Consumption Growth



Note: Figure C.1 shows the cross-correlations between the 4-quarter Consumption growth and the cross-sectional mean, dispersion, and skewness of stock market returns and credit spreads of financial and nonfinancial firms. Correlations are measured either leading (positive x-axis) or lagging (negative x-axis) the cross-sectional moments. Dots denote the correlations that are statistically significant at 1%. The sample is 1973–2020.

Figure C.2
Cross-Correlations with 4-Quarter Investment Growth



(A) Stock Returns, Financial Firms

(B) Stock Returns, Nonfinancial Firms

(C) Credit Spreads, Financial Firms

(D) Credit Spreads, Nonfinancial Firms

Note: Figure C.2 shows the cross-correlations between the 4-quarter Investment growth and the cross-sectional mean, dispersion, and skewness of stock market returns and credit spreads of financial and nonfinancial firms. Correlations are measured either leading (positive x-axis) or lagging (negative x-axis) the cross-sectional moments. Dots denote the correlations that are statistically significant at 1%. The sample is 1973–2020.

TABLE C.1
In-Sample GDP Forecast Regressions, 4 Quarters Ahead

(A) Three Cross-Sectional Moments per Regression

	Returns		Spreads	
	Financial	Nonfinancial	Financial	Nonfinancial
Mean	0.15	0.43*	-1.63	-2.32
Dispersion	0.56*	0.17	1.17	3.36
Skewness	0.68***	0.17	0.09	-1.83
Uncertainty	-0.19	-0.21	0.01	0.03
Real Fed Funds	0.23	0.33	0.41	0.16
Term Spread	0.82***	0.90***	0.86***	0.87***
EBP	-0.47*	-0.36	-0.24	-0.10
R^2	0.42	0.38	0.39	0.40

Note: Table C.1 reports the results from regression (5) on average GDP growth 4 quarters ahead ($h = 4$), with p equals 4 due to the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. Coefficients of lagged GDP growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that the coefficient associated to a regressor equals to zero, where $*$, $**$ and $***$ denote significance levels of 0.1, 0.05 and 0.01, respectively. The sample is 1973–2020.

Table C.2

In-Sample Forecast Regressions on Macro Variables, Financial Firms, Stock Returns

(a) Notation	(b) **Variable** = Mean					(c) **Variable** = Dispersion				
	GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
Variable	0.74***	0.62***	2.60***	0.72***	-0.26***	0.54	0.41	1.01	0.86**	-0.05
Uncertainty	-0.07	0.05	0.09	-0.51**	0.29**	-0.28	-0.11	-0.47	-0.82***	0.34**
Real Fed Funds	0.34	0.36**	-0.22	0.11	0.07	0.28	0.30	-0.28	0.00	0.07
Term Spread	0.89***	0.78***	2.22***	0.93***	-0.34***	0.86***	0.76***	2.27***	0.82***	-0.34***
EBP	-0.44*	-0.11	-1.83**	-0.80**	0.30**	-0.71**	-0.32	-2.61***	-1.18***	0.36***
R^2	0.37	0.40	0.55	0.51	0.61	0.34	0.37	0.50	0.51	0.61

(d) Notation	(e) **Variable** = Skewness				
	GDP	Consumption	Investment	Hours	U-rate
Variable	0.74***	0.58***	1.79***	0.66***	-0.31***
Uncertainty	-0.07	0.04	-0.06	-0.53**	0.28**
Real Fed Funds	0.35	0.37**	-0.17	0.12	0.08
Term Spread	0.94***	0.83***	2.40***	0.97***	-0.34***
EBP	-0.32	-0.02	-1.71*	-0.71**	0.24*
R^2	0.41	0.42	0.54	0.53	0.63

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.3

In-Sample Forecast Regressions on Macro Variables, Nonfinancial Firms, Stock Returns

(a) Notation; (b) **Variable** = Mean; (c) **Variable** = Dispersion

	(b) GDP	(b) Consumption	(b) Investment	(b) Hours	(b) U-rate	(c) GDP	(c) Consumption	(c) Investment	(c) Hours	(c) U-rate
Variable	0.63***	0.51***	2.07***	0.67***	-0.27***	0.24	0.15	0.84	-0.02	-0.56***
Uncertainty	-0.15	-0.02	-0.16	-0.57**	0.31**	-0.20	-0.04	-0.45	-0.62**	0.44***
Real Fed Funds	0.35	0.37**	-0.17	0.13	0.06	0.39	0.39**	-0.08	0.17	0.10
Term Spread	0.91***	0.80***	2.31***	0.96***	-0.35***	0.96***	0.84***	2.41***	0.97***	-0.19*
EBP	-0.35	-0.06	-1.55*	-0.70**	0.26*	-0.64**	-0.26	-2.63***	-0.93***	0.50***
R^2	0.37	0.40	0.54	0.52	0.62	0.34	0.37	0.50	0.49	0.63

(d) Notation; (e) **Variable** = Skewness

	GDP	Consumption	Investment	Hours	U-rate
Variable	0.39***	0.31***	0.95***	0.44***	-0.14**
Uncertainty	-0.20	-0.05	-0.33	-0.65***	0.33**
Real Fed Funds	0.31	0.33*	-0.25	0.08	0.07
Term Spread	0.93***	0.81***	2.38***	0.96***	-0.35***
EBP	-0.31	-0.02	-1.69*	-0.66*	0.26*
R^2	0.37	0.39	0.52	0.52	0.61

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.4

In-Sample Forecast Regressions on Macro Variables, Financial Firms, Credit Spreads

(a) Notation; (b) **Variable** = Mean; (c) **Variable** = Dispersion

(a) Notation	(b) GDP	(b) Consumption	(b) Investment	(b) Hours	(b) U-rate	(c) GDP	(c) Consumption	(c) Investment	(c) Hours	(c) U-rate
Variable	-0.30	-0.11	-0.15	0.07	0.72***	0.08	0.11	0.54	0.34	0.37*
Uncertainty	-0.07	0.02	-0.21	-0.64***	0.15	-0.17	-0.03	-0.34	-0.68***	0.26*
Real Fed Funds	0.33	0.37**	-0.12	0.18	0.30**	0.41	0.41**	0.07	0.26	0.20
Term Spread	0.98***	0.85***	2.46***	0.97***	-0.14	0.96***	0.83***	2.40***	0.95***	-0.27***
EBP	-0.43	-0.16	-2.27**	-0.97***	0.01	-0.58**	-0.24	-2.47***	-1.04***	0.23*
R^2	0.34	0.36	0.49	0.49	0.65	0.33	0.37	0.50	0.50	0.62

(d) Notation; (e) **Variable** = Skewness

(d) Notation	GDP	Consumption	Investment	Hours	U-rate
Variable	0.20	0.17	0.64	0.36	0.19
Uncertainty	-0.19	-0.04	-0.33	-0.67***	0.30**
Real Fed Funds	0.44*	0.43**	0.07	0.26	0.12
Term Spread	0.94***	0.82***	2.37***	0.93***	-0.33***
EBP	-0.61**	-0.25	-2.46***	-1.03***	0.30**
R^2	0.34	0.37	0.50	0.50	0.61

*Note:*This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.5

In-Sample Forecast Regressions on Macro Variables, Nonfinancial Firms, Credit Spreads

(a) Notation | (b) **Variable** = Mean | | | | | (c) **Variable** = Dispersion | | | |

	GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
Variable	-0.75**	-0.56**	-1.88*	-0.85*	0.09	-0.43	-0.39*	-0.86	-0.62	-0.09
Uncertainty	-0.05	0.07	0.02	-0.52**	0.31**	-0.13	0.01	-0.20	-0.60**	0.33**
Real Fed Funds	0.13	0.20	-0.75	-0.12	0.09	0.25	0.26	-0.37	-0.03	0.03
Term Spread	0.95***	0.84***	2.39***	0.93***	-0.35***	0.99***	0.86***	2.50***	0.99***	-0.33***
EBP	-0.08	0.15	-1.10	-0.39	0.29	-0.29	0.03	-1.80*	-0.57	0.40**
R^2	0.38	0.39	0.52	0.53	0.61	0.35	0.38	0.50	0.52	0.61

(d) Notation | (e) **Variable** = Skewness

	GDP	Consumption	Investment	Hours	U-rate
Variable	-0.34	-0.32	-0.75	-0.53	-0.14
Uncertainty	-0.14	0.00	-0.22	-0.62***	0.33**
Real Fed Funds	0.29	0.29	-0.30	0.02	0.03
Term Spread	0.99***	0.87***	2.51***	1.01***	-0.30***
EBP	-0.37	-0.03	-1.90*	-0.65*	0.42***
R^2	0.35	0.38	0.50	0.52	0.61

*Note:*This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.6

In-Sample Forecast Regressions on Macro Variables, Financial Firms, Stock Returns

(A) Notation	(B) **Variable** = Weighted Mean					(C) **Variable** = Weighted Dispersion				
	GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
Variable	0.55***	0.49***	2.00***	0.51***	-0.22***	0.30	0.21	0.87	0.37	0.00
Uncertainty	-0.09	0.04	0.03	-0.54**	0.29**	-0.25	-0.08	-0.52	-0.74***	0.33**
Real Fed Funds	0.33	0.35*	-0.26	0.11	0.07	0.35	0.36*	-0.19	0.12	0.06
Term Spread	0.93***	0.81***	2.33***	0.96***	-0.34***	0.94***	0.82***	2.37***	0.94***	-0.35***
EBP	-0.45*	-0.12	-1.87**	-0.82**	0.30**	-0.67***	-0.29	-2.66***	-1.08***	0.35***
R^2	0.37	0.40	0.54	0.51	0.61	0.34	0.37	0.50	0.50	0.61

(D) Notation	(E) **Variable** = Weighted Skewness				
	GDP	Consumption	Investment	Hours	U-rate
Variable	0.90***	0.71***	2.53***	0.84***	-0.36***
Uncertainty	-0.17	-0.03	-0.26	-0.61***	0.32**
Real Fed Funds	0.32	0.36*	-0.23	0.11	0.07
Term Spread	0.98***	0.85***	2.50***	1.01***	-0.36***
EBP	-0.28	-0.01	-1.50*	-0.69**	0.24*
R^2	0.41	0.43	0.56	0.53	0.63

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.7

In-Sample Forecast Regressions on Macro Variables, Nonfinancial Firms, Stock Returns

(a) Notation	(b) **Variable** = Weighted Mean					(c) **Variable** = Weighted Dispersion				
	GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
Variable	0.62***	0.46***	2.11***	0.67***	-0.31***	0.36	0.38**	0.95	0.22	-0.50***
Uncertainty	-0.15	-0.02	-0.19	-0.58**	0.31**	-0.27	-0.15	-0.60	-0.70**	0.49***
Real Fed Funds	0.33	0.36**	-0.25	0.10	0.07	0.36	0.37**	-0.16	0.14	0.14
Term Spread	0.95***	0.83***	2.41***	0.98***	-0.36***	0.98***	0.86***	2.47***	0.97***	-0.26***
EBP	-0.34	-0.06	-1.51	-0.69**	0.24*	-0.68***	-0.34*	-2.66***	-1.00***	0.48***
R^2	0.37	0.40	0.55	0.52	0.62	0.34	0.38	0.50	0.50	0.64

(d) Notation	(e) **Variable** = Weighted Skewness				
	GDP	Consumption	Investment	Hours	U-rate
Variable	0.23**	0.21**	0.65**	0.27**	-0.08
Uncertainty	-0.18	-0.04	-0.30	-0.64***	0.33**
Real Fed Funds	0.37	0.37**	-0.12	0.15	0.06
Term Spread	0.96***	0.83***	2.44***	0.98***	-0.35***
EBP	-0.42	-0.09	-1.91**	-0.78**	0.30**
R^2	0.34	0.38	0.50	0.50	0.61

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.8

In-Sample Forecast Regressions on Macro Variables, Financial Firms, Credit Spreads

(A) Notation	(B) **Variable** = Weighted Mean					(C) **Variable** = Weighted Dispersion				
	GDP	Consumption	Investment	Hours	U-rate	GDP	Consumption	Investment	Hours	U-rate
Variable	-0.63**	-0.47*	-0.69	-0.17	0.70**	0.07	0.09	0.70	0.36	0.33*
Uncertainty	-0.01	0.09	-0.11	-0.59**	0.18	-0.16	-0.03	-0.36	-0.68***	0.27*
Real Fed Funds	0.29	0.33*	-0.22	0.13	0.27*	0.40	0.41**	0.10	0.26	0.18
Term Spread	1.00***	0.88***	2.47***	0.97***	-0.17	0.96***	0.83***	2.37***	0.94***	-0.29***
EBP	-0.25	0.03	-1.99**	-0.85***	-0.05	-0.58**	-0.23	-2.54***	-1.06***	0.23*
R^2	0.36	0.38	0.50	0.49	0.65	0.33	0.36	0.50	0.50	0.62

(D) Notation	(E) **Variable** = Weighted Skewness				
	GDP	Consumption	Investment	Hours	U-rate
Variable	0.25	0.21	0.83	0.42	0.14
Uncertainty	-0.20	-0.05	-0.35	-0.68***	0.31**
Real Fed Funds	0.45*	0.44**	0.10	0.27	0.10
Term Spread	0.93***	0.81***	2.34***	0.92***	-0.34***
EBP	-0.63**	-0.27	-2.52***	-1.05***	0.31**
R^2	0.34	0.37	0.50	0.51	0.61

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Table C.9

In-Sample Forecast Regressions on Macro Variables, Nonfinancial Firms, Credit Spreads

(a) Notation; (b) **Variable** = Weighted Mean; (c) **Variable** = Weighted Dispersion

(a) Notation	(b) GDP	(b) Consumption	(b) Investment	(b) Hours	(b) U-rate	(c) GDP	(c) Consumption	(c) Investment	(c) Hours	(c) U-rate
Variable	-0.87**	-0.68**	-2.13*	-1.01**	0.06	-0.40	-0.34	-0.80	-0.67*	-0.08
Uncertainty	-0.05	0.06	-0.02	-0.53**	0.32**	-0.12	0.01	-0.20	-0.60**	0.33**
Real Fed Funds	0.15	0.21	-0.69	-0.11	0.07	0.29	0.30	-0.29	0.00	0.04
Term Spread	0.96***	0.85***	2.42***	0.94***	-0.35***	1.00***	0.87***	2.51***	1.00***	-0.33***
EBP	0.06	0.28	-0.79	-0.21	0.30	-0.31	0.00	-1.84	-0.53	0.39**
R^2	0.38	0.40	0.52	0.53	0.61	0.35	0.38	0.50	0.52	0.61

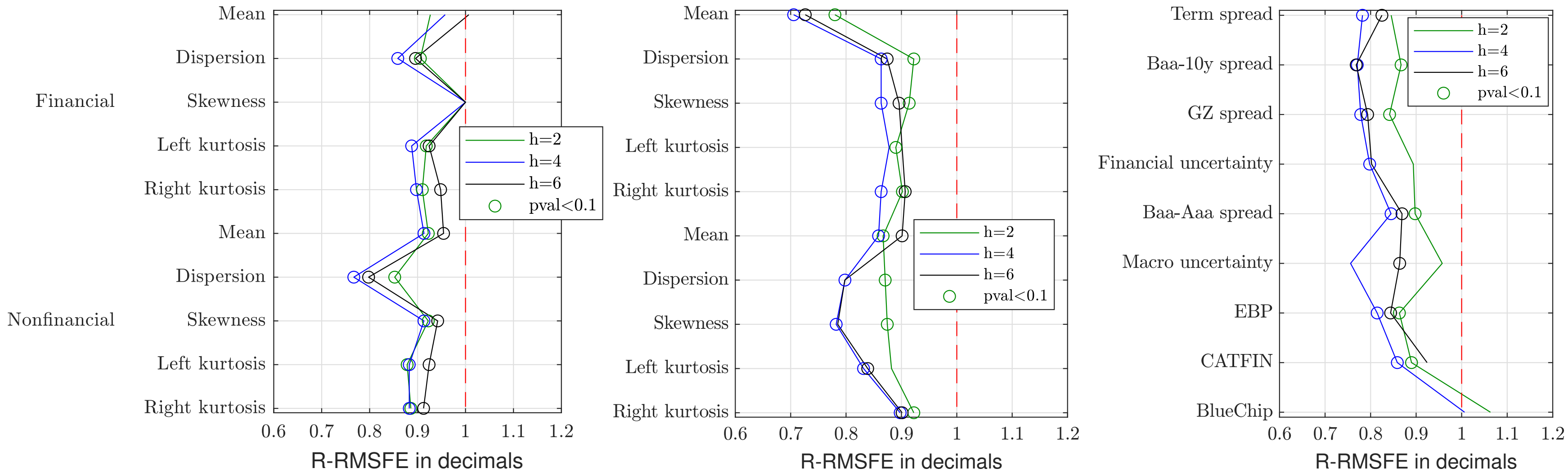
(d) Notation; (e) **Variable** = Weighted Skewness

(d) Notation	GDP	Consumption	Investment	Hours	U-rate
Variable	-0.30	-0.25	-0.67	-0.56*	-0.09
Uncertainty	-0.14	0.00	-0.23	-0.62***	0.33**
Real Fed Funds	0.33	0.34*	-0.22	0.06	0.05
Term Spread	1.00***	0.87***	2.51***	1.01***	-0.32***
EBP	-0.40	-0.07	-1.98*	-0.65	0.39**
R^2	0.34	0.37	0.50	0.52	0.61

Note: This table reports the results from regression (5) on GDP, personal consumption expenditures, private fixed investment, total hours worked, and the unemployment rate. With the exception of the unemployment rate, all predicted variables are used in growth rates, where $h = 4$. For the unemployment rate, I use the levels 4-quarters ahead. I also use $p = 4$ because of the relatively low AIC of this specification. All regressors are standardized. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess Bond Premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Regressors are standardized, allowing comparison between coefficients. 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, respectively. The sample is 1973–2020.

Figure C.3
Out-of-Sample GDP Forecast Regressions, Weighted Measures

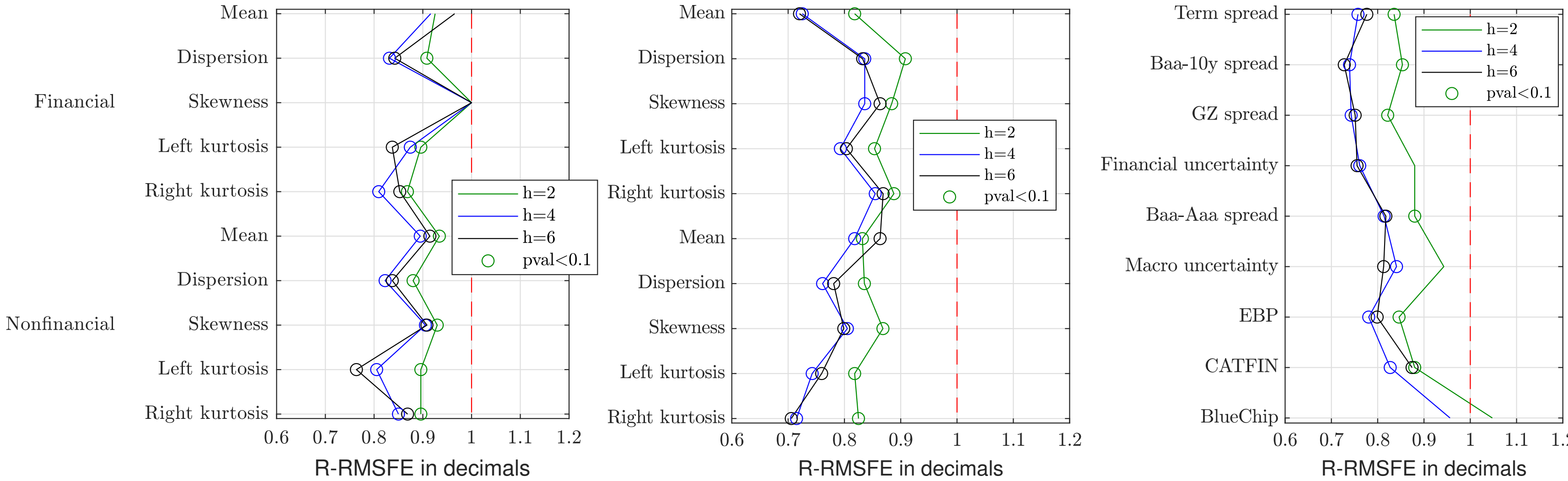
(A) Stock Return Cross-Sectional Moments (B) Credit Spread Cross-Sectional Moments (C) Other variables: Full Sample



Note: Figure C.3 reports the ratio between the root mean squared forecast error (RMSFE) of regressions (6) using SRF relative to RMSFEs from similar regressions using competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. All cross-sectional moments (including the benchmark SRF) are weighted by the associated par value of bonds or market capitalization of stocks. Blue Chip forecasts are used directly without any regressions. I consider three different horizons (h) for GDP growth: 2, 4, and 6 quarters ahead. Statistical significance is relative to the null hypothesis that the predictor variable and SRF have equal predictive power. Circles represent significance levels of at least 10 percent. The sample is 1973–2020.

Figure C.4
Out-of-Sample GDP Forecast Regressions, Kelly Measures

(A) Stock Return Cross-Sectional Moments   (B) Credit Spread Cross-Sectional Moments   (C) Other variables: Full Sample

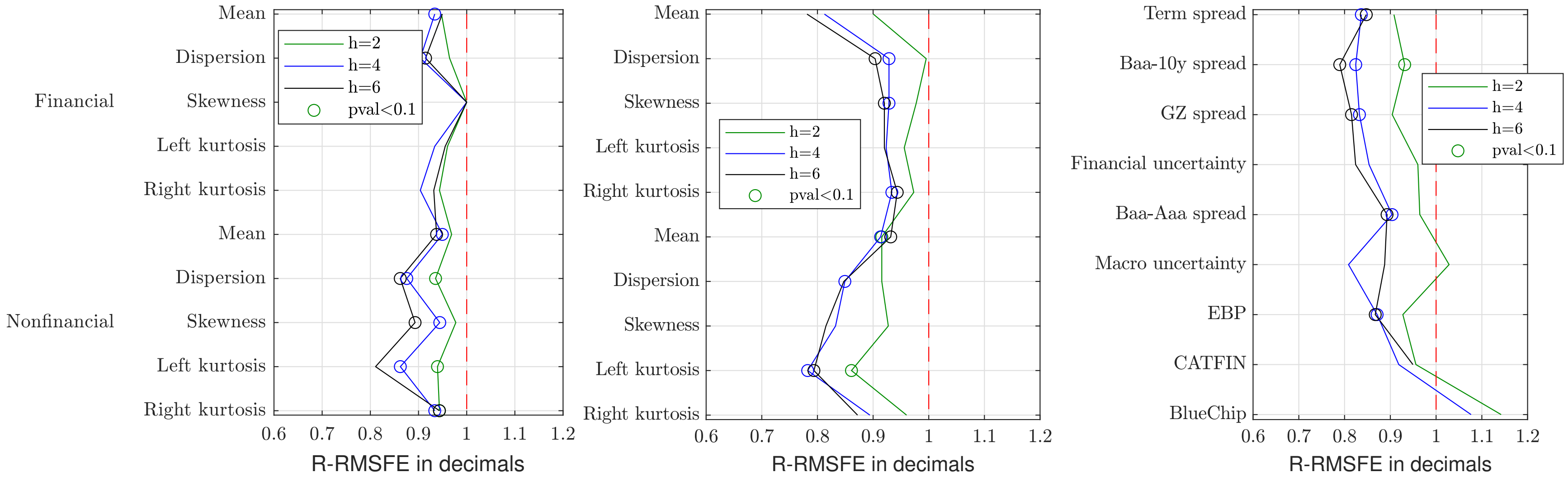


Note: Figure C.4 reports the ratio between the root mean squared forecast error (RMSFE) of regressions (6) using SRF relative to RMSFEs from similar regressions using competing variables. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. All skewness (including the benchmark SRF) and kurtosis measures are normalized in a "Kelly" sense. Blue Chip forecasts are used directly without any regressions. I consider three different horizons (h) for GDP growth: 2, 4, and 6 quarters ahead. Statistical significance is relative to the null hypothesis that the predictor variable and SRF have equal predictive power. Circles represent significance levels of at least 10 percent. The sample is 1973–2020.

Figure C.5

Performance of Out-of-Sample GDP Forecasts, Idiosyncratic Stock Returns

(A) Stock Return Cross-Sectional Moments (B) Credit Spread Cross-Sectional Moments (C) Other variables: Full Sample



Note: For Figure C.5, all cross-sectional moments of the distribution of stock market returns are calculated using the residuals from regressions of individual stock returns on market-wide returns. The figure reports the ratio between the root mean squared forecast error (RMSFE) of regressions (6) using SRF relative to RMSFEs from similar regressions using competing variables as originally defined in Sections 2 and 3. I denote this ratio as relative root mean squared forecast error (R-RMSFE) and report it in decimals. Blue Chip forecasts are used directly without any regressions. I consider three different horizons (h) for GDP growth: 2, 4, and 6 quarters ahead. Statistical significance is relative to the null hypothesis that the predictor variable and SRF have equal predictive power. Circles represent significance levels of at least 10 percent. The sample is 1973–2020.

Table C.10

In-Sample Loan Forecast Regressions, 6 quarters ahead

(a) Stock Returns: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	0.80***	-0.91	1.01***	0.30	-0.75	0.03
Uncertainty	-0.27	-0.12	-0.24	-0.36	-0.18	-0.36
Real Fed Funds	0.03	0.25	0.05	0.07	0.12	0.06
Term Spread	0.23	0.42	0.26	0.28	0.28	0.30
EBP	-2.18***	-2.04***	-1.97***	-2.21***	-2.06***	-2.27***
R^2	0.68	0.67	0.69	0.67	0.67	0.67

(b) Credit Spreads: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	-0.33	0.08	0.09	-1.06	-0.79	-0.86*
Uncertainty	-0.26	-0.37	-0.37	-0.17	-0.28	-0.31
Real Fed Funds	-0.02	0.09	0.09	-0.29	-0.14	-0.10
Term Spread	0.28	0.29	0.29	0.19	0.24	0.25
EBP	-2.14***	-2.32***	-2.31***	-1.59***	-1.81***	-1.82***
R^2	0.67	0.67	0.67	0.68	0.68	0.68

Note: Table C.10 reports the results from regression (5) on average loan growth 6 quarters ahead ($h = 6$), with p equals 4 because of the relatively low AIC of this specification. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess bond premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Coefficients of lagged loan growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that the coefficient associated to a regressor equals to zero, where $*$, $**$ and $***$ denote significance levels of 0.1, 0.05, and 0.01, respectively. The sample is 1973–2020.

Table C.11

In-Sample Debt Forecast Regressions, 6 quarters ahead

(a) Stock Returns: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	0.42	1.32**	-0.14	-0.16	-1.09**	-0.04
Uncertainty	0.51	0.12	0.46	0.48	0.72**	0.48
Real Fed Funds	1.00***	0.81**	1.01***	1.00**	1.07***	1.01***
Term Spread	0.58	0.39	0.62	0.63	0.72*	0.62
EBP	-0.87***	-1.29***	-0.97***	-0.96***	-0.58	-0.95***
R^2	0.47	0.49	0.47	0.47	0.50	0.47

(b) Credit Spreads: One Cross-Sectional Moment per Regression

	Financial Firms			Nonfinancial Firms		
Variable =	Mean	Dispersion	Skewness	Mean	Dispersion	Skewness
Variable	0.96**	0.87***	0.64**	-1.26**	-1.53***	-1.37***
Uncertainty	0.17	0.25	0.34	0.69**	0.60*	0.53
Real Fed Funds	1.29***	1.34***	1.24***	0.68	0.66*	0.77*
Term Spread	0.63	0.55	0.55	0.63	0.78*	0.80*
EBP	-1.39***	-1.20***	-1.09***	-0.04	0.08	-0.12
R^2	0.50	0.50	0.49	0.50	0.54	0.54

Note: Table C.11 reports the results from regression (5) on average debt growth 6 quarters ahead ($h = 6$), with p equals 4 because of the relatively low AIC of this specification. Uncertainty (Ludvigson et al., 2015) measures aggregate uncertainty in financial markets. Excess bond premium or EBP (Gilchrist and Zakrajšek, 2012) measures investor sentiment in the corporate bond market. Real fed funds is measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures. Term spread is the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Coefficients of lagged debt growth are omitted. Standard errors are calculated according to Hodrick (1992). Statistical significance tests the null hypothesis that the coefficient associated to a regressor equals to zero, where $*$, $**$ and $***$ denote significance levels of 0.1, 0.05, and 0.01, respectively. The sample is 1973–2020.

Table C.12
Economic Drivers of Skewness of Returns of Financial Firms (SRF)

(a) Subsample 1990–2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ICRF	0.45***								0.43***	0.28***
ROA		0.39***							0.36***	0.43***
LS-SF			-0.53***							-0.49
LS-LMF				-0.53***						0.20
$\widehat{\text{GDP}}_{t\mid t-1}$					0.06					-0.27*
$\widehat{\text{GDP}}_{t+4\mid t-1}$						0.04				0.25*
EPU							-0.25**			0.38*
EPU-MP								-0.35***		-0.56**
R^2	0.20	0.13	0.27	0.27	0.03	0.01	0.06	0.13	0.31	0.49

(b) Subsample 2008–2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ICRF	0.38**								0.51***	0.55***
ROA		0.43***							0.53***	0.31**
LS-SF			-0.68***							-0.80
LS-LMF				-0.58**						0.08
$\widehat{\text{GDP}}_{t\mid t-1}$					0.10*					0.01
$\widehat{\text{GDP}}_{t+4\mid t-1}$						0.07				-0.08
EPU							-0.28*			-0.10
EPU-MP								-0.26*		-0.03
R^2	0.12	0.19	0.17	0.13	0.08	0.04	0.08	0.07	0.41	0.50

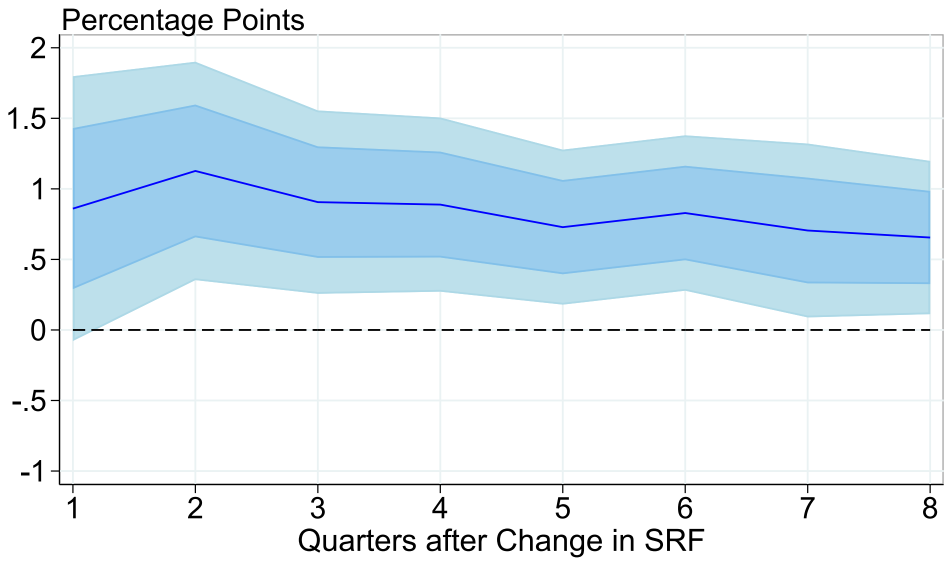
(c) Variables Orthogonal to the Business Cycle, 1990-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ICRF	0.51***								0.45***	0.35***
ROA		0.42***							0.33***	0.30***
LS-SF			-0.27***							-0.06
LS-LMF				-0.20**						0.06
$\widehat{\text{GDP}}_{t\mid t-1}$					0.31***					-0.17
$\widehat{\text{GDP}}_{t+4\mid t-1}$						0.43***				0.28
EPU							-0.31***			-0.14
EPU-MP								-0.24***		0.09
R^2	0.27	0.18	0.08	0.04	0.09	0.18	0.09	0.06	0.37	0.41

Note: Table C.12 shows the results from univariate regressions of several variables on SRF. I standardize both the regressors and SRF, and thus omit the constant from the regressions. Variables are named as follows: the intermediary capital risk factor (ICRF) from He et al. (2017); return on average assets for banks (ROA); changes in banks' lending standards for small (LS-SF), and medium and large firms (LS-LMF); Blue Chip's now-casting ($\widehat{\text{GDP}}_{t\mid t-1}$) and four-quarter-ahead forecast of GDP growth ($\text{GDP}_{t+4\mid t-1}$); economic policy uncertainty (EPU) from Baker et al. (2016) and its sub-index focused monetary policy (EPU-MP). 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, respectively. Table C.12a restricts the sample period to 1990q1–2007q4. Table C.12b restricts the sample period to 2008q1–2019q4. Table C.12c uses the full sample 1990q1–2019q4 and blunts the influence of business cycles on the variables SRF, ROA, LS-LF, LS-LMF, EPU, and EPU-MP by using the residuals of autoregressive processes of 4th order of these variables.

Figure C.6

Elasticity of Firm-Level Investment to SRF, 1973-2007



Note. Figure C.6 shows the elasticity of firm-level investment to SRF (solid blue line) calculated in regression (7). Shaded areas report the 68% and 90% error bands. Controls $\mathbf{F}_t$ of the regression are the following: financial uncertainty (Ludvigson et al., 2015) measuring aggregate uncertainty in financial markets; excess bond premium (Gilchrist and Zakrajšek, 2012) measuring investor sentiment in the corporate bond market; real fed funds measured by the fed funds rate minus the 4-quarter change of core inflation from the personal consumption expenditures; and term spread as the 10-year Treasury constant maturity rate minus the three-month Treasury bill rate. Firm-level controls $\mathbf{Z}_{it}$ of the regression are the following: leverage, measured as the firm's debt-to-asset ratio; distance to default, following the calculation from Gilchrist and Zakrajšek (2012); average credit spread across the firm's bonds; inflation-adjusted sales growth; and the ratio of short-term assets to total assets. Appendix A.5 describes these firm-level variables. The regression also includes firm and credit-rating fixed effects, with OLS estimation and standard errors double clustered in the firm and time dimensions (Cameron et al., 2011). The sample is 1973–2007.