FINANCIAL MARKET RISK PERCEPTIONS AND THE MACROECONOMY

Carolin Pflueger
Emil Siriwardane
Adi Sunderam

Financial Market Risk Perceptions and the Macroeconomy
Carolin Pflueger, Emil Siriwardane, and Adi Sunderam
NBER Working Paper No. 26290
September 2019
JEL No. E03,E22,E44,G12

ABSTRACT

We propose a novel measure of risk perceptions: the price of volatile stocks (PVS_t), defined as the book-to-market ratio of low-volatility stocks minus the book-to-market ratio of high-volatility stocks. PVS_t is high when perceived risk directly measured from surveys and option prices is low. When perceived risk is high according to our measure, safe asset prices are high, risky asset prices are low, the cost of capital for risky firms is high, and real investment is forecast to decline. Perceived risk as measured by PVS_t falls after positive macroeconomic news. These declines are predictably followed by upward revisions in investor risk perceptions. Our results suggest that risk perceptions embedded in stock prices are an important driver of the business cycle and are not fully rational.

Carolin Pflueger
University of Chicago
Harris School of Public Policy
1307 E 60th St
Chicago, IL 60637
and NBER
cpflueger@uchicago.edu

Adi Sunderam
Harvard Business School
Baker Library 359
Soldiers Field
Boston, MA 02163
and NBER
asunderam@hbs.edu

Emil Siriwardane
Harvard Business School
Baker LIbrary 261
Boston, MA 02163
esiriwardane@hbs.edu

An internet appendix is available at http://www.nber.org/data-appendix/w26290

1 Introduction

Classic accounts of economic boom and bust cycles (Keynes (1937); Minsky (1977); Kindleberger (1978)) highlight the importance of financial markets in shaping economic fluctuations. In these accounts, a negative fundamental shock causes perceptions of risk to rise. Investors then value the safety of bonds and charge risky firms a high cost of capital. Consequently, real interest rates are low, firms invest less, and a recession ensues. This risk-centric view of business cycles has been formalized in recent theoretical work (Caballero and Farhi (2018); Caballero and Simsek (2018); Cochrane (2017)), but it has proven difficult to establish empirically because common proxies for financial market conditions are only weakly correlated with bond markets and the real economy.[1]

In this paper, we propose a new measure of risk perceptions based on financial market prices and use it to assess how well risk-centric theories of the business cycle fit the U.S. experience since 1970. We use financial market prices because they capture firms' cost of capital, a key channel through which perceptions of risk impact real outcomes in these theories. Our measure is based on the intuition that the stock prices of the riskiest, most volatile firms should be particularly sensitive to investor perceptions of risk. Thus, we measure perceived risk in the cross section of publicly-traded equities using the price of volatile stocks (PVS_t). Specifically, we define PVS_t as the average book-to-market ratio of low-volatility stocks minus the average book-to-market ratio of high-volatility stocks, so that PVS_t is high when volatile stocks have relatively high prices.

We structure our empirical analysis around a stylized model that highlights the central economic forces in risk-centric theories of the business cycle. The model provides a roadmap for our empirical work by linking perceptions of risk, the price of volatile stocks, the real interest rate, and real investment. In the model, risk aversion is constant, while expectations of risk vary over time. We initially assume that investors have rational expectations so that subjective and objective expected risk are equal. When they perceive risk to be high, investors value the safety of bonds because of precautionary savings motives. At the same time, investors require a high return to invest in the riskiest firms in the economy. Thus, the cost of capital for these firms is high and the model analog of PVS_t is low. As in the standard Q-theory of investment, firms invest less when

---

[1]As we discuss further below, a recent literature, including the seminal work of Bloom (2009) and Bloom et al. (2018), has shown that uncertainty impacts the macroeconomy because it causes firms to delay investment and hiring decisions. This mechanism is complementary to the cost-of-capital channel that we highlight.

their cost of capital is high. The model therefore predicts that when perceived risk is high, PVS_t, real interest rates, and real investment should be low.

We begin our empirical analysis by confirming that PVS_t is indeed tied to investor perceptions of risk. We show that PVS_t is negatively correlated with direct measures of perceived risk based on option prices and equity analyst forecasts. We obtain similar results using surveys of loan officers and businesses, as well as the newspaper-based measure of Baker et al. (2016). PVS_t is low when banks report that they are tightening lending standards because they believe economic risk is rising and when small businesses report that they are pessimistic about the economy. We show that PVS_t also comoves with objective expected risk from statistical forecasting models, but the comovement is weaker than with measures of subjective risk perceptions.

Using PVS_t, we then explore whether the economic linkages highlighted by the model appear in the data, starting with the relationship between risky asset prices and real interest rates. In U.S. quarterly data from 1970 to 2016, the contemporaneous correlation between PVS_t and the one-year real interest rate is 64%, capturing the negative relationship between safe and risky asset prices in risk-centric theories of the business cycle. A one-standard deviation increase in PVS_t is associated with a 1.3 percentage point increase in the real rate. The positive correlation between PVS_t and the real rate holds in expansions and recessions, in high- and low-inflation environments, and controlling for measures of credit and equity market sentiment (Greenwood and Hanson (2013); Baker and Wurgler (2006)). We also rule out discretionary monetary policy as an omitted variable driving both PVS_t and the real rate. Specifically, we show that monetary policy surprises do not differentially affect the prices of high- and low-volatility stocks in narrow windows around the Federal Reserve's policy announcements.

Consistent with the core mechanism in risk-centric theories of business cycles, we find that both PVS_t and the real rate are low when volatile firms' cost of capital is high. In other words, investors require a high return on capital for investing in volatile firms when PVS_t and the real rate are low. Empirically, this means that low values of PVS_t and the real rate forecast high future returns on high-volatility stocks relative to low-volatility stocks. Neither PVS_t nor the real rate forecast differences in cash flows between high- and low-volatility stocks, further confirming that PVS_t captures perceptions of risk, not growth. Moreover, PVS_t forecasts returns on volatile securities in other asset classes, including U.S. corporate bonds, sovereign bonds, options, and credit default

swaps. The fact that PVS_t – and its correlation with the real rate – reflect common variation in the compensation investors demand for holding volatile securities within several asset classes is consistent with the idea that it captures risk perceptions that are relevant to the macroeconomy.

Next, we analyze the relationship between perceptions of risk and the real economy. We show that low perceived risk as measured by PVS_t forecasts expansions in real investment, output, and employment. A one-standard deviation increase in PVS_t is associated with an increase in the investment-capital ratio of 0.4% over the next four quarters. Over the same horizon, output rises 0.7% relative to potential and the unemployment rate decreases by 0.3%. Investment and employment are over twice as sensitive to PVS_t as to the aggregate stock market, illustrating the importance of our focus on the cross section of stocks in measuring financial market risk perceptions. Overall, our analysis suggests that risk-centric theories of the business cycle capture important linkages between stock markets, bond markets, and the real economy.

After establishing the link between financial market risk perceptions and the macroeconomy, we use our measure to investigate why perceptions of risk vary. Using our measure, we find that risk perceptions decline on the heels of good news about the economy. We show that PVS_t rises when GDP and corporate profit growth exceed the expectations of professional forecasters, indicating that positive surprises lead investors to view the economy as less risky. We also confirm that direct measures of perceived and realized risk fall when there is positive economic news. Thus, perceptions of risk appear to be shaped by recent events.

In the last part of the paper, we ask whether risk perceptions are rational, as assumed in our motivating model, or whether they over-extrapolate from recent news. Under rational expectations, revisions in expected risk should be unpredictable because expectations should only change in response to new information. By contrast, we find that high values of PVS_t, which indicate low perceived risk, reliably predict that investors will revise their expectations of risk upwards over the next two to three quarters. Put options provide further evidence that perceptions of risk are not fully rational. If investors are rational, then riskier strategies should always have higher expected returns. Instead, we show that there are several periods where high values of PVS_t forecast negative returns to selling put options on high-volatility stocks relative to low-volatility stocks.

Collectively, these results suggest that perceptions of risk embedded in financial markets are not fully rational, a possibility raised in the classical accounts of Keynes (1937), Minsky (1977), and

Kindleberger (1978). We illustrate one way to adjust the model to account for these findings, replacing rational expectations with diagnostic beliefs as in Bordalo et al. (2018). This modification implies that investors over-extrapolate from recent news, which amplifies the baseline relationships between PVS_t, real interest rates, and investment in the model. It also allows the model to generate the pattern of overreaction and subsequent reversal in subjective expectations of risk that we observe in the data.

Our paper is related to several literatures in both macroeconomics and finance. Broadly speaking, theories of the business cycle have traditionally focused on either aggregate supply (Cooley and Prescott 1995) or aggregate demand (Keynes 1937). Our paper belongs to a recent literature arguing that perceptions of risk can influence aggregate demand through two complementary channels. First, as shown in the seminal work of Bloom (2009) and Bloom et al. (2018), heightened uncertainty increases the option value of delay, leading firms to temporarily pause investment and hiring. Second, when perceived risk is high, the cost of capital for risky investments is high, so firms invest less. Our paper offers empirical support for this cost of capital channel, which has been the subject of much recent theoretical work.[2] We document that perceptions of risk embedded in the stock market connect more broadly with the bond market and the business cycle, and that these risk perceptions appear not to be fully rational.

Our paper is also related to a large body of work in finance seeking to link movements in asset prices to the business cycle. This literature has generally provided limited support for theories of risk-centric business cycles because canonical models imply that risk perceptions (and risk preferences) can be inferred from the aggregate stock market (Campbell and Cochrane (1999); Bansal and Yaron (2004)). It is well known that, unlike PVS_t, the aggregate stock market is only weakly correlated with the real rate and real investment (Campbell and Ammer (1993); Caballero (1999)).[3] The difference in behavior between the aggregate stock market and PVS_t arises because PVS_t emphasizes volatile firms, while the aggregate market is dominated by larger, low-volatility

---

[2]See, e.g., Gourio (2012), Fernández-Villaverde et al. (2015), Basu and Bundick (2017), Caballero and Farhi (2018), and Caballero and Simsek (2018) for theoretical work on the cost of capital channel. To the extent that existing work studies the link between risk and real interest rates, it has typically focused on the secular decline in global real interest rates since the 1980s. See Laubach and Williams (2003); Cúrdia et al. (2015); Del Negro et al. (2017); Kozlowski et al. (2018a,b), among others. By contrast, we find that risk perceptions are important for understanding how real rates evolve over the business-cycle.

[3]Cochrane (1991) shows that aggregate stock returns are contemporaneously correlated with changes in investment, but similar to us he finds that removing the long-term trend in aggregate stock market valuations is important.

firms. Volatile public firms are a small part of the aggregate market, but we show that they are similar in their investment behavior to private firms, which play a large role in the overall economy (Davis et al. (2007); Asker et al. (2014); Zwick and Mahon (2017)). Thus, PVS_t likely captures perceptions of risk that are relevant for a significant part of the U.S. economy.

The disconnect between the aggregate stock market and the real economy also motivates our use of total volatility to measure risk in forming PVS_t. Volatility is a robust measure of risk that does not rely on the assumption that the aggregate stock market fully captures all economic activity – volatility increases with exposure to risks, regardless of what they are.[4] Our use of market prices in constructing PVS_t is complementary to approaches measuring risk perceptions using statistical models of macroeconomic or financial volatility and to the newspaper-based approach of Baker et al. (2016). Market prices reflect how investors' forward-looking subjective expectations affect firms' cost of capital, a key channel in risk-centric theories of the business cycle. They are also readily available over long sample periods and in real time.

Finally, our analysis of risk perceptions connects to work in behavioral finance studying how investor sentiment and biased beliefs impact asset prices (e.g., De Long et al. (1990); Barberis and Thaler (2003); Baker and Wurgler (2007); Gennaioli et al. (2015)). While this literature has focused mainly on beliefs about the level of future cash flows, our results suggest that investor sentiment may also be driven by beliefs about risk. We show that PVS_t is correlated with measures of sentiment for both debt and equity markets, suggesting that variation in perceived risk induces common movements in sentiment across markets. The link between PVS_t and credit markets also implies that recent work connecting credit market sentiment to economic outcomes may in part capture movements in risk perceptions that are common across markets.[5]

The remainder of this paper is organized as follows. Section 2 presents the motivating model, describes the data, and shows that PVS_t correlates with direct measures of investor risk perceptions. Section 3 provides an empirical assessment of risk-centric theories of the business cycle using PVS_t

---

[4]Our results are distinct from past research on idiosyncratic risk in the stock market, which has focused on the average return of high-volatility stocks (see Ang et al. (2006), among many others) or the average return on stocks that are more exposed to the common factor driving idiosyncratic volatility (Herskovic et al. (2016). In contrast, we measure time-series variation in expected returns of high-volatility firms and link it to interest rates and macroeconomic fluctuations. In this sense, our results also complement past research on the relationship between risk premia in stocks and bonds (Fama and French (1993); Lettau and Wachter (2011); Koijen et al. (2017)).

[5]For instance, Gilchrist and Zakrajšek (2012); López-Salido, Stein, and Zakrajšek (2017); Bordalo, Gennaioli, and Shleifer (2018); Mian, Sufi, and Verner (2017).

to measure perceived risk. In Section 4, we investigate why perceptions of risk vary and whether these movements are fully rational. Section 5 discusses our results and concludes.

2 Motivating Framework and Construction of PVS_t

2.1 Motivating Framework

We begin with a simple model to organize our empirical analysis and formalize the key elements of risk-centric theories of the business cycle. The model focuses on equilibrium relationships between perceived risk, the price of volatile stocks, the real interest rate, and investment. The real rate and firm stock prices are determined by investors who face time-varying risk. We start by assuming that investors' perceptions of risk are rational, though we relax this assumption in Section 5.1. We model production as in the standard the Q-theory of investment, meaning that firms invest up to the point where the expected return on a marginal unit of investment equals the return required by investors (Tobin (1969), Hayashi (1982)). Consequently, investment fluctuates in response to movements in asset prices. Though our setup is stylized, the economic forces that we highlight are common across models of risk-centric business cycles (e.g., Gourio (2012), Jermann (1998), Kogan and Papanikolaou (2012), Fernández-Villaverde et al. (2015), Caballero and Simsek (2018)). All proofs can be found in the internet appendix.

2.1.1 Preferences

We assume a representative agent with constant relative risk aversion λ over aggregate consumption and time-discount rate β:

$$U(C_t, C_{t+1}, \ldots) \equiv \sum_{s=0}^{\infty} \beta^s \frac{C_{t+s}^{1-\lambda}}{1-\lambda}. \tag{1}$$

The stochastic discount factor that determines asset prices is therefore:

$$M_{t+1} = \frac{\partial U / \partial C_{t+1}}{\partial U / \partial C_t} = \beta \frac{C_{t+1}^{-\lambda}}{C_t^{-\lambda}}. \tag{2}$$

We model log aggregate consumption growth Δc_{t+1} as a simple heteroskedastic process: $\Delta c_{t+1} =$

6

ε_{t+1}, where ε_{t+1} is normal, mean zero, serially uncorrelated, and heteroskedastic with conditional variance given by:

$$\mathbb{V}_t(\varepsilon_{t+1}) = \exp(a - b\varepsilon_t), \tag{3}$$

where $b > 0$. This assumption generates time variation in expected excess returns – and firms' cost of capital – from exogenous changes in risk, as in Kandel and Stambaugh (1990), Bansal et al. (2012), and much of the literature on risk-centric recessions. Following a negative shock, volatility increases and future consumption becomes riskier, consistent with the evidence that risk rises in recessions (Bloom (2014), Nakamura et al. (2017), and Basu and Bundick (2017)). The exponential functional form for $\mathbb{V}_t(\varepsilon_{t+1})$ ensures that it is positive.

2.1.2 Production

The production side of the model is a simplified version of the Q-theory framework described in Campbell (2017) Chapter 7. Specifically, firms generate output according to a Cobb-Douglas production function. We assume that capital is the only input for production: $Y_{it} = Z_{it}K_{it}$.[6] K_{it} is firm i's capital in period t. Z_{it} is firm i's total factor productivity and we assume that it is driven by the same heteroskedastic shock as consumption:[7]

$$Z_{it+1} = \exp\left(s_i\varepsilon_{t+1} - \frac{1}{2}s_i^2\mathbb{V}_t(\varepsilon_{t+1})\right). \tag{4}$$

Higher s_i means that firm i is riskier in the sense that its production is more volatile. The Jensen's inequality term $-\frac{1}{2}s_i^2\mathbb{V}_t(\varepsilon_{t+1})$ ensures that expected total factor productivity is equalized across firms, so the model isolates differences in risk across firms. To incorporate differences in firm risk as simply as possible, we consider the case where there are two types of firms, H and L. We set $s_H > s_L$, so H-firms are riskier than L-firms. We assume that $s_i > \frac{\lambda}{2}$ for all firms, which ensures

---

[6]This simplification does not impact the model's main qualitative predictions and allows us to focus on how perceptions of risk impact the cost of firm capital. It is well-documented that different assumptions about the capital share affect the level of returns, but not their variability or correlation with other variables, which is our focus (e.g, Cochrane (1991), Liu et al. (2009)).

[7]As in many production-based models with heterogeneous firms (e.g., Zhang (2005)), we take a partial equilibrium approach and do not derive consumption from production and investment decisions.

that an increase in perceived risk raises the cost of capital for all firms.[8]

Capital evolves according to $K_{it+1} = I_{it} + (1 - \delta)K_{it}$, where δ is the depreciation rate. We make the standard assumption that this adjustment is costly and rises with the ratio of investment to already-installed capital: $\Phi_{it} = \phi\left(\frac{I_{it}}{K_{it}}\right)K_{it}$, where $\phi' > 0$ when $I_{it} > 0$ and $\phi'' \geq 0$ everywhere. This assumption captures the idea that firms suffer production losses while new capital is being installed and that these losses increase with the rate of new investment.

We abstract away from capital structure and corporate financing decisions by assuming that firms are completely financed with equity and that there are no taxes. Thus, firm dividends are given by $D_{it} = Y_{it} - \Phi_{it}$. For simplicity, we allow capital to depreciate fully each period ($\delta = 1$), so capital available for production in period $t + 1$ equals period t investment. We also assume that after one period of production firms die and a new generation of firms is born.[9] With these assumptions, the time t and time $t + 1$ dividends for a firm born at t take a particularly simple form:

$$D_{it} = -\Phi_{it}, \quad D_{it+1} = Z_{it+1}K_{it+1}. \tag{5}$$

Firm i takes the stochastic discount factor M_{t+1} as exogenous and maximizes the risk-adjusted present value of current and future dividends:

$$V_{it} = \max_{I_{it}} \{D_{it} + \mathbb{E}_t[M_{t+1}D_{it+1}]\}. \tag{6}$$

2.1.3 Asset Prices

We link firm investment to financial markets using Cochrane (1991, 1996)'s insight that the market return on a financial claim to the firm, R_{it+1}, must equal the return on firm investment. The return on firm investment is defined as the marginal benefit of an additional unit of investment divided by its marginal cost: $R_{it+1} = Z_{it+1}/\phi'\left(\frac{I_{it}}{K_{it}}\right)$. The optimization problem (6) means that firm i's investment return satisfies the asset pricing Euler equation $1 = \mathbb{E}_t[M_{t+1}R_{it+1}]$, which in turn implies that

---

[8]Assuming that s_L and s_H are constant is a simplification to enhance tractability. Allowing s_L and s_H to vary over time would not change our qualitative predictions.

[9]These assumptions are made for tractability and shut off the dynamic response of investment to risk perceptions. The model nonetheless captures the basic channel that investment rises when asset prices are high and the cost of capital is low. As we show in Section 3.3, the dynamic empirical response of investment to changes in PVS_t is hump-shaped. A quantitative account of our empirical results would therefore need to go beyond modeling the sign of the investment response, as we do, and model investment dynamics.

the log expected return in excess of the log risk-free rate r_{ft} equals:

$$\ln \mathbb{E}_t\left[R_{it+1}\right] - r_{ft} \quad = \quad s_i \times \lambda \times \mathbb{V}_t\left(\varepsilon_{t+1}\right). \tag{7}$$

Eq. (7) says that risky firms' expected returns (i.e., cost of capital) should move more with perceived risk $\mathbb{V}_t\left(\varepsilon_{t+1}\right)$ than safe firms' – this simple observation is why we infer perceived risk using the cross section of firms. Because expected returns are not observable in the data at time t, our empirical measure of perceived risk uses firms' market-to-book ratios. In the model, there is a one-to-one relation between a firm's market-to-book ratio and its expected equity return:[10]

$$\frac{V_{it} - D_{it}}{K_{it+1}} \quad = \quad \frac{1}{\mathbb{E}_t[R_{it+1}]} \quad . \tag{8}$$

The left-hand-side of Eq. (8) is Tobin's Q: the ratio of firm i's ex-dividend valuation to its capital. In our empirical work, we will use the price of volatile stocks – the difference between the book-to-market ratios of low- and high-risk stocks – as our measure of perceived risk. In the model, we use log book-to-market ratios for tractability and define the model analogue of PVS_t as:

$$PVS_t^{model} \quad = \quad \ln\left(\frac{K_{Lt+1}}{V_{Lt} - D_{Lt}}\right) - \ln\left(\frac{K_{Ht+1}}{V_{Ht} - D_{Ht}}\right). \tag{9}$$

Eqs. (7) and (8) imply that the price of volatile stocks is directly proportional to perceived risk:

$$PVS_t^{model} \quad = \quad \ln \mathbb{E}_t[R_{L,t+1}] - \ln \mathbb{E}_t[R_{H,t+1}] = -\left(s_H - s_L\right)\lambda \mathbb{V}_t\left(\varepsilon_{t+1}\right). \tag{10}$$

2.1.4   Risk-Free Rate

The Euler equation for the log real risk-free rate r_{ft} gives:

$$r_{ft} \quad = \quad -\ln\beta - \frac{\lambda^2}{2}\mathbb{V}_t\left(\varepsilon_{t+1}\right). \tag{11}$$

---

[10]In reality, market-to-book ratios reflect both expected growth and expected returns. Thus, compared to using an aggregate valuation ratio, an added advantage of using the cross-section of valuation ratios is that growth factors that simultaneously move all stock valuations will be differenced out (e.g., Fama and French (1992), Polk et al. (2006), Cochrane (2011)). We confirm in Section 3.2 that PVS_t in the data is mostly driven by variation in expected returns, not expected growth.

9

The last term of Eq. (11) captures the precautionary savings motive, $-\frac{\lambda^2}{2} \times \mathbb{V}_t(\varepsilon_{t+1})$, which varies with perceived risk. Eqs. (10) and (11) generate a key prediction of risk-centric theories of the business cycle: when perceived risk is high, the price of risky assets is low, the precautionary savings motive is strong, and the real risk-free rate is low. This implies that in the data we expect both the real risk-free rate and PVS_t^{model} to decrease with perceived risk.

2.1.5 Real Investment

Real investment is determined by Eq. (7) – each firm invests up to the point where the expected return on a marginal unit of investment equals the return required by investors to compensate for the risk of the investment. Our results up to this point have not relied on a specific functional form for the adjustment cost function ϕ. To derive investment in closed form, we assume that adjustment costs are quadratic as is common in the literature (e.g., Liu et al. (2009)):

$$\phi\left(\frac{I_{it}}{K_{it}}\right) = \frac{I_{it}}{K_{it}} + \frac{1}{2}\left(\frac{I_{it}}{K_{it}}\right)^2. \tag{12}$$

We define the log investment-to-capital ratio of firm i as $inv_{it} = \ln\left(1 + \frac{I_{it}}{K_{it}}\right)$. Firm i's equilibrium investment-to-capital ratio then equals:

$$inv_{it} = \ln\beta - \left(s_i - \frac{\lambda}{2}\right) \times \lambda \times \mathbb{V}_t(\varepsilon_{t+1}). \tag{13}$$

Eq. (13) shows that investment decreases with perceived risk $\mathbb{V}_t(\varepsilon_{t+1})$ provided that the firm is risky ($s_i > \frac{\lambda}{2}$). The relationship is stronger for riskier firms. Intuitively, the cost of capital of risky firms is more sensitive to fluctuations in perceived risk, so their investment responses are stronger.

2.1.6 Equilibrium Summary

The following proposition summarizes the equilibrium.

Proposition 1: There is a unique equilibrium in which the real risk-free rate satisfies (11), expected returns on firm i satisfy (7), and firm i's investment is given by (13).

We next consider how the economy reacts following a positive macroeconomic shock by computing comparative statics with respect to log consumption growth ε_t. We work in the neighborhood of $\varepsilon_t = 0$ to simplify the expressions so they do not depend on ε_t.

Proposition 2: Suppose we have two types of firms H and L with $s_H > s_L > \frac{\lambda}{2}$. In the neighborhood of $\varepsilon_t = 0$, following a positive shock:

a) Perceptions of risk fall: $\frac{d\mathbb{V}_t(\varepsilon_{t+1})}{d\varepsilon_t} = -\exp(a)b < 0$.

b) PVS_t^{model} rises: $\frac{dPVS_t^{model}}{d\varepsilon_t} = \lambda (s_H - s_L) \exp(a)b > 0$

c) Expected returns of high-volatility firms fall relative to low-volatility firms:
$$\frac{d(\ln \mathbb{E}_t[R_{Ht+1}] - \ln \mathbb{E}_t[R_{Lt+1}])}{d\varepsilon_t} = -\lambda (s_H - s_L) \exp(a)b < 0.$$

d) The risk-free rate increases : $\frac{dr_{ft}}{d\varepsilon_t} = \frac{1}{2}\lambda^2 \exp(a)b > 0$.

e) Aggregate investment increases: $\frac{d\left(\frac{1}{2}(inv_{Ht} + inv_{Lt})\right)}{d\varepsilon_t} = \left(\frac{s_H + s_L}{2} - \lambda\right) \times \lambda \times \exp(a)b > 0$.

f) The investment of volatile firms rises more: $\frac{d(inv_{Ht} - inv_{Lt})}{d\varepsilon_t} = \lambda (s_H - s_L) \exp(a)b > 0$.

2.2 Risk-Centric Business Cycles: Empirical Implications

The comparative statics in Proposition 2 flesh out the main components of risk-centric theories of the business cycle. Following a positive fundamental shock, investor perceptions of risk fall (Proposition 2a). Thus, PVS_t^{model} rises because perceived risk disproportionately affects the valuations of risky firms (Proposition 2b). High valuations mean that the cost of capital is low for risky firms going forward (Proposition 2c). At the same time, the risk-free rate rises because precautionary savings motives decline (Proposition 2d). Aggregate investment increases through a standard Q-theory channel, and the effect is strongest for the riskiest firms because their valuations are most affected by perceived risk (Propositions 2e and 2f).

The model predicts that a number of equilibrium relationships should be present in the data:

1. PVS_t should be low when investor risk perceptions are high.

2. The real risk-free rate and PVS_t should be positively correlated.

3. Low values of PVS_t and the real rate should both forecast high returns on high-volatility stocks relative to low-volatility stocks.

4. High values of PVS_t should be accompanied by an expansion in aggregate investment.

11

5. PVS_t should rise and investor risk perceptions should fall following good news about fundamentals. If investors' risk perceptions are rational, subsequent revisions in expected risk should not be forecastable.

In the model, we hold risk aversion constant and assume that only perceptions of risk vary over time. While our empirical analysis supports the assumed link between PVS_t and perceived risk, in the data we cannot rule out that some changes in PVS_t reflect changes in risk aversion. It is clear from Proposition 2 that changes in risk aversion would have similar macroeconomic implications to changes in perceived risk. It is therefore important to verify in the data the model's prediction that PVS_t moves with direct measures of perceived risk, as we do in Section 2.4.

2.3   Construction of Key Variables and Summary Statistics

Having spelled out the central elements of risk-centric theories of the business cycle, we now explore whether these economic linkages appear in the data. We start by summarizing the construction of our key variables. Details regarding our data construction are provided in the internet appendix. Unless otherwise noted, our sample runs from 1970q2, when survey data on inflation expectations begins, to 2016q2.

Valuation Ratios   The valuation ratios used in the paper derive from the CRSP-Compustat merged database and include all U.S. common equities that are traded on the NYSE, AMEX, or NASDAQ. At the end of each quarter and for each individual stock, we form book-to-market ratios. Book equity comes from CRSP-Compustat Quarterly and is defined following Fama and French (1993). If book equity is not available in CRSP-Compustat Quarterly, we look for it in the annual file and then the book value data of Davis, Fama, and French (2000), in that order. We assume that accounting information for each firm is known with a one-quarter lag. At the end of each quarter, we use the trailing six-month average of market capitalization when computing the book-to-market ratio of a given firm. The six-month average is chosen to match the lag of the accounting data. In the internet appendix, we explore many variants on this procedure and always obtain similar results.

Volatility-Sorted Portfolio Construction   At the end of each quarter, we use daily CRSP data from the previous two months to compute equity volatility, excluding firms that do not have at least

20 observations over this time frame. We choose a two-month horizon to measure return volatility to make the returns on the portfolios that comprise PVS_t directly comparable to the volatility-sorted portfolios on Ken French's website. We compute each firm's volatility using ex-dividend returns.

At the end of each quarter, we sort firms into quintiles based on their volatility. The valuation ratio for a quintile is the equal-weighted average of the valuation ratios of stocks in that quintile. Quarterly realized returns in a given quintile are computed in an analogous fashion, aggregating up from monthly CRSP data. The key variable in our empirical analysis is PVS_t, the difference between the average book-to-market ratio of stocks in the lowest quintile of volatility and the average book-to-market ratio of stocks in the highest quintile of volatility:

$$PVS_t = \left(\overline{B/M}\right)_{low\ vol,t} - \left(\overline{B/M}\right)_{high\ vol,t}. \tag{14}$$

Again, PVS_t stands for the "price of volatile stocks." When market valuations are high, book-to-market ratios are low. Thus, PVS_t is high when the price of high-volatility stocks is high relative to low-volatility stocks.[11] Throughout the analysis, we standardize PVS_t so regression coefficients correspond to a one-standard deviation change in PVS_t.

Our empirical measure follows from the model, with one modification. For simplicity, there is only a single macroeconomic shock that impacts all firms in the model. Thus, exposure to this single shock, i.e., market beta, is the way to measure a stock's risk in the model. In practice, however, investors likely care about many risk factors. Rather than taking a stand on what these factors are, we empirically proxy for a stock's risk with the volatility of its past returns. Volatility increases with exposure to any risk factor, and thus is a robust measure of risk. We obtain qualitatively similar but weaker results if we use risk measures tied to specific models like the CAPM.

The Real Rate   The real rate is the one-year Treasury bill yield net of survey expectations of one-year inflation (the GDP deflator) from the Survey of Professional Forecasters. We use a short-maturity interest rate because inflation risk is small at this horizon, so inflation risk premia are unlikely to affect our measure of the risk-free rate. Our focus is on cyclical fluctuations in the real rate, as opposed to low-frequency movements that are potentially driven by secular changes

---

[11]We use the level of book-to-market in our empirics to mitigate outliers when book values are close to zero. We obtain similar results when defining PVS_t in terms of market-to-book ratios or log book-to-market ratios.

in growth expectations or demographic trends. To control for long-run trends as simply and transparently as possible, we use a linear trend to extract the cyclical component of the real rate. In the internet appendix, we show that all of our results are essentially unchanged if we use the raw real rate or employ more sophisticated filtering methods.

Summary Statistics Table 1 contains summary statistics on our volatility-sorted portfolios. Panel A of the table reports statistics on book-to-market ratios. High-volatility stocks have lower valuations than low-volatility stocks: on average, PVS_t is negative. The standard deviation of PVS_t is about twice the magnitude of its mean, so there is substantial variation in the price of volatile stocks over time. This variation is the focus of our empirical work.

Panel B shows that excess returns on the highest-volatility quintile of stocks are on average 2.7 percentage points per year lower than returns on the lowest-volatility quintile. This is related to the well-known idiosyncratic volatility and low beta puzzles, which highlight that stocks with high risk have historically underperformed (Ang et al. (2009)), potentially due to short sales constraints (Stambaugh et al. (2015)). In contrast, the model presented above implies that volatile firms should unconditionally earn higher returns. One way to address this limitation would be to add a force that increases the demand for volatile securities on average, but leaves room for time variation in their valuations. For instance, investor demand for volatile stocks might be the sum of demand in a frictionless model plus a constant frictional demand due to leverage constraints as in Frazzini and Pedersen (2014). The frictional demand component would tend to weaken the unconditional relationship between risk and return, while the frictionless component generates the time variation of interest for our analysis.

2.4   PVS and Perceptions of Risk

We begin our empirical analysis by confirming that movements in PVS_t are indeed tied to shifts in investor perceptions of risk. In particular, we study how PVS_t relates to measures of expectations of risk based on analyst forecasts, option prices, business and loan officer surveys, the newspaper-based measure of Baker et al. (2016), and statistical models. The results are reported in Table 2, which contains two sets of regressions. In the first set, we run simple univariate regressions relating PVS_t to our measures of expected risk. To verify that PVS_t reflects expected risk rather than

expected growth, our second set of regressions controls for cash flow expectations. All variables are standardized to facilitate interpretation.

In rows (1)-(4), we relate PVS_t to measures of perceived risk that match its construction, quantifying the perceived risk of high-volatility firms relative to low-volatility firms. As we argue in Section 5.2, the perceived risk of high-volatility public firms is likely to be relevant for the macroeconomy because private firms have similar investment behavior to high-volatility public firms and private firms are a large part of the macroeconomy.

Row (1) of Table 2 examines how PVS_t relates to a measure of expected risk derived from the Thompson Reuters IBES dataset of equity analyst forecasts. Specifically, we measure expected earnings risk as the range of analyst forecasts for each firm's earnings divided by the median forecast. We then define the expected risk of the volatility-sorted portfolio as the difference in median dispersion between high- and low-volatility firms.[12] In row (1), we examine the dispersion in forecasts of one-year ahead earnings. PVS_t is low when the expected risk of volatile firms based on analyst forecasts is high. A one-standard deviation increase in expected risk is associated with a 0.67 standard deviation decline in PVS_t. The univariate R^2 in the regression is 61%. Panel A of Figure 1 provides visual confirmation that PVS_t and the dispersion in one-year ahead earnings forecasts are highly correlated. Since dispersion is sometimes used as a measure of investor disagreement, it is important to note that disagreement should drive up stock valuations (Harrison and Kreps (1978); Scheinkman and Xiong (2003); Diether et al. (2002)). In contrast, we find that the price of volatile stocks declines with the dispersion of analyst forecasts about volatile stocks, consistent with dispersion capturing expectations of risk.

Row (2) shows that PVS_t is also correlated with dispersion in forecasts of one-quarter ahead earnings. The univariate R^2 is 28%, and a one-standard deviation increase in expected risk from analyst forecasts is associated with a 0.45 standard deviation decline in PVS_t.[13]

---

[12]We would ideally measure analysts' expectations of risk using their perceptions of the full distribution of future earnings. However, in the IBES data, analysts only reports their mean estimate of future earnings. While across-analyst dispersion is an imperfect measure of expected risk, we only need it to be positively correlated with true subjective expectations of risk. Bachmann et al. (2013) show empirically that analyst dispersion is a good proxy for expected risk.

[13]The primary reason PVS_t is more strongly correlated with expected risk measured from one-year ahead forecasts than one-quarter ahead forecasts is data availability. The one-year forecast field is better populated in IBES so it is less noisy in the early sample. For the period when the one-quarter measure is relatively well populated, we obtain similar results for the two measures.

Row (3) studies how PVS_t relates to expectations of risk derived from option prices. Using data from OptionMetrics, we compute the difference in the median implied volatility of one-year at-the-money options for high- and low-volatility firms. When the option-implied volatility of volatile firms is relatively high, PVS_t is relatively low. A one-standard deviation increase in expected risk is associated with a 0.47 standard deviation decline in PVS_t.

Option-implied volatilities contain expectations of future volatility and premia for volatility risk (Bollerslev et al. (2009)). If these risk premia are zero or constant, then options provide a clean measure of expected future volatility. If they vary over time, they could bias the relation between PVS_t and implied volatilities. However, risk premia cannot account for our results on analyst forecasts, providing some comfort that movements in PVS_t reflect changing expectations of risk. Moreover, to the extent that risk premia in options are driven by forces orthogonal to those that drive PVS_t (e.g., supply and demand imbalances specific to option markets (Gârleanu et al. (2009)), they will act as measurement error and bias us against finding a link between PVS_t and option-implied volatilities. Taken together, our results suggest that PVS_t moves with investors' expectations of risk, as predicted by the model.

In row (4) of Table 2, we take a statistical approach to measuring the expected risk of the portfolio underlying PVS_t. We examine the forecasted difference in return volatility between the low- and high-volatility portfolios, where we forecast the volatility of each portfolio with an AR(1) model. We refer to this measure as an objective measure of risk because it derives from a statistical model. Row (4) indicates that PVS_t correlates with this objective measure of expected risk, though the R^2 of 9% is lower than that for subjective measures of expected risk.

In rows (5)-(9), we show that PVS_t moves with broader measures of perceived risk relevant for the macroeconomy. In row (5), instead of taking the difference in analyst dispersion between high and low-volatility firms, we average analyst dispersion across all firms. Hence, this measure is high when expected risk rises for all firms. The negative point estimates in row (5) indicate that PVS is high when the perceived risk of all public firms is low; rows (1) and (2) imply that high-volatility firms are also perceived to be safer than usual at these times.[14]

---

[14]We argue below that low-volatility firms are "bond-like" and relatively insensitive to fluctuations in perceived risk. Consistent with this interpretation, in untabulated results we find that analyst dispersion for the lowest volatility quintile is not correlated with PVS_t, while dispersion for quintiles 2-5 is. These findings are also consistent with previous work documenting that stock return volatilities of individual firms tends to rise and fall together over time but that the magnitude of these movements is larger for volatile firms (Herskovic et al., 2016).

Figure 1: PVS_t and Expected Risk

Panel A: Analyst Expected Risk

Panel B: Bank Lending Standards
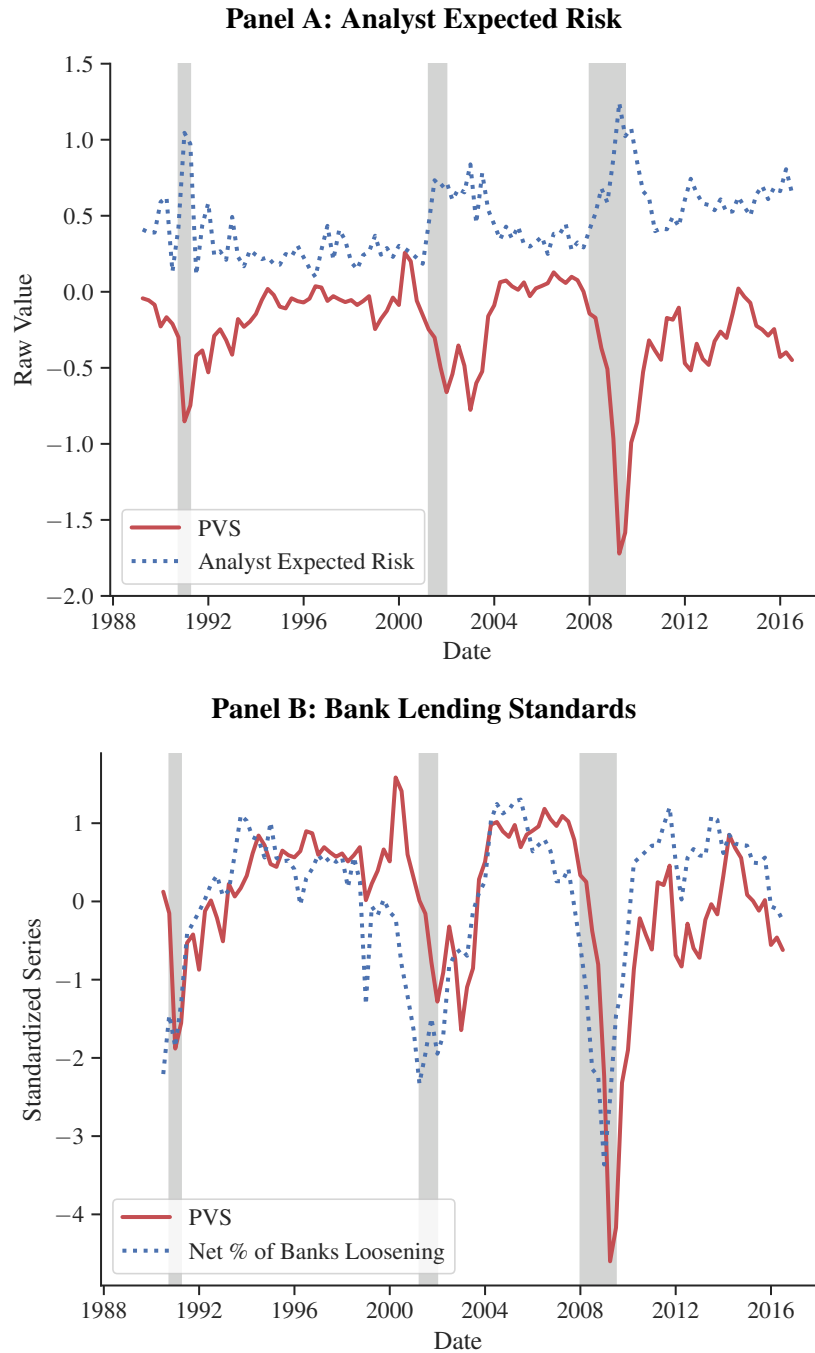
Notes: Panel A plots PVS_t against analyst expected risk of high-volatility stocks relative to low-volatility stocks. We construct analyst expected risk at the firm-level based on the dispersion of analyst forecasts from Thompson Reuters IBES data, defined as the range of analyst forecasts of one-year ahead annual earnings divided by the average forecast of earnings. The analyst expected risk of stocks in either the low or high-volatility stock portfolio is the median of firm-level disagreement for firms in that portfolio. Panel B plots PVS_t against the net percentage of U.S. banks loosening lending standards, taken from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS). For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. PVS_t is the difference between the average book-to-market (BM) ratio of low-volatility stocks and the average BM-ratio of high-volatility stocks. The internet appendix contains details on variable construction. Data is quarterly and the sample size depends on availability.

17

In row (6), we use the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) to study risk perceptions from credit markets. Row (6) shows that PVS_t is high when loan officers report that they are loosening lending standards, presumably because they perceive risk to be low. A one-standard deviation loosening in lending standards is associated with a 0.5 standard deviation higher value of PVS_t. Panel B of Figure 1 shows the relation visually. Our interpretation that PVS_t reflects expected risk is further corroborated by row (7), which shows that PVS_t is high when loan officers cite a "more favorable or less uncertain economic outlook" as the reason for loosening lending standards. Row (8) shows that PVS_t is negatively correlated with small business optimism about economic conditions, measured using survey data from the National Federation of Independent Business (NFIB). Row (9) shows PVS_t is negatively correlated with the Baker et al. (2016) measure of economic policy uncertainty. These results are consistent with the idea that PVS_t captures a broad notion of perceived risk that operates simultaneously in many asset classes and is relevant for the macroeconomy.

One concern with these results is that expectations of risk may comove with expectations of the future cash flows. In particular, expected risk could be high when expected cash flows are low, confounding our interpretation of PVS_t as a measure of perceived risk. In the second set of regressions in Table 2, we control for expectations of cash flows using analyst long-term growth forecasts from IBES.[15] Across specifications, the same overall conclusion emerges: controlling for cash flow expectations has little impact on the relationship with expected risk and typically adds little to the overall R^2. In the internet appendix, we use univariate regressions to show directly that expectations of cash flows have a low correlation with PVS_t.

The takeaway from this analysis is that PVS_t closely tracks perceptions of risk, validating our use of PVS_t as a measure of perceived risk. The connection between PVS_t and expected risk is strongest when using subjective measures from surveys or market data rather than objective measures from statistical forecasting models. In the internet appendix, we relate PVS_t to additional measures of aggregate macroeconomic and stock market risk. These additional results further support the conclusion that PVS_t is related to expected risk, and that this connection is most evident

---

[15]IBES defines long-term growth as the "expected annual increase in operating earnings over the company's next full business cycle", a period ranging from three to five years. For each stock, we construct the consensus analyst forecast of ROE. We then compute the difference between the median forecast for high-volatility stocks and the median forecast for low-volatility stocks, and control for this variable in our regressions relating PVS_t to expectations of risk.

for subjective measures of risk that reflect both public and private firms. For the remainder of the paper, we use PVS_t to measure perceived risk because PVS_t is more closely tied to firms' cost of capital and is available over a longer sample than the direct measures examined here.

3 The Price of Volatile Stocks and the Macroeconomy

In this section, we empirically assess risk-centric theories of the business cycle using PVS_t as a measure of perceived risk. We explore links between PVS_t, real interest rates, volatile firms' cost of capital, and real outcomes. We find that when PVS_t is high, the price of safe bonds is low, so the real rate is high. In addition, we use return forecasting regressions to show that PVS_t and the real rate are both high when the cost of capital is low for risky firms. Turning to the real economy, we document that high values of PVS_t forecast a boom in real investment, an expansion of output, and an increase in aggregate employment with peak responses after four to six quarters. These patterns are consistent with the predictions of our stylized model of risk-centric business cycles from Section 2.1.

3.1 Real Rates

We begin by documenting the relationship between the detrended one-year real rate and PVS_t, running regressions of the form:

$$\text{Real Rate}_t = a + b \times PVS_t + \varepsilon_t. \tag{15}$$

To facilitate interpretation, we standardize PVS_t so regression coefficients correspond to a one-standard deviation move. We report Newey and West (1987) standard errors using five lags. In the internet appendix, we also consider several other methods for dealing with the persistence of these variables, including parametric corrections to standard errors, generalized least squares, and bootstrapping p-values. Our conclusions are robust to these alternatives.

Column (1) of Table 3 shows that the real rate is positively correlated with PVS_t. In other words, safe asset prices are low when the price of volatile stocks is high. The effect is economically large and precisely measured. A one-standard deviation increase in PVS_t is associated with a 1.3

19

Figure 2: One-Year Real Rate and PVS
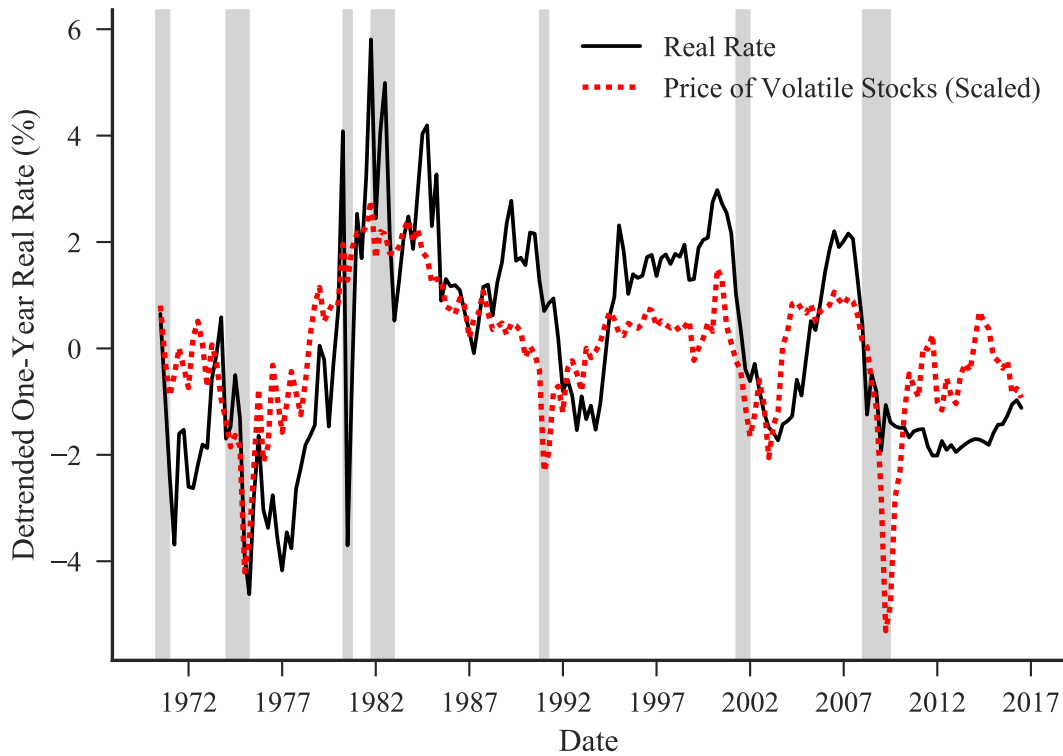
Notes: This figure plots the one-year real rate and the fitted value from a regression of the real rate on PVS_t. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. PVS_t is the difference between the average book-to-market (BM) ratio of low-volatility stocks and the average BM-ratio of high-volatility stocks. The internet appendix contains details on variable construction. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage terms and linearly detrended to focus on business-cycle fluctuations. Data is quarterly and spans 1970Q2-2016Q2.

percentage point increase in the real rate. For reference, the standard deviation of the detrended real rate is 2.0 percentage points. The R^2 of the univariate regression is 41%.

Figure 2 presents the relation between PVS_t and the real rate visually. The plot shows that the fitted value from the regression in Eq. (15), labeled "Price of Volatile Stocks (Scaled)," tracks the real rate well since 1970. The relation holds in expansions and recessions (shown in gray), as well as in both high- and low-inflation periods. We present formal evidence of subsample stability in the internet appendix.

Column (2) of Table 3 indicates that our focus on the cross section of stock valuations is critical. We find no relationship between the book-to-market ratio of the aggregate stock market and the real rate. This non-result is not due to statistical precision. The economic magnitude of the point

estimate on the aggregate book-to-market ratio is quite small – a one-standard deviation movement in the aggregate book-to-market ratio is associated with only a 0.17 percentage point movement in the real rate. Moreover, the aggregate book-to-market ratio adds only one percentage point to the R^2 relative to our baseline regression in column (1), and the coefficient on PVS_t remains unchanged when controlling for the aggregate book-to-market ratio.[16]

The finding that the aggregate market is only weakly correlated with the real rate, previously documented in Campbell and Ammer (1993), might initially appear surprising in the light of our model. Our stylized model contains only one aggregate risk factor and would therefore appear to imply that the aggregate market should move with the real rate. One way to reconcile the model with the data would be to assume that low-volatility firms are bond-like in the sense that relatively insensitive to risk perceptions: $s_L \approx \frac{\lambda}{2}$ or even $s_L < \frac{\lambda}{2}$. If the public stock market tends to overweight these bond-like firms relative to the aggregate economy, this would dampen the response of the aggregate stock market to risk perceptions, while strengthening the response of PVS_t. Column (3) of Table 3 shows that low-volatility stocks do appear to be more bond-like: their market values tend to rise when the real rate falls. We revisit the distinction between PVS_t and the aggregate market in Section 5.2.

In column (4), we control for variables traditionally thought to enter into monetary policy: four-quarter inflation, as measured by the GDP price deflator, and the output gap from the Congressional Budget Office (Clarida et al. (1999); Taylor (1993)). Both coefficients are noisily estimated and statistically indistinguishable from the traditional Taylor (1993) monetary policy rule values of 0.5. The internet appendix provides further evidence that our baseline result is not driven by inflation and does not simply capture the component of monetary policy that is attributable to a standard Taylor (1993) rule.

Columns (5)-(8) of Table 3 rerun the preceding regressions in first differences to ensure that our statistical inference is not distorted by the persistence of either the real rate or PVS_t. We obtain similar results.[17] We again find no relationship between the real rate and the aggregate book-to-

---

[16]As we discuss further in the internet appendix, the aggregate book-to-market ratio does enter significantly in some variants of our baseline specification. However, the statistical significance is irregular across specifications, and the economic significance is always negligible.

[17]The coefficients are somewhat smaller in first differences, likely due to the fact that we use past realized volatility as a proxy for expected risk in constructing PVS_t. This introduces measurement error into our variable, which is amplified in first differences because perceived risk is somewhat persistent.

market ratio. Overall, the evidence in Table 3 indicates an economically meaningful and robust relationship between the real rate and financial market risk perceptions.

3.1.1 Robustness

The relationship between the real rate and PVS_t is our first key result. Our preferred interpretation is that both the price of volatile stocks and the natural, or frictionless, real risk-free rate respond to changes in perceived risk. In the next two subsections, we address concerns that the relation between PVS_t and the real rate might instead be driven by (i) stock-level factors other than perceived risk or (ii) discretionary monetary policy.

We address the first concern by sorting stocks by alternative characteristics that could explain the comovement between PVS_t and the real rate and showing that volatility is the crucial firm characteristic. We run robustness tests for both the full and pre-crisis samples, in levels and in changes. All regressions include the aggregate book-to-market ratio as a control and use Newey and West (1987) standard errors using five lags. For reference, the first row of Panel A in Table 4 reproduces our baseline results from columns (2) and (6) of Table 3.

Alternative Constructions of PVS_t

We first show that we obtain similar results for alternative definitions of PVS_t. In row (2) of Table 4, we recompute PVS_t by value-weighting the book-to-market ratio of stocks within each volatility quintile, as opposed to equal-weighting. In row (3), we obtain similar results sorting stocks on volatility measured over a two-year window, rather than a two-month window. Our baseline result therefore captures changes in the valuation of stocks that historically have been volatile, not changes in the volatility of low-valuation stocks. This distinction is important to our interpretation of PVS_t as a measure of investors' risk perceptions relevant to the macroeconomy.

Relationship to Other Stock Characteristics

Rows (4)-(9) of Table 4 Panel A investigate whether stock return volatility is really the key stock characteristic for the relationship between stock prices and the real rate. In row (4), we run a horse race of PVS_t against the difference in yields between 10-year off-the-run and on-the-run Treasuries, a measure of liquidity premia in the fixed income market (Krishnamurthy (2002), Kang

22

and Pflueger (2015)). The table reports the estimated coefficient on PVS_t. The explanatory power of PVS_t for the real rate is unchanged, suggesting that PVS_t subsumes any information about the real rate that is captured in the demand for liquid assets like on-the-run Treasuries.

Next, we test whether volatility simply proxies for another stock characteristic by controlling for book-to-market spreads based on alternative characteristics. These tests help us rule out that the PVS_t-real rate relationship captures the pricing of these alternative characteristics, including leverage, growth, and the duration of cash flows. For an alternative characteristic Y, we construct a book-to-market spread the same way we construct PVS_t. We report the coefficient on PVS_t, while controlling for the Y-sorted book-to-market spread and the aggregate book-to-market ratio. We consider characteristics Y that capture alternative economic mechanisms through which the real rate might correlate with PVS_t: cash flow duration, firm leverage, systematic risk (i.e., CAPM beta), firm size, and value (i.e., book-to-market ratio).

Rows (5)-(9) show that in all cases the regression coefficient on PVS_t is essentially unchanged relative to our baseline results. Row (5) shows that PVS_t is not capturing differences in the duration of cash flows (Weber (2016)) between low- and high-volatility stocks, which would cause their values to move mechanically with interest rates. We draw a similar conclusion when studying leverage sorts in row (6). The results on CAPM beta in row (7) confirm that the relation between PVS_t and the real rate is not simply picking up on aggregate stock market risk, suggesting that investors care about risk factors that are broader than the aggregate stock market.[18] In row (8), we find that our volatility sorts do not simply proxy for size, despite the fact that smaller firms tend to be more volatile. The value-sorted book-to-market spread is sometimes thought to capture the value of growth options, so the results in row (9) suggests that the relation between PVS_t and the real rate is not driven by growth options. In the internet appendix, we use double sorts to show that the relationship between PVS and the real rate is not driven by industry, whether the firm is a dividend payer, as well as the characteristics studied here.

Based on this analysis, we conclude that sorting stocks on volatility is key to our construction of PVS_t. From a statistical perspective, it may not be surprising that there exists a cross section

---

[18]As we discuss in the internet appendix, there is a correlation between the real rate and the spread in valuations of beta-sorted portfolios, confirming the intuition that the price of safe assets is high when prices of risky stocks are low. However, the relationship between the real rate and PVS_t is stronger in univariate regressions and in horse races, consistent with our interpretation of total volatility as a more robust measure of an individual stock's risk.

of stocks that is correlated with real rates. The economic content of our findings is that volatility, while not a fundamental firm characteristic, is a robust measure of risk. We therefore view these results as supportive of our interpretation of PVS_t as a measure of investor risk perceptions.

Relationship to Other Financial Market Conditions

We next show that PVS_t has distinct explanatory power for the real rate compared to other measures of financial market activity, including the BAA minus 10-year Treasury credit spread, the Gilchrist and Zakrajšek (2012) credit spread, the Greenwood and Hanson (2013) measure of credit market sentiment, the Baker and Wurgler (2006) measure of equity market sentiment, the Kelly and Pruitt (2013) optimal forecast of aggregate equity market returns, and the Baker et al. (2016) economic policy uncertainty index.

The first set of columns in Table 4 Panel B shows that PVS_t is correlated with many of these measures, though the R^2s indicate that the magnitudes are generally not large. The second set of columns in Panel B of Table 4 runs univariate regressions of the real rate on the alternative measures. None of these measures is as correlated with the real rate as PVS_t, though the Baker and Wurgler (2006) measure is highly correlated with the real rate. Moreover, the third set of columns shows that the relationship between PVS_t and the real rate remains strong when controlling for these alternative measures and that the R^2s increase substantially when adding PVS_t in all cases.

One potential reason that PVS_t contains information beyond these alternative measures is that PVS_t is based on a long-short portfolio, and thus nets out factors affecting an entire asset class. For instance, suppose equity market sentiment has a perceived risk component and an equity cash flow component, while credit market sentiment shares the same perceived risk component but has a distinct bond cash flow component. PVS_t should difference out optimism about aggregate equity cash flows, which affects equity market sentiment, but not credit market sentiment.[19] Consistent with this logic, PVS_t is positively correlated with both the Greenwood and Hanson (2013) measure of credit market sentiment and the Baker and Wurgler (2006) measure of equity market sentiment, despite the fact that the two sentiment measures are negatively correlated.

---

[19]Similar logic suggests that effects like the inflation illusion (Modigliani and Cohn (1979), Cohen et al. (2005)) may contaminate the aggregate market's valuation, but will affect PVS_t less.

3.1.2 Monetary Policy

We next rule out the possibility that discretionary monetary policy acts as an omitted variable driving both PVS_t and the real risk-free rate. To formalize this concern, consider an extension of the model presented in Section 2.1 where the central bank has the ability to set short-term real interest rates. This extension could be microfounded by adding price-setting frictions to the model (Woodford (2003)). In such a model, the key predictions outlined in Section 2.1 apply to the unobservable "natural" real rate r_{ft} and the "natural" rate of economic activity. By contrast, our empirical analysis relies on the observable interest rate set by the central bank (denoted r_{ft}^M).[20]

The basic prescription for optimal monetary policy when the natural real rate varies is simple. Clarida et al. (1999) and Woodford (2003) show that a central bank seeking to stabilize prices will lower the actual interest rate one-for-one when the natural real rate declines.[21] If the central bank deviates from this prescription and adjusts the actual interest rate less than one-for-one – perhaps because it seeks to smooth nominal rates – output and investment will temporarily rise above their natural levels. Thus, in the canonical New Keynesian framework, monetary policy is expansionary when r_{ft}^M is below the natural real rate and contractionary when it is above. We can therefore write the observed interest rate as a sum of the natural rate and discretionary monetary policy:

$$r_{ft}^M \;\; = \;\; r_{ft} + u_t, \tag{16}$$

where the discretionary monetary policy term u_t absorbs any deviations of the actual real rate from the natural rate.[22]

Eq. (16) implies that the covariance between the observed real rate and PVS_t consists of two terms:

$$Cov[r_{ft}^M, PVS_t] = Cov[r_{ft}, PVS_t] + Cov[u_t, PVS_t], \tag{17}$$

---

[20]It is important to note that the natural real rate and natural rate of output do not necessarily reflect the economy's long-run equilibrium, but instead represent the hypothetical values that would obtain in a world without sticky product prices. Modeling the price-setting frictions needed to ensure that the central bank can affect the real risk-free rate would unnecessarily complicate the analysis and is beyond the scope of this paper.

[21]We do not require that the Federal Reserve reacts directly to PVS_t, only that perceived risk is reflected in both Fed actions and the price of volatile stocks. For a comprehensive narrative account of financial market considerations in Fed meetings, see Cieslak and Vissing-Jorgensen (2018).

[22]For examples of such deviations, see e.g., Brainard (1967); Woodford (2003); Coibion and Gorodnichenko (2012); Stein and Sunderam (2018).

where the model predicts $Cov[r_{ft}, PVS_t] > 0$. Our empirics in Table 3 necessarily use the observed interest rate r_{ft}^M rather than the natural real rate r_{ft}, so we need to rule out the possibility that the positive covariance in Table 3 is driven by discretionary monetary policy, u_t.

Following the literature on identified monetary policy shocks, we rule out this potential bias using narrow windows around Federal Reserve announcement dates. The identification assumption in this literature is that no information other than discretionary monetary policy is released in narrow windows around the Federal Reserve's announcements of monetary policy decisions. Under this assumption, we can regress the returns of the low-minus-high volatility portfolio on identified monetary policy shocks to test whether discretionary monetary policy causes a shift in the relative price of volatile stocks. If discretionary monetary policy were an omitted variable driving the positive empirical covariance between PVS_t and r_{ft}^M, we would expect to obtain a negative slope coefficient in this regression. For robustness, we use several approaches to identifying monetary shocks, drawing on Romer and Romer (2004), Bernanke and Kuttner (2005), Gorodnichenko and Weber (2016), and Nakamura and Steinsson (2018).

The results in Table 5 indicate that discretionary monetary policy does not differentially impact the price of high-volatility stocks relative to low-volatility stocks. The first set of columns regress returns of the low-minus-high volatility portfolio on monetary policy surprises using quarterly data. The estimated point estimates are not statistically distinguishable from zero and have inconsistent signs. In the second set of columns, we narrow the window and focus on daily data. We again find small and statistically insignificant effects. In all of these regressions, we exclude monetary policy changes that occur outside of regularly scheduled meetings because such changes are often made in response to financial market conditions. In the internet appendix, we obtain similar results when including monetary policy surprises from unscheduled meetings. Overall, these results suggest that $Cov[u_t, PVS_t]$ is zero and support our interpretation that PVS_t and the natural real rate comove because both respond changes in perceived risk.[23]

---

[23]The evidence in Section 3.3 further supports the conclusion that discretionary monetary policy does not drive the positive correlation between PVS_t and the real risk-free rate. An increase in the real rate due to discretionary monetary policy should lead to declines in macroeconomic activity (Christiano et al. (1999)). By contrast, we find that PVS_t forecasts expansions.

3.2 Return Predictability

We have established that real interest rates and PVS_t are positively correlated in the data. In other words, safe bond prices are high when perceptions of risk as measured by PVS_t are also high. We next document that the correlation between the real rate and PVS_t is attributable to movements in the cost of capital for volatile firms, as opposed to movements in their expected cash flows. We use forecasting regressions to show that both the real rate and PVS_t are low when the expected return (i.e., the cost of capital) for volatile stocks is high. This observation is consistent with the core mechanism in risk-centric theories of the business cycle and makes it unlikely that PVS_t proxies for expected cash flows, supporting our use of PVS_t as a proxy for expected risk.

3.2.1 The Low-minus-High Volatility Equity Portfolio

Standard present value logic (Campbell and Shiller (1988); Vuolteenaho (2002)) implies that variation in PVS_t must correspond to changes in either the future returns on a portfolio that is long low-volatility stocks and short high-volatility stocks (i.e., the portfolio underlying PVS_t) or the future cash flow growth of the same portfolio. Thus, our findings in Table 3 imply that the real rate covaries with either future returns or future cash flow growth for volatile stocks.

We run forecasting regressions to show that PVS_t and the real rate comove with expected future returns for volatile stocks:

$$R_{t \to t+4} = a + b \times X_t + \xi_{t+4}, \tag{18}$$

where X_t is either PVS_t or the real rate. To start, $R_{t \to t+4}$ is the annual return of a portfolio that is long the lowest volatility quintile of stocks and short the highest volatility quintile of stocks, so a high forecasted $R_{t \to t+4}$ corresponds to a low cost of capital for volatile firms. Panel A in Table 6 contains the results. We use Hodrick (1992) standard errors to be maximally conservative in dealing with overlapping returns.

Column (1) shows that a high price of volatile stocks forecasts low returns on high-volatility stocks relative to low-volatility stocks. A one-standard deviation increase in PVS_t forecasts a 15.1 percentage point higher annual return on the volatility-sorted portfolio. The annual standard deviation of returns is 29.6%. The R^2 of 0.26 is also large. For comparison, the aggregate price-dividend ratio forecasts aggregate annual stock returns with an R^2 of 0.09 (Cochrane (2011)). Thus,

it appears that variation in PVS_t largely reflects variation in expected future returns, consistent with much of the empirical asset pricing literature (e.g., Cochrane (2011)).

Column (2) makes the connection between the real rate and expected returns on the volatility-sorted portfolio. A one-standard deviation increase in the real rate forecasts an 8.1 percentage point higher annual return on the volatility-sorted portfolio. When the real rate is high, high-volatility stocks tend to do poorly relative to low-volatility stocks going forward. In other words, the cost of capital for volatile firms is relatively low.

In columns (3) and (4), $R_{t \to t+4}$ is the cash flow of the volatility-sorted portfolio, measured as accounting return on equity (ROE). We find economically small and statistically insignificant effects forecasting with either PVS_t or the real rate. PVS_t and the real rate contain little information about the future cash flows of the volatility-sorted portfolio.

Taken together, columns (1)-(4) of Table 6 Panel A suggest that the real rate comoves with PVS_t because it comoves with the cost of capital for volatile stocks. In the internet appendix, we use the present value decomposition of Vuolteenaho (2002) to show that nearly 90% of the comovement between the real rate and PVS_t can be attributed to the real rate's ability to forecast returns on volatile stocks. Consistent with our model's predictions, when perceived risk is high, safe asset prices are high and investors demand high compensation for holding volatile stocks.

Columns (5) and (6) of Panel A in Table 6 show that neither the real rate nor PVS_t forecast the aggregate market excess return, echoing earlier findings by Campbell and Ammer (1993). This again highlights the importance of our focus on the cross-section of stocks sorted by volatility.

3.2.2 Other Asset Classes

Next, we show that PVS_t captures common variation in the compensation investors demand for holding volatile securities within several different asset classes, consistent with the idea that it is a broad measure of risk perceptions relevant to the macroeconomy.

We use test asset portfolios from He et al. (2017), which cover six asset classes: U.S. corporate bonds, sovereign bonds, options, credit default swaps (CDS), commodities, and currencies.[24] Within each asset class, we form a portfolio that is long the lowest-volatility and short the highest-

---

[24]For U.S. stocks, He et al. (2017) use the Fama-French 25 portfolios. We use our own volatility-sorted portfolios for consistency and because this induces a bigger spread in volatility. We obtain qualitatively similar results with the Fama-French 25.

volatility portfolio in the asset class, where volatility is measured with a 5-year rolling window of prior monthly returns. The first three columns in Table 6 Panel B contain summary statistics on the volatility-sorted portfolios in each asset class. In contrast to equities, the average returns of long-short portfolios are negative for several asset classes, showing that the low-volatility premium in U.S. equities (Ang et al. (2006)) is not a systematic feature of all asset classes.

The second set of columns in Table 6 Panel B shows that both PVS_t and the real interest rate forecast quarterly returns on volatility-sorted portfolios for many asset classes. The top row shows our results for U.S. equities. The remaining rows show economically and statistically significant evidence that PVS_t and the real rate forecast long-short returns within three other asset classes: U.S. corporate bonds, options, and CDS. There is also a positive, marginally significant correlation between PVS_t and sovereign bond returns, and a positive but insignificant correlation between PVS_t and commodity returns. We obtain similar results forecasting annual returns.

These regressions show that both PVS_t and the real rate reflect common variation in the compensation investors demand for holding volatile securities across a variety of asset classes. To quantify the strength of this common variation, we compute for each asset class c the correlation ρ_c between the low-minus-high volatility return in c and the average return of the low-minus-high volatility trade in all other asset classes excluding c. For example, ρ_c for $c =$ options computes the correlation of the return on the volatility trade in options and the average return of the trade across all asset classes except options. The average ρ_c is 0.42, comparable to common variation in value and momentum strategies across asset classes (Asness et al. (2013)).

3.3 Real Outcomes

In risk-centric theories of the business cycle, changes in risk perceptions have real effects: when perceptions of risk are high, risky firms invest less because their cost of capital is high. In the previous subsection, we showed that when perceived risk as measured by PVS_t is high volatile firms do face a high cost of capital. We now explore whether this high cost of capital has real effects.

To do so, we trace out the response of different macroeconomic quantities to PVS_t using local

29

projections similar to Jordà (2005). We run regressions of the form:

$$y_{t+h} = a + b_X^h \times X_t + b_{RR}^h \times RealRate_t + b_y^h \times y_t + \varepsilon_{t+h}$$

where h is the forecast horizon and X_t is either PVS_t or the aggregate book-to-market ratio.

Panel A of Table 7 reports the results. In columns (1)-(4), we forecast the ratio of private non-residential investment to capital. A one-standard deviation increase in PVS_t is associated with an investment-capital ratio that is 0.22 percentage points higher at a one-quarter horizon. The magnitude is 0.35 percentage points at a four-quarter horizon. The standard deviation of the investment-capital ratio is 1.16%, so these magnitudes are economically meaningful. In the internet appendix, we also show that the investment rates of high-volatility firms are more sensitive to PVS_t than the investment rates of low-volatility firms, consistent with the model in Section 2.1. In columns (5)-(8) of Table 7, we report results for the output gap. A one-standard deviation increase in PVS_t is associated with an output gap that is 0.32 percentage points more positive after one quarter, and 0.66 percentage points higher after four quarters. In columns (9)-(12) of the table, we report results for the change in the unemployment rate. A one-standard deviation increase in PVS_t is associated with a 0.11 percentage point fall in the unemployment rate after one quarter, and a 0.27 percentage point decline after four quarters.

In Figure 3 we depict these results visually, reporting impulse responses to a one-standard deviation increase in PVS_t for horizons of $h = 1, ..., 12$ quarters. The figure shows that an increase in PVS_t forecasts a persistent increase in private investment, peaking around six quarters and then slowly reverting over the next six quarters. Forecasts for the output gap and unemployment are somewhat less persistent, peaking after five quarters and then dissipating. In the internet appendix, we complement these results with standard vector autoregression (VAR) evidence. These VARs allow us to quantify the importance of PVS_t shocks using forecast error variance decompositions. At a ten-quarter horizon, PVS_t shocks account for 14% of variation in the unemployment rate and 38% of the variation in investment-to-capital ratios. For comparison, monetary policy shocks account for 17% of variation in unemployment and only 5% of variation in the investment-to-capital ratio.

For comparison, Panel A of Table 7 also reports results using the aggregate book-to-market

30

Figure 3: Impulse Responses of the Macroeconomy to PVS (Local Projections)
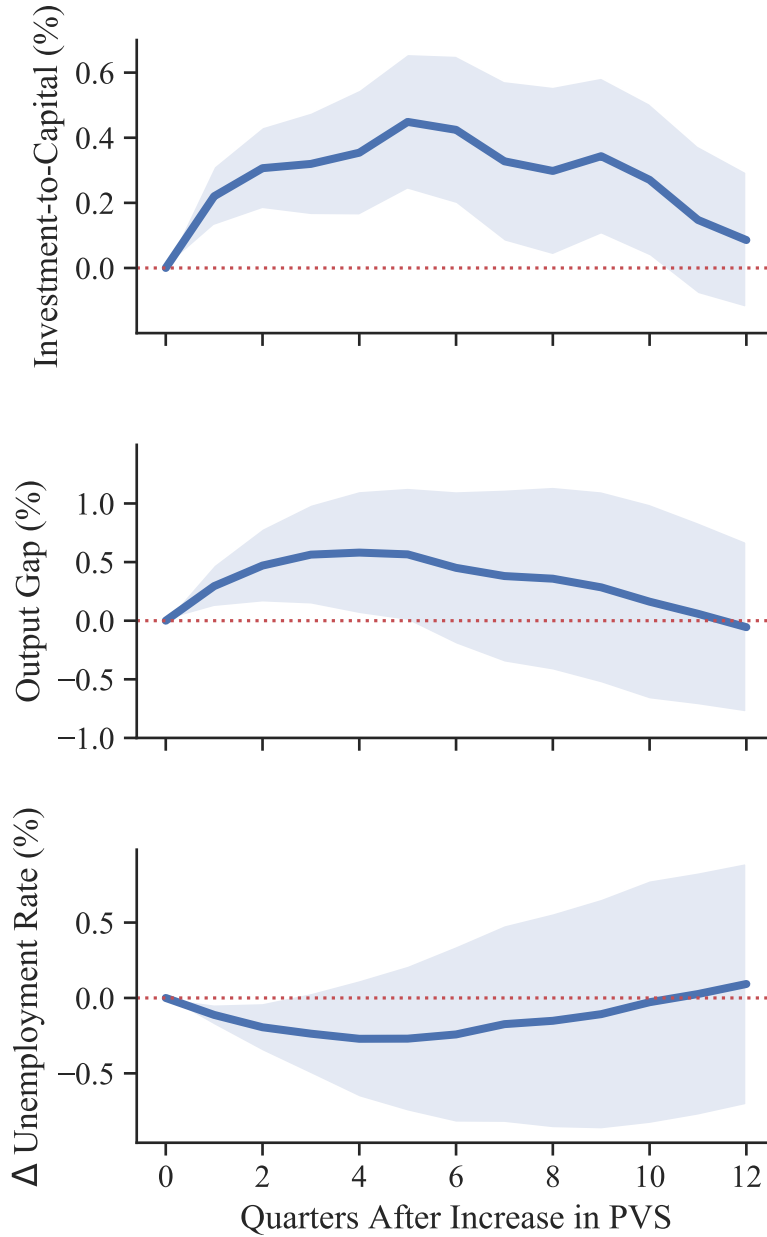
Notes: This figure plots the estimated impulse responses (and associated 95% confidence bands) of several macroeconomic variables to a one-standard deviation increase in PVS_t using local projections. We compute impulse responses using Jordà (2005) local projections of each macroeconomic outcome onto PVS_t. In all cases, we run regressions of the following form: $y_{t+h} = a + b_{PVS}^h \times PVS_t + b_{RR}^h \times \text{Real Rate}_t + b_y^h \times y_t + \varepsilon_{t+h}$. We consider three different macroeconomic outcomes for the *y*-variable. The first is the investment-to-capital ratio, defined as the level of real private nonresidential fixed investment (PNFI) divided by the previous year's current-cost net stock of fixed private nonresidential assets (K1NTOTL1ES000). The second is the real output gap, defined as the percent deviation of real GDP from real potential output. The third is the change in the U.S. civilian unemployment rate. When forecasting the investment-capital ratio, y_{t+h} is the level of the investment-capital ratio at time $t+h$. For the output gap, y_{t+h} is the level of the output gap at time $t+h$. Finally, for the unemployment rate, y_{t+h} is the change in the unemployment rate between t and $t+h$, and y_t is the change between $t-1$ and t. All macroeconomic variables come from the St. Louis FRED database and are expressed in percentage points. PVS_t is defined as in the main text. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. For all regressions, we use Newey and West (1987) standard errors with five lags. Data is quarterly and spans 1970Q2-2016Q2.

ratio instead of PVS_t in the local projections. The aggregate book-to-market ratio does not have economically or statistically meaningful forecasting power for future investment and employment. The point estimates show that the responses of investment and employment to PVS_t are two to five times stronger (in absolute value) than their responses to the aggregate book-to-market ratio, depending on horizon. We do find some evidence that the output gap rises following an increase in the value of the aggregate stock market. However, the relation between PVS_t and future macroeconomic activity is more robust across different macroeconomic aggregates. In the internet appendix, we show that the relationship between PVS_t and future economic outcomes remains when controlling for both the aggregate book-to-market ratio and the Cochrane and Piazzesi (2005) term-structure factor, suggesting that PVS_t contains information about the macroeconomy that is distinct from the information in those variables.

One might be concerned that Figure 3 suggests that PVS_t reflects variation in expected growth rather than risk perceptions. For instance, more volatile stocks could have cash flows that are more sensitive to aggregate growth. This alternative explanation is unlikely for a few reasons. For one, we find no evidence that PVS_t forecasts the cash flows of volatile stocks, while it strongly forecasts their future returns. In addition, if aggregate growth expectations were important, aggregate stock market valuations should forecast real investment more strongly. We therefore believe that the most natural interpretation of our results is that PVS_t captures risk perceptions, which in turn drive the natural rate and real economic outcomes.

4   Why Do Perceptions of Risk Vary?

We have documented relationships between PVS_t, the real rate, and macroeconomic outcomes that are consistent with risk-centric theories of the business cycle. When our measure indicates that perceived risk is high, the price of safe bonds is high, the cost of capital for volatile firms is high, and output and investment are forecast to contract. In this section we use PVS_t to investigate why perceptions of risk vary over time. We first show that expectations of risk fall on the heels of good news about the economy. We then provide evidence that investors over-extrapolate in the sense that expectations of risk are predictably revised upwards after periods of low perceived risk.

4.1 PVS and Macroeconomic News

Early articulations of risk-centric theories of the business cycle (e.g., Keynes (1937), Minsky (1977), and Kindleberger (1978)) posited that investors expectations of risk are shaped by recent events: following good news, investors expect future risk to be low. In Table 8 Panel A, we examine this prediction in the data by regressing the 4-quarter change in PVS_t onto measures of macroeconomic news. We standardize all variables to aid interpretation.

Column (1) shows a positive correlation between the 4-quarter change in PVS_t and the surprise in real GDP growth relative to survey expectations from the Survey of Professional Forecasters over the same period. A one-standard deviation higher real GDP growth surprise is associated with a 0.6 standard deviation increase in PVS_t. Column (2) reveals similar results for the surprise in corporate profit growth. A one-standard deviation increase in the corporate profit growth surprise is associated with a 0.4 standard deviation increase in PVS_t. At the firm level, column (3) shows that PVS_t comoves with the difference in contemporaneous cash flow growth (ROE) between low- and high-volatility firms. Finally, column (4) shows that PVS_t moves with recent conditions in credit markets, consistent with our interpretation that PVS_t is a measure that extends beyond equity markets. We measure credit market conditions as the 4-quarter change in charge-off rates on bank loans. A one-standard deviation increase in charge-offs is associated with a 0.6 standard deviation decrease in PVS_t. Column (5) shows that in a multivariate regression all four of these explanatory variables appear to contain independent information. Overall, the results here show that perceived risk falls on the heels of good news about the state of the economy.

In Table 8 Panel B, we directly examine the link between measures of realized and expected risk and macroeconomic news that we assumed in the model. For compactness, we include all macroeconomic news measures in every column.[25] In column (1), we show that the realized volatility of high-volatility stocks falls relative to low-volatility stocks following good news. Columns (2)-(4) repeat the analysis using three different measures of expected risk. Column (2) shows that analysts' perceived risk of high-volatility firms declines when there is positive news about GDP and corporate profit growth. The same general pattern emerges when we use the percentage of banks loosening lending standards (column 3) and the NFIB Small Business Optimism Index (column 4)

---

[25]The fact that the real GDP surprise does not come in significant in columns (1) and (3) is a product of the multivariate regression. In univariate regressions, it comes in negative and significant.

as our measures of expected risk.

4.2 PVS Forecasts Revisions in Expected Risk

We next examine whether the fluctuations in perceived risk we document are justified by economic fundamentals. In other words, are expectations of risk rational, as assumed in the model in Section 2.1? If expectations of risk over-extrapolate from recent events, as proposed by Keynes (1937) and Minsky (1977), then our results in Section 3 suggest that irrational perceptions of risk amplify business cycle fluctuations.

If expectations are fully rational, two conditions should hold. First, forecast errors – the difference between the realized outcome and forecasted outcome – should be unpredictable. All information available should be incorporated in the time-t expectation, so no information available at time t should correlate with forecast errors. Second, revisions in expectations should be unpredictable because they should only occur in response to purely unpredictable news events (Coibion and Gorodnichenko (2015)). To test these predictions, we construct several different measures of forecast errors and revisions in expectations. We then try to forecast them with PVS_t. For each measure, we first build a firm-level measure and then aggregate up to the portfolio level by taking the median of high-volatility firms minus the median of low-volatility firms. The internet appendix contains more information on the variable construction for this analysis and shows that PVS_t does not forecast expectations of cash flows.

In row (1) of Table 9, we examine expectations of risk based on analyst forecasts. We ask how expectations of the risk of quarterly earnings at quarter $t + 3$ are revised between quarters t and $t + 2$. Row (1) shows that high values of PVS_t forecast an upward revision in expected risk over the next two quarters. Intuitively, when PVS_t is high, analyst expectations of risk are low, and analysts are likely to revise their views of risk upwards. This suggests that there are times when investors underestimate risk and therefore overvalue volatile stocks. Eventually, investors realize their mistake and revise their expectations of risk upward. Conversely, the results suggest that when PVS_t is low, investors overestimate risk, underprice volatile stocks, and eventually revise their expectations of risk downwards.

In row (2), we study revisions to the risk expectations embedded in stock options. We examine

revisions from quarter t to $t+3$ in the expected volatility of stock returns that will be realized between $t+3$ and $t+4$.[26] The forecasting regression shows that a one-standard deviation increase in PVS_t is associated with a revision in future expected risk that is 0.45 standard deviations higher. Thus, like analyst forecasts, option prices suggest that when PVS_t is high and expected risk is low, expected risk tends to be revised upwards. As discussed before, option-implied volatilities contain both investor expectations of risk and volatility risk premia, so the results in row (2) could reflect the ability of PVS_t to forecast changes in future volatility risk premia. However, this would not account for the predictability of analyst-based revisions.[27]

The loan officer survey variable is not associated with a fixed future date, so we cannot construct true revisions in expectations of risk based on it. We can only examine the measure's mean reversion over time. Row (3) shows that the percentage of banks loosening lending standards tends to fall after periods of high PVS_t. In untabulated results, we control for unconditional mean reversion in the survey variable by including its level in the regression, and find that the relationship with PVS_t remains unchanged. In other words, even controlling for its unconditional mean reversion, the percentage of banks loosening lending standards tends to fall after periods of high PVS_t.

Finally, rows (4) and (5) of the table provide an indication of what might cause revisions in expected risk. PVS_t forecasts rising realized volatility for both the aggregate market return and the volatility-sorted portfolio over the subsequent four quarters. In other words, realized risk increases just as investors revise their expectations of risk upwards. The fact that PVS_t forecasts increases in realized risk is consistent with mean reversion in objective risk, as assumed in our model in Section 2.1; however, if expectations of risk were fully rational, investors should anticipate this mean reversion and revisions in risk perceptions should not be predictable. Taken together, the evidence in Table 9 therefore suggests that investors' risk perceptions over-extrapolate from objective variation in risk.

In Table 10, we use options data to examine errors in risk expectations at the firm level. Specif-

---

[26]We infer expectations of volatility using implied option volatilities from OptionsMetrics. By the law of total variance, the implied volatility at time t contains both the time t expectation of volatility at $t+3$ and the time-t variance of expected returns at $t+3$. In the internet appendix, we show PVS_t forecasts revisions in the expectation of volatility, not the variance of expected returns. Ideally, we would use variance swaps, which isolate expectations of future volatility, rather than options, but variance swaps are not broadly available for individual stocks.

[27]Moreover, Dew-Becker et al. (2017) find that, on average, volatility risk is not priced for horizons beyond one quarter. Their evidence therefore suggests that volatility risk premia in options are not a relevant for the 3-4 quarter option maturities we consider.

ically, we define the volatility forecast error as the realized volatility of stock returns between $t+k$ to $t+h$ minus the expected volatility of those returns implied by options prices at quarter t. We then predict these errors using PVS_t and allow the forecasting relationship to vary based on the stock's volatility quintile. Formally, we run:

$$\text{Realized Volatility}_i(t+k,t+h) - \text{IV}_{i,t}(t+k,t+h) = a + b_{PVS} \times PVS_t + \sum_{q=2}^{5} b_{q,pvs} \cdot 1_{it}^q \times PVS_t + \varepsilon_{i,t+h}.$$

where $\text{IV}_{i,t}(t+k,t+h)$ is the implied volatility of firm i's returns from $t+k$ to $t+h$, measured at t.

The table shows that forecast errors are larger when PVS_t is high, particularly for high-volatility stocks. The effect is economically significant. The standard deviation of the one-year forecast error examined in columns (1) and (2) is 19%. A one-standard deviation increase in PVS_t is associated with an increase in the forecast error of 3% for low-volatility stocks and 5-6% for high-volatility stocks. Column (2) shows that we obtain similar results if we include industry-time fixed effects, which purge the regression of any volatility risk premia that are constant within an industry at a given point in time. In columns (3) and (4) we examine forecast errors for the volatility of stock returns between quarters $t+3$ to $t+4$ and find even stronger results. The standard deviation of the forecast error is 27%. A one-standard deviation increase in PVS_t is associated with an increase in the forecast error of 5% for low-volatility stocks and 10-13% for high-volatility stocks. These results are consistent with the idea that investors underestimate risk when PVS_t is high, particularly for volatile stocks.

Taken together, these results on forecast revisions and forecast errors suggest that expectations of risk are not fully rational. Together with our finding that PVS_t is more correlated with subjective than objective measures of risk, the evidence points towards a violation of rational expectations.

4.3   Forecasting Negative Returns

We next examine return forecasts as a complementary way of assessing whether the expectations of risk underlying PVS_t are rational. We study the profitability of strategies that sell put options because their returns depend directly on the accuracy of investors' expectations of risk. Under rational expectations, riskier strategies should always have higher expected returns. Assuming that options on high-volatility stocks are riskier than options on low-volatility stocks, rational investors

should always require higher expected returns for selling puts on high-volatility firms. In contrast, if investors underestimate risk when PVS_t is high, as our previous results suggest, then expected returns to selling puts on high-volatility firms may be lower than returns to selling puts on low-volatility firms at these times.

We compute the returns to selling puts using data from OptionMetrics, following the procedure of Jurek and Stafford (2015). For each firm i and quarter t, this procedure finds the set of out-of-the-money put options with the lowest maturity greater than 182 days. From this set, we then select the put option that is closest-to-the-money and require that the delta of the option is at least -0.4 to account for differences in volatility across firms and time. We sell this option at the best bid price, hold it for one quarter, then buy it at the best offer price.[28] At the portfolio level, we take the equal-weighted average of high-volatility firm returns minus the equal-weighted average of low-volatility firm returns.

Panel A of Figure 4 plots the realized returns to this strategy at time $t+1$ as a function of PVS_t, as well as the fitted value from the forecasting regression and the 95% confidence interval for the fitted value. We label forecast dates with significantly negative expected returns. The figure shows that conditional expected returns were significantly negative in 2000q1 and 2000q2, as indicated by the 95% confidence interval falling below zero. This suggests that when PVS_t is high, investors underestimate risk and therefore charge too little when selling put options on volatile firms.

The option price data is available for a relatively short sample, so there are only two quarters in which we forecast negative expected returns. Reassuringly, Figure 4 Panel B shows that the periods when we forecast negative returns to selling puts on volatile stocks coincide with periods when we forecast negative excess returns to holding volatile stocks themselves. Taken together, the evidence on return predictability suggests that investors sometimes underestimate risk. At these times, volatile stocks are too expensive and puts on volatile stocks are too cheap. Subsequently, investors realize that they under-estimated risk and revise their expectations of risk upward. The prices of volatile stocks then fall, and the prices of puts on volatile stocks rise. Investors underestimate risk enough that during the quarters with the highest values of PVS_t, we forecast significantly negative returns to selling puts on volatile stocks and to holding volatile stocks.

[28]Following Jurek and Stafford (2015), we also assume the put writing strategy is twice levered. Leverage only affects the level of returns, not our return forecasting results. The assumed amount of leverage is well within the Chicago Board Options Exchange (CBOE) margin requirements for single name options.

Figure 4: PVS_t and Negative Returns

Panel A: Returns to Selling Puts on Volatile Stocks

Panel B: Returns on the Volatile Stocks
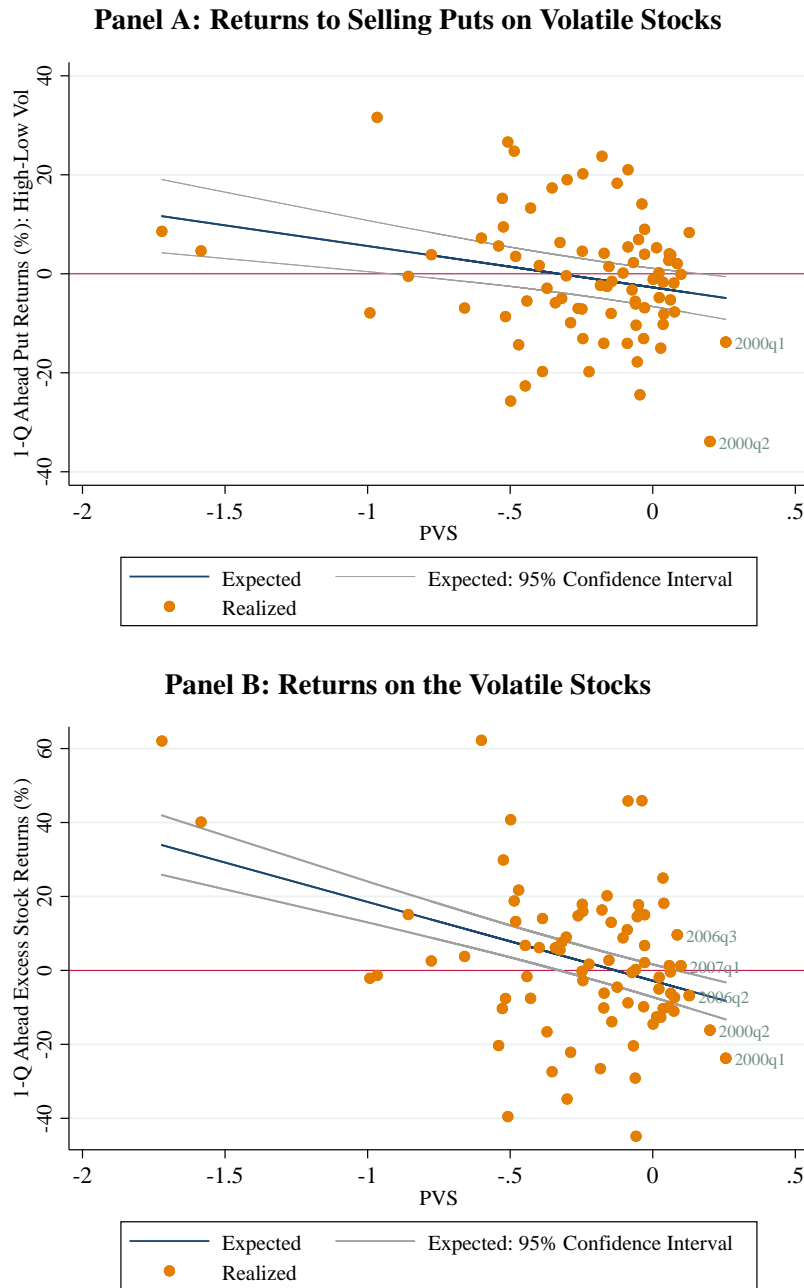
Notes: Both panels of this figure relate PVS_t to future returns. In Panel A, we form a portfolio that sells out-of-the-money put options on high-volatility firms and buys out-of-the-money put options on low-volatility firms. In Panel B, we instead forecast excess returns on high-volatility stocks alone (i.e., not the long-short portfolio underlying PVS_t). In both cases, realized returns are depicted by orange dots in the graph. In addition, we forecast returns at $(t+1)$ with PVS_t at time t and plot the fitted value from the regression in blue. The gray bands are the 95% confidence interval for the fitted value in the regression and are based on Newey-West standard errors with five lags. In instances where the upper bound of the 95% confidence interval is negative – meaning expected returns are negative and statistically significant – we label the realized return with the date of the forecast. PVS_t is the difference between the average book-to-market (BM) ratio of low-volatility stocks and the average BM-ratio of high-volatility stocks. The internet appendix contains details on variable construction. For both panels, data is quarterly and runs from 1996Q1 to 2016Q2.

5 Discussion and Conclusion

We have documented that the data support our model of risk-centric business cycles along multiple dimensions. In particular, we have shown that PVS_t is low when direct measures of perceived risk are high. Further, we have found a negative correlation between the prices of safe bonds and perceived risk, as measured by PVS_t. As in risk-centric theories of the business cycle, this correlation reflects changes in expected returns that occur simultaneously across many asset markets. Moreover, risk perceptions appear to be connected to the macroeconomy in the data. We find risk perceptions, as measured by PVS_t, decrease on the heels of good macroeconomic news, and that a decrease in perceived risk forecasts a boom in output and investment.

However, we have also documented some empirical patterns that our simple motivating model does not capture. First, the model assumes that investors have rational expectations of risk, yet the evidence in Section 4.2 suggests that investors overreact to recent news when forming expectations of future risk. Below we show how to accommodate these findings in the model by loosening the assumption of rational expectations and instead assuming that investors have diagnostic expectations as in Bordalo et al. (2018). Second, the model suggests that the aggregate stock market should have many of the same properties as PVS_t, while empirically the strong comovement between PVS_t, the real rate, and future economic activity distinguishes our measure from the aggregate market. We provide evidence suggesting that PVS_t is a better measure of risk perceptions for the macroeconomy than the aggregate stock market because it better captures private firms, which account for a large fraction of economic activity in the U.S.

5.1 Model with Diagnostic Beliefs

While the model in Section 2.1 features rational expectations, we find that PVS_t forecasts revisions in expected risk. In this section, we augment the model in Section 2.1 with the diagnostic expectations of Gennaioli and Shleifer (2010, 2018); Bordalo et al. (2018) to rationalize this additional evidence.

The key properties of subjective expectations of risk that we are trying to capture are that (i) they fall after good news, and (ii) they fall too far, so that there are predictable upward revisions. We now show that one can account for these features of the data by assuming that investors update

using diagnostic expectations, overweighting states of the world that are representative. Following the assumptions in Gennaioli and Shleifer (2018, Chapter 5), under diagnostic expectations and the subjective perceived time-t conditional mean and variance of ε_{t+1} are:

$$\mathbb{E}_t^\theta\left(\varepsilon_{t+1}\right) = 0, \tag{19}$$

$$\mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right) = \frac{\mathbb{V}_t\left(\varepsilon_{t+1}\right)}{1 + \theta\left(1 - \exp(-b\varepsilon_t)\right)}, \tag{20}$$

where $\mathbb{V}_t\left(\varepsilon_{t+1}\right)$ continues to denote the objective conditional variance.[29] For $\theta > 0$, Eq. (20) implies that investors tend to underestimate macroeconomic risk following a positive ε_t shock and overestimate risk following a negative ε_t shock. In our model, objective risk falls after a positive consumption surprise, but subjective risk falls even more. Thus, diagnostic beliefs capture the over-extrapolation we document in the data.

Assuming that preferences and the firm's problem are the same as in Section 2.1, the equilibrium under diagnostic expectations is characterized by the same equations as before (Eqs. (11), (7), and (13)), simply replacing objective risk $\mathbb{V}_t\left(\varepsilon_{t+1}\right)$ with subjective risk $\mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right)$.[30] Similarly, the comparative statics in Proposition 2 that capture key elements of risk-centric theories have the same signs as before and are amplified by a factor of $(1 + \theta)$. In other words, diagnostic expectations strengthen risk-centric economic fluctuations because investors' expectations of risk overreact to recent news.

Finally, we show that diagnostic expectations lead to predictable revisions in investor expectations of risk. We assume that at the end of period t investors learn the true volatility and revise their beliefs to $\mathbb{V}_t\left(\varepsilon_{t+1}\right) = exp(a - b\varepsilon_t)$. The following proposition gives the relationship between the revision in beliefs and PVS_t^{model}.

---

[29]This result follows from Proposition 1 in Gennaioli and Shleifer (2018, Chapter 5) under the following assumptions: The representativeness of state ε_{t+1} is given by $\frac{h(\varepsilon_{t+1}|\varepsilon_t)}{\bar{h}(\varepsilon_{t+1})}$, where h is the likelihood function and $\bar{h}\left(\varepsilon_{t+1}\right)$ is the reference likelihood. As in Gennaioli and Shleifer (2018, Chapter 6), we assume that agents' reference distribution is the distribution at the state in the absence of news, i.e. $\bar{h}\left(\varepsilon_{t+1}\right) = h(\varepsilon_{t+1}|\varepsilon_t = 0)$. The distorted likelihood h^θ equals $h^\theta\left(\varepsilon_{t+1}|\varepsilon_t\right) = h^\theta\left(\varepsilon_{t+1}|\varepsilon_t\right)\left(\frac{h(\varepsilon_{t+1}|\varepsilon_t)}{\bar{h}(\varepsilon_{t+1})}\right)^\theta Z$, where Z is a constant ensuring that the likelihood of different states integrates up to one. The parameter θ indexes the degree of belief distortion, where $\theta = 0$ corresponds to rational expectations and $\theta > 0$ implies that agents overweight representative states.

[30]To ensure that subjective expected total factor productivity is equalized across firms, we continue to assume that the representative investor perceives firm i's total factor productivity $Z_{i,t+1} = \exp\left(s_i\varepsilon_{t+1} - \frac{1}{2}s_i^2\mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right)\right)$.

Proposition 3: Suppose we have two types of firms H and L with $s_H > s_L > \frac{\lambda}{2}$ and that investors have diagnostic beliefs ($\theta > 0$). In the neighborhood of $\varepsilon_t = 0$, high values of PVS_t^{model} forecast positive revisions in expected risk:

$$\frac{d(\mathbb{V}_t[\varepsilon_{t+1}] - \mathbb{V}_t^{\theta}[\varepsilon_{t+1}])}{dPVS_t^{model}} = \frac{\theta}{1+\theta} \frac{1}{\lambda(s_H - s_L)} > 0.$$

Proposition 3 formalizes the intuition in classical risk-centric accounts of the business cycle that expectations of risk contain an element of overreaction (Keynes (1937), Minsky (1977)). Following a good shock, investors lower their subjective expectations of risk too much, resulting in a value of PVS_t^{model} that is too high. They then predictably revise their beliefs back up, so high values of PVS_t^{model} forecast positive revisions in expectations of risk. Proposition 3 shows that the model with diagnostic expectations can rationalize the finding that PVS_t positively forecasts revisions in expected risk (Table 9) and volatility forecast errors (Table 10). These findings cannot be explained by the rational model with $\theta = 0$. A simple calculation shows that our empirical results imply reasonable magnitudes for the belief distortion parameter, θ. Rows (1) and (4) of Table 2 Panel B suggest that subjective expectations of risk move about twice as much in response to PVS_t as objective expectations, which implies that we need $\theta \approx 1$, in line with the estimates of Bordalo et al. (2018) and Bordalo et al. (2018).

5.2 PVS_t and the Aggregate Stock Market

We have seen that PVS_t comoves more strongly with the real rate and future real investment than the aggregate stock market does. Moreover, in the data PVS_t does not forecast returns on the aggregate market. The empirical disconnect between PVS_t and the aggregate stock market might appear surprising in the light of the model in Section 2.1, where valuations of all firms are driven by the same risk perceptions.

The model and data can be reconciled by noting that private firms are responsible for a substantial portion of aggregate real investment. Private firms make up roughly 50% of aggregate non-residential fixed investment, 70% of private-sector employment, 60% of sales, and 50% of pre-tax profits (Davis et al. (2007); Asker et al. (2014); Zwick and Mahon (2017)). In the internet

41

appendix, we find similar statistics in our data, as the ratio of public firm investment and R&D (measured in Compustat) to aggregate investment is about 50% in our sample.

Crucially, high-volatility public firms appear to be a better proxy for private firms than low-volatility public firms. In Table 11 we show that aggregate investment is significantly more correlated with the investment of high-volatility public firms than with the investment of low-volatility public firms. The correlation of aggregate investment with high-volatility public firms' investment is 79%, while the correlation for low-volatility public firms is only 35%, indicating that the investment of public high-volatility firms is highly correlated with the investment of private firms. In the internet appendix, we show that like private firms, high-volatility public firms are smaller, less profitable, and invest more than low-volatility public firms. Taken together, these results suggest that PVS_t measures risk perceptions relevant for real investments across the economy, not just for the particular set of publicly-listed companies that enter the construction of our variable.

In the language of the model, we can express these results as follows. The aggregate stock market is dominated by large, low-volatility public firms that are relatively safe. For these bond-like firms, we have $s_L \approx \frac{\lambda}{2}$, so low-volatility firms' valuations and investment are relatively insensitive to perceived risk. This implies that the aggregate stock market does not fluctuate much in response to changes in risk perceptions. In contrast, both high-volatility public firms and private firms are relatively risky and have $s_H > \frac{\lambda}{2}$. This has two implications. First, the valuation of high-volatility public firms (i.e., PVS_t) fluctuates strongly in response to changes in perceived risk, making it a good measure of risk perceptions. Second, the investment of both high-volatility public firms and private firms – and hence aggregate macroeconomic investment – is sensitive to perceived risk.

This discussion of the aggregate stock market is also related to our measure of a firm's riskiness. In the model, a firm's risk is captured by its beta with respect to the aggregate stock market, while in the data we construct PVS_t using total stock return volatility to proxy for its risk. We use volatility because it is a robust measure of risk that does not rely on the assumption that the aggregate stock market fully captures all economic activity. Intuitively, volatility increases with exposure to risks, regardless of what they are.

In the model, fluctuations in real investment are driven by expectations of macroeconomic risk. Our empirical approach seeks to measure these expectations using financial market prices, rather than statistical measures of risk derived from the past realization of macroeconomic aggregates for

three reasons. First, financial market prices are the channel through which perceived risk affects real outcomes in risk-centric theories of the business cycle. Second, financial market variables capture the forward looking expectations of investors. Third, macroeconomic quantities are available at lower frequencies, making statistical models of risk necessarily imprecise.

Finally, our analysis emphasizes fluctuations in stock markets, bonds markets, and the real economy, rather than the unconditional properties of prices and economic activity. We do not address longstanding issues in finance like the equity premium puzzle or the low-volatility anomaly.

5.3 Conclusion

This paper proposes a new measure of risk perceptions relevant to the macroeconomy, PVS_t. Our measure is based on the idea that when investors perceive risk to be high, they are only willing to pay low prices for volatile assets. Using PVS_t, we present empirical evidence that supports classic narratives of economic booms and busts emphasizing financial market conditions. Our measure indicates that investors' expectations of risk fall on the heels of positive macroeconomic news. When perceived risk, as measured by PVS_t, is high real risk-free rates are low, the cost of capital for risky firms is high, and real investment is forecast to decline.

Our findings suggest that subjective expectations of risk may not be fully rational. Given the link between risk perceptions and the broader economy, future work measuring the risk perceptions of individual actors in the economy, such as investors or firm managers, and studying how their perceptions of risk affect real economic decisions is likely to be fruitful.

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *Journal of Finance 61*(1), 259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics 91*(1), 1–23.

Asker, J., J. Farre-Mensa, and A. Ljungqvist (2014). Corporate investment and stock market listing: A puzzle? *Review of Financial Studies 28*(2), 342–390.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. *Journal of Finance 68*(3), 929–985.

Bachmann, R., S. Elstner, and E. R. Sims (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics 5*(2), 217–49.

Baker, M. and J. Wurgler (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance 61*(4), 1645–1680.

Baker, M. and J. Wurgler (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives 21*(2), 129–152.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics 131*(4), 1593–1636.

Bansal, R., D. Kiku, A. Yaron, et al. (2012). An empirical evaluation of the long-run risks model for asset prices. *Critical Finance Review 1*(1), 183–221.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance 59*(4), 1481–1509.

Barberis, N. and R. Thaler (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, and R. M. Stulz (Eds.), *Financial Markets and Asset Pricing*, Volume 1 of *Handbook of the Economics of Finance*, pp. 1053–1128. Elsevier.

Basu, S. and B. Bundick (2017). Uncertainty shocks in a model of effective demand. *Econometrica 85*(3), 937–958.

Bernanke, B. S. and K. N. Kuttner (2005). What explains the stock market's reaction to federal reserve policy? *Journal of Finance 60*(3), 1221–1257.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*(3), 623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–76.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *Review of Financial Studies 22*(11), 4463–4492.

Bordalo, P., N. Gennaioli, R. La Porta, and A. Shleifer (2018). Diagnostic expectations and stock returns. *Journal of Finance*, forthcoming.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic expectations and credit cycles. *Journal of Finance 73*(1), 199–227.

Brainard, W. (1967). Uncertainty and the effectiveness of policy. *American Economic Review 57*, 411–425.

Caballero, R. J. (1999). Aggregate investment. *Handbook of macroeconomics 1*, 813–862.

Caballero, R. J. and E. Farhi (2018). The safety trap. *Review of Economic Studies 85*(1), 223–274.

Caballero, R. J. and A. Simsek (2018). A risk-centric model of demand recessions and macroprudential policy. NBER Working paper 23614.

Campbell, J. (2017). *Financial Decisions and Markets: A Course in Asset Pricing*. Princeton University Press.

Campbell, J. Y. and J. Ammer (1993). What moves the stock and bond markets? A variance decomposition for long-term asset returns. *Journal of Finance 48*(1), 3–37.

Campbell, J. Y. and J. H. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy 107*(2), 205–251.

Campbell, J. Y. and R. J. Shiller (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies 1*(3), 195–228.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). Monetary policy shocks: What have we learned and to what end? In J. B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, Volume 1, pp. 65–148. Elsevier.

Cieslak, A. and A. Vissing-Jorgensen (2018). The economics of the Fed put. Technical report, Duke University and University of California at Berkeley.

Clarida, R., J. Galí, and M. Gertler (1999). The science of monetary policy: A New Keynesian perspective. *Journal of Economic Literature 37*(4), 1661–1707.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance 46*(1), 209–237.

Cochrane, J. H. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy 104*(3), 572–621.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance 66*(4), 1047–1108.

Cochrane, J. H. (2017). Macro-finance. *Review of Finance 21*(3), 945–985.

Cochrane, J. H. and M. Piazzesi (2005). Bond risk premia. *American Economic Review 95*(1), 138–160.

Cohen, R. B., C. Polk, and T. Vuolteenaho (2005). Money illusion in the stock market: The Modigliani-Cohn hypothesis. *Quarterly Journal of Economics 120*(2), 639–668.

Coibion, O. and Y. Gorodnichenko (2012). Why are target interest rate changes so persistent? *American Economic Journal: Macroeconomics 4*, 126–162.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–2678.

Cúrdia, V., A. Ferrero, G. C. Ng, and A. Tambalotti (2015). Has US monetary policy tracked the efficient interest rate? *Journal of Monetary Economics 70*, 72–83.

Davidson, R. and J. MacKinnon (1993). *Estimation and Inferences in Econometrics*. Oxford University Press.

Davis, J. L., E. F. Fama, and K. R. French (2000). Characteristics, covariances, and average returns: 1929 to 1997. *Journal of Finance 55*(1), 389–406.

Davis, S. J., J. Haltiwanger, R. Jarmin, J. Miranda, C. Foote, and E. Nagypal (2007). Volatility and dispersion in business growth rates: Publicly traded versus privately held firms. *NBER macroeconomics annual 21*, 107–180.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann (1990). Noise trader risk in financial markets. *Journal of Political Economy 98*(4), 703–738.

Del Negro, M., D. Giannone, M. P. Giannoni, and A. Tambalotti (2017). Safety, liquidity, and the natural rate of interest. *Brookings Papers on Economic Activity 2017*(1), 235–316.

Dew-Becker, I., S. Giglio, A. Le, and M. Rodriguez (2017). The price of variance risk. *Journal of Financial Economics 123*(2), 225 – 250.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *Journal of Finance 57*(5), 2113–2141.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2015). Fiscal volatility shocks and economic activity. *American Economic Review 105*(11), 3352–84.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Gârleanu, N., L. H. Pedersen, and A. M. Poteshman (2009). Demand-based option pricing. *Review of Financial Studies 22*(10), 4259–4299.

Gennaioli, N., Y. Ma, and A. Shleifer (2015). Expectations and investment. In M. Eichenbaum and J. A. Parker (Eds.), *NBER Macroeconomics Annual*, Volume 30.

Gennaioli, N. and A. Shleifer (2010). What comes to mind. *Quarterly Journal of Economics 125*, 1399–1433.

Gennaioli, N. and A. Shleifer (2018). *A Crisis of Beliefs: Investor Psychology and Financial Fragility*. Princeton University Press.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American Economic Review 102*(4), 1692–1720.

Gorodnichenko, Y. and M. Weber (2016). Are sticky prices costly? Evidence from the stock market. *American Economic Review 106*(1), 165–199.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review 102*(6), 2734–66.

Greenwood, R. and S. G. Hanson (2013). Issuer quality and corporate bond returns. *Review of Financial Studies 26*(6), 1483–1525.

Harrison, J. M. and D. Kreps (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *Quarterly Journal of Economics 92*(2), 323–336.

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica*, 213–224.

He, Z., B. Kelly, and A. Manela (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics 126*(1), 1–35.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuwerburgh (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics 119*(2), 249–283.

Hodrick, R. (1992). Common risk factors in currency markets. *Review of Financial Studies 5*(3), 357–386.

Jermann, U. J. (1998). Asset pricing in production economies. *Journal of Monetary Economics 41*(2), 257–275.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Jurek, J. W. and E. Stafford (2015). The cost of capital for alternative investments. *Journal of Finance 70*(5), 2185–2226.

Kandel, S. and R. F. Stambaugh (1990). Expectations and volatility of consumption and asset returns. *Review of Financial Studies 3*(2), 207–232.

Kang, J. and C. E. Pflueger (2015). Inflation risk in corporate bonds. *Journal of Finance 70*(1), 115–162.

Kelly, B. and S. Pruitt (2013). Market expectations in the cross-section of present values. *Journal of Finance 68*(5), 1721–1756.

Keynes, J. M. (1937). The general theory of employment. *Quarterly Journal of Economics 51*(2), 209–223.

Kindleberger, C. P. (1978). *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Basic Books.

Kogan, L. and D. Papanikolaou (2012). Economic activity of firms and asset prices. *Annual Review of Financial Economics 4*(1), 361–384.

Koijen, R. S., H. Lustig, and S. Van Nieuwerburgh (2017). The cross-section and time-series of stock and bond returns. *Journal of Monetary Economics 88*, 50–69.

Kozlowski, J., L. Veldkamp, and V. Venkateswaran (2018a). The tail that keeps the riskless rate low. In M. Eichenbaum and J. A. Parker (Eds.), *NBER Macroeconomics Annual*, Volume 33.

Kozlowski, J., L. Veldkamp, and V. Venkateswaran (2018b). The tail that wags the economy: Beliefs and persistent stagnation. NBER Working paper 21719.

Krishnamurthy, A. (2002). The bond/old-bond spread. *Journal of Financial Economics 66*(2), 463–506.

Laubach, T. and J. C. Williams (2003). Measuring the natural rate of interest. *Review of Economics and Statistics 85*(4), 1063–1070.

Lettau, M. and J. A. Wachter (2011). The term structures of equity and interest rates. *Journal of Financial Economics 101*(1), 90–113.

Liu, L. X., T. M. Whited, and L. Zhang (2009). Investment-based expected stock returns. *Journal of Political Economy 117*(6), 1105–1139.

López-Salido, D., J. C. Stein, and E. Zakrajšek (2017). Credit-market sentiment and the business cycle. *Quarterly Journal of Economics 132*(3), 1373–1426.

Mian, A., A. Sufi, and E. Verner (2017). Household debt and business cycles world wide. *Quarterly Journal of Economics 132*(4), 1755–1817.

Minsky, H. P. (1977). The financial instability hypothesis: An interpretation of keynes and an alternative to "standard" theory. *Nebraska Journal of Economics and Business 16*(1), 5–16.

Modigliani, F. and R. A. Cohn (1979). Inflation, rational valuation and the market. *Financial Analysts Journal 35*(2), 24–44.

Nakamura, E., D. Sergeyev, and J. Steinsson (2017). Growth-rate and uncertainty shocks in consumption: Cross-country evidence. *American Economic Journal: Macroeconomics 9*(1), 1–39.

Nakamura, E. and J. Steinsson (2018). High frequency identification of monetary non-neutrality: The information effect. *Quarterly Journal of Economics 133*(3), 1283–1330.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Polk, C., S. Thompson, and T. Vuolteenaho (2006). Cross-sectional forecasts of the equity premium. *Journal of Financial Economics 81*(1), 101–141.

Romer, C. D. and D. H. Romer (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review 94*(4), 1055–1084.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of Political Economy 111*(6), 1183–1220.

Stambaugh, R. F., J. Yu, and Y. Yuan (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance 70*(5), 1903–1948.

Stein, J. C. and A. Sunderam (2018). The Fed, the bond market, and gradualism in monetary policy. *Journal of Finance 73*(3), 1015–1060.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy 39*, 195–214.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking 1*(1), 15–29.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *Journal of Finance 57*(1), 233–264.

Weber, M. (2016). Cash flow duration and the term structure of equity returns. Working paper, University of Chicago.

Woodford, M. (2003). Optimal interest-rate smoothing. *Review of Economic Studies 70*(4), 861–886.

Zhang, L. (2005). The value premium. *Journal of Finance 60*(1), 67–103.

Zwick, E. and J. Mahon (2017). Tax policy and heterogeneous investment behavior. *American Economic Review 107*(1), 217–48.

TABLES

Table 1: Summary Statistics for Volatility-Sorted Portfolios and the Real Rate

Panel A*: Book-to-Market Ratios of Volatility Sorted Portfolios*

| | High Volatility → Low Volatility | | | | | PVS |
	5	4	3	2	1	1-5
Mean	1.04	0.87	0.83	0.82	0.86	-0.18
Std Dev	0.45	0.31	0.26	0.25	0.28	0.37
Min	0.45	0.48	0.48	0.51	0.54	-1.72
Median	0.92	0.78	0.78	0.74	0.75	-0.12
Max	3.10	2.13	1.80	1.71	1.70	0.63

Panel B*: Realized Excess Returns of Volatility Sorted Portfolios*

	5	4	3	2	1	1-5
Mean	7.44	9.65	12.04	11.15	10.15	2.71
Std Dev	39.17	31.19	25.07	19.99	15.42	29.57
Median	-0.11	6.83	12.07	13.13	12.60	9.47
Min	-44.87	-37.31	-31.72	-29.25	-22.28	-49.51
Max	74.19	55.22	45.14	35.82	27.32	50.48

Panel C*: Real Rate*

	Mean	Volatility	Median	Min	Max
Raw Real Rate	1.86	2.30	2.18	-1.86	8.72
Detrended Real Rate	0.00	1.96	-0.21	-4.62	5.81

Notes: This table presents summary statistics for portfolios formed on volatility. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Panel A shows summary statistics on the average book-to-market (BM) ratio within each quintile. The internet appendix contains details on variable construction. Panel B displays summary statistics on the realized excess returns of each quintile (in percentage terms). The mean, volatility, and median returns are all annualized. Data is quarterly and runs from 1970Q2 through 2016Q2. The riskless rate for computing excess returns and quarterly returns on the Fama and French (1993) factors are aggregated using monthly data from Ken French's website. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points. We detrend the real rate using a linear trend. We explore alternative de-trending methodologies in the internet appendix.

Table 2: PVS and Perceptions of Risk

	X-variable	$PVS_t = a + b \times X_t$				$PVS_t = a + b \times X_t + c \times \mathbb{E}_t\,[\text{LTG}]$			
		N	b	$t(b)$	R^2	N	b	$t(b)$	R^2
	High-Minus-Low Volatility Stocks:								
(1)	Analyst $\sigma_t\,(\text{EPS}_{t+5})$	110	-0.67	-5.06	0.61	110	-0.63	-5.08	0.61
(2)	Analyst $\sigma_t\,(\text{EPS}_{t+1})$	110	-0.45	-2.49	0.28	110	-0.38	-2.24	0.29
(3)	Option-Implied $\sigma_t^{IV}\,(Ret_{t,t+4})$	80	-0.47	-2.53	0.24	80	-0.70	-5.75	0.62
(4)	Objective $\sigma_t\,(Ret_{t,t+1})$	184	-0.31	-2.13	0.09	109	-0.38	-2.52	0.34
(5)	All-Firms: Analyst $\sigma_t\,(\text{EPS}_{t+5})$	110	-0.71	-8.27	0.70	110	-0.77	-8.60	0.70
(6)	% Banks Loosening	105	0.50	3.46	0.32	105	0.55	5.16	0.56
(7)	% Banks Loosening b/c of Outlook	90	0.48	2.51	0.27	90	0.61	4.65	0.56
(8)	Small Business Optimism	170	0.49	2.84	0.22	110	0.54	3.57	0.41
(9)	Baker et al. (2016) Policy Uncertainty	126	-0.41	-3.49	0.23	110	-0.39	-3.35	0.34

Notes: This table shows contemporaneous regressions of PVS_t on measures of investor risk perceptions. For each firm i and date t, we proxy for the time-t expected volatility of earnings-per-share (EPS) at time $t+h$, denoted $\sigma_{it}(\text{EPS}_{t+h})$, using the range of analyst EPS forecasts divided by the absolute value of the median analyst EPS forecast. At the portfolio level, $\sigma_t(\text{EPS}_{t+h})$ is the cross-sectional median for high-volatility stocks minus the median for low-volatility stocks, where stocks are designated as high or low volatility at time t based on their past 60 days of realized returns. When building $\sigma_t(\text{EPS}_{t+5})$ for row (1), we choose for each (i,t) the shortest forecast horizon h such that the EPS forecast is at least two fiscal periods away. In calendar time this is generally between five and six quarters from date t, i.e. $h \approx 5$. For this horizon, we use annual EPS forecasts. $\sigma_t(\text{EPS}_{t+1})$ in row (2) is built using one-quarter ahead quarterly EPS forecasts. The variable Option-Implied $\sigma_t^{IV}\,(Ret_{t,t+4})$ in row (3) is the median at-the-money one-year implied volatility of high-volatility firms minus the median for low-volatility firms. Options data comes from OptionsMetrics. In row (4), we use a statistical model to forecast the average volatility of high-volatility stocks minus low-volatility stocks. Denote the average realized quarterly volatility of high-volatility firms at time t by $rv_{H,t}$ and the same quantity for low-volatility firms by $rv_{L,t}$. We fit an AR(1) model to $rv_{H,t} - rv_{L,t}$ and use the time-t expectation of $rv_{H,t+1} - rv_{L,t+1}$ from the AR(1) model to form Objective $\sigma_t(Ret_{t,t+1})$. Row (5) is based on the analyst dispersion measure from row (2), but we average across all of the volatility-sorted portfolios instead of taking the difference in analyst dispersion between high- and low-volatility firms. Row (6) uses the net percent of U.S. banks loosening lending standards and row (7) uses the net percent of U.S. banks loosening lending standards because "more favorable or less uncertain conditions", both taken from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS). Row (8) uses the NFIB Small Business Optimism index. Row (9) uses the Baker et al. (2016) economic policy uncertainty index, which draws on newspapers, temporary tax measures, and economic forecaster disagreement. PVS_t is the average book-to-market ratio of low-minus-high- volatility stocks. The first set of regressions in the table are univariate regressions of PVS_t on the measures of expected risk. In the second set of regressions, we include IBES analyst expectations of long-term growth for the high-minus-low volatility portfolio ($\mathbb{E}_t[\text{LTG}]$), as described in Table A.11 of the Internet Appendix. t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and sample periods depend on data availability, though the full sample for PVS_t spans 1970Q2 to 2016Q2. All variables are standardized to have a mean of zero and variance one. See the internet appendix for more details on variable construction.

Table 3: The Real Rate and PVS

Dep. Variable:				One-Year Real Rate				
		Levels				First-Differences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PVS	1.27**	1.27**		1.26**	0.39**	0.43**		0.37**
	(5.36)	(5.01)		(4.99)	(2.73)	(2.65)		(2.36)
BM Low-Vol			0.84**				0.12*	
			(3.11)				(1.80)	
BM High-Vol			-1.55**				-0.41**	
			(-5.39)				(-2.70)	
Aggregate BM		-0.17		-0.06		0.08		0.13
		(-0.71)		(-0.18)		(0.88)		(1.16)
Output Gap				0.02				0.36**
				(0.24)				(2.53)
Inflation				-0.10				0.22
				(-0.75)				(1.16)
Constant	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(-0.19)	(-0.18)	(-0.19)	(-0.33)
Adj. R^2	0.41	0.41	0.42	0.41	0.13	0.12	0.13	0.19
N	185	185	185	185	184	184	184	184

Notes: This table reports regression estimates of the one-year real rate on PVS_t. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Within each quintile, we compute the average book-to-market (BM) ratio. PVS_t is defined as the difference in BM ratios between the bottom and top quintile portfolios. Aggregate BM is computed by summing book equity values across all firms and dividing by the corresponding sum of market equity values. Aggregate BM and PVS_t are standardized to have mean zero and variance one, where we standardize separately for the levels and first differences regressions. The internet appendix contains full details on variable construction. The output gap is the percentage deviation of real GDP from the CBO's estimate of potential real GDP. Inflation is the annualized four quarter percentage growth in the GDP price deflator from the St. Louis Fed (GDPDEF). The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. We also independently detrend the output gap, inflation, and the aggregate book-to-market ratio. Results using the raw series for all variables are contained in the internet appendix. t-statistics are listed below each point estimate in parentheses and are computed using Newey-West (1987) standard errors with five lags. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2.

Table 4: Robustness: The Real Rate and PVS

Panel A: *Alternative Constructions and Other Stock Characteristics*

| | | Levels | | | | | | First-Differences | | | | | |
| | | Full | | | Pre-Crisis | | | Full | | | Pre-Crisis | | |
		b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2
(1)	Baseline	1.27	**5.01**	0.42	1.51	**7.61**	0.47	0.43	**2.65**	0.13	0.63	**3.67**	0.20
Alternative Constructions:													
(2)	Value-Weight	1.12	**4.48**	0.32	1.42	**6.01**	0.41	0.31	**2.45**	0.08	0.40	**2.59**	0.10
(3)	2-Yr Volatility	1.42	**6.27**	0.52	1.62	**8.20**	0.54	0.26	**2.32**	0.05	0.43	**4.21**	0.10
Horse-Races:													
(4)	Liquidity	1.40	**6.54**	0.47	1.58	**7.73**	0.51	0.36	**2.14**	0.15	0.56	**3.02**	0.21
(5)	Duration	1.19	**4.26**	0.42	1.33	**5.24**	0.49	0.43	**3.13**	0.12	0.61	**4.31**	0.20
(6)	Leverage	1.51	**6.15**	0.44	1.66	**7.57**	0.48	0.57	**2.87**	0.14	0.74	**3.34**	0.21
(7)	CAPM Beta	1.27	**5.50**	0.41	1.48	**7.73**	0.48	0.31	**2.55**	0.15	0.50	**4.35**	0.22
(8)	Size	1.12	**2.48**	0.42	1.47	**3.80**	0.47	0.61	**2.42**	0.13	0.74	**2.59**	0.20
(9)	Value	1.53	**4.97**	0.43	1.73	**7.03**	0.48	0.69	**3.05**	0.16	0.80	**3.24**	0.22

Notes: This table reports a battery of robustness exercises for the relationship between PVS_t and the real rate documented in Table 3. Specifically, we report time-series regression results of the following form: Real Rate$_t = a + b \times PVS_t + \theta X_t + \varepsilon_t$, where PVS_t is the average book-to-market ratio of low-minus-high volatility stocks. We run this regression in levels and in first differences and, in each case, we standardize PVS_t (or its first-difference) to have a mean of zero and variance of one over the full sample. X_t is a one of several control variables. For all specifications, the table reports the estimated coefficient on PVS_t. Row (1) repeats our baseline result from Table 3, columns (2) and (6). Row (2) uses value weights instead of equal weights when forming PVS_t. Row (3) constructs PVS_t using the past two years of return volatility, as opposed to the past two months. In rows (4)-(9), we run horse races of PVS_t against several other variables. Row (4) controls for the spread between off-the-run and on-the-run Treasury yields (Krishnamurthy (2002)). In rows (5)-(9), we control for the book-to-market spread based on other characteristic sorts. The CAPM beta is based daily stock returns over a rolling two-month window. See the internet appendix for a description of each characteristic, details on variable construction, and alternative CAPM betas. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percent and linearly detrended. The listed *t*-statistics are computed using Newey-West (1987) standard errors with five lags. Italic point estimates indicates a *p*-value of less than 0.1 and bold indicates a *p*-value of less than 0.05. Data is quarterly and the full sample spans 1970Q2-2016Q2, while the pre-crisis sample ends in 2008Q4.

Table 4: Robustness: The Real Rate and PVS

Panel B*: Other Measures of Financial Conditions*

	Z-variable	N	$PVS_t = a + b \times Z_t$			$\text{RealRate}_t = a + c \times Z_t$			$\text{RealRate}_t = a + c \times Z_t + d \times PVS_t$		
			b	$t(b)$	R^2	c	$t(c)$	R^2	d	$t(d)$	R^2
(1)	BAA-10Y Spread	185	-0.43	-3.32	0.18	-0.60	-2.77	0.09	1.24	5.08	0.41
(2)	GZ Spread	151	-0.53	-4.12	0.23	-0.33	-1.53	0.02	1.40	6.15	0.48
(3)	Credit Sentiment	133	0.35	3.21	0.15	0.16	0.78	0.00	1.16	4.47	0.35
(4)	Equity Sentiment	182	0.49	3.47	0.24	1.21	6.33	0.37	0.89	3.97	0.52
(5)	$\mathbb{E}_t\left[\text{Mkt-Rf}_{t,t+4}\right]$	180	-0.27	-1.26	0.06	-0.20	-0.62	0.00	1.30	6.04	0.41
(6)	Policy Uncertainty	126	-0.41	-3.49	0.23	-0.85	-6.54	0.30	0.60	2.75	0.38

Notes: This table compares other measures of financial conditions and market sentiment to PVS_t, the average book-to-market ratio of low-minus-high volatility stocks. The first set of results shows univariate regressions of PVS_t on each alternative financial market measure. The second set of results shows univariate regressions of the real rate on each alternative measure of financial market conditions. The last set of results regresses the real rate on both PVS_t and each alternative measure. In rows (1)-(4), the alternative variables are the spread between Moody's BAA corporate bond yields and the 10-year Treasury yield, the credit spread index from Gilchrist and Zakrajšek (2012), credit market sentiment from Greenwood and Hanson (2013) (four-quarter moving average), and equity market sentiment (orthogonalized) from Baker and Wurgler (2006), respectively. In row (5), we use the procedure in Kelly and Pruitt (2013) to form a statistically optimal linear forecast of one-year ahead excess stock market returns. Row (6) uses the Baker et al. (2016) economic policy uncertainty index. The listed *t*-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and the sample spans 1970Q2-2016Q2. See the internet appendix for details on variable construction. In all regressions, we standardized both PVS_t and the other measures of financial market conditions to have mean zero and variance one. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended.

Table 5: Volatility-Sorted Returns and Monetary Policy Surprises

$$\text{Low-High Vol Ret}_{t \to t+1} = a + b \times \text{MP Shock}_{t \to t+1} + \varepsilon_{t \to t+1}$$

MP Shock	Quarterly Data		Daily Data		Sample	
	b	$t(b)$	b	$t(b)$	Start	End
Romer and Romer (2004)	0.71	0.44	0.27	0.77	1970.Q1	1996.Q4
Bernanke and Kuttner (2005)	-1.65	-0.07	-1.08	-0.49	1989.Q2	2008.Q2
Gorodnichenko and Weber (2016)	1.60	0.03	3.67	0.94	1994.Q1	2009.Q4
Nakamura and Steinsson (2018)	12.83	0.20	5.29	1.03	1995.Q1	2014.Q1

Notes: This table reports regressions of volatility-sorted returns onto monetary policy shocks. Volatility-sorted returns are returns on the lowest minus highest volatility quintile portfolios. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Quarterly return regressions aggregate daily monetary policy shocks by summing over all shocks within a quarter. The Romer and Romer (2004) shock is the change in the intended federal funds rate inferred from narrative records around monetary policy meetings, after controlling for changes in the Federal Reserve's information. The Bernanke and Kuttner (2005) shock is derived from the price change in federal funds future contracts relative to the day before the policy action. The Gorodnichenko and Weber (2016) shock is derived from the price change in federal funds futures from 10 minutes before to 20 minutes after a FOMC press release. The Nakamura and Steinsson (2018) shock is the unanticipated change in the first principal component of interest rates with maturity up to one year from 10 minutes before to 20 minutes after a FOMC news announcement. Starting in 1994, we consider only policy changes that occurred at regularly scheduled FOMC meetings. Prior to 1994, policy changes were not announced after meetings so the distinction between scheduled and unscheduled meetings is not material. In the internet appendix, we repeat the analysis for all policy changes. The listed *t*-statistics are computed using Davidson and MacKinnon (1993) standard errors for heteroskedasticity in small samples.

Table 6: PVS_t, the Real Rate, and Future Returns to Volatile Assets

Panel A: *Forecasting Returns and Cash Flows*

| | Volatility-Sorted Portfolio (Low-High) | | | | | |
| | $Ret_{t\to t+4}$ | | $ROE_{t\to t+4}$ | | $VW\text{-}Mkt - Rf_{t\to t+4}$ | |
	(1)	(2)	(3)	(4)	(5)	(6)
PVS_t	15.08**		-1.35		-2.31	
	(4.11)		(-1.40)		(-0.90)	
Real Rate$_t$		4.13**		0.48		0.03
		(2.13)		(0.96)		(0.03)
Constant	2.41	2.49	10.95**	10.93**	6.98**	6.95**
	(0.60)	(0.59)	(8.31)	(8.29)	(2.74)	(2.73)
Adj. R^2	0.26	0.07	0.02	0.01	0.01	-0.01
N	181	181	181	181	181	181

Notes: This table reports several return forecasting regressions where the predictor variables are either the real interest rate or PVS_t, the average book-to-market ratio of low-minus-high volatility stocks. We standardize PVS_t to have mean zero and variance one for the full sample. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. The columns listed under "Volatility-Sorted Portfolio (Low-High)" pertain to an equal-weighted portfolio that is long low-volatility stocks and short high-volatility stocks. $Ret_{t\to t+4}$ is the realized stock market return between t and $t+4$ for the low-minus-high volatility portfolio. $ROE_{t\to t+4}$ is the accounting return on equity between t and $t+4$ for the low-minus-high volatility portfolio, which we compute following Cohen, Polk, and Vuolteenaho (2003). $VW\text{-}Mkt - Rf$ is the excess return of the CRSP Value-Weighted index obtained from Ken French's website. t-statistics are listed below point estimates in parentheses. We use Hodrick (1992) standard errors. * indicates a p-value of less than 0.1, and ** indicates a p-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2. All returns are expressed in percentage points.

Table 6: PVS_t, the Real Rate, and Future Returns to Volatile Assets

Panel B: *Evidence from Other Asset Classes*

| Asset Class | N | Mean | Volatility | Forecasting Low-High Vol Ret$_{t\to t+1}$ with | | | | | |
| | | | | PVS_t | | | Real Rate$_t$ | | |
				b	$t(b)$	R^2	b	$t(b)$	R^2
U.S. Stocks	184	2.7	29.6	5.30	5.07	0.12	1.57	2.81	0.04
U.S. Corporate Bonds	136	-3.1	8.9	2.37	3.39	0.27	0.51	1.88	0.03
Sovereign Bonds	50	-10.9	19.5	2.89	1.81	0.09	0.46	0.60	-0.02
Options	88	-16.0	17.8	1.94	2.41	0.03	1.07	1.89	0.02
CDS	31	-7.0	6.4	1.78	4.44	0.48	0.77	2.45	0.11
Commodities	89	10.3	35.4	1.24	0.51	-0.01	-0.34	-0.26	-0.01
FX	120	1.2	10.8	-0.22	-0.65	-0.01	-0.57	-1.49	0.02

Notes: This table reports summary statistics and forecasting results for portfolios sorted on volatility in other asset classes. For U.S. stocks, the low-minus-high vol return is defined as in Panel A. For other asset classes, we use the portfolios in He et al. (2017) as test assets. Within each asset class and in each quarter, we sort the test portfolios based on their trailing 5-year monthly volatility. We then form a new portfolio that is long the lowest-volatility portfolio and short the highest-volatility portfolio within each asset class. For U.S. stocks, we use our own low-minus-high volatility portfolio based on all CRSP stocks. The reported mean and the volatility are annualized and in percentage terms. The columns under "Forecasting Low-High Vol Ret$_{t\to t+1}$" report the point estimate, *t*-statistic, and adjusted R^2 from forecasting one-quarter ahead returns on the low-minus-high volatility trade within each asset class using PVS_t or Real Rate$_t$. *t*-statistics are based on Newey-West (1987) standard errors with two lags. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. PVS_t is the average book-to-market ratio of low-minus-high volatility stocks. We standardize PVS_t to have mean zero and variance one for our full sample (1970Q2-2016Q2). Quarterly return data from He et al. (2017) ends in 2012 and data availability varies with asset class. All returns are expressed in percentage points.

Table 7: PVS and Real Outcomes

	Investment-to-Capital				Output Gap				ΔUnemployment Rate			
	$h=1$		$h=4$		$h=1$		$h=4$		$h=1$		$h=4$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PVS_t	0.22**		0.35**		0.32**		0.66**		-0.11**		-0.27	
	(4.66)		(3.56)		(3.27)		(2.35)		(-3.17)		(-1.36)	
Agg. B/M$_t$		-0.09		-0.16		-0.22**		-0.68**		0.02		-0.07
		(-1.59)		(-1.53)		(-2.17)		(-2.40)		(0.85)		(-0.57)

Notes: This table reports the results of running Jordà (2005) local projections of macroeconomic outcomes onto either PVS_t or the aggregate book-to-market ratio. In all cases, we run regressions of the following form:

$$y_{t+h} = a + b_X^h \times X_t + b_{RR}^h \times \text{Real Rate}_t + b_y^h \times y_t + \varepsilon_{t+h}$$

where X_t is either PVS_t or the aggregate book-to-market ratio (Agg B/M). The table reports the estimation results for b_X^h. PVS_t is the average book-to-market ratio of low-minus-high volatility stocks and is standardized to have a mean of zero and variance of one. The aggregate book-to-market ratio is linearly detrended, then standardized to have a mean zero and variance one. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. We consider three different macroeconomic outcomes for the *y*-variable. The first is the investment-capital ratio, defined as the level of real private nonresidential fixed investment (PNFI) divided by the previous year's current-cost net stock of fixed private nonresidential assets (K1NTOTL1ES000). The second is the real output gap, defined as the percent deviation of real GDP from real potential output. Lastly, we consider is the change in the U.S. unemployment rate. When forecasting the investment-capital ratio, y_{t+h} is the level of the investment-capital ratio at time $t+h$. For the output gap, y_{t+h} is the level of the output gap at time $t+h$. Finally, for the unemployment rate, y_{t+h} is the change in the unemployment rate between t and $t+h$, and y_t is the change between $t-1$ and t. All macroeconomic variables come from the St. Louis FRED database and are expressed in percentage points. *t*-statistics are listed below each point estimate in parentheses and are computed using Newey-West standard errors with five lags. * indicates a *p*-value of less than 0.1 and ** indicates a *p*-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2.

Table 8: What occurs in the rest of the economy during the build up of PVS?

Panel A: *PVS and Good News*

Dependent Variable			$\Delta_4 PVS_t$		
	(1)	(2)	(3)	(4)	(5)
Real GDP Surprise$_{t-4\to t}$	0.56**				0.24**
	(3.86)				(2.68)
Corporate Profit Surprise$_{t-4\to t}$		0.43**			0.23**
		(4.39)			(2.42)
LMH-Vol ROE$_{t-4\to t}$			-0.27**		-0.19**
			(-3.21)		(-3.89)
Δ_4Bank Net Chargeoffs$_t$				-0.61**	-0.45**
				(-5.12)	(-8.11)
Adj. R^2	0.31	0.17	0.07	0.38	0.56
N	181	181	181	158	158

Notes: This table reports univariate regressions of four-quarter changes in PVS_t on: (1) the surprise in real GDP growth, defined as realized real GDP growth from time $t-4$ to t minus the expected annual growth forecast at time $t-4$ made by the Survey of Professional Forecasters; (2) the surprise in corporate profit growth, defined as realized corporate profit growth from time $t-4$ to t, taken from U.S. Burueau of Economic Analysis NIPA tables, minus the expected annual growth forecast at time $t-4$ made by the Survey of Professional Forecasters; (3) the trailing annual ROE of the low-minus-high volatility portfolio; and (4) the four-quarter change in bank net chargeoff rate, taken from bank call reports. PVS_t is the average book-to-market ratio of low-minus-high- volatility stocks. The operator $\Delta_4 Z_t$ denotes Z_t - Z_{t-4} for variable Z. In each regression, we include a constant and standardize all variables to have mean zero and variance one. In all cases, t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and depends on data availability, though the full sample for PVS_t spans 1970Q2 to 2016Q2. See the internet appendix for more details on variable construction.

Table 8: What occurs in the rest of the economy during the build up of PVS?

Panel B: *Realized Risk, Expected Risk, and Good News*

Dependent Variable	Δ_4HML-Realized Vol	$\Delta_4\sigma_t$ (EPS$_{t+5}$)	Δ_4(% Banks Loose)	Δ_4Small Business Opt.
	(1)	(2)	(3)	(4)
Real GDP Surprise$_{t-4\rightarrow t}$	-0.12	-0.38**	-0.03	0.36**
	(-1.23)	(-3.00)	(-0.21)	(3.28)
Corporate Profit Surprise$_{t-4\rightarrow t}$	-0.44**	-0.14**	0.54**	0.16*
	(-3.28)	(-2.06)	(4.99)	(1.85)
LMH-Vol ROE$_{t-4\rightarrow t}$	-0.05	0.04	0.14**	0.06
	(-0.51)	(0.55)	(2.03)	(0.79)
Δ_4Bank Net Chargeoffs$_t$	0.27**	0.31**	-0.23**	-0.17**
	(3.17)	(3.82)	(-3.00)	(-2.80)
Adj. R^2	0.34	0.43	0.47	0.27
N	158	106	101	158

Notes: This table reports univariate regressions of four-quarter changes of various measures of realized and expected risk on: (1) the surprise in real GDP growth, defined as realized real GDP growth from time $t-4$ to t minus the expected annual growth forecast at time $t-4$ made by the Survey of Professional Forecasters; (2) the four-quarter change in analysts' expected risk for high-volatility versus low-volatility firms as described in Table 2; (3) the trailing annual ROE of the low-minus-high volatility portfolio; and (4) the four-quarter change in bank net chargeoff rate, taken from bank call reports. In terms of our risk measures, in column (1), we use the change in the average realized stock return volatility of high-volatility firms minus that of low-volatility firms. In column (2), we use the change in expected analyst uncertainty over earnings (see Table 2 for a complete description). In column (3), we use the change in the net percent of U.S. banks loosening lending standards, taken from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS). In column (4), we use the change in the NFIB Small Business Optimism index. The operator $\Delta_4 Z_t$ denotes Z_t - Z_{t-4} for variable Z. In each regression, we include a constant and standardize all variables to have mean zero and variance one. In all cases, *t*-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and depends on data availability.

Table 9: PVS and Revisions in Expectations of Risk

$$Y = a + b \times PVS_t + \varepsilon$$

		b	$t(b)$	Adj. R^2	N
	Expected Risk:				
(1)	$\sigma_{t+2}(\text{EPS}_{t+3}) - \sigma_t(\text{EPS}_{t+3})$	0.38	2.35	0.10	94
(2)	$\sigma_{t+3}^{IV}(Ret_{t+4}) - \sigma_t^{IV}(Ret_{t+4})$	0.45	3.17	0.17	80
(3)	Δ_4 Prc. of Banks Loosening$_{t+4}$	-0.83	-8.64	0.53	98
	Realized Risk:				
(4)	$\Delta_4 \sigma_{t+4}(\text{Mkt-Rf})$	0.21	1.97	0.04	181
(5)	$\Delta_4 \sigma_{t+4}(\text{HML-Vol})$	0.34	1.90	0.11	181

Notes: This table uses PVS_t to forecast future revisions in expected risk. In row (1), we compute revisions in expected earnings-per-share (EPS) volatility using the Thompson Reuters IBES database of analyst forecasts. For each firm i and date t, we proxy for the time-t expected EPS volatility at time $t+3$, denoted $\sigma_{it}(EPS_{t+3})$, using the range of analyst annual EPS forecasts divided by the absolute value of the median analyst EPS forecast. For each (i,t), we choose the shortest forecast horizon h such that the quarterly earnings are at least two fiscal quarters away, which in calendar time is generally between 3 and 4 quarters from date t. For each firm i, we define the revision in expected earnings growth volatility at time as $\sigma_{i,t+2}(EPS_{t+3}) - \sigma_{i,t}(EPS_{t+3})$. At the portfolio level, $\sigma_{t+2}(EPS_{t+3}) - \sigma_t(EPS_{t+3})$ is the cross-sectional median revision for high-volatility stocks minus the median revision for low-volatility stocks. In row (2), we use option implied volatilities to define revisions in expected return volatility. For each firm i and date t, denote $\sigma_{i,t}^{IV}(t+4)$ as the option implied volatility of returns between quarters $(t+3)$ and $(t+4)$. The time-$(t+3)$ revision in expected volatility based on option prices is then $\sigma_{i,t+3}^{IV}(t+4) - \sigma_{i,t}^{IV}(t+4)$. We aggregate this option-based measure of revisions to the portfolio level in a similar manner to our IBES-based measure. Options data comes from OptionsMetrics. Row (3) regresses Δ_4 Prc. of Banks Loosening$_{t+4}$ on PVS_t, where Prc. of Banks Loosening is the net percent of U.S. banks loosening lending standards from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS) and Δ_4 denotes the four-quarter difference operator. In rows (4) and (5), we instead use PVS_t to forecast changes in future realized risk, as opposed to changes in expectations of risk. $\sigma_t(\text{Mkt-Rf})$ is the realized quarterly volatility of the CRSP value-weighted index at time t. $\sigma_t(\text{HML-Vol})$ is the average volatility of high-volatility stocks at time t minus the average volatility of low-volatility stocks. PVS_t is the average book-to-market ratio of low-minus-high- volatility stocks. We include a constant in all regressions and all variables are standardized to have mean zero and unit variance. t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and depends on data availability, though the full sample for PVS_t spans 1970Q2 to 2016Q2. See the internet appendix for more details.

Table 10: PVS and Implied Volatility Forecast Errors

Dependent Variable	Realized Volatility$(t+k, t+h) - \text{IV}_t(t+k, t+h)$			
	$k=0, h=4$		$k=3, h=4$	
	(1)	(2)	(3)	(4)
PVS_t	0.03**		0.05**	
	(3.96)		(4.01)	
$PVS_t \times 1_{it}^{q=2}$	0.01**	0.01**	0.02**	0.01**
	(2.57)	(2.50)	(2.93)	(2.14)
$PVS_t \times 1_{it}^{q=3}$	0.02**	0.01**	0.03**	0.03**
	(3.28)	(3.32)	(4.47)	(3.40)
$PVS_t \times 1_{it}^{q=4}$	0.03**	0.03**	0.05**	0.04**
	(2.73)	(3.41)	(3.31)	(2.82)
$PVS_t \times 1_{it}^{q=5}$	0.02	0.02*	0.08**	0.05**
	(1.28)	(1.80)	(3.15)	(2.28)
FE		(industry $\times t$)		(industry $\times t$)
R^2	0.05	0.53	0.08	0.51
N	38,135	38,010	37,811	37,687

Notes: This table uses PVS_t to predict errors in volatility forecasts from firm-level options. For each firm i, we define the error in volatility forecasts in options as the realized volatility in stock returns between $t+k$ and $t+h$, minus the time-t option implied volatility for returns over the same horizon. For $k=3$ and $h=4$, we use the term structure of implied volatilities at time t to back out the implied volatility of returns for the horizon $t+k$ to $t+h$, under the assumption that quarterly returns are not autocorrelated. We then run the following panel regression:

$$\text{Realized Volatility}_i(t+k, t+h) - \text{IV}_{i,t}(t+k, t+h) = a + \sum_{q=2}^{5} a_q \cdot 1_{it}^q + b_{PVS} \times PVS_t + \sum_{q=2}^{5} b_{q,pvs} \cdot 1_{it}^q \times PVS_t + \varepsilon_{i,t}$$

where 1_{it}^q is an indicator function for whether firm i is in volatility-quintile q at time t. PVS_t is average book-to-market ratio of low-minus-high volatility stocks and in all regressions is standardized to have mean zero and variance one for the period 1970q2-2016q2, the period of our main analysis for most of the paper. We use all firms in the CRSP-OptionMetrics merged database. The row FE indicates whether a fixed effect was included in the regression, where industries are defined using the 30 industry definitions from Ken French's website. t-statistics are listed below point estimates and are double-clustered by firm and by quarter. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. The full sample runs from 1996Q1-2016Q2. The size of the subsamples that include fixed effects do not match their full-sample counterparts because we drop fixed-effect groups of size one.

Table 11: High-Volatility and Low-Volatility Firm Investment

	Aggregate I/K	Low-Vol	Medium-Vol	High-Vol
Aggregate I/K	1	0.35	0.59	0.79
Low-Vol	0.35	1	0.87	-0.08
Medium-Vol	0.59	0.87	1	0.27
High-Vol	0.79	-0.08	0.27	1

Notes: This table shows the correlation of aggregate investment (private nonresidential fixed investment divided by the aggregate capital stock) with the investment rates of firms sorted into volatility terciles. At each date t, we compute the trailing 60-day volatility of each firm in the CRSP-COMPUSTAT merged database and them sort stocks into terciles based on their volatility. The investment rate for each firm is defined as the trailing four-quarter sum of CAPX and R&D, scaled by the book value of assets at $t-4$. The investment rate within each tercile is the average rate across firms in that tercile. Data is quarterly and spans 1990Q1-2016Q2. We start in 1990Q1 because the level of total investment in COMPUSTAT quarterly data aligns with total investment from COMPUSTAT annual from that point forward.