A Measure of Risk Appetite for the Macroeconomy*

Carolin Pflueger† Emil Siriwardane‡ Adi Sunderam§

October 2018

Abstract

We propose a new measure of the economy's risk appetite based on the valuation of volatile stocks. Unlike proxies for risk appetite derived from aggregates, our measure is strongly correlated with safe asset prices and future economic activity. When risk appetite is high, safe bonds fall in value and risky assets rally, setting off an investment boom. Risk appetite is closely tied to investors' expectations of risk and appears to extrapolate from recent economic conditions. Periods of elevated risk appetite are predictably followed by upward revisions in expectations of risk, suggesting that investor forecasts of risk may not be perfectly rational.

*This paper was previously circulated under the title "Does Precautionary Savings Drive the Real Interest Rate?" Evidence from the Stock Market." We thank Pedro Bordalo, Michael Brennan (discussant), John Campbell, Josh Coval, Robert Engle, Xavier Gabaix, Nicola Gennaioli, Sam Hanson, Espen Henriksen (discussant), Bryan Kelly, Arvind Krishnamurthy, Hanno Lustig (discussant), Thomas Maurer (discussant), Monika Piazzesi, Robert Ready (discussant), Larry Schmidt (discussant), Martin Schneider, Josh Schwartstein, Andrei Shleifer, Jeremy Stein, and Luis Viceira for helpful comments. We also benefited from the input of seminar participants at the 2018 AQR Insight Award Presentation, BI-SHoF Conference 2017, CEF 2017, CITE 2017, Chicago Harris, CMU Tepper, Federal Reserve Board, FRBSF conference on Advances in Finance Research 2017, Harvard, HEC-McGill Winter Finance Workshop, London School of Economics, McGill Desaultels, NBER Fall 2017 Asset Pricing Meeting, Northwestern Kellogg, SFS Cavalcade, SITE 2017, University of British Columbia, and University of Indiana. The Appendix to the paper can be found here.

†Pflueger: University of British Columbia and NBER. E-mail: carolin.pflueger@sauder.ubc.ca

‡Siriwardane: Harvard Business School. E-mail: esiriwardane@hbs.edu.

§Sunderam: Harvard Business School and NBER. E-mail: asunderam@hbs.edu.

1 Introduction

Classic accounts of economic boom and bust cycles (Keynes (1937); Minsky (1977); Kindleberger (1978); Minsky (1986)) point to the role of financial market risk appetite in shaping economic fluctuations. These accounts typically start with a negative fundamental shock that causes investors' risk appetite to fall – investors either expect future risk to be high or become less willing to bear risk. They then value the safety of bonds and require higher returns on risky projects, leading to a decline in real interest rates, a drop in real investment, and a recession. As risk appetite subsequently reverses, interest rates, investment, and economic activity recover.

This risk-centric view of business cycles has received renewed attention in recent theoretical work (Caballero and Farhi (2017); Caballero and Simsek (2017); Cochrane (2017)), but the link between risk appetite and the macroeconomy has proven elusive empirically. Traditional asset pricing models, such as Campbell and Cochrane (1999) and Bansal and Yaron (2004), suggest that the economy's risk appetite can be inferred from aggregate consumption or the aggregate stock market. However, measures of risk appetite derived from aggregates (e.g., Lettau and Ludvigson (2004)) generally fail to explain meaningful amounts of real rate variation and do not consistently forecast future macroeconomic outcomes.

In this paper, we propose a new measure of risk appetite and use it to provide empirical evidence in favor of the risk-centric view of business cycles. Our empirical approach relies on the idea that when risk appetite is low, investors should be more averse to holding high-volatility assets and instead value low-volatility assets such as risk-free bonds. We operationalize this idea in the cross section of equities by comparing the price of volatile stocks (PVS_t) to the price of low-volatility stocks. 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 PVS_t is high when high-volatility stocks have relatively high market values.

Using PVS_t, we show that the risk-centric narrative of business cycles fits the data well along several dimensions. To start, PVS_t captures the narrative's intuitive negative correlation between safe and risky asset prices. When risk appetite is high, the price of volatile stocks is high and the price of safe assets is low, so real interest rates are high. A one-standard deviation increase in PVS_t is associated with a 1.3 percentage point increase in the real risk-free rate, and PVS_t explains

41% of the quarterly variation in the real rate from 1970 to 2016. The relation between PVS_t and the real rate is robust through different macroeconomic environments, holds in both levels and first differences, and holds for both short-term and long-term real rates. Furthermore, the relation is robust to controlling for contemporaneous changes in the Taylor (1993) monetary policy rule variables (the output gap and inflation) and for measures of credit and equity market sentiment (Greenwood and Hanson (2013); Baker and Wurgler (2006)).

As in the risk-centric narrative, the comovement between PVS_t and the real rate is almost entirely attributable to changes in risk premia rather than expected cash flows. We use return forecasting regressions to show that PVS_t and real rates are both low when investors demand high returns for holding volatile stocks. Moreover, PVS_t forecasts returns on volatile securities in other asset classes, including U.S. corporate bonds, sovereign bonds, options, and credit default swaps. In other words, PVS_t – and its covariation with the real rate – reflect 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 appetite relevant to the macroeconomy.

Intuitively, the returns investors require for holding volatile stocks depend on their expectations of the risk and their willingness to bear risk. We provide evidence that PVS_t moves with expectations of risk based on analyst forecasts, option prices, and surveys of loan officers. High values of PVS_t coincide with periods when volatile firms are expected to have relatively low risk according to equity analysts and options markets. Similarly, data from the Federal Reserve's Senior Loan Officer Opinion Survey indicates that when PVS_t is high, banks are loosening lending standards, suggesting that they believe risks are low. We also show that PVS_t is linked to objective measures of risk from statistical forecasting models, though the connection between PVS_t and expected risk is stronger when using subjective measures from surveys or market data. These results further support our interpretation of PVS_t as a measure of risk appetite by tying it directly to financial market participants' expectations of risk.

We then document that elevated risk appetite leads to an expansion of investment and a macroeconomic boom. We first rule out that changes in PVS_t, and thus the macroeconomic outcomes we document, are caused by changes in monetary policy. Using methods from the literature on monetary policy shocks, we show that shocks to monetary policy do not differentially affect the prices of high- and low-volatility stocks in narrow windows around the Federal Reserve's policy announcements. We then show that a positive innovation in PVS_t forecasts increases in private investment and output and a decline in unemployment over the following four quarters. The relation between PVS_t and real investment is strongest for high-volatility firms, indicating that risky firms are particularly hesitant to invest when risk appetite is low.

Taken together, these facts favor the risk-centric view of business cycles and support the idea that PVS_t is a good gauge of the economy's risk appetite. We next show that the reasons that risk appetite varies in the first place are also consistent with the risk-centric view. Motivated by the accounts of Keynes (1937), Minsky (1977), and Kindleberger (1978), we examine whether good news leads investor risk appetite to increase. We find that PVS_t rises following positive economic outcomes, including positive surprises in GDP, high corporate profit growth, and low bank loan charge offs. These patterns suggest that risk appetite extrapolates from past news.

Since PVS_t is driven in part by subjective expectations of risk, it is natural to ask whether this extrapolation is fully rational. Under the null of perfectly rational expectations, revisions in the expected risk of high volatility firms should be unpredictable. In contrast, we find that high values of PVS_t, which coincide with low subjective expected risk, reliably predict future upward revisions in expectations of risk. None of our measures is perfect, so these findings do not unambiguously reject the null of rational expectations. However, we find similar results using a variety of different measures of expected risk, suggesting that there are times when risk appetite is high because investors are underestimating future risk.

We close by presenting a stylized model that ties together our empirical evidence on the price of volatile stocks, investment, and investor expectations of risk. The model has three main elements: i) volatility increases after adverse aggregate shocks, ii) investors have diagnostic beliefs as in Bordalo et al. (2018), which leads them to over-extrapolate from recent events, and iii) real firm investment is determined according to standard Q-theory. Since risk aversion is constant in the model, risk appetite corresponds to investors' subjective expectations of volatility. Following an adverse shock, objective expected risk increases, but subjective expected risk increases more. At these times, investors value safe bonds, and the real risk-free rate falls due to a standard precautionary savings channel. At the same time, investors demand high risk premia for investing in volatile firms, leading to a drop in the price of these firms relative to less volatile firms; in other words, the model analog of PVS_t falls. Investment then falls, particularly for volatile firms, to meet investors' demand for higher returns. As information about true risk becomes available, subjective expected risk reverts towards objective expected risk. The model nests a rational expectations benchmark and shows that diagnostic expectations are necessary to match our empirical evidence on revisions in expected risk.

Our paper contributes to several strands of the literature. The idea that risk and uncertainty drive macroeconomic fluctuations has received significant attention in recent years.[1] This work typically studies long-run changes in the real rate, as does the recent literature attributing the long-run decline in real rates to expected growth and Treasury convenience yields.[2] By contrast, our empirical findings emphasize that time-varying risk appetite is important for understanding quarterly variation, after accounting for long-term trends due to growth expectations and other factors.

In this respect, our paper is closer to the long literature in asset pricing arguing that considerations of risk drive variation in asset prices (e.g., Campbell and Shiller (1988); Cochrane (2011)). We label PVS_t a measure of risk appetite, rather than risk aversion, to allow for the possibility that it reflects both expectations of risk and risk aversion. We highlight expectations of risk in part due to data limitations – there are more direct measures of risk expectations than of risk aversion. However, our results do not rule out risk aversion as a driver of risk appetite, and it may be important for understanding the empirical strength of our results. Furthermore, some of our evidence suggests that PVS_t does not correspond directly to the definition of risk in standard frictionless, rational, representative agent models, where aggregate market risk is the only relevant risk factor. Empirically, we show that our emphasis in the construction of PVS_t on stocks' total volatility rather than other characteristics is critical, and discuss possible microfoundations for why the economy's risk appetite is revealed by the price that investors will pay for volatile securities.

Our paper also contributes to the literature 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)). 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 future risk. Indeed, previous work finds that sentiment disproportionately affects securities with highly uncertain values

[1] See, e.g., Bloom (2009); Caballero and Farhi (2017); Bloom et al. (2014); Hall (2016); Caballero and Simsek (2017); McKay et al. (2016).

[2] E.g., Laubach and Williams (2003); Cúrdia et al. (2015); Del Negro et al. (2017); Krishnamurthy and Vissing-Jorgensen (2012)

(Baker and Wurgler (2006)), consistent with the special role of volatility in our results. Furthermore, PVS_t is correlated with measures of sentiment for both debt and equity markets, suggesting that variation in risk appetite induces common movements in sentiment across markets. The link between PVS_t and credit markets suggests that recent work connecting credit market sentiment to economic outcomes[3] may in part reflect the effects of a broad notion of investor risk appetite that is common across markets, as opposed to one that is specific to credit markets.

Finally, this paper contributes to the literature on the relation between risk premia in bonds and stocks (Fama and French (1993); Koijen et al. (2017); Lettau and Wachter (2011); van Binsbergen et al. (2012)). We build on this research by showing that the pricing of volatility in the cross section of stocks sheds light on the fundamental drivers of the real rate, despite the fact that aggregate stock market valuations do not reliably explain the real rate. Our results differ from the literature on idiosyncratic risk in the stock market, which has focused on the average returns of high-volatility stocks.[4] We study time-variation in their risk premia and how it connects to interest rates and macroeconomic performance.

The remainder of this paper is organized as follows. Section 2 motivates our variable construction and describes the data. Section 3 shows that PVS_t fits the requirements of a measure of risk appetite along multiple dimensions. In Section 4 we use PVS_t to understand the fundamental economic drivers of risk appetite. Section 5 presents the stylized model. Section 6 concludes.

2 Motivating Framework and Variable Construction

2.1 Motivating Framework

Our measure of risk appetite is based on the difference in valuations between high- and low-volatility stocks. We begin by providing a framework to motivate the construction of this measure and to understand why it should be correlated with the real rate.

The first-order condition for the real interest rate r_{ft} that emerges from the standard consumption-

[3]E.g., Gilchrist and Zakrajšek (2012); López-Salido, Stein, and Zakrajšek (2017); Krishnamurthy and Muir (2017); Bordalo, Gennaioli, and Shleifer (2018)

[4]E.g., Ang et al. (2006); Johnson (2004); Ang et al. (2009); Fu (2009); Stambaugh et al. (2015); Hou and Loh (2016) Herskovic et al. (2016) focus on a different cross-section of stocks, sorting stocks by their exposure to the common factor driving idiosyncratic volatility and studying how this exposure is priced on average.

savings choice is

$$r_{ft} = \delta + \frac{1}{\psi} \times \mathbb{E}_t\left[g_{c,t+1}\right] - \gamma_t \times \mathbb{V}_t\left[g_{c,t+1}\right], \tag{1}$$

where $g_{c,t+1}$ is consumption growth, δ is the rate of time preference, ψ is the elasticity of intertemporal substitution, and γ_t is risk aversion. Eq. (1) implies that the price of safe assets depends on two forces. The first is a consumption smoothing (i.e., intertemporal substitution) motive, captured by the $\frac{1}{\psi}\mathbb{E}_t[g_{c,t+1}]$ term. When investors' expectations of growth are high, they wish to borrow to smooth consumption, driving up real rates.

The second component of the real rate, $-\gamma_t \mathbb{V}_t[g_{c,t+1}]$, reflects investors' expectations of volatility and aversion to this volatility. We label this term "risk appetite" in the spirit of Keynes (1937) and Minsky (1977), though studies that focus on the level of the real interest rate refer to it as precautionary savings (e.g., Carroll and Samwick (1998)). Risk appetite can be low for two reasons. First, investors may expect the future to be risky (i.e., $\mathbb{V}[g_{c,t+1}]$ is high), and thus save more to hedge against this risk, driving down the real risk-free rate. Second, investors may be unwilling to bear risk (i.e.,γ_t is high), driving up the price of safe bonds up and thus lowering the real rate.

The Euler equation for risky assets is given by

$$\mathbb{E}_t\left[r_{i,t+1}\right] - r_{ft} = \beta_{ic} \times \gamma_t \times \mathbb{V}_t\left[g_{c,t+1}\right], \tag{2}$$

where β_{ic} measures the exposure of asset i to risk. Eqs. (1) and (2) imply that the difference in expected returns between low- and high-risk stocks should be a good measure of risk appetite $-\gamma_t \mathbb{V}_t[g_{c,t+1}]$, and that a measure of risk appetite constructed in this manner should correlate positively with the real interest rate. These equations are valid so long as investors are optimizing, regardless of whether their expectations of risk are perfectly rational or not.

We implement the logic implied by Eqs. (1) and (2) using PVS_t, the difference in valuation ratios between low- and high-volatility stocks. Volatility is a useful sorting characteristic because it captures the underlying risks investors care about at each point in time, even if those risks are hard to measure and change over time (e.g., financial crises at some points, oil supply shocks at others). Volatility increases with exposure to risks, regardless of what they are. We use valuation ratios because expected returns are not directly observable. Valuation ratios mechanically must depend on either expected returns or expected cash-flow growth (Campbell and Shiller (1988)), and we confirm empirically in Section 3.2 that PVS_t is driven primarily by variation in investors' expectations of returns and not their expectations of cash flow growth.

The central bank has played no role in our motivating framework so far. In practice, however, short-term real rates are set by the central bank. Thus, any relationship we find between risk appetite and the real rate must be intermediated by the central bank. The reason the central bank reacts to risk appetite shocks can be seen by rewriting the Euler equation in the style of a New Keynesian model (Clarida et al. (1999); Woodford (2003)):

$$x_t \quad = \quad \mathbb{E}_t[x_{t+1}] - \psi(r_t - r_t^n). \tag{3}$$

Here, x_t is the gap between current output and its natural rate, ψ is the elasticity of intertemporal substitution, and r_t is the observed real rate ,which is set by the central bank. r_t^n is the unobservable natural interest rate that is consistent with stable inflation and output. As in Eq. (1), a positive risk appetite shock acts like a traditional demand shock, increasing r_t^n. If the central bank does not fully offset the shock, output and investment will boom, temporarily rising above their natural level. Thus, a central bank seeking to stabilize the economy will adjust the real rate r_t in response to changes in the natural rate r_t^n driven by risk appetite.[5]

2.2 Construction of Key Variables

With this motivation in mind, we summarize the construction of our key variables. Details regarding our data construction are provided in the online appendix. Unless otherwise noted, our full 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 equity that are traded on the NYSE, AMEX, or NASDAQ exchanges. At the end of each quarter and for each individual stock, we form book-to-market ratios. The value of book equity comes from COMPUSTAT Quarterly and is defined following Fama and French (1993). If book equity is not available in COMPUSTAT Quarterly, we

[5] r_t^n does not necessarily reflect the economy's long-run equilibrium, but instead represents the hypothetical interest rate that would obtain in a world without sticky product prices. For a central bank seeking price stability, it is optimal to adjust interest rates one-for-one to shocks to r_t^n (Woodford, 2003).

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. This smooths out any short-term fluctuations in market value. We have experimented with many variants on the construction of book-to-market, and our results are not sensitive to these choices.

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. This approach mirrors the construction of variance-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. At any given point in time, the valuation ratio for a quintile is simply the equal-weighted average of the valuation ratios of stocks in that quintile. 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:

$$PVS_t = \left(\overline{B/M}\right)_{low\ vol,t} - \left(\overline{B/M}\right)_{high\ vol,t}. \tag{4}$$

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 large relative to low-volatility stocks. Throughout the analysis, we standardize PVS_t so regression coefficients can be interpreted as the effect of a one-standard deviation change in PVS_t. Quarterly realized returns in a given quintile are computed in an analogous fashion, aggregated up using monthly CRSP data.

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, meaning 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 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 online appendix, we show that all of our results are essentially unchanged if we use the raw real rate or employ more sophisticated filtering methods.

2.3 Summary Statistics

Table 1 contains summary statistics on our volatility-sorted portfolios. Panel A of the table reports statistics on book-to-market-ratios, while Panel B reports statistics on excess returns. Note that high-volatility stocks have lower valuations than low-volatility stocks: on average, PVS_t is negative. However, the standard deviation of PVS_t is about twice the magnitude of its mean, so there is substantial variation the price of volatile stocks through time. This variation is the focus of our empirical work.

Panel B shows that returns on the low-minus-high volatility portfolio are themselves quite volatile, with an annualized standard deviation of 29.6%. 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 puzzle, which highlights that stocks with high volatility have historically underperformed (Ang et al. (2009)), potentially due to short sales constraints (Stambaugh et al. (2015)).

3 Risk Appetite and the Macroeconomy

This section presents four facts showing that the risk-centric narrative of economic fluctuations fits the data well using PVS_t as a measure of risk appetite. First, PVS_t captures the narrative's intuitive negative correlation between safe and risky asset prices: when PVS_t is high, the price of safe bonds is low, so the real risk-free rate is high. Second, considerations of risk, not cash flow growth, are the source of this correlation. PVS_t and its covariation with the real rate are driven by the returns that investors require to hold volatile stocks. Third, investors' required returns vary in part because their expectations of risk vary. Finally, increases in PVS_t forecast booms in real investment, output, and employment, as the risk-centric narrative predicts.

3.1 Real Rates

3.1.1 The One-Year Rate

We begin by documenting the relationship between the one-year real rate and PVS_t. Specifically, we run regressions of the form:

$$\text{Real Rate}_t = a + b \times PVS_t + \varepsilon_t. \tag{5}$$

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

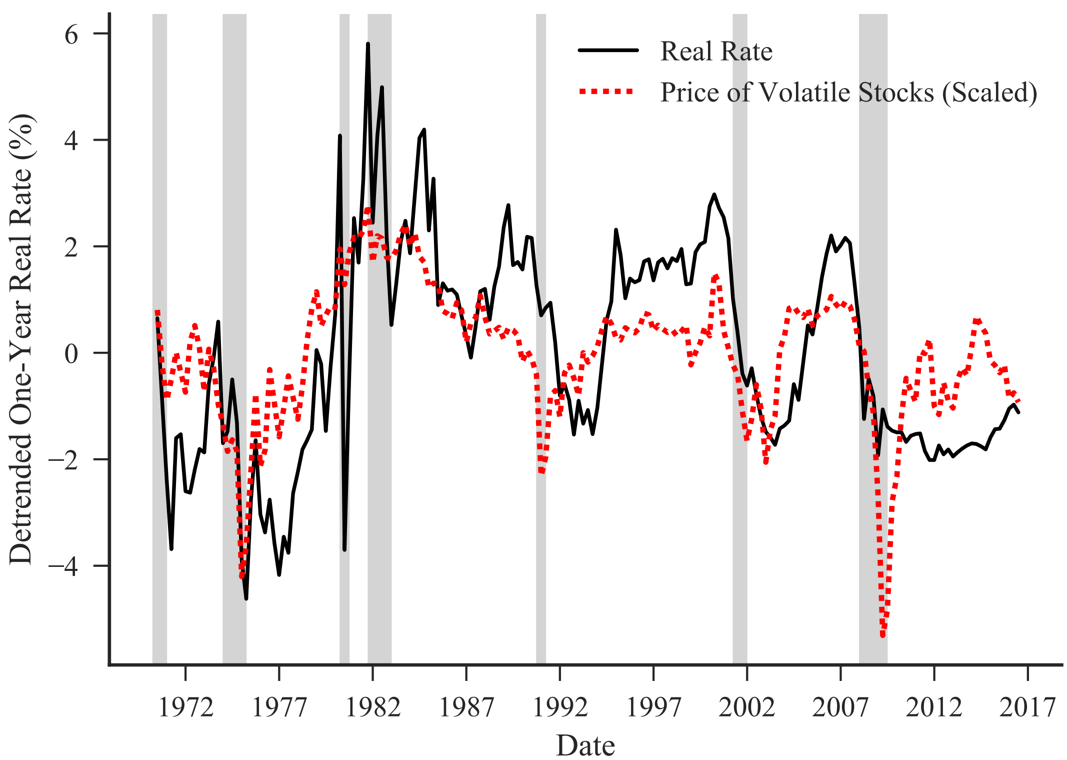
Column (1) of Table 2 shows that the real rate tends to be high when PVS_t is high. In other words, safe asset prices are low when volatile stocks have high prices. The effect is economically large and measured precisely. A one-standard deviation increase in PVS_t is associated with a 1.3 percentage point increase in the real rate. For reference, the standard deviation of the real rate is 2 percentage points. The R^2 of the univariate regression is a 41%.

Figure 1 presents the relation between PVS_t and the real rate graphically. Figure 1 shows that the fitted value from the regression in Eq. (5) tracks the real rate well since 1970. The relation holds throughout the sample and hence is robust across different economic environments. It also holds through both expansions and recessions, which are shown in gray. We present formal evidence of subsample stability in the internet appendix.

As discussed in Section 2.1, the relationship between risk appetite and short-term real rates must be intermediated by the central bank. Anecdotal evidence suggests that it is plausible the Federal Reserve responds to financial market risk appetite. For instance, as PVS_t spiked in March 2000 the Federal Open Market Committee justified raising the federal funds rate because "Financial market conditions (..) affect labor costs and prices... The growth in aggregate demand continued to display remarkable vigor, evidently driven by high levels of consumer and business confidence and accommodative financial markets."[6] Our results do not require that the Federal

[6]Minutes of the Federal Open Market Committee of March 21, 2000. For a comprehensive narrative account of

Figure 1: 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 the spread in book-to-market ratios between low and high volatility stocks (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 the average book-to-market (BM) ratio of low-volatility stocks, less the average BM-ratio of high-volatility stocks. The online appendix contains full details on how we compute BM ratios. 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.

Reserve tracks PVS_t itself, but rather that risk appetite is reflected both in Fed actions and how investors price volatile stocks.

Column (2) of Table 2 separates PVS_t into its constituent parts. The valuations of low-volatility and high-volatility stocks enter with opposite signs, so both components of PVS_t play a role in driving the relation with the real rate. Column (3) of Table 2 indicates that our focus on the cross section of stock valuations is important. 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 also 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.[7] Insofar as the aggregate book-to-market ratio proxies for expected returns on the aggregate market (Cochrane (2007)), column (3) indicates that the expected return on the aggregate market has different drivers than PVS_t and the real rate.

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 online appendix provides further evidence that the relation between our baseline result is not driven by inflation and does not simply capture the reaction of monetary policy along a standard Taylor (1993) rule.

Columns (5)-(8) of Table 2 rerun the preceding regression in first differences to ensure that our statistical inference is not distorted by the persistence of either the real rate or PVS_t. Running regression (5) in differences generates similar point estimates, both in terms of magnitude and statistical significance. The R^2s in columns (5)-(8) are somewhat lower, because the short-term oscillations in the real rate during Paul Volcker's tenure as Federal Reserve chairman lead to espe-

financial market considerations in FOMC meetings, see Cieslak and Vissing-Jorgensen (2017).

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

cially large outliers in the changes regression. We again find no relationship between the real rate and the aggregate book-to-market ratio. Overall, the evidence in Table 2 indicates an economically meaningful and robust relationship between the real rate and PVS_t.

3.1.2 Robustness

Table 3 shows that the link between PVS_t and the real interest rate is robust along several dimensions. We run horse races 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 compute Newey-West standard errors using five lags. As a reference point, the first row of Panel A in Table 3 reproduces our baseline results from columns (3) and (7) of Table 2.

The Term Structure of Real Interest Rates

Table 3 Panel A starts by showing a statistically significant positive relationship between PVS_t and longer-term real rates, with magnitudes that are similar to our estimates for the one-year real rate. We construct k-year real rates as the k-year nominal Treasury bond yield minus survey expectations of one-year inflation (the GDP deflator) from the Survey of Professional Forecasters. We use one-year inflation expectations when constructing the term structure of real rates simply because the data go back further, though our conclusions are not sensitive to this choice. In rows (2)-(3), the relationship between PVS_t and long-term real rates suggests that when risk appetite is low, there is a simultaneous increase in the price of all real safe assets, regardless of maturity. Given that the correlation between PVS_t and real rates is similar across maturities, we focus on the one-year real rate for the remainder of the paper in order to match the horizon of our inflation expectations data.

Alternative Constructions of PVS_t

Next, we show that we obtain similar results for alternative definitions of PVS_t. In row (4) of Table 3, we recompute PVS_t value-weighting the book-to-market ratio of stocks within each volatility quintile, as opposed to equal-weighting. In row (5), we obtain similar results sorting stocks on volatility measured over a two-year window, rather than a two-month window.[8] Our

[8] In the internet appendix we show that nearly identical results obtain when sorting stocks on their idiosyncratic

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 critical to our interpretation of PVS_t as a measure of investors' willingness to hold volatile stocks.

Relationship to Other Stock Characteristics

Rows (6)-(11) of Table 3 Panel A investigate whether stock return volatility is really the key characteristic that drives the relationship between PVS_t and the real rate. In row (6), we run a horse race of PVS_t against the spread 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 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. 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. We consider characteristics Y that capture alternative economic mechanisms for the real rate to correlate with PVS_t: cash flow duration, firm leverage, systematic risk (i.e., beta), firm size, and value (i.e., book-to-market ratio).

Rows (7)-(11) show that in all cases the regression coefficient on PVS_t is unchanged relative to our baseline results. The results on cash flow duration suggests that low-volatility stocks are not "bond like" because of their cash flow duration (e.g., Baker and Wurgler (2012)). Instead, we find that low volatility is the key characteristic determining whether a stock's valuation correlates with the prices of safe bonds, indicating that PVS_t captures how investors price risk and not duration. The results on beta confirm that the relation between PVS_t and the real rate is not simply picking up risk related to the aggregate stock market. The value-sorted book-to-market spread is sometimes thought to capture the value of growth options, so the value result suggests that the relation between PVS_t and the real rate is not driven by growth options. The results on size show that despite the fact that smaller firms tend to be more volatile, our volatility sorts do not simply proxy for size.

volatility because the total volatility of an individual stock is mostly idiosyncratic (Herskovic et al. (2016)).

In the online appendix, we use double sorts to provide additional evidence that the relationship between PVS and the real rate is not driven by other stock characteristics, including industry and whether the firm is a dividend payer, as well as the characteristics studied here.

Thus, 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 of stocks that is correlated with real rates. The interesting economic content of our findings is that volatility, while not a fundamental firm characteristic, is a robust measure of risk. Volatility captures the risk factors investors are worried about at each point in time, regardless of what they are, and PVS_t captures how worried investors are about these risks.

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 3 Panel B show 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 3 runs univariate regressions of the real rate on the alternative measures. None of these measures match the R^2 of 41% for PVS_t, though the Baker and Wurgler (2006) equity sentiment measure has high explanatory power. Moreover, the third set of columns shows that the relationship between PVS_t and the real interest rate survives when controlling for these alternative measures and that the R^2s increases substantially by adding PVS_t in all cases.

One potential reason that PVS_t has separate explanatory power over these alternative measures is that PVS_t is based on a long-short portfolio, so it nets out factors affecting an entire asset class. For instance, suppose equity market sentiment has a risk appetite component and an equity cash flow component, while credit market sentiment shares the same risk appetite 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. Consistent with this interpretation, 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.

3.2 Return Predictability

We next show that the comovement between PVS_t and the real rate is almost entirely attributable to changes in risk premia rather than expected cash flows. This finding supports the risk-centric narrative and validates our use of PVS_t as a proxy for expected returns on volatile stocks, as discussed in our motivating framework in Section 2.1.

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, the real rate must covary with either future returns or future cash flow growth on the portfolio.

We run forecasting regressions to show that PVS_t and its correlation with the real rate are primarily driven by future returns:

$$R_{t\to t+4} = a + b \times X_t + \xi_{t+4}, \tag{6}$$

where X_t is either PVS_t or the real rate. To start, $R_{t\to t+4}$ is either the realized annual return on the low-minus-high volatility portfolio or cash flows, measured as accounting return on equity (ROE). Panel A in Table 4 contains the results of this exercise. 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 forecasting 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 0.15 (Cochrane (2009)).

Thus, it appears that variation in PVS_t largely reflects variation in 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 directly. 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 columns (3) and (4), $R_{t\rightarrow t+4}$ is the cash flow on the volatility-sorted portfolio, measured as return on equity (ROE). The columns show that PVS_t and the real rate contain little information about the future cash flows of the low-minus-high volatility portfolio. We find economically small and statistically insignificant effects when forecasting with either PVS_t or the real rate. Under rational expectations, this lack of cash flow predictability is evidence that time-varying expected returns drive PVS_t. An alternative is that PVS_t is driven by incorrect beliefs about future cash flows. If investors become overly optimistic about the future earnings of volatile stocks, PVS_t will rise. Investors will then predictably be negatively surprised when high future earnings are not realized. PVS_t will then fall, and realized returns on high-volatility stocks will be low. This alternative would match the patterns in columns (1)-(4).

We empirically examine this possibility using analyst forecasts from the Thompson Reuters IBES dataset. We define a stock's quarterly ROE surprise as the difference between its realized ROE and the analyst consensus ROE forecast. The annual ROE surprise is the average surprise over the previous four quarters. We then forecast the spread between the median annual ROE surprise of low-volatility minus high-volatility stocks. If PVS_t is high because of overoptimistic beliefs about the future ROE of volatile securities, then PVS_t should also positively predict ROE surprises for this long-short volatility portfolio. However, columns (5) and (6) show there is no evidence that either PVS_t or the real rate forecast earnings surprises.[9]

Taken together, columns (1)-(6) of Table 4 Panel A show that the real rate comoves with PVS_t because it comoves with the returns that investors require to hold volatile stocks. PVS_t does not forecast future cash flows and does not correlate strongly with analyst forecasts, suggesting that it comoves not only with regression-based expected returns, but also with financial market par-

[9]The time series for these regressions is shorter because IBES data is only reliable for our cross-section after the early 1990s. In the internet appendix, we also show that movements in PVS_t are largely unexplained by contemporaneous changes in analysts' expected ROE.

ticipants' own expectations of returns. In Section A.2 of the 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 arises because the real rate forecasts future returns to volatility-sorted stocks. Consistent with the risk-centric narrative, when risk appetite is low, safe asset prices are high and investors demand high compensation for holding volatile stocks.

Columns (7) and (8) of Panel A in Table 4 show that neither the real rate nor PVS_t forecast the aggregate market excess return, echoing earlier findings by Campbell and Ammer (1993). While this highlights the importance of our focus on volatility sorts, it might seem puzzling that the real rate does not forecast the aggregate market return. Column (2) of Table 2 suggests this lack of relation is driven by the composition of the aggregate stock market. The real rate is negatively correlated with valuations of the lowest-volatility, "bond like" stocks, while it is positively correlated with the valuations of high-volatility stocks. The aggregate market averages over both high-volatility and low-volatility stocks and thus has a relatively weak relationship with the real rate, whereas PVS_t isolates risky stocks.

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 it is a broad measure of risk appetite 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.[10] Within each asset class, we form a portfolio that is long the lowest-volatility and short the highest-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 4 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 of Table 4 Panel B shows that both PVS_t and the real interest rate

[10] For US 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.

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 interest 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 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 Expectations of Risk

The previous section showed that PVS_t is driven by the expected returns investors demand to hold volatile securities. As discussed in Section 2.1, expected returns vary due to fluctuations in investors' expectations of risk or their willingness to bear risk. In this section, we run simple contemporaneous regressions to study how PVS_t relates to measures of expectations of risk based on analyst forecasts, option prices, surveys, and statistical models. The results are reported in Table 5. We standardize both PVS_t and the explanatory variables to facilitate interpretation of economic significance. The number of observations varies across columns because the independent variables are available starting at different dates. We find similar results if we restrict the sample to the common period where all explanatory variables are available.

Column (1) of Table 5 examines how PVS_t relates to a measure of expected risk derived from analyst earnings forecasts in IBES. Ideally, we would measure analysts' expectations of risk using their perceptions of the full distribution of future earnings. However, in the IBES data, each analyst only reports their mean estimate of future earnings. To overcome this data limitation, we instead use the dispersion of earnings forecasts across analysts as a proxy for their expectations of risk. 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. While this is an imperfect measure of expected risk, our empirical analysis only requires that it be correlated with true subjective expectations of risk.[11]

In column (1), we use dispersion in forecasts of one-quarter ahead earnings. When expected risk from analyst forecasts for volatile firms is high, PVS_t is low. 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. 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.

Column (2) shows a stronger correlation between PVS_t and dispersion in forecasts of one-year ahead earnings. The R^2 shows that this measure of subjective expectations of risk explains over half of the variation in PVS_t. A one-standard deviation increase in expected risk is associated with a 0.67 standard deviation decline in PVS_t. Figure 2 Panel A depicts the relationship visually.[12]

Column (3) studies how PVS_t relates to expectations of risk derived from option prices. Using data from OptionsMetrics, we compute the difference in the median implied volatility of one-year at-the-money options for high- and low-volatility firms. When option-implied volatility for volatile firms is relatively high, PVS_t is relatively low. A one-standard deviation increase in expected risk is associated with a 0.46 standard deviation decline in PVS_t. In addition, this option-based measure of expected volatility explains about 24% of PVS_t variation over the sample. One reason the relationship between expected risk and PVS_t is weaker with the option-based measure than the analyst-based measure is that option prices are driven by both expected future volatility and the

[11] Consistent with our interpretation of dispersion as expected risk, it is correlated with the volatility of individual analysts' forecasts over time. Because computing the volatility of individual forecasts requires continuous time series data, the measure cannot be constructed for many firms in our sample and is noisy for the firms it can be constructed for. We therefore use dispersion as our baseline measure.

[12] 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 our one-quarter measure of expected risk is noisier in the early sample. For the post-1992 sample, when the one-quarter measure is relatively well populated, we obtain similar results for the two measures.

variance risk premium, defined as the difference between implied volatilities from options and investor expectations of volatility. To the extent that the variance risk premium is driven by forces orthogonal to those that drive PVS_t, for instance supply and demand imbalances specific to option markets (Garleanu et al. (2009)), it will act as measurement error and weaken the link between PVS_t and our option-based measure. The relationship between PVS_t and option prices may also be driven in part by a time-varying variance risk premium. If shocks to volatility are priced and risk aversion is time-varying, then when risk aversion is low, PVS_t will be high and option prices for volatile firms will also be high. However, time-varying risk premia would not explain our results on analyst forecasts, and the literature on the variance risk premium largely suggests that it is driven by variation in risk quantities, not risk aversion (e.g., Bollerslev et al. (2009)).

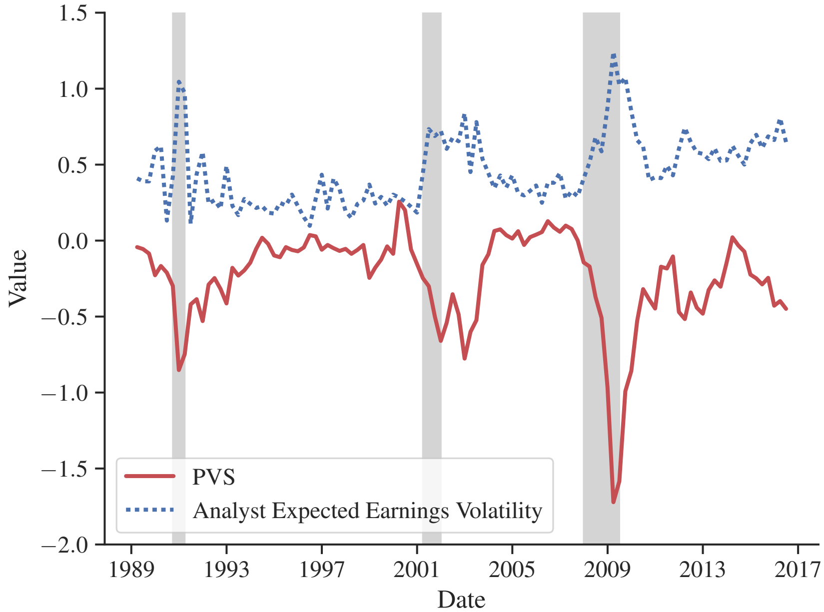
In column (4), we take a statistical approach to measuring the expected risk of the portfolio underlying PVS_t. We examine the forecasted difference in return volatility between the low- and high-volatility portfolios, where we estimate the forecasted volatility of each portfolio with an AR(1) model.[13] We refer to this measure as an objective measure of risk because it derives from a statistical model. The regression in column (4) indicates that PVS_t correlates with this objective measure of expected risk, though the R^2 of 9% is lower than what our subjective measures of expected risk deliver.

In column (5) of Table 5, we examine a measure of expected risk that is less directly tied to the portfolio underlying PVS_t. We use the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) to study expectations of risk from credit markets. Column (4) shows that when loan officers report that they are loosening lending standards, PVS_t is high, consistent with the idea that loan officers' expectations of risk are low at these times. The regression has a R^2 of over 30%, and a one-standard deviation loosening in lending standards is associated with a 0.5 standard deviation higher value of PVS_t. Figure 2 Panel B shows the relation visually. The interpretation of column (4) as reflecting expected risk is corroborated by column (5), 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. Taken together, the results from the SLOOS reinforce the idea that PVS_t captures a broad notion of risk appetite that operates simultaneously across asset classes.

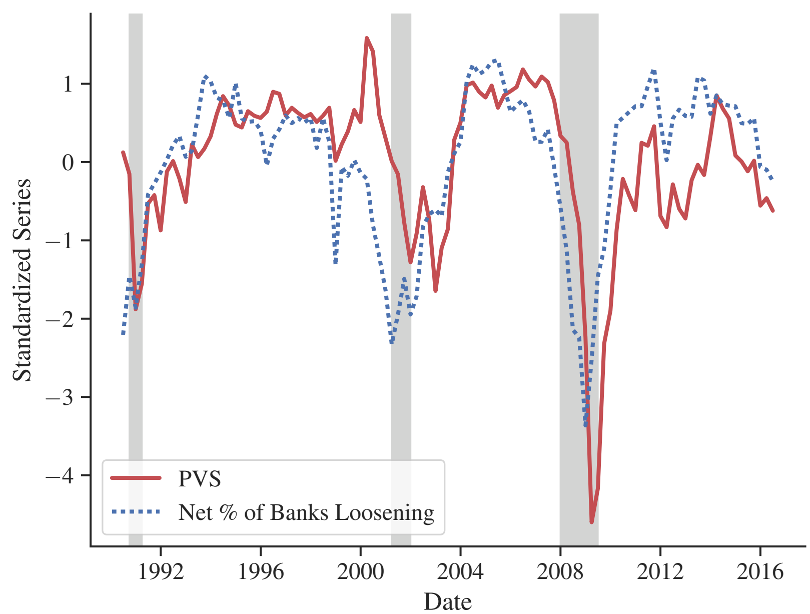
[13]It is well known that individual stock volatility increases over our sample period (Campbell et al. (2002)). In the internet appendix, we show that we get similar, but slightly stronger, results if we first extract the cyclical component of volatility and then forecast it with an AR(1).

Figure 2: PVS_t and Expected Risk

Panel A: Analyst Expected Risk



Panel B: Bank Lending Standards



Notes: Panel A plots PVS_t against the perceived risk of high-volatility stocks relative to low-volatility stocks. We construct perceived 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-quarter ahead earnings divided by the average forecast of earnings. The perceived risk of stocks in either the low or high-volatility stock portfolio is the equal-weighted average of firm-level disagreement for firms in that portfolio. Panel B plots PVS_t against the net percent 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 the average book-to-market (BM) ratio of low-volatility stocks, less the average BM-ratio of high-volatility stocks. The online appendix contains full details on how we compute the data for this figure. In each panel, the variables have been rescaled to have a mean of zero and a variance of one. Data is quarterly and the sample size depends on availability.

Column (7) of Table 5 runs a multivariate regression of PVS_t on dispersion in forecasts of one-year ahead earnings, our measure of objective expected risk, and the percent of banks loosening from SLOOS. We exclude the option-based measure and the SLOOS variable that pertains specifically to the economic outlook because they have shorter time series. Collectively the three explanatory variables explain about 70% of the variation in PVS_t. In untabulated results, we examine the relationship between PVS_t and measures of aggregate risk, including aggregate market volatility. We find much weaker correlations, highlighting the importance of our focus on the cross section to isolate risk appetite.

The broad takeaway from this analysis is that PVS_t fluctuates in part due to changes in expectations of risk. The connection between PVS_t and expected risk is strongest when using subjective measures from surveys or market data, as compared to objective measures from statistical forecasting models. We investigate the nature of these expectations further in Section 4 below.

3.4 Real Outcomes

We have established that PVS_t has several financial market properties that one would expect if it revealed the economy's risk appetite. The risk-centric view further predicts that shocks to risk appetite have real effects: when investors are willing to bear risk or expect risk to be low, they fund risky projects, leading to boom in investment and output. We next provide evidence of this prediction, showing that positive shocks to PVS_t are followed by a boom in the real economy.

3.4.1 Ruling out Reverse Causality

To start, we first rule out the possibility that changes in PVS_t are caused by changes in monetary policy. In the notation of our motivating framework in Section 2.1, we want to ensure PVS_t and the real rate r_t comove because PVS_t and the natural rate r_t^n both respond to risk appetite shocks, and the central bank adjusts r_t in responses to changes in r_t^n. We want to rule out the reverse causality story that when the central bank changes r_t while r_t^n remains fixed, this causes movements in PVS_t. We previously provided evidence against this reverse causality story in Section 3.1.2 by controlling for a range of additional firm characteristics. Here, we corroborate that analysis using methods from the literature on monetary policy shocks. This additional evidence is useful for interpreting how future investment, unemployment, and output respond to PVS_t, because they show that PVS_t innovations are distinct from monetary policy surprises.

The identification assumption shared across the monetary policy shocks literature is that within a narrow window around the Federal Reserve's announcements of monetary policy decisions, no other information affects the federal funds rate. Individual measures of monetary policy shocks differ in the details of their construction. Rather than tying ourselves to a particular measure, we show results for measures from Romer and Romer (2004), Bernanke and Kuttner (2005), Gorodnichenko and Weber (2016), and Nakamura and Steinsson (2018).

Table 6 provides evidence against the reverse causality story. We regress returns on the low-minus-high volatility portfolio onto monetary policy shocks. Anecdotally, surprise policy changes made outside of regularly scheduled meetings are often driven by financial market conditions and could thus confound our analysis. We therefore exclude them here and in the internet appendix show that we obtain similar results when including them.

If reverse causality was responsible for our baseline result, high-volatility stocks should increase in response to a positive shock to interest rates. Since the independent variable is the low-minus-high volatility return, reverse causality should therefore show up as negative coefficients in Table 6. In the first set of columns, we use quarterly data and find coefficients that are statistically insignificant with 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.

This exercise indicates that changes in the real rate do not directly cause movements in PVS_t. We will use this identification assumption in the next section when we estimate how the macroeconomy responds to PVS_t shocks.

3.4.2 Evidence from Local Projections

We next show that periods of high prices for volatile stocks are followed by an economic boom. We estimate the impulse responses of macroeconomic variables to a shock to PVS_t using Jorda (2005) local projections. Specifically, we run regressions of the form:

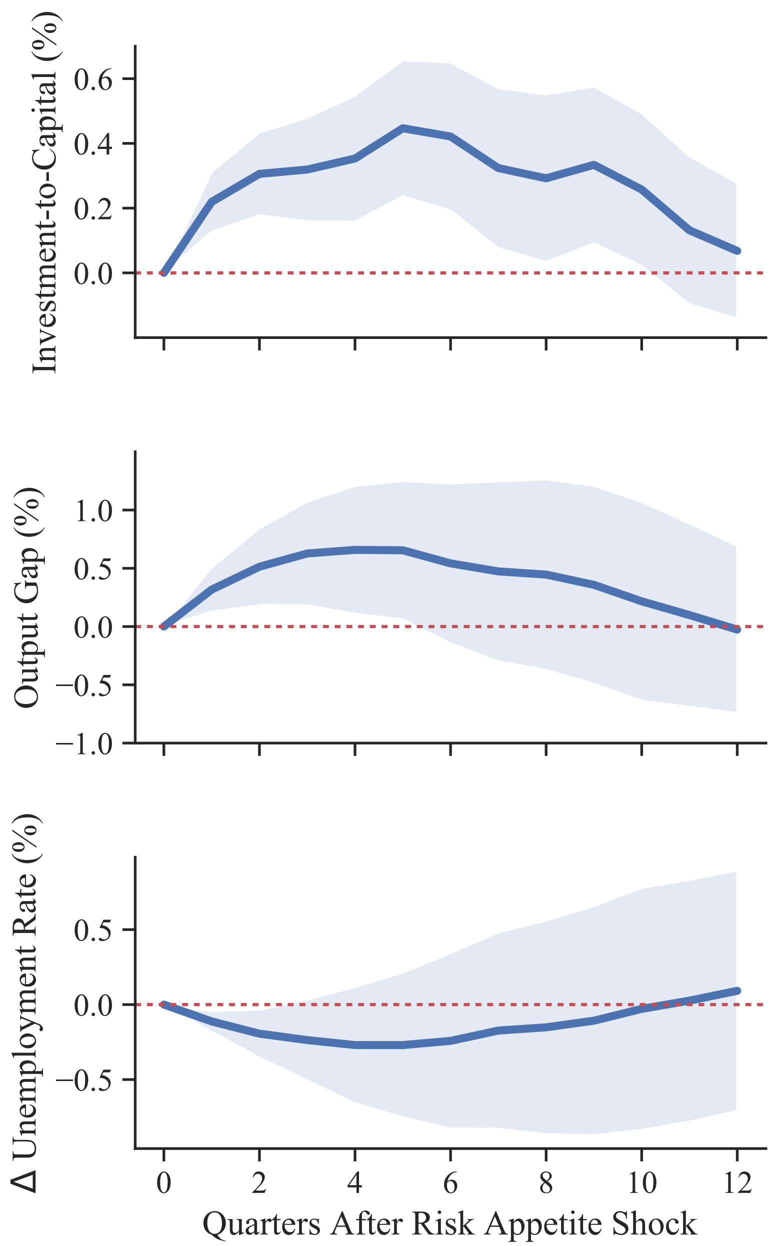
$$y_{t+h} = a + b^h_{PVS} \times PVS_t + b^h_{RR} \times RealRate_t + b^h_y \times y_t + \varepsilon_{t+h}$$

where h is the forecast horizon. In the context of the New Keynesian Euler equation for the real interest rate from Section 2.1, any macroeconomic responses to shocks to PVS_t are consistent with the Federal Reserve not completely offsetting risk appetite shocks in interest rates and instead allowing for some quantity responses.

Panel A of Table 7 reports the results. In the first row, we forecast the ratio of private nonresidential investment to capital for horizons of $h = 1$ and $h = 4$ quarters. We find meaningful effects. 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 and 0.35 percentage points higher at a four-quarter horizon. The standard deviation of the investment-capital ratio is 1.16%. In the second row of Table 7, we report results for the output gap. Here, 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 the third row 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 untabulated results, we find similar results when controlling for the aggregate book-to-market ratio and the Cochrane and Piazzesi (2005) term structure factor, suggesting that the information PVS_t contains about the macroeconomy is distinct from the information in those variables.

In Figure 3 we report the impulse responses to a one-standard deviation shock to PVS_t for horizons of $h = 1, \ldots, 12$ quarters. The figure shows that the effect of a shock to PVS_t on private investment is quite persistent, peaking around six quarters and then slowly reverting over the next six quarters. In contrast, the effects on the output gap and unemployment are somewhat less persistent, peaking after five quarters and then dissipating. In the online appendix, we complement these results with standard vector autoregression (VAR) evidence. The VARs serve two purposes. First, they show that monetary policy shocks and shocks to PVS_t have opposite effects on economic activity, consistent with our evidence ruling out reverse causality above. Second, they allow us to quantify the importance of PVS_t shocks using forecast error variance decompositions. At a ten-quarter horizon, PVS_t shocks explain 14% of variation in the unemployment rate and 38% of the variation in investment-to-capital ratios. For comparison, the monetary policy shocks explain 17% of variation in unemployment and only 5% of variation in the investment-to-capital ratio.

Figure 3: Impulse Responses of the Macroeconomy to PVS Shocks (Local Projections)



Notes: This figure plots the estimated impulse response (and its associated 95% confidence band) of several macroeconomic variables to a one-standard deviation shock to PVS_t using local projections. We compute impulse responses using Jordà (2005) local projections of each macroeconomic outcomes onto PVS_t. In all cases, we run regressions of the following form: $y_{t+h} = a + b^h_{PVS} \times PVS_t + b^h_{RR} \times \text{Real Rate}_t + b^h_y \times y_t + \varepsilon_{t+h}$. 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 percent and linearly detrended. For all regressions, we use Newey-West standard errors with five lags. Data is quarterly and spans 1970Q2-2016Q2.

The logic of the risk-based narrative further suggests that a decline in risk appetite should disproportionately affect real investment at high-risk firms. To examine this prediction, we run firm-level regressions in COMPUSTAT data of investment on indicators for the firm's volatility quintile, PVS_t, and the interactions between PVS_t and the quintile dummies, controlling for cash flows and firm and time fixed effects:

$$\frac{CAPX_{i,t\to t+4}}{A_{i,t}} = a_i + a_t + \sum_{q=1}^{5} b_q \cdot 1_{it}^{q} + b_{PVS} \times PVS_t + \sum_{q=2}^{5} b_{q,pvs} \cdot 1_{it}^{q} \times PVS_t + b_{CF} \frac{CF_{i,t\to t+4}}{A_{i,t}} + \varepsilon_{i,t}.$$

where 1_{it}^{q} is an indicator function firm i is in volatility quintile q at time t. The variable $CAPX_{i,t\to t+4}/A_t$ measures investment for each firm from time t to $t+4$ and $CF_{i,t\to t+4}/A_t$ measures the cash flows of the firm over the same period. The coefficient of interest in the regression is the interaction between the firm's volatility quintile and PVS_t. Panel B of Table 7 reports the regression results. The investment of the higher-volatility firms is more sensitive to PVS_t than the investment of lower volatility firms and this result is robust across pre- and post-2000 subsamples.

4 Why does Risk Appetite Vary?

We have documented relationships between PVS_t, the real rate, investor expectations, and macroeconomic outcomes that fit the risk-centric view of business cycles and support the idea that PVS_t captures the economy's risk appetite. In this section, we use PVS_t to explore the fundamental forces that cause risk appetite to vary over time.

4.1 PVS Extrapolates from Past News

In early risk-centric narratives (e.g., Keynes (1937), Minsky (1977), and Kindleberger (1978)), extrapolation plays an important role: following good news, risk appetite rises because investors either believe that future risk is low or become more willing to bear risk. We examine this prediction in the data, running regressions of the 4-quarter change in PVS_t on measures of macroeconomic news. Specifically, we use the surprise in real GDP growth relative to survey expectations from the Survey of Professional Forecasters, corporate profit growth, the realized past cash flows of the low-minus-high volatility portfolio, and the change in charge off rates on bank loans.

Table 8 reports the regression results. We standardize the dependent and independent 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 over the same period. A one-standard deviation real GDP growth surprise is associated with a 0.6 standard deviation increase in PVS_t.

Column (2) reveals similar results for corporate profit growth. If corporate profit growth is one-standard deviation higher, PVS_t increases by 0.4 standard deviations on average. Column (3) shows that PVS_t comoves with the difference in past cash flow growth (ROE) between low- and high-volatility firms.

Finally, row (4) shows that PVS_t responds to recent conditions in credit markets, consistent with our interpretation of PVS_t as a measure that captures risk appetite across 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 0.4 standard deviation decrease in PVS_t. Column (5) shows that in a multivariate regression all four of these explanatory variables have coefficients that are estimated with statistical precision, so all four measures of economic outcomes appear to contain independent information. Overall, the results here show that risk appetite rises on the heels of good news about the state of the economy.

4.2 PVS Forecasts Revisions in Expected Risk

Since PVS_t is driven in part by subjective expectations of risk, it is natural to ask whether the extrapolation we documented in the last section is fully rational. If expectations are fully rational, then revisions in expected risk should not be forecastable: revisions in expectations only occur in response to purely unpredictable news events (Coibion and Gorodnichenko (2015)). To test this prediction, we construct several different measures of revisions in expectations of risk and try to forecast them with PVS_t. For each measure, we first build a firm-level revision measure and then aggregate up to the portfolio level by taking the median revision of high-volatility firms minus the median of low-volatility firms. The internet appendix contains more information on the variable construction for this analysis.

Our first revision measure is how expectations of risk based on analyst forecasts of annual earnings at $t+5$ evolve from quarter t to $t+4$.[14] Row (1) of Table 9 shows a positive and statistically

[14] Recall from our analysis in Section 3.3 that we proxy for expected earnings volatility using dispersion in analyst

significant association between PVS_t and revisions that occur at $t+4$. In the table, all variables have been standardized, so the point estimate indicates that a one-standard deviation increase in PVS_t today forecasts a 0.72 standard deviation higher revision in expected earnings volatility at time $t+4$.

The scatter plot in Figure 4 provides a visual representation of this forecasting regression. This measure of revisions is on average negative. Annual earnings at $t+5$ are a function of the quarterly earnings that are announced through $t+4$; thus, uncertainty about annual earnings at $t+5$ declines as quarterly earnings are released from t to $t+4$. This also means that our measure is not a true innovation in expected future risk, so these predictability results do not unambiguously point to a violation of rational expectations. Nonetheless, Figure 4 also reveals episodes, like the height of the technology bubble in the early 2000s, when high values of PVS_t predicted positive revisions at $t+4$ for earnings uncertainty at time $t+5$. Our proxy for expectations of the risk of annual earnings at $t+5$ actually increase, despite the fact that information in quarterly earnings from t to $t+4$ has been revealed. These instances are hard to reconcile with a perfectly rational framework in which uncertainty resolves over time.

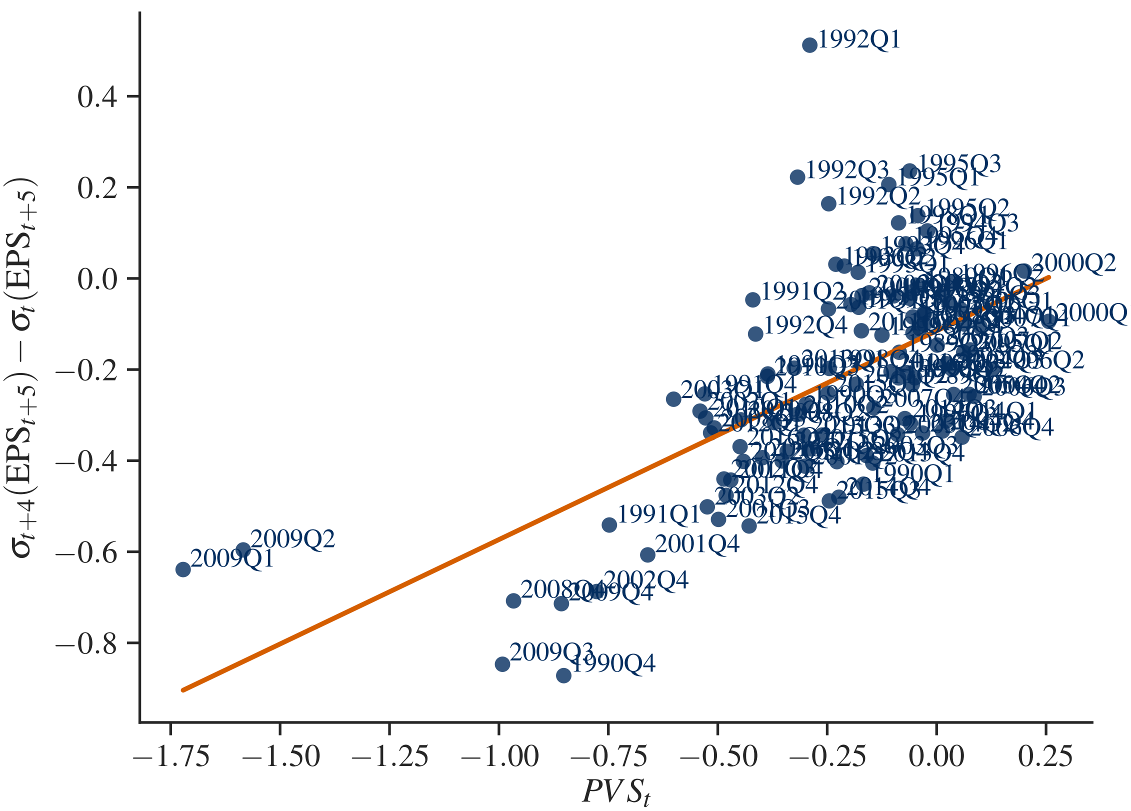
We can build a measure of risk that does not mechanically decline due to the quarterly earnings announcements by studying how analyst expected risk for quarterly earnings at $t+3$ evolves from time t to $t+2$. As discussed in more detail in the internet appendix, we choose these horizons based on data availability in IBES. The results in row (2) indicate that high values of PVS_t forecast a true upward revision in expected risk. When PVS_t is high, analyst expectations of risk are low, and analysts are more likely to revise their views of risk upwards in the future. This suggests that there are times where investors underestimate risk and therefore set the prices of volatile stocks too high. Eventually, investors realize their mistake and revise their expectations of risk upward. Conversely, in periods like the peak of the 2008-2009 global financial crisis, investors appear to overestimate risk, underprice volatile stocks, and eventually revise their expectations of risk downwards.

In row (3), we focus on expectations of return volatility. We use options prices to study how the expected volatility of stock returns that will be realized between $t+3$ to $t+4$ evolves from quarter t to $t+3$.[15] The forecasting regression shows that a one-standard deviation increase in

forecasts from IBES.

[15] We infer expectations of volatility using implied option volatilities from OptionsMetrics, and again pick the horizons based on data availability.

Figure 4: PVS_t and Revisions in Expected Risk



Notes: This figure plots the spread in book-to-market ratios between low and high volatility stocks (PVS_t) against future changes in analyst expectations of risk. 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 the average book-to-market (BM) ratio of low-volatility stocks, less the average BM-ratio of high-volatility stocks. The online appendix contains full details on how we compute BM ratios. Our measure of analyst risk perceptions come from the Thompson Reuters IBES database. For each firm i, we define $\sigma_{i,t}(u)$ as the range of analyst earnings-per-share (EPS) forecasts made on date t about EPS on date $u > t$. Holding fixed u, we then compute the change in this measure from t to $t+4$, defined as $\Delta_4\sigma_{i,t+4}(u)$. Next, we take the median value of $\Delta_4\sigma_{i,t+4}(u)$ for high-volatility stocks minus the median for low-volatility stocks, where volatility is computed at time t. The plot therefore shows how PVS_t relates to how the expected risk of its constituents changes in the future. See the online appendix for more details on how we construct these variables. Data is quarterly and spans 1989Q1-2016Q2.

PVS_t is associated with a 0.45 standard deviation increase in future expected risk based on option prices. Like analyst forecasts, option prices suggest that when PVS_t is high and expected risk is low, expected risk tends to be revised upwards in the future.

Because our loan officer survey variable is not associated with a fixed future date, we cannot construct true revisions in expectations of risk based on this measure. We can only examine the measure's mean reversion over time. Row (4) shows that the percentage of banks loosening lending standards tends to fall after periods of high PVS_t. In untabulated results, we control for general mean reversion in the survey variable by including its level in the regression, and find that the effect of PVS_t remains unchanged. In other words, the percentage of banks loosening lending standards tends to fall after periods of high PVS_t, even controlling for its natural mean reversion.

Finally, rows (5) and (6) 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, the predictable revisions in expected risk that we document are happening at the same time that realized risk is increasing. The fact that PVS_t forecasts increases in realized risk could naturally occur due to predictable mean-reversion in realized risk; however, if expectations of risk were fully rational, they should anticipate this mean reversion and we would not observe the predictable revisions that we see in our expectations data.

Our measures of risk expectations are imperfect, so the results in this section do not unequivocally reject a null of rational expectations. Our analyst forecast measure comes from dispersion across analysts as opposed to the distribution of earnings analysts perceive. And our option-based measure captures both expected volatility and the variance risk premium, so PVS_t may be forecasting changes in the latter. However, we find similar results using a variety of different measures of expected risk, suggesting that variation in PVS_t may not be fully rational.

5 Model

In this section, we present a stylized model that formalizes the narrative of risk-driven business cycles and ties together our empirical evidence on the price of volatile stocks, investment, and investor perceptions of risk.

5.1 Preferences and Beliefs

There is a representative agent, who has constant relative risk aversion λ over aggregate consumption and time-discount rate β. Log aggregate consumption growth is assumed to follow a heteroskedastic process:

$$\Delta c_{t+1} = \varepsilon_{t+1}, \tag{7}$$

$$\varepsilon_{t+1} = \sigma_t \eta_{t+1}, \tag{8}$$

$$\sigma_t^2 = exp(a - b\varepsilon_t), \tag{9}$$

where η_{t+1} is an i.i.d. normal shock with mean zero and variance one. High realizations of the fundamental shock ε_{t+1} therefore correspond to good times with low marginal utility of consumption. Time-varying volatility ensures that agents face a non-trivial updating problem for volatility, and our formulation of it generates GARCH-like effects that are ubiquitous in the financial econometrics literature. We could extend the model to contain an autoregressive term in (7), which would make expected growth predictable, without changing the mechanism. However, since our empirical results indicate that risk appetite does not vary with expected cash flows, we proceed with the simpler setup. Since risk aversion is constant in the model, risk appetite corresponds to investors' subjective expectations of volatility.

We assume that the representative agent updates according to the diagnostic expectations of Gennaioli and Shleifer (2010, 2018), where investors overweight states of the world that are representative. In particular, following Bordalo et al. (2018), we assume the most representative state is the one exhibiting the largest increase in its likelihood based on recent news.[16] The degree of belief distortion is indexed by a parameter θ, where $\theta = 0$ means that agents update rationally and $\theta > 0$ implies that agents overweight states of the world that have a high conditional likelihood given, or are representative of, previously observed data.

Combining these assumptions with Eqs. (7) and (9), the subjective distribution of ε_{t+1} is con-

[16] Formally, state ε_{t+1} is more representative at t if it more likely to occur given the realization of ε_t than on the basis of the past state ε_{t-1}. The representativeness of ε_{t+1} is given by

$$\frac{h(\varepsilon_{t+1}|\varepsilon_t)}{h(\varepsilon_{t+1}|\varepsilon_{t-1})},$$

where h is the likelihood function.

ditionally normally distributed with subjective mean and variance:

$$\begin{aligned} \mathbb{E}_t^{\theta}(\varepsilon_{t+1}) &= 0, & (10) \\ \mathbb{V}_t^{\theta}(\varepsilon_{t+1}) &= \left(\frac{1}{1+\theta(1-exp(-b\varepsilon_t)}\right)\sigma_t^2. & (11) \end{aligned}$$

Here, we use superscript θ to denote subjective expectations. Eq. (11) shows that investors under-estimate volatility following good news and over-estimate volatility following bad news.

5.2 Production

Firm i is perceived to produce according to a decreasing returns to scale production function with random total factor productivity $A_{i,t+1}$:

$$Y_{i,t+1} = A_{i,t+1}K_{i,t+1}^{\alpha}. \tag{12}$$

Here, $K_{i,t+1}$ denotes the time $t+1$ capital stock of firm i and α is the capital share of production. Firm i's exposure to the aggregate shock ε_{t+1} enters through shocks to productivity $A_{i,t+1}$. We assume that firms differ in their exposure s_i to the aggregate shock ε_{t+1}, but that investors expect the same average productivity for all firms, consistent with our empirical finding that PVS_t is largely uncorrelated with analysts' earnings forecasts. Thus, investors expect productivity to follow the process:

$$A_{i,t+1} = \exp\left(s_i\varepsilon_{t+1} - \frac{1}{2}s_i^2\mathbb{V}_t^{\theta}(\varepsilon_{t+1})\right). \tag{13}$$

Higher s_i means that firm i has a riskier and more volatile production process. The Jensen's inequality term ensures that expected total factor productivity is equalized across firms, so cross-firm differences in real investment are driven only by the subjective expectations of volatility and not the level of expected returns. We assume that $s_i > \frac{\lambda}{2}$ for all firms, so all firms have risky production.

We assume that capital depreciates fully each period and that there are no investment frictions, so one unit of consumption goods at time t can be turned into one unit of investment. This simplifies the problem by making capital at $t+1$ equal to investment at t.

5.3 Equilibrium Prices and Investment

It follows from consumer preferences that the representative agent values contingent claims paying off at time $t+1$ with the stochastic discount factor:

$$M_{t+1} = \beta \exp\left(-\lambda \varepsilon_{t+1}\right).$$

The log real risk-free rate r_{ft} is given by

$$r_{ft} = -\ln(\beta) - \frac{1}{2}\lambda^2 \mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right). \tag{14}$$

Equation (14) is standard except for the use of diagnostic expectations. The second term corresponds to risk appetite in the model and captures the precautionary savings motive, which drives down the risk-free rate when subjective expectations of risk are high.

Equilibrium investment must equate the expected marginal rate of return on capital with the return required by investors. Investors' required return equals the real rate plus a firm-specific risk premium, which is proportional to aggregate subjective risk and firm exposure s_i. The required return takes a simple form in logs:

$$\ln\left(\mathbb{E}_t^{\theta}\left[R_{i,t+1}^K\right]\right) = r_{ft} + \lambda s_i \mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right). \tag{15}$$

We obtain the expected marginal rate of return on capital by taking the first derivative of (12) and then taking subjective expectations over ε_{t+1}:

$$\ln \mathbb{E}_t^{\theta}\left[R_{i,t+1}^K\right] = \ln\alpha - (1-\alpha)k_{i,t+1}. \tag{16}$$

Here, we again use logs and use lower-case $k_{i,t+1}$ to denote log firm capital. Note that (16) is independent of θ, so investors' subjective expected return on capital agrees with objective forecasts, consistent with our empirical results in Section 3.2. Equating (15) with (16) and substituting in the expression for the real rate shows that:

$$k_{i,t+1} = \frac{\ln(\alpha\beta)}{1-\alpha} - \frac{\lambda s_i - \frac{1}{2}\lambda^2}{1-\alpha}\mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right). \tag{17}$$

The following proposition summarizes the equilibrium.

Proposition 1. *There is a unique equilibrium in which the real risk-free rate satisfies (14), subjective expected returns on firm i satisfy (15), and firm i's investment is given by (17).*

We next consider how the economy reacts following a positive macroeconomic shock by computing comparative statics with respect to ε_t. For simplicity, we consider the case where there are two types of firms H and L with $s_H > s_L$. We use the expected return on L firms minus the expected return on H firms as a simple model analog for PVS_t, consistent with our empirical finding that nearly all movement in PVS_t is driven by expected returns:

$$PVS_t^{model} = \ln \mathbb{E}_t[R_{L,t+1}] - \ln \mathbb{E}_t[R_{H,t+1}] = \lambda (s_L - s_H) \mathbb{V}_t^{\theta} (\varepsilon_{t+1}). \tag{18}$$

It is worth noting that objective expected returns equal investors' subjective expected returns. However if $\theta > 0$, an objective observer (i.e., one with $\theta = 0$) would disagree with investors about the risk of firms' production and thus the appropriate required return for investment.

The following proposition gives comparative statics with respect to 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) Subjective risk falls: $\frac{d\mathbb{V}_t^{\theta}(\varepsilon_{t+1})}{d\varepsilon_t} = -exp(a)b(1+\theta) < 0$.

b) PVS_t^{model} rises and the expected return of high-volatility firms falls relative to low-volatility firms: $\frac{dPVS_t^{model}}{d\varepsilon_t} = \lambda\,(s_H - s_L)\,exp(a)b(1+\theta) > 0$ and $\frac{d\left(\ln \mathbb{E}_t[R_{L,t+1}] - \ln \mathbb{E}_t[R_{H,t+1}]\right)}{d\varepsilon_t} = -\lambda\,(s_L - s_H)\,exp(a)b\,(1+\theta) >$ 0.

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

d) Aggregate investment increases: $\frac{d(k_{H,t+1}+k_{L,t+1})}{d\varepsilon_t} = \frac{\lambda(s_H+s_L)-\lambda^2}{1-\alpha} exp(a)b\,(1+\theta)$.

e) The investment of volatile firms rises more: $\frac{d\left(k_{H,t+1}-k_{L,t+1}\right)}{d\varepsilon_t} = \frac{\lambda(s_H-s_L)}{1-\alpha} exp(a)b\,(1+\theta) > 0$.

These effects are all amplified if investors have diagnostic beliefs ($\theta > 0$).

Comparative static 2b shows that if volatility is countercyclical ($b > 0$), PVS_t^{model} falls following a bad shock, or equivalently the expected return on high-volatility minus low-volatility firms rises. Intuitively, investors expect that returns will be riskier after a bad shock and wish to be compensated for this risk. The effect is amplified if investors have diagnostic beliefs ($\theta > 0$) because diagnostic beliefs lead investors to over-extrapolate the increase in risk following a bad shock.

Comparative static 2c shows that the real rate falls following bad shocks. Intuitively, following a bad fundamental shock, future risk rises and thus precautionary savings demand for risk-free bonds increases. Again, the effect is stronger if investors have diagnostic beliefs.

Comparative static 2d shows that aggregate investment in the model falls following a bad shock. Intuitively, investors expect more risk following a bad fundamental shock, especially if they have diagnostic beliefs. With our assumption that firms are risky ($s_i > \frac{\lambda^2}{2}$), investors require a higher return on risky real investment relative to risk-free bonds. They therefore do not undertake investment that would have been marginal at a lower required return, leading to a drop in real investment. Comparative static 2e shows that the effect is particularly strong for volatile firms. Their investment falls more following a negative shock because they are more exposed to the shock, so investors require a particularly high return for these firms.

Finally, we ask how investors revise their beliefs. We assume that at the end of period t investors learn the true volatility and revise their beliefs to $\mathbb{V}_t[\varepsilon_{t+1}] = exp(a - b\varepsilon_t)$. The following proposition gives the relationship between the revision in beliefs and PVS_t^{model}.

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

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

Intuitively, following a good shock, investors overreact and lower their subjective beliefs about risk too much, resulting in a value of PVS_t^{model} that is too high. Investors will then predictably revise their beliefs back up towards the truth, so high values of PVS_t^{model} forecast positive revisions in expectations of risk.

5.4 What the Model Delivers

The model formalizes the risk-centric narrative of economic cycles and delivers our key empirical findings. In the model, PVS_t^{model} captures risk appetite and is driven by subjective expectations of risk, consistent with our empirical results in Table 5.

The comparative statics in Proposition 2 flesh out the risk-centric narrative. Proposition 2b shows that PVS_t^{model} rises following positive macroeconomic surprises, as we find in the data in Table 8. In the model, risk appetite rises because investors' subjective expectations of risk fall following a positive fundamental shock due to investor extrapolation. Following the shock, Propositions 2b and 2c show that the real risk-free rate and PVS_t^{model} both rise. Thus, the model also captures the empirical correlation between safe and risky asset prices, as in our baseline empirical result in Table 2. Furthermore, this correlation is driven by expected returns not cash flows, consistent with our empirical results in Table 4. In the model, the correlation arises because expectations of low risk reduce the precautionary savings motive, so investors require a higher return to hold the risk-free bond at the same time they are demanding relatively low compensation for holding volatile stocks. In addition, the model captures our results on real outcomes. Propositions 2d and 2e show that real investment rises when PVS_t^{model} is high through a standard Q-theory channel, and the investment response is strongest for the riskiest firms. These model implications are in line with our empirical findings in Table 7.

Finally, Proposition 3 completes the narrative, capturing our results on revisions in expectations of risk. When investors have diagnostic expectations ($\theta > 0$), their subjective expected risk rises more in response to a negative shock than does objective expected risk, but is subsequently revised downward. These patterns align with our finding in Table 5 that PVS_t is more sensitive to subjective than objective risk, as well the fact that PVS_t positive forecasts revisions in expected risk (Table 9). For the most part, diagnostic expectations amplify the model's comparative statics relative to the rational expectations benchmark. However, diagnostic expectations are essential for generating over-reaction and subsequent revisions in subjective expectations of risk. A simple calculation shows that our empirical results imply reasonable magnitudes for the belief distortion parameter, θ. Column (2) of Table 5 and Column (4) of Table 5 suggest that subjective expectations of risk move about twice as much in response to PVS_t as objective expectations. Proposition 2a implies that in order to make subjective risk twice as sensitive as objective risk, we need $\theta \approx 1$, in line with the estimates of Bordalo et al. (2018) and Bordalo et al. (2017).

The model is stylized and thus necessarily has limitations. First, for simplicity there is only a single macroeconomic shock that impacts all firms. This assumption implies that risk premia on the aggregate market move with the real rate, though in the data we find a negligible correlation between the aggregate book-to-market ratio and the real rate. One way to address this limitation would be to assume that the aggregate stock market is exposed to a wide range of factors, with volatile stocks isolating the subset of factors that are relevant for investment and real interest rates. Another way to move the model closer to the data is to assume that low-volatility firms are quite bond-like in the sense that $s_L \approx \frac{\lambda}{2}$. This would dampen the response of the aggregate market to expectations of risk, while strengthening the response of PVS_t^{model}. As discussed in Section 3.2 above, there is some evidence of this: low-volatility stocks are bond like in the sense that their market values tend to rise when the real rate falls.

Second, the model implies that volatile firms should unconditionally earn higher returns. However, in the data, there is little relation between average stock returns and measures of risk such as volatility and market beta (Ang et al. (2009), Black et al. (1972)). 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 risk premia. 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 demand component generate the time variation we find.

Third, risk aversion λ is constant in the model to isolate the subjective expected risk channel that emerges from our empirical results in Section 3.3. In the model, subjective expectations of risk are fully responsible for movements in PVS_t^{model}, while Section 3.3 indicates that they may explain closer to 50% of PVS_t variation in the data. It would be straightforward to allow for λ to vary through time, as in Campbell and Cochrane (1999). Indeed, time-varying risk aversion is a complementary channel that would generate many of our results. For example, the Campbell and Cochrane (1999) mechanism would generate the relationship between PVS_t and past macroeconomic news that we observe in the data.

6 Conclusion

This paper proposes a new measure of macroeconomic risk appetite, PVS_t, based on the idea that investors are more averse to holding volatile assets when their risk appetite is low. Using PVS_t, we present empirical evidence in favor of classic narratives of economic booms and busts that emphasize financial market risk appetite. Following a positive fundamental shock, investor risk appetite rises, in part because subjective perceptions of risk decline. Investors then find safe bonds less attractive and are more willing to fund risky projects, leading real interest rates to rise as investment booms and spurring an economic expansion. Risk appetite subsequently reverses following a negative fundamental shock, and investors seek out safe bonds as they become less willing to fund risky investments, driving down real rates and leading to an economic contraction.

Our findings also suggest that risk appetite reflects subjective expectations of risk that may not be fully rational. Given the link between risk appetite and the broader economy, future work seeking to measure investors' expectations of risk and understand what drives them 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.

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

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 returns. *Journal of Economic Perspectives 21*(2), 129–151.

Baker, M. and J. Wurgler (2012). Comovement and predictability relationships between bonds and the cross-section of stocks. *Review of Asset Pricing Studies 2*(1), 57–87.

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

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. Stulz (Eds.), *Financial Markets and Asset Pricing*, Volume 1 of *Handbook of the Economics of Finance*, pp. 1053–1128. Elsevier.

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

Black, F., M. Jensen, and M. Scholes (1972). The capital asset pricing model: some empirical tests. In M. Jensen (Ed.), *Studies in the Theory of Capital*. Praeger.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*, 623–85.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta, and S. Terry (2014). Really uncertain business cycles. NBER Working paper 18245.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *Review of Financial Studies 22*(11), 4463–92.

Bordalo, P., N. Gennaioli, R. La Porta, and A. Shleifer (2017). Diagnostic expectations and stock returns. Technical report, Oxford University, Universita Bocconi, Brown University, and Harvard University.

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

Caballero, R. J. and E. Farhi (2017, Forthcoming). The safety trap. *Review of Economic Studies 85*(1), 223–274.

Caballero, R. J. and A. Simsek (2017, October). A risk-centric model of demand recessions and macroprudential policy. Working paper, MIT.

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., M. Lettau, B. G. Malkiel, and Y. Xu (2002). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *The Journal of Finance 56*(1), 1–43.

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.

Carroll, C. D. and A. A. Samwick (1998). How important is precautionary saving? *Review of Economics and Statistics 80*(3), 410–419.

Cieslak, A. and A. Vissing-Jorgensen (2017). 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*, 1661–1707.

Cochrane, J. H. (2007). The dog that did not bark: A defense of return predictability. *Review of Financial Studies 21*(4), 1533–1575.

Cochrane, J. H. (2009). *Asset Pricing (Revised Edition)*. Princeton University Press.

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). Determinacy and identification with Taylor rules. *American Economic Review 95*(1), 138–160.

Coibion, O. and Y. Gorodnichenko (2015, August). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–78.

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.

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.

De Long, J. B., A. Shleifer, L. Summers, and R. 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.

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

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.

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

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics 91*(1), 24–37.

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

Gilchrist, S. and E. Zakrajšek (2012, June). 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), 165–99.

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

Hall, R. E. (2016, April). Understanding the decline in the safe real interest rate. NBER Working paper 22196.

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

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.

Hou, K. and R. K. Loh (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics 121*(1), 167–194.

Johnson, T. C. (2004). Forecast dispersion and the cross section of expected returns. *Journal of Finance 59*(5), 1957–1978.

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

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. *The 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.

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.

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

Krishnamurthy, A. and T. Muir (2017, August). How credit cycles across a financial crisis. Working paper, Stanford University.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012). The aggregate demand for treasury debt. *Journal of Political Economy 120*(2), 233–267.

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 S. C. Ludvigson (2004, March). Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption. *American Economic Review 94*(1), 276–299.

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

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.

McKay, A., E. Nakamura, and J. Steinsson (2016). The power of forward guidance revisited. *American Economic Review 106*(10), 3133–3158.

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.

Minsky, H. P. (1986). *Stabilizing an unstable economy*. New Haven: Yale University Press.

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

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

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.

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

van Binsbergen, J. H., R. S. Koijen, and M. W. Brandt (2012). On the timing and pricing of dividends. *American Economic Review 102*(4), 1596–1618.

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

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

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 Appendix contains full details on how we form portfolios and compute book-to-market ratios. 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 percent. We detrend the real rate using a linear trend and explore alternative methodologies in the internet appendix.

Table 2: What Explains Real Rate Variation?

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 the spread in book-to-market (BM) ratios between low- and high-volatility stocks (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. The Appendix contains full details on how we compute BM ratios. PVS_t is defined as the difference in BM ratios between the bottom (BM Low Vol) and top quintile (BM High Vol) portfolios. Aggregate BM is computed by summing book equity values across all firms and divided by the corresponding sum of market equity values. 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 percent 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 is 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. In the table, all book-to-market ratios, including PVS_t, are standardized to have mean zero and variance one. This is true in both the levels regression and the first-differenced regressions. Data is quarterly and spans 1970Q2-2016Q2.

Table 3: Robustness: The Real Rate and PVS

Panel A: *Alternative Constructions, the Term Structure of Real Rates, 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
The Term Structure:													
(2)	5-Yr Real Rate	1.07	**3.82**	0.35	1.30	**6.06**	0.41	0.33	**2.63**	0.12	0.51	**4.17**	0.22
(3)	10-Yr Real Rate	0.92	**3.32**	0.30	1.14	**5.08**	0.36	0.25	**2.41**	0.10	0.40	**4.22**	0.20
Alternative Constructions:													
(4)	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
(5)	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:													
(6)	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
(7)	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
(8)	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
(9)	2M 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
(10)	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
(11)	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 our main results. 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 directly 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) uses our baseline PVS_t measure and the full sample. In row (2) and (3), we use the five and ten-year real interest rates as the dependent variable in the regression, as opposed to the one-year rate that we use in all other specifications. Row (4) uses value weights instead of equal weights when forming our PVS_t. Row (5) constructs our PVS_t using the past two years of return volatility, as opposed to the past two months. In rows (6)-(11), we run horse races of PVS_t against several other variables. Row (6) controls for the spread between off-the-run and on-the-run Treasury yields (Krishnamurthy (2002)). In rows (6)-(10), we sequentially add the book-to-market spread based on other characteristic sorts as control variables in the regression. See the internet appendix for a description of each characteristic and for 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 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 (pre-crisis ends in 2008Q4).

Table 3: Robustness: The Real Rate and PVS

Panel B: *Other Measures of Financial Conditions, PVS, and the Real Rate*

			$PVS_t = a + b \times X_t$			$\text{RealRate}_t = a + c \times Z_t$			$\text{RealRate}_t = a + c \times Z_t + d \times PVS_t$		
	Z-variable	N	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, where PVS_t is the average book-to-market ratio of low-minus-high volatility stocks. The first set of regressions in the table shows the results of a univariate regression of each alternative financial market measure on PVS_t. The second set of regressions in the table shows the results of a univariate regression of the real rate on contemporaneous values of each financial market measure. The last set of results regresses the real rate on both PVS_t and each alternative measures. In rows (1)-(6), the alternative variables are the spread between Moody's BAA credit yields and the 10-year Treasury rate, 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 full sample spans 1970Q2-2016Q2. See the internet for more details on our optimal stock market forecast and on other 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 percent and linearly detrended.

Table 4: PVS_t, the Real Rate, and Future Returns to Volatile Assets

Panel A*: Forecasting Returns and Earnings Surprises*

	Volatility-Sorted Portfolio							
	$\text{Ret}_{t\to t+4}$		$\text{ROE}_{t\to t+4}$		ROE $\text{Surprise}_{t\to t+4}$		$\text{VW-Mkt} - \text{Rf}_{t\to t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{PV}S_t$	15.08**		-1.35		-0.03		-2.31	
	(4.11)		(-1.40)		(-1.03)		(-0.90)	
Real Rate_t		4.13**		0.48		0.00		0.03
		(2.13)		(0.96)		0.22		(0.03)
Constant	2.41	2.49	10.95**	10.93**	0.00	0.01	6.98**	6.95**
	(0.60)	(0.59)	(8.31)	(8.29)	(0.06)	0.15	(2.74)	(2.73)
Adj. R^2	0.26	0.07	0.02	0.01	0.01	0.00	0.01	-0.01
N	181	181	181	181	94	94	181	181

Notes: This table reports several return forecasting regressions where the predictor variables are either the real interest rate or PVS_t, where the latter 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 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 percent and linearly detrended. The columns listed under "Volatility-Sorted Portfolio" pertain an equal-weighted portfolio that is long low-volatility stocks and short high-volatility stocks. $\text{ROE}_{t\to t+4}$ is the return on equity between t and $t+4$ for the low-minus-high volatility portfolio, which we compute following Cohen, Polk, and Vuolteenaho (2003). ROE surprise is the median ROE surprise for low-volatility stocks minus the median ROE surprise for high-volatility stocks, where ROE surprises are computed using Thomson Reuters IBES data (see the internet appendix for more details). VW-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. The stock return forecasting regressions use Hodrick (1992) standard errors and all other forecasting regressions use 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. All returns are expressed in percentage points.

Table 4: PVS_t, the Real Rate, and Future Returns to Volatile Assets

***Panel B**: Evidence from Other Asset Classes*

				Forecasting Vol-Sorted $\text{Ret}_{t\to t+1}$ with					
				PVS_t			Real Rate_t		
Asset Class	N	Mean	Volatility	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. The portfolios we use are the test assets in He et al. (2017), except for U.S. stocks. 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 low-volatility portfolio and short the high-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 Vol-Sorted $\text{Ret}_{t,t+1}$" 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 percent 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 5: PVS and Expectations of Risk

Dependent Variable	PVS_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High-Minus-Low Volatility Stocks:							
$\sigma_t\,(\text{EPS}_{t+1})$	-0.45**						
	(-2.49)						
$\sigma_t\,(\text{EPS}_{t+5})$		-0.67**					-0.64**
		(-5.06)					(-5.45)
Option-Implied $\sigma_t^{IV}(Ret_{t,t+4})$			-0.46**				
			(-2.47)				
Model-Based $\sigma_t(Ret_{t,t+1})$				-0.31**			-0.22**
				(2.13)			(-3.49)
% Banks Loosening					0.50**		0.12
					(3.46)		(1.65)
% Banks Loosening b/c of Outlook						0.48**	
						(2.51)	
Adj. R^2	0.28	0.61	0.24	0.09	0.32	0.27	0.73
N	110	110	80	184	105	90	104

Notes: This table shows contemporaneous regressions of PVS_t on several explanatory variables. 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 $\sigma_{it}(EPS_{t+h})$, 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. $\sigma_t(EPS_{t+1})$ in column (1) is built using one-quarter ahead quarterly EPS forecasts. When building $\sigma_t(EPS_{t+5})$ for column (2), 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. The variable Option-Implied $\sigma_t^{IV}(Ret_{t,t+4})$ 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 column (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 what we call Model-Based $\sigma_t(Ret_{t,t+1})$. Column (4) uses the net percent of U.S. banks loosening lending standards and column (5) uses the net percent of U.S. banks loosening lending standards because of a change in risk tolerance, both taken from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS). 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 Online Appendix for more details.

Table 6: Volatility-Sorted Returns and Monetary Policy Surprises

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

	Quarterly Data		Daily Data		Sample	
MP Shock	b	$t(b)$	b	$t(b)$	Start	End
Romer and Romer (2004)	0.71	0.44	-0.06	-0.43	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. 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. Volatility-sorted returns are returns on the lowest minus highest volatility quintile portfolios. 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 an 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 an 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 7: PVS and Real Outcomes

***Panel A**: PVS and Real Aggregate Outcomes*

	Forecast Horizon (Qtrs)	
	$h=1$	$h=4$
Dep. Variable: Investment-to-Capital		
PVS_t	0.22**	0.35**
	(4.66)	(3.56)
Dep. Variable: Output Gap		
PVS_t	0.32**	0.66**
	(3.27)	(2.35)
Dep. Variable: ΔUnemployment Rate		
PVS_t	-0.11**	-0.27
	(-3.17)	(-1.36)

Notes: This table reports the results of running Jordà (2005) local projections of macroeconomic outcomes onto PVS$_t$. In all cases, we run regressions of the following form:

$$y_{t+h} = a + b^h_{PVS} \times PVS_t + b^h_{RR} \times \text{Real Rate}_t + b^h_y \times y_t + \varepsilon_{t+h}$$

and report the estimation results for b^h_{PVS},. PVS_t is the average book-to-market ratio of low-minus-high volatility stocks and in all cases is standardized to have a mean of zero and variance of 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 percent 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 7: PVS and Real Outcomes (continued)

***Panel B**: PVS and Firm-Level Investment*

Dependent Variable	$\% \, CAPX^{Ann}_{i,t+4}/A_{i,t}$					
	Full Sample		*1983Q1-1999Q4*		*2000Q1-2016Q2*	
	(1)	(2)	(3)	(4)	(5)	(6)
$\% \, CF^{Ann}_{i,t+4}/A_{i,t}$	0.08**	0.07**	0.09**	0.09**	0.05**	0.05**
	(17.96)	(16.95)	(14.30)	(13.79)	(13.06)	(13.88)
PVS_t	0.65**		0.51**		0.33**	
	(6.58)		(3.13)		(5.50)	
$PVS_t \times 1^{q=2}_{it}$	0.15**	0.17**	0.20**	0.17*	0.13**	0.13**
	(4.15)	(4.62)	(2.03)	(1.69)	(3.67)	(3.79)
$PVS_t \times 1^{q=3}_{it}$	0.23**	0.29**	0.30**	0.30**	0.27**	0.28**
	(5.35)	(6.35)	(2.50)	(2.36)	(5.58)	(5.67)
$PVS_t \times 1^{q=4}_{it}$	0.28**	0.38**	0.45**	0.47**	0.36**	0.38**
	(4.49)	(6.32)	(2.95)	(3.09)	(6.76)	(6.67)
$PVS_t \times 1^{q=5}_{it}$	0.16*	0.33**	0.39**	0.45**	0.42**	0.45**
	(1.77)	(4.11)	(2.50)	(2.62)	(5.99)	(5.80)
FE	i	(i,t)	i	(i,t)	i	(i,t)
R^2	0.57	0.59	0.59	0.59	0.68	0.69
# of Firms	9,356	9,356	6,792	6,792	5,604	5,604
N	315,333	315,333	155,080	155,080	160,073	160,073

Notes: Panel B of this table studies how firm-level investments interacts with PVS. We measure firm i's investment at time t as the running four-quarter total CAPX (denoted $CAPX^{Ann}_{i,,t}$) divided by the book value of assets at time $t-4$ (denoted $A_{i,t-4}$). $CF^{Ann}_{i,t}$ is the running four-quarter total cash flow for the firm, computed as depreciation and amortization plus income before extraordinary items. Both are winsorized at their 1% tails. We run regressions of the form: $CAPX^{Ann}_{i,t+4}/A_{i,t} = FEs + b_1 \times CF^{Ann}_{i,t+4}/A_{i,t} + \sum_{q=1}^{5} c_q \times 1^q_{it} + d_2 \times PVS_t + \sum_{q=2}^{5} d_q \times PVS_t \times 1^q_{it} + \varepsilon_{i,t}$, where 1^j_{it} is an indicator function for whether firm i is in volatility-quintile j at time t. PVS_t is average book-to-market ratio of low-minus-high volatility stock 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. FE is a set of fixed effects as indicated in the table. We use all firms in the CRSP-COMPUSTAT merged database where the value of book assets is greater than $10 million and we also exclude financial firms (one-digit SIC of six). Firms with negative investment are also excluded (less than 0.5% of observations). 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 1983Q1-2016Q2. The total size of the subsamples does not match the full sample because we drop fixed-effect groups of size one.

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

Dependent Variable	$\Delta_4 PVS_t$				
	(1)	(2)	(3)	(4)	(5)
Real GDP Surprises$_{t-4\to t}$	0.56**				0.34**
	(3.86)				(2.82)
Corporate Profit Growth$_{t-4\to t}$		0.42**			0.27**
		(3.81)			(2.55)
LMH-Vol ROE$_{t-4\to t}$			-0.27**		-0.16**
			(-3.21)		(-2.82)
Δ_4Bank Net Chargeoffs$_t$				-0.40**	-0.25**
				(-2.68)	(-3.16)
Adj. R^2	0.31	0.17	0.07	0.16	0.42
N	181	181	181	158	158

Notes: This table reports univariate regressions of four-quarter changes in PVS 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) realized corporate protfit growth from time $t-4$ to t, taken from U.S. Burueau of Economic Analysis NIPA tables; (3) the trailing annual ROE of the low-minus-high volatility portfolio; and (4) the four-quarter change in bank net chargeoff rate, taken directly 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 Online Appendix for more details on variable construction.

Table 9: PVS and Revisions in Expected Risk

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

		b	$t(b)$	Adj. R^2	N
	Expected Risk:				
(1)	$\sigma_{t+4}(\text{EPS}_{t+5}) - \sigma_t(\text{EPS}_{t+5})$	0.72	7.14	0.37	110
(2)	$\sigma_{t+2}(\text{EPS}_{t+2,t+3}) - \sigma_t(\text{EPS}_{t+2,t+3})$	0.41	2.50	0.12	94
(3)	$\sigma^{IV}_{t+3}(Ret_{t+3,t+4}) - \sigma^{IV}_t(Ret_{t+3,t+4})$	0.45	3.18	0.17	80
(4)	Δ_4 Prc. of Banks Loosening$_{t+4}$	-0.83	-8.64	0.53	101
	Realized Risk:				
(5)	$\Delta_4\sigma_{t+4}(\text{Mkt-Rf})$	0.21	1.97	0.04	181
(6)	$\Delta_4\sigma_{t+4}(\text{HML-Vol})$	0.34	1.90	0.11	181

Notes: This table uses PVS_t to forecast future revisions in 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 $t+h$, denoted $\sigma_{it}(EPS_{t+h})$, 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 annual earnings are at least two fiscal periods away, which in calendar time is generally between five and six quarters from date t, i.e. $h \approx 5$. For each firm i, we define the revision in expected earnings growth volatility at time as $\sigma_{i,t+4}(EPS_{t+5}) - \sigma_{i,t}(EPS_{t+5})$. At the portfolio level, $\sigma_{t+4}(EPS_{t+5}) - \sigma_t(EPS_{t+5})$ is the cross-sectional median revision for high-volatility stocks minus the median revision for low-volatility stocks. Stocks are designated as high or low volatility at time t based on their past 60 days of realized returns. In row (2), we use option implied volatilities to define revisions in expected return volatility. For each firm i and date t, denote $\sigma^{IV}_t(t+3,t+4)$ 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 $\sigma^{IV}_{i,t+3}(t+3,t+4) - \sigma^{IV}_{i,t}(t+3,t+4)$. 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. σ_t(Mkt-Rf) is the realized quarterly volatility of the CRSP value-weighted index at time t. σ_t(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 Online Appendix for more details.