A Measure of Risk Appetite for the Macroeconomy*

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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 aggregate quantities, 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 related to investors' expectations of risk and appears to extrapolate from recent economic conditions. Periods of elevated risk appetite tend to be followed by upward revisions in expected risk, suggesting that investor forecasts of risk may not be perfectly rational.

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1 Introduction

Classic accounts of economic boom and bust cycles (Keynes (1937); Minsky (1977); Kindleberger (1978); Minsky (1986)) emphasize the role that financial market risk appetite plays in shaping macroeconomic 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, real interest rates, real investment, and economic activity recover.

This risk-centric view has recently resurfaced in theoretical models of business cycles (Caballero and Farhi (2017); Caballero and Simsek (2017); Cochrane (2017)), but the empirical link between risk appetite and the macroeconomy has proven elusive. Traditional rational 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. First, 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 also 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. In contrast, the real rate is essentially uncorrelated with the book-to-market ratio of the aggregate stock market. 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)).

Second, consistent with the risk-centric view of business cycles, 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 – reflects 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.

Third, we 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 appear to 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.

The relationships we document between the real rate, macroeconomic outcomes, and PVS_t are support the risk-centric view of economic cycles. We next directly study the dynamics of PVS_t to understand the fundamental forces that drive risk appetite. We show 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. This is true when using subjective measures of expected risk derived from analyst earnings forecasts or market-based measures of expected risk based on the implied volatility of options. In addition, data from the Federal Reserve's Senior Loan Officer Opinion Survey indicates that when PVS_t is high, banks are loosening lending standards, consistent with the idea that they believe risks are low. These results support our interpretation of PVS_t as a measure of risk appetite by tying it directly to financial market participants' expectations of risk.

Motivated by the risk-centric accounts of Keynes (1937), Minsky (1977), and Kindleberger (1978), we then investigate whether these expectations of risk are fully rational. Under the null of perfectly rational expectations, revisions in the expected risk of high volatility firms should be unpredictable. We find that high values of PVS_t, which coincide with low expected risk at time t, predict future upward revisions in expected risk. Thus, the data suggests that there are times when PVS_t is high because investors underestimate the risk of volatile firms, though investors eventually realize their mistake and revise their expectation of risk upwards. We explore this possibility further by constructing objective forecasts of macroeconomic risk using time-series models to forecast the volatility of several aggregate quantities, including total factor productivity (TFP) growth, real GDP growth, and real consumption growth. In addition, we consider financial market variables like the expected volatility of volatile stocks and the expected volatility of the aggregate stock market. Under rational expectations, PVS_t should move with these objective forecasts of risk, but we find that both PVS_t and the real rate are only weakly correlated with them. The fact that PVS_t is weakly correlated with objective forecasts of macroeconomic risk – and is significantly more correlated with subjective expectations of risk – suggests movements in risk appetite may in part be driven by departures from fully rational expectations.

Finally, we study the conditions that precede a run up in risk appetite. In particular, PVS_t rises following positive macroeconomic outcomes, such as positive surprises in GDP, high corporate profit growth, and low bank loan charge offs. Thus, as originally posited by Keynes (1937) and Minsky (1977), risk appetite appears to extrapolate from recent economic news.

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), leading them to over-estimate the increase in volatility, 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. 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 decade-by-decade changes in real rates primarily to expected growth and Treasury convenience yields.[2] By contrast, our empirical findings emphasize that time-varying risk appetite plays an important role 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); Cochrane (2017)). We label PVS_t a measure of risk appetite, rather than risk aversion, because we want to allow for the possibility that it reflects both expectations of risk and risk aversion. We highlight expectations of risk, not risk aversion, in part due to data limitations – there are more direct measures of expectations of risk than of risk aversion. However, our results do not rule out risk aversion as an important driver of risk appetite. Indeed, 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

[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)

our emphasis on stocks' total volatility rather than other stock characteristics in the construction of PVS_t 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 (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 speculative securities with highly uncertain values (e.g., Baker and Wurgler (2006)), consistent with the special role of volatility in our results. 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. Moreover, the relationship between PVS_t and volatility-sorted returns is present across asset classes and particularly strong for credit markets. In this regard, our work is related to recent findings that credit market conditions forecast future macroeconomic performance.[3] Our results suggest that recent work connecting credit market sentiment to economic outcomes 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, a long-standing question in financial economics (Fama and French (1993); Koijen et al. (2010); Baker and Wurgler (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 in that we study time variation in risk premia of high-volatility stocks, whereas the previous literature has primarily focused on their average risk premium, and how this time variation stocks connects to real interest rates and macroeconomic performance.[4]

The remainder of this paper is organized as follows. Section 2 motivates our variable construc-

[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.

tion and describes the data. Section 3 shows that PVS_t fits the requirements of a measure of risk appetite along multiple dimensions. Then, 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 a measure of risk appetite should be correlated with the real rate.

The first-order condition for the real interest rate r_{ft} that emerges from the standard consumption-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 (or, more generally, any measure of marginal utility), δ is the rate of time preference, ψ is the elasticity of intertemporal substitution, and γ_t is risk aversion. This Euler equation for the real interest rate 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 interest 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". Risk appetite might 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 take on risk (i.e.,γ_t is high) less willing to take on risk, driving up the valuations of safe real bonds and driving down the real risk-free interest 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 fundamental risk. Eqs. (1) and (2) hold under whatever expectations investors have, so long as they are optimizing. These equations imply that the difference in expected returns between high- and low-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: when risk appetite is high, real rates should be high. Constructing a measure of risk appetite by taking the difference in expected returns between different types of stocks is advantageous, because it subtracts out common factors that drive all stocks but are unrelated to risk, such as aggregate growth expectations.

We empirically implement the logic implied by Eqs. (1) and (2) by sorting stocks based on their volatility. Volatility is useful because it is a robust characteristic that does not require an understanding of the true underlying risks investors care about at a point in time. Regardless of the true risks, volatility will increase with exposure to those risks. An empirical challenge is that expected returns are not directly observable. To ensure that our measure is simple and does not depend on a specific forecasting model, we use valuations. Valuations mechanically must depend on either expected returns or expected growth (Campbell and Shiller (1988)), and we can check which they are driven by in the data. Thus, our measure of risk appetite takes the difference between the valuations of high-volatility minus low-volatility stocks.

In practice, 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. Why would the central bank react to risk appetite shocks? The intuition for this interpretation can be seen by rewriting the Euler equation in the style of a New Keynesian model (Clarida et al., 1999; Woodford, 2003):

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

Here, x_t is the output gap between current output and its natural rate, ψ is the elasticity of intertemporal substitution, r_t is the actual real rate, and r_t^n is the natural real rate: the interest rate consistent with stable inflation and output at its natural rate.[5] The important term in (3) is the last

[5]Here, 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, p. 250).

one, showing that macroeconomic activity today depends negatively on the gap between the real rate and the natural rate. While the natural rate r_t^n may reflect a range of factors, demand shocks are an important component (Woodford (2003, p. 250)). A shock to PVS_t acts like a demand shock that increases r_t^n, leading output to temporarily rise above its natural level unless the central bank raises interest rates to completely offset the shock. In contrast, a typical monetary policy shock, or a positive shock to r_t, has the standard contractionary effect on output. If the central bank does not fully offset a shock to risk appetite that increases r_t^n, then output and investment will boom.

Anecdotal evidence suggests that the Federal Reserve plausibly responds to financial market risk appetite as an important type of demand shock. For instance, just 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 Reserve tracks PVS_t itself, but rather that risk appetite is reflected both in Fed action and how investors price volatile stocks.

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 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.

[6] Minutes of the Federal Open Market Committee of March 21, 2000. For a comprehensive narrative account of financial market considerations in FOMC meetings, see Cieslak and Vissing-Jorgensen (2017).

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 stock data from the previous two months to compute equity volatility. We exclude 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 firm returns.[7]

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:

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

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. Quarterly realized returns in a given quintile are computed in an analogous fashion, aggregated up using monthly data from CRSP.

The Real Rate The real rate is the one-year Treasury bill yield net of one-year survey expectations of the 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. In addition, our focus is on understanding 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 (Laubach and Williams

[7] In earlier versions of the paper, we instead sorted stocks on idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006). Our results are nearly identical when using idiosyncratic volatility, mainly because the total volatility of an individual stock is dominated by idiosyncratic volatility (Herskovic et al. (2016)) .

(2003)). To control for long run growth and other 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 just use the raw real rate or if we employ more sophisticated filtering methods that allow for stochastic trends (Hamilton (2017)).

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. The first thing to note in Panel A is that high-volatility stocks have lower valuations than low-volatility stocks: on average, PVS_t is negative. However, as Figure **??** shows, this masks considerable variation in PVS_t. Indeed, the standard deviation of PVS_t is about twice the magnitude of its mean. This variation is at the heart 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%. The highest-volatility quintile of stocks on average has excess returns that are 2.71 percentage points per year lower than for the lowest-volatility quintile. This is related to the well-known idiosyncratic volatility puzzle, which emphasizes that stocks with high short-term volatility, but not long-term volatility, have traditionally underperformed (Ang et al. (2009)), potentially due to shorting constraints (Stambaugh et al. (2015)). The second-to-last row of Table 1 Panel B shows that high-volatility portfolios load significantly on the SMB factor, suggesting that highly volatile stocks being smaller on average and that we need to be careful to distinguish between volatility and size as the key stock characteristics.

3 The Price of Volatile Stocks and the Macroeconomy

This section presents three facts showing that the risk-centric narrative of economic fluctuations fits the data well using PVS_t as a measure of risk appetites. First, PVS_t captures the narrative's intuitive negative correlation between safe and risky asset prices: it is positively correlated with the real risk-free rate and hence negatively correlated with the value of safe bonds. Second, this correlation is driven by considerations of risk – variation in expected returns on volatile stocks, not variation in expected cash flow growth. Third, increases in PVS_t forecast booms in real investment,

output, and employment.

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:

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

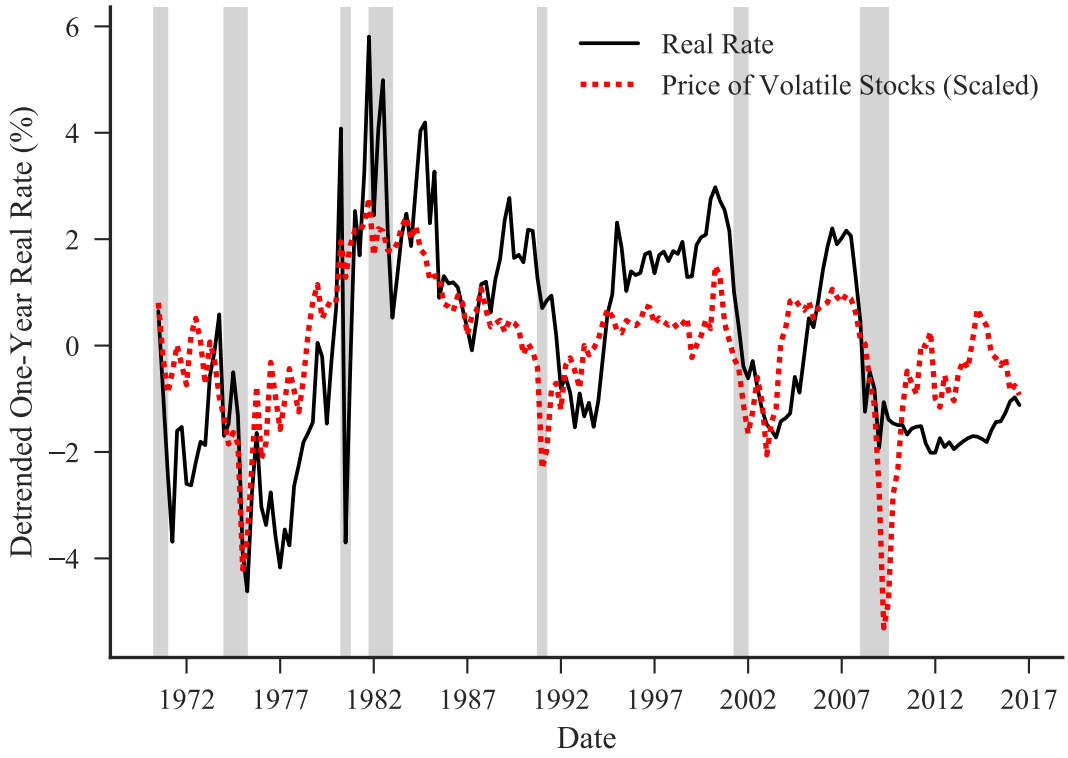
We report Newey and West (1987) standard errors using five lags. In the online appendix, we also consider several other methods for dealing with the persistence of these variables, such as parametric corrections to standard errors, generalized least squares, bootstrapping p-values. Our conclusions are 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 1.9 percentage points. The R^2 of the univariate regression is a substantial 41%. 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.

Figure 1 presents the relation between PVS_t and the real rate graphically. Figure 1 shows that the fitted value from regression in Equation (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 for sub-sample stability of this baseline result in the online appendix.

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 just an issue of statistical precision. The economic magnitude

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.

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 17 basis 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.[8] If the aggregate book-to-market ratio proxies for expected returns on the aggregate market (Cochrane (2007)), its low correlation with the real rate indicates that the aggregate stock market have 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)). While the output gap enters with a positive coefficient, inflation enters with a slightly negative coefficient. Despite the negative point estimate, both estimates are 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 especially 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. All regressions in Table 3 include the aggregate book-to-market ratio as a control and

[8] 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.

compute Newey-West standard errors using five lags.

Alternative Constructions of PVS_t

We first show that we obtain similar results for alternative definitions of PVS_t. The first row of Panel A in Table 3 reproduces our baseline results from columns (3) and (7) of Table 2. In row (2) of Table 3, we recompute PVS_t by value-weighting the book-to-market ratio of stocks within each volatility quintile, as opposed to equal-weighting. In row (3), we obtain similar results sorting stocks on volatility measured over a two-year window, rather than a two-month window. Our baseline result therefore captures changes in the valuation of stocks that historically have been volatile, not changes in the volatility of low-valuation stocks. This distinction is critical to our interpretation of PVS_t as a measure of investors' willingness to hold volatile stocks. The finding that our baseline result is equally strong for short- and long-term measures of stock return volatility also distinguishes it from the idiosyncratic volatility puzzle, which centers around the fact that firms with low short-run, recent volatility have historically earned a risk premium (Ang et al. (2009); Stambaugh et al. (2015)).

The Term Structure of Real Interest Rates

Rows (4)-(5) of Table 3 Panel A show 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 analogously to the one-year real rate as the k-year nominal Treasury bond rate minus the one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters. We use one-year survey 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. The relation 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 expectation data.

Relationship to Other Stock Characteristics

Rows (6) through (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. This also helps to rule out some mechanical reasons that PVS_t may relate to the real rate. Starting in row (6) of Panel A in Table 3, we run a horse race of PVS_t against the spread between 10-year off-the-run and on-the-run Treasury yields, a measure of liquidity premia in the fixed income market (Krishnamurthy (2002)).[9] 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. As before, we run these horse races for both the full and pre-crisis samples, as well as in levels and in changes. As alternative characteristics Y, we consider characteristics 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 that of safe bonds, indicating that PVS_t capture how investors price risk and not duration.[10] 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 results 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.

[9] The off-the-run spread is the difference between the continuously compounded 10-year off-the-run and on-the-run bond yields. On-the-run bond yields are from the monthly CRSP Treasury master file. The off-the-run bond yield is obtained by pricing the on-the-run bond's cash flows with the off the- run bond yield curve of Gürkaynak et al. (2007). For details of the off-the-run spread construction see Kang and Pflueger (2015).

[10] In the internet appendix, we use whether a firm pays dividends as another measure of cash flow duration, and again find no impact on the PVS_t-real rate relationship, indicating that PVS_t is not driven by the demand for dividends (Hartzmark and Solomon, 2017).

In the online appendix, we use double sorts as a complementary way to rule out alternative explanations for why PVS relates to the real rate. Specifically, we construct a Y-neutral version of PVS_t: the book-to-market spread from sorting stocks on volatility within each tercile of characteristic Y. This spread measures the difference in valuations of low-volatility and high-volatility stocks that have similar values of characteristic Y. Consistent with the horse-races presented here, we find that our baseline relation between PVS_t continues to hold for these double sorted book-to-market spread. Moreover, by forming PVS_t within industries, we can rule out that the PVS_t-real rate relation is driven by specific industries, such as finance.

Thus, sorting stocks on volatility is key to our construction of PVS_t. From a purely statistical perspective, it is perhaps not surprising that there exists a cross-section of equities that is correlated with real rates. The interesting economic aspect of our findings is that volatility, while not a fundamental firm characteristic, is a robust measure of risk. Volatility reveals the risks markets are worried about at each point in time, and PVS_t captures how worried markets 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 Panel B of Table 3 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, in the third set of columns, we show that the relationship between PVS_t and the real interest rate remains unchanged when controlling for these alternative measures and that the R^2s increases substantially by addingPVS_t in all cases, including Baker and Wurgler (2006) equity sentiment.

One potential reason why PVS_t has separate explanatory power over these alternative measures

is that PVS_t is based on a long-short portfolio, so PVS_t nets out factors affecting an entire asset class. For instance, PVS_t should difference out optimism about aggregate equity cash flows, which would correlate with measures of aggregate equity market sentiment, but not necessarily 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.[11]

3.2 Return Predictability

We now show that the negative correlation between safe asset prices and PVS_t is driven by the compensation that investors require to hold risky assets, as opposed to their growth expectations.

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 either changes in 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 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 its 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

[11] In the online appendix, we provide further evidence of the uniqueness of PVS_t from return forecasting exercises. Specifically, we show that, in contrast to PVS_t, none of the alternative measures of financial conditions we examine here can forecast returns on volatility-sorted portfolios across asset classes.

15.2 percentage point higher annual return on the volatility-sorted portfolio. The annual standard deviation of the long-short portfolio is 30%. 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 time-varying 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, low-volatility stocks tend to do relatively well and high-volatility stocks tend to do relatively poorly going forward.

In columns (3) and (4), $R_{t\to t+4}$ 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. By present value logic, time-variation in valuations must either reflect expected returns or expected cash flows, so this lack of cash flow predictability points again towards time-varying expected returns as the main source of variation in PVS_t.

Columns (5) and (6) investigate whether PVS_t comoves with financial market participants' forecasts of portfolio cash flows. If investors have biased beliefs about cash flows, PVS_t could forecasts excess returns and not cash flows, even if investors believe that PVS_t reflects expected cash flows. We define a stock's quarterly ROE surprise as the difference between its realized ROE and the analyst consensus ROE forecast.[12] 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 high PVS_t reflects irrationally high analyst expectations of volatile stocks' cash flows, high PVS_t should forecast positive ROE surprises on low-minus-high volatility stocks. However, columns (5) and (6) show there is no evidence that either PVS_t or the real rate forecast earnings surprises.

Taken together, columns (1)-(6) of Table 4, Panel A suggest that the real rate comoves with

[12]IBES data becomes reliable for our cross-section only in the early 1990s, so the time series for these regressions is shorter.

PVS_t because it comoves with the returns that investors require to hold volatile stocks. In Section A.3 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. This decomposition Vuolteenaho (2002) holds not only for rational expectations, but for any expectations that respect accounting identities. Thus, our results suggest that PVS_t comoves not only with an econometrician's, but also financial market participants', expected returns. 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 appear puzzling that the real rate does not forecast the aggregate market return. Table 2 column (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 only 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, CDS, commodities, and currencies.[13] 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 for each portfolio 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-

[13]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.

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 forecast quarterly returns on volatility-sorted portfolios systematically across asset classes. The top row replicates our results for U.S. equities from Panel A. 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 forecasting regressions reveal 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 this covariation, we compute for each asset class c the correlation ρ_c between the low-minus-high volatility trade in asset class c and the average return of the low-minus-high volatility trade in all of the other asset classes excluding c. For example, ρ_c for $c =$ Corporate Bonds computes the correlation of the volatility-trade in corporate bonds and the average return of the trade across all asset classes except corporate bonds. We find that the average ρ_c is 0.42, comparable to what is observed for value and momentum strategies across asset classes (Asness et al. (2013)).

3.3 Real Outcomes

We have established that PVS_t is negatively correlated with safe asset prices and that this correlation is driven by considerations of risk, properties that one would expect if PVS_t reveals the economy's risk appetite. We next show that positive shocks to PVS_t are followed by a boom in the real economy, as predicted by the risk-centric view of business cycles.

3.3.1 Ruling out Reverse Causality

To start, we first rule out the possibility that changes in PVS_t are caused by changes in monetary policy. We previously provided evidence against this reverse causality story in Section 3.1.2

by controlling for a range of additional firm characteristics. In this section, we corroborate that analysis using methods from the literature on monetary policy shocks. This additional evidence is useful for interpreting the responses of investment, unemployment, and output 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: Romer and Romer (2004) read transcripts of Fed meetings; Bernanke and Kuttner (2005) and Gorodnichenko and Weber (2016) use price innovations in the federal funds rate futures market in a narrow window around monetary policy announcements; and Nakamura and Steinsson (2018) use changes in a broader set of interest rates around monetary policy announcements. Rather than tying ourselves to a particular measure, we show results for a range of measures.

Table 5 provides evidence against the reverse causality story. We regress returns on the low-minus-high volatility portfolio onto monetary policy shocks at both quarterly and daily frequencies. 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 5. In the first set of columns, we find that the coefficients are always statistically insignificant with inconsistent signs. To ensure that policy changes outside of regularly scheduled meetings do not confound our analysis, we exclude them for the second set of columns and find similar results.[14] In the third set of columns, we narrow the window and focus on daily data. While the quarterly results are useful because they match the rest of our analysis, daily returns further alleviate concerns of endogeneity for the monetary policy shock measures. Using daily returns, we find a positive correlation that is borderline statistically significant for some specifications. However, this is the opposite of what we would expect if there was reverse causality. Instead, a

[14] Anecdotally, such surprise policy changes are often driven by financial market conditions and could thus confound our analysis. Moreover, on inter-meeting dates the aggregate stock market does not follow its usual relation with monetary policy shocks, suggesting that the cross-section of stock returns is also likely to be erratic (Gorodnichenko and Weber, 2016). In restricting the analysis to regularly scheduled meetings, we exclude quarters after 1993Q4 where the Federal Reserve made policy changes outside of scheduled meetings. Prior to 1994, policy changes were not announced after meetings so the distinction between scheduled and unscheduled meetings is not material.

positive correlation is consistent with the Fed cutting interest rates in times of financial market turmoil. This interpretation is also consistent with the final set of columns, where the coefficients are small and statistically insignificant using shocks on regularly scheduled meeting dates only.[15]

The collective evidence from this exercise indicate 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.

3.3.2 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.

Panel A of Table 6 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 0.23 percentage points higher at a one-quarter horizon and 0.36 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 6, we report results for the output gap. Here, a one-standard deviation increase in PVS_t is associated with an output gap that is 0.30 percentage points more positive after one quarter, and 0.58 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 0.13 percentage point fall in the unemployment rate after one quarter, and a 0.41 percentage point decline after four quarters.

In Figure 2 we report the impulse responses for these three macroeconomic variables to a one-

[15] Consistent with the idea that surprise policy changes are often driven by financial market conditions, the positive correlation between policy shocks and the returns on the volatility-sorted portfolio when we examine all shocks appears to be entirely driven by surprise changes in 2001. In that year, the Fed cut rates aggressively outside of regularly scheduled meetings in the aftermath of the technology bubble.

standard deviation shock to PVS_t for horizons of $h = 1, ..., 12$ 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 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.

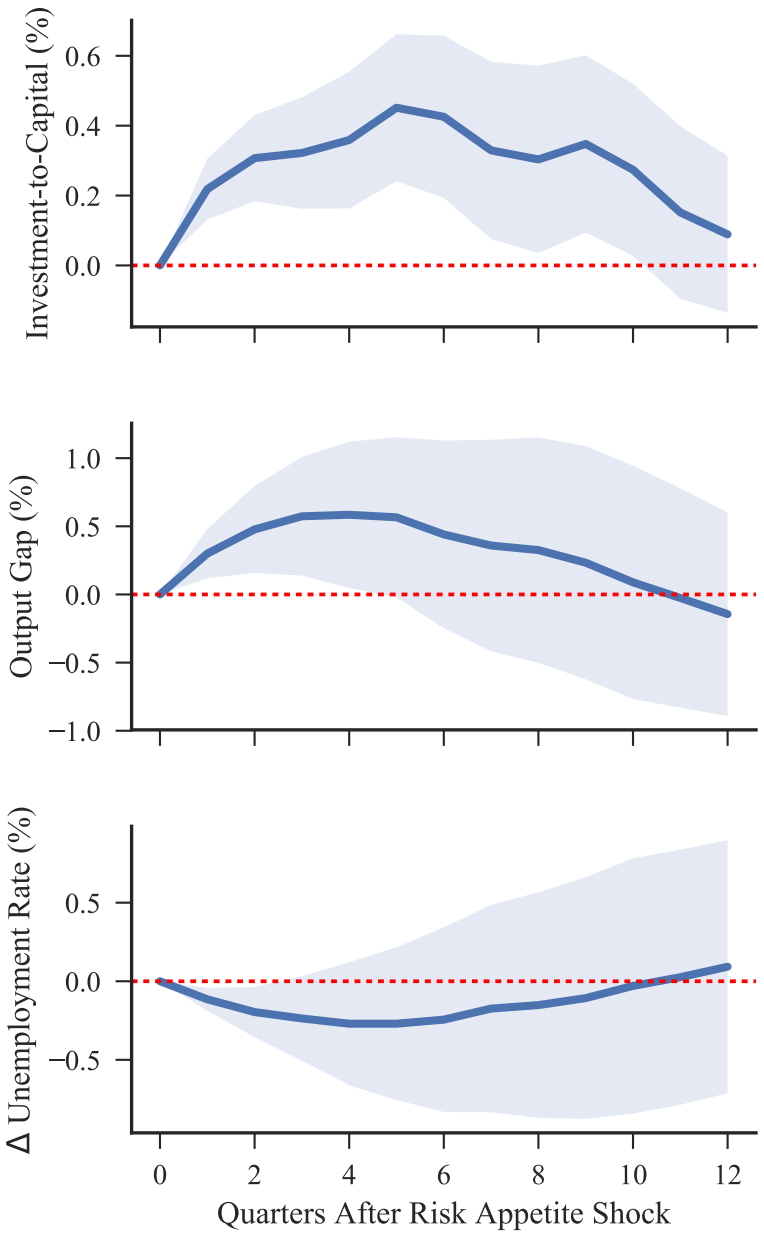
The risk-based narrative of business cycles suggests that a decline in risk appetite should disproportionately affect real investment at high-risk firms. Consistent with this prediction and the construction of PVS_t, 6, Panel C shows that the correlation between PVS_t and future capital expenditures increases from the lowest-volatility portfolio of firms to the highest. We run firm-level regressions 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:

$$\frac{CAPX_{i,t\to t+4}}{A_{i,t}} = a_i + a_t + \sum_{q=1}^{5} b_q \cdot 1_{it}^q + b_{PVS} \times PVS_t + \sum_{q=2}^{5} b_{q,pvs} \cdot 1_{it}^q \times PVS_t + b_{CF} \frac{CF_{i,t\to t+4}}{A_{i,t}} + \varepsilon_{i,t}. \tag{7}$$

where 1_{it}^q is an indicator function firm i is in volatility-quintile q at time t. The coefficient of interest is the interaction between the firm's volatility quintile and PVS_t. Panel B of Table 6 reports summary statistics of investment and cash flow data and Panel C reports the regression results. Consistent with intuition, the investment of higher volatility firms in quintiles 4 and 5 is more sensitive to PVS than the investment of lower volatility firms and this result is robust across pre- and post-2000 subsamples.

As discussed in Section 2.1, the positive 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.

Figure 2: 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.

4 Why does Risk Appetite Vary?

So far we have documented relationships between the real rate, macroeconomic outcomes, and our measure of risk appetite that are all consistent with a risk-centric view of economic cycles. In this section, we examine the properties of PVS_t to better understand what drives risk appetite.

4.1 Expectations of Risk

4.1.1 Subjective Expectations of Risk

As discussed in Section 2.1, a natural reason for risk appetite to vary is that investors' expectations of risk vary over time. In this section, we show that PVS_t is negatively correlated with expectations of risk based on analyst forecasts, option prices, and surveys.

We analyze the relation between PVS_t and expectations of risk by means of simple contemporaneous regressions:

$$PVS_t = a + bX_t + \varepsilon_t, \tag{8}$$

where X_t is one of several measures of expected risk. The results are reported in Table 7. We standardize both PVS_t and the explanatory variables to facilitate interpretation of economic significance. The number of observations varies across columns because the right-hand-side variables are available starting at different dates. In untabulated results, we find similar results if we restrict the sample to the common period where all explanatory variables are available.

Column (1) of Table 7 examines how PVS_t relates to a measure of expected risk derived from analyst forecasts in the Thompson Reuters IBES database. Ideally, we would observe analysts' expected distribution of future earnings. Because each analyst only reports one estimate, not a distribution, in the IBES data, we build a firm level measure of expected risk using the dispersion of earnings forecasts across analysts. Specifically, we measure firm-level risk as the range of analyst estimates for that divided by the average estimate. We define the expect risk of the volatility-sorted portfolio as the difference in the median dispersion of high- and low-volatility firms.[16]

[16] We provide more details of our data construction in the internet appendix. Consistent with our interpretation of dispersion as expected risk, it is correlated with the volatility of individual analysts' forecasts over time. The volatility of individual forecasts over time requires time series data. Therefore, it cannot be constructed for many firms and is

In column (1), we examine dispersion in 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 our measure of risk may also pick up on 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.

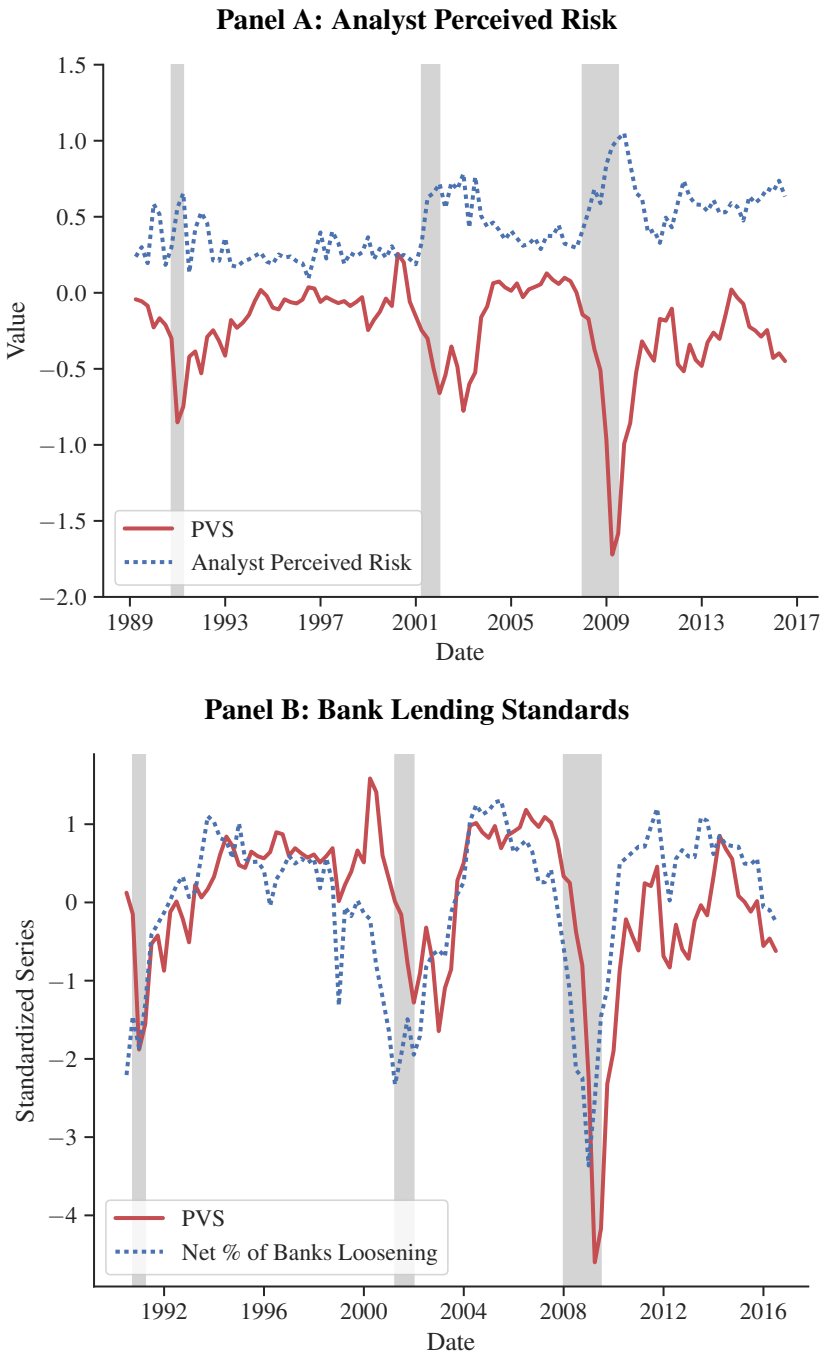
Column (2) shows an even stronger correlation between PVS_t and dispersion in forecasts of one-year ahead earnings. The univariate R^2 is 54%, and a one-standard deviation increase in expected risk is associated with a 0.63 standard deviation decline in PVS_t. Figure 3 Panel A depicts the relationship visually, showing that it is driven not only by business cycle variation but smaller comovements as well. The 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, where the one-quarter measure is relatively well populated, we obtain similar results for the two measures.

Column (3) examines how PVS_t relates to expected risk derived from option prices. Using data from OptionsMetrics, we compute the difference between high- and low-volatility firms in the median implied volatility of one-year at-the-money options. When expected risk from option prices for volatile firms is high, PVS_t is low. The univariate R^2 is 24%, and a one-standard deviation increase in expected risk is associated with a 0.47 standard deviation decline in PVS_t. One reason the relationship between expected risk and PVS_t is weaker with the option-based measure than the analyst forecast measure is that option prices are driven by both expected future volatility and the variance risk premium. 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.

In column (4) of Table 7, we examine a measure of risk that is less specifically tied to the portfolio underlying PVS_t. We use the Federal Reserve Board's Senior Loan Officer Opinion

noisier for the firms it can be constructed for. We therefore use dispersion as our baseline measure.

Figure 3: PVS_t and Expected Risk



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.

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' perception of risk is low at these times. The regression has a R^2 of nearly 30%, and a one-standard deviation increase in loan officer outlook is associated with a 0.5 standard deviation higher value of PVS_t. Figure 3 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.

Column (6) of Table 7 runs a multivariate regression of PVS_t on analyst dispersion 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. All three explanatory variables in the regression retain their statistical significance, indicating that they each contain independent information about PVS_t. These proxies for expected risk collectively explain about 70% of the variation in PVS_t, consistent with expected risk being an important driver of macroeconomic risk appetite.

4.1.2 PVS and Revisions in Expected Risk

Our results so far all fit the risk-centric narrative of economic fluctuations. When investors expect high risk, their risk appetite is low, and they have safe bonds so real interest rates are low. At the same time, prices of risky assets are low across a variety of asset classes, and investment drops. A key element of classic versions of the risk-centric narrative (Keynes (1937); Minsky (1977, 1986)) is that investor expectations are not fully rational. We examine this hypothesis in Table 8. In Panel A, we use PVS_t to forecast revisions in expectations of risk. If expectations are fully rational, then revisions in expectations of risk should not be forecastable.

Column (1) shows that when PVS_t is high, our measure of analyst expected risk tends to be revised up. For each quarter t, we examine how the firm-level expected risk of earnings one full fiscal year ahead $(t+5)$ are revised over time. Specifically, we compute the revision in risk as the dispersion in time $t+4$ analyst forecasts of $t+5$ earnings, minus the dispersion in time-t analyst forecasts of $t+5$ earnings. We then compute the difference in median revisions for high-volatility

stocks minus low-volatility stocks.[17]

Column (1) shows that a one-standard deviation increase in $PVS_t$is associated with a 0.6 standard devation more positive revision in expected risk from analyst forecasts. The regression has an R^2 of 28%. Figure 4 depicts this result graphically. The expected risk of high-volatility stocks tends to be resolved over time, since the revision is negative on average. However, this is not always the case. There are several episodes, such as during the height of the technology bubble in the early 2000s, when high values of PVS_t were followed by positive revisions in the expected risk of high-volatility stocks. In other words, when PVS_t is low and expected risk is high, expected risk tends to fall going forward. Conversely, when PVS_t is high and expected risk is low, expected risk tends to rise going forward.

In column (2), we perform a similar exercise using option prices. For each quarter t, we examine how option implied volatility for $t+3$ to $t+4$ evolves over time. Specifically, we compute the revision in risk as firm-level implied volatility from $t+3$ to $t+4$ using option prices at time $t+3$, minus implied volatility from $t+3$ to $t+4$ using option prices at time t. We then compute the difference in median revisions for high-volatility stocks minus low-volatility stocks.[18]

Column (2) shows that a one-standard deviation increase in PVS_t is associated with a 0.45 standard deviation increase in expected risk from option prices. The regression has an R^2 of 17%. Again, option prices suggest that when PVS_t is high and expected risk is low, expected risk tends to rise going forward.

Because the loan officer survey variable is not associated with a fixed future date, we cannot construct true revisions in expected risk for this measure. We can only examine its mean reversion over time. Column (3) shows that the percentage of banks loosening lending standards tends to fall after periods of high PVS_t. In untabulated results, we find that we can control for general mean reversion in the loan officer survey variable by including its level in the regression, and 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.

[17]Formally, let$\sigma^s_{i,t}(u)$ be the time-t expected risk of firm i's earnings at time $u > t$. Fixing $u = t+5$, we compute the change in expected risk as $\Delta_4\sigma^s_{i,t+4}(u) \equiv \sigma^s_{i,t+4}(u) - \sigma^s_{i,t}(u)$.We then aggregate to the portfolio level by defining $\Delta_4\sigma^s_{t+4}$ as the median of $\Delta_4\sigma^s_{i,t+4}(u)$ for high-volatility stocks minus low-volatility stocks.

[18]Formally, let $\sigma^{IV}_t(t+3,t+4)$ be the volatility of returns between quarters $(t+3)$ and $(t+4)$ implied by options at time t. 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.

Finally, rows (4) and (5) of the table show that these revisions in expected risk are not random. PVS_t forecasts rising realized volatility for both the aggregate market return and the volatility-sorted portfolio – in other words, realized volatility is mean-reverting. Nonetheless, if expectations of risk were fully rational, revisions in expectations should not be forecastable, as they should anticipate this mean reversion.

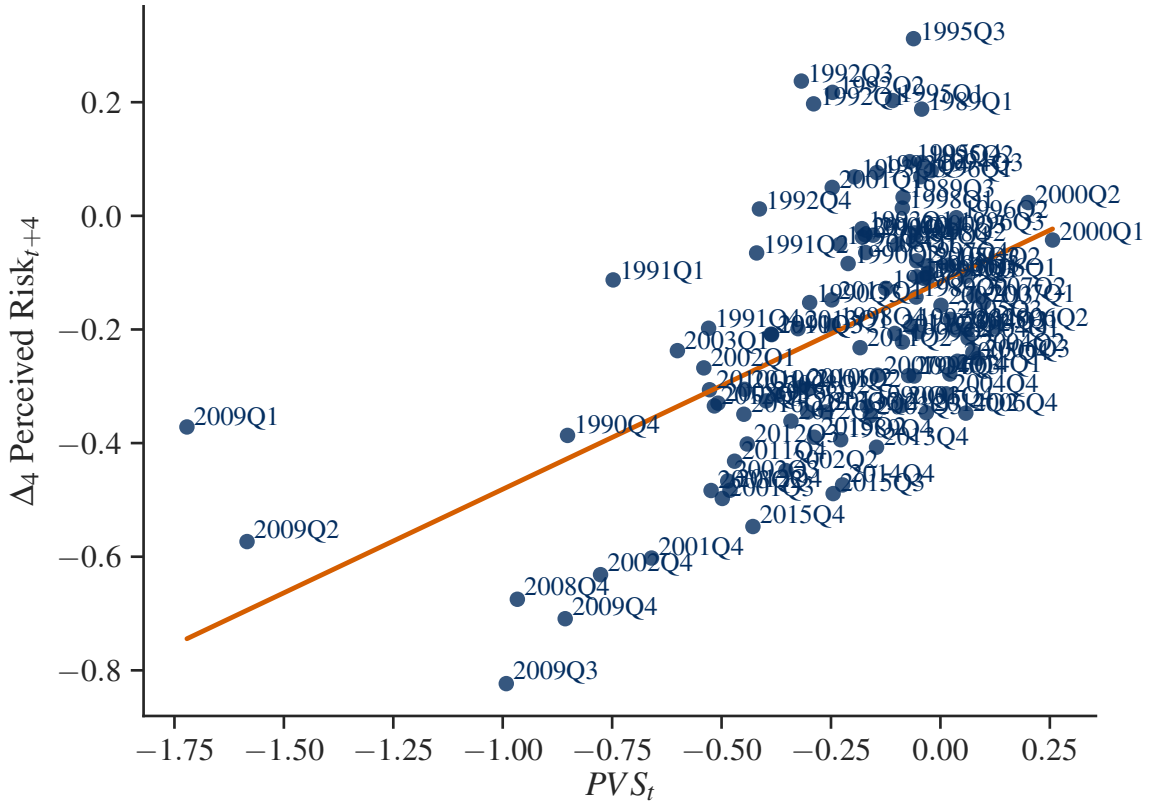
These results are not unambiguous because our proxies for expected risk are imperfect. Our analyst forecast measure comes from dispersion across analysts as opposed to the distribution of earnings analysts perceive. Our option-based measure captures both expected volatility and the variance risk premium, so PVS_t may be forecasting changes in the latter. Nonetheless, while these results are subject to limitations, they are suggestive that PVS_t moves with expectations of risk, which may not be entirely rational. The instances where high values of PVS_t forecast positives revisions in expected risk with PVS_t are especially hard to reconcile with the resolution of uncertainty over time.

4.1.3 PVS and Regression Forecasts of Risk

Next, we take another approach to gauging whether investors have perfectly rational expectations of risk. We construct empirical forecasts for the volatility of several aggregate quantities, including total factor productivity (TFP) growth, real GDP growth, and real consumption growth. For each of these variables, we fit ARMA(1,1)-GARCH(1,1) models and then define the objective expectation of risk as the one-period forecast of volatility from the GARCH component of the model, denoted by $\sigma_{t+1}(Y)$ for variable Y. The recursive structure of the GARCH model means that σ_{t+1} is known at time t, so we then compare $\sigma_{t+1}(\cdot)$ with both PVS_t and the real rate at time t.

Rows (1)-(3) of Table 8 Panel B collects the results of this exercise. We standardize the variables to facilitate comparison of magnitudes. The main takeaway is a null result — in our sample there is almost no evidence that the real rate or PVS_t correlate with econometric forecasts of macroeconomic uncertainty. The first set of columns regress PVS_t on the econometric forecasts of macroeconomic uncertainty and finds small t-statistics and low R^2s, indicating little correlation. The second set of columns regress the real rate on the same right-hand-side variables and again find very little correlation. The last three columns show that none of our econometric forecasts of macroeconomic uncertainty drive out PVS_t in multivariate regressions with the real rate as the

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 perceptions 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 perceived 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.

left-hand-side variable.

In rows (4)-(6) we consider alternative measures of risk from financial markets. In row (4), we build a measure of the expected volatility of the aggregate stock market. From 1986 onward, we follow Bloom (2009) and use the VXO implied volatility index of the S&P 100. Options data is not available prior to 1986, so we use the one-step ahead forecast from fitting an AR(1) model to the within-quarter realized volatility of the aggregate stock market, which we scale to create a smooth series when the VXO becomes available. The results show that both PVS_t and the real rate tend to be lower when expected market volatility is high, but the strength of the relationship is statistically weak, with an R^2 of 5%. In rows (5) and (6), we examine measures of risk specific to the portfolio that underlies PVS_t. In row (5), we examine the forecasted difference in volatility between low- and high-volatility stock portfolio returns, where we estimate the forecasted volatility of each portfolio with an AR(1) model. The relation between volatility forecasts and PVS_t is again negative, as one might expect if a high price of volatile stocks reflects rational anticipation of low volatility, but statistically weak with an R^2 of 9%. Moreover, in the online appendix, we find that PVS_t positively forecasts the realized Sharpe ratio on the volatility-sorted portfolio, showing that the high returns forecast by low values of PVS_t are not simply compensation for high volatility at times when PVS_t is low.

In row (7), we consider a measure of cash flow risk specific to the portfolio that underlies PVS_t. Firm-level measures of realized fundamental risk are difficult to construct because earnings are reported infrequently. We therefore proxy for the realized fundamental risk by looking at the realized cross-sectional dispersion of ROE. This is a viable approach if, for example, there is a common factor that drives ROE, and not all firms load equally on the factor. We are interested in the difference in realized fundamental risk between low- and high-volatility firms, so our ultimate measure is the realized cross-sectional dispersion in ROEs for low-volatility firms minus realized dispersion for high-volatility firms. Row (7) shows that PVS_t is not correlated with objective forecasts of this variable.

In row (8), we find similar results using the macroeconomic uncertainty index from Jurado et al. (2015), which may better filter noise from volatility forecasts. Jurado et al. (2015) define the uncertainty of a macroeconomic series as the conditional volatility of the purely unforecastable component of that series. They employ sophisticated econometric techniques to compute uncer-

tainty measures for a wide range of macroeconomic and financial series, and then combine them into a single aggregate index of macroeconomic uncertainty. As row (8) shows, the Jurado et al. (2015) macroeconomic uncertainty index has little correlation with both PVS_t and the real rate.

The fact that PVS_t is largely uncorrelated with objective forecasts of macroeconomic risk – yet is quite correlated with subjective expectations of risk – suggests that movements in risk appetite may reflect a departure from fully rational expectations, as suggested by Keynes (1937) and Minsky (1977). At the same time, our results do not rule out complementary channels of time-varying risk appetite, such as time-varying risk aversion as in Campbell and Cochrane (1999). These channels generally work in the same direction and may be important for understanding the empirical strength of our results. Our results here highlight expectations of risk, not risk aversion, in part due to data limitations – there are more direct measures of expectations of risk than of risk aversion.

4.2 Risk Appetite Rises Following Good News

What conditions lead PVS_t to rise and investors' subjective perceptions of risk to fall in the first place? To examine this question, we run regressions of the 4-quarter change in PVS_t on macroeconomic variables, that may lead investors to revise their assessment of risk: 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 9 reports the results. The dependent and independent variables are standardized to facilitate 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 more with the profits of high-volatility firms than low-volatility firms. In this column, we regress the 4-quarter change in PVS_t on the cash flow growth (ROE) of the portfolio that is long low-volatility stocks and short high-volatility stocks.

Finally, row (4) shows that PVS_t responds to recent conditions in credit markets as well as

equity 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 macroeconomic news in a variety of markets, consistent with many of the classical accounts from Keynes (1937) or Minsky (1977).

5 Model

In this section, we present a stylized model with analytic comparative statics. The model 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 one 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:

$$\Delta c_{t+1} = \varepsilon_{t+1}, \tag{9}$$

$$\varepsilon_{t+1} = \sigma_t \eta_{t+1}, \tag{10}$$

$$\sigma_t^2 = a - b\varepsilon_t, \tag{11}$$

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 aggregate volatility is consistent with our evidence in Table 8 Panel B, and ensures that agents face a non-trivial updating problem for volatility. While the process (11) can in principle become negative, for a/b large enough this probability is negligible and we therefore

ignore it. We could extend the model to contain an autoregressive term in (9) 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.

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.[19] 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, or are representative, of previously observed data.

Combining these assumptions with Equations (9) and (11) , the subjective distribution of ε_{t+1} is conditionally normally distributed with subjective mean and variance:

$$\mathbb{E}_t^{\theta}(\varepsilon_{t+1}) = 0, \tag{12}$$

$$\mathbb{V}_t^{\theta}(\varepsilon_{t+1}) = \left(\frac{a}{a+\theta b \varepsilon_t}\right)\sigma_t^2. \tag{13}$$

Here, we use superscript θ to denote subjective expectations. Expression (13) 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 $A_{i,t+1}$:

$$Y_{i,t+1} = A_{i,t+1}K_{i,t+1}^{\alpha}. \tag{14}$$

[19] 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.

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:

$$A_{i,t+1} = \exp\left(s_i \varepsilon_{t+1} - \frac{1}{2} s_i^2 \mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right)\right). \tag{15}$$

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' production functions are risky.

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 period $t+1$ capital equal to period t investment.

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:

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

From the asset pricing Euler equation:, the log real risk-free rate r_{ft} is given by

$$r_{ft} \quad = \quad -\ln\left(\beta\right) - \frac{1}{2}\lambda^2 \mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right). \tag{16}$$

Equation (16) is standard except for the use of diagnostic expectations. The second term corresponds to risk appetite in the model and captures the precautionary motive, which drives down the risk-free rate when risk is perceived to be 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 risk s_i. The required return takes a simple form in logs:

$$\ln\left(\mathbb{E}_t^\theta\left[R_{i,t+1}^K\right]\right) = r_{ft} + \lambda s_i \mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right). \tag{17}$$

We obtain the expected marginal rate of return on capital by taking the first derivative of (14) and then subjective expectations over ε_{t+1}:

$$\ln \mathbb{E}_t^\theta\left[R_{i,t+1}^K\right] = \ln\alpha - (1-\alpha)k_{i,t+1}. \tag{18}$$

Here, we again use logs and use lower-case $k_{i,t+1}$ to denote log firm capital. Note that (18) is independent of θ, so investors' subjective expected return on capital agrees with the econometrician's objective forecast, consistent with our empirical results in section 3.2. Equating (17) with (18) and substituting in the expression for the real rate shows that:

$$k_{i,t+1} = \frac{\ln(\alpha\beta)}{1-\alpha} - \frac{\lambda s_i - \frac{1}{2}\lambda^2}{1-\alpha}\mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right). \tag{19}$$

The following proposition summarizes the equilibrium.

Proposition 1. *There is a unique equilibrium in which the real risk-free rate satisfies (16), subjective expected returns on firm i satisfy (17), and firm i's investment is given by (19).*

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:

$$PVS_t^{model} = \ln\mathbb{E}_t[R_{L,t+1}] - \ln\mathbb{E}_t[R_{H,t+1}] = \lambda(s_L - s_H)\mathbb{V}_t^\theta\left(\varepsilon_{t+1}\right). \tag{20}$$

It is worth noting that the objective expected return on low-minus-high volatility firms also equals the investors' subjective expected return. However if $\theta > 0$, an objective observer (i.e., one with

$\theta = 0$) would disagree with investors about the risk of investing in these firms and hence with the optimal level of real 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: $\frac{d\mathbb{V}_t^{\theta}(\varepsilon_{t+1})}{d\varepsilon_t} = -b(1+\theta) < 0$.

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

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

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

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

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

Comparative static b) 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 c) 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 increase. Again, the effect is stronger if investors have diagnostic beliefs.

Comparative static d) shows that aggregate investment in the model falls following an adverse 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. Investors therefore do not undertake investment that would have been marginal at a lower required return, leading to a drop in real investment. Comparative static e) 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 and thus investors require an even higher 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 $\mathbb{V}_{t+}[\varepsilon_{t+1}] = a - b\varepsilon_t$. 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 7. Proposition 2 b) shows that PVS_t^{model} rises following positive macroeconomic surprises, as we find in the data in Table 9. In the model, risk appetite rises because investors' subjective expectations of risk fall following a positive fundamental shock as investors extrapolate from the shock.

The model also captures the empirical relationship between safe and risky asset prices. Comparative statics b) and c) of Proposition 2 show that the real risk-free rate is positively correlated with PVS_t^{model}, as in our baseline empirical result in Tables 2 and 3. And this correlation is driven by expected returns on volatile firms, consistent with our empirical results in section 3.2. 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. In the model, comparative statics

d) and e) show that real investment rises when risk appetite and PVS_t^{model} are 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 6.

Finally, the model captures our results on revisions in expectations of risk. Proposition 3 shows that subjective expected risk moves more than objective expected risk and is then subsequently revised back towards objective expected risk, as documented in Table 8, provided that expectations are diagnostic ($\theta > 0$). While diagnostic expectations strengthen all model implications, they are crucial 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 iparameter, θ. Column (2) of 7 and row (6) of 8 Panel B suggest that subjective expectations of risk move about twice as much in response to PVS_t as objective expectations. Proposition 2 b) 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).

Because the model is stylized, it necessarily has limitations. First, for simplicity there is only a single macroeconomic shock, which all firms are exposed to. This assumption implies that risk premia on the aggregate market move with the real rate, in contrast to the data. One way to address this limitation would be to assume that the aggregate stock market is an imperfectly proxy with the true risk investors face, which would imply that return volatility is a more robust measure of risk than aggregate market risk. 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, risk aversion λ is constant in the model to isolate the subjective risk channel that emerges from our empirical results in section 4.1. However, it would be straightforward to allow for risk aversion that responds to aggregate shocks as in Campbell and Cochrane (1999). Indeed, as discussed above, time-varying risk aversion is a complementary channel that would generate many of our results.

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 evidence consistent with 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 results shed new light on the connection between financial markets and the macroeconomy. They suggest that a broad concept of risk appetite — one that is revealed by common movements in the relative pricing of low- versus high-volatility securities in many asset classes — plays a central role in determining economic outcomes and real interest rates. Our findings suggest that future work seeking to understand investor perceptions of risk is likely to be fruitful.

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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
α	-4.99	-0.96	2.57	2.41	2.94	7.92
$t(\alpha)$	-2.08	-0.84	3.87	3.01	2.52	2.58
CAPM-β	1.25	1.17	1.03	0.92	0.73	-0.51
SMB-β	1.86	1.39	1.04	0.66	0.40	-1.46
HML-β	0.19	0.09	0.18	0.33	0.37	0.18

***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 α is the (annualized) intercept from a regression of excess returns on the Fama and French (1993) factors. Standard errors are computed via GMM by pooling all portfolios. We allow for within-portfolio heteroskedasticity and cross-portfolio correlations. 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 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	3.44**		3.45**	3.34**	2.22**		2.45**	2.09**
	(5.36)		(5.01)	(4.70)	(2.73)		(2.65)	(2.36)
BM Low-Vol		3.02**				1.99*		
		(3.11)				(1.80)		
BM High-Vol		-3.46**				-2.22**		
		(-5.39)				(-2.70)		
Aggregate BM			-1.10	0.26			2.30	3.59
			(-0.71)	(0.12)			(0.88)	(1.16)
Output Gap				0.09				0.36**
				(0.79)				(2.51)
Inflation				-0.12				0.22
				(-0.95)				(1.16)
Constant	0.62**	1.01	0.62**	0.60**	-0.00	-0.00	-0.01	-0.01
	(2.64)	(1.49)	(2.65)	(2.52)	(-0.07)	(-0.08)	(-0.13)	(-0.31)
Adj. R^2	0.41	0.41	0.42	0.42	0.13	0.12	0.13	0.18
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 high volatility and low 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 Appendix. t-statistics are listed below each point estimate in parentheses and are computed using Newey-West (1987) standard errors with five lags. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2.

Table 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	**3.45**	5.01	0.42	**4.11**	7.61	0.47	**2.45**	2.65	0.13	**3.58**	3.67	0.20
(2)	VW	**3.16**	4.48	0.32	**4.01**	6.01	0.41	**1.39**	2.45	0.08	**1.81**	2.59	0.10
(3)	2YR Vol	**4.49**	6.27	0.52	**5.13**	8.20	0.54	**2.22**	2.32	0.05	**3.64**	4.21	0.10
Term Structure:													
(4)	5-Yr Real Rate	**2.90**	3.82	0.35	**3.53**	6.06	0.41	**1.87**	2.63	0.12	**2.86**	4.17	0.22
(5)	10-Yr Real Rate	**2.51**	3.32	0.30	**3.11**	5.08	0.36	**1.40**	2.41	0.10	**2.25**	4.22	0.20
Horse-Races:													
(6)	Liquidity	**3.80**	6.54	0.47	**4.30**	7.73	0.51	**2.06**	2.14	0.15	**3.17**	3.02	0.21
(7)	Duration	**3.23**	4.26	0.42	**3.62**	5.24	0.49	**2.46**	3.13	0.12	**3.46**	4.31	0.20
(8)	Leverage	**4.12**	6.15	0.44	**4.53**	7.57	0.48	**3.20**	2.87	0.14	**4.19**	3.34	0.21
(9)	2M-Beta	**3.47**	5.50	0.41	**4.02**	7.73	0.48	**1.77**	2.55	0.15	**2.82**	4.35	0.22
(10)	Size	**3.04**	2.48	0.42	**4.01**	3.80	0.47	**3.44**	2.42	0.13	**4.18**	2.59	0.20
(11)	Value	**4.16**	4.97	0.43	**4.70**	7.03	0.48	**3.88**	3.05	0.16	**4.49**	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: $\text{Real Rate}_t = a + b \times PVS_t + \theta X_t + \varepsilon_t$. We run this regression directly in levels and in first differences. 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 and top quintile portfolios. X_t is a vector of control variables, which always includes the Aggregate BM (linearly detrended), computed by summing book equity values across all firms and divided by the corresponding sum of market equity values. Row (1) uses our baseline PVS_t measure and the full sample. Row (2) uses value weights instead of equal weights when forming our PVS_t. Row (3) constructs our PVS_t using the past two years of return volatility, as opposed to the past two months. Row (4) controls for the spread between off-the-run and on-the-run Treasury yields (Krishnamurthy (2002)). Rows (5)-(9) run bivariate horse races by adding book-to-market spreads based on other characteristic sorts to our control variables X_t. See the Table 2 of the Appendix for a description of each characteristic. In rows (10)-(16), we instead use a double-sorted PVS_t, with complete details also contained in the Appendix. 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	-0.31	-2.77	0.09	0.63	5.08	0.41
(2)	GZ Spread	151	-0.53	-4.12	0.23	-0.17	-1.53	0.02	0.71	6.15	0.48
(3)	Credit Sentiment	133	0.35	3.21	0.15	0.08	0.78	0.17	0.59	4.47	0.35
(4)	Equity Sentiment	182	0.49	3.47	0.24	0.62	6.33	0.37	0.45	3.97	0.52
(5)	$\mathbb{E}_t\left[\text{Mkt-Rf}_{t,t+4}\right]$	180	-0.27	-1.26	0.06	-0.10	-0.62	0.00	0.66	6.04	0.41
(6)	Policy Uncertainty	126	-0.41	-3.49	0.23	-0.43	-6.54	0.30	0.30	2.75	0.38

Notes: This table compares other measures of financial conditions and market sentiment to PVS_t. The first set of regressions in the table shows the results of a univariate regression of each alternative risk appetite 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 variable. The last set of results regresses the real rate on both PVS_t and each alternative risk appetite measure. In rows (1)-(6), the alternative risk appetite 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 Appendix for more details on our optimal stock market forecast. In all regressions, we standardized variables to have mean zero and variance one in order to facilitate comparison of magnitudes.

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

***Panel A**: Forecasting Returns and Earnings Surprises*

	Volatility-Sorted Portfolio							
	$\text{Ret}_{t\to t+4}$		$\text{ROE}_{t\to t+4}$		$\text{ROE Surprise}_{t\to t+4}$		$\text{VW-Mkt} - \text{Rf}_{t\to t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PVS_t	40.99**		-3.66		-0.07		-6.27	
	(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	9.77**	2.49	10.30**	10.93**	-0.01	0.01	5.85*	6.95**
	(2.46)	(0.59)	(8.19)	(8.29)	-0.22	0.15	(2.24)	(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. 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. 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 and top quintile portfolios. Vol-Sorted Ret in the forecasting regression corresponds to returns on the low-minus-high volatility portfolio. 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. Vol-Sorted ROE is the accounting return on equity of the the low-minus-high volatility portfolio, which we compute following Cohen, Polk, and Vuolteenaho (2003). Vol-Sorted 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 online 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 and are based on Hodrick (1992) standard errors. * indicates a p-value of less than 0.1, and ** indicates a p-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2. All returns are 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	14.42	5.07	0.12	1.57	2.81	0.04
U.S. Corporate Bonds	136	-3.1	8.9	6.45	3.39	0.27	0.51	1.88	0.03
Sovereign Bonds	50	-10.9	19.5	7.86	1.81	0.09	0.46	0.60	-0.02
Options	88	-16.0	17.8	5.28	2.41	0.03	1.07	1.89	0.02
CDS	31	-7.0	6.4	4.83	4.44	0.48	0.77	2.45	0.11
Commodities	89	10.3	35.4	3.38	0.51	-0.01	-0.34	-0.26	-0.01
FX	120	1.2	10.8	-0.60	-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. Quarterly data from He et al. (2017) ends in 2012 and data availability varies with asset class.

Table 5: 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					
	All		Scheduled		All		Scheduled		Sample	
MP Shock	b	$t(b)$	b	$t(b)$	b	$t(b)$	b	$t(b)$	Start	End
Romer and Romer (2004)	0.75	0.47	0.71	0.44	-0.04	-0.30	-0.06	-0.43	1970.Q1	1996.Q4
Bernanke and Kuttner (2005)	-2.94	-0.19	-1.65	-0.07	5.55	1.32	-1.08	-0.49	1989.Q2	2008.Q2
Gorodnichenko and Weber (2016)	-1.14	-0.06	1.60	0.03	13.34	1.89	3.67	0.94	1994.Q1	2009.Q4
Nakamura and Steinsson (2018)	1.46	0.06	12.83	0.20	18.74	1.98	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. Columns listed as "All" include all policy changes and "Scheduled" includes only changes that occurred at regularly scheduled policy meetings. In restricting the analysis to regularly scheduled meetings, we exclude quarters after 1993Q4 where the Federal Reserve made policy changes outside of scheduled meetings. Prior to 1994, policy changes were not announced after meetings so the distinction between scheduled and unscheduled meetings is not material. The listed t-statistics are computed using Davidson and MacKinnon (1993) standard errors for heteroskedasticity in small samples.

Table 6: 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	0.59**	0.97**
	(4.92)	(3.59)
Dep. Variable: Output Gap		
PVS_t	0.81**	1.58**
	(3.24)	(2.14)
Dep. Variable: ΔUnemployment Rate		
PVS_t	-0.36**	-1.12**
	(-2.57)	(-2.20)

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}. 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. 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. 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 6: PVS and Real Outcomes (continued)

***Panel B**: Summary Statistics for Firm-Level Analysis*

	Full Sample						Subsample Means	
	Mean	SD	Median	Min	Max	*N*	1983-1999	2000-2016
$\% \, CAPX^{Ann}_{i,t+4}/A_{i,t}$	6.67	7.83	4.22	0.09	51.60	315,333	8.01	5.37
$\% \, CF^{Ann}_{i,t+4}/A_{i,t}$	5.47	17.53	8.40	-86.99	42.92	315,333	7.46	3.56

***Panel C**: 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	1.76**		1.38**		0.91**	
	(6.58)		(3.13)		(5.50)	
$PVS_t \times 1^{q=2}_{it}$	0.40**	0.46**	0.53**	0.47*	0.36**	0.35**
	(4.15)	(4.64)	(2.03)	(1.69)	(3.67)	(3.79)
$PVS_t \times 1^{q=3}_{it}$	0.64**	0.79**	0.82**	0.81**	0.73**	0.75**
	(5.35)	(6.35)	(2.50)	(2.36)	(5.58)	(5.67)
$PVS_t \times 1^{q=4}_{it}$	0.75**	1.03**	1.23**	1.27**	0.98**	1.04**
	(4.49)	(6.32)	(2.95)	(3.09)	(6.76)	(6.67)
$PVS_t \times 1^{q=5}_{it}$	0.43*	0.89**	1.07**	1.22**	1.13**	1.21**
	(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: Panels B and C of this table study 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. Panel B provides summary statistics of these two measures, both of which are winsorized at their 1% tails. In Panel C, 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 defined as in the main text and 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 quartert. * 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 7: PVS and Expectations of Risk

Dependent Variable	PVS_t					
	(1)	(2)	(3)	(4)	(5)	(6)
High-Minus-Low Volatility Stocks:						
$\sigma_t\left(\text{EPS}_{t+1}\right)$	-0.45**					-0.19**
	(-2.49)					(-3.00)
$\sigma_t\left(\text{EPS}_{t+5}\right)$		-0.63**				-0.45**
		(-4.78)				(-5.03)
Option-Implied $\sigma_t^{IV}\left(Ret_{t,t+4}\right)$			-0.47**			
			(-2.51)			
% Banks Loosening				0.50**		0.28**
				(3.46)		(4.22)
% Banks Loosening b/c of Outlook					0.48**	
					(2.51)	
Adj. R^2	0.28	0.54	0.24	0.32	0.27	0.68
N	110	110	80	105	90	105

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. 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 8: Are Expectations of Risk Rational?

***Panel A**: Forecasting Revisions in Risk*

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

		b	$t(b)$	Adj. R^2	N
	Expected Risk:				
(1)	$\sigma_{t+4}(\text{EPS}_{t+5}) - \sigma_t(\text{EPS}_{t+5})$	0.63	5.50	0.28	110
(2)	$\sigma^{IV}_{t+3}(Ret_{t+3,t+4}) - \sigma^{IV}_t(Ret_{t+3,t+4})$	0.46	3.19	0.17	80
(3)	Δ_4 Prc. of Banks Loosening$_{t+4}$	-0.83	-8.64	0.53	101
	Realized Risk:				
(4)	$\Delta_4\sigma_{t+4}(\text{Mkt-Rf})$	0.21	1.97	0.04	181
(5)	$\Delta_4\sigma_{t+4}(\text{HML-Vol Ret})$	0.34	1.90	0.11	181

Notes: **Panel A** of the table use 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. $\sigma_t(\text{Mkt-Rf})$ is the realized quarterly volatility of the CRSP value-weighted index at time t. $\sigma_t(\text{HML-Vol Ret})$ 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.

Table 8: Are Expectations of Risk Rational?

***Panel B**: Objective Expectations of Risk*

			$PVS_t = a + b \times X_t$			$\text{RealRate}_t = a + c \times X_t$			$\text{RealRate}_t = a + c \times X_t + d \times PVS_t$		
	X-variable	N	b	$t(b)$	R^2	c	$t(c)$	R^2	d	$t(d)$	R^2
(1)	σ_t (TFP Growth$_{t+1}$)	184	-0.08	-0.32	0.00	-0.11	-0.54	0.01	0.64	5.06	0.41
(2)	σ_t (Real GDP Growth$_{t+1}$)	184	0.01	0.07	-0.01	-0.14	-0.72	0.01	0.65	4.73	0.43
(3)	σ_t (Real Consumption Growth$_{t+1}$)	184	0.20	1.07	0.03	0.06	0.32	-0.00	0.66	5.25	0.41
(4)	σ_t (CRSP VW-Ret$_{t+1}$)	185	-0.23	-1.48	0.05	-0.02	-0.20	-0.00	0.67	6.04	0.43
(5)	$\mathbb{E}_t[\overline{\sigma}_{L,t+1}] - \mathbb{E}_t[\overline{\sigma}_{H,t+1}]$	184	0.31	2.13	0.09	-0.16	-1.15	0.02	0.77	6.95	0.55
(6)	σ_t (Vol-Sorted Ret$_{t+1}$)	184	-0.23	-1.26	0.05	0.01	0.07	-0.01	0.68	6.60	0.43
(7)	$\mathbb{E}_t\left[\sigma^{XS}(ROE_{L,t+1}) - \sigma^{XS}(ROE_{H,t+1})\right]$	184	-0.09	-0.90	0.00	-0.12	-0.82	0.01	0.64	5.28	0.41
(8)	Macro Uncertainty Index$_t$	185	0.07	0.31	-0.00	0.18	1.15	0.03	0.64	5.91	0.43

Notes: **Panel B** of this table compares objective expectations of macroeconomic risk with PVS$_t$ and the real rate. We define the objective expectation of variable X as the expectation that comes from a statistical forecasting model. Specifically, we fit ARMA(1,1)-GARCH(1,1) models to TFP Growth (Row 1), real consumption growth (Row 2), real consumption growth (Row 3), and industrial production growth (Row 4). σ_{t+1} in the table then represents the GARCH forecast for the volatility of each growth series, which is in the information set at time t. σ_{t+1} (Agg. Stock Market) in Row (5) is the expected volatility of the aggregate stock market. From 1986 onward, it is the time t value of the VXO option implied volatility index from the CBOE. To fill in the data prior to 1986, we fit an AR(1) model to within-quarter realized volatility of the CRSP Value-Weighted index. We then use the one-step ahead forecast made at time t from the AR(1) model, reindexed to create a smooth series when appending the VXO after 1986. In row (6), $\overline{\sigma}_{L,} - \overline{\sigma}_H$ is the average volatility of low-volatility stocks minus the average volatility of high-volatility stocks. At time t,we compute our forecast of $\overline{\sigma}_{L,t+1} - \overline{\sigma}_{H,t+1}$ using an AR(1) model fit to the whole sample. In row (7), we instead fit an AR(1) to the actual realized volatility of the volatility-sorted portfolio. σ_{t+1}(LMH-Vol Port.) is the one-period ahead forecast made at time t from the AR(1) model. Row (8) uses the macroeconomic uncertainty index from Jurado et al. (2015). The first set of regressions in the table shows the results of a univariate regression of PVS$_t$ on each of these expected risk measures. The second set of regressions in the table shows the results of a univariate regression of the real rate on contemporaneous values of each variable. The last set of results regresses the real rate on both PVS$_t$ and each expected risk measure. 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. In all regressions, we standardized variables to have mean zero and variance one in order to facilitate comparison of magnitudes.

Table 9: 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)
HML-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 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.