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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 aggregates, our measure is strongly correlated with safe asset prices and future economic activity. When our measure is high, safe bonds fall in value and risky assets rally, forecasting a boom in investment. Risk appetite is closely linked to investors' expectations of future risk and rises following positive macroeconomic outcomes. Periods of elevated risk appetite are predictably followed by upward revisions in expectations of risk, suggesting that these expectations may not be rational.

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1 Introduction

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

This risk-centric view of business cycles has received renewed attention in recent theoretical work (Caballero and Farhi (2018); Caballero and Simsek (2018); Cochrane (2017)), but the empirical link between risk appetite and the macroeconomy has proven elusive. Traditional asset pricing models, such as Campbell and Cochrane (1999) and Bansal and Yaron (2004), suggest that the economy's risk appetite can be inferred from aggregate consumption or the aggregate stock market. However, measures of risk appetite derived from aggregates (e.g., Lettau and Ludvigson (2004)) generally fail to explain meaningful amounts of real rate variation and do not consistently forecast future macroeconomic outcomes.

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

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

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

As in the risk-centric narrative, we find that the comovement between PVS_t and the real rate is almost entirely attributable to changes in risk premia rather than expected growth. 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 correlation with the real rate – reflect common variation in the compensation investors demand for holding volatile securities within several different asset classes, consistent with the idea that it is a broad measure of risk appetite relevant to the macroeconomy.

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

Taken together, these facts favor the risk-centric view of business cycles and suggest that PVS_t is a good gauge of the economy's risk appetite. When risk appetite is high, the price of safe bonds is low, risk premia on volatile stocks are low, and output and investment boom.

Having established that PVS_t has the properties of a good measure of risk appetite, we next use it to shed light on potential drivers of risk appetite. We first explore the link between risk appetite and investor expectations. While expectations of the level of future cash flows do not explain much of the variation in PVS_t, PVS_t strongly moves with expectations of risk measured from several sources. Risk appetite is low when equity analysts and options markets expect volatile firms to be particularly risky. Similarly, when PVS_t is low, the Federal Reserve's Senior Loan Officer Opinion Survey indicates that banks are tightening standards, in part because they believe risks are high. We also show that PVS_t is correlated with objective measures of risk from statistical forecasting models, though the correlation is somewhat weaker compared to subjective measures of risk from surveys or market data. These results further support our interpretation of PVS_t as a measure of risk appetite by tying it directly to financial market participants' expectations of risk. We then document that PVS_t rises on the heels of good news, such as positive surprises to GDP growth, suggesting that investor expectations of risk are shaped by recent events.

Since PVS_t is closely linked to investors' expectations of risk, it is natural to ask whether these expectations are rational. Under the null of rational expectations, revisions in expectations should be unpredictable. By contrast, we find that high values of PVS_t, which occur when investors' expectations of risk are low, reliably predict that investors will revise their expectations of risk upwards over the next two to three quarters. Expected returns on put options provide further evidence that expectations of risk are not fully rational. Under rational expectations, riskier strategies should always have higher expected returns. By contrast, we show that high values of PVS_t reliably forecast lower – and sometimes even negative – returns to selling put options on high-volatility stocks relative to low-volatility stocks. Given data limitations, it is difficult to measure investors' expectations of risk. However, using a variety of measures and approaches, we consistently find evidence suggesting that expectations of risk are not fully rational, a possibility first raised in the classical accounts of Keynes (1937), Minsky (1977), and Kindleberger (1978).

We close by presenting a stylized model that ties together our empirical evidence on the price of volatile stocks, the valuation of safe bonds, investment, and investor expectations of risk. The model has three main elements: i) volatility increases after adverse shocks, ii) investors have diagnostic beliefs as in Bordalo et al. (2018), leading them to over-extrapolate from recent news, and iii) real firm investment is determined according to standard Q-theory. Since risk aversion is constant in the model, risk appetite is determined by investors' subjective expectations of risk. Following an adverse shock, objective expected risk increases. Diagnostic beliefs amplify the increase in investors' subjective expectations of future risk. Expecting high risk, 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, so the prices of these firms fall relative to less volatile firms; in other words, the model analog of PVS_t falls along with risk appetite. Real investment also falls, particularly for volatile firms, because required returns rise. Subsequently, subjective expected risk predictably reverts back towards objective expected risk. Thus, our main empirical results emerge from the model. Importantly, the model nests a rational expectations benchmark, allowing us to delineate the role of diagnostic expectations. Diagnostic expectations are necessary for generating over-reaction and subsequent revisions in subjective expectations of risk, and amplify movements in asset prices and real investment.

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 literature attributing the long-run decline in real rates to expected growth and Treasury convenience yields.[2] By contrast, our empirical findings emphasize that risk appetite is important for understanding quarterly real rate variation, after accounting for long-term trends due to growth expectations and other factors.

In this respect, our paper is closer to the long literature in asset pricing arguing that considerations of risk drive variation in asset prices (e.g., Campbell and Shiller (1988); Cochrane (2011)). We emphasize stocks' total volatility in the construction of PVS_t because it is a robust measure of risk. Intuitively, volatility increases with exposure to risks, regardless of what they are. We also confirm empirically that volatility is not proxying for other stock characteristics such as the level of cash flows or growth expectations. We label PVS_t a measure of risk appetite, rather than risk aversion, to allow for the possibility that it reflects both expectations of risk and risk aversion. We highlight expectations of risk empirically because we can obtain direct measures of them. However, our results do not rule out risk aversion as a driver of risk appetite, and it may be important for understanding the empirical strength of our results.

Our paper also contributes to the literature studying how investor sentiment and biased beliefs impact asset prices (e.g., De Long et al. (1990); Barberis and Thaler (2003); Baker and Wurgler (2007)). While this literature has focused mainly on beliefs about the level of future cash flows, our

[1] Examples include Bloom (2009); Caballero and Farhi (2018); Bloom et al. (2018); Hall (2017); Caballero and Simsek (2018); McKay et al. (2016).

[2] See Laubach and Williams (2003); Cúrdia et al. (2015); Del Negro et al. (2017); Krishnamurthy and Vissing-Jorgensen (2012); Kozlowski et al. (2018a,b), among others.

results suggest that investor sentiment may also be driven by beliefs about future risk. Indeed, previous work finds that sentiment disproportionately affects securities with highly uncertain values (Baker and Wurgler (2006)), consistent with the special role of volatility in our results. Furthermore, PVS_t is correlated with measures of sentiment for both debt and equity markets, suggesting that variation in risk appetite induces common movements in sentiment across markets. The link between PVS_t and credit markets suggests that recent work connecting credit market sentiment to economic outcomes 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.[3]

Finally, this paper contributes to the literature on the relation between risk premia in bonds and stocks (Fama and French (1993); Koijen et al. (2017); Lettau and Wachter (2011); Binsbergen et al. (2012)). We build on this research by showing that the pricing of volatility in the cross section of stocks sheds light on the fundamental drivers of the real rate. Our results differ from the literature on idiosyncratic risk in the stock market, which has focused on the average returns of high-volatility stocks.[4] We study time variation in their risk premia and how it connects to interest rates and macroeconomic performance.

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

2 Motivating Framework and Variable Construction

2.1 Motivating Framework

Our measure of risk appetite is the difference between the valuations of low- and high-volatility stocks. We begin by providing a framework that motivates the construction of this measure and shows why it should be correlated with the real rate.

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

[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.

We start with the standard consumption-based Euler equation for risky assets:

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

where $r_{i,t+1}$ is the return on asset i from time t to time $t+1$, r_{ft} is the real risk-free rate at time t, $g_{c,t+1}$ is consumption growth, $\mathbb{V}\left[g_{c,t+1}\right]$ is the expected variance of consumption growth, and λ_t is risk aversion. The coefficient β_i measures asset i's exposure to risk.[5] In the spirit of Keynes (1937) and Minsky (1977), we refer to $-\lambda_t \times \mathbb{V}_t\left[g_{c,t+1}\right]$ as "risk appetite." Risk appetite can be low either because investors expect the future to be risky (i.e., $\mathbb{V}[g_{c,t+1}]$ is high) or because they are unwilling to bear risk (i.e., λ_t is high). In either case, Eq. (1) shows that expected excess returns on risky assets will be high when risk appetite is low. Furthermore, the riskier the asset, the more sensitive its expected excess returns should be to risk appetite.

Following the logic of Eq. (1), we build an empirical proxy for risk appetite, PVS_t, as the difference in valuation ratios between low- and high-volatility stocks. We use the volatility of past returns to proxy for an individual stock's risk because it does not require knowledge of the true risk factors that investors care about at each point in time. Volatility increases with exposure to any risk factor, and thus is a robust measure of risk. We obtain qualitatively similar but weaker results if we use risk measures tied to specific models like the CAPM. We use valuation ratios because expected returns are not directly observable. Valuation ratios are a natural proxy because they mechanically must depend on either expected returns or expected cash flow growth (Campbell and Shiller (1988)). Differences in valuation ratios are widely used to isolate risk premia (e.g., Fama and French (1992), Polk et al. (2006), Cochrane (2011)) because they difference out factors like aggregate growth that simultaneously move the valuations of all stocks without affecting risk premia. We confirm in Section 3.2 that PVS_t is indeed driven primarily by expected returns.

Risk appetite also affects the price of safe assets. The first-order condition for the real interest rate that emerges from the standard consumption-savings choice is:

$$r_{ft} = \delta + \frac{1}{\psi} \times \mathbb{E}_t\left[g_{c,t+1}\right] - \frac{\lambda_t^2}{2} \times \mathbb{V}_t\left[g_{c,t+1}\right], \tag{2}$$

[5] The intuitions captured by Eq. (1) broadly generalize to a variety of preferences and specifications of marginal utility.

where δ is the rate of time preference and ψ is the elasticity of intertemporal substitution. The last term of Eq. (2) captures the precautionary savings motive, $-\frac{\lambda_t^2}{2} \times \mathbb{V}_t\left[g_{c,t+1}\right]$, which varies with risk appetite. When risk appetite is low, the precautionary motive is strong. At these times, the real rate is low, and the price of safe assets is high.

This key prediction remains in a world where central banks set short-term interest rates. In standard models, the central bank should track variation in the natural, or frictionless, rate of interest one-for-one (Clarida et al. (1999), Woodford (2003)).[6] If changes in risk appetite are a source of variation in the natural rate, the Fed will optimally choose to track this variation. Intuitively, an increase in risk appetite acts like a traditional demand shock, increasing the natural rate. A central bank seeking to stabilize the economy will adjust the real rate in response to such a shock. If the central bank does not fully offset the shock, perhaps because it also seeks to smooth nominal rates,[7] output and investment will boom, temporarily rising above their natural levels.

Of course, the Fed takes other considerations into account as well. We expect such additional considerations to appear in the residual variation of the real rate not explained by PVS_t. For instance, when the Fed is particularly concerned with inflation, such as during the early 1980s, we expect it to adopt a contractionary stance and set the actual real risk-free rate above the natural real rate implied by the level of risk appetite. Conversely, during periods of financial instability, such as the years after the financial crisis, the Fed might believe that a more expansionary monetary policy is needed. In this case, we expect actual interest rates to be below the natural rate implied by the level of risk appetite. However, in general we expect the Fed to adjust interest rates in response to changes in the natural real rate, implying that high risk appetite should be associated with a high real rate on average.

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 internet appendix. Unless otherwise noted, our full

[6] It is important to note that the natural real rate 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 the natural rate (Woodford (2003)).

[7] E.g., Brainard (1967); Woodford (2003); Coibion and Gorodnichenko (2012); Stein and Sunderam (2018).

sample runs from 1970q2, when survey data on inflation expectations begins, to 2016q2.

Valuation Ratios The valuation ratios used in the paper derive from the CRSP-Compustat merged database and include all U.S. common equities that are traded on the NYSE, AMEX, or NASDAQ. At the end of each quarter and for each individual stock, we form book-to-market ratios. The value of book equity comes from CRSP-Compustat Quarterly and is defined following Fama and French (1993). If book equity is not available in CRSP-Compustat Quarterly, we look for it in the annual file and then the book value data of Davis, Fama, and French (2000), in that order. We assume that accounting information for each firm is known with a one-quarter lag. At the end of each quarter, we use the trailing six-month average of market capitalization when computing the book-to-market ratio of a given firm. This smooths out any short-term fluctuations in market value. We have experimented with many variants on the construction of book-to-market, and our results are not sensitive to these choices.

Volatility-Sorted Portfolio Construction At the end of each quarter, we use daily CRSP data from the previous two months to compute equity volatility, excluding firms that do not have at least 20 observations over this time frame. This approach mirrors the construction of variance-sorted portfolios on Ken French's website. We compute each firm's volatility using ex-dividend returns.

At the end of each quarter, we sort firms into quintiles based on their volatility. At any given point in time, the valuation ratio for a quintile is simply the equal-weighted average of the valuation ratios of stocks in that quintile. The key variable in our empirical analysis is PVS_t, the difference between the average book-to-market ratio of stocks in the lowest quintile of volatility and the average book-to-market ratio of stocks in the highest quintile of volatility:

$$PVS_t = \left(\overline{B/M}\right)_{low\ vol,t} - \left(\overline{B/M}\right)_{high\ vol,t}. \tag{3}$$

Again, PVS_t stands for the "price of volatile stocks." When market valuations are high, book-to-market ratios are low. Thus, PVS_t is high when the price of high-volatility stocks is high relative to low-volatility stocks. Throughout the analysis, we standardize PVS_t so regression coefficients can be interpreted as the effect of a one-standard deviation change in PVS_t. Quarterly realized returns in a given quintile are computed in an analogous fashion, aggregated up from monthly CRSP data.

The Real Rate The real rate is the one-year Treasury bill yield net of survey expectations of one-year inflation (the GDP deflator) from the Survey of Professional Forecasters. We use a short-maturity interest rate because inflation risk is small at this horizon, meaning inflation risk premia are unlikely to affect our measure of the risk-free rate. Our focus is on cyclical fluctuations in the real rate, as opposed to low-frequency movements that are potentially driven by secular changes in growth expectations or demographic trends. To control for long-run trends as simply and transparently as possible, we use a linear trend to extract the cyclical component of the real rate. In the internet appendix, we show that all of our results are essentially unchanged if we use the raw real rate or employ more sophisticated filtering methods.

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. High-volatility stocks have lower valuations than low-volatility stocks: on average, PVS_t is negative. The standard deviation of PVS_t is about twice the magnitude of its mean, so there is substantial variation in the price of volatile stocks over time. This variation is the focus of our empirical work.

Panel B shows that returns on the low-minus-high volatility portfolio are quite volatile, with an annualized standard deviation of 29.6%. Excess returns on the highest-volatility quintile of stocks are on average 2.7 percentage points per year lower than returns on the lowest-volatility quintile. This is related to the well-known idiosyncratic volatility puzzle, which highlights that stocks with high volatility have historically underperformed (Ang et al. (2009)), potentially due to short sales constraints (Stambaugh et al. (2015)).

3 Risk Appetite and the Macroeconomy

This section presents three facts showing that the risk-centric narrative of business cycles fits the data well using PVS_t as a measure of risk appetite. First, PVS_t captures the narrative's intuitive negative correlation between safe and risky asset prices: when PVS_t is high, the price of safe bonds is low, so the real rate is high. Second, considerations of risk, not cash flow growth, are the source of this correlation. PVS_t and its covariation with the real rate are driven by movements in risk premia. Third, as predicted by the risk-centric narrative, increases in PVS_t forecast booms in real investment, output, and employment.

3.1 Real Rates

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

$$\text{Real Rate}_t = a + b \times PVS_t + \varepsilon_t. \tag{4}$$

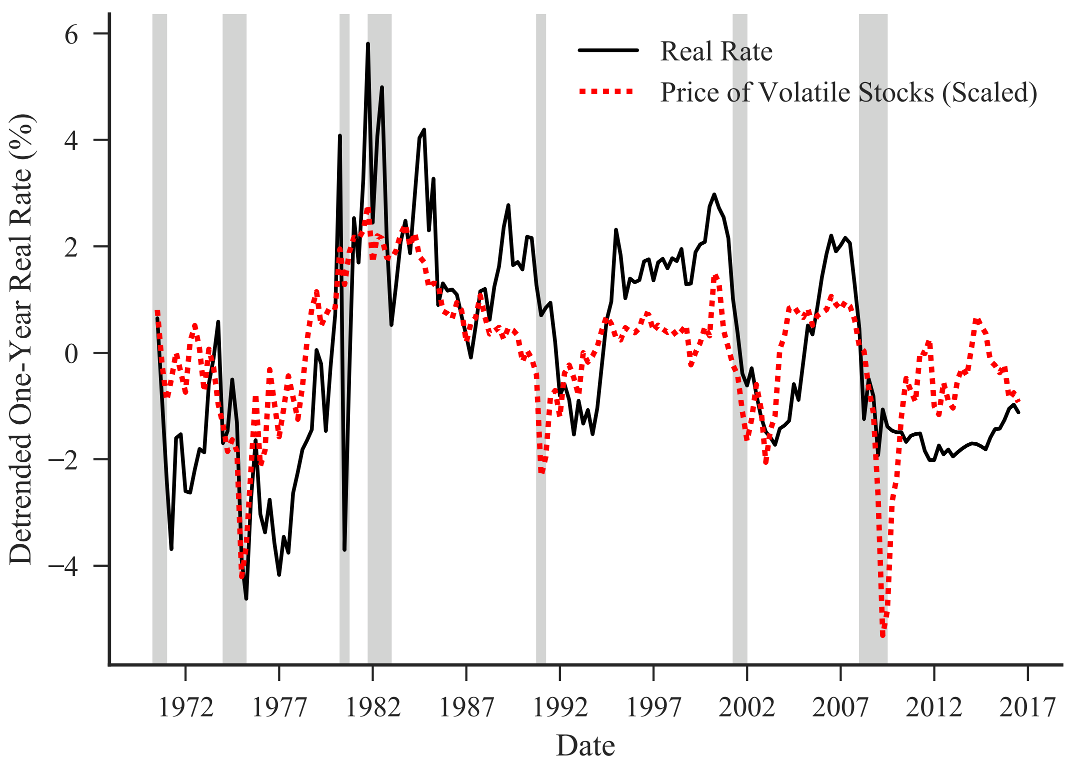
To facilitate interpretation, we standardize PVS_t so regression coefficients correspond to the effect of a one-standard deviation change. We report Newey and West (1987) standard errors using five lags. In the internet appendix, we also consider several other methods for dealing with the persistence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

Column (1) of Table 2 shows that the real rate tends to be high when PVS_t is high. In other words, safe asset prices are low when the prices of volatile stocks are high. The effect is economically large and precisely measured. A one-standard deviation increase in PVS_t is associated with a 1.3 percentage point increase in the real rate. For reference, the standard deviation of the real rate is 2.0 percentage points. The R^2 of the univariate regression is 41%.

Figure 1 presents the relation between PVS_t and the real rate visually. Figure 1 shows that the fitted value from the regression in Eq. (4), labeled "Price of Volatile Stocks (Scaled)," tracks the real rate well since 1970. The relation holds throughout the sample and is robust across different economic environments. It also holds through both expansions and recessions, which are shown in gray. We present formal evidence of subsample stability in the internet appendix.

Column (2) of Table 2 separates PVS_t into its constituent parts. The valuations of low-volatility and high-volatility stocks enter with opposite signs, so both components of PVS_t play a role in driving the relation with the real rate. Column (3) of Table 2 indicates that our focus on the cross section of stock valuations is important. We find no relationship between the book-to-market ratio of the aggregate stock market and the real rate. This non-result is not due to statistical precision. The economic magnitude of the point estimate on the aggregate book-to-market ratio is quite small

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 between the average book-to-market (BM) ratio of low-volatility stocks and the average BM-ratio of high-volatility stocks. The internet appendix contains details on variable construction. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage terms and linearly detrended to focus on business-cycle fluctuations. Data is quarterly and spans 1970Q2-2016Q2.

– a one-standard deviation movement in the aggregate book-to-market ratio is associated with only a 0.17 percentage point movement in the real rate. Moreover, the aggregate book-to-market ratio adds only one percentage point to the R^2 relative to our baseline regression in column (1), and the coefficient on PVS_t remains unchanged when controlling for the aggregate book-to-market ratio.[8] Insofar as the aggregate book-to-market ratio proxies for expected returns on the aggregate market (Cochrane (2008)), column (3) indicates that the expected return on the aggregate market has different drivers than PVS_t and the real rate.

In column (4), we control for variables traditionally thought to enter into monetary policy: four-quarter inflation, as measured by the GDP price deflator, and the output gap from the Congressional Budget Office (Clarida et al. (1999); Taylor (1993)). Both coefficients are noisily estimated and statistically indistinguishable from the traditional Taylor (1993) monetary policy rule values of 0.5. The internet 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 according to a standard Taylor (1993) rule.

Columns (5)-(8) of Table 2 rerun the preceding regressions in first differences to ensure that our statistical inference is not distorted by the persistence of either the real rate or PVS_t. We obtain similar results, both in terms of magnitude and statistical significance. The R^2s in columns (5)-(8) are somewhat lower because short-term oscillations in the real rate during Volcker's tenure as Fed 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.

Anecdotal evidence supports the idea that the Federal Reserve takes risk appetite into account when setting interest rates.[9] For instance, shortly after his appointment as Fed chairman in 1979, Paul Volcker called a meeting to consider actions "to improve control over the expansion of money and bank credit in the light of developing speculative excesses in financial and commodity markets."[10] Figure 1 shows that indeed PVS_t was increasing during the late 1970s, consistent with the

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

[9] We do not require that the Federal Reserve reacts directly to PVS_t, but only that risk appetite is reflected in both Federal Reserve actions and in the price of volatile stocks.

[10] Federal Open Market Committee (FOMC) Record of Policy Actions from October 6, 1979.

Fed's assessment of high financial market risk appetite. Anecdotal evidence is not limited to the 1970s. The spikes in PVS_t and the real rate in March 2000 occurred as the Fed decided to raise 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."[11]

The results in this section suggest that the Fed adjusts interest rates in response to changes in the natural rate, which are in part driven by risk appetite. At the same time, they paint a conventional picture of historical U.S. monetary policy. As discussed in Section 2.1, monetary policy is contractionary when the actual real rate is above the natural real rate, and expansionary when below. Taking the fitted value from the regression in Eq. (4) as a proxy for the natural rate, Figure 1 suggests that monetary policy was expansionary prior to Volcker's appointment as Federal Reserve chairman in 1979. During Volcker's chairmanship the real rate rises above the fitted value, implying a contractionary monetary policy stance. By contrast, during the financial crisis of 2008-2009, PVS_t and the fitted rate fell sharply. This fall was not fully mirrored in actual rates, which were constrained by the zero lower bound. Figure 1 suggests that the natural rate recovered quickly after the crisis, but that the recovery in actual interest rates was slower, consistent with the Fed trying to support the real economy for an extended period of time.

3.1.1 Robustness

Table 3 shows that the link between PVS_t and the real interest rate is robust along several dimensions. We run robustness tests for both the full and pre-crisis samples, in levels and in changes. All regressions include the aggregate book-to-market ratio as a control and use Newey and West (1987) standard errors using five lags. For reference, the first row of Panel A in Table 3 reproduces our baseline results from columns (3) and (7) of Table 2.

The Term Structure of Real Interest Rates

Table 3 Panel A starts by showing a statistically significant positive relationship between PVS_t and longer-term real rates, with magnitudes that are similar to our estimates for the one-year real

[11]FOMC minutes for March 21, 2000. For a comprehensive narrative account of financial market considerations in FOMC meetings, see Cieslak and Vissing-Jorgensen (2018).

rate. We construct k-year real rates as the k-year nominal Treasury bond yield minus survey expectations of one-year inflation. We use one-year inflation expectations when constructing the term structure of real rates simply because the data go back further, though our conclusions are not sensitive to this choice. The relationship between PVS_t and long-term real rates in rows (2) and (3) suggests that when risk appetite is low, there is a simultaneous increase in the price of all real safe assets, regardless of maturity. Since 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 to match the horizon of our inflation expectations data.

Alternative Constructions of PVS_t

Next, we show that we obtain similar results for alternative definitions of PVS_t. In row (4) of Table 3, we recompute PVS_t by value-weighting the book-to-market ratio of stocks within each volatility quintile, as opposed to equal-weighting. In row (5), we obtain similar results sorting stocks on volatility measured over a two-year window, rather than a two-month window. Our baseline result therefore captures changes in the valuation of stocks that historically have been volatile, not changes in the volatility of low-valuation stocks. This distinction is important to our interpretation of PVS_t as a measure of investors' willingness to hold volatile stocks.

Relationship to Other Stock Characteristics

Rows (6)-(11) of Table 3 Panel A investigate whether stock return volatility is really the key characteristic that drives the relationship between PVS_t and the real rate. In row (6), we run a horse race of PVS_t against the difference in yields between 10-year off-the-run and on-the-run Treasuries, a measure of liquidity premia in the fixed income market (Krishnamurthy (2002), Kang and Pflueger (2015)). The table reports the estimated coefficient on PVS_t. The explanatory power of PVS_t for the real rate is unchanged, suggesting that PVS_t subsumes any information about the real rate that is captured in the demand for liquid assets like on-the-run Treasuries.

Next, we test whether volatility simply proxies for another stock characteristic by controlling for book-to-market spreads based on alternative characteristics. For an alternative characteristic Y, we construct a book-to-market spread the same way we construct PVS_t. We report the coefficient on PVS_t, while controlling for the Y-sorted book-to-market spread and the aggregate book-to-market ratio. We consider characteristics Y that capture alternative economic mechanisms for the real rate to correlate with PVS_t: cash flow duration, firm leverage, systematic risk (i.e., CAPM 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. Row (7) shows that PVS_t is not capturing differences in the duration of cash flows between low- and high-volatility stocks, which would cause their values to move mechanically with interest rates. Instead, we find that low volatility is the key characteristic determining whether a stock's valuation correlates with the prices of safe bonds, indicating that PVS_t captures how investors price risk and not duration. The results on beta confirm that the relation between PVS_t and the real rate is not simply picking up on aggregate stock market risk, suggesting that investors care about a more complex set of risk factors.[12] The value-sorted book-to-market spread is sometimes thought to capture the value of growth options, so the value result suggests that the relation between PVS_t and the real rate is not driven by growth options. The results on size show that despite the fact that smaller firms tend to be more volatile, our volatility sorts do not simply proxy for size. In the internet appendix, we use double sorts to provide additional evidence that the relationship between PVS and the real rate is not driven by other stock characteristics, including industry and whether the firm is a dividend payer, as well as the characteristics studied here.

Thus, sorting stocks on volatility is key to our construction of PVS_t. From a statistical perspective, it may not be surprising that there exists a cross section of stocks that is correlated with real rates. The interesting economic content of our findings is that volatility, while not a fundamental firm characteristic, is a robust measure of risk. Volatility increases with stocks' exposure to any risk factors that investors care about, and PVS_t captures how worried investors are about these risks.

Relationship to Other Financial Market Conditions

We next show that PVS_t has distinct explanatory power for the real rate compared to other measures of financial market activity, including the BAA minus 10-year Treasury credit spread,

[12] As we discuss in the internet appendix, there is a correlation between the real rate and the spread in valuations of beta-sorted portfolios, confirming the intuition that the price of safe assets is high when prices of risky stocks are low. However, the relationship between the real rate and PVS_t is stronger in univariate regressions and in horse races, consistent with our interpretation of total volatility as a more robust measure of an individual stock's risk. In contrast to Adrian and Franzoni (2009), who study decade-by-decade changes in the risk spread between value and growth portfolios, we focus on quarterly variation in the valuation spread between high- and low-risk portfolios.

the Gilchrist and Zakrajšek (2012) credit spread, the Greenwood and Hanson (2013) measure of credit market sentiment, the Baker and Wurgler (2006) measure of equity market sentiment, the Kelly and Pruitt (2013) optimal forecast of aggregate equity market returns, and the Baker et al. (2016) economic policy uncertainty index.

The first set of columns in Table 3 Panel B shows that PVS_t is correlated with many of these measures, though the R^2s indicate that the magnitudes are generally not large. The second set of columns in Panel B of Table 3 runs univariate regressions of the real rate on the alternative measures. None of these measures match the R^2 of 41% for PVS_t, though the Baker and Wurgler (2006) equity sentiment measure has high explanatory power. Moreover, the third set of columns shows that the relationship between PVS_t and the real rate survives when controlling for these alternative measures and that the R^2s increase substantially by adding PVS_t in all cases.

One potential reason that PVS_t has separate explanatory power over these alternative measures is that PVS_t is based on a long-short portfolio, and thus nets out factors affecting an entire asset class. For instance, suppose equity market sentiment has a risk appetite component and an equity cash flow component, while credit market sentiment shares the same risk appetite component but has a distinct bond cash flow component. PVS_t should difference out optimism about aggregate equity cash flows, which affects equity market sentiment, but not credit market sentiment.[13] Consistent with this interpretation, PVS_t is positively correlated with both the Greenwood and Hanson (2013) measure of credit market sentiment and the Baker and Wurgler (2006) measure of equity market sentiment, despite the fact that the two sentiment measures are negatively correlated.

3.2 Return Predictability

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

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

3.2.1 The Low-minus-High Volatility Equity Portfolio

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

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

$$R_{t \to t+4} = a + b \times X_t + \xi_{t+4}, \tag{5}$$

where X_t is either PVS_t or the real rate. To start, $R_{t \to t+4}$ is either the low-minus-high volatility portfolio's annual return or annual cash flow. Panel A in Table 4 contains the results. We use Hodrick (1992) standard errors to be maximally conservative in dealing with overlapping returns.

Column (1) shows that a high price of volatile stocks forecasts low returns on high-volatility stocks relative to low-volatility stocks. A one-standard deviation increase in PVS_t forecasts a 15.1 percentage point higher annual return on the volatility-sorted portfolio. The annual standard deviation of returns is 29.6%. The R^2 of 0.26 is also large. For comparison, the aggregate price-dividend ratio forecasts aggregate annual stock returns with an R^2 of 0.15 (Cochrane (2009)). Thus, it appears that variation in PVS_t largely reflects variation in future returns, consistent with much of the empirical asset pricing literature (e.g., Cochrane (2011)).

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

In columns (3) and (4), $R_{t \to t+4}$ is the cash flow on the volatility-sorted portfolio, measured as accounting return on equity (ROE). We find economically small and statistically insignificant effects forecasting with either PVS_t or the real rate. PVS_t and the real rate contain little information about the future cash flows of the volatility-sorted portfolio. Under rational expectations, this lack of cash flow predictability is evidence that investors' time-varying expected returns drive PVS_t.

Taken together, columns (1)-(4) of Table 4 Panel A suggest that the real rate comoves with PVS_t because it comoves with risk premia on volatile stocks. In the internet appendix, we use the present value decomposition of Vuolteenaho (2002) to show that nearly 90% of the comovement between the real rate and PVS_t arises because the real rate forecasts future returns on volatile stocks. Consistent with the risk-centric narrative, when risk appetite is low, safe asset prices are high and investors demand high compensation for holding volatile stocks.

Columns (5) and (6) of Panel A in Table 4 show that neither the real rate nor PVS_t forecast the aggregate market excess return, echoing earlier findings by Campbell and Ammer (1993). While this highlights the importance of our focus on volatility sorts, it might seem puzzling that the real rate does not forecast the aggregate market return. Column (2) of Table 2 suggests this lack of relation is driven by the composition of the aggregate stock market. The real rate is negatively correlated with valuations of the lowest-volatility, "bond like" stocks, while it is positively correlated with the valuations of high-volatility stocks. The aggregate market averages over both high-volatility and low-volatility stocks and thus has a relatively weak relationship with the real rate, whereas PVS_t isolates risky stocks.

3.2.2 Other Asset Classes

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

We use test asset portfolios from He et al. (2017), which cover six asset classes: U.S. corporate bonds, sovereign bonds, options, credit default swaps (CDS), commodities, and currencies.[14] Within each asset class, we form a portfolio that is long the lowest-volatility and short the highest-volatility portfolio in the asset class, where volatility is measured with a 5-year rolling window of prior monthly returns. The first three columns in Table 4 Panel B contain summary statistics on the volatility-sorted portfolios in each asset class. In contrast to equities, the average returns of long-short portfolios are negative for several asset classes, showing that the low-volatility premium in U.S. equities (Ang et al. (2006)) is not a systematic feature of all asset classes.

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

The second set of columns in Table 4 Panel B shows that both PVS_t and the real interest rate forecast quarterly returns on volatility-sorted portfolios for many asset classes. The top row shows our results for U.S. equities. The remaining rows show economically and statistically significant evidence that PVS_t and the real rate forecast long-short returns within three other asset classes: U.S. corporate bonds, options, and CDS. There is also a positive, marginally significant correlation between PVS_t and sovereign bond returns, and a positive but insignificant correlation between PVS_t and commodity returns. We obtain similar results forecasting annual returns.

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

3.3 Real Outcomes

We have established that PVS_t has several properties that one would expect of a measure of broad risk appetite. The risk-centric view further predicts that shocks to risk appetite have real effects: when investors are willing to bear risk or expect risk to be low, they fund more risky projects, leading to booms in investment and output. We now provide evidence of this prediction.

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. In the language of our motivating framework in Section 2.1, we want to ensure PVS_t and the actual real rate comove because PVS_t and the natural rate both respond to risk appetite shocks, and the central bank adjusts the actual real rate in responses to changes in the natural rate. Put differently, we want to rule out the possibility that movements in PVS_t are driven by monetary policy shocks (i.e., changes in the actual real rate when the natural rate is not moving). We previously provided evidence against this reverse causality story in Section 3.1.1 by controlling for characteristics that determine firms' exposure to exogenous changes in interest rates. In this section, we further rule out reverse causality using methods from the literature on monetary policy shocks. Showing that PVS_t innovations are distinct from monetary policy surprises helps us interpret our results on real economic outcomes below.

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

Table 5 provides evidence against the reverse causality story. We regress returns on the low-minus-high volatility portfolio onto monetary policy shocks. Anecdotally, surprise policy changes made outside of regularly scheduled meetings are often driven by financial market conditions and could thus confound our analysis. We therefore exclude them here and show in the internet appendix that results are similar when including them.

If reverse causality was responsible for our baseline result, high-volatility stocks should increase in response to a positive shock to interest rates. Since the dependent variable is the low-minus-high volatility return, reverse causality should show up as negative coefficients in Table 5. In the first set of columns, we use quarterly data and find coefficients that are statistically insignificant with inconsistent signs. In the second set of columns, we narrow the window and focus on daily data. We again find small and statistically insignificant effects.

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

3.3.2 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 Jordà

(2005) local projections. Specifically, we run regressions of the form:

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

where h is the forecast horizon. In the context of the framework in Section 2.1, macroeconomic responses to shocks to PVS_t are consistent with the Federal Reserve not completely offsetting changes in risk appetite and instead allowing for some quantity responses.

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 0.22 percentage points higher at a one-quarter horizon and 0.35 percentage points higher at a four-quarter horizon. The standard deviation of the investment-capital ratio is 1.16%. In the second row of Table 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 0.32 percentage points more positive after one quarter, and 0.66 percentage points higher after four quarters. In the third row of the table, we report results for the change in the unemployment rate. A one-standard deviation increase in PVS_t is associated with a 0.11 percentage point fall in the unemployment rate after one quarter, and a 0.27 percentage point decline after four quarters. In the internet appendix, we find similar results when controlling for the aggregate book-to-market ratio and the Cochrane and Piazzesi (2005) term structure factor, suggesting that the information PVS_t contains about the macroeconomy is distinct from the information in those variables.

In Figure 2 we report impulse responses to a one-standard deviation shock to PVS_t for horizons of $h = 1, \ldots, 12$ quarters. The figure shows that the effect of a shock to PVS_t on private investment is quite persistent, peaking around six quarters and then slowly reverting over the next six quarters. In contrast, the effects on the output gap and unemployment are somewhat less persistent, peaking after five quarters and then dissipating. In the internet 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.

Thus, investment and macroeconomic activity rise following an increase in PVS_t. These findings also further alleviate concerns that PVS_t simply proxies for monetary policy shocks, or exogenous variation in interest rates. Contractionary exogenous interest rate increases should forecast declines in investment, output, and employment (Christiano et al. (1999)). By contrast, we find that these variables rise following an increase in PVS_t, instead supporting the interpretation that PVS_t moves with investor risk appetite.

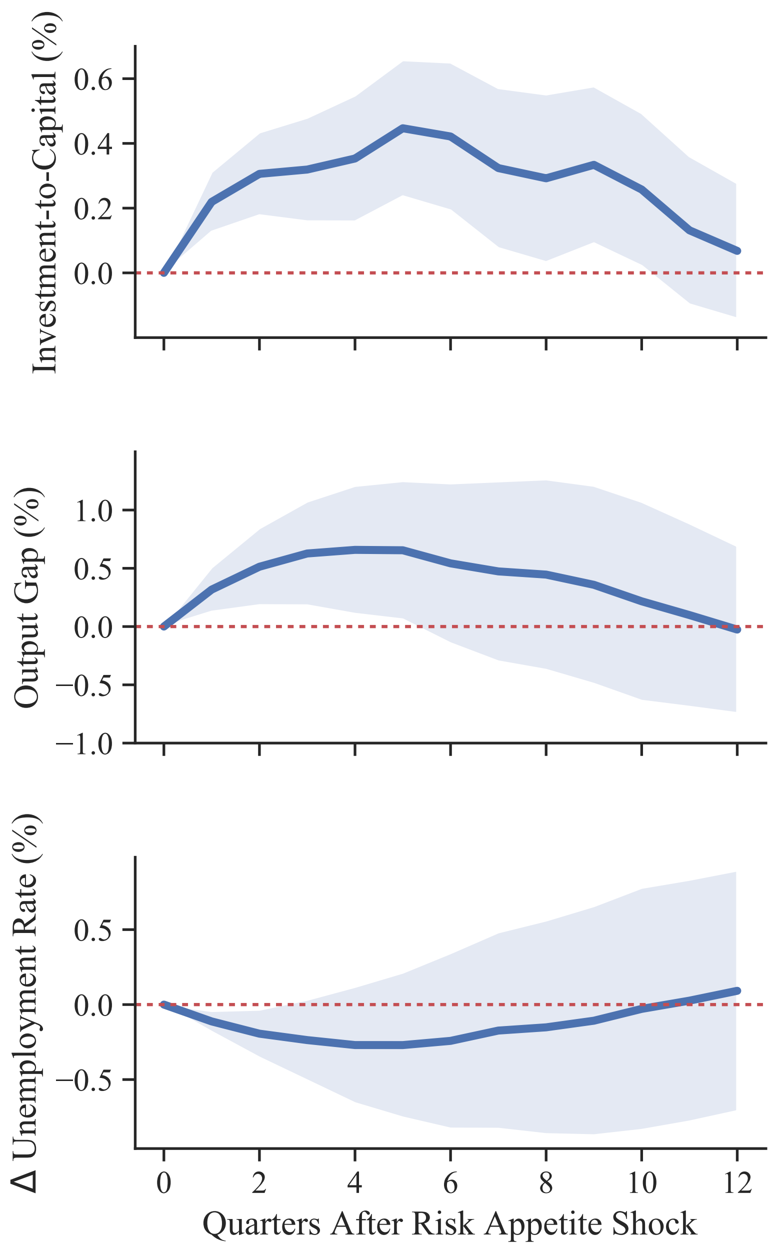
One might be concerned that Figure 2 suggests that PVS_t reflects variation in expected growth, not risk appetite. For instance, more volatile stocks could have cash flows that are more sensitive to aggregate growth. As discussed above, we think this alternative explanation is unlikely for two reasons. First, we find no evidence that PVS_t forecasts the cash flows of volatile stocks, while it strongly forecasts their expected returns. Second, if aggregate growth expectations were important, one would expect aggregate stock market valuations as well as duration-sorted stock valuations to explain more variation in the real rate. However, in the data, neither can match the explanatory power of PVS_t for the real rate. We therefore believe that the most natural interpretation of our results is that the risk appetite, as measured by PVS_t, is a fundamental determinant of the natural real rate, and, in turn, shocks to PVS_t act as traditional demand shocks.

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

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

where 1_{it}^q is an indicator that firm i is in volatility quintile q at time t. a_i and a_t are firm and time fixed effects, respectively. The variable $CAPX_{i,t\to t+4}/A_t$ captures investment for the firm from time t to $t+4$ and $CF_{i,t\to t+4}/A_t$ controls for the cash flows of the firm over the same period. The coefficient of interest in the regression is the interaction between the firm's volatility quintile and

Figure 2: Impulse Responses of the Macroeconomy to PVS Shocks (Local Projections)



Notes: This figure plots the estimated impulse responses (and associated 95% confidence bands) 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 outcome 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 percentage points and linearly detrended. For all regressions, we use Newey and West (1987) standard errors with five lags. Data is quarterly and spans 1970Q2-2016Q2.

PVS_t. Panel B of Table 6 reports the regression results: the investment of higher-volatility firms is more sensitive to PVS_t than the investment of lower-volatility firms, and this result is robust across pre- and post-2000 subsamples.

4 Why does Risk Appetite Vary?

We have documented relationships between PVS_t, the real rate, and macroeconomic outcomes that fit the risk-centric view of business cycles and support the idea that PVS_t captures the economy's risk appetite. When our measure of risk appetite is high, the price of safe bonds is low, risk premia on volatile stocks are low, and output and investment boom.

In this section, we use PVS_t to explore the fundamental forces that lead risk appetite to vary over time. To start, we show that periods of high risk appetite are times when investors expect future risk to be low. We then document that expectations of risk fall following good news about the economy. Finally, we provide evidence that investors over-extrapolate in the sense that expectations of risk are predictably revised upwards after periods of high risk appetite.

4.1 PVS and Investor Expectations

4.1.1 Expectations of Future Cash Flows

In Section 3.2, we saw that PVS_t forecasts future returns but not future cash flows. Under the assumption that investors have rational expectations about future cash flows, this predictability implies that PVS_t is driven by expectations of future returns. However, if beliefs about future cash flows are not rational, PVS_t could still be driven by cash flow expectations, yet fail to forecast future realized cash flows. We examine this alternative explanation directly using investor expectations of cash flows from analyst forecasts. The results confirm that PVS_t varies primarily because of movements in expected returns.

In Table 7 Panel A, we run contemporaneous regressions of PVS_t on expectations of future cash flows constructed from the Thompson Reuters IBES dataset of equity analyst forecasts. For each stock, we construct the consensus analyst forecast of ROE. We then compute the difference between the median forecast for high-volatility stocks and the median forecast for low-volatility stocks. We regress PVS_t on this spread in expected cash flows. In column (1), we use analyst forecasts for the next quarter, in column (2), we examine annual forecasts, and in column (3) we use analyst forecasts for long-term growth.[15] We standardize both PVS_t and the explanatory variables. The sample for these regressions is shorter because IBES data is only reliable for our cross section after the early 1990s, and the number of observations varies across columns because different forecasts are available starting at different dates. We find similar results if we restrict the sample to the common period where all variables are available.

As one would expect, expectations of future cash flows are positively correlated with PVS_t. When investors expect high cash flows for high-volatility stocks, PVS_t tends to be high. However, the correlation is quite weak – across the three specifications, expectations of cash flows explain at most 15% of the variation in PVS_t. Mechanically, this means that the remaining 85% of variation in PVS_t must be explained by variation in expectations of future returns (Campbell and Shiller (1988)). This accords with our results in Section 3.2, where we concluded 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. The main takeaway here is that variation in PVS_t is primarily driven by investor expectations of returns, not their expectations of cash flows.

4.1.2 Expectations of Risk

We next examine investor expectations of risk. Because our measure of risk appetite is driven by the expected return that investors demand for holding volatile securities, it must vary due to fluctuations in investors' expectations of risk or their willingness to bear risk. We study how PVS_t relates to measures of expectations of risk based on analyst forecasts, option prices, surveys, and statistical models. The results are reported in Table 7 Panel B, which contains two sets of regressions. In the first set, we run simple univariate regressions relating PVS_t to our measures of expectations of risk. Our second set of regressions controls for cash flow expectations to ensure we are truly picking up a correlation between risk expectations and PVS_t.

We start by focusing on the univariate regressions. Row (1) of Table 7 Panel B examines how PVS_t relates to a measure of expected risk derived from analyst earnings forecasts in IBES. We

[15] IBES defines long-term growth as the "expected annual increase in operating earnings over the company's next full business cycle", a period ranging from three to five years.

use the dispersion of earnings forecasts across analysts as a proxy for their expectations of risk.[16] Specifically, we measure expected earnings risk as the range of analyst forecasts for each firm's earnings divided by the median forecast. We then define the expected risk of the volatility-sorted portfolio as the difference in median dispersion between high- and low-volatility firms. While this is an imperfect measure of expected risk, our empirical analysis only requires that it be positively correlated with true subjective expectations of risk.

In row (1), we use dispersion in forecasts of one-quarter ahead earnings. When expected risk from analyst forecasts for volatile firms is high, PVS_t is low. The univariate R^2 is 28%, and a one-standard deviation increase in expected risk from analyst forecasts is associated with a 0.45 standard deviation decline in PVS_t. Since dispersion is sometimes used as a measure of investor disagreement, it is important to note that disagreement should drive up stock valuations (Harrison and Kreps (1978); Scheinkman and Xiong (2003); Diether et al. (2002)). In contrast, we find that the price of volatile stocks declines with the dispersion of analyst forecasts about volatile stocks, consistent with our dispersion measure capturing expectations of risk.

Row (2) shows a stronger correlation between PVS_t and dispersion in forecasts of one-year ahead earnings. The R^2 shows that this measure of subjective expectations of risk explains over half of the variation in PVS_t. A one-standard deviation increase in expected risk is associated with a 0.67 standard deviation decline in PVS_t. Figure 3 Panel A depicts the relationship visually.[17]

Row (3) studies how PVS_t relates to expectations of risk derived from option prices. Using data from OptionMetrics, we compute the difference in the median implied volatility of one-year at-the-money options for high- and low-volatility firms. When the option-implied volatility of volatile firms is relatively high, PVS_t is relatively low. A one-standard deviation increase in expected risk is associated with a 0.46 standard deviation decline in PVS_t.

Option-implied volatilities contain expectations of future volatility and premia for volatility

[16] Ideally, we would measure analysts' expectations of risk using their perceptions of the full distribution of future earnings. However, in the IBES data, each analyst only reports their mean estimate of future earnings. Consistent with our interpretation of dispersion as expected risk, it is correlated with the volatility of individual analysts' forecasts over time. Because computing the volatility of individual forecasts requires continuous time series data, the measure cannot be constructed for many firms in our sample and is noisy when it can be constructed. We therefore use dispersion.

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

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

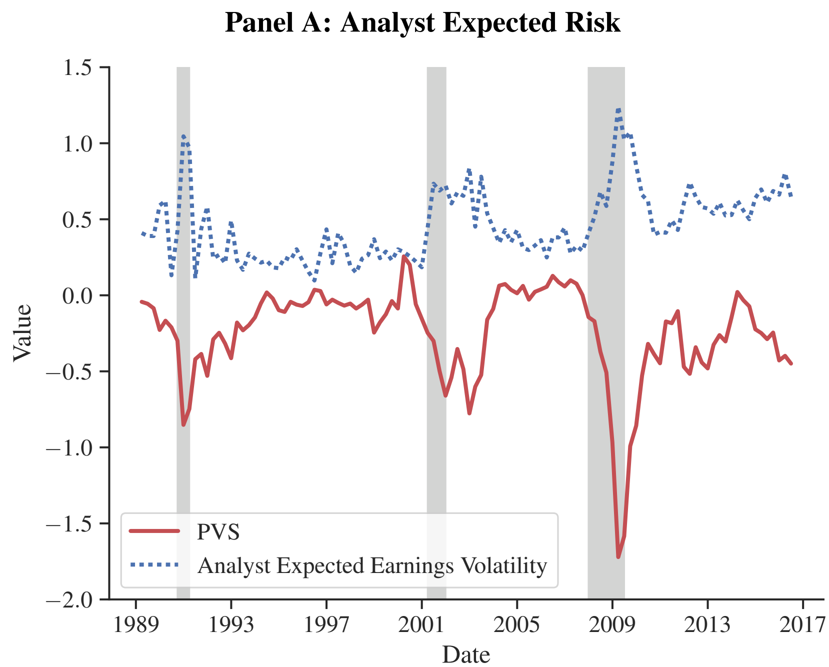
In row (4) of Table 7 Panel B, we take a statistical approach to measuring the expected risk of the portfolio underlying PVS_t. We examine the forecasted difference in return volatility between the low- and high-volatility portfolios, where we estimate the forecasted volatility of each portfolio with an AR(1) model.[18] We refer to this measure as an objective measure of risk because it derives from a statistical model. The regression in row (4) indicates that PVS_t correlates with this objective measure of expected risk, though the R^2 of 9% is lower than what our subjective measures of expected risk deliver.

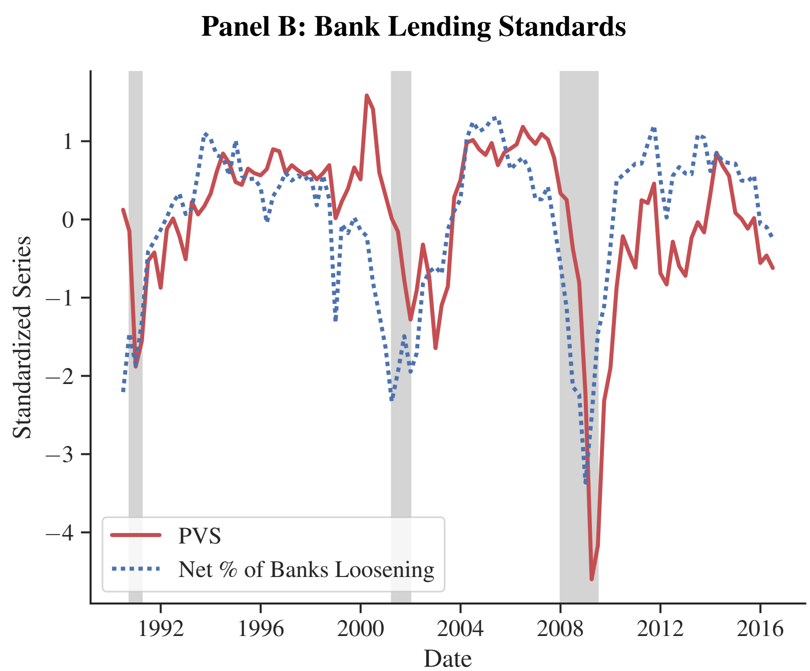
In row (5), we examine a measure of expected risk that is less directly tied to the portfolio underlying PVS_t. We use the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) to study expectations of risk from credit markets. Row (5) shows that when loan officers report that they are loosening lending standards, PVS_t is high, consistent with the idea that loan officers' expectations of risk are low at these times. A one-standard deviation loosening in lending standards is associated with a 0.5 standard deviation higher value of PVS_t. Figure 3 Panel B shows the relation visually. Our interpretation that the SLOOS measure reflects expected risk is corroborated by row (6), 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 in many asset classes.

We next turn to the second set of regressions in Table 7 Panel B. In these regressions, we control

[18] There are slow-moving trends in individual stock volatility (e.g., Campbell et al. (2001)). In the internet appendix, we show that we get similar, but slightly stronger, results if we first extract the cyclical component of volatility and then forecast it with an AR(1).

Figure 3: PVS_t and Expected Risk





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

for expectations of cash flows using analyst long-term growth forecasts, which we found to have the most explanatory power for PVS_t in Table 7 Panel A. Across specifications, the same overall conclusion emerges: controlling for cash flow expectations has little impact on the importance of expectations of risk and typically adds little explanatory power.

The broad takeaway from this analysis is that much of the variation in PVS_t is due to changes in expectations of risk, consistent with the risk-centric narrative. Expectations of risk explain significantly more variation in PVS_t than expectations of future cash flows. The connection between PVS_t and expected risk is strongest when using subjective measures from surveys or market data rather than objective measures from statistical forecasting models. In the internet appendix, we examine the relationship between PVS_t and measures of aggregate risk, including aggregate market volatility. We find much weaker correlations, highlighting the importance of our focus on the cross section to isolate risk appetite.

4.2 PVS Extrapolates from Past News

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

Table 8 reports the regression results. We standardize the dependent and independent variables to aid interpretation. Column (1) shows a positive correlation between the 4-quarter change in PVS_t and the surprise in real GDP growth over the same period. A one-standard deviation higher real GDP growth surprise is associated with a 0.6 standard deviation increase in PVS_t.

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

Finally, column (4) shows that PVS_t responds to recent conditions in credit markets, consistent with our interpretation that PVS_t is a measure that extends beyond equity markets. We measure credit market conditions as the 4-quarter change in charge-off rates on bank loans. A one-standard deviation increase in charge-offs is associated with a 0.4 standard deviation decrease in PVS_t. Column (5) shows that in a multivariate regression all four of these explanatory variables appear to contain independent information. Overall, the results here show that risk appetite rises on the heels of good news about the state of the economy.

4.3 PVS Forecasts Revisions in Expected Risk

So far, we have shown that PVS_t is driven in part by expectations of risk and rises following good news. Our findings to this point have little to say about whether these expectations are rational or not. However, given that early versions of the risk-centric narrative feature an element of irrational over-extrapolation, it is natural to ask whether the expectations driving PVS_t are indeed fully rational. If expectations are fully rational, then two conditions should hold. First, forecast errors – the difference between the realized outcome and forecasted outcome – should be unpredictable. All information available should be incorporated in the time-t expectation, so no information available at time t should correlate with forecast errors. Second, revisions in expectations should be unpredictable because they should only occur in response to purely unpredictable news events (Coibion and Gorodnichenko (2015)). To test these predictions, we construct several different measures of forecast errors and revisions in expectations. We then try to forecast them with PVS_t. For each measure, we first build a firm-level measure and then aggregate up to the portfolio level by taking the median of high-volatility firms minus the median of low-volatility firms. The internet appendix contains more information on the variable construction for this analysis.

4.3.1 Expectations of Future Cash Flows

We start by examining expectations of cash flows. We define a stock's quarterly ROE surprise as the difference between its realized ROE and the analyst consensus ROE forecast. The annual ROE surprise is the average surprise over the previous four quarters. Row (1) of Table 9 shows that there is no evidence that PVS_t forecasts earnings surprises. In row (2), we examine revisions in expectations of future cash flows. We study how analyst expectations for quarterly earnings at quarter $t+3$ evolve from quarter t to $t+2$. As discussed in more detail in the internet appendix, we choose these horizons based on data availability in IBES. Row (2) shows that PVS_t does not forecast revisions in expected earnings. These results reiterate the point that PVS_t is largely driven by expectations of risk, and not by incorrect beliefs about the future cash flows of volatile firms.

4.3.2 Expectations of Risk

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

In row (4), we study revisions to the risk expectations embedded in stock options. We examine revisions from quarter t to $t+3$ in the expected volatility of stock returns that will be realized between $t+3$ and $t+4$.[19] The forecasting regression shows that a one-standard deviation increase in PVS_t is associated with a revision in future expected risk that is 0.45 standard deviations higher. Thus, like analyst forecasts, option prices suggest that when PVS_t is high and expected risk is low, expected risk tends to be revised upwards. As discussed before, option-implied volatilities contain both investor expectations of risk and volatility risk premia, so the results in row (4) could reflect the ability of PVS_t to forecast changes in future volatility risk premia. However, this would not explain the predictability of analyst-based revisions.[20]

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

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

The loan officer survey variable is not associated with a fixed future date, so we cannot construct true revisions in expectations of risk based on it. We can only examine the measure's mean reversion over time. Row (5) shows that the percentage of banks loosening lending standards tends to fall after periods of high PVS_t. In untabulated results, we control for unconditional mean reversion in the survey variable by including its level in the regression, and find that the effect of PVS_t remains unchanged. In other words, even controlling for its unconditional mean reversion, the percentage of banks loosening lending standards tends to fall after periods of high PVS_t.

Finally, rows (6) and (7) of the table provide an indication of what might cause revisions in expected risk. PVS_t forecasts rising realized volatility for both the aggregate market return and the volatility-sorted portfolio over the subsequent four quarters. In other words, realized risk increases at the same time as predictable revisions in expected risk are occurring. The fact that PVS_t forecasts increases in realized risk could simply capture predictable mean reversion in realized risk; however, if expectations of risk were fully rational, they should anticipate this mean reversion, and we should not observe the predictable revisions that we see in our expectations data.

In Table 10, we use options data to examine errors in forecasts of risk at the firm level. Specifically, we define the volatility forecast error as the realized volatility of stock returns between $t+k$ to $t+h$ minus the expected volatility of those returns implied by options prices at quarter t. We then predict these errors using PVS_t and allow the forecasting relationship to vary based on the stock's volatility quintile. Formally, we run:

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

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

The table shows that forecast errors are larger when PVS_t is high. Moreover, this is particularly true for high-volatility stocks. The effect is economically significant. The standard deviation of the one-year forecast error examined in columns (1) and (2) is 19%. A one-standard deviation increase in PVS_t is associated with an increase in the forecast error of 3% for low-volatility stocks and 5-6% for high-volatility stocks. Column (2) shows that we obtain similar results if we include industry-time fixed effects, which purge the regression of any volatility risk premia that are constant

option maturities we consider. This observation is also useful below when we use PVS_t to predict forecast errors.

within an industry at a given point in time. In columns (3) and (4) we examine forecast errors for the volatility of stock returns between quarters $t+3$ to $t+4$ and find even stronger results. The standard deviation of the forecast error is 27%. A one-standard deviation increase in PVS_t is associated with an increase in the forecast error of 5% for low-volatility stocks and 10-13% for high-volatility stocks. These results are consistent with the idea that investors underestimate risk when PVS_t is high, particularly for volatile stocks.

Taken together, these results suggest that variation in PVS_t is not fully rational. Our measures of risk expectations are imperfect, so we cannot unequivocally reject a null of rational expectations. However, we find similar results using a variety of different measures of expected risk from different data sources. Combined with our finding that PVS_t is more correlated with subjective than objective measures of risk, the evidence overall points towards violations of rational expectations.

4.3.3 Forecasting Negative Returns

We next examine return forecasts as a complementary way of assessing whether the expectations of risk underlying PVS_t are rational. We study the profitability of strategies that sell put options because their returns depend directly on the accuracy of investors' expectations of risk. Under rational expectations, riskier strategies should always have higher expected returns. Since options on high-volatility stocks tend to be riskier than options on low-volatility stocks, this implies that rational investors should always demand higher expected returns for selling puts on high-volatility firms. In contrast, if investors underestimate risk when PVS_t is high, as our previous results suggest, then expected returns to selling puts on high-volatility firms may be lower than returns to selling puts on low-volatility firms at these times.

We compute the returns to selling puts using data from OptionMetrics, following the procedure of Jurek and Stafford (2015). For each firm i and quarter t, this procedure finds the set of out-of-the-money put options with the lowest maturity greater than 182 days. From this set, we then select the put option that is closest-to-the-money and require that the delta of the option is at least -0.4 to account for differences in volatility across firms and time. We sell this option at the best bid price, hold it for one quarter, then buy it at the best offer price.[21] At the portfolio level, we

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

take the equal-weighted average of high-volatility firm returns minus the equal-weighted average of low-volatility firm returns.

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

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

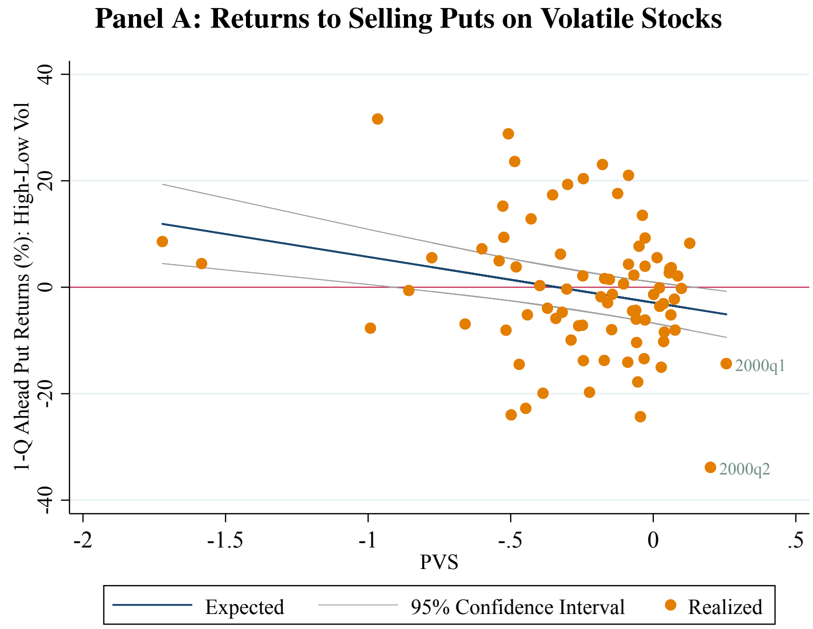
5 Model

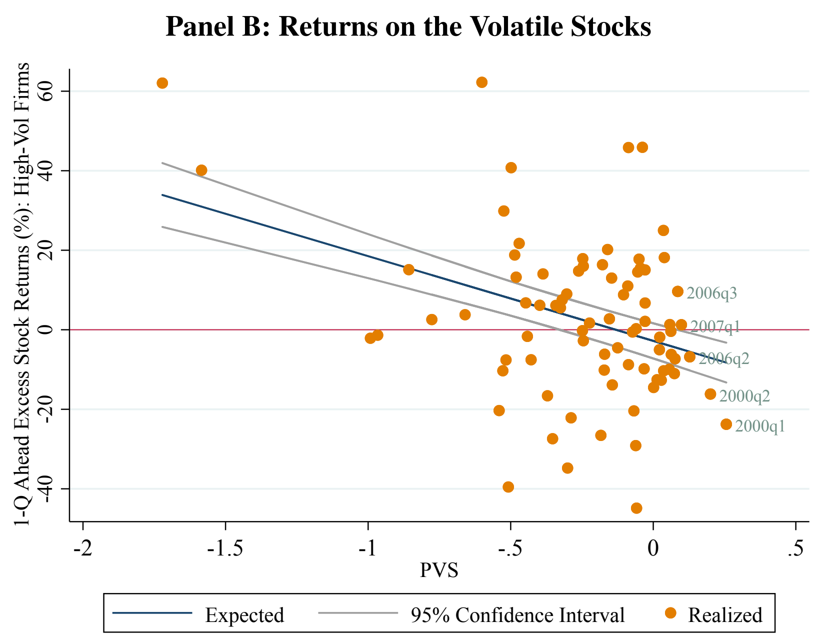
In this section, we present a stylized model that formalizes the narrative of risk-driven business cycles and ties together our empirical evidence on the price of volatile stocks, the real rate, investment, and investor expectations of risk. All proofs can be found in the internet appendix.

5.1 Preferences and Beliefs

There is a representative agent with constant relative risk aversion λ over aggregate consumption and time-discount rate δ. Log aggregate consumption growth is assumed to follow a heteroskedas-

Figure 4: PVS_t and Negative Returns





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

tic process:

$$\Delta c_{t+1} = \varepsilon_{t+1}, \tag{6}$$

$$\varepsilon_{t+1} = \sigma_t \eta_{t+1}, \tag{7}$$

$$\sigma_t^2 = exp(a - b\varepsilon_t), \tag{8}$$

where η_{t+1} is an i.i.d. normal shock with mean zero and variance one. High realizations of the fundamental shock ε_{t+1} therefore correspond to good times with low marginal utility of consumption. Time-varying volatility ensures that agents face a non-trivial updating problem for volatility, and our formulation generates GARCH effects that are ubiquitous in the financial econometrics literature. We could extend the model to contain an autoregressive term in Eq. (6), which would make expected growth predictable, without changing the mechanism. However, since our empirical results indicate that risk appetite does not vary much with expected cash flows, we proceed with the simpler setup. Since risk aversion is constant in the model, risk appetite corresponds to investors' subjective expectations of volatility.

We assume that the representative agent updates using 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.[22] 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 have biased beliefs.

Combining these assumptions with Eqs. (6) and (8), the subjective distribution of ε_{t+1} is conditionally normally distributed with subjective mean and variance:

$$\mathbb{E}_t^\theta(\varepsilon_{t+1}) = 0, \tag{9}$$

$$\mathbb{V}_t^\theta(\varepsilon_{t+1}) = \left(\frac{1}{1+\theta(1-exp(-b\varepsilon_t)}\right)\sigma_t^2. \tag{10}$$

[22] Formally, state ε_{t+1} is more representative at t if it is 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, we use superscript θ to denote subjective expectations. Eq. (10) shows that investors under-estimate volatility following good news and over-estimate volatility following bad news. Risk appetite in the model is given by $-\lambda V_t^{\theta}(\varepsilon_{t+1})$.

5.2 Production

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

$$Y_{i,t+1} = A_{i,t+1} K_{i,t+1}^{\alpha}. \tag{11}$$

$K_{i,t+1}$ 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:

$$A_{i,t+1} = \exp\left(s_i \varepsilon_{t+1} - \frac{1}{2} s_i^2 \mathbb{V}_t^{\theta}\left(\varepsilon_{t+1}\right)\right). \tag{12}$$

Higher s_i means that firm i has riskier and more volatile production. 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 productivity. We assume that $s_i > \frac{\lambda}{2}$ for all firms, so all firms have risky production.

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

5.3 Equilibrium Prices and Investment

It follows from consumer preferences that the representative agent values contingent claims paying off at time $t+1$ with the stochastic discount factor $M_{t+1} = \delta \exp(-\lambda \varepsilon_{t+1})$.The log real risk-free rate r_{ft} is given by

$$r_{ft} \quad = \quad -\ln(\delta) - \frac{1}{2}\lambda^2 \mathbb{V}_t^{\theta}(\varepsilon_{t+1}). \tag{13}$$

Eq. (13) is standard except for the use of diagnostic expectations. The second term captures the precautionary savings motive, which drives down the risk-free rate when risk appetite is low (i.e., subjective expectations of risk are high).

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

$$\ln\left(\mathbb{E}_t^{\theta}\left[R_{i,t+1}^K\right]\right) \quad = \quad r_{ft} + \lambda s_i \mathbb{V}_t^{\theta}(\varepsilon_{t+1}). \tag{14}$$

We obtain the expected marginal rate of return on capital by taking the first derivative of Eq. (11) and then taking subjective expectations over ε_{t+1}:

$$\ln \mathbb{E}_t^{\theta}\left[R_{i,t+1}^K\right] \quad = \quad \ln \alpha - (1-\alpha)k_{i,t+1}. \tag{15}$$

Here, we again use logs and use $k_{i,t+1}$ to denote log firm capital. Note that Eq. (15) is independent of θ, so investors' subjective expected return on capital agrees with objective forecasts, consistent with our empirical results in Section 4.1.1. Equating Eqs. (14) and (15) and substituting in the expression for the real rate shows that:

$$k_{i,t+1} \quad = \quad \frac{\ln(\alpha\delta)}{1-\alpha} - \frac{\lambda s_i - \frac{1}{2}\lambda^2}{1-\alpha}\mathbb{V}_t^{\theta}(\varepsilon_{t+1}). \tag{16}$$

The following proposition summarizes the equilibrium.

Proposition 1. *There is a unique equilibrium in which the real risk-free rate satisfies (13), subjective expected returns on firm i satisfy (14), and firm i's investment is given by (16).*

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. H firms are riskier 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 variation in PVS_t is driven by expected returns:

$$PVS_t^{model} = \ln \mathbb{E}_t [R_{L,t+1}] - \ln \mathbb{E}_t [R_{H,t+1}] = \lambda (s_L - s_H) \mathbb{V}_t^{\theta} (\varepsilon_{t+1}). \tag{17}$$

It is worth noting that objective expected returns equal investors' subjective expected returns. However if $\theta > 0$, an objective observer (i.e., one with $\theta = 0$) would disagree with investors about whether expected returns appropriately compensate for risk.

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 expected risk falls: $\frac{d\mathbb{V}_t^{\theta}(\varepsilon_{t+1})}{d\varepsilon_t} = -exp(a)b(1+\theta) < 0$.

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

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

d) Aggregate investment increases: $\frac{d(k_{H,t+1}+k_{L,t+1})}{d\varepsilon_t} = \frac{\lambda(s_H+s_L)-\lambda^2}{1-\alpha} exp(a)b(1+\theta) > 0$.

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

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

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

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

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

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

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

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

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, 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.

The comparative statics in Proposition 2 flesh out the risk-centric narrative. Proposition 2b shows that PVS_t^{model} rises following positive macroeconomic surprises, as we find in the data in Table 8. In the model, risk appetite rises because investors' subjective expectations of risk fall following a positive fundamental shock due to investor extrapolation. Following the shock, Propositions 2b and 2c show that the real risk-free rate and PVS_t^{model} both rise. Thus, the model also captures the empirical correlation between safe and risky asset prices, as in our baseline empirical result in Table 2. Furthermore, this correlation is driven by expected returns not cash flows, consistent with our empirical results in Table 4. In the model, the correlation arises because expectations of low risk reduce the precautionary savings motive, so investors require a higher return to hold the risk-free bond at the same time that they demand relatively low compensation for holding risky stocks. In addition, the model captures our results on real outcomes. Propositions 2d and 2e show that real investment rises when PVS_t^{model} is high through a standard Q-theory channel, and the investment response is strongest for the riskiest firms. These model implications are in line with our empirical findings in Table 6.

Finally, Proposition 3 completes the narrative, capturing our results on revisions in expectations of risk. When investors have diagnostic expectations ($\theta > 0$), subjective expected risk rises more in response to a negative shock than does objective expected risk, but is subsequently revised downward. These patterns match our finding in Table 7 that PVS_t is more sensitive to subjective than objective risk, as well as the fact that PVS_t positively forecasts revisions in expected risk (Table 9).

For the most part, diagnostic expectations amplify the model's comparative statics relative to the rational expectations benchmark. However, diagnostic expectations are essential for generating over-reaction and subsequent revisions in subjective expectations of risk. A simple calculation shows that our empirical results imply reasonable magnitudes for the belief distortion parameter, θ. Rows (2) and (4) of Table 7 Panel B suggest that subjective expectations of risk move about twice as much in response to PVS_t as objective expectations. Proposition 2a implies that in order to make subjective risk twice as sensitive as objective risk, we need $\theta \approx 1$, in line with the estimates of Bordalo et al. (2018) and Bordalo et al. (2018).

The model is stylized and thus necessarily has limitations. First, for simplicity there is only a single macroeconomic shock that impacts all firms. This assumption implies that risk premia on the aggregate market move with the real rate, though in the data we find a negligible correlation between the aggregate book-to-market ratio and the real rate. One way to address this limitation would be to assume that the aggregate stock market is exposed to a wide range of factors, with volatile stocks isolating the subset of factors that are relevant for investment and real interest rates. Another way to move the model closer to the data is to assume that low-volatility firms are more 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, there is some evidence of this: low-volatility stocks are bond like in the sense that their market values tend to rise when the real rate falls.

Second, the model implies that volatile firms should unconditionally earn higher returns. However, in the data, there is little relation between average stock returns and measures of risk such as volatility and market beta (Ang et al. (2009), Black et al. (1972)). One way to address this limitation would be to add a force that increases the demand for volatile securities on average, but leaves room for time variation in their risk premia. For instance, investor demand for volatile stocks might be the sum of demand in a frictionless model plus a constant frictional demand due to leverage constraints as in Frazzini and Pedersen (2014). The frictional demand component would tend to weaken the unconditional relationship between risk and return, while the frictionless demand component generate the time variation we find.

Third, risk aversion λ is constant in the model to isolate the subjective expected risk channel that emerges from our empirical results in Section 4.1. In the model, subjective expectations of risk are fully responsible for movements in PVS_t^{model}, while Section 4.1 indicates that they may explain closer to 50% of PVS_t variation in the data. It would be straightforward to allow for λ to vary through time, as in Campbell and Cochrane (1999).[23] Indeed, time-varying risk aversion is a complementary channel that would generate many of our results. For example, the Campbell and Cochrane (1999) mechanism would generate the relationship between PVS_t and past macroeconomic news that we observe in the data. It would be more challenging, however, for time-varying risk aversion to explain our results on expectations of risk and predictable revisions in those expectations.

6 Conclusion

This paper proposes a new measure of macroeconomic risk appetite, PVS_t, based on the idea that investors are averse to holding volatile assets when risk appetite is low. Using PVS_t, we present empirical evidence in favor of classic narratives of economic booms and busts that emphasize financial market risk appetite. We find that investor risk appetite rises following a positive funda-

[23] Bekaert et al. (2009) and Bekaert et al. (2017) are models with time-varying risk aversion and time-varying risk.

mental shock, in part because subjective expectations of risk decline. Following an increase in risk appetite, the real risk-free interest rate rises and real investment and output boom, suggesting that investors find safe bonds less attractive and are more willing to fund risky projects. Risk appetite subsequently reverses, accompanied by declines in the real risk-free rate, low or even negative returns on high-volatility stocks, and contractions in real investment and output, suggesting that investors become more willing to hold safe bonds and less willing to fund risky investments.

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

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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

***Panel C**: Real Rate*

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

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

Table 2: What Explains Real Rate Variation?

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

Notes: This table reports regression estimates of the one-year real rate on the spread in book-to-market (BM) ratios between low- and high-volatility stocks (PVS_t). For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Within each quintile, we compute the average book-to-market (BM) ratio. The internet appendix contains full details on variable construction. 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 dividing 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 percentage points and linearly detrended. We also independently detrend the output gap, inflation, and the aggregate book-to-market ratio. Results using the raw series for all variables is contained in the internet appendix. t-statistics are listed below each point estimate in parentheses and are computed using Newey-West (1987) standard errors with five lags. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. In the table, all book-to-market ratios, including PVS_t, are standardized to have mean zero and variance one. This is true in both the levels regression and the first-differenced regressions. Data is quarterly and spans 1970Q2-2016Q2.

Table 3: Robustness: The Real Rate and PVS

***Panel A**: Alternative Constructions, the Term Structure of Real Rates, and Other Stock Characteristics*

		Levels						First-Differences					
		Full			Pre-Crisis			Full			Pre-Crisis		
		b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2
(1)	Baseline	1.27	**5.01**	0.42	1.51	**7.61**	0.47	0.43	**2.65**	0.13	0.63	**3.67**	0.20
The Term Structure:													
(2)	5-Yr Real Rate	1.07	**3.82**	0.35	1.30	**6.06**	0.41	0.33	**2.63**	0.12	0.51	**4.17**	0.22
(3)	10-Yr Real Rate	0.92	**3.32**	0.30	1.14	**5.08**	0.36	0.25	**2.41**	0.10	0.40	**4.22**	0.20
Alternative Constructions:													
(4)	Value-Weight	1.12	**4.48**	0.32	1.42	**6.01**	0.41	0.31	**2.45**	0.08	0.40	**2.59**	0.10
(5)	2-Yr Volatility	1.42	**6.27**	0.52	1.62	**8.20**	0.54	0.26	**2.32**	0.05	0.43	**4.21**	0.10
Horse-Races:													
(6)	Liquidity	1.40	**6.54**	0.47	1.58	**7.73**	0.51	0.36	**2.14**	0.15	0.56	**3.02**	0.21
(7)	Duration	1.19	**4.26**	0.42	1.33	**5.24**	0.49	0.43	**3.13**	0.12	0.61	**4.31**	0.20
(8)	Leverage	1.51	**6.15**	0.44	1.66	**7.57**	0.48	0.57	**2.87**	0.14	0.74	**3.34**	0.21
(9)	2M CAPM Beta	1.27	**5.50**	0.41	1.48	**7.73**	0.48	0.31	**2.55**	0.15	0.50	**4.35**	0.22
(10)	Size	1.12	**2.48**	0.42	1.47	**3.80**	0.47	0.61	**2.42**	0.13	0.74	**2.59**	0.20
(11)	Value	1.53	**4.97**	0.43	1.73	**7.03**	0.48	0.69	**3.05**	0.16	0.80	**3.24**	0.22

Notes: This table reports a battery of robustness exercises. Specifically, we report time-series regression results of the following form: Real Rate$_t = a + b \times PVS_t + \theta X_t + \varepsilon_t$, where PVS_t is the average book-to-market ratio of low-minus-high volatility stocks. We run this regression in levels and in first differences and, in each case, we standardize PVS_t (or its first-difference) to have a mean of zero and variance of one over the full sample. X_t is a one of several control variables. For all specifications, the table reports the estimated coefficient on PVS_t. Row (1) uses our baseline PVS_t measure. In rows (2) and (3), we use the five and ten-year real interest rates as the dependent variable in the regression, as opposed to the one-year rate that we use in all other specifications. Row (4) uses value weights instead of equal weights when forming PVS_t. Row (5) constructs PVS_t using the past two years of return volatility, as opposed to the past two months. In rows (6)-(11), we run horse races of PVS_t against several other variables. Row (6) controls for the spread between off-the-run and on-the-run Treasury yields (Krishnamurthy (2002)). In rows (6)-(10), we sequentially add the book-to-market spread based on other characteristic sorts as control variables in the regression. See the internet appendix for a description of each characteristic and for details on variable construction. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percent and linearly detrended. The listed t-statistics are computed using Newey-West (1987) standard errors with five lags. Italic point estimates indicates a p-value of less than 0.1 and bold indicates a p-value of less than 0.05. Data is quarterly and the full sample spans 1970Q2-2016Q2, while the pre-crisis sample ends in 2008Q4.

Table 3: Robustness: The Real Rate and PVS

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

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

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

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

***Panel A**: Forecasting Returns and Cash Flows*

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

Notes: This table reports several return forecasting regressions where the predictor variables are either the real interest rate or PVS_t, the average book-to-market ratio of low-minus-high volatility stocks. We standardize PVS_t to have mean zero and variance one for the full sample. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage points and linearly detrended. The columns listed under "Volatility-Sorted Portfolio" pertain to an equal-weighted portfolio that is long low-volatility stocks and short high-volatility stocks. $\text{ROE}_{t\to t+4}$ is the return on equity between t and $t+4$ for the low-minus-high volatility portfolio, which we compute following Cohen, Polk, and Vuolteenaho (2003). 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. We use Hodrick (1992) standard errors. * indicates a p-value of less than 0.1, and ** indicates a p-value of less than 0.05. Data is quarterly and spans 1970Q2-2016Q2. All returns are expressed in percentage points.

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

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

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

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

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

Notes: This table reports regressions of volatility-sorted returns onto monetary policy shocks. 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 a FOMC press release. The Nakamura and Steinsson (2018) shock is the unanticipated change in the first principal component of interest rates with maturity up to one year from 10 minutes before to 20 minutes after a FOMC news announcement. Starting in 1994, we consider only policy changes that occurred at regularly scheduled FOMC meetings. Prior to 1994, policy changes were not announced after meetings so the distinction between scheduled and unscheduled meetings is not material. In the internet appendix, we repeat the analysis for all policy changes. The listed t-statistics are computed using Davidson and MacKinnon (1993) standard errors for heteroskedasticity in small samples.

Table 6: PVS and Real Outcomes

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

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

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

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

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

Table 6: PVS and Real Outcomes (continued)

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

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

Notes: Panel B of this table studies how firm-level investment interacts with PVS. We measure firm i's investment at time t as the running four-quarter total CAPX (denoted $CAPX^{Ann}_{i,t}$) divided by the book value of assets at time $t-4$ (denoted $A_{i,t-4}$). $CF^{Ann}_{i,t}$ is the running four-quarter total cash flow for the firm, computed as depreciation and amortization plus income before extraordinary items. Both are winsorized at their 1% tails. We run regressions of the form: $CAPX^{Ann}_{i,t+4}/A_{i,t} = FE + \sum_{q=2}^{5} a_q \cdot 1^q_{it} + b_1 \times CF^{Ann}_{i,t+4}/A_{i,t} + \sum_{q=1}^{5} c_q \times 1^q_{it} + d_2 \times PVS_t + \sum_{q=2}^{5} d_q \times PVS_t \times 1^q_{it} + \varepsilon_{i,t+4}$, where 1^j_{it} is an indicator function for whether firm i is in volatility-quintile j at time t. PVS_t is average book-to-market ratio of low-minus-high volatility stock and in all regressions is standardized to have mean zero and variance one for the period 1970q2-2016q2. 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. We exclude financial firms and firms with negative investment. t-statistics are listed below point estimates and are double-clustered by firm and by quarter. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. The full sample runs from 1983Q1-2016Q2. The total size of the subsamples does not match the full sample because we drop fixed-effect groups of size one.

Table 7: PVS and Investor Expectations

***Panel A**: Expectations of Cash Flows*

Dependent Variable		PVS_t	
	(1)	(2)	(3)
High-Minus-Low Volatility Stocks:			
$\mathbb{E}_t\left[\text{ROE}_{t+1}\right]$	0.28**		
	(2.40)		
$\mathbb{E}_t\left[\text{ROE}_{t+1\to t+4}\right]$		0.30**	
		(2.31)	
$\mathbb{E}_t\left[\text{Long-Term Growth}\right]$			0.34*
			(1.70)
Adj. R^2	0.10	0.11	0.15
N	102	110	110

Notes: Panel A of this table shows contemporaneous regressions of PVS_t on investor expectations of cash flows. In column (1), for each firm i and date t, we use the time-t expectation of quarterly accounting return on equity (ROE) at time $t+1$, denoted $\mathbb{E}_t\left[\text{ROE}_{i,t+1}\right]$, from the Thompson Reuters IBES dataset. At the portfolio level, $\mathbb{E}_t\left[\text{ROE}_{t+1}\right]$ 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. In column (2), we mirror the expected ROE measure in column (1) but instead use the annual ROE forecast from IBES for the next fiscal year. Column (3) again follows the same approach, but instead uses the "long-term growth" estimate provided by IBES. PVS_t is the average book-to-market ratio of low-minus-high-volatility stocks. We include a constant in all regressions and all variables are standardized to have mean zero and unit variance. t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and depends on data availability, though the full sample for PVS_t spans 1970Q2 to 2016Q2. See the internet appendix for more details.

Table 7: PVS and Investor Expectations

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

	X-variable	$PVS_t = a + b \times X_t$				$PVS_t = a + b \times X_t + c \times \mathbb{E}_t\,[\text{LTG}]$			
		N	b	$t(b)$	R^2	N	b	$t(b)$	R^2
	High-Minus-Low Volatility Stocks:								
(1)	$\sigma_t\,(\text{EPS}_{t+1})$	110	-0.45	-2.49	0.28	110	-0.38	-2.24	0.29
(2)	$\sigma_t\,(\text{EPS}_{t+5})$	110	-0.67	-5.06	0.61	110	-0.63	-5.08	0.61
(3)	Option-Implied $\sigma_t^{IV}\,(Ret_{t,t+4})$	80	-0.47	-2.51	0.24	80	-0.70	-5.81	0.63
(4)	Model-Based $\sigma_t(Ret_{t,t+1})$	184	-0.31	-2.13	0.09	109	-0.38	-2.52	0.34
(5)	% Banks Loosening	105	0.55	5.16	0.56	105	0.50	3.46	0.32
(6)	% Banks Loosening b/c of Outlook	90	0.48	2.51	0.27	90	0.61	4.65	0.56

Notes: Panel B of this table shows contemporaneous regressions of PVS_t on measures of investor expectations of risk. 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 row (1) is built using one-quarter ahead quarterly EPS forecasts. When building $\sigma_t(EPS_{t+5})$ for row (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 $\sigma_t^{IV}\,(Ret_{t,t+4})$ in row (3) is the median at-the-money one-year implied volatility of high-volatility firms minus the median for low-volatility firms. Options data comes from OptionsMetrics. In row (4), we use a statistical model to forecast the average volatility of high-volatility stocks minus low-volatility stocks. Denote the average realized quarterly volatility of high-volatility firms at time t by $rv_{H,t}$ and the same quantity for low-volatility firms by $rv_{L,t}$. We fit an AR(1) model to $rv_{H,t} - rv_{L,t}$ and use the time-t expectation of $rv_{H,t+1} - rv_{L,t+1}$ from the AR(1) model to form what we call Model-Based $\sigma_t(Ret_{t,t+1})$. Row (5) uses the net percent of U.S. banks loosening lending standards and row (6) uses the net percent of U.S. banks loosening lending standards because "more favorable or less uncertain conditions", both taken from the Federal Reserve Senior Loan Officer Opinion Survey (SLOOS). PVS_t is the average book-to-market ratio of low-minus-high- volatility stocks. The first set of regressions in the table are univariate regressions of PVS_t on the measures of expected risk. In the second set of regressions, we include IBES analyst expectations of long-term growth for the high-minus-low volatility portfolio ($\mathbb{E}_t[\text{LTG}]$), as described in Panel A of this table. 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. All variables are standardized to have a mean of zero and variance one. See the internet appendix for more details on variable construction.

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

Dependent Variable	$\Delta_4 PVS_t$				
	(1)	(2)	(3)	(4)	(5)
Real GDP Surprise$_{t-4\rightarrow t}$	0.56**				0.31**
	(3.86)				(2.67)
Corporate Profit Surprise$_{t-4\rightarrow t}$		0.43**			0.31**
		(4.39)			(2.98)
LMH-Vol ROE$_{t-4\rightarrow t}$			-0.27**		-0.16**
			(-3.21)		(-3.05)
Δ_4Bank Net Chargeoffs$_t$				-0.40**	-0.27**
				(-2.68)	(-3.70)
Adj. R^2	0.31	0.17	0.07	0.16	0.46
N	181	181	181	158	158

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

Table 9: PVS and Revisions in Expectations

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

		b	$t(b)$	Adj. R^2	N
	Expected Cash Flows:				
(1)	ROE Surprise$_{t+1 \to t+4}$	0.14	1.03	0.00	94
(2)	$\mathbb{E}_{t+2}[\text{ROE}_{t+3}] - \mathbb{E}_t[\text{ROE}_{t+3}]$	-0.09	-0.94	-0.00	102
	Expected Risk:				
(3)	$\sigma_{t+2}(\text{EPS}_{t+3}) - \sigma_t(\text{EPS}_{t+3})$	0.38	2.35	0.10	94
(4)	$\sigma^{IV}_{t+3}(Ret_{t+4}) - \sigma^{IV}_t(Ret_{t+4})$	0.45	3.17	0.17	80
(5)	Δ_4 Prc. of Banks Loosening$_{t+4}$	-0.83	-8.64	0.53	98
	Realized Risk:				
(6)	$\Delta_4 \sigma_{t+4}$(Mkt-Rf)	0.21	1.97	0.04	181
(7)	$\Delta_4 \sigma_{t+4}$(HML-Vol)	0.34	1.90	0.11	181

Notes: This table uses PVS_t to forecast future revisions in expected cash flows and risk. In row (1), we forecast the median return on equity (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. The time horizon for our ROE surprises is time $t+1$ to $t+4$. In row (2), we compute revisions in expected ROE$_{t+3}$ based on the Thompson Reuters IBES database of analyst forecasts. Specifically, for each firm i and date t, we use the median forecast of ROE time $t+3$, denoted $\mathbb{E}_{t+2}[\text{ROE}_{i,t+3}]$. For each (i,t), we choose the shortest forecast horizon h such that the quarterly earnings are at least two fiscal quarters away, which in calendar time is generally between 3 and 4 quarters from date t. For each firm i, we then define the revision in expected ROE at time $(t+2)$ as $\mathbb{E}_{t+2}[\text{ROE}_{i,t+3}] - \mathbb{E}_t[\text{ROE}_{i,t+3}]$. At the portfolio level, $\mathbb{E}_{t+2}[\text{ROE}_{t+3}] - \mathbb{E}_t[\text{ROE}_{t+3}]$ 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 (3), we compute revisions in expected earnings-per-share (EPS) volatility using the Thompson Reuters IBES database of analyst forecasts. For each firm i and date t, we proxy for the time-t expected EPS volatility at time $t+3$, denoted $\sigma_{it}(EPS_{t+3})$, using the range of analyst annual EPS forecasts divided by the absolute value of the median analyst EPS forecast. For each (i,t), we choose the shortest forecast horizon h such that the quarterly earnings are at least two fiscal quarters away, which in calendar time is generally between 3 and 4 quarters from date t. For each firm i, we define the revision in expected earnings growth volatility at time as $\sigma_{i,t+2}(EPS_{t+3}) - \sigma_{i,t}(EPS_{t+3})$. At the portfolio level, $\sigma_{t+2}(EPS_{t+3}) - \sigma_t(EPS_{t+3})$ is the cross-sectional median revision for high-volatility stocks minus the median revision for low-volatility stocks. In row (4), we use option implied volatilities to define revisions in expected return volatility. For each firm i and date t, denote $\sigma^{IV}_t(t+4)$ 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 $\sigma^{IV}_{i,t+3}(t+4) - \sigma^{IV}_{i,t}(t+4)$. 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 (5) 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 (6) and (7), we instead use PVS_t to forecast changes in future realized risk, as opposed to changes in expectations of risk. σ_t(Mkt-Rf) is the realized quarterly volatility of the CRSP value-weighted index at time t. σ_t(HML-Vol) is the average volatility of high-volatility stocks at time t minus the average volatility of low-volatility stocks. PVS_t is the average book-to-market ratio of low-minus-high- volatility stocks. We include a constant in all regressions and all variables are standardized to have mean zero and unit variance. t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and depends on data availability, though the full sample for PVS_t spans 1970Q2 to 2016Q2. See the internet appendix for more details.

Table 10: PVS and Implied Volatility Forecast Errors

Dependent Variable	Realized Volatility$(t+k,t+h)-\text{IV}_t(t+k,t+h)$			
	$k=0,h=4$		$k=3,h=4$	
	(1)	(2)	(3)	(4)
PVS_t	0.03**		0.05**	
	(3.92)		(4.00)	
$PVS_t \times 1_{it}^{q=2}$	0.01**	0.01**	0.02**	0.01**
	(2.77)	(2.60)	(3.02)	(2.21)
$PVS_t \times 1_{it}^{q=3}$	0.02**	0.01**	0.03**	0.03**
	(3.39)	(3.40)	(4.43)	(3.38)
$PVS_t \times 1_{it}^{q=4}$	0.03**	0.03**	0.05**	0.04**
	(2.76)	(3.47)	(3.31)	(2.81)
$PVS_t \times 1_{it}^{q=5}$	0.02	0.02*	0.08**	0.05**
	(1.30)	(1.84)	(3.18)	(2.30)
FE		$(\text{industry} \times t)$		$(\text{industry} \times t)$
R^2	0.05	0.53	0.08	0.51
N	38,673	38,548	38,343	38,219

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

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

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