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ABSTRACT

We document a strong and robust positive relationship between real rates and the contemporaneous valuation of volatile stocks, which we contend measures the economy's risk appetite. Our novel proxy for risk appetite explains 41% of the variation in the one-year real rate since 1970, while the valuation of the aggregate stock market explains just 1%. In addition, the real rate forecasts returns on volatile stocks, confirming our interpretation that changes in risk appetite drive the real rate. Increases in our measure of risk appetite are followed by a boom in investment and output.

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1 Introduction

Financial market participants often ascribe movements in asset prices to changes in investor risk appetite. Intuitively, changes in risk appetite should affect the macroeconomy. When investors have a greater appetite for risk, they should find safe bonds less attractive and be more willing to fund risky projects. Thus, real interest rates should be high and investment should boom, spurring an economic expansion. Conversely, when risk appetite is low, investors should seek out safe bonds as they become less willing to fund risky investments, driving down the real rate and leading to an economic contraction.[1]

This link between risk appetite and the macroeconomy has proven elusive empirically. Traditional rational asset pricing models with a representative agent (e.g., Campbell and Cochrane (1999); Bansal and Yaron (2004)) suggest that the economy's risk appetite should be reflected in data on 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 or forecast future macroeconomic outcomes.[2]

In this paper, we propose a new measure of risk appetite that is highly correlated with real interest rates and has significant predictive power for economic activity. 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 prefer low-volatility assets like riskless bonds. We operationalize this idea in the cross section of equities by comparing the price of volatile stocks (henceforth PVS_t) to the price of low-volatility stocks. Specifically, we define PVS_t as the average book-to-market ratio of low-volatility stocks minus the average book-to-market ratio of high-volatility stocks. Consequently, PVS_t is high when the market values of high-volatility stocks are large relative to low-volatility stocks. Using this measure, we document five key facts:

1. PVS_t has a strong, robust positive correlation with the one-year real rate, explaining 41% of its quarterly variation from 1970 to 2016.

[1]Risk appetite is often labeled as precautionary savings or a flight to quality. We use these terms interchangeably. While these terms are sometimes used to describe day-to-day variation in market prices, our focus is on quarterly variation in risk appetite, which is more likely to have macroeconomic effects.

[2]This echoes the Campbell and Ammer (1993) result that most variation in the aggregate stock market cannot be attributed to real rate news or news about future cash flows. We confirm these findings through a variety of forecasting regressions discussed below.

2. PVS_t and the real rate positively forecast returns on a portfolio that is long low-volatility stocks and short high-volatility stocks. Both also forecast returns on volatility-sorted portfolios in other asset classes beyond equities.

3. PVS_t and the real rate are both only weakly correlated with standard measures of the quantity of risk in the economy.

4. Outflows from high-volatility mutual funds are large relative to low-volatility funds when the real rate is low.

5. Shocks to PVS_t initially lead to a boom in investment, output, and employment, which is subsequently partially reversed.

Taken together, these facts strongly suggest that PVS_t measures the macroeconomy's risk appetite. The tight relationship between PVS_t and the one-year real rate is our headline result. This relationship is economically significant and robust. It appears in the data consistently through different macroeconomic environments, holding in both levels and first differences. Furthermore, the link between PVS_t and the real rate is robust to controlling for contemporaneous changes in the Taylor (1993) monetary policy rule variables (the output gap and inflation) and measures of credit and equity market sentiment (Greenwood and Hanson (2013); Baker and Wurgler (2006)). In addition, PVS_t has similarly strong explanatory for longer term real rates. Consistent with the risk appetite interpretation of our headline result, our emphasis on stocks' total volatility in the construction of PVS_t is critical. Using a combination of horse races and double sorts, we show that PVS_t contains information about the real rate that is independent of how investors price other stock characteristics such as size, value, leverage, duration of cash flows, and CAPM beta.

Return forecasting regressions further support the idea that PVS_t reflects the economy's risk appetite. As a valuation ratio, movements in PVS_t must be driven by variation in: (i) future cash flow differences between low- and high-volatility firms; or (ii) future return differences between low- and high-volatility firms. Thus, the correlation between the real rate and PVS_t must be driven by one of these factors. The data points to expected returns, as the real rate and PVS_t both strongly forecast future returns on a portfolio that is long low-volatility stocks and short high-volatility stocks (Fact #2). Consistent with this finding, PVS_t mean reverts quite quickly, with a half life of about 1.5 years. Intuitively, when risk appetite is low, PVS_t and the real rate are also low, and investors require high future returns for holding volatile stocks. Neither PVS_t nor the real rate forecasts cash flows for the same volatility-sorted portfolio, alleviating concerns that they are jointly driven by time-varying growth expectations.

Evidence from other asset classes (Fact #2) bolsters the notion that PVS_t is a broad measure of risk appetite, rather than one specific to equity markets. We show that the real rate and PVS_t forecast returns on portfolios that are long low-volatility securities and short high-volatility securities within several different asset classes, including U.S. corporate bonds, sovereign bonds, options, and credit default swaps (CDS). These results are particularly strong for credit markets. In this regard, our work is related to recent findings that credit market conditions are related to future macroeconomic performance (Gilchrist and Zakrajšek (2012); López-Salido, Stein, and Zakrajšek (2017)). Our results suggest that a broader concept of risk appetite — one that is revealed by common movements in the relative pricing of low- versus high-volatility securities in several asset classes — plays a central role in determining macroeconomic outcomes and real interest rates.

Because movements in PVS_t are driven by changes in the returns investors demand for holding volatile stocks, they must reflect changes in either investor aversion to risk or the quantity of risk. We investigate the quantity of risk channel by examining correlations between the real rate, PVS_t, and a wide range of risk proxies, including the realized volatility of volatile stocks, the Herskovic et al. (2016) common idiosyncratic volatility factor, the realized volatility of the aggregate stock market, and total factor productivity (TFP) volatility. These variables explain substantially less real rate variation than PVS_t, and importantly, controlling for them does not affect the explanatory power of PVS_t for the real rate (Fact #3). While it is impossible to account for all potential sources of time-varying volatility, these results suggest that PVS_t is mostly driven by time-varying aversion to risk, again consistent with our interpretation that it measures the economy's risk appetite.

We then move past asset prices and examine the behavior of mutual fund investors. If risk appetite is really about investor attitudes towards volatile securities, then when risk appetite is low, investors should exit high-volatility mutual funds and move into safe bonds. This is precisely what we find in the data: high-volatility funds experience larger capital outflows than low-volatility funds during periods of low real rates (Fact #4).

We close by directly examining the relationship between risk appetite and macroeconomic performance, aiming to understand how the economy responds to risk appetite shocks. To start, we first rule out the alternative explanation that changes in PVS_t are caused by changes in monetary policy. Following the literature on monetary policy shocks, we examine narrow windows around the Federal Reserve's policy announcements. We show that shocks to monetary policy are uncorrelated with returns on the portfolio of low-minus-high volatility stocks in these windows, confirming that monetary policy does not differentially affect the prices of high-volatility stocks.

We then turn to real variables, showing that when risk appetite is high, as measured by PVS_t, an economic boom follows. In particular, following a positive shock to PVS_t, private investment and output rise over the following four quarters, while unemployment falls (Fact #5). The magnitudes are economically significant: a one-standard deviation increase in PVS_t is associated with an increase in the investment-capital ratio of 0.4%. Similarly, output rises 0.6% relative to potential and the unemployment rate decreases by 0.4%. These gains are then partially reversed over the following eight quarters. These macroeconomic dynamics are broadly consistent with the notion that fluctuations in risk appetite play an important role in determining the course of the business cycle.

Collectively, these facts raise significant questions for theories of asset pricing and macroeconomics. A necessary ingredient for a model to fit the strong empirical correlation between PVS_t and the real rate is that some investors must evaluate risk based on total volatility. This is challenging for standard rational models with perfect risk sharing, in which agents care about a security's systematic risk or beta – not its total volatility – because idiosyncratic risk can be diversified away. Investors might care about total volatility for several reasons, including behavioral biases, institutional frictions, and market incompleteness. A second key ingredient for a model to fit our empirical findings is that investor attitudes towards total volatility (i.e., risk appetite) must vary over time. These two ingredients are sufficient to generate most of our results. When risk appetite is low, investors will want to hold riskless bonds, driving down the real rate. At the same time, they will be reluctant to hold high-volatility assets, driving their valuations down and their future returns up, without much change in the quantity of risk. This reluctance to hold risky assets in turn drives down real investment. Conversely, when risk appetite is high, investors will have less demand for bonds and more demand for volatile assets, driving up the real rate, PVS_t, and real investment.

Mechanically, the relationship between the one-year real rate and PVS_t must be intermediated by the central bank, which sets short-term interest rates. Thus, our results imply that the Federal Reserve treats shocks to risk appetite like traditional demand or discount rate shocks in a standard New Keynesian framework and reacts to these shocks by adjusting interest rates. Moreover, the quantitative strength of the relationship between the real rate and risk appetite suggests that risk appetite shocks are a particularly important type of shock to the macroeconomy. Our results do not imply that the Federal Reserve tracks PVS_t itself, but rather that the component of risk appetite that the Fed reacts to is discernible from how investors price volatile stocks.

Our paper is related to several strands of the literature. The idea that risk and uncertainty drive macroeconomic fluctuations has received significant attention in recent years (Bloom (2009); Caballero and Farhi (2017); Bloom et al. (2014); Hall (2016); Caballero and Simsek (2017); McKay et al. (2016)). This work typically focuses on the quantity of risk as the driving force and studies long-run changes in the real rate. By contrast, our empirical findings emphasize that time-varying risk appetite plays an important role for understanding quarterly variation, after accounting for long-term trends due to growth expectations and other factors. In this respect, our paper is closer to the long literature in asset pricing arguing that considerations of risk drive variation in asset prices (e.g., Campbell and Shiller (1988); Cochrane (2011); Cochrane (2016)). This also distinguishes our paper from the recent literature studying the trend in the natural rate of interest, attributing decade-by-decade changes in real rates primarily to expected growth and Treasury convenience yields (Laubach and Williams (2003); Cúrdia et al. (2015); Del Negro et al. (2017); Krishnamurthy and Vissing-Jorgenson (2012)).

Our paper is also related to the literature studying how investor sentiment impacts asset prices (De Long et al. (1990); Baker and Wurgler (2007)). While this literature has focused mainly on connecting sentiment to mistaken beliefs about future cash flows, our results suggest that changes in investors' sentiment may also be driven by changes in their appetite for risk. This connection is intuitive for two reasons. First, PVS_t mean reverts quickly, suggesting it is not driven by slow-moving fundamentals. Second, previous work finds that sentiment disproportionately affects speculative securities with highly uncertain values (e.g., Baker and Wurgler (2006)), consistent with the special role of volatility in our results. Indeed, 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. Our results suggest that recent work connecting credit market sentiment to economic outcomes (e.g., Bordalo et al. (2018); Krishnamurthy and Muir (2017); López-Salido et al. (2017)) 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.

This paper also contributes to the literature on the relation between risk premia in bonds and stocks, a long-standing question in financial economics (Fama and French (1993); Koijen et al. (2010); Baker and Wurgler (2012)). We build on this research by showing that the pricing of volatility in the cross section of stocks sheds light on the fundamental drivers of the real rate, despite the fact that aggregate stock market valuations do not reliably explain the real rate. Our results differ from the literature on idiosyncratic risk in the stock market (Ang et al. (2006); Johnson (2004); Ang et al. (2009); Fu (2009); Stambaugh et al. (2015); Hou and Loh (2016)) in that we study time variation in risk premia of high-volatility stocks, whereas the previous literature has primarily focused on their average risk premium. 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. Our focus is on how the relative valuation of high- and low-volatility stocks connects to real interest rates and macroeconomic performance.

The remainder of this paper is organized as follows. Section 2 describes the data and portfolio construction. Section 3 presents the main empirical results. Section 4 describes the implications of our results for models of asset prices and the macroeconomy. Section 5 concludes.

2 Data

We construct a quarterly data set running from 1970q2, when survey data on inflation expectations begins, to 2016q2. We include all U.S. common equity in the CRSP-COMPUSTAT merged data set that is traded on the NYSE, AMEX, or NASDAQ exchanges. We provide full details of all of the data used in the paper in the Appendix. Here, we briefly describe the construction of some of our key variables.

2.1 Construction of Key Variables

Valuation Ratios

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

Volatility-Sorted Portfolio Construction

At the end of each quarter, we use daily CRSP stock data from the previous two months to compute equity volatility. We exclude firms that do not have at least 20 observations over this time frame. This approach mirrors the construction of variance-sorted portfolios on Ken French's website. We compute each firm's volatility using ex-dividend firm returns.[3]

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:

$$PVS_t = \left(\overline{B/M}\right)_{low\ vol,t} - \left(\overline{B/M}\right)_{high\ vol,t}. \quad (1)$$

PVS_t stands for the "price of volatile stocks." When market valuations are high, book-to-market

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

ratios are low. Thus, PVS_t is high when the price of high-volatility stocks is large relative to low-volatility stocks. Quarterly realized returns in a given quintile are computed in an analogous fashion, aggregated up using monthly data from CRSP.

The Real Rate

The real rate is the one-year Treasury bill yield net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters. We use a short maturity interest rate because inflation risk is small at this horizon, meaning inflation risk premia are unlikely to affect our measure of the risk-free rate. In addition, our focus is on understanding cyclical fluctuations in the real rate, as opposed to low-frequency movements that are likely driven by secular changes in growth expectations (Laubach and Williams (2003)). To control for long run growth and other trends as simply and transparently as possible, we use a linear trend to extract the cyclical component of the real rate. In the Appendix, we show that all of our results are essentially unchanged if we just use the raw real rate or if we employ more sophisticated filtering methods that allow for stochastic trends.

2.2 Summary Statistics

Table 1 contains basic summary statistics on our volatility-sorted portfolios. Panel A of the table reports statistics on book-to-market-ratios, while Panel B reports statistics on excess returns. The first thing to note in Panel A is that high-volatility stocks have lower valuations than low-volatility stocks: on average, PVS_t is negative. However, as Figure 1 shows, this masks considerable variation in PVS_t. Indeed, the standard deviation of PVS_t is about twice the magnitude of its mean. This variation is at the heart of our empirical work.

Panel B shows that returns on the low-minus-high volatility portfolio are themselves quite volatile, with an annualized standard deviation of 29.6%. The highest-volatility quintile of stocks on average has excess returns that are 2.71 percentage points per year lower than for the lowest-volatility quintile. This is related to the well-known idiosyncratic volatility puzzle, which emphasizes that stocks with high short-term volatility, but not long-term volatility, have traditionally underperformed (Ang et al. (2009)), potentially due to shorting constraints (Stambaugh et al. (2015)).

The second-to-last row of Table 1 Panel B shows that high-volatility portfolios load significantly on the SMB factor, consistent with highly volatile stocks being smaller on average. We show that our results are primarily about volatility and not size below.

3 Empirical Results

3.1 Valuation Ratios and Real Rates

3.1.1 The One-Year Real Rate

We begin by documenting the strong relationship between the one-year real rate and the book-to-market spread between low- and high-volatility stocks. Specifically, we run regressions of the form:

$$\text{Real Rate}_t = a + b \times PVS_t + \varepsilon_t. \tag{2}$$

We report Newey and West (1987) standard errors using five lags. In the Appendix, we also consider several other methods for dealing with the persistence of these variables (e.g., parametric corrections to standard errors, generalized least squares, simulated bootstrap p-values, etc.). Our conclusions are robust to these alternatives.

Column (1) of Table 2 reveals a strong positive correlation between the real rate and PVS_t — the real rate tends to be high when investors favor high-volatility stocks, and is low when investors prefer low-volatility stocks. This simple fact is the first piece of evidence that PVS_t captures variation in the economy's risk appetite. The magnitude of the effect is economically large and measured precisely. A one-standard deviation increase in PVS_t is associated with about a 1.3 percentage point increase in the real rate. For reference, the standard deviation of the real rate is 1.9 percentage points. The R^2 of the univariate regression is 41%, indicating that PVS_t explains a large fraction of variation in the real rate. 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.

Figures 2 and 3 present visual evidence of our primary finding. Figure 2 plots the time series of the real rate against the fitted value from regression in Eq. (2). As the figure shows, PVS_t tracks a remarkable amount of real rate variation since 1970. Additionally, the scatter plot in Panel A of

Figure 3 reinforces our linear regression specification and confirms that outliers are not driving our results. Panel B of Figure 3 shows that the relationship is equally strong if we remove recession quarters, which are shaded in light gray. Thus, the relationship between PVS_t and the real rate is stable across different macroeconomic environments.

Column (3) of Table 2 indicates that our focus on the cross section of stock valuations is important. There is no relationship between the book-to-market ratio of the aggregate stock market and the real rate. This fact is not just an issue of statistical precision. The economic magnitude of the point estimate on the aggregate book-to-market ratio is also quite small – a one-standard deviation movement in the aggregate book-to-market ratio is associated with only a 17 basis point movement in the real rate.[4] The aggregate book-to-market ratio is generally interpreted as a proxy for expected stock market returns (Cochrane (2007)). Thus, its low correlation with the real rate suggests that expected returns on the aggregate market may be driven by factors beyond risk appetite like growth expectations and sentiment. In contrast, column (3) of Table 2 shows that the statistical significance and the magnitude of the coefficient on PVS_t are unchanged when controlling for the aggregate book-to-market ratio.

In column (4), we control for variables thought to influence monetary policy: four-quarter inflation, as measured by the GDP price deflator, and the output gap from the Congressional Budget Office (Clarida et al. (1999); Taylor (1993)). While the output gap enters with a positive coefficient, inflation enters with a slightly negative coefficient. However, both coefficients on the output gap and inflation are statistically indistinguishable from the traditional Taylor (1993) monetary policy rule values of 0.5.[5] In the Appendix we do further tests to show that our results are not driven by inflation or variables that enter into traditional monetary policy rules. Specifically, we decompose the real rate into the one-year nominal Treasury bill rate and inflation expectations. The correlation between PVS_t and the real rate primarily comes from the nominal rate, as one would expect if risk appetite were driving demand for government bonds. In addition, we separate the real rate into a component attributable to the Taylor (1993) rule and a residual, and show that the explanatory

[4] As we discuss further in the Appendix, the aggregate book-to-market ratio does enter significantly in a small number of variants on our baseline specification. However, the statistical significance is irregular across various specifications, and the economic significance is always negligible.

[5] Section A.5 in the Appendix shows that the economic and statistical significance of PVS_t remains unchanged when controlling for expected growth and the volatility of industrial production implied by an ARMA(1,1)-GARCH(1,1,) model.

power of PVS_t for the real rate comes from its explanatory power for the residuals. The main takeaway is that the relationship between the real rate and PVS_t is stable throughout all of these regression specifications, implying that PVS_t does not just simply capture the reaction of the central bank to standard Taylor (1993) rule variables. We revisit the relationship between monetary policy, the real interest rate, and PVS_t in Section 3.5.

In columns (5)-(8) of Table 2, we rerun the preceding regression analysis in first differences rather than levels. This helps to ensure that our statistical inference is not distorted by the persistence of either the real rate or PVS_t. Running regression (2) in differences yields very similar results to running it in levels. Changes in the real rate are strongly correlated with changes in PVS_t. Moreover, the magnitudes and statistical significance of the point estimate on PVS_t are close to what we observe when we run the regression in levels. The differenced regression also reinforces the nonexistent relationship between the real rate and the aggregate book-to-market ratio. Overall, the evidence in Table 2 indicates a strong and robust relationship, both in economic and statistical terms, between the real rate and PVS_t. This is the central empirical finding of the paper, and as we show below, these results stand up to the inclusion of a battery of additional control variables and various regression specifications.

3.1.2 Long-Term Real Rates

Does the relationship between the one-year real interest rate and PVS_t extend to the long-term real rates? It seems natural to think that periods of low risk appetite coincide with a broad demand for safe assets of all maturities. To explore this possibility further, we construct k-year real rates in the same way we construct the one-year real rate: the k-year nominal Treasury bond rate minus the one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters. We use one-year survey expectations when constructing the term structure of real rates simply because the data go back further, though our conclusions are not sensitive to this choice. Table 3 shows regressions of the following form:

$$k\text{-Year Real Rate}_t = a + b \times PVS_t + c \times \text{Agg. BM}_t + \varepsilon_t, \quad k = 1, 2, 5, 7, 10.$$

These regressions mirror our baseline regression in Equation (2), but replace the one-year real rate with longer-term rates as the dependent variable. In all regressions, we include the aggregate book-to-market ratio as a control and compute Newey-West standard errors using five lags.

For comparison, Row (1) of Table 3 reproduces our results for the one-year rate from Table 2, Columns (3) and (7). Rows (2)-(5) of Table 3 show a strong positive relationship between contemporaneous movements in PVS_t and longer-term real rates, similar to our results for the one-year real rate. The results are statistically and economically significant in both levels and first differences. When investors' willingness to pay for volatile stocks falls, there is a simultaneous increase in the price of all real safe assets, regardless of maturity. Furthermore, the R^2s in these regressions indicate that PVS_t explains a large amount of real rate variation across the maturity term structure. Short-term real rates increase a bit more than long-term rates when PVS_t rises, as evidenced by the fact that the coefficients on PVS_t decrease with maturity. Thus, an increase in PVS_t is associated with a strong increase in the level of the real yield curve and a slight decrease in its slope. Because the correlation between PVS_t and real rates is largely independent of maturity, we focus on the one-year real rate throughout the rest of the paper for brevity.

3.2 Robustness

Because the relation between PVS_t and real rates is at the heart of our empirical results, we now show that this relation is robust to a wide range of additional tests. We first show our headline result is robust to how we construct PVS_t. We then test whether our regression results change when we control for cross-sectional valuation spreads formed on alternative stock characteristics like CAPM Beta. The regression analysis that we use for our robustness analysis takes the following form:

$$\text{Real Rate}_t = a + b \times PVS_t + \theta^{'} X_t + \varepsilon_t, \tag{3}$$

where X_t is a vector of control variables that always includes the aggregate book-to-market ratio. In our horse races, it also contains book-to-market spreads based on alternative cross-sectional sorts. We run these tests in both levels and changes, using both the full sample and the pre-crisis sample. In complementary robustness checks, we also form double-sorted versions of PVS_t by sorting on volatility and these same alternative characteristics. As a preview of the results, the economic and statistical significance of PVS_t remains essentially unchanged throughout these robustness checks – investors' willingness to hold volatile stocks indeed plays a special role in understanding real rate variation.

We start our robustness analysis by exploring alternative definitions of PVS_t. The first row of Table 4 reproduces our baseline results from columns (3) and (7) of Table 2. In row (2) of Table 4, we recompute PVS_t by value-weighting the book-to-market ratio of stocks within each volatility quintile, as opposed to equal-weighting. The coefficients and statistical significance are comparable to the baseline, showing that our results are not exclusively driven by small stocks. In row (3), we construct PVS_t by sorting stocks on volatility measured over a two-year window, rather than a two-month window. As row (3) shows, this variant of PVS_t is still highly correlated with the real rate. Computing volatility over a long period helps ensure that our results are not driven by changing portfolio composition. That is, we are capturing changes in the valuations of stocks with a long history of being volatile, not changes in the volatility of value stocks. This distinction is critical to our interpretation of PVS_t as a measure of investors' willingness to hold volatile stocks. The fact that the relation between PVS_t and the real rate is robust to measuring volatility over longer horizons also distinguishes our main result from the idiosyncratic volatility puzzle, which centers around the fact that firms with low recent return volatility have historically earned a risk premium (Ang et al. (2009); Stambaugh et al. (2015)).

In row (4), we run a horse race of PVS_t against the spread between 10-year off-the-run and on-the-run Treasury yields, a measure of liquidity premia in the fixed income market (Krishnamurthy (2002)).[6] 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 characteristic that may drive the relation between the real rate and the cross-section of stocks. We do so by controlling for book-to-market spreads based on alternative characteristics in regression (3). For an alternative characteristic Y, we sort stocks in quintiles based on Y and then compute the difference between the

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

book-to-market ratio of the lowest Y and highest Y quintiles. In other words, we construct book-to-market spreads for other characteristics the same way we construct PVS_t. Rows (5)-(9) of Table 4 shows the coefficient on PVS_t, while controlling for the Y-sorted book-to-market spread and the aggregate book-to-market. As before, we run these horse races for both the full and pre-crisis samples, as well as in levels and in changes.

Row (5) of Table 4 considers cash flow duration as an alternative characteristic. If low-volatility stocks simply have longer duration cash flows than high-volatility stocks, then a decline in real rates would increase their valuations relative to high-volatility stocks, potentially driving our results. To rule out this particular reverse causality story, we follow Weber (2016) and construct the expected duration of cash flows for each firm in our data. The duration-sorted valuation spread does not drive PVS_t out of the regression. This observation cuts against the idea that low-volatility stocks are "bond like" because of their cash flow duration (e.g., Baker and Wurgler (2012)) and instead supports our point that volatility is the key characteristic determining whether stocks are bond like.

Row (6) shows that PVS_t is robust to controlling for leverage-sorted valuation ratios. Highly-levered firms may suffer disproportionately from a decrease in the real rate because they are effectively short bonds, but they may also have high volatility, which could confound our results. Row (6) helps alleviate these concerns, as the leverage-sorted valuation ratio does not impact PVS_t in the regression.

In row (7), we show that the economic and statistical significance of PVS_t is unchanged when controlling for spreads based on systematic risk (i.e., beta). This test has important implications for interpreting our results because perfectly diversified investors should care about beta and not volatility. We use the past two months of daily returns to compute beta, mimicking our construction of volatility.[7] The regression coefficient on PVS_t is statistically and economically very similar to our baseline results. Thus, it does not appear that our measure of volatility is simply picking up on beta. The results in row (7) are consistent with the weak relation between the real rate and the aggregate book-to-market ratio in Table 2, and more broadly, cut against the idea that PVS_t is simply measuring aversion to aggregate stock market risk.

[7] In the Section 1.1 of the Appendix, we try a number of additional constructions of beta. Specifically, we compute beta using (i) the past two years of monthly returns and (ii) the past ten years of semi-annual returns. In addition, we compute a measure of cash-flow beta as opposed to stock market beta, using rolling twelve-quarter regressions of quarter-on-quarter EBITDA growth on quarter-on-quarter national income growth. Our results are essentially unchanged using any of these additional measures.

In addition, we compare PVS_t to book-to-market spreads based on the popular Fama-French sorting variables, size and value. Consistent with our value-weighted results in row (2), the horse race in row (8) shows that the relationship between the real rate and PVS_t is robust to controlling for the difference in valuation between small and large stocks. Row (9) shows that PVS_t is robust to controlling for the book-to-market spread between value and growth stocks. The robustness to value-sorted book-to-market spreads is reassuring because this sort is sometimes thought to capture the value of growth options. Row (9) suggests that the relation between PVS_t and the real rate is robust to controlling for the time-varying value of growth options.

In rows (10)-(16), we use double sorts as a complementary way to rule out alternative explanations for why PVS relates to the real rate. Specifically, we assemble a Y-neutral version of PVS_t: the book-to-market spread from sorting stocks on volatility within each tercile of characteristic Y. This spread measures the difference in valuations of low-volatility and high-volatility stocks that have similar values of characteristic Y. For example, in row (10) we form a duration-neutral version of PVS_t by first sorting stocks into terciles based on their cash flow duration. Within each tercile we then compute the book-to-market spread between low and high volatility firms. The duration-neutral version of PVS is the average low-minus-high volatility valuation spread across the three duration terciles. In rows (10)-(14) of Table 4, we show that these double sorted book-to-market spreads are still strongly correlated with the real rate.

Row (15) ensures that PVS_t is not driven by differences between dividend payers and nonpayers. We first divide stocks based on whether they have paid a dividend over the previous twenty-four months. We then compute PVS_t separately within the set of dividend-paying and non-dividend paying firms. The dividend-adjusted PVS_t is just the average across the two. Row (15) indicates that the explanatory power of PVS_t for the real rate is robust to controlling for dividends in this fashion.

Finally, our PVS_t measure might be simply capturing industries that are particularly exposed to interest rate changes like finance. To alleviate this concern, we construct an industry-adjusted version of PVS_t. Within each of the Fama-French 48 industries, we compute the book-to-market spread between low- and high-volatility stocks. The industry-adjusted PVS_t is then the average of these spreads across all of the industry. Row (16) shows that this industry-adjusted spread still possesses significant explanatory power for the real rate.

The upshot of these robustness tests is that the sorting stocks on volatility is the key to our construction of PVS_t. Sorting on other characteristics does not perform nearly as well in terms of informational content about the real rate. This is a key reason we view PVS_t as measuring the economy's risk appetite.

3.3 Unpacking the Mechanism

In this subsection, we provide additional empirical evidence suggesting that PVS_t captures the economy's risk appetite using several types of evidence, including forecasting regressions, data on asset classes other than stocks, direct measures of the quantity of risk, and mutual fund flows.

3.3.1 Returns on Volatility-Sorted Portfolios and the Real Rate

Standard present value logic (Campbell and Shiller (1988); Vuolteenaho (2002)) implies that variation in PVS_t is driven by either changes in the future returns of 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 this portfolio. If our interpretation of PVS_t as a measure of risk appetite is correct, its variation should largely be driven by returns, as opposed to cash flow growth. When risk appetite is low, investors should demand high compensation for owning volatile stocks. To explore what drives variation in PVS_t, we begin by forecasting the return on the volatility-sorted portfolio with either PVS_t or the real rate. Formally, we run:

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

where X_t is either PVS_t or the real rate. Table 5 contains the results of this exercise.

In Column (1) of Table 5, we set $k = 1$ and forecast one-quarter ahead returns, computing standard errors using Newey and West (1987) with five lags. PVS_t has strong forecasting power for returns on the long-short portfolio. A one-standard deviation increase in PVS_t is associated with a 5.3 percentage point increase in returns on the long-short portfolio. To put this in perspective, the quarterly standard deviation of the long-short portfolio is 15%. Thus, it appears that variation in PVS_t largely reflects variation in expected returns, consistent with much of the empirical asset pricing literature (e.g., Cochrane (2011)).

Column (2) makes the connection between the real rate and time-varying expected returns on the volatility-sorted portfolio directly. It shows that the real rate also strongly forecasts returns on the long-short portfolio. When the real rate is high, low-volatility stocks tend to do well relative to high-volatility stocks going forward. In contrast, a low real rate means low risk appetite, with investors requiring a premium to hold high-volatility stocks, as evidenced by the fact that these stocks tend to do relatively well in the future. In economic terms, the real rate forecasts returns on the long-short portfolio nearly as well as PVS_t. A one-standard deviation increase in the real rate is associated with a 3.1 percentage point increase in returns on the long-short portfolio. As we discuss in further detail below, this implies that the correlation between the real rate and PVS_t documented in Section 3.1 is largely driven by changes in expected returns, not changes in expected cash flow growth.

Columns (3) and (4) repeat these exercises, setting $k = 4$ and forecast four-quarter returns. We use Hodrick (1992) standard errors to be maximally conservative in dealing with overlapping returns. The magnitude of the forecasting power of the real rate is again comparable to the forecasting power of PVS_t. The forecasting R^2 of 0.26 is large. For comparison, the aggregate price-dividend ratio forecasts aggregate annual stock returns with an R^2 of 0.15 (Cochrane (2009)). Return predictability is also large relative to average excess return on low-minus-high volatility portfolios. While on average low-volatility stocks have outperformed high-volatility stocks by 2.71% over our sample, a value of PVS_t one standard deviation below its average predicts an annual underperformance of low-volatility stocks relative to high volatility stocks of -8.63%.

In the remaining columns of Table 5, we show that neither the real rate nor PVS_t have much forecasting power for the aggregate market excess return. Again, this highlights the importance of our focus on volatility sorts as a proxy for the strength of the economy's risk appetite.

3.3.2 Covariance Decomposition

The preceding forecasting regressions allow us to quantitatively decompose the source of covariation between the real rate and PVS_t. In Section A.3 of the Appendix, we use the present value decomposition in Vuolteenaho (2002) to show that the covariance between PVS_t and the real rate can be approximately decomposed as follows:

$$\begin{aligned} Cov\left(\text{Real Rate}_t, PVS_t\right) &\approx (1-\rho\phi)^{-1} \times \left[Cov\left(\text{Real Rate}_t, Ret_{t+1}\right)\right. \\ &\quad \left. - Cov\left(\text{Real Rate}_t, ROE_{t+1}\right) + Cov\left(\text{Real Rate}_t, \xi_{t+1}\right)\right]. \end{aligned} \tag{5}$$

Here, ρ is a log-linearization constant, $\phi$is the persistence of PVS_t, Ret_{t+1} is the return on the volatility-sorted portfolio, ROE_{t+1} is the return on equity of the same portfolio. We follow Vuolteenaho (2002) in setting $\rho = 0.969$. The parameter $\phi = 0.88$ is estimated using a simple AR(1) regression. ξ_{t+1} is an error term that is comprised mainly of future innovations to PVS_t, but also collects the usual approximation errors that arise from these types of present value decompositions.

To operationalize Eq. (5) in the data we must estimate each of the terms on the right hand side. The first covariance term on the right hand side can be inferred by forecasting future returns on the volatility-sorted portfolio with the real rate, as we did in Table 5. Similarly, the second term can be estimated by forecasting ROE_{t+1} on the volatility-sorted portfolio with the real rate. In the Appendix, we directly show that neither PVS_t nor the real rate forecast ROE for low- versus high-volatility stocks.[8]

Combining these estimates, we find that nearly 90% of the comovement between the real rate and PVS_t arises because the real rate forecasts future returns to volatility-sorted stocks, consistent with our interpretation of PVS_t as a measure of risk appetite. Since most of the variation in PVS_t is driven by changing expected returns, most of its covariation with the real rate must be driven by covariation between the real rate and expected returns. This fact corroborates our argument that the covariance between the real rate and PVS_t is due to time-varying risk appetite, not time-varying growth expectations. If the covariance were driven by growth, high expected aggregate growth would increase the real rate, reflecting the desire of investors to borrow to smooth intertemporally,

[8]Furthermore, we can show that this is not simply a product of sampling error in the regression. Following Cochrane (2007)'s logic, the Vuolteenaho (2002) decomposition of returns implies that

$$\beta = 1 - \rho\phi + \beta_{ROE},$$

where β is the coefficient from a regression of future returns on log book-to-market and β_{ROE} is the coefficient from a regression of future log ROE on log book-to-market. Our point estimates are $\beta = 0.14$ and $\phi = 0.88$, implying a point estimate of $\beta_{ROE} = \beta - (1 - \rho\phi) = -0.01$. Thus, both direct evidence from cash flow forecasting regressions and indirect evidence from return forecasting regressions show that movements in PVS_t reflect changes in future returns, not future cash flows.

and simultaneously increase PVS_t, reflecting high expected cash flow growth for volatile stocks. In this case, high real rates would forecast high ROE for volatile stocks, contrary to what we find in the data.

3.3.3 Other Asset Classes

Our evidence thus far has focused on the relationship between the price of highly volatile stocks and real interest rates, which is driven by changes in the compensation investors demand to hold volatile stocks. But if PVS_t is indeed a broad measure of risk appetite, the logic of our approach should hold in other asset classes as well. Risk appetite should be revealed by common movements in the pricing of volatile securities relative to less volatile securities. This implies that both PVS_t and the real rate should forecast returns on volatility-sorted portfolios in other asset classes.

We explore these predictions in Table 6. Specifically, we use test asset portfolios from He et al. (2017), which are drawn from six asset classes: U.S. corporate bonds, sovereign bonds, options, CDS, commodities, and currencies.[9] Within each asset class, we form a portfolio that is long the lowest-volatility portfolio in the asset class and short the highest-volatility portfolio. Volatility for each portfolio at time t is measured with a 5-year rolling window of prior monthly returns. Table 6 contains some basic summary statistics on the volatility-sorted portfolios in each asset class. Interestingly, the average returns of these long-short portfolios are not consistently positive across assets, showing that the low volatility premium in U.S. equities (Ang et al. (2006)) is not a systematic feature of all asset classes.

Table 6 also shows that both PVS_t and the real interest rate forecast quarterly returns on volatility-sorted portfolios systematically across asset classes. The top row replicates our results for U.S. equities from Table 5. The remaining rows show economically and statistically significant evidence that PVS_t and the real interest rate similarly 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 though insignificant correlation between PVS_t and commodity returns. We obtain similar conclusions if we forecast annual returns.

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

3.3.4 Prices versus Quantities of Risk

The analysis above reveals that movements in PVS_t, and comovement between PVS_t and the real rate, are driven by variation in the expected return to the low-minus-high volatility stock portfolio. What drives this movement in expected returns? Movements in expected returns must derive from changes in either investor aversion to volatility or changes in the quantity of volatility. If the quantity of the risk is the main driver, then the explanatory power of PVS_t for the real rate should be subsumed by proxies for the quantity of risk.

In Table 7, we show that the relation between the real rate and PVS_t is not subsumed by contemporaneous volatility. Specifically, we run the regression in Eq. (2) with measures of contemporaneous realized volatility on the right-hand side. In particular, we include the realized return volatility on our low-minus-high volatility portfolio in quarter t, computed with daily data. To proxy for macroeconomic volatility, we include the volatility of TFP growth implied from a GARCH model, as in Bloom, Floetotto, Jaimovich, Saporta, and Terry (2014).[10] In addition, we include the realized within-quarter volatility of the aggregate market and the Fama and French (1993) factors, computed using daily data, and the common factor in idiosyncratic volatility variable of Herskovic et al. (2016).

The results are presented in Table 7. Column (1) finds no relationship between the real rate and the volatility on our low-minus-high volatility portfolio, so the baseline relation between the real rate and PVS_t does not appear to be driven by changes in the volatility of our portfolios. Column (2) shows that there is some evidence that the real rate is related to volatility of the aggregate market and volatility of the SMB portfolio. However, the five volatility measures in column (2) jointly achieve only an R^2 of 0.15, while the R^2 rises to 0.60 when we include PVS_t in column (3). In columns (4) to (6), we obtain similar results when running the analysis in first differences. Either way, the only variable robustly correlated with the real rate is PVS_t, whereas the volatility variables have a small impact.[11] In the Appendix, we also show that the quantity of risk cannot be forecasted with either the real rate or PVS_t and that the quantity of risk does not forecast excess returns on the long-short portfolio of volatility sorted stocks. These additional findings are again consistent

[10]See Table A.1 of the Appendix for further discussion of the estimation of TFP volatility.

[11]These results are in contrast to Hartzmark (2016), who argues that changes in expected macroeconomic volatility are an important driver of real interest rates. We attribute this difference to the fact that Hartzmark's sample includes the Great Depression, while ours does not. See Section A.5 of the Appendix for more detail.

with our results being mostly driven by time variation in investor aversion to volatility. Overall, our results indicate that the strong relation between the real rate and the pricing of volatile stocks cannot be explained by variation in volatility alone, or at least volatility that is easily observable in the data. By deduction then, PVS_t appears driven by time-varying aversion to risk, consistent with our interpretation that PVS_t measures the economy's risk appetite.

3.3.5 Evidence from Mutual Fund Flows

So far, we have inferred investor preferences from asset prices, which have the advantage of aggregating over a broad range of investors, including households, institutions, firms, and international investors. In this section, we provide evidence that a specific but important class of investors, namely mutual funds investors, behaves consistently with the evidence from prices. If real rate variation indeed reflects time variation in risk appetite, we expect investors to leave high-volatility mutual funds when the real rate is low. Specifically, a decrease in risk appetite should lead to outflows from high-volatility mutual funds, an increase in the demand for bonds, and a drop in the real rate. Mutual fund flows are also useful because they allow us to separately verify our baseline results in a completely different data set.

Our sample is the CRSP mutual fund data base, from which we have monthly return data from 1973q2 through 2015q3. We first need to determine whether some mutual funds are more exposed to high-volatility stocks than others. We use two simple measures. First, we estimate the return beta of each fund with respect to the high-volatility portfolio. Second, we simply calculate the volatility of the fund's returns. We use the full sample of monthly return data available for each fund to minimize measurement error. We then compute quarterly fund flows for each fund, winsorizing at the 5th and 95th percentiles, and restrict our data set to fund-quarter observations where the fund has total net assets of over \$100 million to ensure that our results are not driven by small funds.[12]

Panel A of Table 8 contains summary statistics for our sample of mutual funds. The average fund appears in our sample for 31 quarters and has around \$750 million in assets under management. We find substantial heterogeneity in mutual funds' exposure to volatile stocks, regardless of how we measure exposure. The average fund has an annualized return volatility of about 12%,

[12] We obtain similar results if we use the full sample.

though this ranges from 4.6% to 17.3% when moving from the 25th to 75th percentile of fund volatility. Similarly, the beta of fund returns with respect to the high-volatility portfolio is 0.30 for the average fund, with a cross-sectional standard deviation of 0.24. This cross-sectional dispersion in volatility exposure allows us to study how movements in risk appetite differentially impacts our sample of mutual funds.

In Panel B of Table 8, we explore the relationship between fund flows, the real rate, and fund volatility. Specifically we run

$$Flows_{f,t} = \alpha_f + \theta_1 Real\ Rate_t + \theta_2 Real\ Rate_t \times VolExp_f + \varepsilon_{f,t},$$

where $VolExp_f$ is a measure of the fund's exposure to high-volatility stocks. In columns (1)-(3) $VolExp_f$ is the beta of the fund's returns with respect to the high-volatility portfolio. In columns (4)-(6), it is the volatility σ_f of the fund's returns. For all regressions, we use Driscoll-Kraay standard errors, clustered by fund and time with five lags.[13]

Panel B of Table 8 shows that mutual fund flows indeed tell the same story as our baseline results. The magnitudes are economically meaningful. In column (1), a one percentage point drop in the real rate is associated with a 0.9 percentage point outflow for a fund with zero exposure to the high-volatility portfolio. A one-standard deviation increase in the fund's volatility exposure increases the impact of the real rate by over 50%: a one percentage point drop in the real rate is now associated with a 1.4 percentage point outflow.[14] Column (2) shows the results are robust to including time fixed effects. Column (3) shows that they are robust to controlling for the fund's contemporaneous and lagged performance, so we are not simply picking up a performance-flow relationship. Similarly, Columns (4) through (6) show that mutual funds with higher overall volatility tend to experience outflows when the real rate is low.

Overall, the results in this section show that investor behavior, as measured by mutual fund flows, is consistent with our main results and support the interpretation that PVS_t is a good measure of risk appetite. To be clear, we are not claiming that flows out of high-volatility equity mutual funds are solely responsible for the contemporaneous fall in real rates. These results simply provide

[13] We have also tried double clustered errors by fund and time and are reporting the more conservative standard errors.

[14] Because we include fund fixed effects, the base effect of the fund's volatility is absorbed.

a glimpse into the behavior of investors that we think is representative of the broader economy. Indeed, the fact that the real rate forecasts returns on the low-minus-high volatility trade in other asset classes suggests that investors in those asset classes likely behave similarly.

3.4 Other Measures of Financial Conditions

The evidence we have provided suggests that PVS_t is a good measure of risk appetite. One may be concerned, however, that other measures of financial market conditions have similar properties to PVS_t and thus are equally good measures of risk appetite. In this section, we examine the properties other measures, including the BAA minus 10-year Treasury credit spread, the Gilchrist and Zakrajšek (2012) credit spread, the Greenwood and Hanson (2013) measure of credit market sentiment, the Baker and Wurgler (2006) measure of equity market sentiment, the Baker et al. (2016) economic policy uncertainty index, and the Kelly and Pruitt (2013) optimal forecast of aggregate equity market returns.[15]

The first set of columns in Table 9 show that PVS_t is correlated with many of these measures, though the R^2s indicate that the magnitudes are generally not very large. PVS_t is most strongly correlated with the Gilchrist and Zakrajšek (2012) credit spread and the Baker and Wurgler (2006) measure of equity market sentiment. Interestingly, while the Greenwood and Hanson (2013) measure of credit market sentiment is negatively correlated with the Baker and Wurgler (2006) measure of equity market sentiment, PVS_t is positively correlated with both. This suggests that our measure of risk appetite induces common variation in sentiment across debt and equity markets.

The second set of columns in Table 9 runs univariate regressions of the real rate on these alternative measures. Recall from Table 2 that PVS_t explains 41% of real rate variation on its own. Thus, none of these measures match the ability of PVS_t to explain real rate variation, though the Baker and Wurgler (2006) equity sentiment measure and the Baker et al. (2016) policy uncertainty index have fairly high explanatory power. Importantly, the third set of columns show that the relationship between PVS_t and the real interest rate remains unchanged when controlling for these alternative measures. These results indicate that PVS_t contains information for the real rate that is distinct from existing measures of financial conditions and market sentiment.

In the Appendix, we provide further evidence of the uniqueness of PVS_t from return forecasting

[15] See the Appendix for details about how we construct the the Kelly and Pruitt (2013) optimal forecast.

exercises. Specifically, we show that, in contrast to PVS_t, none of the alternative measures of financial conditions we examine here can forecast returns on volatility-sorted portfolios across asset classes. In other words, as these measures of financial conditions move around, the compensation investors demand for bearing volatility does not change.[16]

3.5 Macroeconomic Implications

Finally, we turn to the macroeconomic implications of time variation in risk appetite. This section provides suggestive evidence that our new stock-market based measure of risk appetite is indeed linked to fundamental elements of the macroeconomy.

3.5.1 Ruling out Reverse Causality

To start, we first rule out the alternative explanation that changes in PVS_t are caused by changes in monetary policy, rather than our interpretation that risk appetite drives the real rate. We previously provided evidence against this reverse causality story in Section 3.2 by controlling for a range of additional firm characteristics. In this section, we provide further evidence, building on the literature on monetary policy shocks. This additional evidence is useful for interpreting the responses of investment, unemployment, and output to PVS_t, because they show that PVS_t innovations reflect risk appetite shocks and not monetary policy surprises.

The identification assumption shared across the monetary policy shocks literature is that within a narrow window around the Federal Reserve's announcements of monetary policy decisions, no other information affects the federal funds rate. Individual measures of monetary policy shocks differ in the details of their construction: Romer and Romer (2004) read transcripts of Fed meetings; Bernanke and Kuttner (2005) and Gorodnichenko and Weber (2016) use price innovations in the federal funds rate futures market in a narrow window around monetary policy announcements; and Nakamura and Steinsson (2018) use changes in a broader set of interest rates around monetary policy announcements. Rather than tying ourselves to a particular measure, we show results for a range of measures.

Table 10 provides evidence against the reverse causality story. We regress returns on the low-

[16]None of the measures, including PVS_t, have the ability to forecast aggregate asset class returns across a variety of asset classes.

minus-high volatility portfolio onto monetary policy shocks at both quarterly and daily frequencies. If reverse causality was responsible for our baseline result, we should see that high-volatility stocks increase following a positive shock to interest rates. Since the independent variable is the low-minus-high volatility return, reverse causality should therefore show up as negative coefficients in Table 10. In the first set of columns, we find that the coefficients are always statistically insignificant with inconsistent signs. To ensure that policy changes outside of regularly scheduled meetings do not confound our analysis, we exclude them for the second set of columns and find similar results.[17] In the third set of columns, we narrow the window and focus on daily data. While the quarterly results are useful because they match the rest of our analysis, daily returns further alleviate concerns of endogeneity for the monetary policy shock measures. Using daily returns, we find a positive correlation that is borderline statistically significant for some specifications. However, this is the opposite of what we would expect if there was reverse causality. Instead, a positive correlation is consistent with the Fed cutting interest rates and stabilizing high-volatility stocks in times of market turmoil. This interpretation is also consistent with the final set of columns, where the coefficients are small and statistically insignificant using shocks on regularly scheduled meeting dates only.[18]

The collective evidence from this exercise makes us confident that risk appetite drives the real rate and not vice versa. We will use this identification assumption in the next section when we estimate how the macroeconomy responds to risk appetite shocks.

3.5.2 Evidence from Local Projections

We next show in reduced form that when risk appetite is strong, as measured by PVS_t, an economic boom follows. We estimate the impulse responses of macroeconomic variables to a shock to PVS_t

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

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

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

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

where h is the forecast horizon.

Table 11 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 strong effects. A one-standard deviation increase in PVS_t is associated with an investment-capital ratio that is 0.23 percentage points higher at a one-quarter horizon and 0.36 percentage points higher at a four-quarter horizon. The standard deviation of the investment-capital ratio is 1.16%. In the second row of Table 11, we report results for the output gap. Here, a one-standard deviation increase in PVS_t is associated with an output gap that is 0.30 percentage points more positive after one quarter, and 0.58 percentage points higher after four quarters. In the third row of the table, we report results for the change in the unemployment rate. A one-standard deviation increase in PVS_t is associated with a 0.13 percentage point fall in the unemployment rate after one quarter, and a 0.41 percentage point decline after four quarters.

In Figure 4 we report the full impulse responses for these three macroeconomic variables to a one-standard deviation shock to PVS_t for horizons of $h = 1, ..., 12$ quarters. The figure shows that the effect of a shock to PVS_t on private investment is quite persistent, peaking around six quarters and then slowly reverting over the next six quarters. In contrast, the effects on the output gap and unemployment are somewhat less persistent, peaking after five quarters and then dissipating.

Taken together, our results suggest that risk appetite shocks act as macroeconomic demand shocks and that the Federal Reserve considers these shocks sufficiently important to adjust interest rates. Moreover, the positive macroeconomic responses are consistent with the Federal Reserve not completely offsetting risk appetite shocks in interest rates and instead allowing for some quantity responses. The intuition for this interpretation can be seen by writing the Euler equation in the style of a New Keynesian model (Clarida et al., 1999; Woodford, 2003):

$$x_t = E_t x_{t+1} - \psi(r_t - r^n_t). \tag{6}$$

Here, x_t is the output gap between current output and its natural rate, ψ is the elasticity of intertemporal substitution, r_t is the actual real rate, and r_t^n is the natural real rate: the interest rate consistent with stable inflation and output at its natural rate.[19] The important term in (6) is the last one, showing that macroeconomic activity today depends negatively on the gap between the real rate and the natural rate. While the natural rate r_t^n may reflect a range of factors, demand shocks are an important component (Woodford (2003, p. 250)). A shock to PVS_t acts like a demand shock that increases r_t^n, leading output to temporarily rise above its natural level unless the central bank raises interest rates to completely offset the shock. In contrast, a typical monetary policy shock, or a positive shock to r_t, has the standard contractionary effect on output.

At first glance, one might be concerned that Figure 4 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. Thus, for aggregate growth expectations to explain our results, they would have to affect the discount rate associated with volatile stocks without impacting the cash flows of those stocks. It is difficult to imagine a reasonable model of asset markets and the macroeconomy with these features. Second, if aggregate growth expectations were important, one would expect that aggregate stock market valuations as well as duration-sorted stock valuations would 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 or discount rate shocks in a New Keynesian model.

3.5.3 Evidence from VARs

In this section, we complement our results in Table 11 and Figure 4 with standard vector autoregression (VAR) evidence. This evidence shows that monetary policy shocks and shocks to PVS_t have opposite effects on economic activity, as predicted by the Euler equation (6).

We estimate a VAR that is as simple and transparent as possible, while following a common set

[19] Here, r_t^n does not necessarily reflect the economy's long-run equilibrium, but instead represents the hypothetical interest rate that would obtain in a world without sticky product prices. For a central bank seeking price stability, it is optimal to adjust interest rates one-for-one to shocks to r_t^n (Woodford, 2003, p. 250).

of recursiveness assumptions, similar to Sims (1980), Bernanke and Mihov (1998) and Gilchrist and Zakrajšek (2012). We use the following strategy for measuring dynamic effects:

$$Y_t = \sum_{i=1}^{k} B_i Y_{t-i} + \sum_{i=1}^{k} C_i P_{t-i} + A^y v_{y,t} \tag{7}$$

$$P_t = \sum_{i=0}^{k} D_i Y_{t-i} + \sum_{i=0}^{k} G_i P_{t-i} + \begin{bmatrix} v_{PVS,t} \\ v_{MP,t} \end{bmatrix}. \tag{8}$$

Here, Y_t is a vector of quarterly non-policy variables, consisting of unemployment, the investment-to-capital ratio, and detrended inflation. P_t is a vector of policy variables consisting of PVS_t and the detrended real rate. Eq. (7) describes a set of structural relationships in the economy, where macroeconomic variables depend on lagged values of macroeconomic and policy variables. Eq. (8) describes the stance of monetary policy conditional on contemporaneous macroeconomic variables. Our baseline estimation uses $k = 1$ lag.

We estimate the structural policy shocks under the restriction that $v_{PVS,t}$ does not respond to $v_{MP,t}$ contemporaneously, but $v_{MP,t}$ may respond to $v_{PVS,t}$, consistent with the Federal Reserve actively monitoring macroeconomic and financial variables. It is plausible that investors' risk preferences shift gradually over time and do not jump in response to monetary policy actions. Indeed, this identification restriction is supported by our analysis of monetary policy shocks in Table 10.[20] We estimate the model using a two-step efficient GMM procedure, as in Bernanke and Mihov (1998). The first step is an equation-by-equation OLS estimation of the VAR coefficients. The second step consists of matching the second moments to the covariance matrix of the policy block VAR residuals. We use two-step GMM using a Bartlett kernel with two lags and the initial weighting matrix equal to the identity. See the Appendix for estimation details.

Both Wald and Hansen J-tests provide clear evidence that the real rate reacts contemporaneously to PVS_t, consistent with the Federal Reserve reacting to risk appetite shocks. For the reaction coefficient $v_{MP,t}$ onto $v_{PVS,t}$, we obtain a point estimate of 2.33 with a t-statistic of 3.71. The over-

[20] This identification restriction is not crucial to our findings. In the Appendix, we show that our conclusions are unchanged if instead we make the opposite identification assumption that PVS_t responds to the real rate contemporaneously, but the real rate reacts to risk appetite demand with a lag. This second identification assumption is different from saying that the Fed does not pay attention to the stock market. It merely requires that the Fed historically did not react instantaneously to the cross-sectional valuation spread newly documented in this paper. Impulse responses are also robust to excluding the post-crisis period and to including additional lags.

identifying restriction that the real rate does not react contemporaneously to v_{PVS} is rejected by a Hansen J-test at any conventional significance level with a p-value of 0.0008.

As a baseline, the left panel of Figure 5 shows responses to an unexpected tightening by the Federal Reserve. Consistent with the long literature on monetary policy shocks, summarized in Christiano et al. (1999), unemployment increases and and inflation decreases after a one-standard-deviation shock to the real interest rate. The effect on the investment-to-capital ratio is not statistically different from zero. Interestingly, PVS_t does not respond to monetary policy shocks with tight 95% confidence intervals, consistent with our interpretation that risk appetite shocks drive the real rate, and not vice versa.

The right panel of Figure 5 shows that a positive PVS_t shock significantly decreases unemployment and increases real investment, despite being associated with a similar increase in the real rate as the MP shock. The difference in responses across the left and right panels in Figure 5 is exactly what the Euler equation would suggest if an increase in PVS_t acts as a demand shock increasing the natural real rate.

Risk appetite shocks are both statistically significant and quantitatively important for unemployment and investment, as shown by forecast error variance decompositions. Ten quarters after the shock, PVS_t shocks explain 12% of variation in the unemployment rate and 21% of the variation in investment-to-capital ratios. It is intuitive that risk appetite shocks should matter most for real investment, since it is the interface between financial market attitudes towards risk and the real economy. For comparison, the monetary policy shocks explain 24% of variation in unemployment and only 2.5% of variation in the investment-to-capital ratio.

4 Discussion

We have shown that real interest rates are strongly correlated with PVS_t, with the correlation driven by the fact that real rates covary with future returns on volatile stocks – real rates are low when investors demand more compensation for holding volatile stocks. This relationship appears to be driven by changes in investor aversion to risk, rather than changes in the quantity of risk. Moreover, we find that movements in PVS_t impact future macroeconomic outcomes, with increases in PVS_t resulting in a boom in investment and output.

Taken together, these facts support the view that PVS_t measures the risk appetite of the economy. When risk appetite is low, investors want to hold riskless bonds, driving down real rates. At the same time, they will be reluctant to hold high-volatility assets, driving their valuations down and their future returns up, without changing the quantity of risk much. This reluctance to hold risky assets in turn drives down real investment. Conversely, when risk appetite is high, investors will have less demand for bonds and more demand for volatile assets, driving up real rates, PVS_t, and real investment. This simple intuition captures most of our results.

As mentioned before, the relationship between the one-year real rate and PVS_t must mechanically be intermediated by the central bank, which sets short term interest rates. Thus, our results imply that the Fed treats shocks to risk appetite like an important type of demand or discount rate shock in a standard New Keynesian framework. Of course, our results do not imply that the Federal Reserve tracks PVS_t itself, but rather that investors' attitudes towards volatile stocks reflect the same component of risk appetite that the Fed reacts to.

Our analysis in Section 3.4 indicates that PVS_t has distinct explanatory power for the real rate compared to other measures of financial market activity and sentiment. This likely stems from two factors. First, as shown in Section 3.2, our focus on volatility is key. The set of stocks that are relatively volatile captures whatever risks markets are worried about at each point in time, even if the nature of these risks varies over time (e.g., financial stability at some times, trade wars at others). The price of volatile stocks then captures how worried markets are about these risks.

The second factor likely to drive the distinctive explanatory power of PVS_t is that it is based on a long-short portfolio. This means factors affecting a single asset class will be netted out of the measure. For instance, general optimism about firm cash flows affects aggregate equity valuations and measures of equity market sentiment, but may not affect credit markets and credit market sentiment much. The construction of PVS_t nets out such factors and reveals a broad measure of risk appetite that operates across asset classes, as we showed in Section 3.3.3. 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 themselves negatively correlated.

Our measure of risk appetite relies on at least some investors having a particular notion of risk: total volatility. This differs from the notion of risk in standard rational models with perfect risk sharing, in which investors care about systematic risk. In such models, investors' willingness to hold risky assets is best summarized by the price of the aggregate claim or the risk premium required to hold market beta, as opposed to their willingness to hold volatile securities.

Our empirical results do not shed light on the microfoundations for why some investors care about total volatility, but there are several possibilities. Behavioral explanations include non-standard preferences (Barberis and Xiong (2012)), narrow framing (Tversky and Kahneman (1981)), or failures to diversify due to lack of sophistication (Benartzi (2001)). Alternatively, institutional frictions like specialization (Shleifer and Vishny (1997); Gromb and Vayanos (2010)) or segmentation (Merton (1987)) may prevent investors from fully diversifying, rendering total volatility relevant to their portfolio problem. For instance, financial intermediaries such as mutual funds and broker-dealers take concentrated positions (Kacperczyk et al. (2005); Veldkamp (2006); Cremers and Petajisto (2009); Agarwal et al. (2013)), and recent research indicates that they appear important for pricing a wide range of assets (He and Krishnamurthy (2013); Adrian et al. (2014); He et al. (2017)). In the Appendix, we present a stylized model along these lines to illustrate how one might generate our empirical facts. In the model, segmentation is the key reason that total volatility, not just systematic risk, is priced into valuations. This exercise is also useful because it clearly demonstrates why models with perfect risk sharing will have trouble matching our empirical findings.[21]

Regardless of the exact reason some investors care about total volatility, one might wonder why other sophisticated diversified agents do not arbitrage away the return predictability we document. For instance, when high-volatility stocks have high valuations relative to low-volatility stocks, sophisticated investors should short high-volatility stocks and go long low-volatility stocks, making a positive risk-adjusted return. However, if they face standard limits to arbitrage (De Long et al. (1990); Shleifer and Vishny (1997)), these investors will not completely eliminate return differ-

[21] In the model, investors have time-varying risk aversion and are borrowing constrained, so bonds are priced by the investors with the highest bond valuations – precisely the investors with low risk appetite. Consequently, an increase in the risk appetite of these investors simultaneously increases the valuations of high volatility stocks, reduces their risk premia, and increases the real rate. It is worth noting that the opposite is true in the model of Herskovic et al. (2016), despite the fact the main friction in their model is also a form of market incompleteness. In their model, a positive shock to idiosyncratic volatility drives down the risk-free rate but drives up the price of high-volatility stocks relative to low-volatility stocks due to a convexity effect. Empirically, we also find little evidence that their common idiosyncratic volatility factor is correlated with the real rate. Rationalizing our findings therefore requires a different pricing mechanism, which in our model is achieved with market segmentation and time-varying preferences.

entials between high-volatility and low-volatility stocks. Taking concentrated positions in stocks with high idiosyncratic volatility would expose sophisticated investors to significant interim noise trader risk while they wait for prices to correct. Moreover, our results show that their trading strategy would be exposed to economy-wide factors such as risk attitudes and interest rates, and thus would involve bearing fundamental risk in addition to noise trader risk.

5 Conclusion

This paper proposes a new measure of macroeconomic risk appetite, PVS_t, based on the idea that investors are more averse to holding volatile assets when their risk appetite is low. PVS_t has several characteristics that strongly support our interpretation that it measures the economy's risk appetite. First, it is positively correlated with real interest rates: when risk appetite is low, investors favor riskless bonds, driving down real rates. Second, variation in PVS_t is driven by variation in the compensation investors demand for holding volatile assets, which appears to comove across a variety of asset classes. Third, PVS_t is not strongly correlated with measures of the quantity of risk. Fourth, when risk appetite is low, investors exit high-volatility mutual funds. Finally, we show that risk appetite affects economic performance: when PVS_t is high, a boom in investment and output follows.

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

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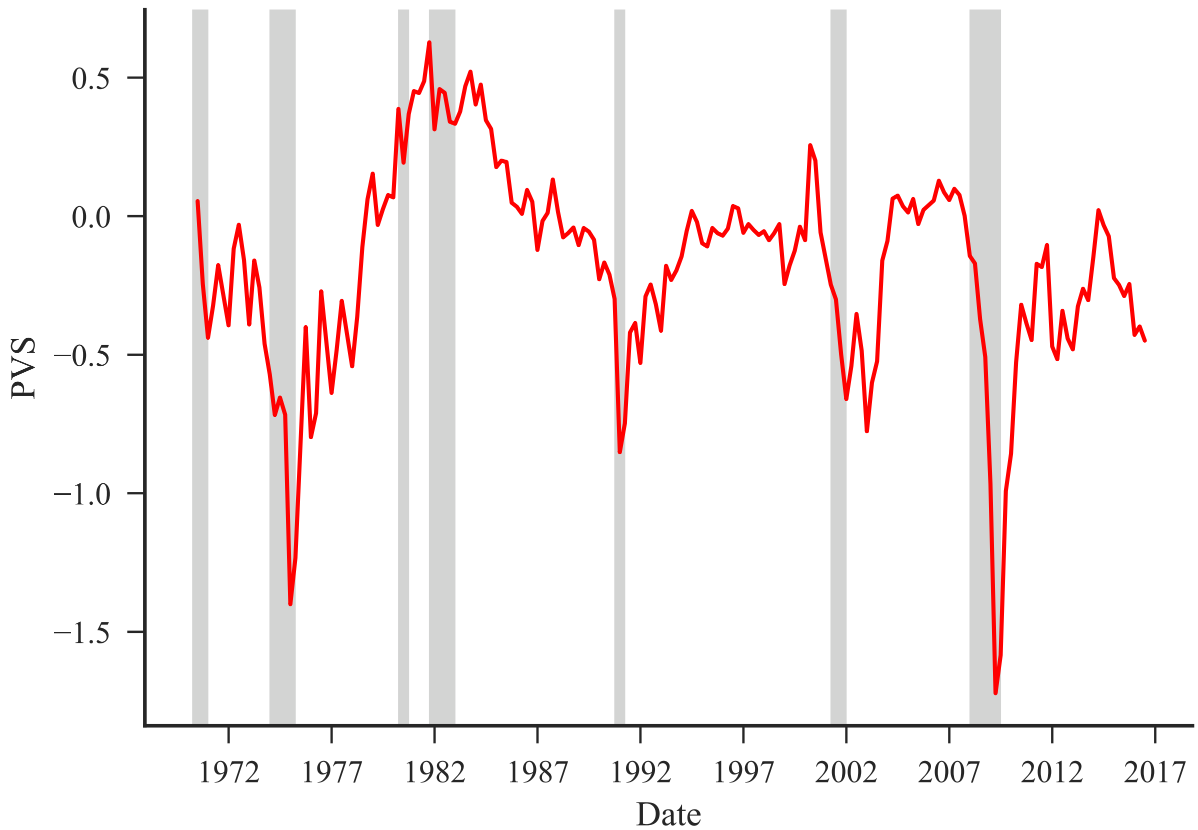
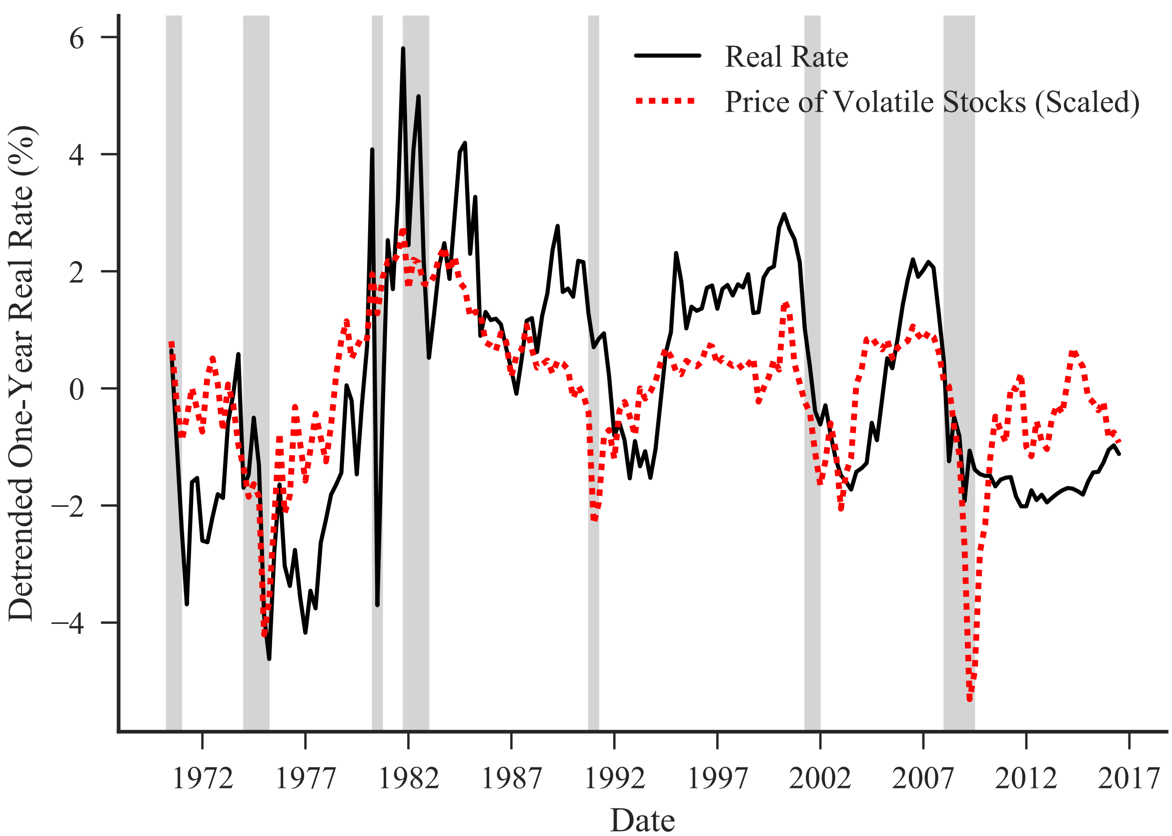
FIGURES

Figure 1: Book-to-Market Spread Between Low- and High-Volatility Stocks (PVS)



Notes: This figure plots the spread in book-to-market ratios between low and high volatility stocks. 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, which we call PVS_t. The Appendix contains full details on how we compute BM ratios. The plotted series is the difference in average book-to-market ratios between the low volatility and high volatility portfolios. Data is quarterly and spans 1970Q2-2016Q2.

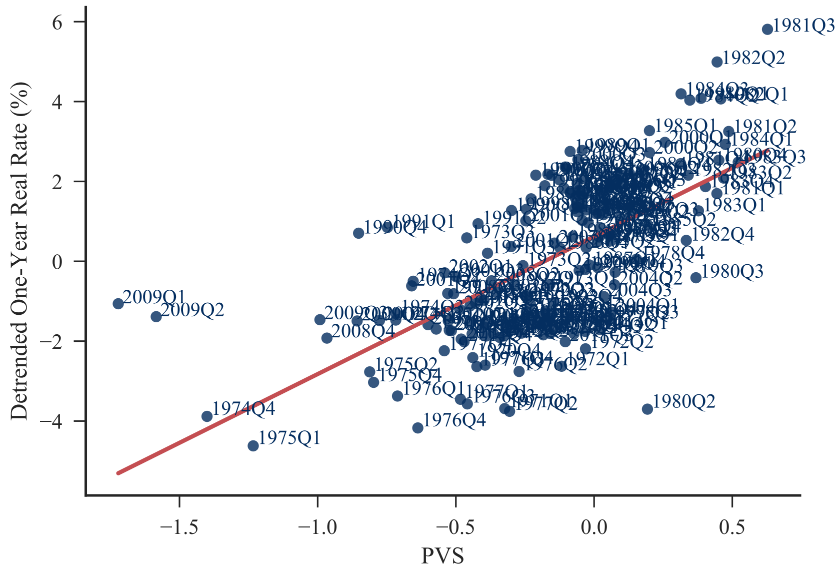
Figure 2: One-Year Real Rate: Actual and Fitted Value



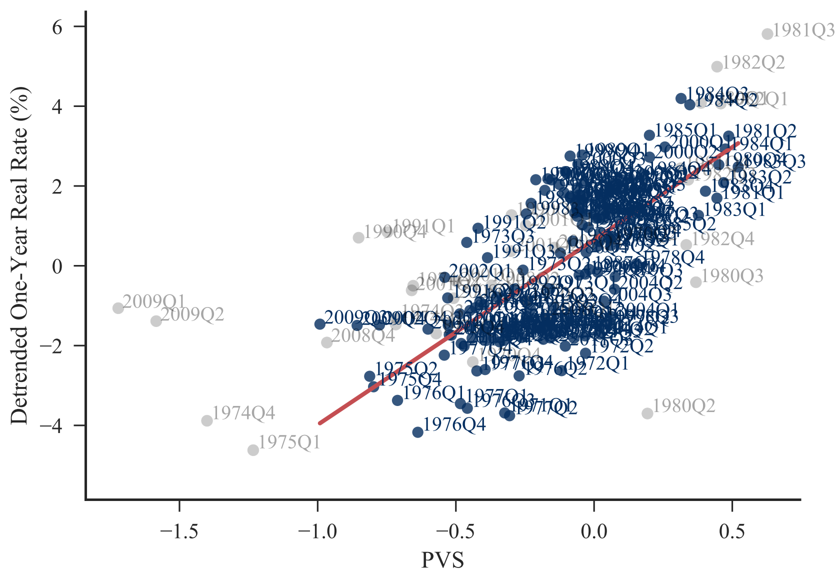
Notes: This figure plots the linearly detrended one-year real rate, as described in Table 1, and the fitted value from a regression of the real rate on the spread in book-to-market ratios between low and high volatility stocks (PVS_t). For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility 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. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percentage terms and linearly detrended. Data is quarterly and spans 1970Q2-2016Q2.

Figure 3: Scatter plot of One-Year Real Rate against PVS

Panel A: Full Sample

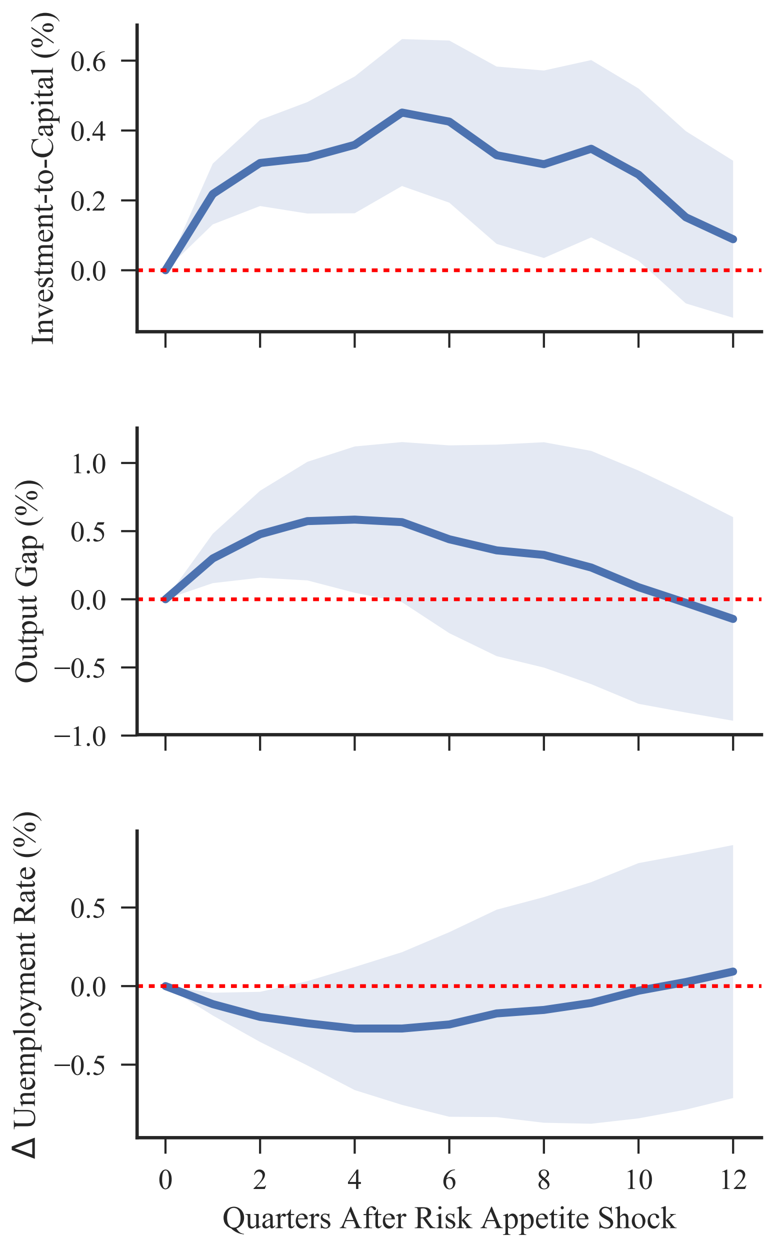


Panel B: Excluding NBER Recessions



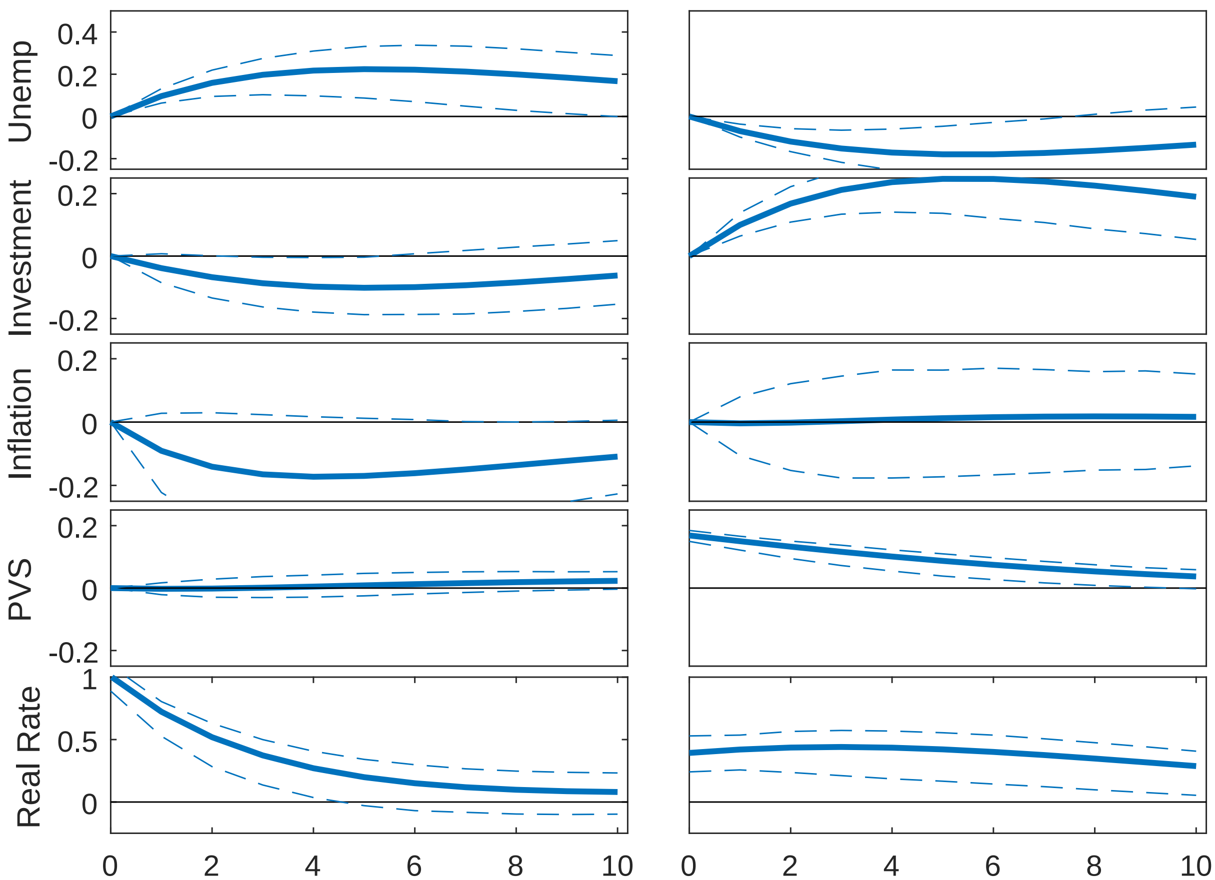
Notes: This figure plots the detrended one-year real interest rate against the spread in book-to-market ratios between low and high volatility stocks (PVS_t). Panel A shows the full sample, while Panel B excludes NBER recessions. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. 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. Data is quarterly and spans 1970Q2-2016Q2.

Figure 4: Impulse Responses of the Macroeconomy to PVS Shocks (Local Projections)



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

Figure 5: Impulse Responses to Monetary Policy and PVS Shocks (Traditional VAR)



Notes: This figure plots impulse responses to monetary policy and PVS shocks. Impulse responses to one-standard deviation shocks are estimated from a five-variable VAR(1) in unemployment, the investment-capital ratio, inflation, PVS, and detrended real rate with one lag using quarterly data 1970Q-2016Q2. Unemployment is the civilian unemployment rate (UNRATE). The investment-capital ratio is computed as private nonresidential fixed investment (PNFI) divided by the previous year's current-cost net stock of fixed private nonresidential assets (K1NTOTL1ES000). Following Bernanke and Mihov (1998), structural innovations in the real rate are assumed to affect output, inflation, and precautionary savings demand with a lag. Precautionary savings (PVS) shocks are assumed to affect output and inflation with a lag, but have a contemporaneous effect on the real rate. Dashed lines denote 95% confidence bands, generated by simulating 1000 data processes with identical sample length as in the data from the estimated VAR dynamics.

TABLES

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

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

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

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

	5	4	3	2	1	1-5
Mean	7.44	9.65	12.04	11.15	10.15	2.71
Std Dev	39.17	31.19	25.07	19.99	15.42	29.57
Median	-0.11	6.83	12.07	13.13	12.60	9.47
Min	-44.87	-37.31	-31.72	-29.25	-22.28	-49.51
Max	74.19	55.22	45.14	35.82	27.32	50.48
α	-4.99	-0.96	2.57	2.41	2.94	7.92
$t(\alpha)$	-2.08	-0.84	3.87	3.01	2.52	2.58
CAPM-β	1.25	1.17	1.03	0.92	0.73	-0.51
SMB-β	1.86	1.39	1.04	0.66	0.40	-1.46
HML-β	0.19	0.09	0.18	0.33	0.37	0.18

***Panel C**: Real Rate*

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

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

Table 2: What Explains Real Rate Variation?

Dep. Variable:	One-Year Real Rate							
	Levels				First-Differences			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PVS	3.44**		3.45**	3.34**	2.22**		2.45**	2.09**
	(5.36)		(5.01)	(4.70)	(2.73)		(2.65)	(2.36)
BM Low-Vol		3.02**				1.99*		
		(3.11)				(1.80)		
BM High-Vol		-3.46**				-2.22**		
		(-5.39)				(-2.70)		
Aggregate BM			-1.10	0.26			2.30	3.59
			(-0.71)	(0.12)			(0.88)	(1.16)
Output Gap				0.09				0.36**
				(0.79)				(2.51)
Inflation				-0.12				0.22
				(-0.95)				(1.16)
Constant	0.62**	1.01	0.62**	0.60**	-0.00	-0.00	-0.01	-0.01
	(2.64)	(1.49)	(2.65)	(2.52)	(-0.07)	(-0.08)	(-0.13)	(-0.31)
Adj. R^2	0.41	0.41	0.42	0.42	0.13	0.12	0.13	0.18
N	185	185	185	185	184	184	184	184

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

Table 3: The Term Structure of Real Rates and PVS

k-Year Real Rate$_t = a + b \times PVS_t + c \times$ Agg. BM$_t + \varepsilon_t$

	Levels			First-Differences		
	b	$t(b)$	R^2	b	$t(b)$	R^2
1-Year	**3.45**	5.01	0.42	**2.45**	2.65	0.13
2-Year	**2.53**	2.72	0.32	**2.07**	2.05	0.09
5-Year	**2.90**	3.82	0.35	**1.87**	2.63	0.12
7-Year	**2.69**	3.48	0.32	**1.60**	2.45	0.10
10-Year	**2.51**	3.32	0.30	**1.40**	2.41	0.10

Notes: This table reports contemporaneous regressions of real rates of various maturities on PVS_t. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Volatility-sorted returns are returns on the lowest minus highest volatility quintile portfolios. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. PVS_t is defined as the difference in BM ratios between the bottom and top quintile portfolios. The k-year real rate is the k-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. All regressions include the Aggregate BM (linearly detrended) as a control variable. 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.

Table 4: Robustness: The Real Rate and PVS

		Levels						First-Differences					
		Full			Pre-Crisis			Full			Pre-Crisis		
		b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2	b	$t(b)$	R^2
(1)	Baseline	**3.45**	5.01	0.42	**4.11**	7.61	0.47	**2.45**	2.65	0.13	**3.58**	3.67	0.20
(2)	VW	**3.16**	4.48	0.32	**4.01**	6.01	0.41	**1.39**	2.45	0.08	**1.81**	2.59	0.10
(3)	2YR Vol	**4.49**	6.27	0.52	**5.13**	8.20	0.54	**2.22**	2.32	0.05	**3.64**	4.21	0.10
Horse-Races:													
(4)	Liquidity	**3.80**	6.54	0.47	**4.30**	7.73	0.51	**2.06**	2.14	0.15	**3.17**	3.02	0.21
(5)	Duration	**3.23**	4.26	0.42	**3.62**	5.24	0.49	**2.46**	3.13	0.12	**3.46**	4.31	0.20
(6)	Leverage	**4.12**	6.15	0.44	**4.53**	7.57	0.48	**3.20**	2.87	0.14	**4.19**	3.34	0.21
(7)	2M-Beta	**3.47**	5.50	0.41	**4.02**	7.73	0.48	**1.77**	2.55	0.15	**2.82**	4.35	0.22
(8)	Size	**3.04**	2.48	0.42	**4.01**	3.80	0.47	**3.44**	2.42	0.13	**4.18**	2.59	0.20
(9)	Value	**4.16**	4.97	0.43	**4.70**	7.03	0.48	**3.88**	3.05	0.16	**4.49**	3.24	0.22
Double-Sorts:													
(10)	Duration	**3.85**	3.96	0.17	**3.98**	3.73	0.14	**3.19**	2.70	0.10	**4.10**	3.23	0.15
(11)	Leverage	**4.76**	5.08	0.35	**5.40**	5.79	0.38	**3.53**	2.81	0.12	**4.96**	3.52	0.18
(12)	2M-Beta	**4.52**	5.54	0.43	**5.25**	8.29	0.50	**1.90**	2.33	0.04	**2.88**	4.10	0.07
(13)	Size	**5.21**	4.79	0.39	**6.30**	7.90	0.46	**3.76**	2.60	0.12	**4.85**	3.12	0.17
(14)	Value	**8.61**	4.96	0.31	**9.49**	4.88	0.32	**6.16**	2.25	0.09	**8.97**	2.73	0.15
(15)	Dividend-Adj	**3.35**	4.20	0.28	**3.97**	4.91	0.28	**2.00**	2.59	0.08	**2.52**	2.93	0.11
(16)	Industry-Adj	**3.56**	5.18	0.34	**4.03**	5.65	0.35	**1.66**	2.39	0.06	**2.74**	3.96	0.11

Notes: This table reports a battery of robustness exercises for our main results. Specifically, we report time-series regression results of the following form: Real $\text{Rate}_t = a + b \times PVS_t + \theta X_t + \varepsilon_t$. We run this regression directly in levels and in first differences. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. PVS_t is defined as the difference in BM ratios between the bottom and top quintile portfolios. X_t is a vector of control variables, which always includes the Aggregate BM (linearly detrended), computed by summing book equity values across all firms and divided by the corresponding sum of market equity values. Row (1) uses our baseline PVS_t measure and the full sample. Row (2) uses value weights instead of equal weights when forming our PVS_t. Row (3) constructs our PVS_t using the past two years of return volatility, as opposed to the past two months. Row (4) controls for the spread between off-the-run and on-the-run Treasury yields (Krishnamurthy (2002)). Rows (5)-(9) run bivariate horse races by adding book-to-market spreads based on other characteristic sorts to our control variables X_t. See the Table 2 of the Appendix for a description of each characteristic. In rows (10)-(16), we instead use a double-sorted PVS_t, with complete details also contained in the Appendix. The one-year real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percent and linearly detrended. The listed t-statistics are computed using Newey-West (1987) standard errors with five lags. Italic point estimates indicates a p-value of less than 0.1 and bold indicates a p-value of less than 0.05. Data is quarterly and the full sample spans 1970Q2-2016Q2 (pre-crisis ends in 2008Q4).

Table 5: Forecasting Returns with PVS and the Real Rate

	Vol-Sorted $\text{Ret}_{t\to t+1}$		Vol-Sorted $\text{Ret}_{t\to t+4}$		$\text{Mkt-Rf}_{t\to t+1}$		$\text{Mkt-Rf}_{t\to t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{PV}S_t$	14.42**		40.99**		-2.22		-6.27	
	(5.07)		(4.11)		(-1.25)		(-0.90)	
Real Rate_t		1.57**		4.13**		-0.26		0.03
		(2.81)		(2.13)		(-0.91)		(0.03)
Constant	3.15**	0.58	9.77**	2.49	1.39**	1.79**	5.85*	6.95**
	(2.83)	(0.53)	(2.46)	(0.59)	(2.04)	(2.82)	(2.24)	(2.73)
Adj. R^2	0.12	0.04	0.26	0.07	0.00	-0.00	0.01	-0.01
N	184	184	181	181	184	184	181	181

Notes: This table reports several return forecasting regressions. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Volatility-sorted returns are returns on the lowest minus highest volatility quintile portfolios. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. PVS_t is defined as the difference in BM ratios between the bottom and top quintile portfolios. Vol-Sorted Ret in the forecasting regression corresponds to returns on the low-minus-high volatility portfolio. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percent and linearly detrended. When forecasting the aggregate stock market, we use the excess return of the CRSP Value-Weighted index obtained from Ken French's website. For quarterly regressions, standard errors are computed using Newey-West (1987) with two lags. For annual horizons we use Hodrick (1992) standard errors. t-statistics are listed below point estimates in parentheses, * 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. Returns are in percentage points.

Table 6: Evidence from Other Asset Classes

				Forecasting Vol-Sorted $\text{Ret}_{t\to t+1}$ with					
				PVS_t			Real Rate_t		
Asset Class	N	Mean	Volatility	b	$t(b)$	R^2	b	$t(b)$	R^2
U.S. Stocks	184	2.7	29.6	14.42	5.07	0.12	1.57	2.81	0.04
U.S. Corporate Bonds	136	-3.1	8.9	6.45	3.39	0.27	0.51	1.88	0.03
Sovereign Bonds	50	-10.9	19.5	7.86	1.81	0.09	0.46	0.60	-0.02
Options	88	-16.0	17.8	5.28	2.41	0.03	1.07	1.89	0.02
CDS	31	-7.0	6.4	4.83	4.44	0.48	0.77	2.45	0.11
Commodities	89	10.3	35.4	3.38	0.51	-0.01	-0.34	-0.26	-0.01
FX	120	1.2	10.8	-0.60	-0.65	-0.01	-0.57	-1.49	0.02

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

Table 7: The Real Rate and Contemporaneous Volatility

Dependent Variable:	Real Rate (Level)			Real Rate (Changes)		
	(1)	(2)	(3)	(4)	(5)	(6)
σ (Vol-Sorted Portfolio)	0.00		-0.04	0.02		0.03
	(0.05)		(-1.63)	(0.84)		(1.19)
CIV_t		0.03	0.06**		-0.04**	0.00
		(1.19)	(3.28)		(-2.29)	(0.12)
σ (Mkt-Rf)		-0.18**	-0.05		-0.02	-0.05*
		(-3.94)	(-1.44)		(-0.66)	(-1.70)
σ (SMB)		0.31**	0.07		0.09	0.07
		(3.88)	(1.36)		(1.28)	(1.22)
σ (HML)		0.07	0.10**		0.03	0.02
		(0.94)	(2.22)		(1.40)	(0.88)
σ (TFP Growth)		0.09	0.06		0.71**	0.72**
		(0.19)	(0.31)		(2.54)	(2.81)
PVS_t			4.01**			2.50**
			(8.66)			(3.10)
Adj R^2	-0.01	0.15	0.60	0.00	0.08	0.20
N	185	185	185	184	184	184

Notes: This table reports regression estimates of the one-year real rate on various measures of risk. σ (TFP Growth) is the volatility of TFP growth that is implied by a GARCH model (see Table A1 of the Appendix). σ (Mkt-Rf), σ (SMB), and σ (HML) are the within-quarter annualized volatility (percentage terms) of the three Fama and French (1993) factors, which we compute using daily data. CIV_t is the average idiosyncratic volatility factor of Herskovic et al. (2016). PVS_t is the difference in book-to-market ratios between high volatility and low volatility stocks. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Within each quintile, we compute the average book-to-market (BM) ratio. The Appendix contains full details on how we compute BM ratios. σ (LMH-Vol Portfolio) is the annualized percentage volatility of the low-minus-high volatility portfolio, which we compute using daily data. The real rate is the one-year Treasury bill rate net of one-year survey expectations of the inflation (the GDP deflator) from the Survey of Professional Forecasters, expressed in percent and linearly detrended. Columns (1)-(3) run the regression in levels. Columns (4)-(6) run the regression in first differences. t-statistics are listed below point estimates 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. All regressions have a constant, but we omit the estimates to save space. Data is quarterly and spans 1970Q2-2016Q2.

Table 8: The Real Rate and Mutual Fund Flows

***Panel A**: Summary Statistics*

	Mean	Std. Dev.	p25	p50	p75	Min	Max	# Funds
Quarterly Obs./Fund	31	28	11	24	43	2	170	20,253
AUM ($ mm)	754	2,049	155	266	597	100	65,339	20,253
Net Inflows (%)	5.55	8.53	0.49	3.21	7.80	-19.70	66.54	20,253
Quarterly Return (%)	1.47	2.32	0.65	1.38	2.34	-38.77	58.76	20,253
Annual Volatility (%)	11.84	7.92	4.57	12.61	17.29	0.31	36.62	20,253
$\beta_{f,HVOL}$	0.30	0.24	0.02	0.32	0.49	-0.05	0.83	20,253

***Panel B**: High Volatility Funds and the Real Rate*

Dependent Variable	$Flows_{f,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Real Rate$_t$	0.92**			0.94**		
	(4.56)			(4.27)		
Real Rate$_t \times \beta_{f,HVOL}$	2.08**	2.09**	1.52**			
	(4.11)	(4.17)	(4.30)			
Real Rate$_t \times \sigma_f$				0.04**	0.04**	0.03**
				(3.09)	(3.12)	(2.87)
$Ret_{f,t}$			0.22**			0.23**
			(6.47)			(6.46)
$Ret_{f,t-1}$			0.22**			0.22**
			(6.85)			(6.84)
FE	f	(f,t)	(f,t)	f	(f,t)	(f,t)
Adj. R^2	0.11	0.15	0.16	0.11	0.14	0.16
N	630,592	630,592	630,592	630,592	630,592	630,592

Notes: This table studies whether high-volatility mutual fund flows are more sensitive to real rate movements, relative to low-volatility mutual funds. In Panel B, our baseline regression is $Flow_{f,t} = FE(f) + b_1$Real Rate$_t + b_2$Real Rate$_t \times \beta_{f,HVOL} + \varepsilon_{f,t}$. $Flow_{f,t}$ is the net percentage inflow into fund f at time t, computed as the dollar inflow divided by assets under management. Flows are winsorized at the 5% tails. $\beta_{f,HVOL}$ is the beta of fund f's return with respect to a portfolio of high-minus-low volatility stocks. 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. Betas of each fund are computed using the high-minus-low volatility portfolio return over the life of the fund. σ_f is the return volatility of the fund, computed using the full sample of year-quarter observations. We drop fund with assets under management of under $100 mm. Panel A presents summary statistics for the funds in our sample. We first compute statistics for each fund (across time), and then report summary stats across funds. In Panel B, t-statistics are listed below point estimates in parentheses and are computed using Driscoll-Kraay (1998) standard errors with five lags within each fund cluster. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Quarterly mutual fund data derives from CRSP and spans 1973Q2-2015Q3. Returns are in percentage terms.

Table 9: Other Measures of Financial Conditions, PVS, and the Real Rate

			$Z_t = a + b \times PVS_t$			$\text{RealRate}_t = a + c \times Z_t$			$\text{RealRate}_t = a + b \times PVS_t + c \times Z_t$		
	Z-variable	N	b	$t(b)$	R^2	c	$t(c)$	R^2	b	$t(b)$	R^2
(1)	BAA-10Y Spread	185	-0.84	-2.52	0.18	-0.83	-2.77	0.09	3.36	5.08	0.41
(2)	GZ Spread	151	-1.26	-2.24	0.23	-0.32	-1.53	0.02	3.80	6.15	0.48
(3)	Credit Sentiment	133	0.13	2.65	0.15	1.44	0.78	0.00	3.17	4.47	0.35
(4)	Equity Sentiment	182	1.19	3.98	0.24	1.35	6.33	0.37	2.41	3.97	0.52
(5)	Policy Uncertainty	126	-53.02	-4.25	0.23	-0.03	-6.54	0.30	1.62	2.75	0.38
(6)	$\mathbb{E}_t\left[\text{Mkt-Rf}_{t,t+4}\right]$	180	-0.49	-1.27	0.06	-0.28	-0.62	0.00	3.53	6.04	0.41

Notes: This table compares other measures of financial conditions and market sentiment to PVS_t. The first set of regressions in the table shows the results of a univariate regression of each alternative risk appetite measure on PVS_t. The second set of regressions in the table shows the results of a univariate regression of the real rate on contemporaneous values of each variable. The last set of results regresses the real rate on both PVS_t and each alternative risk appetite measure. In rows (1)-(6), the alternative risk appetite variables are the spread between Moody's BAA credit yields and the 10-year Treasury rate, the credit spread index from Gilchrist and Zakrajšek (2012), credit market sentiment from Greenwood and Hanson (2013) (four-quarter moving average), equity market sentiment (orthogonalized) from Baker and Wurgler (2006), and the Baker et al. (2016) economic policy uncertainty index, respectively. In row (6), we use the procedure in Kelly and Pruitt (2013) to form a statistically optimal linear forecast of one-year ahead excess stock market returns. The listed t-statistics are computed using Newey-West (1987) standard errors with five lags. Data is quarterly and the full sample spans 1970Q2-2016Q2. See the Appendix for more details on our optimal stock market forecast.

Table 10: Volatility-Sorted Returns and Monetary Policy Surprises

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

	Quarterly Data				Daily Data					
	All		Scheduled		All		Scheduled		Sample	
MP Shock	b	$t(b)$	b	$t(b)$	b	$t(b)$	b	$t(b)$	Start	End
Romer and Romer (2004)	0.75	0.47	0.71	0.44	-0.04	-0.30	-0.06	-0.43	1970.Q1	1996.Q4
Bernanke and Kuttner (2005)	-2.94	-0.19	-1.65	-0.07	5.55	1.32	-1.08	-0.49	1989.Q2	2008.Q2
Gorodnichenko and Weber (2016)	-1.14	-0.06	1.60	0.03	13.34	1.89	3.67	0.94	1994.Q1	2009.Q4
Nakamura and Steinsson (2018)	1.46	0.06	12.83	0.20	18.74	1.98	5.29	1.03	1995.Q1	2014.Q1

Notes: This table reports regressions of volatility-sorted returns onto monetary policy shocks. For all NYSE, AMEX, and NASDAQ firms in CRSP, we compute volatility at the end of each quarter using the previous sixty days of daily returns. We then form equal-weighted portfolios based on the quintiles of volatility. Volatility-sorted returns are returns on the lowest minus highest volatility quintile portfolios. Quarterly return regressions aggregate daily monetary policy shocks by summing over all shocks within a quarter. The Romer and Romer (2004) shock is the change in the intended Federal Funds rate inferred from narrative records around monetary policy meetings, after controlling for changes in the Federal Reserve's information. The Bernanke and Kuttner (2005) shock is derived from the price change in Federal Funds future contracts relative to the day before the policy action. The Gorodnichenko and Weber (2016) shock is derived from the price change in Federal Funds futures from 10 minutes before to 20 minutes after an FOMC press release. The Nakamura and Steinsson (2018) shock is the unanticipated change in the first principal component of interest rates with maturity up to one year from 10 minutes before to 20 minutes after an FOMC news announcement. Columns listed as "All" include all policy changes and "Scheduled" includes only changes that occurred at regularly scheduled policy meetings. In restricting the analysis to regularly scheduled meetings, we exclude quarters after 1993Q4 where the Federal Reserve made policy changes outside of scheduled meetings. Prior to 1994, policy changes were not announced after meetings so the distinction between scheduled and unscheduled meetings is not material. The listed t-statistics are computed using Davidson and MacKinnon (1993) standard errors for heteroskedasticity in small samples.

Table 11: Shocks to Risk Appetite and Real Outcomes

	Forecast Horizon (Qtrs)	
	$h = 1$	$h = 4$
Dep. Variable: Investment-to-Capital		
PVS_t	0.59**	0.97**
	(4.92)	(3.59)
Dep. Variable: Output Gap		
PVS_t	0.81**	1.58**
	(3.24)	(2.14)
Dep. Variable: ΔUnemployment Rate		
PVS_t	-0.36**	-1.12**
	(-2.57)	(-2.20)

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

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

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