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"Déjà vol" revisited: Survey forecasts of macroeconomic variables predict volatility in the cross-section of industry portfolios

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University of Heidelberg

Department of Economics



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Survey forecasts of macroeconomic variables predict
volatility in the cross-section of industry portfolios**

Christian Conrad and Alexander Glas

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Christian Conrad* and Alexander Glas†

September 11, 2018

Abstract

We investigate the question of whether macroeconomic variables contain information about future stock volatility beyond that contained in past volatility. We show that forecasts of GDP growth from the Federal Reserve’s Survey of Professional Forecasters predict volatility in a cross-section of 49 industry portfolios. The expectation of higher growth rates is associated with lower stock volatility. Our results are in line with both counter-cyclical volatility in dividend news as well as in expected returns. Inflation forecasts predict higher or lower stock volatility depending on the state of the economy and the stance of monetary policy. Forecasts of higher unemployment rates are good news for stocks during expansions and go along with lower stock volatility. Our results hold in- as well as out-of-sample and pass various robustness checks.

JEL classification: E17, E37, G11, G17

Keywords: Realized volatility, Survey of Professional Forecasters, forecast evaluation, predictive regressions.

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1 Introduction

“The puzzle highlighted by the results in this paper is that stock volatility is not more closely related to other measures of economic volatility.” (Schwert, 1989 p.1146)

“Because volatility co-varies with business conditions, a tendency exists to suspect that incorporating macroeconomic information should greatly improve longer horizon volatility forecasts. The relatively comprehensive analysis in this paper shows that only modest forecasting gains are possible.” (Paye, 2012 p.545)

The notion that macroeconomic variables should have predictive power for financial volatility has a long tradition in economics. Theoretically, a counter-cyclical behavior of stock market volatility can be rationalized based on the present value models of Campbell (1991) and Campbell and Shiller (1988) but also within the context of more recent models of asset valuation such as Bansal and Yaron (2004), Mele (2007), Bollerslev et al. (2009), David and Veronesi (2013) or Campbell et al. (2018), among others. Against this background, it is astonishing that the empirical evidence for such a link is rather scant. One of the early empirical studies is Schwert (1989). The above quote from Schwert (1989) refers to the puzzling finding that macroeconomic variables appear to be only weakly related to stock market volatility when conditioning on past volatility. Although subsequent studies have frequently revisited the question of whether macroeconomic variables help to forecast volatility, the quote from Paye (2012) illustrates that the empirical evidence is still somewhat at odds with modern approaches to asset valuation. Because volatility forecasts are of great importance for portfolio choice, risk management and the surveillance of risks to financial stability, we take a fresh look at this question.

In contrast to the previous literature which focuses almost exclusively on the realizations of macroeconomic variables, we argue that survey forecasts of these variables can be more informative or may contain complementary information about future stock volatility and, what is more, are available in real-time. Using expectations data from the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia, we contribute to the literature by providing strong evidence that macroeconomic variables do successfully predict quarterly stock volatility in a cross-section of 49 industry portfolios. We consider an AR(2) specification for quarterly realized industry volatility as a benchmark model and test whether additionally including macroeconomic variables improves forecast performance in- and out-of-sample. Our econometric approach follows Paye (2012), which ensures comparability of our results with his. In detail, our findings can be summarized as follows.

First, based on full sample estimates, we show that one-quarter-ahead SPF forecasts of gross domestic product (GDP) growth are significant predictors of realized volatility in 24

out of the 49 industries. The sign of the estimated effect is in line with a counter-cyclical behavior of volatility, which is consistent with both a higher volatility of dividend news during contractions than during expansions (see, for example, Bansal and Yaron, 2004) and/or more volatile discount rates during bad times (see Mele, 2007). In sharp contrast, realizations of GDP growth are essentially insignificant predictors in all industries. In the full sample, there is little evidence for the predictive ability of realizations/forecasts of inflation and the unemployment rate for future volatility. In addition, it is important to notice that the release schedule of quarterly macroeconomic figures rules out the estimation of predictive regressions with realizations in real-time.

Second, we argue that predictive regressions with realized volatility as the dependent variable suffer from measurement error. As discussed in Engle et al. (2013) and Conrad and Schienle (2018), realized volatility should be considered a noisy proxy for the latent long-term component of volatility that is driven by macroeconomic conditions. The measurement error problem suggests that macroeconomic variables may often falsely appear to be insignificant in predictive regressions despite a potentially existing effect. We use the procedure proposed in Conrad and Schienle (2018) to test for an existing relationship. This test simply consists of running the same predictive regression as before but with realized volatility being replaced by ‘volatility-adjusted realized volatility’. The latter is a more precise proxy for the latent long-term volatility which mitigates the measurement error problem. The test results strengthen the evidence in favor of the predictive ability of GDP growth. Specifically, we find that forecasts of GDP growth are significant predictors in 38 out of the 49 industries. In addition, we now find that the unemployment rate plays a prominent role: For 26 industries, the realization of a higher unemployment rate predicts a significant increase in stock volatility.

Third, the relationship under consideration may be time-varying. In particular, the general equilibrium model of David and Veronesi (2013) suggests that the relation between inflation and stock volatility depends on the prevailing macroeconomic regime. This may explain why inflation turned out to be insignificant in the full sample predictive regressions. Motivated by these considerations, we run predictive regressions for subsamples of 15 years each. Indeed, we observe a time-varying effect for inflation. While higher inflation rates predominantly go along with higher stock volatility during the stagflation period of the 1970s and during the Volcker disinflation, increasing inflation rates are associated with lower levels of stock volatility during the 2000s. The predictive power of GDP growth for future volatility is strongest for the turbulent 1970s and early 1980s, decreases during the Great Moderation period but upraises again for subsamples that include the Great Recession. Finally, we observe an interesting dichotomy for the unemployment rate. While higher realized unemployment rates go along with elevated levels of stock market volatility, higher expected unemployment rates predict lower volatility in recent subsamples. The former effect suggests that higher realized unemployment rates are perceived as bad news for stocks (via the cash flow effect), while the latter effect appears to be driven by

monetary policy: The expectation of higher unemployment rates reduces the probability of a monetary tightening and, hence, is good news for stocks (via the discount effect). Finally, our results highlight that not all industries are alike, i.e., stock volatility in some industries is closely related to macroeconomic conditions while the volatility in others is not. Averaging over all industries, i.e., considering the broad stock market, surely makes it more difficult to detect a robust relationship.

Fourth, we evaluate the out-of-sample predictive ability of the macroeconomic variables by means of the Clark and West (2007) as well as Giacomini and White (2006) tests. The null hypothesis of the Clark and West (2007) test is that the population mean squared errors (MSE) of the AR(2) benchmark model and the model that is augmented with the macroeconomic explanatory variable are the same. At the 10% significance level, the null hypothesis is rejected in favor of the augmented model for all three macroeconomic variables in the majority of the 49 industries. In contrast, the Giacomini and White (2006) test is concerned with superior predictive ability, i.e., it compares the sample MSEs. As expected, the rejection rates are a bit lower for this test. At the 10% significance level, we find that the null hypothesis is rejected for 14 out of the 49 industries when including forecasts of GDP growth and for 20/25 industries when including forecasts of inflation or the unemployment rate. Interestingly, we find that macroeconomic expectations are most informative during the onset of recessions and, in particular, during the period after the Great Recession.

In summary, we provide much more optimistic results regarding the predictive power of macroeconomic variables for stock volatility than the previous literature. Our empirical findings confirm the implications with recent models of asset valuation such as Bansal and Yaron (2004) and David and Veronesi (2013). Moreover, our results call for further research into volatility models that directly incorporate macroeconomic variables for long-term volatility forecasting. Those models are of particular interest when making long-term investment decisions. Lastly, our results contribute to a better understanding of the sources of the so-called ‘low-volatility puzzle’ and the interplay between monetary policy and financial volatility.

The remainder of the paper is organized as follows. Section 2 reviews the related empirical literature and Section 3 presents some theoretical arguments on the relation between macroeconomic conditions and stock volatility. We present the econometric framework in Section 4 and the data in Section 5. The empirical results are discussed in Section 6. Section 7 provides extensions and robustness checks. Section 8 summarizes and concludes.

2 Related Literature

In this section, we review the empirical literature on macroeconomic predictors of stock market volatility. Officer (1973) and Schwert (1989) were among the first to investigate this link. More recent papers are Campbell and Diebold (2009), Paye (2012) and Chris-

tiansen et al. (2012). The main econometric workhorse in all those papers is a predictive regression with a measure of realized stock volatility as the dependent variable. The question of interest is whether macroeconomic conditions have forecasting power for future stock volatility when controlling for past volatility. While Paye (2012) and Christiansen et al. (2012) find that financial variables such as default spreads and dividend yields have some predictive power for stock volatility, macroeconomic variables such as GDP or industrial production (IP) growth are not found to be useful. Campbell et al. (2001) consider industry- and firm-level volatility and find no evidence that GDP growth predicts those volatilities. Similarly, Chong and Lin (2017) analyze industry-level stock volatility and find that IP growth is not a meaningful predictor. More promising results are presented in Campbell and Diebold (2009) based on six-month growth forecasts from the Livingston survey. They show that higher growth expectations forecast lower levels of CRSP-based realized volatility in-sample. However, Campbell and Diebold (2009) do not provide out-of-sample evidence.

A second strand of literature employs GARCH-type component models for volatility. In particular, Engle and Rangel (2008) and Engle et al. (2013) decompose volatility into a short- and a long-term component and provide evidence that low GDP/IP growth and high inflation predict high long-term volatility. Further evidence is provided in Asgharian et al. (2013) and Conrad and Loch (2015). In particular, Conrad and Loch (2015) show that GDP/IP growth and the unemployment rate are lagging with respect to the long-term component of stock market volatility and that the SPF expectations contain useful information that is not included in past realizations.

At first, it might be puzzling why the evidence based on predictive regressions is much less optimistic than the evidence based on GARCH-type models. Engle et al. (2013) and Conrad and Schienle (2018) explain that this might be due to a measurement error problem in the predictive regressions. Conrad and Schienle (2018) propose a test for checking whether macroeconomic conditions are related to the long-term component of volatility. We make use of their test and show that standard predictive regressions indeed tend to overlook existing relationships.

While we focus on the effects of macroeconomic conditions on financial volatility, other studies investigate the relation between macroeconomic uncertainty and financial volatility or, reversely, the effects of financial volatility on the macroeconomy. For a recent review of the literature see Andersen et al. (2013).

3 The Economics of Volatility

Although the evidence in favor of the predictive ability of macroeconomic variables is rather weak, there is strong empirical evidence suggesting that financial volatility behaves counter-cyclical. The present value models of Campbell and Shiller (1988) and Campbell (1991) provide a theoretical framework for intuitively illustrating the mechanics of the

relationship between macroeconomic conditions and stock volatility. Let $r_{i,t}$ denote the log return on asset i in period t . Unexpected returns due to news can be decomposed into two surprise components:

$$r_{i,t+1} - \mathbf{E}_t[r_{i,t+1}] = \varepsilon_{i,t+1}^{div} - \varepsilon_{i,t+1}^{ret}, \quad (1)$$

where $\varepsilon_{i,t+1}^{div}$ represents revisions in expectations about future dividend payments and $\varepsilon_{i,t+1}^{ret}$ denotes revisions in expectations about future returns. We refer to the first term as the ‘cash flow effect’ of news and to the second term as the ‘discount rate effect’ of news. Because the same piece of news can have a positive cash flow effect (i.e., $\varepsilon_{i,t+1}^{div} > 0$) but a negative discount rate effect (i.e., $-\varepsilon_{i,t+1}^{ret} < 0$), the overall effect of news on unexpected returns is often ambiguous ex-ante and may even vary over the business cycle. For example, Boyd et al. (2005) show that bad news about the unemployment rate are typically good news for stocks during expansions but bad news during contractions. During expansions the discount effect dominates: An increasing unemployment rate reduces interest rate expectations and, hence, is good news for stocks. On the other hand, during contractions the cash flow effect dominates: A higher unemployment rate lowers expected future dividend payments and, hence, is bad news for stocks.

The conditional variance of returns can be written as

$$\mathbf{Var}_t[r_{i,t+1}] = \mathbf{Var}_t[\varepsilon_{i,t+1}^{div}] + \mathbf{Var}_t[\varepsilon_{i,t+1}^{ret}] - 2\mathbf{Cov}_t(\varepsilon_{i,t+1}^{div}, \varepsilon_{i,t+1}^{ret}). \quad (2)$$

If expected returns are constant, the conditional variance of returns is time-varying only because of time-variation in $\mathbf{Var}_t[\varepsilon_{i,t+1}^{div}]$. In this case, return volatility is counter-cyclical if the volatility of dividend news is counter-cyclical. If expected returns are time-varying, the conditional volatility of news about expected returns, $\mathbf{Var}_t[\varepsilon_{i,t+1}^{ret}]$, can also generate counter-cyclical stock volatility. This will be the case if changes in expected returns are more pronounced during contractions than during expansions. For examples of models that can generate the former or latter effect see Bansal and Yaron (2004) or Mele (2007). In the general equilibrium model of David and Veronesi (2013) changes in stock market volatility are driven by changes in market participants’ beliefs about the prevailing economic regime. Agents learn about the current regime by observing inflation, the price-earnings ratio and other variables. In particular, David and Veronesi (2013, p.687) emphasize the “time-varying signalling role of inflation” (for details see the discussion below).

Theory not only suggests a counter-cyclical behavior of return volatility but also a negative relation between returns and volatility. If the conditional volatility of returns goes up/down in contractions/expansions and contractions/expansions are predominantly associated with bad/good news, returns and volatility are negatively related. This relationship is often referred to as the volatility-feedback effect (see, for example, Campbell and Hentschel, 1992).

The most important implication of the previous discussion is that changes in expected

macroeconomic conditions should be associated with variation in $\text{Var}_t[\varepsilon_{i,t+1}^{div}]$ and/or $\text{Var}_t[\varepsilon_{i,t+1}^{ret}]$ and, hence, should be able to predict future stock volatility. Below, we briefly discuss what kind of relationship we expect for the three macroeconomic variables that are employed in the empirical analysis.

GDP growth expectations: If the conditional volatility of cash flow news behaves counter-cyclical, then forecasts of higher GDP growth rates should be associated with lower levels of financial volatility. Nevertheless, the relationship might not be stable over time. For example, the subdued volatility of GDP growth rates during the Great Moderation might have weakened the link between the business cycle and financial volatility. Moreover, if monetary policy is rules-based and responsive to changes in inflation and GDP growth, higher growth expectations go along with the expectation of a tighter monetary policy. If the economy is in an expansion the discount rate effect might dominate, stock prices fall and volatility increases (see Andersen et al., 2007).

Inflation expectations: The relationship between stock volatility and inflation expectations is complex. As highlighted by David and Veronesi (2013), higher inflation expectations can be associated with higher or lower stock volatility. For example, David and Veronesi (2013, p.684) argue that during the early 1980s “investors faced large uncertainty about whether the United States would enter a persistent stagflation regime”. During this period, higher inflation expectations went along with lower growth expectations, declining stock prices and higher stock volatility. This type of reasoning is consistent with Fama and Schwert (1977) who provide evidence for a negative relationship between inflation and stock returns. Fama (1981) argues that this negative relation can be explained by a negative relation between inflation and growth, whereby growth is the fundamental factor that relates to stock prices. During the 1970s and early 1980s, high inflation simply ‘proxies’ low growth. On the other hand, the model of David and Veronesi (2013) predicts that higher inflation can lead to decreasing stock volatility when the market fears a deflationary regime. In this situation higher inflation expectations are signalling that market participants believe that a deflationary regime can be avoided. As a result, (stock prices increase and) stock volatility declines.

The relation between stock volatility and inflation is also likely to depend on the market participants’ beliefs about the central bank’s reaction function. If the central bank follows an inflation objective, then higher inflation expectations should be accompanied by the expectation of higher policy rates in the future (see Engel and West, 2006, Conrad and Lamla, 2010, and Dräger et al., 2016, for theoretical and empirical evidence). In response, the stock market might decline and higher inflation expectations can be associated with higher volatility. Such a relationship might be expected, for example, for the years of the Volcker disinflation.

Unemployment rate expectations: Because the unemployment rate is inversely related to the business cycle, we should expect that a higher unemployment goes along with higher volatility in cash flow news. Thus, the unemployment rate should be positively

associated with stock volatility. However, according to Boyd et al. (2005) news about higher unemployment rates during expansions are typically good news for the stock market. If monetary policy is forward looking, an increase in the expected unemployment rate during an expansion can create the expectation that a tightening of monetary policy becomes less likely. Hence, we conjecture that an increase in the expected unemployment rate can also be associated with lower volatility.

4 Predictive Regressions for Financial Volatility

Our main workhorse for the empirical analysis is the predictive regression. We employ the same specification as in Paye (2012) and model the volatility in industry $i = 1, \dots, N$ as

$$\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \nu_{i,t+1}, \quad (3)$$

where $Vol_{i,t}$ denotes a certain measure of stock volatility.¹ The predictor x is either the realization, x_t , of one of the previously discussed macroeconomic variables, the corresponding nowcast, $x_{t|t}$, or the one-step-ahead forecast, $x_{t+1|t}$, from the Survey of Professional Forecasters. Since the macroeconomic variables are observed at the quarterly frequency, the index $t = 1, \dots, T$ refers to subsequent quarters. Finally, the error term, $\nu_{i,t+1}$, captures all factors that are related to volatility but not included in the model. We are mainly interested in testing the hypothesis $H_0 : \theta_i = 0$ against $H_1 : \theta_i \neq 0$. Thus, our benchmark model is a simple AR(2). Inference is based on autocorrelation- and heteroskedasticity-robust standard errors (Newey and West, 1987). Prior to estimation, we standardize the explanatory variable x by dividing it by its standard deviation. To improve the readability, the coefficients and standard errors reported in the corresponding tables and figures below are the estimated ones times 100.

The most commonly used measure of the unobservable volatility is *realized volatility*. We allow for a constant, non-zero industry-specific expected return, μ_i , and model industry returns as

$$r_{i,d,t} = \mu_i + \varepsilon_{i,d,t}, \quad (4)$$

where $r_{i,d,t}$ denotes the daily log excess return in industry i on trading day $d = 1, \dots, D_t$ of quarter t . We compute the demeaned excess return in each sector as the residual from the estimate of Eqn. (4), i.e., $\hat{\varepsilon}_{i,d,t} = r_{i,d,t} - \hat{\mu}_i$. Realized volatility in industry i and quarter

¹The AR(2) specification can be justified based on the use of information criteria for lag length selection. However, all our results are robust to reasonable modifications of the lag length.

t is defined as the square root of the sum over the squared residuals, i.e.,

$$RV_{i,t} = \sqrt{\sum_{d \in t} \hat{\varepsilon}_{i,d,t}^2}. \quad (5)$$

In the empirical analysis, we will rank the different industries according to their systematic risk, SR_i . We measure the systematic risk of each industry by the coefficient of determination from a regression of industry-specific excess returns on a constant and the market portfolio, i.e.,

$$r_{i,d,t} = \mu_i + \beta_i r_{m,d,t} + \eta_{i,d,t}. \quad (6)$$

In Section 7 on robustness, we will consider a measure of idiosyncratic volatility which is based on the residuals of Eqn. (6).

5 Data

In this section, we describe the return and macroeconomic data that are used in the main part of our paper. Data that are exclusively employed in Section 7 on robustness will be introduced in the respective subsections.

Stock Market and Industry Portfolios

Financial return data are obtained from the Fama-French Data Library.² We use daily excess returns of the aggregate stock market (*mkt*) and the daily value-weighted excess returns from the 5 and 49 industry portfolios. Broadly speaking, the market return is the value-weighted excess return of all firms listed in the NYSE, AMEX, or NASDAQ. The 5 industry portfolios are defined as follows: Business equipment (*hitec*), consumer durables (*cnsmr*), healthcare (*hlth*), manufacturing (*manuf*) and other (*other*). A description of the 49 industry portfolios is provided in Table 7 in the Appendix.³ Our sample covers the 1968Q4 to 2017Q4 period, such that $T = 197$. As will be discussed below, the starting point of our sample period is determined by the availability of the macroeconomic expectations data. As before, we denote the log excess returns on day d of quarter t for industry portfolio i by $r_{i,d,t}$ and for the market portfolio by $r_{m,d,t}$. For the market as well as for each industry portfolio, we calculate quarterly realized volatility, $RV_{m,t}$ and $RV_{i,t}$, as described in Eqns. (4) and (5). Table 1 provides summary statistics for the market and the 5 industry portfolios. The portfolios are sorted in decreasing order according to their systematic risk, SR_i . We retain this sorting throughout the following sections. Table 1

²http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

³A more detailed description/definition of ‘the market’ and the industry portfolios is available on the website of the Fama-French Data Library.

presents the systematic risk as well as the corresponding estimate of β_i , the average annualized return and the average annualized realized volatility of each industry. The other measures that are presented in the table will be introduced and discussed later on.

[TABLE 1 HERE]

Figure 1 depicts the annualized time series of quarterly realized volatility. While the first panel shows the market, the other panels show the 5 industry portfolios. Shaded gray areas indicate recession periods as classified by the National Bureau of Economic Research (NBER).⁴

[FIGURE 1 HERE]

As expected, all time series of realized volatility are characterized by a distinct counter-cyclical behavior, i.e., volatility is high during economic contractions and low during expansion periods. While there is an obvious comovement in the realized volatilities of the 5 industry portfolios, there are also clear idiosyncracies such as the marked increase in volatility in the *business equipment* industry during the period of the dot-com bubble and its final burst. We illustrate the cross-sectional heterogeneity in the quarterly realized volatilities of the 49 industry portfolios in Figure 2.

[FIGURE 2 HERE]

The left panel shows that the average annualized $RV_{i,t}$ is around 12% for ‘low-volatility industries’ and above 30% for ‘high-volatility industries’.⁵ For comparison, the average annualized realized volatility of the market is 14.34% (see Table 1). The right panel is based on yearly regressions of daily industry excess returns on a constant and the market’s excess return. For each year, we estimate the systematic risk of all 49 industries and then average over the industries. The graph shows the individual systematic risks for the 49 industries (red crosses) and the evolution of the cross-sectional average systematic risk (black line) over time. For a sample that ends in 1997, Campbell et al. (2001) provide a similar figure and find that average systematic risk is trending downwards (see their Figure 5). The right panel of Figure 2 shows that this was only a temporary phenomenon and that the average systematic risk has spiked again around 2010. If macroeconomic variables affect industry volatility mainly through their effect on stock market volatility, then their ability to forecast industry-specific volatility may be positively related to the average systematic risk and, hence, may vary over time. We investigate this issue in Section 6.3.

⁴<http://www.nber.org/cycles.html>

⁵The lowest/highest average annualized realized volatility is observed in the *utilities* (11.86%) and *precious metals* (34.55%) industries, respectively.

Macroeconomic Expectations Data

Data on survey expectations and realizations of macroeconomic variables are taken from the Federal Reserve’s SPF which is available on a quarterly basis from 1968Q4 onwards.⁶ We focus on three key economic variables. We consider real GDP growth (Δgdp) as a measure of economic activity.⁷ Growth rates are defined as annualized quarter-over-quarter percentage changes. Inflationary developments are proxied by percentage changes in the GDP price index (inf). Finally, we employ the change (first difference) of the civilian unemployment rate (Δune).

For each of the three variables, we employ nowcasts and forecasts of the growth rates/changes based on the median of the predictions reported by the individual survey respondents. The SPF is conducted in the middle month of each quarter and consists of approximately 35-45 participants per questionnaire. Our analysis is based on the nowcasts for the current quarter, $x_{t|t}$, as well as on the one-quarter-ahead forecasts, $x_{t+1|t}$.

In addition to the expectations, the SPF provides different data vintages of the realizations for each outcome variable, x_t . We employ first-release data of the realizations.⁸ It is important to note that, for example, the first release of GDP growth in quarter t becomes available in quarter $t + 1$. Thus, strictly speaking the predictive regression in Eqn. (3) is infeasible in real-time when using the realizations x_t .⁹ In contrast, predictive regressions based on $x_{t|t}$ and $x_{t+1|t}$ are feasible in real-time.

Figure 3 shows the realizations (black solid line), nowcasts (red dashed line) and forecasts (green dotted line) of the macroeconomic variables. The horizontal axis depicts the period during which the predictions are reported and realizations are observed.

[FIGURE 3 HERE]

[TABLE 2 HERE]

All three variables are volatile in the 1970s and early 1980s, but become increasingly tranquil during the Great Moderation period which ends with the Great Recession. Table 2 provides summary statistics. Interestingly, for GDP growth and the inflation rate the standard deviation of the forecasts is lower than the standard deviation of the realizations. Similarly, forecasts have a lower interquartile range and a lower kurtosis than the

⁶<https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/>

⁷We also considered industrial production growth as an alternative measure of economic activity. Using industrial production instead of GDP growth leads to very similar results in the subsequent analysis.

⁸We replace the missing observations for the first releases of Δgdp and inf in 1995Q4 with the corresponding values from the second releases.

⁹Note that this problem is less severe for the unemployment rate where the quarterly observations are based on data that is released on a monthly basis. For example, at the end of quarter t , unemployment figures for the first two months of quarter t are already available and only the figure for the last month is missing.

realizations. This may indicate that forecasters are ‘overconfident’ with respect to those two variables.¹⁰ Finally, forecasts are usually more persistent than realizations.

6 Empirical analysis

In this section, we discuss the main empirical results. Full-sample predictive regressions for the 5 and 49 industry portfolios are presented in Section 6.1. The Conrad and Schienle (2018) test is implemented in Section 6.2. Rolling-window estimates and an out-of-sample forecast evaluation are presented in Sections 6.3 and 6.4, respectively.

6.1 Predictive regressions based on realized volatility

In the first step, we discuss the ordinary least squares (OLS) estimates of the predictive regressions for realized volatility based on Eqn. (3).

For illustrative purposes, we begin by discussing the findings for the broad stock market and the 5 industry portfolios. The first double-column in Table 3 displays the results for the market, the other double-columns the estimates for the individual industries. In each row, we present the parameter estimate, $\hat{\theta}_i$, based on either (i) the realization, x_t , (ii) the nowcast, $x_{t|t}$, or (iii) the one-quarter-ahead forecast, $x_{t+1|t}$, of the respective macroeconomic variable.¹¹ In addition to the parameter estimates, we present the percentage increase in the R^2 (denoted by ΔR^2) relative to the AR(2) benchmark.

[TABLE 3 HERE]

In line with the previous literature, the realizations of the macroeconomic variables have no predictive power for future market volatility when controlling for past volatility. Moreover, as mentioned before, predictive regressions based on x_t are infeasible in real-time. Hence, we replace the realizations with the SPF nowcasts. However, none of the nowcasts significantly affect market volatility. Next, we consider the one-quarter-ahead forecasts of the macroeconomic variables. In this case, we obtain a negative and highly significant estimate of θ_m for GDP growth which is in line with the notion of a counter-cyclical behavior of volatility. The magnitude of the estimated coefficient is also economically significant: A one standard deviation increase in expected real GDP growth is associated with a predicted decline in future market volatility by 4.07% ($100 \cdot [\exp(\hat{\theta}_m \cdot \Delta x_{t+1|t}) - 1] = 100 \cdot [\exp(-0.0416 \cdot 1) - 1] = -4.07\%$). When including the

¹⁰This observation squares with the findings of Giordani and Söderlind (2003, 2006) and Clements (2014, 2016) that the SPF participants tend to be ‘overconfident’ in the sense that the ex-ante variance of the reported histogram is frequently too small compared to the ex-post variance derived from the historical time series of prediction errors.

¹¹Recall that we standardize each variable x prior to estimation. The reported coefficients and standard errors are the estimated ones times 100.

SPF expectations, $x_{t+1|t}$, the percentage increase in R^2 is roughly 2% for GDP growth.¹² In contrast, neither the inflation nor the unemployment expectations are found to be significant.

Our finding that realizations of GDP growth do not forecast stock market volatility are in line with the results in Paye (2012). The evidence that expectations regarding future developments of GDP growth are useful predictors for stock market volatility squares with the results in Campbell and Diebold (2009) and Conrad and Loch (2015).¹³

The results for the 5 industry portfolios are in line with those for the market. Again, we find that realizations and nowcasts of the macroeconomic variables are insignificant in essentially all cases. To the contrary, GDP growth expectations for $t + 1$ are significantly negative for four industry portfolios and have the strongest effect on the *manufacturing* industry. We also observe notable increases in the R^2 of the predictive regressions when adding $x_{t+1|t}$.¹⁴ For example, for one-quarter-ahead GDP growth forecasts the increase in the R^2 is 2.51% for the *consumer durables* sector. Thus, the predictive regressions for the industry portfolios confirm our results for the stock market, but also illustrate that the estimates of θ_i as well as the percentage increases in R^2 vary across industries.

To investigate the relation between macroeconomic conditions and industry-specific stock volatility on a more disaggregate level, we now turn to the 49 industry portfolios. To simplify the interpretation, the estimation results from the predictive regressions are presented graphically. The left panel of Figure 4 depicts the number of estimates of θ_i that are significantly different from zero at the 5% critical level for each macroeconomic variable $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$. The blue/red bars indicate significantly positive/negative estimates.

[FIGURE 4 HERE]

In line with the evidence from Table 3, we find that future volatility is almost always unrelated to the realizations of GDP growth. The association between realized volatility, inflation and the unemployment rate appears to be weak as well. The effect of inflation is significantly negative in only three out of the 49 industry portfolios and an increase in the unemployment rate tends to significantly increase future volatility in three industries. When using nowcasts instead of realizations, we observe a few more significant estimates for GDP growth as well as for inflation. In line with the results for the 5 industry portfolios, forecasts of GDP growth are a much stronger predictor of realized volatility. Expected GDP growth significantly predicts lower volatility in 24 industries. Interestingly, we observe that higher unemployment rate forecasts now predict decreasing realized volatility

¹²For reference, the goodness of fit from the AR(2) benchmark is 0.44 for the market portfolio.

¹³To the contrary, Paye (2012) uses 6- to 12-months GDP growth forecasts from the Livingston Survey and finds no evidence of predictive power of the forecasts.

¹⁴The R^2 from the AR(2) benchmark range from 0.32 (*healthcare*) to 0.54 (*business equipment*).

in four industries. We will discuss and explain this switch in signs in detail in Section 6.3, which presents rolling-window estimates of the predictive regressions.

The panels in Figure 5 depict the percentage improvement in the goodness of fit compared to the baseline AR(2) model, ΔR^2 , when including either the realization (horizontal axis) or the forecast (vertical axis) of the respective macroeconomic variable as a predictor in Eqn. (3).¹⁵ The R^2 from the AR(2) benchmark range from 0.26 (*medical equipment*) to 0.69 (*computer software*).¹⁶ Red dots indicate that in the underlying regression, θ_i is significantly different from zero at the 5% level either for x_t , $x_{t+1|t}$, or both.

[FIGURE 5 HERE]

In line with our previous considerations, Figure 5 clearly shows that the one-step-ahead SPF forecasts of GDP growth lead to higher percentage increases in R^2 than the corresponding realizations. The largest percentage increase in R^2 is observed for the *ships* industry (9.84%). For inflation, forecasts as well as realizations lead to percentage increases of comparable size. In contrast, the evidence for the unemployment rate is mixed. For some industries, we observe the strongest increases for the realizations (e.g., *medical equipment*: 6.99%) while in other industries for the forecasts (e.g., *retail*: 3.10%).

In sum, our results show that forecasts of GDP growth are a strong predictor of future volatility in roughly 50% of the industry portfolios. The size of the estimated effects as well as the percentage change in the goodness-of-fit as compared to the AR(2) benchmark suggest that the increase in predictive ability is economically significant. In Sections 6.2 and 6.3, we provide explanations for why the results for inflation and unemployment forecasts appear to be more modest. In particular, we show that for these two variables the signs of the effects change over time and, hence, full sample regressions may be misleading.

6.2 Volatility-adjusted realized volatility

The literature on component models suggests that macroeconomic conditions are most closely related to the long-term component of volatility. Realized volatility can be considered a noisy proxy for this latent long-term component. In the following, we explain why predictive regressions based on realized volatility suffer from measurement error and propose a procedure to overcome this problem.

Based on the representation in Eqn. (1), Engle and Rangel (2008) and Engel et al. (2013) suggest that daily unexpected returns can be modeled as

$$\varepsilon_{i,d,t+1}^{div} - \varepsilon_{i,d,t+1}^{ret} = \varepsilon_{i,d,t+1} = \sqrt{\tau_i(\mathbf{s}_{i,t+1})} h_{i,d,t+1} z_{i,d,t+1}, \quad (7)$$

¹⁵We have also considered the improvement in the goodness of fit for the nowcasts. A detailed account is omitted here for brevity.

¹⁶The (financial) *trading* sector, which may be of particular interest, has a benchmark R^2 of 0.67.

where $z_{i,d,t+1}$ represents (industry-specific) news and $\tau_i(\mathbf{s}_{i,t+1})h_{i,d,t+1}$ is the time-varying impact multiplier, which consists of two multiplicative components. The $\tau_i(\mathbf{s}_{i,t+1})$ component depends on low-frequency state variables, $\mathbf{s}_{i,t+1}$, and changes at the quarterly frequency only, while $h_{i,d,t+1}$ represents day-to-day changes in the impact multiplier. Following Engle and Rangel (2008), we refer to $\tau_i(\mathbf{s}_{i,t+1})$ and $h_{i,d,t+1}$ as the long- and short-term volatility component, respectively. Naturally, $\mathbf{s}_{i,t+1}$ depends on variables that proxy the state of the macroeconomy. As discussed in Section 3, we might expect that, for example, the same piece of news has a stronger effect in a recession than in an expansion. Alternatively, $\sqrt{h_{i,d,t+1}}z_{i,d,t+1}$ can also be viewed as representing news with time-varying intensity $h_{i,d,t+1}$, where $h_{i,d,t+1}$ follows a GARCH (or some other conditionally heteroskedastic) process.

If Eqn. (7) holds, the predictive regression in Eqn. (3) with $RV_{i,t+1}$ as the volatility proxy can be interpreted as the linear projection of

$$\ln(RV_{i,t+1}) = \frac{1}{2} \ln(\tau_i(\mathbf{s}_{i,t+1})) + \frac{1}{2} \ln \left(\sum_{d \in t+1} h_{i,d,t+1} z_{i,d,t+1}^2 \right) \quad (8)$$

on a constant and $\mathbf{s}_{i,t+1} = (\ln(RV_{i,t}), \ln(RV_{i,t-1}), x)'$. While the first term in Eqn. (8) depends on x , the second term depends on the sum of a squared daily GARCH process. Thus, as discussed in Engel et al. (2013) and Conrad and Schienle (2018), the dependent variable, $\ln(RV_{i,t+1})$, is a noisy proxy for the variable of interest, $\ln(\tau_i(\mathbf{s}_{i,t+1}))$. Clearly, the presence of the strongly persistent measurement error, $\ln(\sum_{d \in t+1} h_{i,d,t+1} z_{i,d,t+1}^2)$, will tend to mask the existence of a relationship between long-term volatility and x .

Conrad and Schienle (2018) propose a test for the existence of a time-varying long-term component that is driven by x . In their framework, $\tau_{i,t} = \tau_i(x)$, and the null hypothesis is $H_0 : \tau_{i,t} = \tau_i$, where τ_i would be an industry-specific constant. The actual test can be implemented by a two-step procedure. In the first step and under the null hypothesis, we estimate the following GJR-GARCH specification for each industry:

$$r_{i,d,t} = \mu_i + \varepsilon_{i,d,t}, \quad (9)$$

$$\varepsilon_{i,d,t} = \sqrt{h_{i,d,t}} z_{i,d,t}, \quad (10)$$

$$h_{i,d,t} = \omega_i + (\alpha_i + \gamma_i \cdot \mathbb{1}(\varepsilon_{i,d-1,t} < 0)) \varepsilon_{i,d-1,t}^2 + \delta_i h_{i,d-1,t}, \quad (11)$$

where $z_{i,d,t} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$. In this model, τ_i is given by $\omega_i / (1 - \alpha_i - \delta_i - \gamma_i/2)$. Based on the parameter estimates, we obtain the volatility-adjusted residuals,

$$\hat{\varepsilon}_{i,d,t} = \frac{\hat{\varepsilon}_{i,d,t}}{\sqrt{\hat{h}_{i,d,t}}}, \quad (12)$$

and construct the volatility-adjusted realized volatility in sector i and quarter t as

$$\widetilde{RV}_{i,t} = \sqrt{\frac{\hat{\omega}_i}{1 - \hat{\alpha}_i - \hat{\delta}_i - \hat{\gamma}_i/2}} \cdot \sqrt{\sum_{d \in t} (\hat{\varepsilon}_{i,d,t})^2}, \quad (13)$$

where the first term is a scaling factor that ensures that $\widetilde{RV}_{i,t}$ is measured on the same scale as $RV_{i,t}$. In the second step, we estimate the predictive regression given in Eqn. (3) but with $\widetilde{RV}_{i,t+1}$ instead of $RV_{i,t+1}$ on the left and right hand side. As before, we test the null hypothesis $H_0 : \theta_i = 0$. As shown in Conrad and Schienle (2018), the new predictive regression is much less prone to measurement error and, hence, more powerful.

Table 1 shows that for the market and the 5 industry portfolios the average of the volatility-adjusted realized volatility is close to the mean of the realized volatility. Figure 6 plots the annualized time series of the volatility-adjusted realized volatilities, $\widetilde{RV}_{i,t}$ (red lines), along with the annualized estimates of $\sqrt{\tau_i}$ (black lines).

[FIGURE 6 HERE]

Under the null hypothesis, the volatility-adjusted residuals $\varepsilon_{i,d,t}/\sqrt{h_{i,d,t}}$ and, hence, $\sum_{d \in t} \varepsilon_{i,d,t}^2/h_{i,d,t}$ are *i.i.d.* and, therefore, unpredictable using past information. Although Figure 6 shows that $\widetilde{RV}_{i,t}$ fluctuates around $\sqrt{\hat{\tau}_i}$, there are persistent deviations of $\widetilde{RV}_{i,t}$ from $\sqrt{\hat{\tau}_i}$. The Conrad and Schienle (2018) test checks whether these movements can be explained by changes in macroeconomic conditions.

The right panel in Figure 4 shows the number of significantly positive/negative estimates of θ_i in the 49 industry portfolios when $RV_{i,t+1}$ is replaced with $\widetilde{RV}_{i,t+1}$.¹⁷ The figure shows that for almost all choices of $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$, we now observe more rejections of the null hypothesis than when using $RV_{i,t+1}$ as the volatility proxy (left panel). For example, for expected GDP growth we observe 24 rejections when using $RV_{i,t+1}$ as the volatility proxy whereas we observe 38 rejections in the case of $\widetilde{RV}_{i,t+1}$. Interestingly, when using $\widetilde{RV}_{i,t+1}$, the null hypothesis that x_t does not predict volatility is rejected for 14 industry portfolios for realized GDP growth, while we hardly observe any rejections in those cases when $RV_{i,t+1}$ is considered. In contrast, for the inflation rate there is no such effect. Finally, when looking at the unemployment rate, we find 26 rejections for x_t in the predictive regression based on $\widetilde{RV}_{i,t+1}$ but only three rejections in the regression based on $RV_{i,t+1}$. In line with a counter-cyclical behavior of stock volatility, the estimates suggest that the unemployment rate is positively related to long-term industry volatility.

In summary, we find that predictive regressions based on volatility-adjusted realized volatility lead to much stronger rejections of the null hypothesis that macroeconomic conditions do not affect industry-level volatility. Still, forecasts of GDP growth are most

¹⁷For completeness, Table 8 in the Appendix presents the parameter estimates for the market and the 5 industry portfolios.

important, while for the unemployment rate the realizations are more relevant. We conclude that there is a severe problem with measurement error in the standard predictive regression with $RV_{i,t+1}$ as the proxy for long-run volatility. The measurement error tends to mask an existing relationship between macroeconomic conditions and volatility. To facilitate the comparison with previous studies, we report the results for both measures of volatility in the next subsection.

6.3 Intertemporal stability of the macro-volatility nexus

Next, we investigate the stability of the relationship between macroeconomic conditions and financial volatility over time. This is accomplished by estimating a rolling-window version of Eqn. (3) for a fixed sample size of 15 years (i.e., 60 quarterly observations). The results over the full sample period are presented in Figures 7 to 9 for Δgdp , inf and Δune , respectively. The employed industry-specific volatility proxy is either realized volatility, $RV_{i,t+1}$ (left), or volatility-adjusted realized volatility, $\widetilde{RV}_{i,t+1}$ (right). We denote by $\theta_{i,t}$ the estimated coefficient on x in the 15-year sample that ends at the respective point in time given on the horizontal axis, i.e., quarter t . In each panel, the 49 industry portfolios are depicted on the vertical axis (again sorted by their systematic risk: As can be seen in Table 7 in the Appendix, industry ‘1’ (*precious metals*) has the lowest and industry ‘49’ (*business services*) the highest SR_i). A blue/red cross indicates that for the specific industry the estimate of $\theta_{i,t}$ is significantly positive/negative (at the 5% level). Insignificant estimates are not presented. The bold black lines indicate for how many industries the estimates of $\theta_{i,t}$ in each window are significant.

[FIGURES 7 TO 9 HERE]

Figure 7 presents the results for GDP growth realizations (top), nowcasts (middle) and one-step-ahead forecasts (bottom). The figures clearly show that the nowcasts and one-step-ahead forecasts are more often significant than the realizations. In addition, they reveal that the relevance of GDP growth expectations has changed over time. GDP growth nowcasts/forecasts are statistically significant for almost all industries with a negative estimate of $\theta_{i,t}$ for subsamples ending before 1995. Note that for those early subsamples the average systematic risk was high (see Figure 2). For samples that end after 1995, the estimates of $\theta_{i,t}$ become insignificant in most cases and for a few industries even positive for samples that end around 2007. The latter effect is visible for $RV_{i,t+1}$ but hardly for $\widetilde{RV}_{i,t+1}$. For more recent subsamples, the estimated coefficients are again significantly negative but in fewer industries than at the beginning of our sample. Note that the predictive regressions based on $\widetilde{RV}_{i,t+1}$ lead to more rejections of the null hypothesis than regressions based on $RV_{i,t+1}$. Again, this confirms our argument that $\widetilde{RV}_{i,t+1}$ accurately proxies the unobservable long-term volatility whereas $RV_{i,t+1}$ is contaminated by short-term movements in volatility. The observation that GDP growth was a more powerful predictor of volatility during the seventies and eighties was already made in Paye (2012)

for the broad stock market. However, the finding that the relevance of GDP growth forecasts has increased recently is new. The recent samples with significant estimates include the Great Recession while the early samples include the oil price shocks of the turbulent 1970s. For both phases, it is reasonable to assume that decreasing GDP growth forecasts/realizations (see Figure 3) went along with increasing cash flow uncertainty and, hence, more volatile returns.

As expected, we observe a time-varying relation for inflation in Figure 8. For quite a few industries, realizations/nowcasts/forecasts of higher inflation rates tend to increase stock volatility in subsamples that end before the mid-1990s and also in very recent samples (particularly in regressions based on $RV_{i,t+1}$). For the turbulent 1970s, our finding is consistent with the stagflation argument of David and Veronesi (2013) and in the 1980s with a hawkish monetary policy during the Volcker disinflation and thereafter. Similarly, during recent years, forecasts of higher inflation rates are likely to increase the probability of a monetary policy tightening and, hence, – via the discount effect – predict higher volatility.

In sharp contrast, for samples that end just before the financial crisis of 2007/8, the estimates of $\theta_{i,t}$ for inflation are significantly negative for many industries. That is, before the financial crisis higher inflation rates were associated with lower industry volatility. The empirical results in David and Veronesi (2013) suggest that the 2000s are characterized by deflationary fears and, therefore, higher inflation expectations are good news and accompanied with lower stock volatility.

The results for the unemployment rate from Figure 9 are of particular interest. First, we observe a positive effect of the realizations for subsamples that end before 1995. Those subsamples include data from the late 1970s/early 1980s and the estimated effect is in line with the one that we obtain for GDP growth. Higher rates of unemployment signal economic downturns and go along with high cash flow uncertainty as well as higher stock volatility. Again, the effect is most clearly visible in regressions based on $\widetilde{RV}_{i,t+1}$. Second, for samples that end after the 2000s unemployment rate forecasts have a negative effect in many industries in regressions based on $RV_{i,t+1}$. The latter effect is in line with the view that the expectation of an increasing unemployment rate creates the expectation of a more accommodative monetary policy which is good news for financial markets and, hence, stock volatility declines (see Boyd et al., 2005). Thus, while realizations of higher unemployment rates typically go along with increasing long-run volatility, short-run volatility may decline in response to the expectation of higher unemployment rates.

For each choice of x , Table 4 lists the five industry portfolios with the highest number of significantly negative/positive estimates of $\theta_{i,t}$ based on the rolling-window regressions with $RV_{i,t+1}$ as the volatility proxy.¹⁸ The numbers in parentheses indicate how many of

¹⁸For completeness, the rankings for $\widetilde{RV}_{i,t+1}$ are reported in Table 9 in the Appendix.

the 137 estimates are significantly negative/positive at the 5% critical level.

[TABLE 4 HERE]

For example, for each choice of x we obtain the highest number of significantly negative estimates of $\theta_{i,t}$ in the *ships* industry in the case of realized GDP growth. The number of significant estimates increases further when using the nowcasts or forecasts instead of the realizations. This example serves to illustrate that the same industries gain significance when replacing the realizations with the forecasts.

6.4 Out-of-sample predictive ability

While the analysis in Sections 6.1 and 6.2 was purely in-sample, we can use the rolling-window estimates from the previous subsection for an out-of-sample evaluation of the predictive ability of the macroeconomic variables. Since we are interested in predicting the actual level of volatility, we exclusively focus on realized volatility for the analysis presented in this subsection. Based on the rolling-window regressions for $RV_{i,t+1}$ in the left panels of Figures 7 to 9, we calculate one-quarter-ahead out-of-sample predictions. We denote the prediction from the AR(2) benchmark model as $\widehat{\ln(RV)}_{i,t+1|t}^{(AR)}$. For each AR(2) model that is augmented by the regressor x , the prediction is denoted by $\widehat{\ln(RV)}_{i,t+1|t}^{(x)}$, where $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$. The out-of-sample mean squared prediction errors are calculated as

$$MSE_{i,AR} = \frac{1}{K} \sum_{k=1}^K \left(\widehat{\ln(RV)}_{i,k+1|k}^{(AR)} - \ln(RV)_{i,k+1|k} \right)^2 = \frac{1}{K} \sum_{k=1}^K e_{i,k,AR}^2 \quad (14)$$

and

$$MSE_{i,x} = \frac{1}{K} \sum_{k=1}^K \left(\widehat{\ln(RV)}_{i,k+1|k}^{(x)} - \ln(RV)_{i,k+1|k} \right)^2 = \frac{1}{K} \sum_{k=1}^K e_{i,k,x}^2, \quad (15)$$

where K denotes the number of out-of-sample forecasts. We denote the difference in the squared forecast errors from the AR(2) and the model augmented with x by

$$\Delta SE_{i,k,x} = e_{i,k,AR}^2 - e_{i,k,x}^2. \quad (16)$$

We first consider the Clark and West (2007) test. This one-sided test checks for the equality of the population MSEs of the benchmark AR(2) and the model that is augmented by x . The test can be implemented by regressing

$$\Delta SE_{i,k,x} + \left(\widehat{\ln(RV)}_{i,t+1|t}^{(AR)} - \widehat{\ln(RV)}_{i,t+1|t}^{(x)} \right)^2 \quad (17)$$

on a constant and testing for its significance using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. The second term in Eqn. (17) adjusts for the larger noise associated with $\widehat{\ln(RV)}_{i,t+1|t}^{(x)}$ (compared to $\widehat{\ln(RV)}_{i,t+1|t}^{(AR)}$) due to the estimation of the additional parameter θ_i in the augmented model. The upper panel of Table 5 presents a summary of the test decisions. For each variable $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$, the table displays the number of industries for which the model including x significantly improves upon the AR(2) benchmark at the 5% and 10% significance level.

[TABLE 5 HERE]

The results indicate that the population MSE of the model that includes x is significantly lower than the population MSE of the benchmark AR(2) model in most of the 49 industries. For example, for the unemployment rate the Clark and West (2007) test rejects the null hypothesis for 44/45/48 industries (at the 10% critical level) when using the realizations/nowcasts/forecasts as the predictor.

Second, we employ the Giacomini and White (2006) test of superior forecast accuracy. Now, the null hypothesis is that both sample MSEs are equal. The Giacomini and White (2006) test is two-sided and can be implemented by regressing $\Delta SE_{i,k,x}$ on a constant and testing for its significance using HAC standard errors.¹⁹ Again, Table 5 shows the number of rejections in favor of the model that is augmented by x .²⁰ The table shows that out-of-sample macroeconomic variables are useful predictors of volatility. For example, for the unemployment rate the Giacomini and White (2006) test rejects the null hypothesis for 26/19/25 industries (at the 10% critical level) when using the realizations/nowcasts/forecasts as the predictor. Again, it is important to highlight that the realizations are not available in real-time. Hence, only the forecasting gains from the nowcasts and forecasts can be realized in real-time.

Following Campbell and Thompson (2008), we calculate the out-of-sample R^2 ($R_{i,x,OOS}^2$) for each industry as

$$R_{i,x,OOS}^2 = 1 - \frac{MSE_{i,x}}{MSE_{i,AR}}. \quad (18)$$

The out-of-sample R^2 provides a gauge of the economic significance of the improvements over the AR(2) model. Figure 10 shows scatterplots of $R_{i,x,OOS}^2$ (in percent) for the SPF predictions versus $R_{i,x,OOS}^2$ (in percent) for the realizations based on the three macro variables. The left panels compare the models based on nowcasts and realizations and the right panels the models based on forecasts and realizations. Points highlighted in red indicate that the MSE for at least one of the models including x is significantly lower than for the AR(2) model at the 5% critical level.

¹⁹We also considered the Giacomini and White (2006) test based on the QLIKE loss function instead of the MSE and obtained qualitatively similar results.

²⁰For none of the tests, the null hypothesis is rejected in favor of the benchmark model.

[FIGURE 10 HERE]

First, the figure shows that for almost all industries the mean squared prediction error based on the predictive regression including x is lower than the mean squared prediction error of the AR(2) benchmark model, i.e., $R_{i,x, OOS}^2 > 0$. Second, for GDP growth the forecasting gains of the nowcasts/forecasts are often higher than or comparable to the goodness-of-fit gains of the realizations. For inflation and the unemployment rate the realizations generate the largest out-of-sample gains. Both findings are broadly in line with our discussion of the Clark and West (2007) and Giacomini and White (2006) tests.

Finally, we investigate how the forecasting gains of the predictive regressions including x relative to the benchmark AR(2) evolve over time. Following Paye (2012), we calculate the cumulated $\Delta SE_{i,k,x}$, i.e.,

$$cum\Delta SE_{i,\tilde{t},x} = \sum_{k=1}^{\tilde{t}} \Delta SE_{i,k,x}, \quad (19)$$

for each industry i and $\tilde{t} = 1, \dots, K$. For each variable, Figure 11 shows the median of the cumulated $\Delta SE_{i,k,x}$ over the 49 industries as well as the 20% and 80% percentiles.

[FIGURE 11 HERE]

The median cumulated $\Delta SE_{i,k,x}$ is upward trending for all variables, i.e., predictive regressions that are augmented with a macroeconomic variable outperform the benchmark AR(2) essentially over the full out-of-sample period. For expected GDP growth the largest gains are realised during the onset of the Great Recession. Similarly, for all measures of unemployment the largest forecasting gains materialize in the Great Recession and the period thereafter. The biggest gains for inflation are observed for forecasts that are based on rolling-window estimates that do not include the 1970s. That is, when forecasts are based on rolling-window estimates during which the Fed followed a strong inflation objective, the inflation augmented model clearly dominates the benchmark. The fact that the strongest upward trend is observed for realized inflation confirms our previous findings from the Giacomini and White (2006) tests.²¹

7 Extensions and Robustness

7.1 Rolling-window regressions for the stock market

Most of the previous literature has focused on predictive regressions for the broad stock market. To facilitate comparison, we repeat our analysis from Section 6.3 for the stock

²¹In unreported tests, we have analyzed whether the forecasting gains are evenly spread across the 49 sectors. For inflation and unemployment, the Gini coefficients were close to 0.2. For GDP growth we observed a higher inequality of the forecasting gains with Gini coefficients around 0.3.

market. Figures 12 and 13 depict the estimates of $\theta_{m,t}$ (times 100) when regressing $\ln(RV_{m,t+1})$ or $\ln(\widetilde{RV}_{m,t+1})$ on their own lags and the macroeconomic explanatory variable x . As before, each estimate stems from a rolling-window regression with a length of 15 years. Significantly positive/negative estimates are indicated by blue/red dots.

[FIGURES 12 AND 13 HERE]

The plots confirm our previous evidence from the 49 industry portfolios. The figures also illustrate why full sample estimates are likely to yield insignificant estimates: The predictive power of the macroeconomic variables is concentrated around specific episodes and, again, we observe switches in the signs of the estimated coefficients. In particular, note the strong relation between expected GDP growth and $\widetilde{RV}_{m,t+1}$.

7.2 Idiosyncratic volatility

The CAPM model in Eqn. (6) (with $\mu_i = 0$) implies that realized industry volatility can be decomposed into the sum of the squared industry Beta times the realized volatility of the market and idiosyncratic volatility. The findings in Section 7.1 suggest that the effect of macroeconomic variables on industry volatility via market volatility is incomplete. Macroeconomic conditions could affect industry volatility also via idiosyncratic volatility. In the following, we investigate this channel more closely. Based on the residuals from Eqn. (6), $\hat{\eta}_{i,d,t} = r_{i,d,t} - \hat{\mu}_i - \hat{\beta}_i r_{m,d,t}$, quarterly idiosyncratic volatility in industry i is calculated as

$$IVol_{i,t} = \sqrt{\sum_{d \in t} \hat{\eta}_{i,d,t}^2}. \quad (20)$$

Following the approach in Section 6.2, we also construct a measure of volatility-adjusted idiosyncratic volatility. Using Eqn. (6) as the mean equation, we obtain

$$\widetilde{IVol}_{i,t} = \sqrt{\frac{\hat{\omega}_i}{1 - \hat{\alpha}_i - \hat{\delta}_i - \hat{\gamma}_i/2}} \cdot \sqrt{\sum_{d \in t} (\hat{\eta}_{i,d,t}^2 / \hat{h}_{i,d,t})}. \quad (21)$$

Summary statistics for both measures of idiosyncratic volatility for the market and the 5 industry portfolios are reported in Table 1. Below, we consider the 49 industry portfolios. Our findings for $IVol_{i,t}$ and $\widetilde{IVol}_{i,t}$ are presented in Figure 14. The improvements in the goodness of fit as compared to predictive regressions based on the AR(2) benchmark in the case of $IVol_{i,t}$ are depicted in Figure 15.

[FIGURES 14 AND 15 HERE]

Interestingly, the number of significant estimates of θ_i is only marginally smaller than in Figure 5 for realized volatility. Thus, the empirical results suggest that macroeconomic conditions affect industry-specific volatility also via idiosyncratic volatility. Engle and

Rangel (2012) question the standard CAPM assumption that $\mathbf{Cov}(\eta_{i,d,t}, \eta_{j,d,t}) = 0$ for $i \neq j$ and propose the Factor-Spline-GARCH model which allows for comovements in $\eta_{i,d,t}$ and specifies the conditional variance of $\eta_{i,d,t}$ as a two component process. Our findings suggest that $\mathbf{Cov}(\eta_{i,d,t}^2, \eta_{j,d,t}^2) \neq 0$ for $i \neq j$ and that the idiosyncratic long-term volatilities in different industries are driven by the same macroeconomic variables.

7.3 Controlling for other predictors

In this section, we investigate whether the predictive power of the macroeconomic variables remains intact when controlling for other variables that are frequently associated with financial volatility in both the theoretical and empirical literature (see, for example, Christiansen et al., 2012, David and Veronesi, 2013, and Mele, 2007). That is, we now ask whether the macroeconomic variables contain information about future volatility beyond that contained in variables that have been shown to predict volatility (and/or returns). This question is of particular interest because the previous literature has found that financial variables (such as the dividend-price ratio) predict volatility while macroeconomic variables “hardly show up as important predictors” (Christiansen et al., 2012, p.958). We thus employ an extended specification of the predictive regression in Eqn. (3),

$$\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \lambda_i w_t + \xi_{i,t+1}, \quad (22)$$

where w_t is one of the following variables: First, we consider financial predictors such as the (log) dividend-price ratio (*dpr*) and the cyclically adjusted (log) price-earnings ratio (*per*). The data are taken from Robert Shiller’s website.²² In addition, we consider the term spread (*ts*), which is defined as the difference between 10-year government bonds and 1-year T-bill rates.²³ Second, we account for the level of uncertainty by including the News Implied Volatility Index (NVIX, *nvix*) proposed by Manela and Moreira (2017) which measures (investor) uncertainty based on newspaper articles.²⁴ The NVIX is based on machine learning techniques and resembles the behavior of the Volatility Index released by the Chicago Board Options Exchange which is only available from 1990 onwards. Third, we use the quarterly consumption-wealth ratio (*cay*) of Lettau and Ludvigson (2001), which is defined as the residual from an estimated cointegration relationship between aggregate consumption, wealth and labor income, as well as the Index of Consumer Sentiment (*ics*) from the Michigan Survey of Consumers.^{25,26} Data on *nvix* are available through 2016Q1. All other variables are observed throughout the entire sample period.

²²<http://www.econ.yale.edu/~shiller/data.htm>

²³<https://research.stlouisfed.org/pdl/183>

²⁴<http://apps.olin.wustl.edu/faculty/manela/data.html>

²⁵We use an updated version of the data used in Goyal and Welch (2008), which is available from Amit Goyal’s homepage at <http://www.hec.unil.ch/agoyal/>.

²⁶<http://www.sca.isr.umich.edu/charts.html>

We first check whether the additional variables have predictive power for volatility. To this end, we estimate a version of Eqn. (22) that omits the macro variable x . Figure 16 shows how often these variables significantly predict volatility when either $RV_{i,t+1}$ (left panel) or $\widetilde{RV}_{i,t+1}$ (right panel) is used as the volatility proxy.

[FIGURE 16 HERE]

Clearly, the dividend-price ratio, the price-earnings ratio as well as the NVIX have the highest predictive ability. The present value model introduced in Section 3 implies that a high dividend-price ratio today forecasts higher excess returns in the future.²⁷ This is consistent with our finding of a negative effect of the dividend-price ratio on future stock volatility. In contrast, a high price-earnings ratio predicts increasing stock volatility. This result is in line with the findings of Campbell et al. (2018). Because a high price-earnings ratio is empirically found to predict lower returns in the future, this result is again consistent with the present value model. Our finding is also in line with the view that an extreme price-earnings ratio indicates an overvalued market and a subsequent price decline (see Campbell and Shiller, 2001). Similarly, a higher NVIX predicts higher stock volatility in the future. This result squares with the findings in Mitnik et al. (2015) or Conrad and Kleen (2018), among others. The term spread is well known to predict output growth (see, for example, Estrella and Mishkin, 1997, 1998) and, hence, is negatively related to volatility.

As an intermediate step, we check to what extent the additional predictors are related to expected macroeconomic conditions. We thus regress the forecasts, $x_{t+1|t}$, of the macroeconomic variables on the additional predictors w_t . The results are reported in Table 6.²⁸

[TABLE 6 HERE]

Table 6 shows very reasonable relationships. For example, a decrease in the term spread is accompanied by lower growth forecasts and higher inflation forecasts. The former result is in line with the empirical evidence that an inverted yield curve predicts future recessions (see Estrella and Mishkin, 1998). The latter result is consistent with the view that the term spread contains information about the stance of monetary policy (see Estrella and Mishkin, 1997): A central bank responds to increasing inflation expectations by raising short-term interest rates which reduces the term spread.²⁹ Further, a higher dividend-price ratio is associated with the expectation of more economic activity and higher rates

²⁷Alternatively, a high dividend-price ratio today could forecast lower dividend payments in the future. However, the empirical evidence in Cochrane (1992), among others, suggests that historically the variation in the dividend-price ratio almost exclusively relates to changes in expected excess returns.

²⁸Because the dividend-price ratio and the price-earnings ratio are highly correlated (-0.96), we include them separately in order to avoid multicollinearity.

²⁹As discussed in Estrella and Mishkin (1997), the latter effect depends on the credibility of the central bank.

of inflation. The positive relation between GDP growth expectations and ics is in line with the finding in Barsky and Sims (2012) that innovations in consumer confidence contain information about future economic activity. Note that the additional predictor variables explain at maximum 52% of the variation in GDP growth and unemployment rate forecasts. However, up to 82% of the variation in the inflation forecasts can be explained by the additional predictor variables, whereby the price-earnings ratio and the term spread are the dominant drivers of expected inflation.

Next, we rerun the predictive regressions from Sections 6.1 and 6.2 and include both x as well as the additional predictors (one at a time) as described in Eqn. (22). The plots in Figures 17 and 18 show the outcomes conditional on the six predictor variables (using either $RV_{i,t+1}$ or $\widetilde{RV}_{i,t+1}$ as the proxy variable).

[FIGURES 17 AND 18 HERE]

Interestingly, the predictive power of the macroeconomic variables often appears to further increase when including the control variables. For example, when controlling for the dividend-price ratio, the forecasts of GDP growth are significantly related to $RV_{i,t+1}$ in 41 cases in Figure 17 compared to only 24 cases in Figure 4 (left panel). A simple explanation could be that controlling for the additional predictors, we obtain more precise estimates of the effects of the macroeconomic variables.

There are only two major changes to our previous findings. First, in many industries realizations, nowcasts and forecasts of the inflation rate have a positive effect when controlling for the dividend-price ratio or the price-earnings ratio. An explanation could be that – when holding the dividend-price/price-earnings ratio constant – an increase in inflation is very likely to be associated with a decreasing term spread. Because a decreasing term spread often forecasts a recession, investors may fear a stagflation period which goes along with higher stock volatility. Alternatively, a lower term spread could be the result of (the expectation of) tighter monetary policy and, hence, aligned with higher volatility due to the discount rate effect. To the contrary, when controlling for the term spread, all measures of inflation significantly reduce volatility in around 20 industries. Holding the term spread fixed, inflation is likely to comove with the dividend-price/price-earnings ratio. Higher inflation in combination with a higher dividend-price ratio/a lower price-earnings ratio goes along with decreasing stock volatility due to lower earnings uncertainty. Second, the realized unemployment rate is positively and strongly related to financial volatility when controlling for the dividend-price/price-earnings ratio. Since neither the dividend-price nor the price-earnings ratio are significantly related to the realized unemployment rate (estimates not presented), it appears that controlling for those variables simply reduces the standard error of the estimated effect of the realized unemployment rate.

In summary, the macroeconomic variables' predictive ability does not fade away once we control for other standard predictors of returns and volatility. In many cases, the predictive power even increases.

7.4 Portfolios formed on size and book-to-market

We also investigate whether our results extend to other types of portfolios. Instead of the 49 industry portfolios, we consider the volatility of 100 portfolios formed on size and book-to-market. The return data are again obtained from the Fama-French Data Library. Figure 19 shows the results for full sample predictive regressions with $RV_{i,t}$ (left panel) and $\widetilde{RV}_{i,t}$ (right panel) as the employed proxy for volatility. As for the 49 industry portfolios, in the full sample forecasts of GDP growth and inflation are much more often significant than the corresponding realizations. The opposite is true for the unemployment rate. Again, we find that in predictive regressions based on $\widetilde{RV}_{i,t}$ the realizations and nowcasts are more frequently significant than in regressions based on $RV_{i,t}$. This underlines again that $RV_{i,t}$ is a noisy measure of long-term volatility.

[FIGURES 19 AND 20 HERE]

Figure 20 shows the percentage increases in R^2 as compared to the pure AR(2). As in Figure 5, we compare forecasts and realizations and use $RV_{i,t}$ as the volatility proxy. The results strongly support our previous findings. For GDP growth and inflation the strongest percentage increases are observed for the forecasts rather than the realizations. Again, for the unemployment rate the realizations are more important.

Thus, the results for the industry portfolios directly extend to portfolios formed on size and book-to-market. We also considered portfolios formed on size and either operating profitability or investment and, again, obtained very similar results (not reported).

7.5 Multi-step-ahead forecasts

Besides the one-quarter-ahead forecasts, $x_{t+1|t}$, the SPF also contains forecasts for two- and three-quarters-ahead (i.e., $x_{t+2|t}$ and $x_{t+3|t}$).³⁰ Since we exclusively focused on $x_{t+1|t}$ so far, checking for the predictive power of $x_{t+2|t}$ and $x_{t+3|t}$ appears appropriate. Figure 21 shows the number of significant θ_i -estimates in the 49 industry portfolios for all three forecasts when either using $RV_{i,t+1}$ (left panel) or $\widetilde{RV}_{i,t+1}$ (right panel) as the proxy variable.

[FIGURE 21 HERE]

The figure clearly shows that for GDP growth the one-quarter-ahead forecasts are most useful. For inflation and unemployment the evidence is more mixed. Nevertheless, Figure 21 again confirms the view that forecasts of macroeconomic variables are powerful predictors of future stock volatility.

³⁰The SPF also provides four-quarters-ahead forecasts, but – in particular at the beginning of the sample period – there are quite a few missing observations. Therefore, we refrain from using those.

8 Conclusion

We reconsider the question to what extent macroeconomic variables have predictive power for future stock volatility in predictive regressions when controlling for past volatility. The econometric framework of our paper is closest to Paye (2012, p.545) who concludes that “only modest forecasting gains are possible” because “volatility comoves tightly with the business cycle and lagged volatility itself contains a wealth of information about business conditions”. In contrast, our results suggest that macroeconomic variables contain information about future volatility that is complementary to the information included in lagged volatility. By considering 49 industry portfolios, we show that higher forecasts of GDP growth decrease industry-level volatility in many sectors in subsamples that include the 1970s and early 1980s. For subsamples that include the period before the Great Recession or the most recent years, realizations of inflation and realizations/forecasts of the unemployment rate are powerful predictors. Our findings highlight that the relation between macroeconomic conditions and stock volatility changes over time and also varies across industries. This may explain the inconclusive results from the previous literature which usually focused on the aggregate stock market.

9 Acknowledgements

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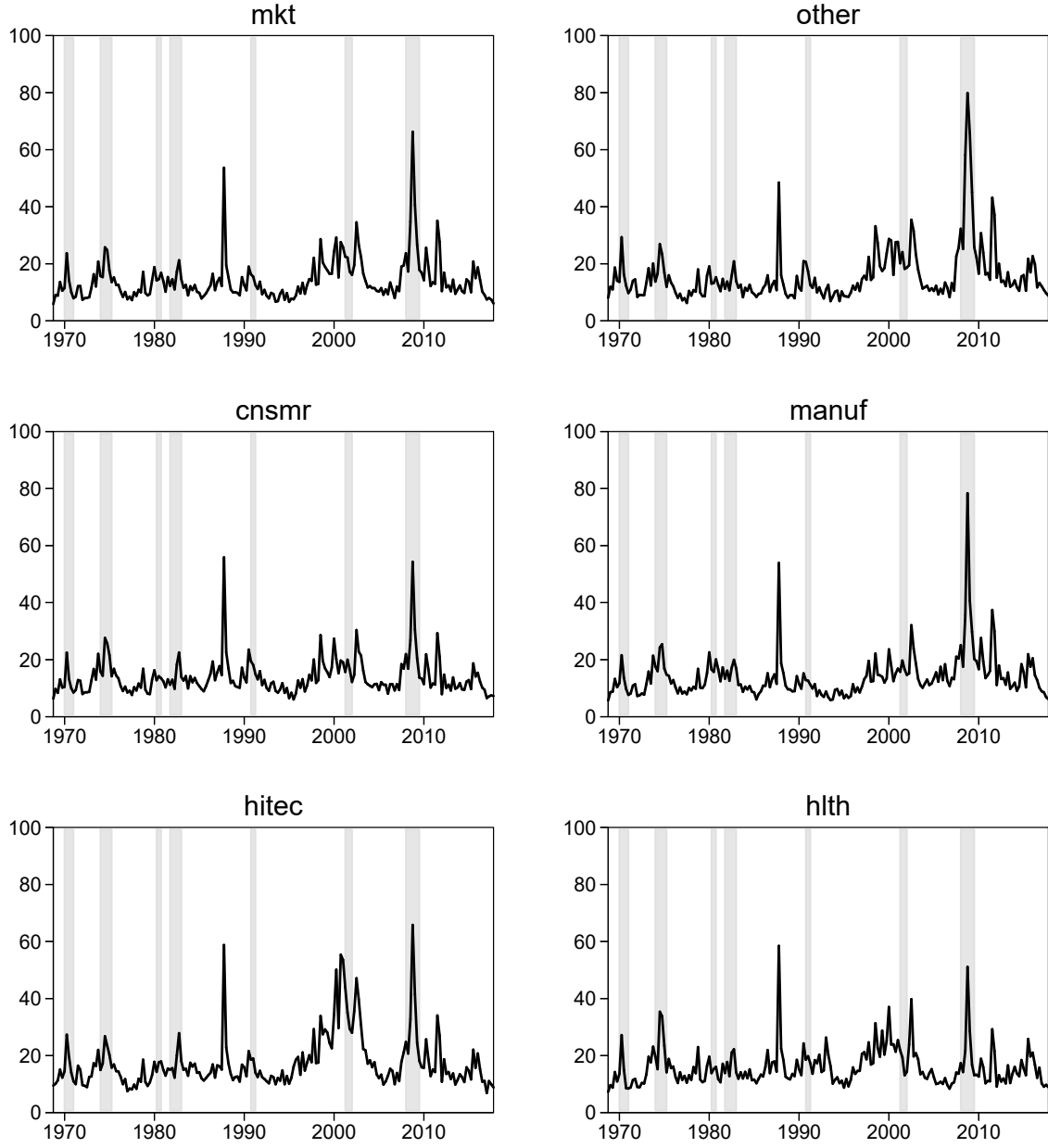
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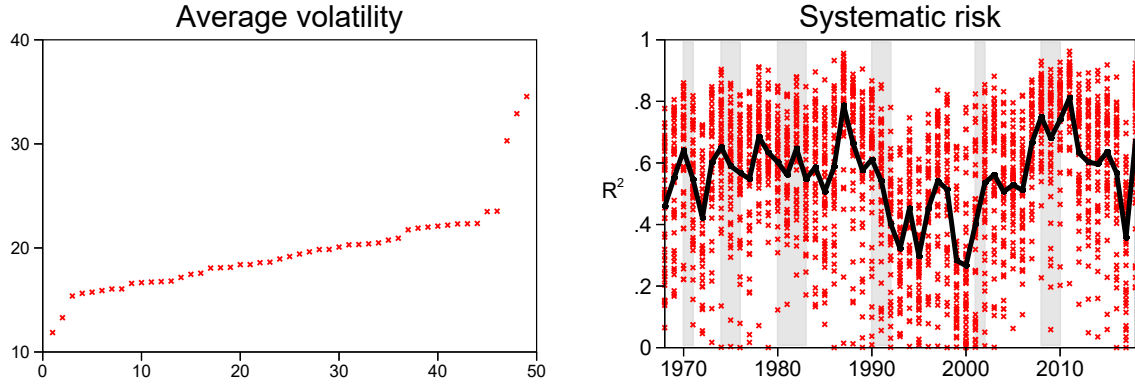
Tables and Figures

Figure 1: Realized volatility for the market and the 5 industry portfolios



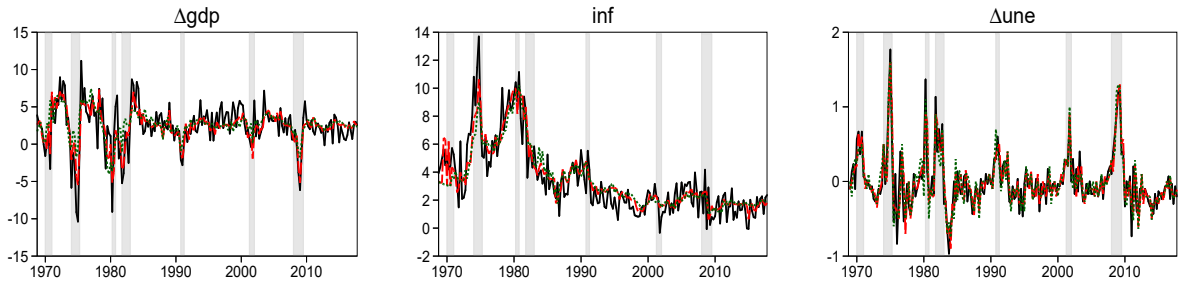
Notes: The plots depict the annualized time series of quarterly realized volatility, i.e., $\sqrt{4} \cdot RV_{i,t}$, for the market (*mkt*) as well as the other (*other*), consumer durables (*cnsmr*), manufacturing (*manuf*), business equipment (*hitec*) and healthcare (*hlth*) industries. Sectors are listed in decreasing order according to the systematic risk from Eqn. (6) (see Table 1). The data are taken from the Fama-French data library. The sample period is 1968Q4-2017Q4. Shaded gray areas indicate NBER-based recession periods.

Figure 2: Average realized volatility and systematic risk for the 49 industry portfolios



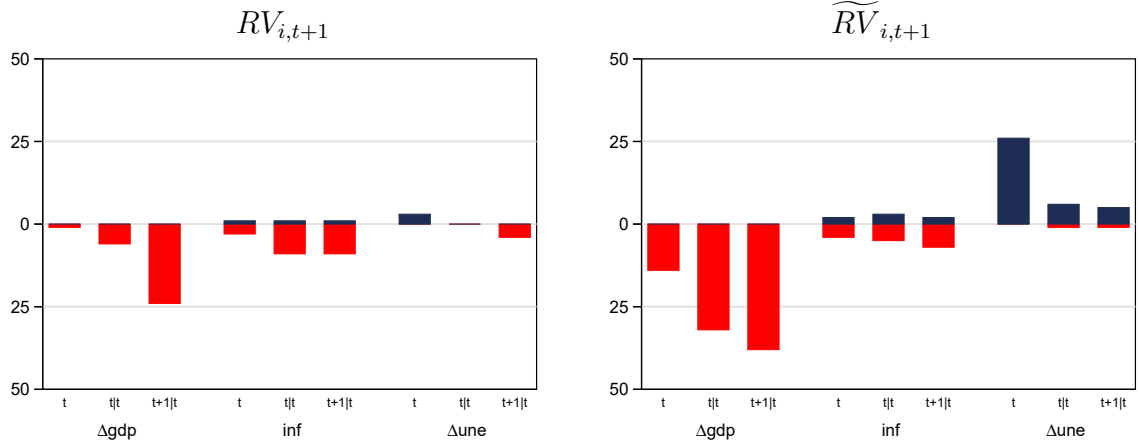
Notes: The left panel depicts the annualized time series average of quarterly realized volatility, i.e., $\overline{RV}_i = (1/T) \sum_{t=1}^T RV_{i,t}$ (vertical axis), for each sector from the 49 industry portfolios (horizontal axis), ordered by magnitude. For each year y , the right panel depicts the cross-section of systematic risk $SR^2_{i,y}$ from the regression $r_{i,d,y} = \mu_{i,y} + \beta_{i,y}r_{m,d,y} + \eta_{i,d,y}$ using daily data for each of the 49 industry portfolios (red crosses). The solid black line is the cross-sectional average systematic risk, i.e., $\overline{SR}_y = (1/49) \sum_{i=1}^{49} SR_{i,y}$. The data are taken from the Fama-French data library. The sample period is 1968Q4-2017Q4. Shaded gray areas indicate NBER-based recession periods. Year y is considered to be a recession year if at least one of the four quarters is defined as a recession period by the NBER.

Figure 3: Forecasts and realizations of macroeconomic variables



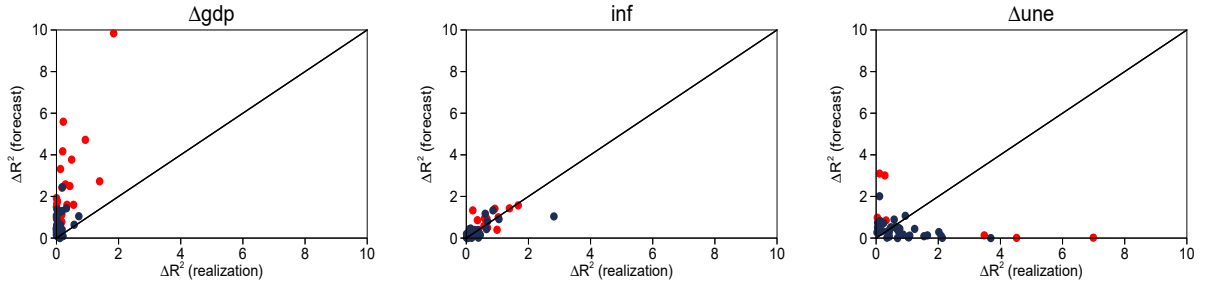
Notes: Plots depict the time series of the realizations (x_t , solid black line) and the annualized percentage change of the median nowcasts ($x_{t|t}$, dashed red line) and one-quarter-ahead median forecasts ($x_{t+1|t}$, green dotted line) for real GDP (Δgdp), inflation (inf) as well as the change in the median forecast of the civilian unemployment rate (Δune). The horizontal axis indicates the period during which predictions are reported and realizations are observed. The data is taken from the Federal Reserve's SPF. The sample period is 1968Q4-2017Q4. Shaded gray areas indicate NBER-based recession periods.

Figure 4: Number of significant estimates of θ_i for the 49 industry portfolios ($RV_{i,t+1}$ and $\widetilde{RV}_{i,t+1}$)



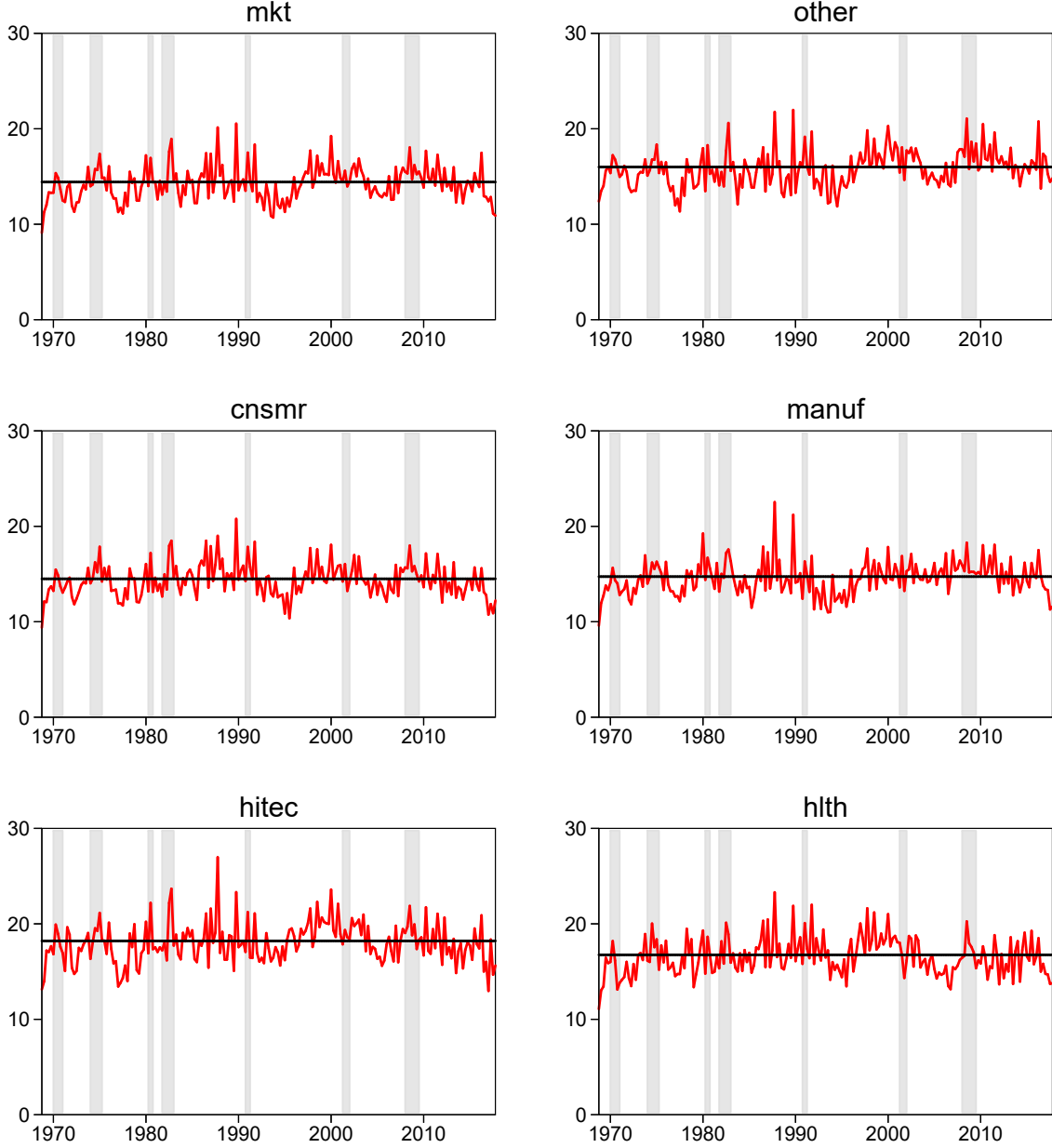
Notes: The plots depict the number of significantly positive (blue bars) and negative estimates (red bars) of θ_i from the regression $\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ when either realized volatility ($RV_{i,t+1}$, left panel) or volatility-adjusted realized volatility ($\widetilde{RV}_{i,t+1}$, right panel) is considered as the volatility proxy. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 5: Gain in the goodness of fit for the 49 industry portfolios ($RV_{i,t+1}$)



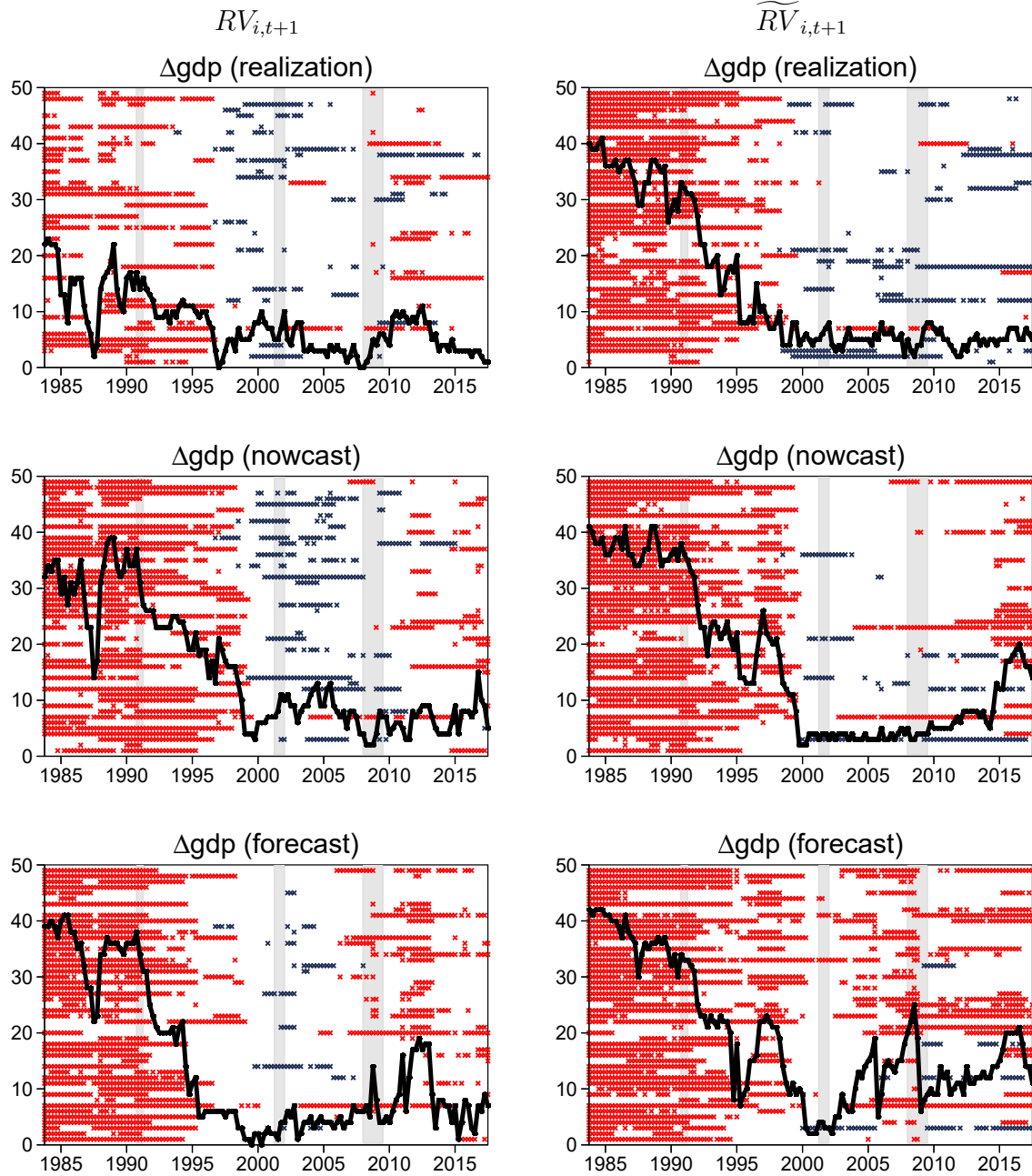
Notes: The plots depict the percentage increase in R^2 relative to the AR(2) benchmark for the 49 industry portfolios when either the forecast ($x_{t+1|t}$ vertical axis) or the realization (x_t , horizontal axis) of the respective macroeconomic variable is considered as the predictor in the model from Eqn. (3) and realized volatility ($RV_{i,t+1}$) is considered as the volatility proxy. Red dots indicate that in the underlying regression, θ_i is significantly different from zero at the 5% level either for x_t , $x_{t+1|t}$, or both. The estimation sample covers the period 1968Q4-2017Q4.

Figure 6: Volatility-adjusted realized volatility and the 5 industry portfolios



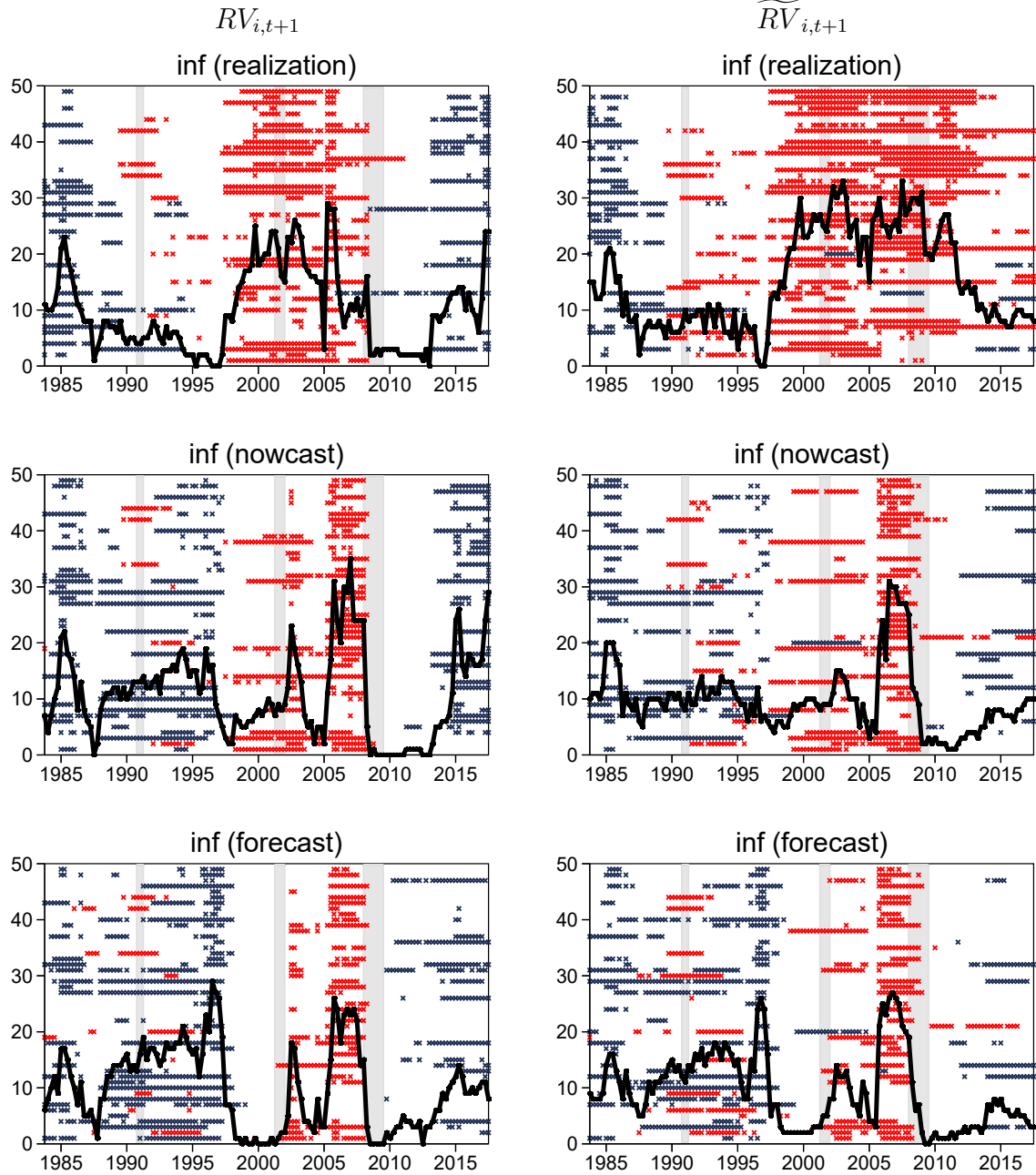
Notes: The plots depict the annualized time series of quarterly volatility-adjusted realized volatility, i.e., $\sqrt{4} \cdot \widetilde{RV}_{i,t}$ (red line), for the market (*mkt*) as well as the other (*other*), consumer durables (*cnsmr*), manufacturing (*manuf*), business equipment (*hitec*) and healthcare (*hlth*) industries. The black lines indicate the annualized estimates of $\sqrt{\tau_i}$. Sectors are listed in decreasing order according to the systematic risk from Eqn. (6) (see Table 1). The data are taken from the Fama-French data library. The sample period is 1968Q4-2017Q4. Shaded gray areas indicate NBER-based recession periods.

Figure 7: Rolling-window estimates of $\theta_{i,t}$ for the 49 industry portfolios (real GDP growth)



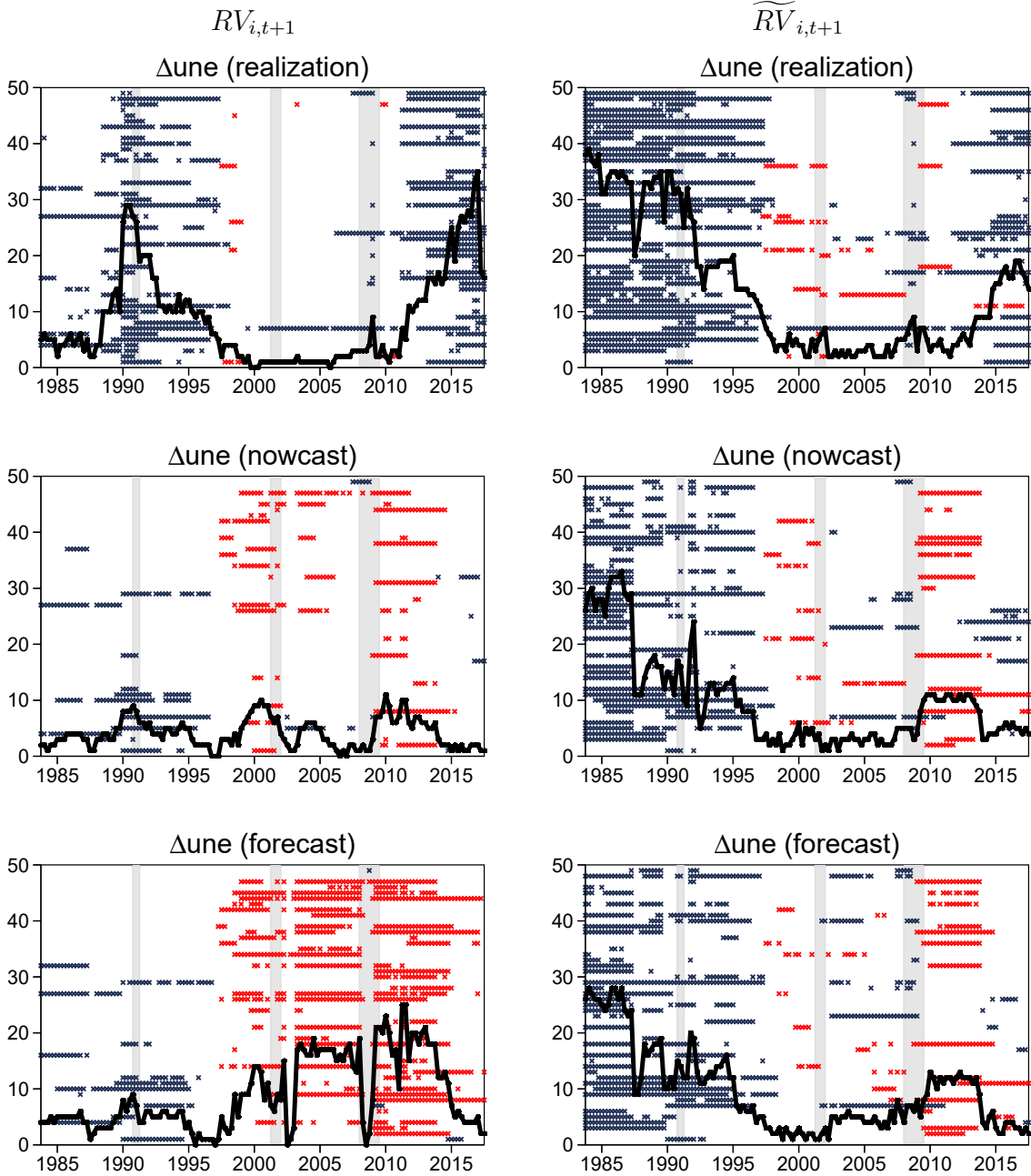
Notes: The plots indicate significantly positive (blue crosses) and negative estimates (red crosses) of $\theta_{i,t}$ from rolling-window regressions $\ln(RV_{i,t+1}) = \phi_{0,i,t} + \phi_{1,i,t} \ln(RV_{i,t}) + \phi_{2,i,t} \ln(RV_{i,t-1}) + \theta_{i,t}x + \nu_{i,t+1}$ with window size $\{t-59, \dots, t\}$ for the 49 industry portfolios, where $RV_{i,t+1}$ denotes realized volatility and $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ is either the realization (first column), nowcast (second column) or forecast (third column) of real GDP growth. The significance level is 5%. Empty spaces indicate insignificant estimates. The bold black lines indicate for how many industries the estimates of $\theta_{i,t}$ in each window are significant. Industries are listed in increasing order in accordance with SR_i . The predictor x is standardized with respect to its (full-sample) standard deviation. The estimation sample covers the period 1968Q4-2017Q4 (i.e., the first window ends in 1983Q4). Coefficients are estimated with OLS. We use the variance-covariance estimator by Newey-West (1987), which accounts for arbitrary levels of heteroskedasticity and autocorrelation in the data. Shaded gray areas indicate NBER-based recession periods.

Figure 8: Rolling-window estimates of $\theta_{i,t}$ for the 49 industry portfolios (inflation rate)



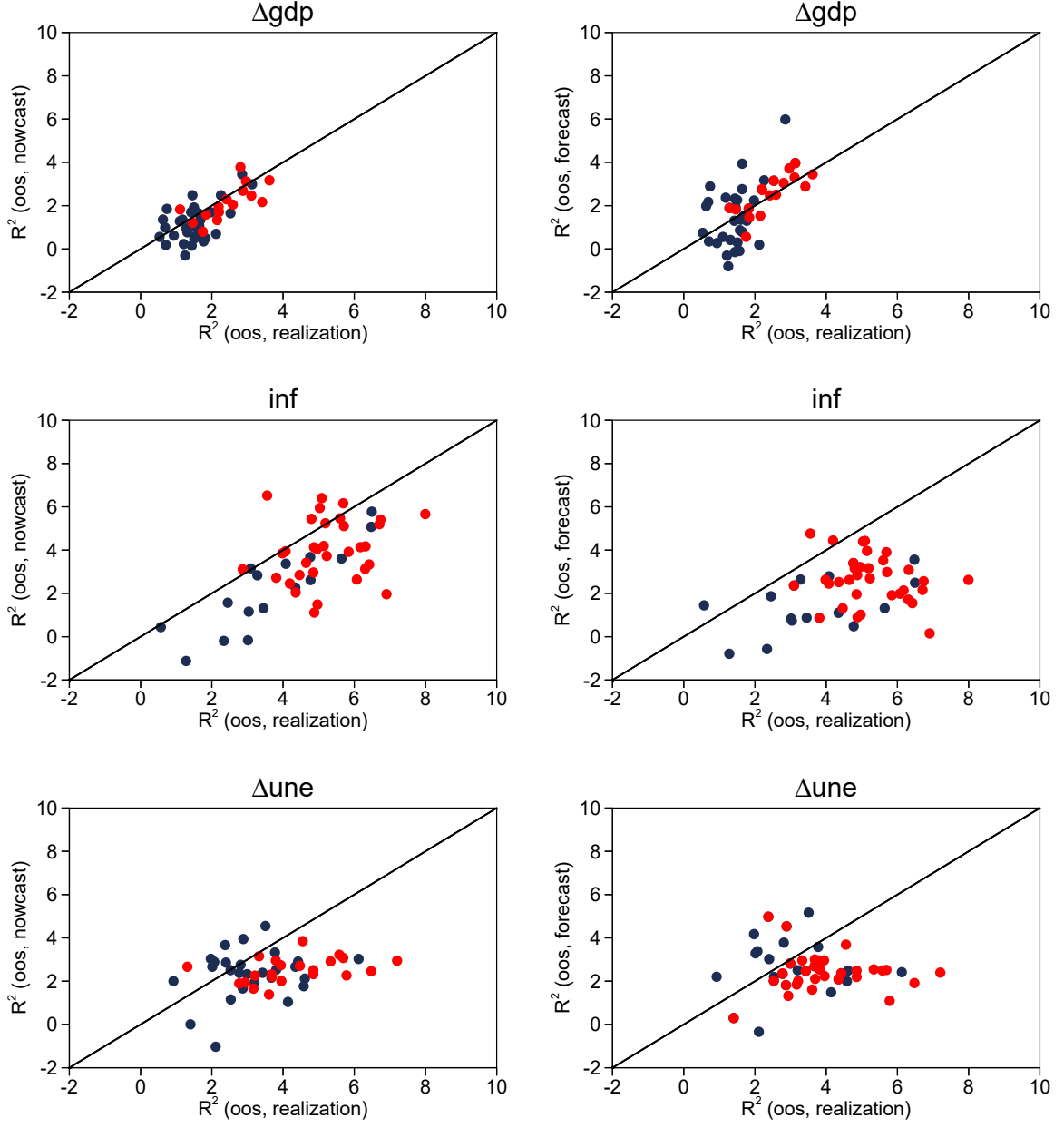
Notes: The plots indicate significantly positive (blue crosses) and negative (red crosses) estimates of $\theta_{i,t}$ from rolling-window regressions $\ln(RV_{i,t+1}) = \phi_{0,i,t} + \phi_{1,i,t} \ln(RV_{i,t}) + \phi_{2,i,t} \ln(RV_{i,t-1}) + \theta_{i,t}x + \nu_{i,t+1}$ with window size $\{t-59, \dots, t\}$ for the 49 industry portfolios, where $RV_{i,t+1}$ denotes realized volatility and $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ is either the realization (first column), nowcast (second column) or forecast (third column) of the inflation rate. The significance level is 5%. Empty spaces indicate insignificant estimates. The bold black lines indicate for how many industries the estimates of $\theta_{i,t}$ in each window are significant. Industries are listed in increasing order in accordance with SR_i . The predictor x is standardized with respect to its (full-sample) standard deviation. The estimation sample covers the period 1968Q4-2017Q4 (i.e., the first window ends in 1983Q4). Coefficients are estimated with OLS. We use the variance-covariance estimator by Newey-West (1987), which accounts for arbitrary levels of heteroskedasticity and autocorrelation in the data. Shaded gray areas indicate NBER-based recession periods.

Figure 9: Rolling-window estimates of $\theta_{i,t}$ for the 49 industry portfolios (unemployment rate)



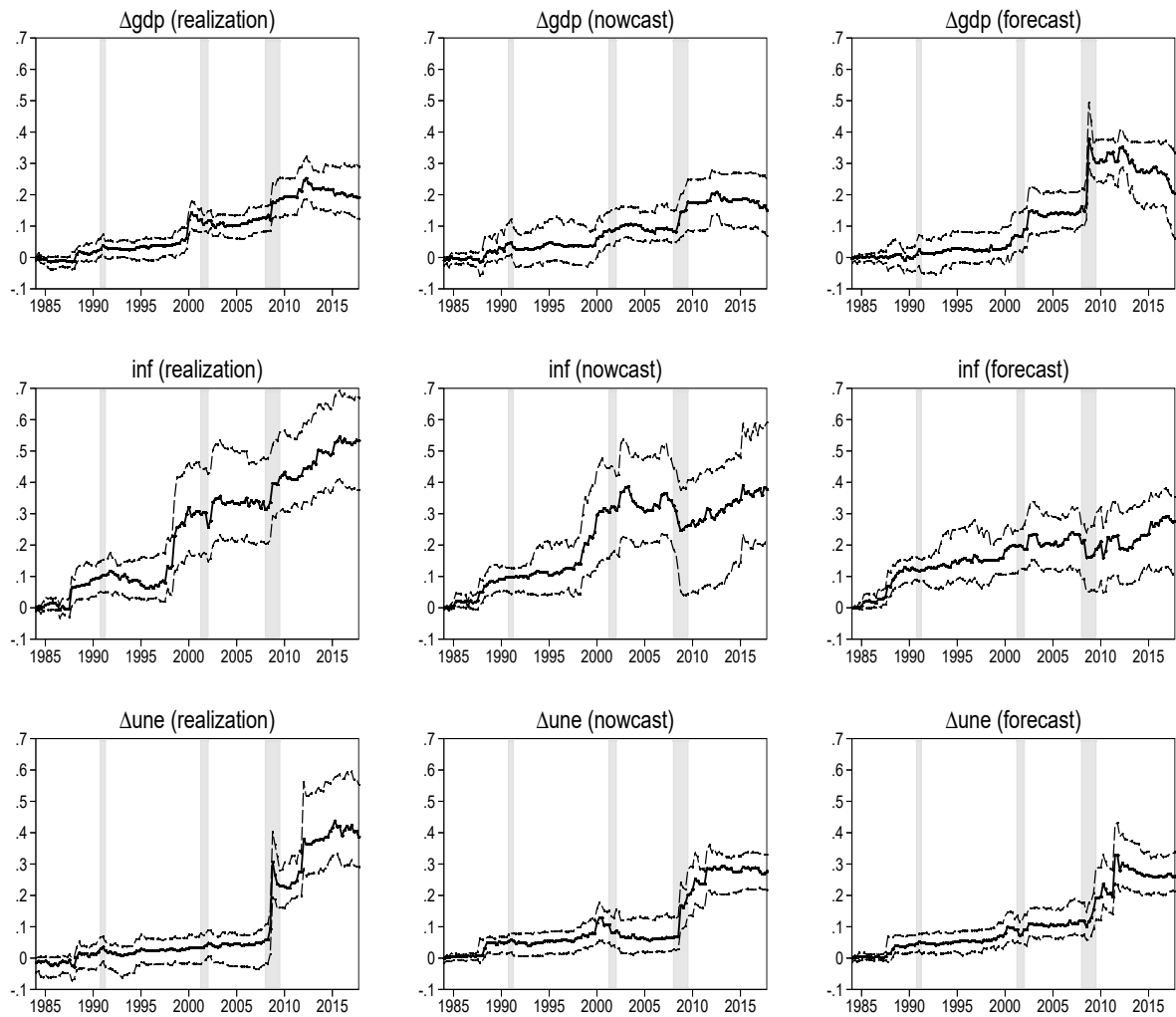
Notes: The plots indicate significantly positive (blue crosses) and negative estimates (red crosses) of $\theta_{i,t}$ from rolling-window regressions $\ln(RV_{i,t+1}) = \phi_{0,i,t} + \phi_{1,i,t} \ln(RV_{i,t}) + \phi_{2,i,t} \ln(RV_{i,t-1}) + \theta_{i,t}x + \nu_{i,t+1}$ with window size $\{t-59, \dots, t\}$ for the 49 industry portfolios, where $RV_{i,t+1}$ denotes realized volatility and $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ is either the realization (first column), nowcast (second column) or forecast (third column) of the change in the unemployment rate. The significance level is 5%. Empty spaces indicate insignificant estimates. The bold black lines indicate for how many industries the estimates of $\theta_{i,t}$ in each window are significant. Industries are listed in increasing order in accordance with SR_i . The predictor x is standardized with respect to its (full-sample) standard deviation. The estimation sample covers the period 1968Q4-2017Q4 (i.e., the first window ends in 1983Q4). Coefficients are estimated with OLS. We use the variance-covariance estimator by Newey-West (1987), which accounts for arbitrary levels of heteroskedasticity and autocorrelation in the data. Shaded gray areas indicate NBER-based recession periods.

Figure 10: Gain in the out-of-sample goodness of fit for the 49 industry portfolios ($RV_{i,t+1}$)



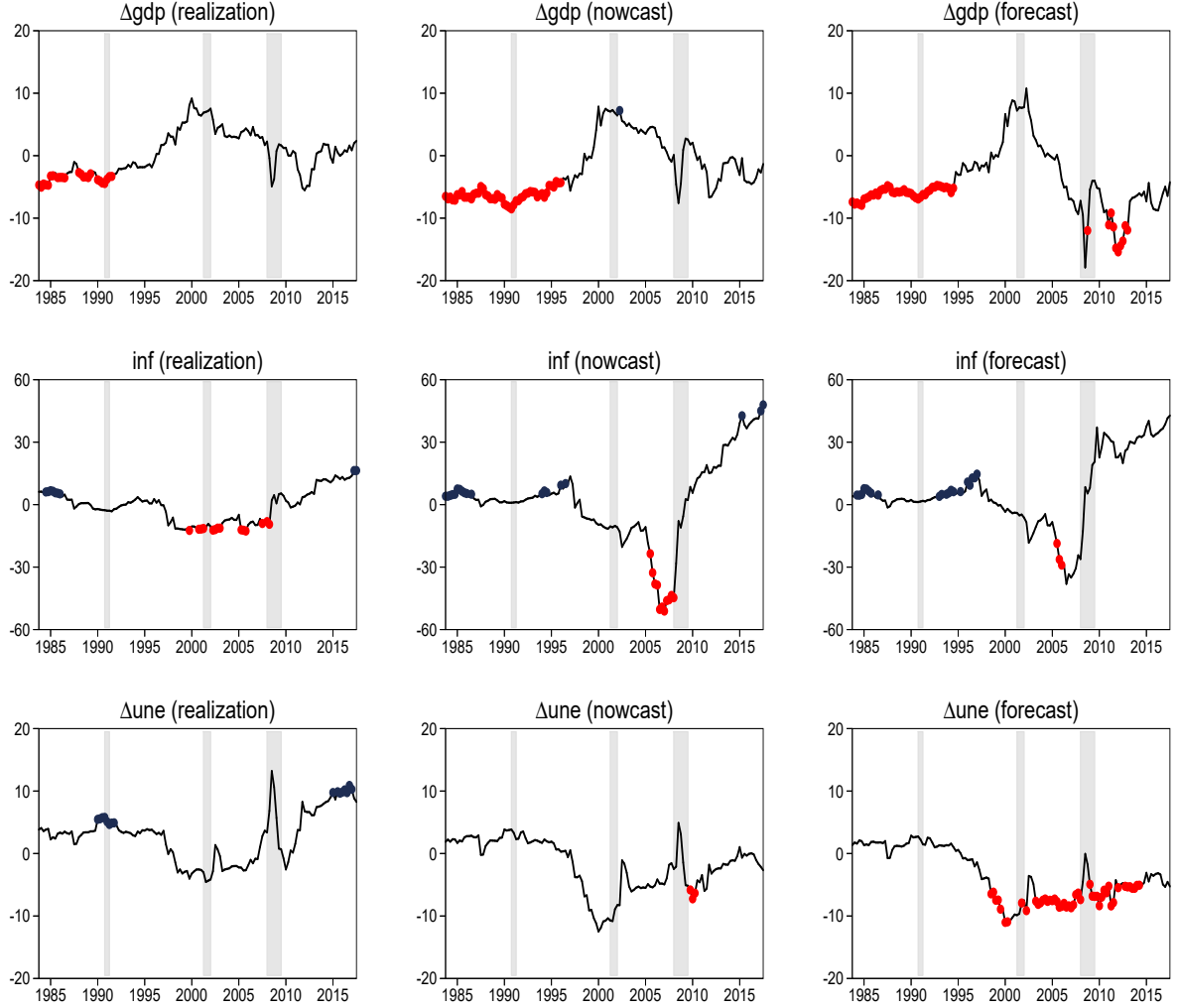
Notes: The plots in the first column depict the out-of-sample R^2 for the 49 industry portfolios when either the nowcast ($x_{t|t}$ vertical axis) or the realization (x_t , horizontal axis) of the respective macroeconomic variable is used as the predictor in the model from Eqn. (3) and realized volatility ($RV_{i,t+1}$) is considered as the volatility proxy. In the right column, we replace the R^2_{OOS} for the nowcasts with those for the forecasts. **Red dots** indicate that the MSE for at least one of the models including x is significantly lower than for the AR(2) model at the 5% critical level. The evaluation sample covers the period 1984Q1-2017Q4.

Figure 11: Cumulative difference in the squared out-of-sample forecast errors for the 49 industry portfolios ($RV_{i,t+1}$)



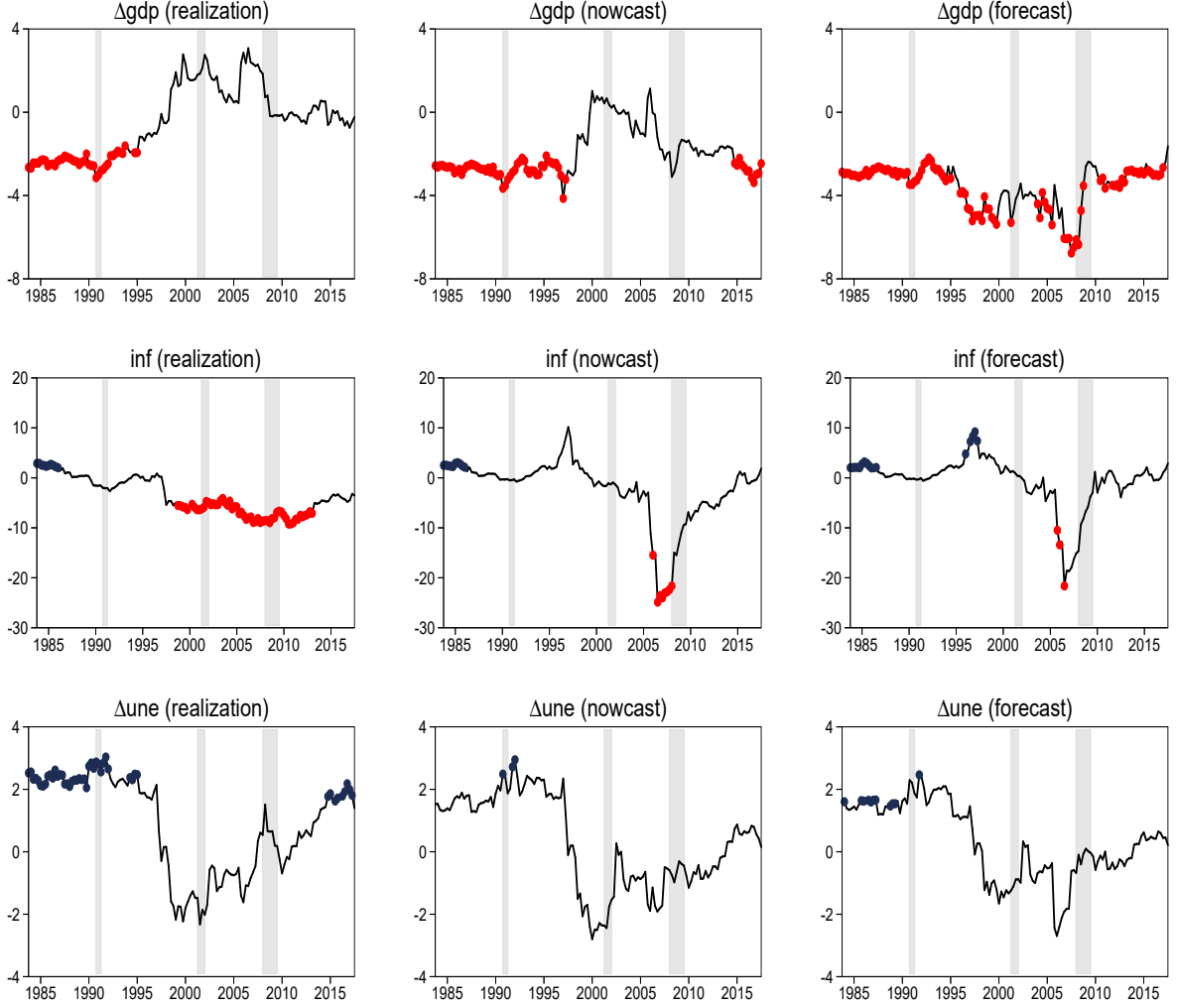
Notes: The plots depict the median across the cumulative differences in the squared out-of-sample forecast errors for the 49 industry portfolios, i.e., $\sum_{k=1}^{\tilde{t}} (e_{i,k,AR}^2 - e_{i,k,x}^2)$ for $i = 1, \dots, 49$, as a solid black line. The dashed lines represent the corresponding 20% and 80% percentiles. The evaluation sample $k = 1, \dots, 136$ covers the period 1984Q1-2017Q4.

Figure 12: Rolling-window estimates of $\theta_{m,t}$ ($RV_{m,t+1}$)



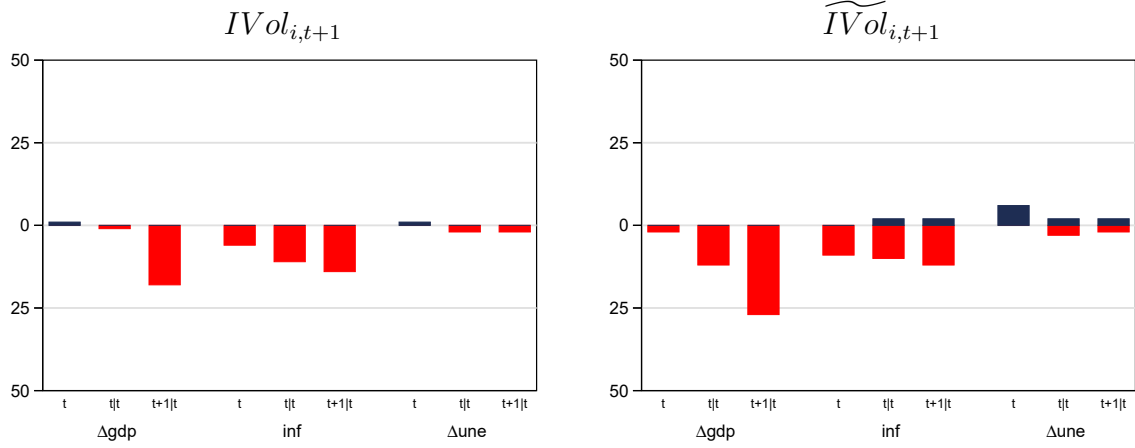
Notes: The plots depict the time series of the estimated slope coefficients $\hat{\theta}_{m,t}$ (times 100) from rolling-window regressions $\ln(RV_{m,t+1}) = \phi_{0,m,t} + \phi_{1,m,t} \ln(RV_{m,t}) + \phi_{2,m,t} \ln(RV_{m,t-1}) + \theta_{m,t}x + \nu_{m,t+1}$ with window size $\{t - 59, \dots, t\}$ for the market portfolio, where $RV_{m,t+1}$ denotes realized volatility and $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ is either the realization (first column), nowcast (second column) or forecast (third column) of the respective macroeconomic variable. The constant and the coefficients on the autoregressive terms are not reported. The predictor x is standardized with respect to its (full-sample) standard deviation. The estimation sample covers the period 1968Q4-2017Q4 (i.e., the first window ends in 1983Q4). Coefficients are estimated with OLS. We use the variance-covariance estimator by Newey-West (1987), which accounts for arbitrary levels of heteroskedasticity and autocorrelation in the data. The depicted coefficients are the estimated ones times 100. Blue dots indicate positive coefficients that are significantly positive at the 5% critical level. Red dots indicate significantly negative estimates. Shaded gray areas indicate NBER-based recession periods.

Figure 13: Rolling-window estimates of $\theta_{m,t}$ ($\widetilde{RV}_{m,t+1}$)



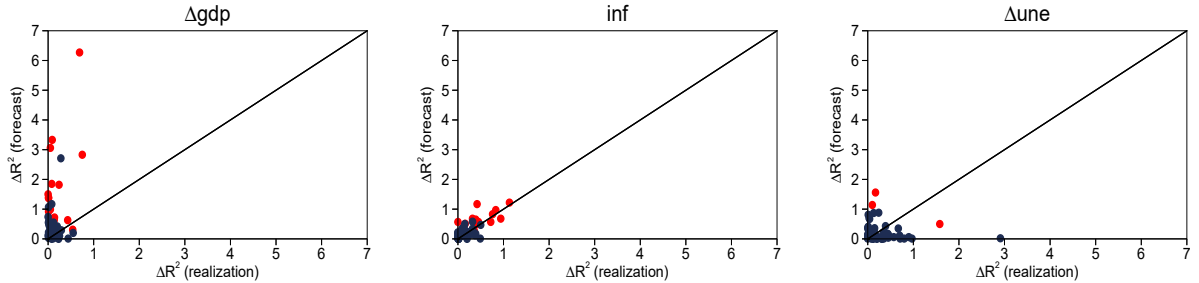
Notes: The plots depict the time series of the estimated slope coefficients $\hat{\theta}_{m,t}$ (times 100) from rolling-window regressions $\ln(\widetilde{RV}_{m,t+1}) = \phi_{0,m,t} + \phi_{1,m,t} \ln(\widetilde{RV}_{m,t}) + \phi_{2,m,t} \ln(\widetilde{RV}_{m,t-1}) + \theta_{m,t}x + \nu_{m,t+1}$ with window size $\{t - 59, \dots, t\}$ for the market portfolio, where $\widetilde{RV}_{m,t+1}$ denotes volatility-adjusted realized volatility and $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ is either the realization (first column), nowcast (second column) or forecast (third column) of the respective macroeconomic variable. The constant and the coefficients on the autoregressive terms are not reported. The predictor x is standardized with respect to its (full-sample) standard deviation. The estimation sample covers the period 1968Q4-2017Q4 (i.e., the first window ends in 1983Q4). Coefficients are estimated with OLS. We use the variance-covariance estimator by Newey-West (1987), which accounts for arbitrary levels of heteroskedasticity and autocorrelation in the data. The depicted coefficients are the estimated ones times 100. Blue dots indicate positive coefficients that are significantly positive at the 5% critical level. Red dots indicate significantly negative estimates. Shaded gray areas indicate NBER-based recession periods.

Figure 14: Number of significant estimates of θ_i for the 49 industry portfolios ($IVol_{i,t+1}$ and $\widetilde{IVol}_{i,t+1}$)



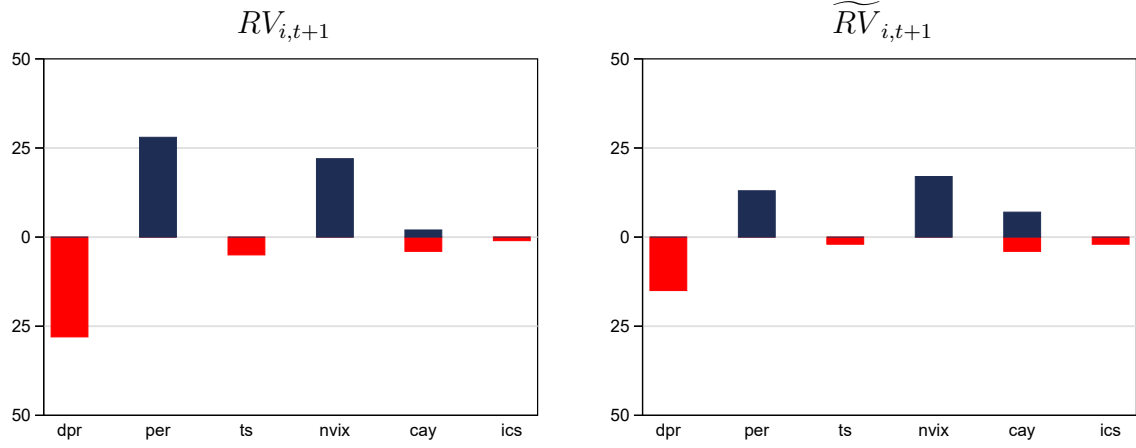
Notes: The plots depict the number of significantly positive (blue bars) and negative (red bars) estimates of θ_i from the regression $\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ when either idiosyncratic volatility ($IVol_{i,t+1}$, left panel) or volatility-adjusted idiosyncratic volatility ($\widetilde{IVol}_{i,t+1}$, right panel) are considered as the volatility proxy. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 15: Gain in the goodness of fit for the 49 industry portfolios ($IVol_{i,t+1}$)



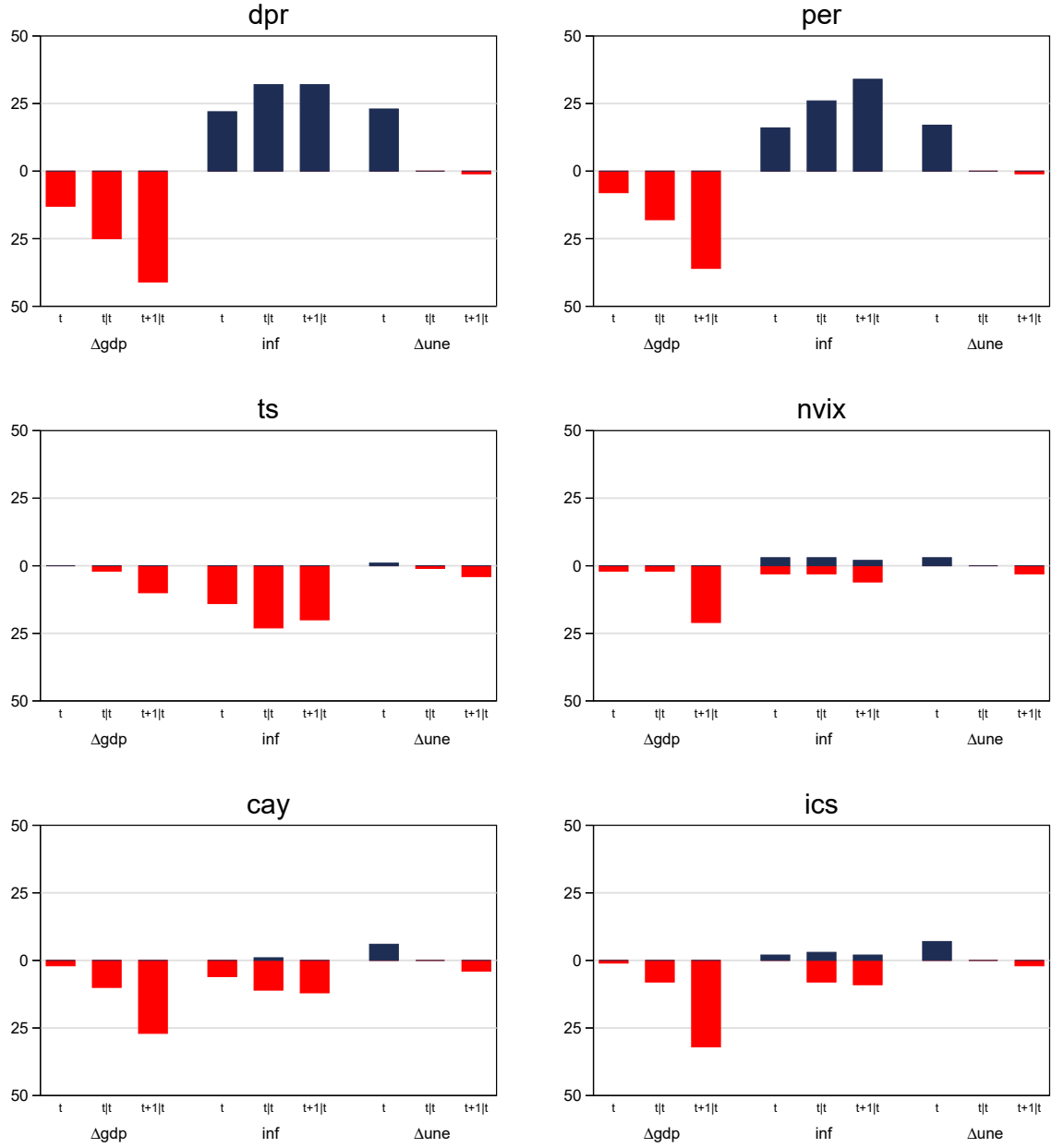
Notes: The plots depict the percentage increase in R^2 relative to the AR(2) benchmark for the 49 industry portfolios when either the forecast ($x_{t+1|t}$ vertical axis) or the realization (x_t , horizontal axis) of the respective macroeconomic variable is considered as the predictor in the model from Eqn. (3) and idiosyncratic volatility ($IVol_{i,t+1}$) is considered as the volatility proxy. Red dots indicate that in the underlying regression, θ_i is significantly different from zero at the 5% level either for x_t , $x_{t+1|t}$, or both. The estimation sample covers the period 1968Q4-2017Q4.

Figure 16: Number of significant estimates of λ_i for the 49 industry portfolios ($RV_{i,t+1}$ and $\widetilde{RV}_{i,t+1}$, additional predictor variables)



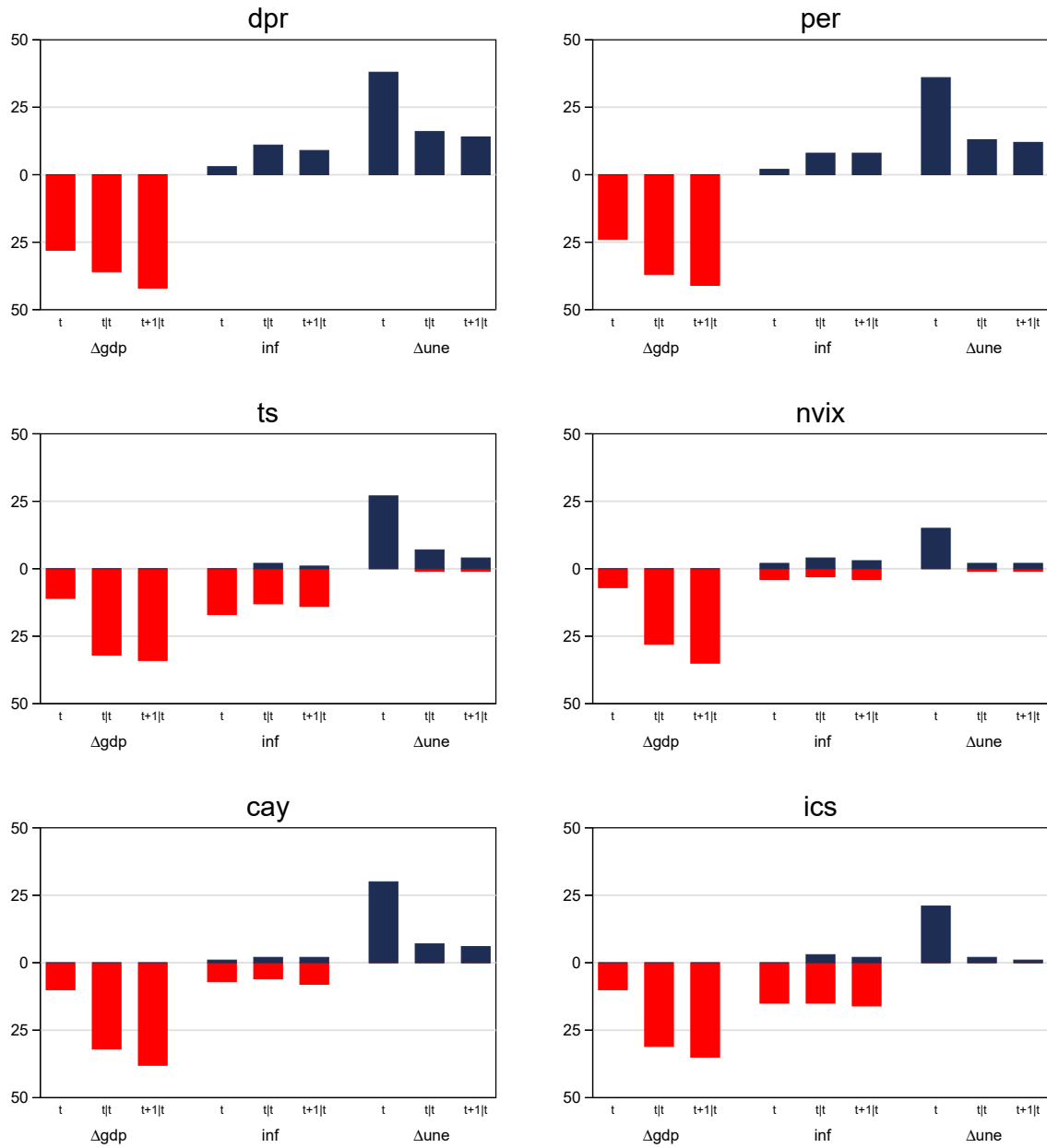
Notes: The plot depicts the number of significantly **positive** (blue bars) and **negative** estimates (red bars) of λ_i from the regression $\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \lambda_i w_t + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $w_t \in \{dpr_t, per_t, ts_t, nvix_t, cay_t, ics_t\}$ when either realized volatility ($RV_{i,t+1}$, left panel) or volatility-adjusted realized volatility ($\widetilde{RV}_{i,t+1}$, right panel) are considered as the volatility proxy. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 17: Number of significant estimates of θ_i for the 49 industry portfolios ($RV_{i,t+1}$, controls included)



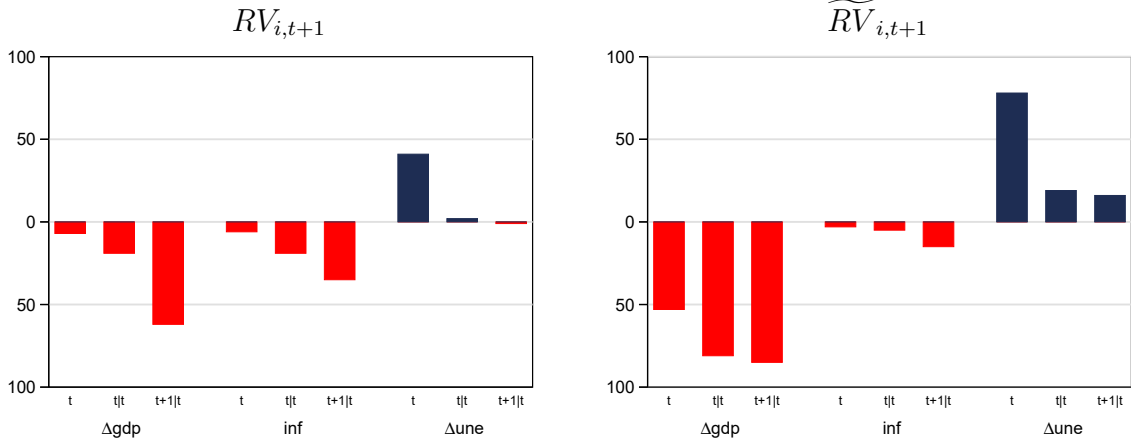
Notes: The plots depict the number of significantly positive (blue bars) and negative estimates (red bars) of θ_i from the regression $\ln(RV_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(RV_{i,t}) + \phi_{2,i} \ln(RV_{i,t-1}) + \theta_i x + \lambda_i w_t + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ and $w_t \in \{dpr_t, per_t, ts_t, nvix_t, cay_t, ics_t\}$. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 18: Number of significant estimates of θ_i for the 49 industry portfolios ($\widetilde{RV}_{i,t+1}$, controls included)



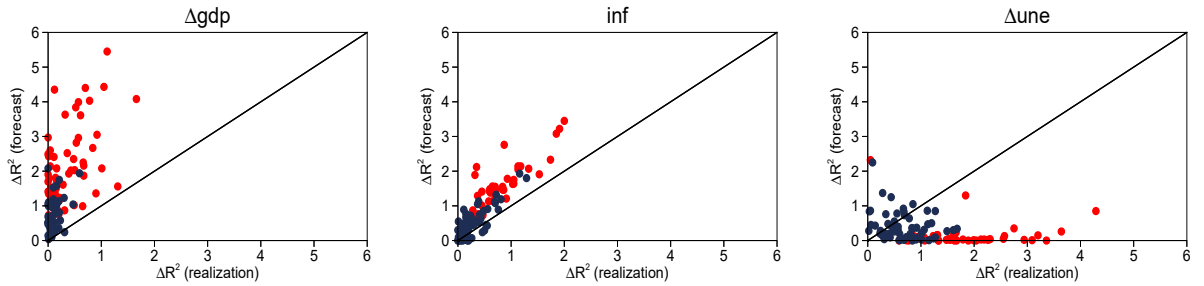
Notes: The plots depict the number of significantly positive (blue bars) and negative estimates (red bars) of θ_i from the regression $\ln(\widetilde{RV}_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(\widetilde{RV}_{i,t}) + \phi_{2,i} \ln(\widetilde{RV}_{i,t-1}) + \theta_i x + \lambda_i w_t + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ and $w_t \in \{dpr_t, per_t, ts_t, nvix_t, cay_t, ics_t\}$. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 19: Number of significant estimates of θ_i for the 100 portfolios formed on size and book-to-market ($RV_{i,t+1}$ and $\widetilde{RV}_{i,t+1}$)



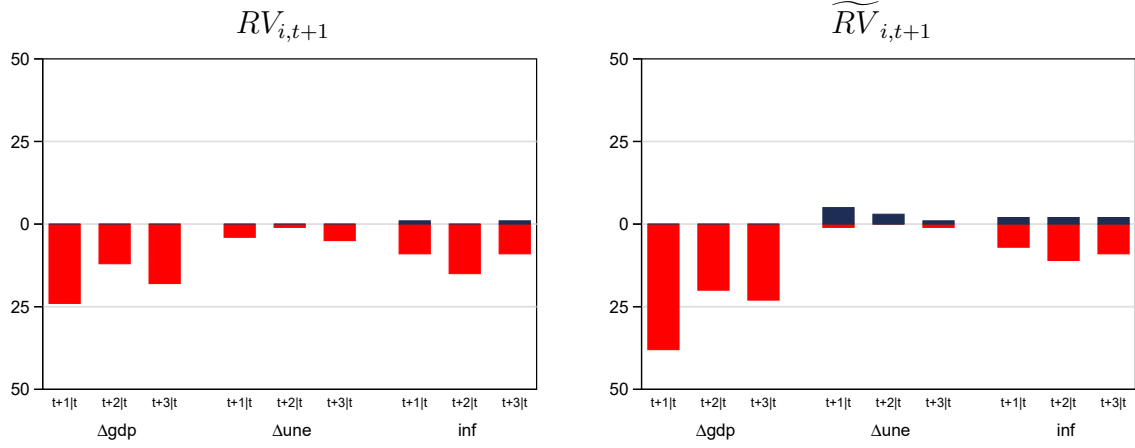
Notes: The plots depict the number of significantly positive (blue bars) and **negative** estimates (red bars) of θ_i from the regression $\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the 100 portfolios formed on size and book-to-market based on predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ when either realized volatility ($RV_{i,t+1}$, left panel) or volatility-adjusted realized volatility ($\widetilde{RV}_{i,t+1}$, right panel) are considered as the volatility proxy. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Figure 20: Gain in the goodness of fit for the 100 portfolios formed on size and book-to-market ($RV_{i,t+1}$)



Notes: The plots depict the percentage increase in R^2 relative to the AR(2) benchmark for the 100 portfolios formed on size and book-to-market when either the forecast ($x_{t+1|t}$ vertical axis) or the realization (x_t , horizontal axis) of the respective macroeconomic variable is considered as the predictor in the model from Eqn. (3) and realized volatility ($RV_{i,t+1}$) is considered as the volatility proxy. **Red dots** indicate that in the underlying regression, θ_i is significantly different from zero at the 5% level either for x_t , $x_{t+1|t}$, or both. The estimation sample covers the period 1968Q4-2017Q4.

Figure 21: Number of significant estimates of θ_i for the 49 industry portfolios ($RV_{i,t+1}$ and $\widetilde{RV}_{i,t+1}$, forecast horizons)



Notes: The plots depict the number of significantly positive (blue bars) and negative estimates (red bars) of θ_i from the regression $\ln(Vol_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(Vol_{i,t}) + \phi_{2,i} \ln(Vol_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the 49 industry portfolios based on predictors $x \in \{x_{t+1|t}, x_{t+2|t}, x_{t+3|t}\}$ when either realized volatility ($RV_{i,t+1}$, left panel) or volatility-adjusted realized volatility ($\widetilde{RV}_{i,t+1}$, right panel) are considered as the volatility proxy. The significance level is 5%. The estimation sample covers the period 1968Q4-2017Q4.

Table 1: Summary statistics for the 5 industry portfolios

	SR_i	$\hat{\beta}_i$	\bar{r}_i	\overline{RV}_i	$\widetilde{\overline{RV}}_i$	\overline{IVol}_i	$\widetilde{\overline{IVol}}_i$
<i>mkt</i>	1.00	1.00	4.90	14.34	14.25		
<i>other</i>	0.87	1.07	4.29	15.86	15.82	5.58	6.05
<i>cnsmr</i>	0.85	0.87	5.92	13.93	14.34	5.19	5.46
<i>manuf</i>	0.84	0.91	5.31	14.13	14.56	5.31	7.06
<i>hitec</i>	0.83	1.13	4.40	17.70	18.02	7.23	7.43
<i>hlth</i>	0.67	0.88	6.40	16.09	16.57	9.06	9.82

Notes: This table displays the systematic risk (SR_i) and the estimate of β_i from the model in Eqn. (6) for the market (*mkt*) as well as the other (*other*), consumer durables (*cnsmr*), manufacturing (*manuf*), business equipment (*hitec*) and healthcare (*hlth*) industries. Moreover, the table contains the annualized time series averages of the quarterly excess return, the realized volatilities ($RV_{i,t}$, $\widetilde{RV}_{i,t}$), and the idiosyncratic volatilities ($IVol_{i,t}$, $\widetilde{IVol}_{i,t}$). The sample period is 1968Q4-2017Q4.

Table 2: Summary statistics for the macroeconomic explanatory variables

	Variable	Timing	Mean	Std. dev.	Skew.	Kurt.	$q_{0.25}$	$q_{0.75}$	ρ_1
Δgdp	Real GDP growth	t	2.39	3.02	-0.96	6.33	1.22	3.90	0.49
		$t t$	2.34	2.19	-0.92	5.14	1.56	3.31	0.71
		$t+1 t$	2.64	1.76	-0.70	5.44	2.17	3.37	0.80
<i>inf</i>	Inflation rate	t	3.45	2.59	1.33	4.58	1.63	4.50	0.83
		$t t$	3.54	2.26	1.31	3.95	1.80	4.34	0.94
		$t+1 t$	3.49	2.11	1.29	3.92	1.91	4.30	0.97
Δune	Unemployment rate	t	0.00	0.37	1.47	7.22	-0.20	0.10	0.51
		$t t$	0.00	0.36	1.41	6.31	-0.20	0.10	0.61
		$t+1 t$	0.00	0.36	1.50	6.73	-0.20	0.10	0.55

Notes: This table displays summary statistics for the realizations (x_t), nowcasts ($x_{t|t}$) and one-quarter-ahead forecasts ($x_{t+1|t}$) of the macroeconomic variables from the SPF data. For each variable the columns report the mean, standard deviation, skewness, kurtosis, lower and upper quantiles and the first-order autocorrelation coefficient. The sample period is 1968Q4-2017Q4.

Table 3: Predictive regressions for realized volatility $RV_{i,t+1}$ (market and 5 industry portfolios)

Industry portfolio																			
Predictor x	Timing	mkt			$other$			$cnsmr$			$manuf$			$hitec$			$hlth$		
		$\hat{\theta}_m$	ΔR^2_m	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i	$\hat{\theta}_i$	ΔR^2_i		
Δgdp	t	-0.45 (1.47)	0.03	-0.33 (1.20)	0.01	-0.73 (1.12)	0.11	-0.76 (1.70)	0.06	0.12 (1.66)	0.00	-0.03 (1.91)	0.00						
Δgdp	$t t$	-2.15 (1.72)	0.51	-2.12 (1.50)	0.39	-2.00 (1.25)	0.74	-2.19 (1.80)	0.46	-0.58 (1.75)	0.03	-1.92 (1.64)	0.80						
Δgdp	$t + 1 t$	-4.16*** (1.45)	2.06	-3.82** (1.76)	1.32	-3.57*** (1.26)	2.51	-4.63*** (1.66)	2.22	-2.69 (1.79)	0.73	-2.99** (1.34)	2.05						
inf	t	-0.34 (1.51)	0.02	-2.33 (1.48)	0.55	0.73 (1.86)	0.12	0.58 (1.36)	0.04	-1.29 (1.50)	0.18	-0.32 (1.97)	0.03						
inf	$t t$	-0.63 (1.46)	0.06	-2.41* (1.32)	0.57	-0.07 (1.52)	0.00	0.05 (1.44)	0.00	-1.14 (1.39)	0.13	-0.28 (1.63)	0.02						
inf	$t + 1 t$	-0.39 (1.38)	0.02	-2.14* (1.20)	0.44	0.18 (1.52)	0.01	0.26 (1.39)	0.01	-0.99 (1.35)	0.10	-0.10 (1.59)	0.00						
Δune	t	2.36 (1.94)	0.65	2.20 (2.14)	0.42	2.58 (1.75)	1.27	2.33 (1.80)	0.58	1.17 (2.20)	0.13	1.71 (2.10)	0.70						
Δune	$t t$	-1.46 (2.04)	0.25	-1.31 (1.95)	0.15	-1.31 (1.76)	0.32	-1.02 (2.21)	0.11	-2.61 (1.86)	0.65	-1.67 (2.16)	0.66						
Δune	$t + 1 t$	-2.54 (2.05)	0.74	-2.37 (1.99)	0.48	-2.55 (1.75)	1.21	-1.60 (2.15)	0.27	-3.49* (1.95)	1.16	-2.44 (2.02)	1.38						

Notes: This table displays the estimated slope coefficients $\hat{\theta}_i$ from the regression $\ln(RV_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(RV_{i,t}) + \phi_{2,i} \ln(RV_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the market portfolio and the 5 industry portfolios, where $RV_{i,t+1}$ denotes realized volatility and $x \in \{x_t, x_{t-1}, x_{t+1}|t\}$ is either the realization, the nowcast or the forecast of the respective macroeconomic variable. The percentage increase in the R^2 relative to the AR(2) benchmark is denoted by ΔR^2 . The R^2_m for the market portfolio based on the AR(2) benchmark is 0.44. The constant and the coefficients on the autoregressive terms are not reported. The predictor x is standardized with respect to its standard deviation. Industries are listed in decreasing order according to the SR_i from Eqn. (6) (see Table 1). The estimation sample $t = 1, \dots, 197$ covers the period 1968Q4-2017Q4. Coefficients are estimated with OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroskedasticity and autocorrelation are reported in parentheses. The coefficients and standard errors are the estimated ones times 100. Asterisks *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table 4: Industry portfolios with highest number of significant estimates of $\theta_{i,t}$ ($RV_{i,t+1}$)

Δgdp		inf		Δune	
$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$	$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$	$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$
Realizations x_t					
<i>ships</i> (58)	<i>chips</i> (29)	<i>insur</i> (45)	<i>rlst</i> (54)	<i>gold</i> (7)	<i>ships</i> (85)
<i>agric</i> (52)	<i>labeq</i> (22)	<i>gold</i> (40)	<i>coal</i> (42)	<i>smoke</i> (6)	<i>mach</i> (54)
<i>mach</i> (45)	<i>fin</i> (20)	<i>telcm</i> (39)	<i>clths</i> (36)	<i>telcm</i> (5)	<i>chems</i> (50)
<i>hardw</i> (45)	<i>smoke</i> (17)	<i>coal</i> (35)	<i>aero</i> (33)	<i>hshld</i> (4)	<i>cnstr</i> (49)
<i>medeq</i> (41)	<i>drugs</i> (15)	<i>paper</i> (33)	<i>trans</i> (28)	<i>fin</i> (3)	<i>trans</i> (45)
Nowcasts $x_{t t}$					
<i>ships</i> (93)	<i>util</i> (32)	<i>util</i> (41)	<i>cnstr</i> (53)	<i>fin</i> (39)	<i>agric</i> (39)
<i>txtls</i> (72)	<i>steel</i> (31)	<i>coal</i> (41)	<i>aero</i> (52)	<i>hshld</i> (25)	<i>hlth</i> (34)
<i>cnstr</i> (67)	<i>chips</i> (28)	<i>persv</i> (33)	<i>ships</i> (52)	<i>softw</i> (24)	<i>ships</i> (31)
<i>banks</i> (66)	<i>mines</i> (27)	<i>gold</i> (32)	<i>hardw</i> (51)	<i>rtail</i> (23)	<i>aero</i> (23)
<i>medeq</i> (65)	<i>labeq</i> (26)	<i>smoke</i> (28)	<i>oil</i> (50)	<i>chips</i> (19)	<i>guns</i> (23)
Forecasts $x_{t+1 t}$					
<i>ships</i> (101)	<i>util</i> (20)	<i>util</i> (26)	<i>oil</i> (61)	<i>rtail</i> (67)	<i>hlth</i> (39)
<i>banks</i> (79)	<i>steel</i> (12)	<i>persv</i> (23)	<i>cnstr</i> (60)	<i>elceq</i> (52)	<i>guns</i> (25)
<i>bussv</i> (66)	<i>labeq</i> (10)	<i>smoke</i> (23)	<i>hardw</i> (54)	<i>aero</i> (52)	<i>gold</i> (24)
<i>bldmt</i> (61)	<i>aero</i> (9)	<i>coal</i> (22)	<i>guns</i> (53)	<i>fin</i> (51)	<i>aero</i> (23)
<i>mach</i> (60)	<i>mines</i> (5)	<i>gold</i> (20)	<i>mines</i> (47)	<i>chips</i> (51)	<i>ships</i> (22)

Notes: This table lists the five industry portfolios with the highest number of significantly negative/positive estimates of $\theta_{i,t}$ from rolling-window regressions with $RV_{i,t+1}$ as the volatility proxy and macroeconomic predictions $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ (depicted in the left panels of Figures 7 to 9). The numbers in parentheses indicate how many of the 137 estimates are significantly negative/positive at the 5% critical level.

Table 5: Clark-West and Giacomini-White tests for the 49 industry portfolios ($RV_{i,t+1}$)

	Δgdp			inf			Δune		
	t	$t t$	$t+1 t$	t	$t t$	$t+1 t$	t	$t t$	$t+1 t$
Clark-West									
5%	25	21	16	47	33	33	35	32	41
10%	43	35	26	48	42	40	44	45	48
Giacomini-White									
5%	13	4	7	29	16	17	17	11	21
10%	17	10	14	36	18	20	26	19	25

Notes: For each macroeconomic variable, this table displays the number of rejections for the Clark and West (2007) as well as the Giacomini and White (2006) tests in favor of the augmented model for the 49 industry portfolios at the 5% (first row) or 10% critical level (second row). The evaluation sample $k = 1, \dots, 136$ covers the period 1984Q1-2017Q4.

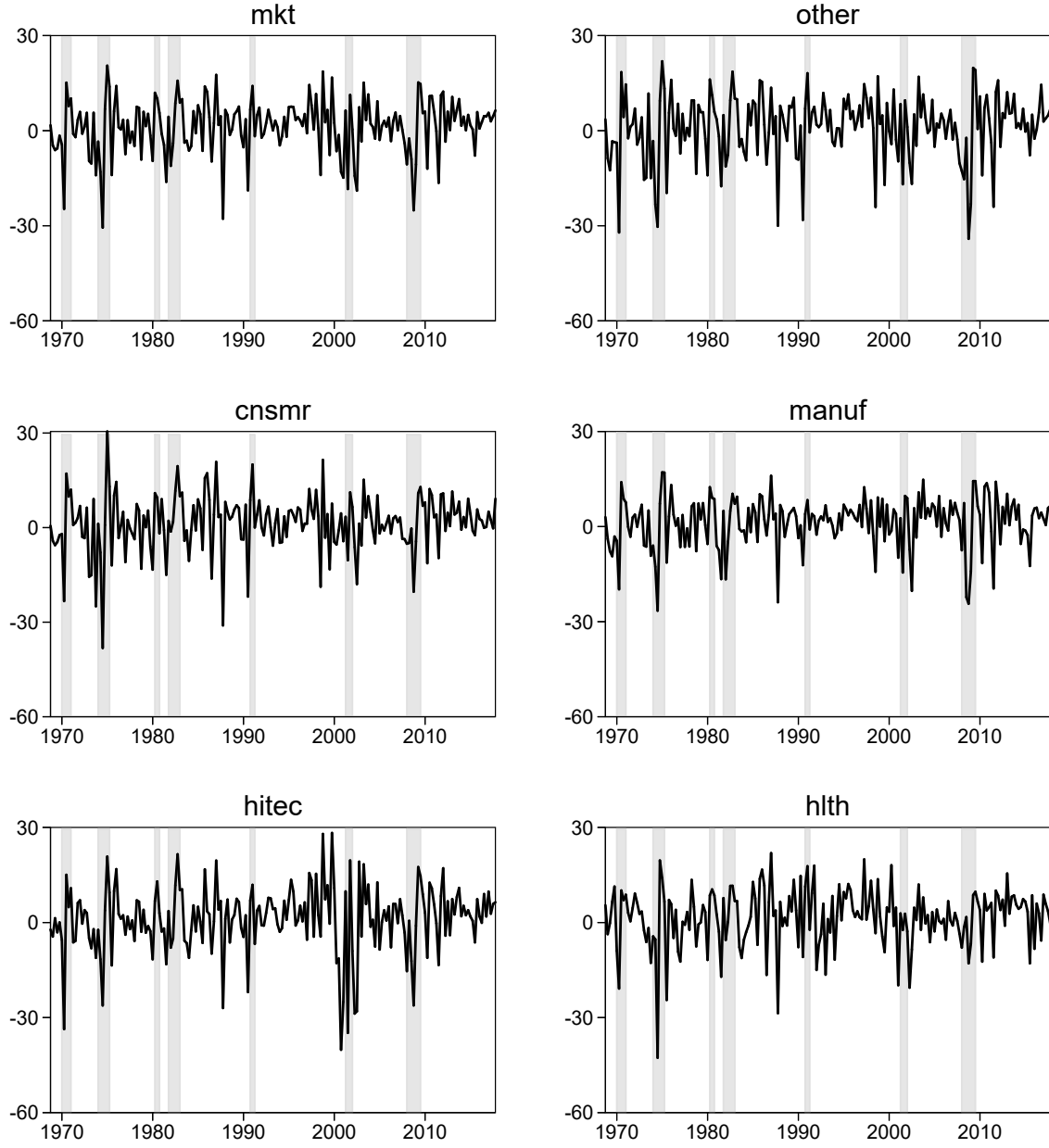
Table 6: Regressions of macroeconomic expectations on other predictors

Predictor w_t	<i>Dependent variable: Macroeconomic forecasts $x_{t+1 t}$</i>					
	Δgdp		inf		Δune	
dpr	0.44** (0.22)		1.31*** (0.21)		-0.03 (0.04)	
per		-0.53** (0.21)		-1.44*** (0.19)		0.05 (0.03)
ts	0.95*** (0.21)	0.94*** (0.19)	-0.70*** (0.17)	-0.75*** (0.13)	-0.07** (0.03)	-0.07* (0.04)
$nvix$	-0.50*** (0.10)	-0.49*** (0.10)	-0.23* (0.12)	-0.23* (0.13)	0.07** (0.04)	0.07* (0.04)
cay	-0.65*** (0.25)	-0.66*** (0.22)	-0.02 (0.17)	-0.00 (0.10)	0.06*** (0.02)	0.06** (0.03)
ics	1.10*** (0.30)	1.17*** (0.29)	-0.31 (0.19)	-0.20 (0.19)	-0.19*** (0.04)	-0.20*** (0.04)
Constant	0.17 (1.40)	-0.68 (1.62)	18.75*** (2.29)	16.07*** (1.62)	0.80** (0.33)	0.85*** (0.30)
Observations	190	190	190	190	189	189
\overline{R}^2	0.51	0.52	0.78	0.82	0.28	0.29

Notes: This table displays the estimates of the regression $x_{t+1|t} = \delta_0 + \delta_1 dpr_t + \delta_2 ts_t + \delta_3 nvix_t + \delta_4 cay_t + \delta_5 ics_t + \zeta_{t+1|t}$ for the forecasts of each macroeconomic variable, i.e., $x_{t+1|t}$. In the even columns, we replace dpr_t with per_t in order to avoid multicollinearity. All predictors are standardized with respect to their standard deviation. The estimation sample $t = 1, \dots, 190$ covers the period 1968Q4-2016Q1. Coefficients are estimated with OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroskedasticity and autocorrelation are reported in parentheses. Asterisks *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Appendix

Figure 22: Quarterly returns for the market and the 5 industry portfolios



Notes: The plots depict the time series of the quarterly value-weighted excess returns, i.e., $r_{i,t}$, for the market (*mkt*) as well as the other (*other*), consumer durables (*cnsmr*), manufacturing (*manuf*), business equipment (*hitec*) and healthcare (*hlth*) industries. Sectors are listed in decreasing order according to the systematic risk from Eqn. (6) (see Table 1). The data are taken from the Fama-French data library. The sample period is 1968Q4-2017Q4. Shaded gray areas indicate NBER-based recession periods.

Table 7: Description of the 49 industry portfolios

i	Sector	Description	SR_i	i	Sector	Description	SR_i
49	<i>bussv</i>	Business Services	0.81	24	<i>rubbr</i>	Rubber and Plastic Products	0.57
48	<i>mach</i>	Machinery	0.77	23	<i>boxes</i>	Shipping Containers	0.56
47	<i>fin</i>	Trading	0.75	22	<i>meals</i>	Restaurants, Hotels, Motels	0.56
46	<i>whlsl</i>	Wholesale	0.71	21	<i>fun</i>	Entertainment	0.55
45	<i>elceq</i>	Electrical Equipment	0.71	20	<i>food</i>	Food Products	0.54
44	<i>rtail</i>	Retail	0.70	19	<i>persv</i>	Personal Services	0.52
43	<i>chems</i>	Chemicals	0.70	18	<i>oil</i>	Petroleum and Natural Gas	0.51
42	<i>insur</i>	Insurance	0.69	17	<i>toys</i>	Recreation	0.50
41	<i>bldmt</i>	Construction Materials	0.69	16	<i>txtls</i>	Textiles	0.49
40	<i>trans</i>	Transportation	0.69	15	<i>other</i>	Almost Nothing	0.49
39	<i>labeq</i>	Measuring and Control Equipment	0.68	14	<i>util</i>	Utilities	0.48
38	<i>chips</i>	Electronic Equipment	0.68	13	<i>rlest</i>	Real Estate	0.46
37	<i>banks</i>	Banking	0.67	12	<i>mines</i>	Non-Metallic and Industrial Metal Mining	0.46
36	<i>telcm</i>	Communication	0.66	11	<i>fabpr</i>	Fabricated Products	0.43
35	<i>paper</i>	Business Supplies	0.65	10	<i>hlth</i>	Healthcare	0.39
34	<i>books</i>	Printing and Publishing	0.63	9	<i>beer</i>	Beer & Liquor	0.37
33	<i>autos</i>	Automobiles and Trucks	0.63	8	<i>softw</i>	Computer Software	0.36
32	<i>steel</i>	Steel Works Etc	0.62	7	<i>ships</i>	Shipbuilding, Railroad Equipment	0.35
31	<i>hardw</i>	Computers	0.62	6	<i>soda</i>	Candy & Soda	0.31
30	<i>drugs</i>	Pharmaceutical Products	0.61	5	<i>agric</i>	Agriculture	0.30
29	<i>cnstr</i>	Construction	0.60	4	<i>guns</i>	Defense	0.29
28	<i>clths</i>	Apparel	0.60	3	<i>coal</i>	Coal	0.29
27	<i>aero</i>	Aircraft	0.60	2	<i>smoke</i>	Tobacco Products	0.26
26	<i>hshld</i>	Consumer Goods	0.58	1	<i>gold</i>	Precious Metals	0.03
25	<i>medeq</i>	Medical Equipment	0.58				

Notes: This table provides a description of the 49 industry portfolios following the definitions from the Fama-French data library. We also report the systematic risk of each portfolio based on the estimates of Eqn. (6).

Table 8: Predictive regressions for volatility-adjusted realized volatility $\widetilde{RV}_{i,t+1}$ (market and 5 industry portfolios)

Industry portfolio																		
Predictor x	Timing	mkt			$other$			$cnsmr$			$manuf$			$hitec$			$hlth$	
		$\hat{\theta}_m$	ΔR_m^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	$\hat{\theta}_i$	ΔR_i^2	
Δgdp	t	-1.36** (0.60)	6.49	-1.17* (0.65)	6.25	-1.02** (0.51)	3.90	-1.24** (0.55)	7.71	-1.10 (0.68)	8.87	-0.36 (0.65)	0.81					
Δgdp	$t t$	-2.15*** (0.42)	14.94	-2.16*** (0.67)	20.08	-1.46*** (0.34)	7.65	-1.78*** (0.53)	15.04	-1.53*** (0.52)	16.09	-1.15* (0.60)	7.77					
Δgdp	$t + 1 t$	-2.83*** (0.48)	26.69	-2.76*** (0.77)	33.26	-1.91*** (0.42)	13.56	-2.37*** (0.48)	26.60	-2.21*** (0.64)	34.30	-1.53*** (0.53)	13.89					
inf	t	-0.29 (0.80)	0.31	-1.39 (0.94)	8.95	0.15 (0.64)	0.08	-0.10 (0.71)	0.05	-0.88 (0.90)	5.74	-0.34 (0.63)	0.75					
inf	$t t$	0.21 (0.61)	0.16	-0.92 (0.61)	3.79	0.44 (0.59)	0.75	0.30 (0.63)	0.48	-0.27 (0.72)	0.51	0.10 (0.56)	0.07					
inf	$t + 1 t$	0.24 (0.60)	0.22	-0.97* (0.55)	4.20	0.41 (0.62)	0.65	0.34 (0.60)	0.60	-0.20 (0.74)	0.28	0.21 (0.62)	0.29					
Δune	t	1.43*** (0.55)	7.19	1.56*** (0.54)	10.92	1.36** (0.61)	6.99	1.10** (0.55)	6.23	1.16* (0.68)	9.09	0.47 (0.71)	1.53					
Δune	$t t$	0.62 (0.65)	1.33	0.88 (0.67)	3.52	0.36 (0.58)	0.48	0.58 (0.66)	1.75	-0.00 (0.68)	0.00	-0.17 (0.69)	0.20					
Δune	$t + 1 t$	0.67 (0.54)	1.58	0.92 (0.66)	3.87	0.24 (0.54)	0.23	0.60 (0.66)	1.89	0.03 (0.76)	0.01	-0.14 (0.73)	0.14					

Notes: This table displays the estimated slope coefficients $\hat{\theta}_i$ from the regression $\ln(\widetilde{RV}_{i,t+1}) = \phi_{0,i} + \phi_{1,i} \ln(\widetilde{RV}_{i,t}) + \phi_{2,i} \ln(\widetilde{RV}_{i,t-1}) + \theta_i x + \nu_{i,t+1}$ for the market portfolio and the 5 industry portfolios, where $\widetilde{RV}_{i,t+1}$ denotes volatility-adjusted realized volatility and $x \in \{x_t, x_{t-1}, x_{t-2}\}$ is either the realization, the nowcast or the forecast of the respective macroeconomic variable. The percentage increase in the R^2 relative to the AR(2) benchmark is denoted by ΔR^2 . The R_m^2 for the market portfolio based on the AR(2) benchmark is 0.18. The constant and the coefficients on the autoregressive terms are not reported. The predictor x is standardized with respect to its standard deviation. Industries are listed in decreasing order according to the SR_i from Eqn. (6) (see Table 1). The estimation sample $t = 1, \dots, 197$ covers the period 1983Q4-2017Q4. Coefficients are estimated with OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroskedasticity and autocorrelation are reported in parentheses. The coefficients and standard errors are the estimated ones times 100. Asterisks *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

Table 9: Industry portfolios with highest number of significant estimates of $\theta_{i,t}$ ($\widetilde{RV}_{i,t+1}$)

Δgdp		inf		Δune	
$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$	$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$	$\hat{\theta}_{i,t} < 0$	$\hat{\theta}_{i,t} > 0$
Realizations x_t					
<i>ships</i> (73)	<i>oil</i> (46)	<i>other</i> (91)	<i>hlth</i> (42)	<i>telcm</i> (22)	<i>ships</i> (100)
<i>trans</i> (60)	<i>smoke</i> (42)	<i>insur</i> (78)	<i>rlest</i> (30)	<i>rlest</i> (22)	<i>trans</i> (69)
<i>mach</i> (59)	<i>mines</i> (37)	<i>fun</i> (73)	<i>cnstr</i> (26)	<i>fun</i> (15)	<i>toys</i> (64)
<i>cnstr</i> (54)	<i>coal</i> (29)	<i>chips</i> (72)	<i>coal</i> (26)	<i>hshld</i> (12)	<i>bussv</i> (59)
<i>oil</i> (53)	<i>fin</i> (24)	<i>hardw</i> (69)	<i>aero</i> (19)	<i>fabpr</i> (12)	<i>banks</i> (58)
Nowcasts $x_{t t}$					
<i>ships</i> (115)	<i>coal</i> (60)	<i>persv</i> (41)	<i>cnstr</i> (52)	<i>chips</i> (24)	<i>cnstr</i> (59)
<i>bussv</i> (77)	<i>oil</i> (21)	<i>coal</i> (40)	<i>hlth</i> (49)	<i>fabpr</i> (24)	<i>ships</i> (59)
<i>trans</i> (75)	<i>mines</i> (20)	<i>fun</i> (37)	<i>ships</i> (44)	<i>softw</i> (22)	<i>mines</i> (55)
<i>medeq</i> (72)	<i>telcm</i> (16)	<i>smoke</i> (37)	<i>mines</i> (42)	<i>oil</i> (21)	<i>hlth</i> (43)
<i>boxes</i> (68)	<i>fun</i> (12)	<i>chips</i> (31)	<i>oil</i> (40)	<i>telcm</i> (20)	<i>beer</i> (38)
Forecasts $x_{t+1 t}$					
<i>ships</i> (113)	<i>coal</i> (48)	<i>smoke</i> (34)	<i>cnstr</i> (65)	<i>oil</i> (27)	<i>cnstr</i> (65)
<i>bussv</i> (94)	<i>mines</i> (21)	<i>coal</i> (31)	<i>mines</i> (52)	<i>chips</i> (24)	<i>ships</i> (63)
<i>bldmt</i> (93)	<i>oil</i> (14)	<i>soda</i> (27)	<i>hlth</i> (45)	<i>softw</i> (24)	<i>mach</i> (61)
<i>trans</i> (93)	<i>steel</i> (10)	<i>chips</i> (24)	<i>coal</i> (41)	<i>fabpr</i> (22)	<i>beer</i> (54)
<i>rubbr</i> (87)	– (0)	<i>persv</i> (24)	<i>trans</i> (40)	<i>coal</i> (21)	<i>mines</i> (53)

Notes: This table lists the five industry portfolios with the highest number of significantly negative/positive estimates of $\theta_{i,t}$ from rolling-window regressions with $\widetilde{RV}_{i,t+1}$ as the volatility proxy and macroeconomic predictors $x \in \{x_t, x_{t|t}, x_{t+1|t}\}$ (depicted in the right panels of Figures 7 to 9). The numbers in parentheses indicate how many of the 137 estimates are significantly negative/positive at the 5% critical level.