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Abstract

We examine the asymmetric impact of shocks to macroeconomic expectations and their underlying dispersion on equity risk premia across different market regimes. First, we rely on a two-state logit mixture vector autoregressive model and use Consensus Economics survey data on GDP growth, inflation, and short-term interest rates to approximate macroeconomic expectations and the underlying disagreement in the United States for the period 1989M10–2022M09. We demonstrate that unexpected changes of survey forecasts and their dispersion significantly affect cyclical factor returns in a dynamic setting and that the state of the economy matters for the magnitude, persistence, and occasionally also for the sign of the effect. Second, by extending the dynamic asset pricing model of Adrian et al. (2015), we show that GDP forecasts and their dispersion are priced in the cross section and drive the size and value premium, whereas inflation expectations serve as robust predictors for the price of risk. We also document that the survey expectations-augmented specification reduces pricing and premium errors when compared to a common benchmark of return predictors.

JEL-Codes: C320, E440, G120, G140.

Keywords: consensus forecasts, dynamic asset pricing model, factor risk premia, macroeconomic expectations, mixture VAR, state-dependency.

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1 Introduction

Asset prices are forward-looking and by nature linked to macroeconomic fundamentals. Hence, expectations about fundamentals play a key role in theoretical macro-financial models and contribute to our understanding of asset pricing. Macroeconomic expectations explain the common variation in returns according to the Arbitrage Pricing Theory (Ross 1976) and hedge state variable risks in line with the Intertemporal Capital Asset Pricing Model (ICPAM, Merton 1973). However, an empirical approximation of these relationships is difficult for two reasons. First, extracting expectations from observable data — such as historical realizations of macro variables, market prices, or survey forecasts — requires assumptions about how expectations are formed or how the mechanisms of pricing channels work. Second, empirical models that link expectations to asset prices are prone to the errors-in-variables problem and typically have unstable parameters.

In this paper, we investigate the state-dependent effects of macroeconomic expectations and the underlying disagreement on stock prices in the United States (US). Methodologically, we follow two directions to assess the relation of macroeconomic survey forecasts on asset prices. First, we evaluate the dynamic stock market reaction to an expectation or disagreement shock using the recently developed logit mixture vector autoregressive (LMVAR) model of Burgard et al. (2019). This allows us to differentiate state-dependent impulse response functions (IRFs) under the assumptions that regimes can coexist.[1] In addition, we are able to model time-varying state weights that follow the dynamics of business and financial cycles by using a concordant logit submodel. Second, we use the Dynamic Asset Pricing Model (DAPM) of Adrian et al. (2015) to estimate risk premia and to test the value-added of expectation data as cross-sectional risk factors and as time series predictors. The DAPM, as a reduced-form macro-finance model, allows for time-varying risk premia by assuming that prices of risk are affine functions of external predictors. In addition, we modify the three-step

1. This is a key advantage of the LMVAR over popular alternatives like Markov-switching VARs or threshold VAR models, which are restricted to be in one regime at a time. See also the discussion in Section 3.2 below.

estimation procedure by substituting the linear VAR model with an LMVAR model to account for state-dependent innovations.

Our empirical analysis focuses on one-year ahead Consensus Economics survey forecasts for three key macroeconomic variables (real GDP growth, CPI inflation, and 3M Treasury bills) and their underlying dispersion. For the stock market, we utilize the four most common factors (market risk premium: MKT, size premium: SMB, value premium: HML, and momentum premium: MOM) as cross-sectional pricing factors since these series historically explain a large fraction of the common variation in stock returns (Fama and French 1993; Carhart 1997). As control variables for the price of risk dynamics, we rely on the log dividend yield, the term spread, and the 10Y Treasury bond yield. Our dataset covers monthly data from 1989M10–2022M09.

Our results indicate, first, that shocks to macroeconomic expectations have a significant impact on cyclical risk premia. Better growth prospects particularly affect the dynamics of stocks with higher systematic risk, such as small and value stocks. Moreover, growth expectations are significantly priced in the cross section and earn — on average — a positive premium. Rising inflation expectations reduce the broad equity risk premium, whereas these increase the attractiveness of value and momentum stocks. Second, dispersion shocks negatively affect long-only equity portfolios, irrespective of the source of the shock. The effects of these shocks are particularly pronounced during crises, but more short-lived. Unconditionally, growth dispersion is negatively priced so that investors are willing to pay a premium to hedge against fundamental uncertainty.

Third, our results also demonstrate the superiority of a state-dependent analysis over a one-state linear VAR model. The magnitude, persistence, and occasionally also the sign of the effect depend on the macro-financial regime. Hence, accounting for different states captures the multimodality of the economy, reduces estimation uncertainty, lowers standard errors, and allows us to understand the time-varying and non-linear relationships between expectations about fundamentals and factor returns. Finally, we provide evidence that adding macroeconomic survey forecasts to the DAPM reduces the in-sample premium errors and lowers the overall pricing errors, in particular for small stocks.

Our paper contributes to several strands of the literature. First, we build on the debate about the sources of risk in characteristic-based factor models. The empirical literature documents many stylized facts that are not consistent with the CAPM. With the rise of factor models since the 1990s, many patterns have been discovered that explain much of the variation in the cross section of stock returns. However, it is unclear whether these actually are risk factors, market anomalies, or just the result of data snooping (Cazalet and Roncalli 2014). As Fama (1996) notes, the size and the value factor are neither state variables in the ICAPM setting nor do these mimic portfolios of state variables. In contrast, these are diversified portfolios that simply correlate with some unknown state variables. We address the question about these unknown state variables and conclude that (innovations in) macroeconomic expectations and their underlying dispersion are promising candidates.

Second, we contribute to the empirical asset pricing literature that estimates the conditional expected value of priced factors. Fama and MacBeth (1973) provide the standard pricing approach for traded and non-traded factors, in which they use a linear beta representation of the stochastic discount factor assuming that loadings as well as the prices of risk are constant. Conditional asset pricing models increase the explanatory power on the cross section of asset prices (e.g., Ferson and Harvey 1991; Campbell 1996; Ang and Kristensen 2012). More recent developments allow for time-varying prices of risk that are directly obtained from asset prices (Giglio and Xiu 2021; Umlandt 2023) or use observable instruments (Ferson and Harvey 1991; Adrian et al. 2015; Gagliardini et al. 2016; Bianchi et al. 2017). Our results support the role of macroeconomic factors and encourage researchers to add macroeconomic expectation measures as sources and/or drivers for risk premia to reduce pricing errors.

Third, we address the question of how disagreement or forecast dispersion about macroeconomic variables affects asset prices. There is a broad debate in the academic literature on the relationship between forecast dispersion and expected stock returns.

Some authors (Miller 1977; Diether et al. 2002) argue that higher dispersion captures an increase in information asymmetry. This — in conjunction with market constraints like short-selling restrictions — leads to an overvaluation so that the price reflects only the opinion of optimists and expected returns should fall. Other researchers (Anderson et al. 2005, 2009) claim that higher forecast dispersion is associated with higher information uncertainty. This leads to higher estimation risk and/or uncertainty in the measurement of expected cash flows and discount rates. Hence, a risk compensation is required and leads to higher expected returns. Buraschi et al. (2014) show that belief disagreement is a priced risk factor for credit spreads, stock returns, and stock market volatility. The authors also emphasize that the relationship between stock returns and disagreement is not monotonic. Our results support the notion that macroeconomic forecast dispersion is strongly related to information uncertainty, as its impact on asset prices is stronger during crisis times when risk premia rise.

Fourth, our empirical results also confirm some implications of Cujean and Hasler (2017)'s theoretical equilibrium model, in which agents assess economic uncertainty differently. In good times, agents interpret news in a homogeneous way so that returns are less persistent. But as fundamentals deteriorate, disagreement increases due to differences in the agents' adjustment speed or due to a polarization of opinions during bad times. We verify that higher disagreement increases return persistence and that short-term momentum is strongest in bad times.

Finally, our paper illustrates the empirical tractability of LMVAR models in a macro-financial context. Since financial variables exhibit a low signal-to-noise ratio and their links to fundamentals are time-varying and mostly non-linear, parameter estimates are notoriously unstable. Therefore, conditioning the estimation on the respective state helps to reduce the estimation uncertainty and provides more stable relationships (for the different states of the economy). Hence, our results encourage researchers to use multi-state VAR models in macro-financial applications.

The remainder of this paper is organized as follows. Section 2 provides an overview of the literature on macroeconomic expectations and their role in asset pricing. Section

3 introduces the dataset and the econometric methodology. Section 4 shows the dynamic response of equity factors to innovations in macroeconomic expectations using a (state-dependent) VAR model. Section 5 explores the usefulness of survey forecasts within a dynamic asset pricing model. Section 6 concludes.

2 Macroeconomic Expectations and Asset Prices

A vast literature broadly confirms that macroeconomic variables matter in asset pricing models (e.g., Chen et al. 1986; Fama and French 1989; Gagliardini et al. 2016; Bianchi et al. 2017). When it comes to macroeconomic *expectations*, the challenge is to identify these and to find adequate asset pricing models to link expectations to asset prices. Several proxies for macroeconomic expectations have been used thus far in the empirical literature.

First, some studies utilize the realization of macroeconomic variables as a proxy and test if and how these are priced (e.g., Chen et al. 1986). Given a certain level of market efficiency, financial markets should already have accounted for the expected part of the macroeconomic variable. Accordingly, only unexpected changes should affect asset prices and, typically, first differences or autoregressive models are used to proxy expectation news from realized macroeconomic data. Second, other papers focus on surprises around macroeconomic announcements, for instance, in the context of an event study. For this purpose, the initial release value is compared to the last survey forecast in order to analyze the (short-term) reaction of asset prices to the surprise (e.g., Savor and Wilson 2014; Bergbrant and Kelly 2016). Third, asset prices themselves are utilized to extract expectations. Due to the predefined cash flow structure, bond market data derived from (an almost) risk-free yield curve is a popular choice to proxy market participants' prospects about future interest rates, inflation, or growth (e.g., Ang et al. 2006; Baumeister 2023). Furthermore, credit spreads (e.g., Vassalou and Xing 2004) and equity prices (e.g., Elton 1999) often serve as proxies for growth expectations and certain risk considerations. A final source of information is the derivative market, including interest rate or foreign exchange forwards, commodity futures, inflation swaps, and implied volatilities from option markets. In the end, however, all market-based measures of expectations have the problem of circularity in common, that is, changes in the extracted expectations have already been priced or the researcher has to control for these by using an independent estimate of the risk premium.

Compared to the previous sources, survey forecasts of economic fundamentals have the key advantage that these are straightforward measures of forward-looking expectations and can be used directly as input to empirical models. Surveys are conducted among consumers (households), firms (CFOs or purchasing managers), financial market participants (corporate analysts), government institutions, central banks, and professional forecasters (banks, research institutes, international agencies, or multi-national enterprises). A growing research strand analyzes the information content of all these sources and the heterogeneity of the corresponding expectations (e.g., Nagel and Xu 2022).

Critical to the reliability of survey forecasts is the possible presence of measurement errors arising from time-constant or time-varying biases. Survey respondents often do not disclose their true expectations (consciously or unconsciously). For example, financial analysts' earnings forecasts are shown to be biased upwards with economic incentives, cognitive biases, and inefficient information processing as underlying reasons (Kothari et al. 2016). Biases also have been documented for surveys of professional forecasters. The anchoring bias (Campbell and Sharpe 2009) is a prominent example where forecasts are systematically biased towards the previous month's data releases, leading to an inefficient information processing due to an underreaction to news and to predictable forecast errors. Similar to financial analysts — albeit to a lesser extent — economists have some incentives to rationally bias their forecasts. Given that professional forecasters are in competition with each other, there are some strategic considerations for over- or underpredicting due to asymmetric loss functions (Capistrán and Timmermann 2009; Ottaviani and Sørensen 2006) or reputation and differentiation motives (Batchelor 2007). Despite these skeptical remarks, surveys of professional forecasters are one of the most reliable data sources for expectations. These often provide better forecast accuracy than financial market expectations or econometric models (Ang et al. 2007) and are most likely to be "objective."

There are many sources of macroeconomic surveys, such as the Survey of Professional Forecasters, Blue Chip Forecasts, Consensus Economics, or the Livingston Survey. Several papers relate survey expectations to asset prices. Campbell and Diebold (2009) document a negative relationship between expected business conditions and expected excess returns and argue that expectations are positively correlated with current business conditions and negatively correlated with future volatility. Hence, the authors link the expectations of business conditions to time-varying risk. Bergbrant and Kelly (2016) relate changes in macroeconomic survey forecasts and macroeconomic news surprises to the four most prominent factors (MKT, SMB, HML, and MOM). However, the authors fail to find robust and significant relationships, casting doubt on the hypothesis that the factors account for macroeconomic risk.

Overall, the existing evidence provides mixed signals about the impact of macroeconomic survey forecasts on asset prices. A key reason for this is that both, the economic environment and the respective perceptions of market participants change over time, making it difficult to obtain stable parameter estimates. Information uncertainty and heterogeneous expectations further complicate the task. This raises the question of whether controlling for the state of the economy helps to disentangle the effect of macroeconomic expectations or their underlying dispersion on asset prices. When information uncertainty is high, information processing is more likely to be inefficient (at least for a fraction of economic agents), economic forecasts are less accurate, the dispersion of beliefs rises, and the amount as well as the price of risk increases. All these developments cause risk premia to rise, encourage under- or overreactions, and open the door to predictable asset prices, at least in a certain state of the economy (Cujean and Hasler 2017).

3 Data and Econometric Methodology

3.1 Data

Our dataset covers monthly data for the US between 1989M10 and 2022M09. Figures A1–A4 in Appendix A show time series plots for macroeconomic expectations, (cyclical) stock market factors, DAPM predictors, and state drivers for the LMVAR weights. Tables A1 and A2 display summary statistics and bivariate correlations.

Macroeconomic Expectations (see Figure A1). We capture macroeconomic expectations for the US using the monthly forecasts of professional economists by Consensus Economics. The survey typically ends on the evening of the second Monday in each month and has a publication lag of three days. We consider forecasts of (i) real GDP growth to capture business cycle prospects (GDP), (ii) the growth rate of the consumer price index as measure for inflation (CPI), and (iii) the 3M Treasury bill rate to approximate the monetary policy stance (SR). Since Consensus Economics usually provides forecasts for the current and next calendar year, we transform all variables into fixed one-year ahead forecasts.[2]

We aggregate the individual survey forecasts alongside two dimensions and calculate the cross-sectional mean for each variable as proxy for macroeconomic expectations ($E_t s_{t+12}$) and the corresponding standard deviation as measure of belief dispersion or disagreement ($D_t s_{t+12}$):

$$E_t s_{t+12} = \frac{1}{L} \sum_{l=1}^{L} E_{l,t} s_{t+12} \tag{1}$$

$$D_t s_{t+12} = \sqrt{\frac{1}{L-1} \sum_{l=1}^{L} (E_{l,t} s_{t+12} - E_t s_{t+12})^2} \tag{2}$$

2. The surveys for the 3M Treasury bill rates are already provided for one-year ahead in the dataset. For the other two indicators, the individual forecasts are transformed into one-year ahead forecasts ($E_{l,t,m} s_{t+12}$) using the following formula: $E_{l,t,m} s_{t+12} = (1 - m/12) \cdot E_{k,t,m} s_{cy} + m/12 \cdot E_{l,t,m} s_{ny}$. $E_{l,t,m} s_{cy}$ and $E_{l,t,m} s_{ny}$ are the individual forecasts of analyst l in month m of variable s for the current calendar year cy and the next calendar year ny, respectively.

We address measurement error concerns by extracting innovations from different VAR models (see Section 3.2 below). These innovation series can be interpreted as unexpected changes in macroeconomic expectations and the underlying disagreement, thereby accounting for possible constant and time-varying biases in the survey forecasts.

Equity Factors (see Figure A2). We approximate the stock market with the four most popular equity factors, that is, market, size, value, and momentum (Fama and French 1993; Carhart 1997). The factor returns are obtained from the website of Kenneth French and measured in US dollar at monthly frequency. The market risk premium is the value-weighted excess return of all available stocks on the NYSE over the risk-free rate. We use the common 2x3 sorting scheme to construct long-short portfolios for the remaining factors (size, value, and momentum). The portfolios are first sorted according to the median NYSE market capitalization and then either by (i) the book-to-market ratio (B/M) or (ii) the trailing 12M–1M returns. The breakpoints for these criteria are the 30th and 70th percentiles and this sorting scheme accounts for the size bias of the factors (cf., Cazalet and Roncalli 2014).

For the impulse response analysis in Section 4, we use these long-short factor portfolios. Following Ang (2022), we de-trend the log cumulative factor return series using the filter by Hodrick and Prescott (1997). The resulting series represent the cyclical variation of factor returns, that is, the percentage deviation from trend and are denoted with $\widetilde{MKT}$, $\widetilde{SMB}$, $\widetilde{HML}$ and $\widetilde{MOM}$.[3] As test assets for the DAPM in Section 5, we use excess returns from 50 long-only portfolios (25 portfolios sorted by size and value and 25 portfolios sorted by size and momentum) obtained from the website of Kenneth French.

3. We follow the recommendation of Ravn and Uhlig (2002) and use $\lambda = 129{,}600$ as smoothing parameter. Note that such a two-sided filtering procedure has been criticized, for instance, by Hamilton (2018). However, in our view it is an important first step to investigate impulse response functions by taking an ex-post perspective. Moreover, we also employed the unfiltered returns as input of the VAR models as part of our robustness tests. The general pattern of the IRFs (available on request) is similar, but less significant (economically and statistically) and features less distinctive differences across regimes due to the higher amount of noise in the unfiltered return data. Nevertheless, our dynamic asset pricing analysis in Section 5 is based on unfiltered equity factor premia.

DAPM Predictors (see Figure A3). According to the stock predictability literature, information from the term structure of Treasury yields as well as valuation indicators are good choices to approximate the price of risk dynamics (Campbell and Shiller 1988; Campbell and Thompson 2008). Therefore, we use the 10Y Treasury bonds yields ($T10Y$), the term spread expressed as yield difference between 10Y and 3M Treasuries (TS), and the log dividend yield of the S&P 500 (DY) as predictors in the dynamic asset pricing model. Bond market date are obtained from the FRED database and the dividend yield is extracted from Nasdaq Data Link.

State Drivers for LMVAR Weights (see Figure A4). As drivers for the state weights in the LMVAR, we approximate the stance of the business cycle with the lagged GDP growth rate and the financial cycle with the lagged National Financial Condition Index (NFCI).[4] The NFCI has been developed by the Federal Reserve of Chicago and aggregates 105 measures of financial activity from the pillars risk, credit, and leverage. Positive (negative) values indicate tighter (looser) conditions than the historical average.

3.2 Logit Mixture VAR Model

There are several approaches to model regime-dependent relationships among macro-financial variables. The most popular choices are Markov-switching VARs (Hamilton 1989) or threshold VARs (Tsay 1998). However, both approaches are restricted to be in strictly one regime at a time. Considering a transition period — as in a smooth transition VAR (Camacho 2004) — offers a more realistic view, but this model still has a high rigidity within a state. Mixture VARs address these concerns and allow for the coexistence of regimes. Fong et al. (2007) propose a version with time-constant and Kalliovirta et al. (2016) with time-varying state weights. In practice, however, both approaches have the shortcoming that their estimation is highly unstable and very sensitive to different starting values of the expectation-maximization (EM) algorithm. The

4. We use the temporal disaggregation method of Chow and Lin (1971) to transform quarterly GDP growth data into monthly data.

instability issue can be solved by the approach of Burgard et al. (2019) who introduce a logit submodel with observable state variables to incorporate economic reasoning into the mixture weight dynamics.[5]

LMVAR Model. We rely on the LMVAR model in the analysis of the dynamic response of cyclical equity factors to shocks in macroeconomic expectations (Specification 1). In addition, we utilize the model to obtain state-dependent innovations for the DAPM model (Specification 2). For reasons of computational feasibility, we limit the number of regimes to two (normal state and crisis state), which yields the following specification:

$$\begin{aligned} F(Y_t|\mathcal{F}_{t-1}) = \tau_t \cdot \Phi(\Omega_1^{-\frac{1}{2}}(Y_t - \Theta_{0,1} - \Theta_{1,1} Y_{t-1} - \ldots - \Theta_{p_1,1} Y_{t-p_1}))+ \\ (1-\tau_t)\cdot \Phi(\Omega_2^{-\frac{1}{2}}(Y_t - \Theta_{0,2} - \Theta_{1,2} Y_{t-1} - \ldots - \Theta_{p_2,2} Y_{t-p_2})) \end{aligned} \tag{3}$$

The dynamics of macroeconomic expectations and asset prices is described by two different components, each being a linear Gaussian VAR process with lag order p_1 and p_2. The information set up to time $t-1$ is denoted by $\mathcal{F}$ and $\Phi(.)$ is the multivariate cumulative distribution function of independent identically distributed standard normal random variables. $\Theta_{0,1}$ and $\Theta_{0,2}$ are the n-dimensional vector of intercepts in states 1 and 2. $\Theta_{1,1},\ldots,\Theta_{p_1,1}$ and $\Theta_{1,1},\ldots,\Theta_{p_2,1}$ are the $n\times n$ coefficient matrices. Ω_1 and Ω_2 are the $n\times n$ variance covariance matrices.

The LMVAR of Burgard et al. (2019) treats τ_t as a logistic function of observable state-driving variables. For the two regime case, the logit submodel is as follows:

$$\hat{\tau}_t = \frac{1}{1+exp(-\mathbf{z}^T\gamma)} \tag{4}$$

The matrix $\mathbf{z}$ might contain a constant and (lagged) covariates, also including the lagged mixture weights $\hat{\tau}_{t-1}$. γ denotes the coefficients of the logit submodel. Since the medium-run asset price dynamics typically depends on the stance of the economy and

5. Another multivariate mixture VAR approach is proposed by Gretener et al. (2022) who derive the state weights with a score-driven approach.

the prevalent financial conditions, we use the lagged real GDP growth rate to track the business cycle and the lagged NFCI to approximate the financial sphere. The choice of both variables is also supported in the literature (e.g., Adrian et al. 2021). Finally, we account for persistence in the mixture weights by employing the first lag of these as additional regressor in Eq. (4). One implication of employing only lagged variables in the submodel is to preclude that shocks in Y_t can (directly or indirectly) change the state weights in the same period t. The LMVAR model is estimated using an EM algorithm.

As benchmark for our regime-dependent analysis, we additionally estimate a conventional linear VAR using OLS with the following form:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + v_t \tag{5}$$

Specification 1: Dynamic Response of Equity Factors. When studying the dynamic response of equity factors to shocks in macroeconomic expectations and their underlying disagreement, vector Y_t in Eqs. (3) and (5) is defined as follows:

$$Y_t = [D_t s_{t+12}, E_t s_{t+12}, \widetilde{MKT}_t, \widetilde{SMB}_t, \widetilde{HML}_t, \widetilde{MOM}_t]. \tag{6}$$

$\widetilde{MKT}_t$, $\widetilde{SMB}_t$, $\widetilde{HML}_t$, and $\widetilde{MOM}_t$ are the de-trended factor returns. $D_t s_{t+12}$ and $E_t s_{t+12}$ are the dispersion and the expectations of a specific macroeconomic measure (GDP, CPI, or SR), for which we estimate separate models for three reasons. First, the cross section of stock returns already includes a lot of information about fundamentals and helps disentangling observed shocks from the survey forecasts. Second, professional forecasters typically provide consistent forecasts across macroeconomic variables, so that, for example, revisions to growth forecasts also affect inflation and interest rate forecasts. This can lead to structural redundancies in shock calculations. Third, when expectations and dispersion of all three macro variables as well as all factor returns are included into a single model, the increased number of parameters might inflate estimation uncertainty. Therefore, a more parsimonious specification is preferable.

In order to eliminate the remaining autocorrelation and to harmonize lag lengths across components and specifications, we set $p_1 = p_2 = 3$. Using the LMVAR results from Eq. (3) and the linear VAR results from Eq. (5), we calculate orthogonalized impulse responses to shocks in macroeconomic expectations and their underlying dispersion using a recursive identification approach. News in vector Y_t first diffuses into asset prices before influencing survey forecasts of macroeconomic measures. In contrast to the end-of-month stock market information, survey data is updated at the beginning of each month. Accordingly, we can assume that the forecasts affect asset prices in the same period and preclude the opposite.[6] For all models, confidence bands are calculated based on the 5% and 95% quantiles of 500 bootstrap samples, each with a horizon of 36 periods. For a comparison across macroeconomic forecasts and different VAR models, we normalize the shock size to 25 bps in the case of macroeconomic expectations and to 10 bps for their underlying dispersion.[7]

3.3 Dynamic Asset Pricing Model

Empirical asset pricing seeks to explain what compensation an investor requires for bearing systematic risk and how well certain risk factors can explain the variation in excess returns. The DAPM of Adrian et al. (2015) has two major benefits. First, it assumes time-varying prices of risk and is therefore consistent with the overwhelming existence of varying time-risk premia (e.g., Campbell and Shiller 1988). By assuming that the prices of risk are affine functions of external predictors, the DAPM represents a realistic reduced-form representation of a dynamic macro-finance model. Second, it combines the computational ease of Fama-MacBeth regressions with the flexibility to test the pricing power and the predictive ability of different specifications. Moreover, the model of Adrian et al. (2015) accounts for conditional heteroskedasticity and esti-

6. The sorting of the equity factor premia variables does not noticeably influence their responsiveness to dispersion and expectation shocks. The same holds for the sorting of the macroeconomic expectation variables.

7. Both states are allowed to co-exist for each t in an LMVAR, which is a major benefit compared to Markov-switching VAR models or threshold VAR models. The overall impulse response function is a continuously varying mixture of the impulse responses for both states, with the weights being determined by the underlying logit model. Further details on the estimation procedure and the derivation of impulse responses can be found in Burgard et al. (2019) and Bennani et al. (2023).

mation uncertainty arising from the use of generated regressors. We apply the DAPM to test whether survey-based macroeconomic expectations and their underlying disagreement are relevant pricing factors and/or significant predictors of the price of risk dynamics.

DAPM. As starting point, the DAPM assumes a first-order stationary vector autoregressive model as data-generating process of the state variables of the economy:

$$x_{t+1} = \mu + \Phi x_t + v_{t+1} \tag{7}$$

x_t represents the $K \times 1$ vector of state variables with $t = 1, 2, ..., T$. The state variables can represent risk factors $x_{1,t}$ ($K_1 \times T$ dimension), price of risk factors $x_{3,t}$ ($K_3 \times T$ dimension), or variables that are both $x_{2,t}$ ($K_2 \times T$ dimension). Risk factors significantly explain the cross section of asset prices, whereas price of risk factors predict the time variation of excess returns. We denote $c_t \in \mathbb{R}^{K_C}$ as risk factors and $f_t \in \mathbb{R}^{K_F}$ as price of risk factors with:

$$\begin{aligned} c_t = [x_{1,t}, x_{2,t}]' \qquad f_t = [x_{2,t}, x_{3,t}]' \qquad u_t = [v_{1,t}, v_{2,t}]' \\ K_C = K_1 + K_2 \qquad K_F = K_2 + K_3 \qquad K = K_1 + K_2 + K_3 \end{aligned} \tag{8}$$

We assume the existence of a unique stochastic discount factor (SDF) m_{t+1}, so that the excess return $r_{i,t+1}$ of every asset i ($i = 1, 2, \ldots, N$) is priced conditional on a time-dependent information set $\mathcal{F}_t$:

$$\mathbb{E}_t[m_{t+1}, r_{i,t+1} | \mathcal{F}_t] = 0 \tag{9}$$

In addition, we let the SDF be affine-linear in the risk factor innovations:

$$\frac{m_{t+1} - \mathbb{E}_t[m_{t+1} | \mathcal{F}_t]}{\mathbb{E}_t[m_{t+1} | \mathcal{F}_t]} = -\lambda_t' \Sigma_u^{-1} u_{t+1} \tag{10}$$

with the conditional variance Σ_u and the time-varying price of risk $\lambda_t = (\lambda_0 + \Lambda_1 f_t)$. From this pricing kernel, we can express the expected excess return of an asset i using a beta representation:

$$\begin{aligned}\mathbb{E}[r_{i,t+1}|\mathcal{F}_t] &= -\frac{Cov[m_{t+1}, r_{i,t+1}|\mathcal{F}_t]}{\mathbb{E}_t[m_{t+1}|\mathcal{F}_t]} \\ &= \lambda_t' \Sigma_u^{-1} Cov[u_{t+1}, r_{i,t+1}|\mathcal{F}_t] \end{aligned} \tag{11}$$

The empirical pricing equation of the DAPM with a vector of time-constant risk exposures β_i relates the excess return $r_{i,t+1}$ to the price of risk and the risk factor innovations:[8]

$$r_{i,t+1} = \beta_i'(\lambda_0 + \Lambda_1 f_t) + \beta_i' u_{t+1} + e_{i,t+1} \tag{12}$$

The first term shows the expected excess return $\beta_i'(\lambda_0 + \Lambda_1 f_t)$. The unexpected part can be decomposed into an innovation term — that is conditionally correlated to the risk factors $\beta_i' u_{t+1}$ — and an independent asset-specific pricing error $e_{i,t+1}$. Given this distinction, the DAPM's aim is to filter the (unobservable) risk premia λ_t from an NT matrix of test assets.[9]

The authors suggest a three-step regression approach to estimate the parameters. For the sake of simplicity, we use OLS estimation:[10]

1. A VAR model is estimated with $\hat{\Psi} = X'\tilde{X}_-'(\tilde{X}_-\tilde{X}_-')^{-1}$ and the contemporaneous innovations to the risk factors $\hat{U}$ are extracted as the first K_C rows of $\hat{V}$ with $\hat{V} = X - \hat{\Psi}\tilde{X}_-$. In addition to a standard linear VAR, we utilize the LMVAR model to obtain state-dependent innovations.

8. We utilize the constant beta framework as Adrian et al. (2015) point out that the benefit of time-varying betas in reducing the pricing errors is — at best — small. A time-varying price of risk is found to be more helpful in that regard.

9. An appealing feature of the DAPM is the close relationship to the Fama and MacBeth (1973) methodology. By setting $\Phi = 0$ and $\Lambda_1 = 0$, both approaches are indeed identical.

10. An alternative would be a quasi-maximum likelihood (QMLE) approach. However, OLS and QMLE estimates of $\hat{\lambda}_0$ and $\hat{\Lambda}_1$ are asymptotically equivalent (Adrian et al. 2015). Concerning the notation, we closely follow Adrian et al. (2015), that is, capital letters are the matrix representation of the corresponding variables, $\tilde{X}_-$ is the lagged matrix of state variables extended by a vector of ones on the left, and F_- is the lagged matrix of the price of risk factors.

2. For each test asset i, we run a time series regression on the lagged price of risk factors and the innovations to infer the corresponding factor exposures. Specifically, we estimate $\hat{A} = R\hat{Z}'(\hat{Z}\hat{Z}')^{-1}$ with Z as stacked vector of $[1, F_{-}, \hat{U}]$ and $\hat{A}$ as stacked vector of loadings $[\hat{A}_0, \hat{A}_1, \hat{B}]$. $\hat{A}_0$ represents the intercept and $\hat{A}_1$ ($\hat{B}$) the asset's sensitivity to the predictors (risk factor innovations).

3. The parameters of the price of risk equation are obtained using a cross-sectional regression of the asset's risk factor loadings $\hat{B}$ on the intercept $\hat{\lambda}_0 = (\hat{B}'\hat{B})^{-1}\hat{B}'\hat{A}_0$ or the predictive slope $\hat{\Lambda}_1 = (\hat{B}'\hat{B})^{-1}\hat{B}'\hat{A}_1$. The latter term represents the sensitivity of the price of risk to the external predictors and causes the risk premium to be time-varying.

In order to draw statistical inference, we account for the estimation uncertainty arising from each estimation step by adjusting the covariance matrix.[11]

Specification 2. In our benchmark model, we filter the price of risk for the four most common factors (MKT, SMB, HML, and MOM). As predictors for the dynamics, we follow Adrian et al. (2015) and Umlandt (2023) and use a three-variable specification consisting of the 10Y constant maturity yield of US Treasury bonds ($T10Y$), the 10Y minus 3M term spread (TS), and the log dividend yield for the S&P 500 (DY). Since asset pricing models are forward-looking and linked to macroeconomic expectations, survey forecasts are natural candidates as pricing variables and as predictors of the risk price dynamics. We investigate the value added of survey forecasts to both variable sets:

$$c_t = [MKT_t, SMB_t, HML_t, MOM_t, D_t s_{t+12}, E_t s_{t+12}] \tag{13}$$

$$f_t = [D_t s_{t+12}, E_t s_{t+12}, T10Y_t, TS_t, DY_t] \tag{14}$$

The broadest setting includes macroeconomic expectations and their dispersion as part of c_t and f_t (denoted by the suffix "_FC"). We also estimate two specifications where

11. For more details on this adjustment and a general derivation of the estimation procedure, we refer to the original paper of Adrian et al. (2015).

survey forecasts are risk factors only (suffix "_C") or where these only affect the price of risk factors (suffix "_F"). For each expectation measure $s = \{GDP, CPI, SR\}$, we estimate the DAPM separately for the same reasons as in the case of Specification 1 (cf. p. 13). Finally, each of the three settings is estimated with innovations extracted from a linear VAR (Linear) or from an LMVAR model (Normal state, Crisis state, or state-weighted Mixture). The latter again utilizes lagged real GDP growth and the lagged NFCI as covariates in the submodel to capture the multimodality of the economy.

4 Dynamic Response of Equity Factors

In order to conserve space, we mostly focus on the results of the LMVAR model. The IRFs of the linear VAR model can be found in Figures B1–B4 in Appendix B. In this analysis, we rely on the cyclical factor returns (cf. footnote 3).

Within the logit submodel of the LMVAR, we approximate the state of the economy with the lagged GDP growth rate and the financial cycle with the lagged NFCI, while also accounting for persistence in the mixture weights by employing their first lag as additional regressor. Figure 1 shows the results. The state weights can be interpreted as depicting the prevalence of a crisis state with the recession in the early-1990s, the Global Financial Crisis, and the COVID-19 crisis standing out. The crisis state has average weights of 6.8% (GDP model), 10.4% (CPI model), and 8.5% (SR model), respectively. Lower GDP growth and, in particular, tighter financial conditions are associated with higher crisis weights. Although the predicted probability plots for the lagged GDP growth rate are relatively flat (with the exception of the GDP expectations model), we always include both variables in line with the multimodality of macro-financial conditions in the US (cf., Adrian et al. 2021).[12]

12. We also tested two other specification of the logit submodel. First, we use only one external regressor, the Conference Board's leading economic index. The path of the state weights is similar, but the peaks during the Global Financial Crisis and the COVID-19 crisis are less pronounced. The estimated IRFs are qualitatively similar to the ones presented in Figures 2–5. Second, we extend the baseline logit submodel with the lagged expectation and dispersion measures with limited value added for the logit submodel. Again, the estimated IRFs largely correspond to our baseline results. All omitted results are available on request.

[Figure 1 around here]

4.1 Responses of Market Factor

Starting with the regime-dependent responses of the aggregate stock market, Figure 2 shows the IRFs to a 25 basis points (bps) shock in macroeconomic expectations (left panel) and a 10 bps shock in forecast dispersion (right panel).

[Figure 2 around here]

An unexpected improvement in GDP expectations has a positive impact on the market factor with an instantaneous peak. The effect gradually dissipates over the following 12 (6) months in normal (crisis) times with a medium-term correction in turbulent times (after 9–24 months), suggesting a short-term overshooting of asset prices after good news. A shock to expected inflation has a negative impact on the market factor, which becomes significant after 6 months in both states and lasts up to 36 (24) months in the normal (crisis) state. The size of the responses differs significantly between the two states. In bad times, an inflation shock has twice the impact on asset prices, underscoring the importance of countercyclical inflation shocks. The effect of higher interest rate expectations is less pronounced with only a weak positive impact that disappears after 18 months in both states.

An unexpected increase in economists' forecast dispersion leads to an immediate reduction of the cyclical stock market component irrespective of the type of shock and state of the economy. For GDP expectations, the negative impact lasts between 7 months (normal state) and 14 months (crisis state). Higher disagreement over inflation and monetary policy expectations is much more persistent in the normal state, depressing the stock market for about 30 months. During crisis times, the reaction is more pronounced, but also more short-lived. In this state, the trough can be found after 2 months (inflation) and 6 months (interest rates). For example, a 10 bps increase in inflation dispersion during the crisis (normal) state leads to a –2.5 (–1) percentage points (pp) deviation from the stock market trend. The effect of inflation belief dispersion reverses in the crisis state after 12–24 months, indicating an initial overreaction of market participants.

To summarize, the state of the economy does not significantly change the direction of the response. However, the persistence of responses decreases and the magnitude of the price reaction increases substantially in the crisis state. Our findings are plausible from a theoretical point of view. The stock market is positively correlated with cash flow news (Hecht and Vuolteenaho 2006) and negatively correlated with unexpected inflation (Fama and Schwert 1977). Moreover, higher belief dispersion translates into higher information uncertainty, which is bad for stocks due to an increase in the risk premium (Anderson et al. 2009) or behavioral-based under- or overreactions (Cujean and Hasler 2017).

Comparing the results to the one-state VAR (see Figure B1 in Appendix B), we find that the regime separation leads to more significant IRFs. In terms of the general direction, the results of the linear VAR are qualitatively similar to those for the normal state of the two-state LMVAR.

4.2 Responses of Size Factor

There is widespread evidence that smaller stocks are riskier than larger ones, since these are more illiquid and financially constrained. Smaller stocks exhibit higher market risk (Hahn and Lee 2006), larger cash flow sensitivity (Aretz et al. 2010), and a more pronounced default risk (Vassalou and Xing 2004).

[Figure 3 around here]

The results of the IRFs in Figure 3 confirm that small stocks benefit more from higher growth expectations than large stocks with a statistically significant effect for up to 12 months. Although small stocks react more sensitively to cash flow news, these are less affected by higher GDP dispersion. Higher short-sale restrictions for small firms may explain this finding, so that higher disagreement leads to higher (relative) prices reflecting the views of optimists (Miller 1977). Expectation or dispersion shocks to inflation do not generate significant responses in the short-run as we observe a small positive effect for the first time 18 months after the shock. The effect of interest rate expectation shocks is initially positive, but turns to be persistently negative after about 9 months. Since higher interest rates are associated with tighter financial conditions, the negative response of the size premium is plausible. Similar to GDP, higher disagreement tends to slightly increase the cyclical size factor. Again, restrictions on short-selling might be an explanation for this finding.

In contrast to the market factor, we find the IRFs of the size premium to be relatively robust with respect to the regime of the economy, so that the difference between the normal and the crisis state is marginal. When comparing the results to those from linear VAR models (see Figure B2 in Appendix B), the general direction of the IRFs is similar.

4.3 Responses of Value Factor

There are two main explanations for the value premium in the literature. The risk-based explanation argues that value stocks have a greater exposure to fundamental risk due to higher adjustment costs (Zhang 2005). The (main) behavioral story highlights that investors overextrapolate growth trends so that the fundamental "true" value of growth stocks is systematically overestimated (Lakonishok et al. 1994). However, this mispricing is corrected in the long-run.

[Figure 4 around here]

Figure 4 shows the relationship between shocks to macroeconomic forecasts and the value premium. Value stocks outperform growth stocks after shocks to GDP expectations and underperform after GDP dispersion shocks. A 25 bps increase in GDP expectation leads to a 0.4 (0.55) pp increase of the cyclical value premium in the normal (crisis) state that lasts for 30 (18) months. Higher dispersion shocks weigh on the value premium for 12 months, with the economic relevance being more pronounced in the crisis state. Hence, our results confirm the findings of Petkova and Zhang (2005) that value stocks are (systematically) riskier due to higher business cyclical sensitivity.

Inflation expectations and the underlying disagreement are also affecting the value premium. Expectation shocks have a positive and very persistent impact during normal times. In the crisis state, their effect is more volatile and much larger (more than twice as large as in the normal state), but disappears after 12 months. The state-dependency of the effects of inflation dispersion is also striking. In normal times, value stocks significantly outperform growth stocks, starting from 3 months after the shock. In contrast, when such a shock occurs in bad times, the value premium declines 2–6 months after the shock, before converging to zero and becoming slightly positive in the medium-run. This different short-term behavior highlights the changing role of inflation uncertainty on the value premium in different states of the economy.

The impact of inflation shocks can be explained by the duration argument, as higher expected inflation implies higher interest rates, which hurts growth stocks more than value stocks through the discount rate channel. This argument is also supported by the results of interest rate expectation shocks. A 25 bps increase leads to a 40–60 basis point rise in the cyclical value premium that persists for 12–18 months. Higher disagreement about monetary policy, which is typically positively correlated with the level of the interest rate, supports value stocks for 6 months. In general, the magnitude and persistence of the response to interest rate shocks is quite similar across the two states.

Once more, the superiority of the two-state model in terms of statistical efficiency is underscored by a comparison to the results of a linear VAR (see Figure B3 in Appendix B) as the IRFs of the latter are — if at all — only marginally significant when considering 90% confidence bands.

4.4 Responses of Momentum Factor

Momentum is different from the previously discussed size and value premia as behavioral explanations are dominant for this factor. Whether investors underreact to news, so that new information diffuses gradually into prices (Hong and Stein 1999), overreact due to overconfidence (Daniel et al. 1998), or even both — due to differences in opinions and adjustment speed (Cujean and Hasler 2017) — is still an active area of research. However, it is evident that behavioral biases are more prevalent in periods of high uncertainty (Zhang et al. 2009), which in combination with different learning mechanisms of investors increases the strength of momentum in bad times (Cujean and Hasler 2017).

As Jegadeesh and Titman (1993) do not consider momentum as a risk factor, a rational pricing explanation was not a major topic in the literature. Nevertheless, Ruenzi and Weigert (2018) argue that higher tail risk may justify a risk compensation for momentum. The relationship with macroeconomic variables is also addressed by some authors as Liu and Zhang (2008) provide support for the risk proxy story by showing that industrial production helps to explain momentum returns. However, Bergbrant and Kelly (2016) find a negative relationship with GDP and consumption growth.

[Figure 5 around here]

Indeed, if we relate the cyclical momentum returns to expectation and dispersion shocks (see Figure 5), we can detect some interesting patterns that depend significantly on the state of the economy. In the normal state, GDP and inflation expectation shocks have a slightly positive effect on the momentum factor, while the effect of interest rate expectations is negative for the first 6 months before turning positive after 12 months. The effect of dispersion shocks in normal times is essentially mirror-inverted to that of expectation shocks.

In contrast, if the economy is in the crisis state, the initial reaction is negative for all expectation shocks, in particular for inflation and interest rates. After 6 months the latest, the sign of the effect changes and becomes significantly positive. For GDP and inflation, however, this positive effect is short-lived, turning negative once more after 12–18 months. A wave-like behavior is also evident for the disagreement proxies in the crisis state. Higher dispersion about all measures increases the returns of the momentum factor for up to 6–12 months before the effect turns negative. In the case of inflation dispersion, we observe a second change in sign after around two years.

It has to be noted that some of the horizon-dependent dynamics is caused by the factor construction itself as it incorporates data of the past 12 months. However, the fact that the peak (or trough) of the IRFs is mostly found between 3 and 12 months after the shock documents that investors underreact to news, in particular during crises, which opens the door to short-run return predictability. These findings are consistent with the theoretical model of Cujean and Hasler (2017), in which polarization of opinions during bad times leads to an underreaction to news. Such a behavior increases the persistence of returns and boosts momentum profits in crisis times.

Finally, the IRFs of the linear model are again only significant for a very short time horizon, which can be attributed to forcing the economy to stay in a single state (see Figure B4 in Appendix B).

5 Dynamic Asset Pricing Results

In this section, we focus on (unfiltered) excess returns.[13] First, we present the DAPM estimation results. Second, we investigate the pricing ability with regard to the root mean square (premium) errors for our universe of test assets.

5.1 Estimation Results

The estimation results of the benchmark model are shown in Table 1. The columns represent the risk factors and the rows the estimated parameters starting with the unconditional risk premium of a factor that can be identified using $\bar{\lambda} = \hat{\lambda}_0 + \hat{\Lambda}_1 E[f_t]$. Testing the null hypothesis of $\bar{\lambda} = 0$ indicates whether a risk factor is unconditionally priced in the cross section. In line with prior results of Adrian et al. (2015) and

13. Potential differences between the results of the IRF analysis and the DAPM model can be explained by at least two reasons. First, filtering out the ex-post trend component might perpetuate the conditional expected value relative to the actual return series. Second, risk premia are predetermined by realized predictors in the DAPM, so that — unlike in the IRF analysis — unexpected shocks are not dynamically related to risk premia.

Umlandt (2023), we identify a significant premium only for MKT. The loadings on the price of risk factors in the rows T10Y, TS, and DY confirm our theoretical priors. Lower long-term bond yields and higher dividend yields significantly predict a higher market premium, whereas the opposite is true for the momentum premium. Finally, the value premium benefits from lower risk aversion and steeper yield curves.

[Table 1 around here]

Extending the benchmark model with the survey forecasts, Table 2 shows the statistically significant relationships and their signs according to a confidence level of 90%. The risk factors are sorted column-wise and differentiated by the different VAR models used to extract the innovations (L: linear VAR, N: normal state of LMVAR, C: crisis state of LMVAR, and M: state-weighted combination of normal and crisis state). To conserve space, we present only the results where the expectations serve as both, pricing variables and predictor of the risk price dynamics (FC-specification; all omitted results are available upon request). The explanatory power of all these models (including the benchmark with 88%) is substantial with an average (adjusted) R^2 of 87–89%.

[Table 2 around here]

GDP Survey Data. No traded risk factor is priced significantly in the cross section when employing GDP expectations and their underlying dispersion as additional predictors. This is primarily caused by larger standard errors due to the extension of the specification. However, $D_t s_{t+12}$ and $E_t s_{t+12}$ serve as unconditional pricing factors. To hedge economic growth uncertainty, investors accept a negative disagreement premium, whereas GDP expectations are positively priced (with the exception of the crisis state). The unconditional significance of these two risk factors emphasizes the relation between stock prices and cash flow news.

The predictive relationships for the market risk premium remain constant across all states compared to the benchmark model, that is, higher dividend yields and lower long-term interest rates increase the market risk premium. The same holds for the momentum premium with an inverse sign. The size premium has a negative relation to GDP expectations, whereas the value premium responds positively to GDP expectations and their dispersion. Including growth forecasts causes the previously significant relationships with the term spread and dividend yields to disappear. This suggests that these relationships (e.g., Petkova 2006) are actually driven by economic expectations and their dispersion. Finally, we do not document a predictive pattern with any variable when relying on GDP dispersion as pricing variable. In contrast, GDP expectations are positively correlated with their past values and with 10Y Treasury yields (in the linear model and during crises) and negatively with their underlying disagreement.

CPI Survey Data. The inclusion of inflation survey measures does not provide any significant unconditional risk premium. However, these significantly drive the future time variation of risk factors. The broad market is no longer affected by the 10Y yields as inflation expectations drive the price of risk instead. The value premium and the momentum premium increase with higher expected inflation, whereas the dividend yield (term spread) still affects these premia negatively (positively). Furthermore, inflation dispersion exhibits positive conditional autocorrelation and a negative (positive) relationship with long-term yields and inflation expectations (with the dividend yields and the term spread).

Interest Rate Survey Data. Similar to the case of inflation survey measures, no risk factors are unconditionally priced in the cross section. Controlling for interest rate expectations causes the significance of the 10Y yields to disappear. However, the importance of the term spread rises. For the value premium and the momentum premium, only the dividend yield preserves a stable predictive pattern, as it increases the disagreement about monetary policy and lowers interest rate expectations. Using the state-weighted specification, we identify a negative effect of interest rate expectations on the future equity risk premium.

A graphical comparison of the time variation in the risk premia of MKT, SMB, HML, MOM, $E_t s_{t+12}$, and $D_t s_{t+12}$ can be found in Figures C1–C4 in Appendix C. Figure C1 shows the (monthly) prices of risk with the FC-specification relying on a linear VAR model to extract the innovations for the different macroeconomic expectations. The black line shows the benchmark DAPM without any survey measure. Extending the DAPM with survey forecasts often produces similar estimates. Remarkable exceptions are GDP expectations-driven dynamics for the size and value premia and inflation expectations-driven dynamics for the market, value, and momentum premia. These findings emphasize the relevance of growth and inflation expectations for risk premium dynamics.

Figures C2 (GDP), C3 (CPI), and C4 (SR) illustrate the variation of the risk premia for the three macroeconomic expectation variables if the innovations are obtained from different VAR specifications. These figures show that in most cases the estimated risk premia are the same with only the crisis state innovations being an exception. The distinctiveness of turbulent phases for asset prices in general and the relation to macroeconomic expectations and disagreement are also highlighted in the theoretical model of Cujean and Hasler (2017).

5.2 Pricing Errors

Next, we evaluate the in-sample pricing and prediction errors of the DAPM models. For this purpose, we calculate two measures. First, the root mean square (pricing) error (RMSE) that combines the expected and unexpected component from each asset i:

$$RMSE_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(r_{t,i} - \hat{\beta}_i \hat{u}_t - \hat{\beta}_i \hat{\lambda}_{t-1}\right)^2} \tag{15}$$

Second, the root mean square premium error (RMSPE) that relies only on the ex ante expected returns:

$$RMSPE_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(r_{t,i} - \hat{\beta}_i \hat{\lambda}_{t-1}\right)^2} \tag{16}$$

Table 3 presents the average root mean square pricing and premium errors across all 50 equity portfolios using the nested (FC) and non-nested specifications (C: risk factors; F: price of risk factors) of the survey measures-extended DAPM. The results highlight the particular importance of using expectation and disagreement measures as drivers of the price of risk dynamics.

[Table 3 around here]

With respect to the overall pricing errors (RMSE), the linear and the normal-state model with survey measures as price of risk factors provide better results than the benchmark throughout all cases. Specifically, the nested framework in which survey forecasts are allowed to affect the cross section and the time variation consistently outperforms the non-nested models. When relying on the RMSPE, the augmented models outperform the benchmark as well. In this case, the linear and mixture models stand out, with the value added being driven by using expectation and disagreement measures as drivers of the price of risk dynamics.

As a final step, we try to figure out which test assets drive the average outperformance and which part of the DAPM — the contemporaneous innovation term or the expected return part — is responsible for this outperformance. The heat maps in Figures 6 (GDP), 7 (CPI), and 8 (SR) show the relative pricing and premium errors expressed as deviation from the benchmark model. The color scale ranges from green (superior to benchmark) to red (inferior to benchmark), with white denoting no difference to the to benchmark.

[Figures 6, 7, and 8 around here]

The benefit with respect to the RMSE is mainly documented for small stock portfolios. These portfolios are typically more affected by a country's economic situation. Their higher systematic risk and the fact that these markets are less efficiently priced is in line with the result that macroeconomic survey measures help to explain these factors. However, this finding is not surprising and the major benefit for investors is small since investing in stocks within the lowest 20% percentile of market capitalization is difficult. Nevertheless, the results for the relative premium errors (RMSPE) provide good news to investors and underline the usefulness of our specification choice. With respect to this measure, the advantage of using macroeconomic survey measures is striking throughout all assets, irrespective of whether these are (i) small or large, (ii) value or growth stocks, or (iii) exhibit high or low prior performance. These findings hold in particular for the linear and the mixture case as well as for all three survey measures. The only exceptions are the models using GDP surveys and high growth and momentum stocks.

6 Conclusions

In this paper, we examine the (asymmetric) impact of macroeconomic expectations and their underlying dispersion on equity risk premia across different market regimes in the US for the period 1989M10–2022M09.

Our results indicate, first, that shocks to macroeconomic expectations have a significant impact on (cyclical) risk premia. Better growth prospects particularly affect the dynamics of stocks with higher systematic risk, such as small and value stocks. Moreover, growth expectations are significantly priced in the cross section and earn — on average — a positive premium. Rising inflation expectations reduce the broad equity risk premium, whereas these increase the attractiveness of value and momentum stocks. Second, dispersion shocks negatively affect long-only equity portfolios, irrespective of the source of the shock. The effects of these shocks are particularly pronounced during crises, but more short-lived. Unconditionally, growth dispersion is negatively priced so that investors are willing to pay a premium to hedge against fundamental uncertainty.

Most important to our paper, however, is the question of whether the macro-financial state matters for the responsiveness of stocks. Indeed, the results for the two-state LMVAR models feature more distinct and less noisy estimates compared to that of linear VAR models. Accounting for different states captures the multimodality of the economy, reduces estimation uncertainty, lowers standard errors, and allows to understand the time-varying and non-linear relationships between expectations about fundamentals and factor returns. In particular, the magnitude, persistence, and occasionally also the sign of the relationship depend on the macro-financial regime.

Our paper adds to the existing evidence that macroeconomic variables matter for equity factors. Survey forecasts can improve the pricing of small stocks within the dynamic asset pricing model and lower premium errors of a broad set of sorted portfolios. Moreover, our results provide evidence that survey dispersion in macroeconomic forecasts is associated with information uncertainty, which justifies risk compensation and higher expected returns.

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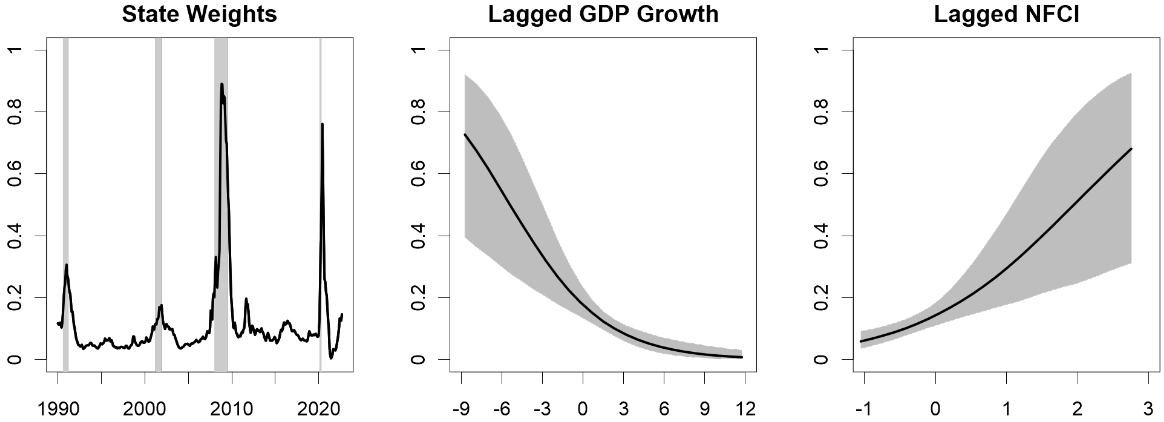
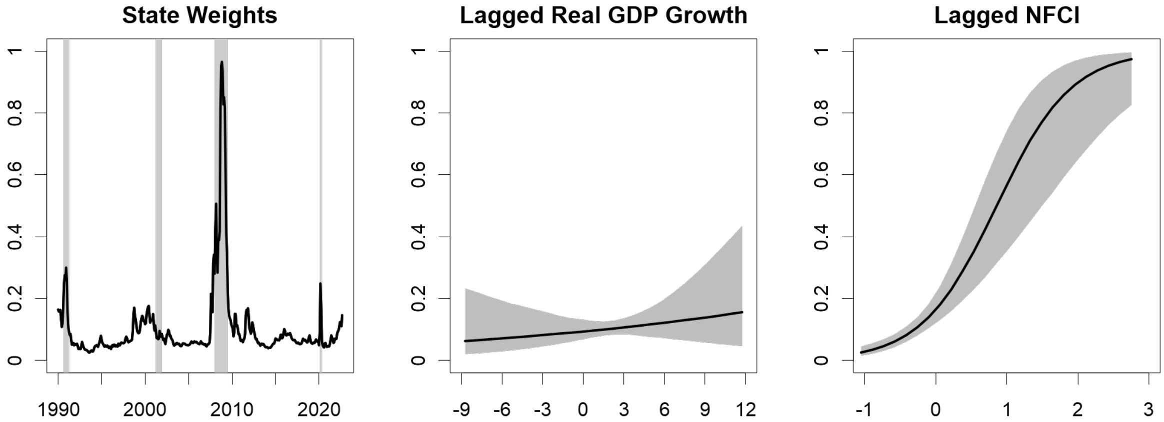
Figures

Figure 1: Logit Submodel of State Weights

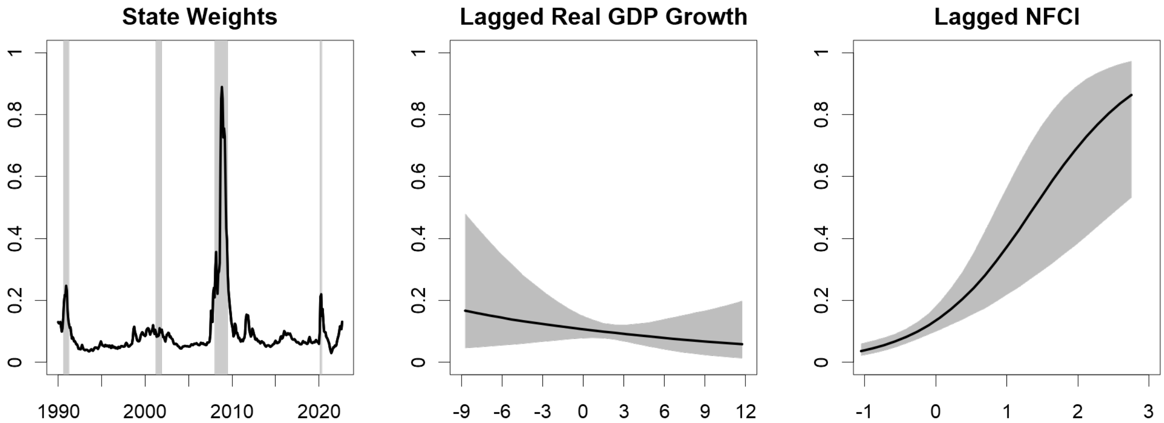
Panel A: Specification with GDP Growth Expectations



Panel B: Specification with Inflation Expectations

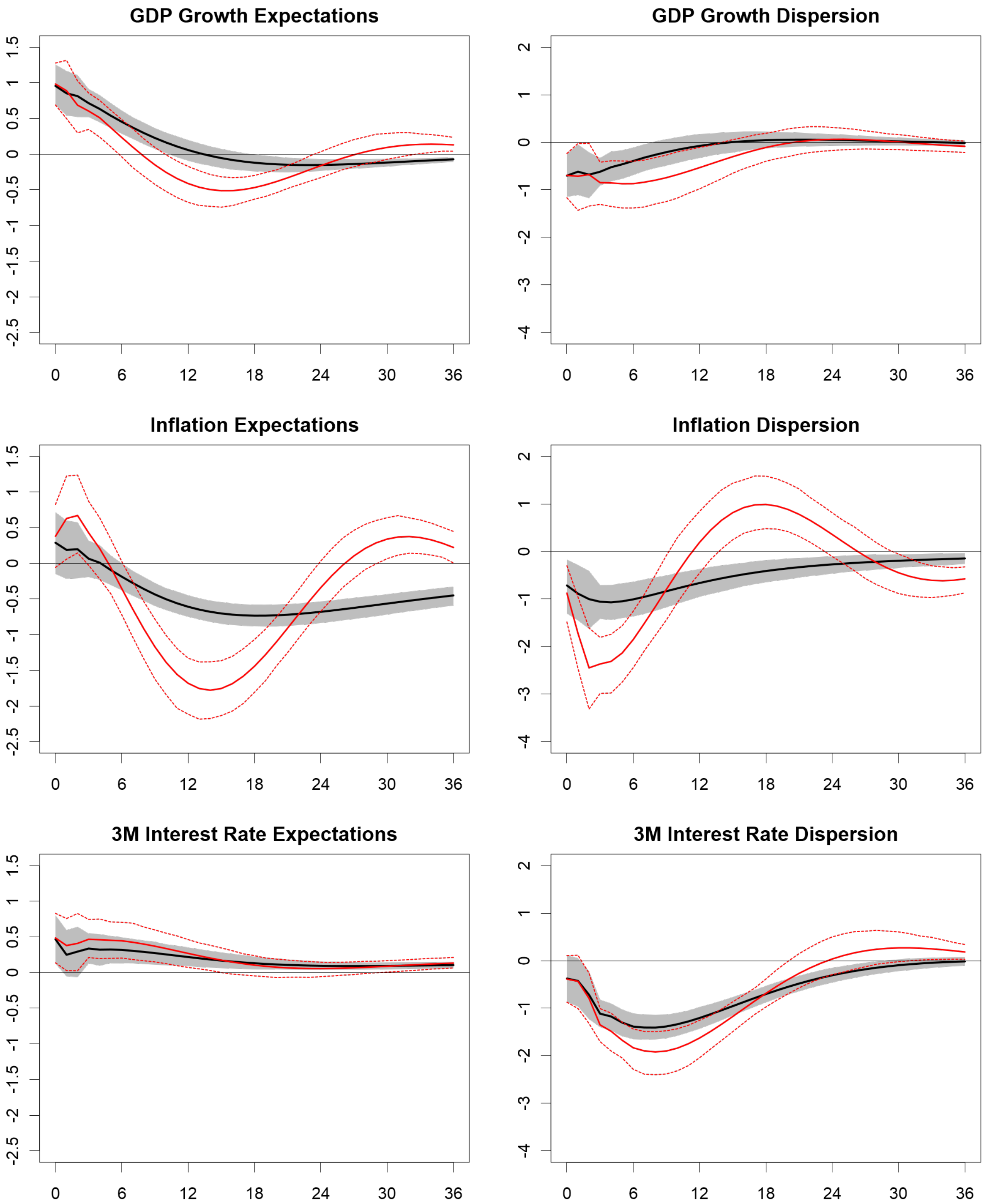


Panel C: Specification with 3M Interest Rate Expectations



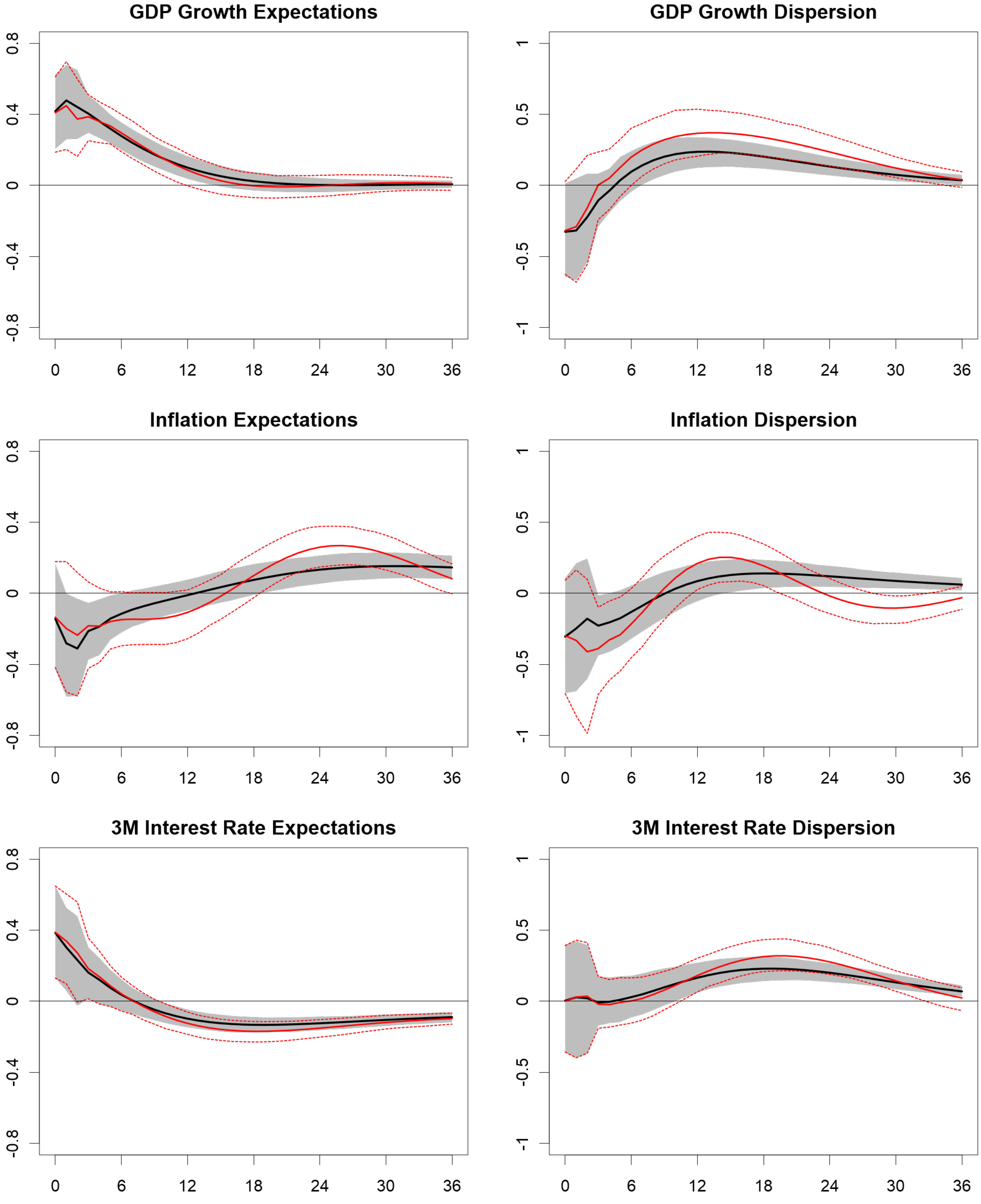
Notes: Left column shows weights of the crisis state for the different expectation variables. Gray-shaded areas indicate NBER recessions. Middle and right columns show the predicted probabilities of the logit submodels for the crisis state and different realized values of the explanatory variables. Gray-shaded areas indicate 90% confidence bands.

Figure 2: IRFs for Cyclical Market Factor ($\widetilde{MKT}$)



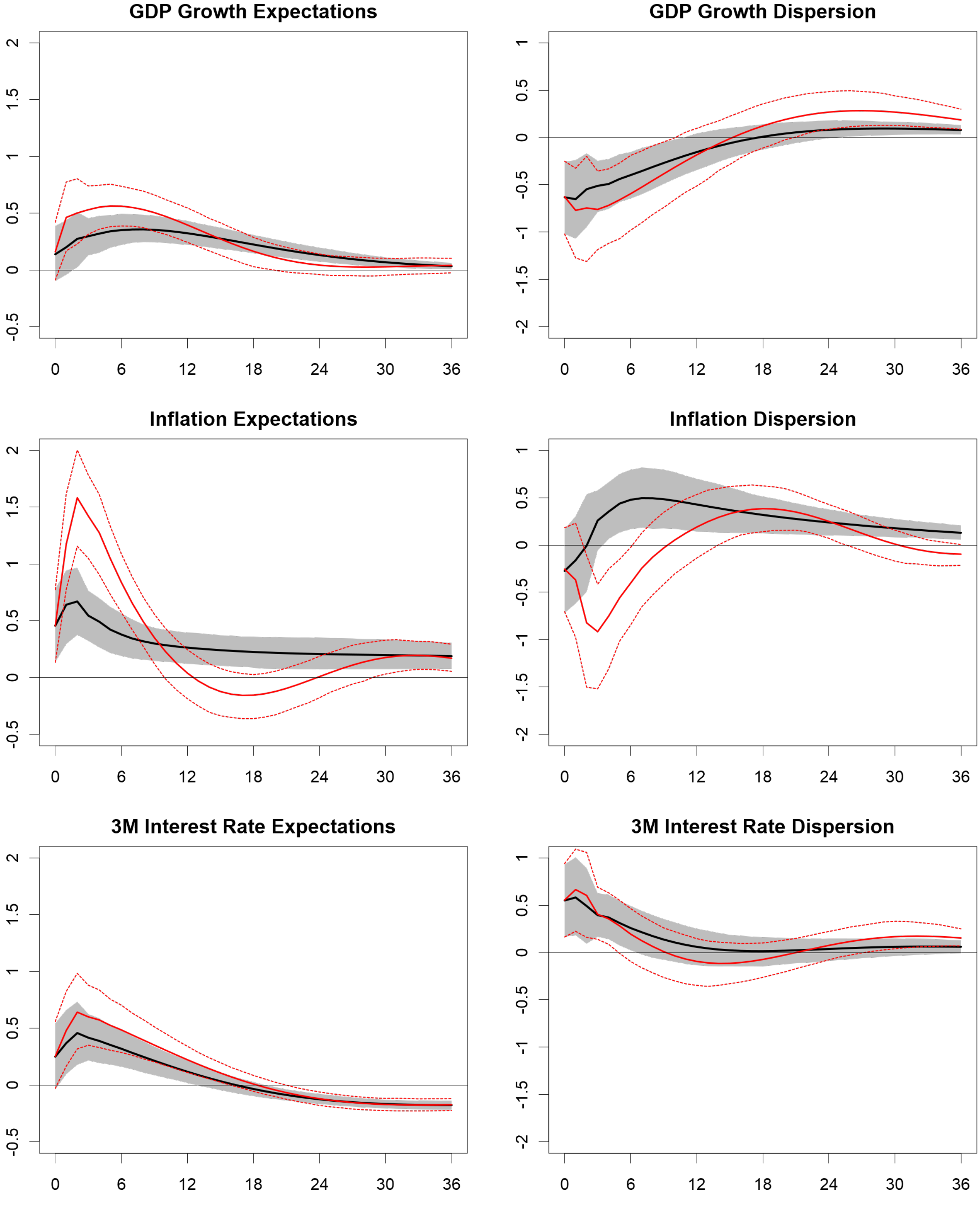
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 90% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request. The corresponding IRFs for a linear VAR model can be found in Figure B1 in Appendix B.

Figure 3: IRFs for Cyclical Size Factor ($\widetilde{SMB}$)



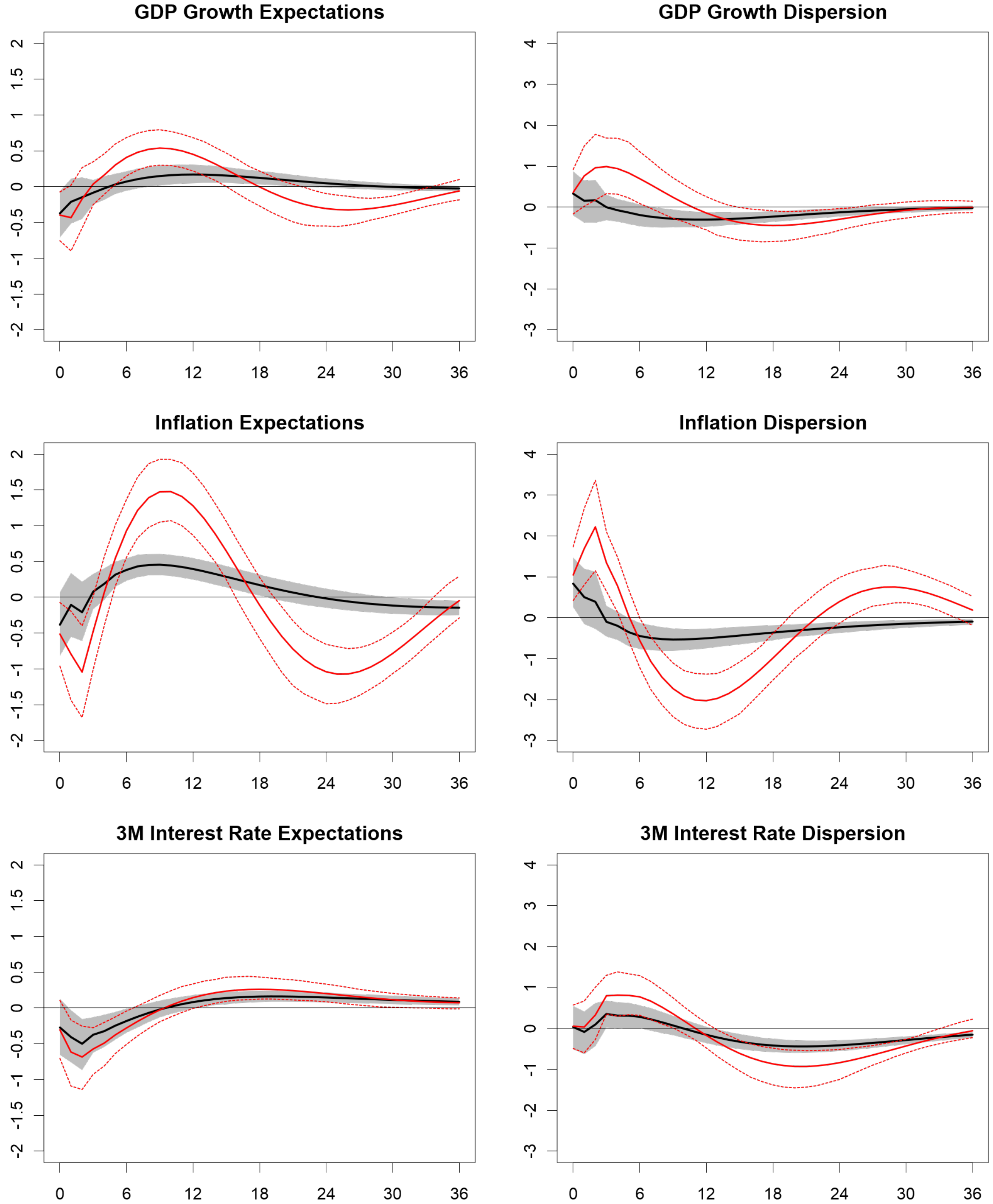
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 90% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request. The corresponding IRFs for a linear VAR model can be found in Figure B2 in Appendix B.

Figure 4: IRFs for Cyclical Value Factor ($\widetilde{HML}$)



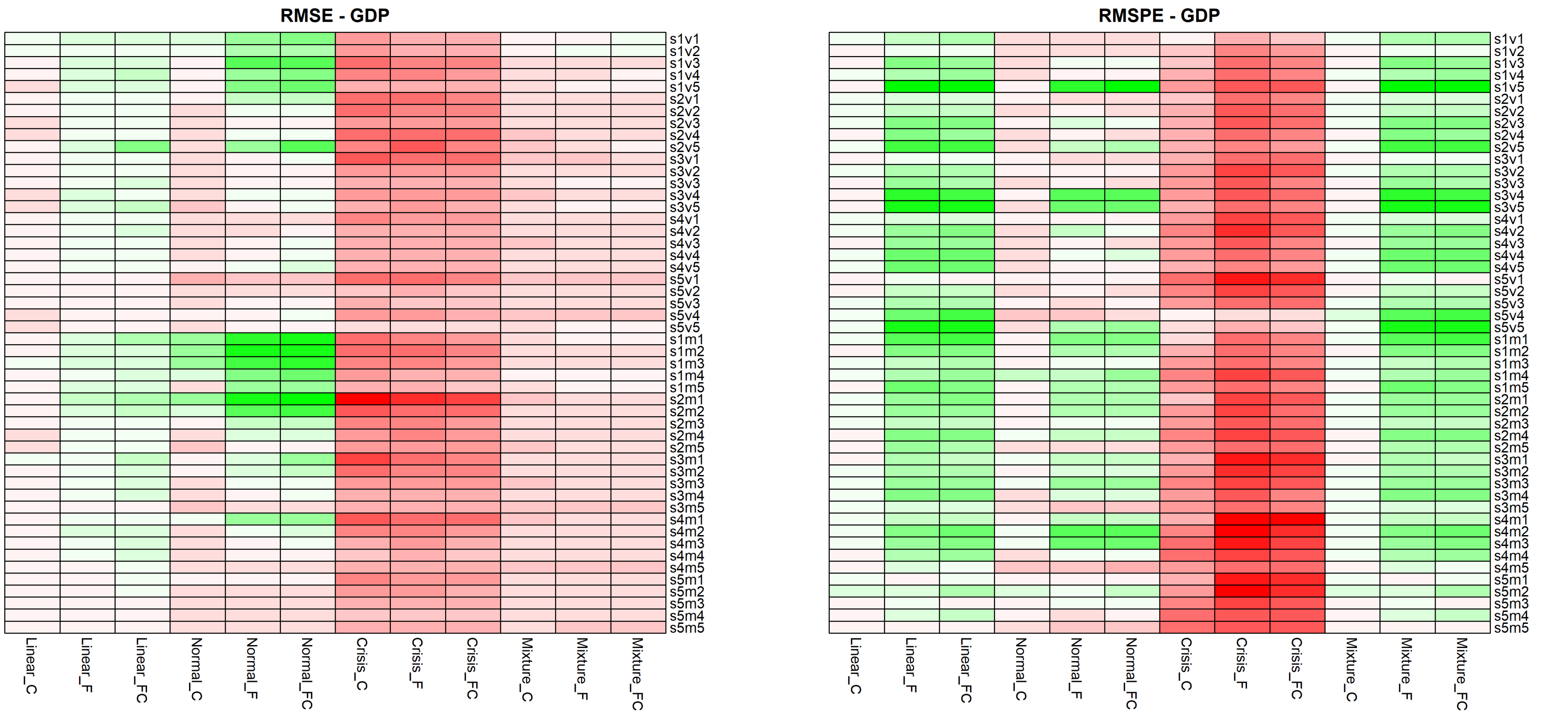
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 90% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request. The corresponding IRFs for a linear VAR model can be found in Figure B3 in Appendix B.

Figure 5: IRFs for Cyclical Momentum Factor ($\widetilde{MOM}$)



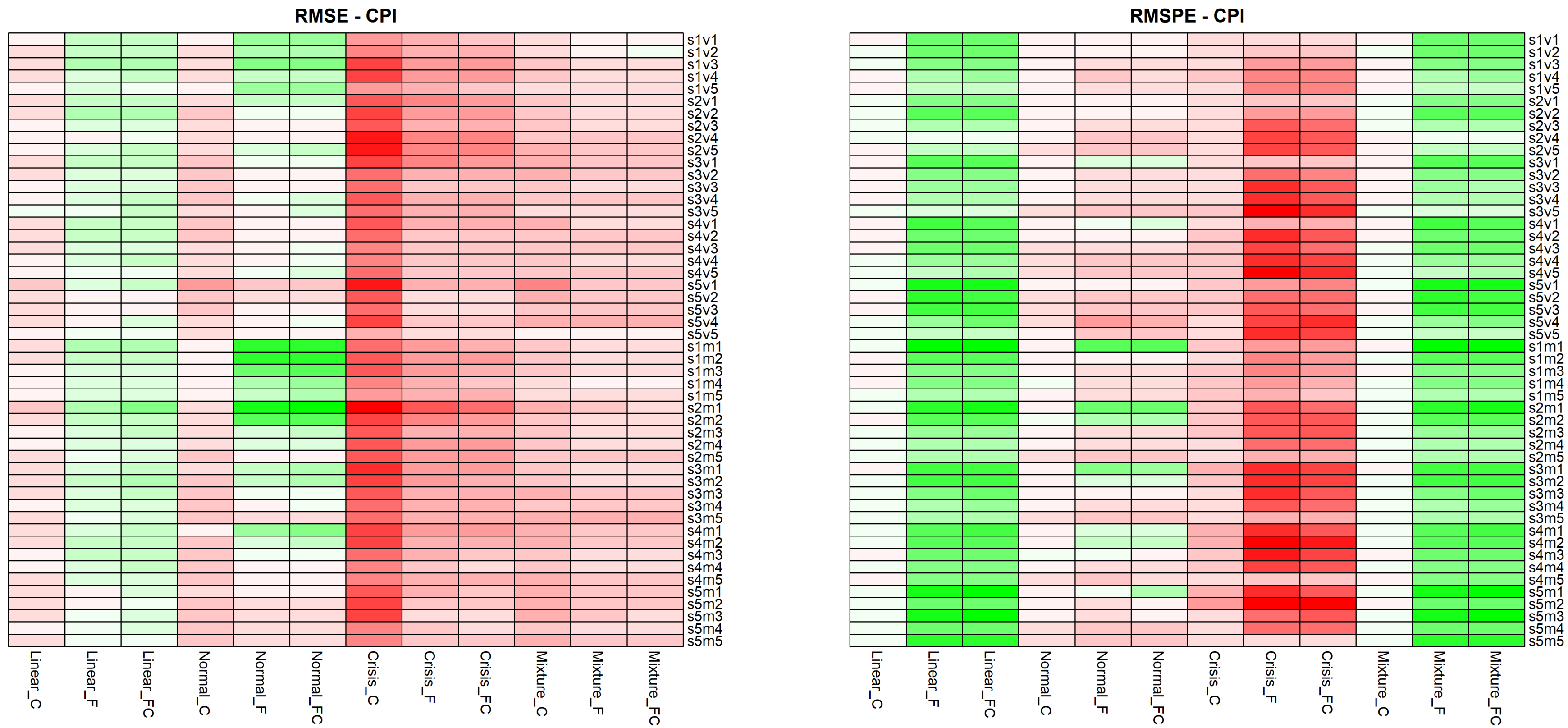
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 90% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request. The corresponding IRFs for a linear VAR model can be found in Figure B4 in Appendix B.

Figure 6: Cross-Sectional Pricing Errors Relative to Benchmark DAPM: GDP Forecasts



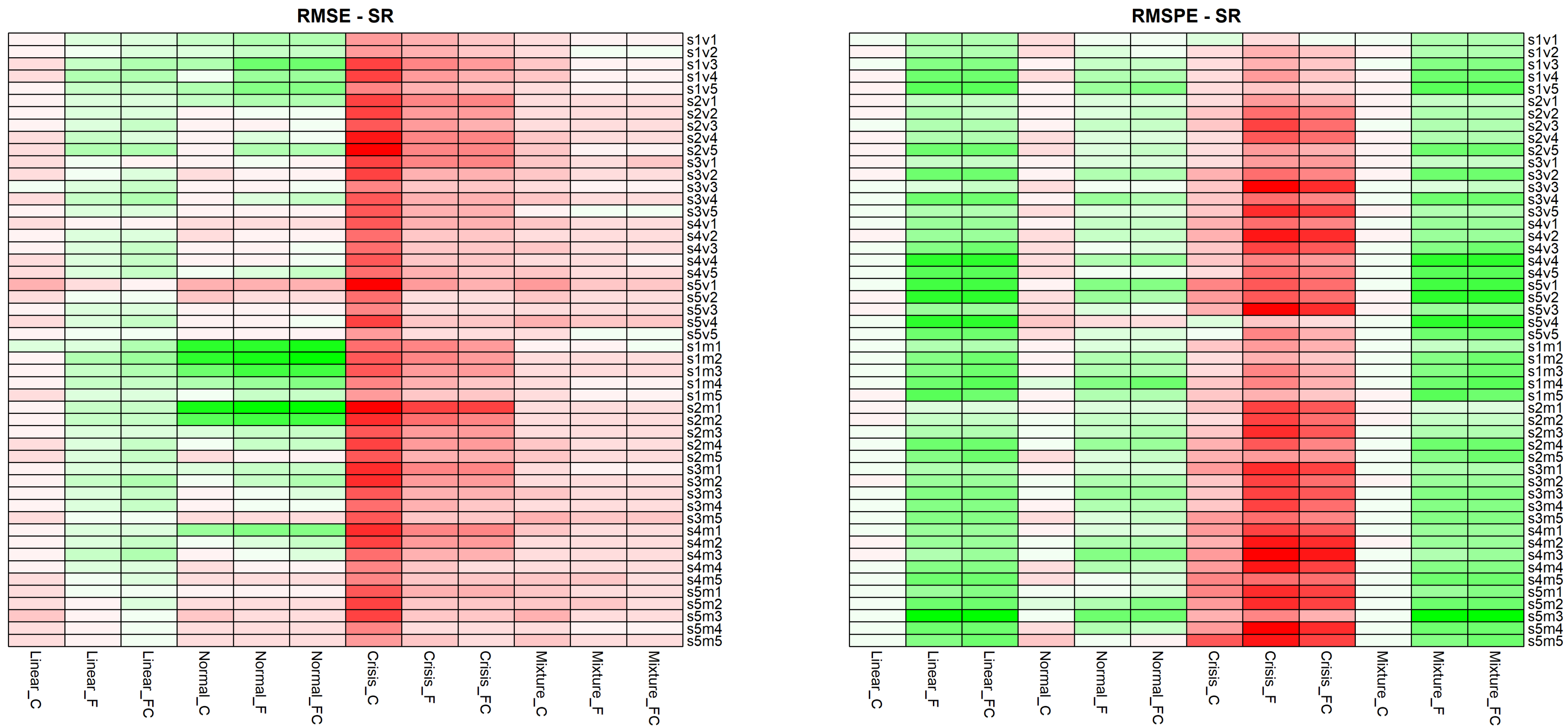
Notes: Heat map shows the relative pricing performance of different specifications of the DAPM compared to a benchmark model. The left panel displays the average root mean square pricing error (RMSE) and the right panel the average root mean square premium error (RMSPE). The benchmark model uses T10Y, TS, and DY as price of risk factors and MKT, SMB, HML, and MOM as pricing factors. GDP forecasts and their dispersion are used to extend the set of pricing variables and the set of price of risk factors. Columns show different models that vary in the pricing specification and the modelling of innovations in the state variables. The pricing specification depends on whether GDP forecasts and their dispersion are used as pricing variable (C), price of risk variable (F), or both (FC). The contemporaneous innovations are extracted from a linear VAR model (Linear) or from an LMVAR model (Normal state, Crisis state, or state-weighted Mixture). Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Green cells indicate an outperformance of the benchmark, red cells an underperformance, and white cells a comparable pricing ability.

Figure 7: Cross-Sectional Pricing Errors Relative to Benchmark DAPM: Inflation Forecasts



Notes: Heat map shows the relative pricing performance of different specifications of the DAPM compared to a benchmark model. The left panel displays the average root mean square pricing error (RMSE) and the right panel the average root mean square premium error (RMSPE). The benchmark model uses T10Y, TS, and DY as price of risk factors and MKT, SMB, HML, and MOM as pricing factors. Inflation forecasts and their dispersion are used to extend the set of pricing variables and the set of price of risk factors. Columns show different models that vary in the pricing specification and the modelling of innovations in the state variables. The pricing specification depends on whether inflation forecasts and their dispersion are used as pricing variable (C), price of risk variable (F), or both (FC). The contemporaneous innovations are extracted from a linear VAR model (Linear) or from an LMVAR model (Normal state, Crisis state, or state-weighted Mixture). Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Green cells indicate an outperformance of the benchmark, red cells an underperformance, and white cells a comparable pricing ability.

Figure 8: Cross-Sectional Pricing Errors Relative to Benchmark DAPM: Interest Rate Forecasts



Notes: Heat map shows the relative pricing performance of different specifications of the DAPM compared to a benchmark model. The left panel displays the average root mean square pricing error (RMSE) and the right panel the average root mean square premium error (RMSPE). The benchmark model uses T10Y, TS, and DY as price of risk factors and MKT, SMB, HML, and MOM as pricing factors. Short-term interest rate forecasts and their dispersion are used to extend the set of pricing variables and the set of price of risk factors. Columns show different models that vary in the pricing specification and the modelling of innovations in the state variables. The pricing specification depends on whether interest rate forecasts and their dispersion are used as pricing variable (C), price of risk variable (F), or both (FC). The contemporaneous innovations are extracted from a linear VAR model (Linear) or from an LMVAR model (Normal state, Crisis state, or state-weighted Mixture). Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Green cells indicate an outperformance of the benchmark, red cells an underperformance, and white cells a comparable pricing ability.

Tables

Table 1: Estimates of the Price of Risk Factors: Benchmark DAPM

	MKT	SMB	HML	MOM
$\bar{\lambda}$	0.692***	0.104	0.284	0.560
	(0.142)	(0.181)	(0.214)	(0.500)
λ_0	0.388	0.255	0.497	0.717
	(0.678)	(0.480)	(0.486)	(0.707)
T10Y	–0.224*	–0.050	0.117	0.437***
	(0.117)	(0.083)	(0.084)	(0.122)
TS	–0.212	0.194	0.368***	0.174
	(0.207)	(0.146)	(0.148)	(0.216)
DY	2.365***	–0.383	–1.944***	–3.377***
	(0.904)	(0.640)	(0.647)	(0.943)

Notes: Table shows the price of risk estimates of the DAPM using OLS and constant betas. Benchmark model uses T10Y, TS, and DY as price of risk factors (F) and MKT, SMB, HML, and MOM as pricing factors (C). Row $\bar{\lambda}$ provides an estimate of the average price of risk and row λ_0 the estimated constant in the affine price of risk specification for each pricing factor. The remaining rows (T10Y, TS, and DY) show the estimated coefficients of the matrix Λ_1, which determine the loadings on the price of risk factors. Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Standard errors (in parentheses) are adjusted for cross-asset correlation in the residuals and for an estimation error of the time series betas. ***/**/* denotes significance at the 1%/5%/10% level.

Table 2: Estimates of the Price of Risk Factors: Significant Signs of Augmented Models

	MKT				SMB				HML				MOM				DISP				EXP			
	L	N	C	M	L	N	C	M	L	N	C	M	L	N	C	M	L	N	C	M	L	N	C	M
GDP-DAPM																								
$\bar{\lambda}$																	−	−		−		+		+
λ_0									−	−	−	−						−						
T10Y	−	−	−	−									+	+	+	+					+		+	
TS																								−
DY	+	+	+	+									−	−	−	−								
DISP									+	+	+	+									−	−	−	−
EXP					−	−	−	−	+	+	+	+									+	+	+	+
CPI-DAPM																								
$\bar{\lambda}$																								
λ_0	+		+	+													−	−	−	−	+	+	+	+
T10Y														+			-	−	−	−	−	−	−	−
TS		−							+	+	+	+	+		+	+	+	+	+	+	−	−	−	−
DY	+	+	+	+					−	−	−	−	−	−	−	−	+	+	+	+		+		+
DISP		+								+							+	+	+	+	−	−	−	−
EXP	−	−	−	−					+	+	+	+	+		+	+	−		−	−				+
SR-DAPM																								
$\bar{\lambda}$																								
λ_0																	+	+	+	+	+	+	+	
T10Y																								
TS	−		−	−																				
DY	+	+	+	+					−	−	−	−	−	−	−	-	+	+	+	+	−	−	−	−
DISP																	−	−	−	−	−	−	−	−
EXP				−																				+

Notes: Table shows the price of risk estimates of the DAPM using OLS and constant betas. Survey forecasts (EXP) and their dispersion (DISP) of GDP (GDP-DAPM), inflation (CPI-DAPM), and the short-term interest rate (SR-DAPM) act as additional risk factors and additional price of risk factors. The other price of risk factors are T10Y, TS, and DY, the other pricing factors MKT, SMB, HML, and MOM. The columns below each risk factor indicate the type of innovations used in the pricing equation. *L* represents innovations from a linear VAR model. *N* (normal state), *C* (crisis state), and *M* (state-weighted mixture) represent innovations from a two-state LMVAR model. Row $\bar{\lambda}$ provides an estimate of the average price of risk and row λ_0 the estimated constant in the affine price of risk specification for each pricing factor. The remaining rows (T10Y, TS, DY, DISP, and EXP) show the estimated coefficients of the matrix Λ_1, which determine the loadings on the price of risk factors. Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Standard errors are adjusted for cross-asset correlation in the residuals and for an estimation error of the time series betas. '+' indicates a positive and '–' a negative relationship according to a significance level of 10%.

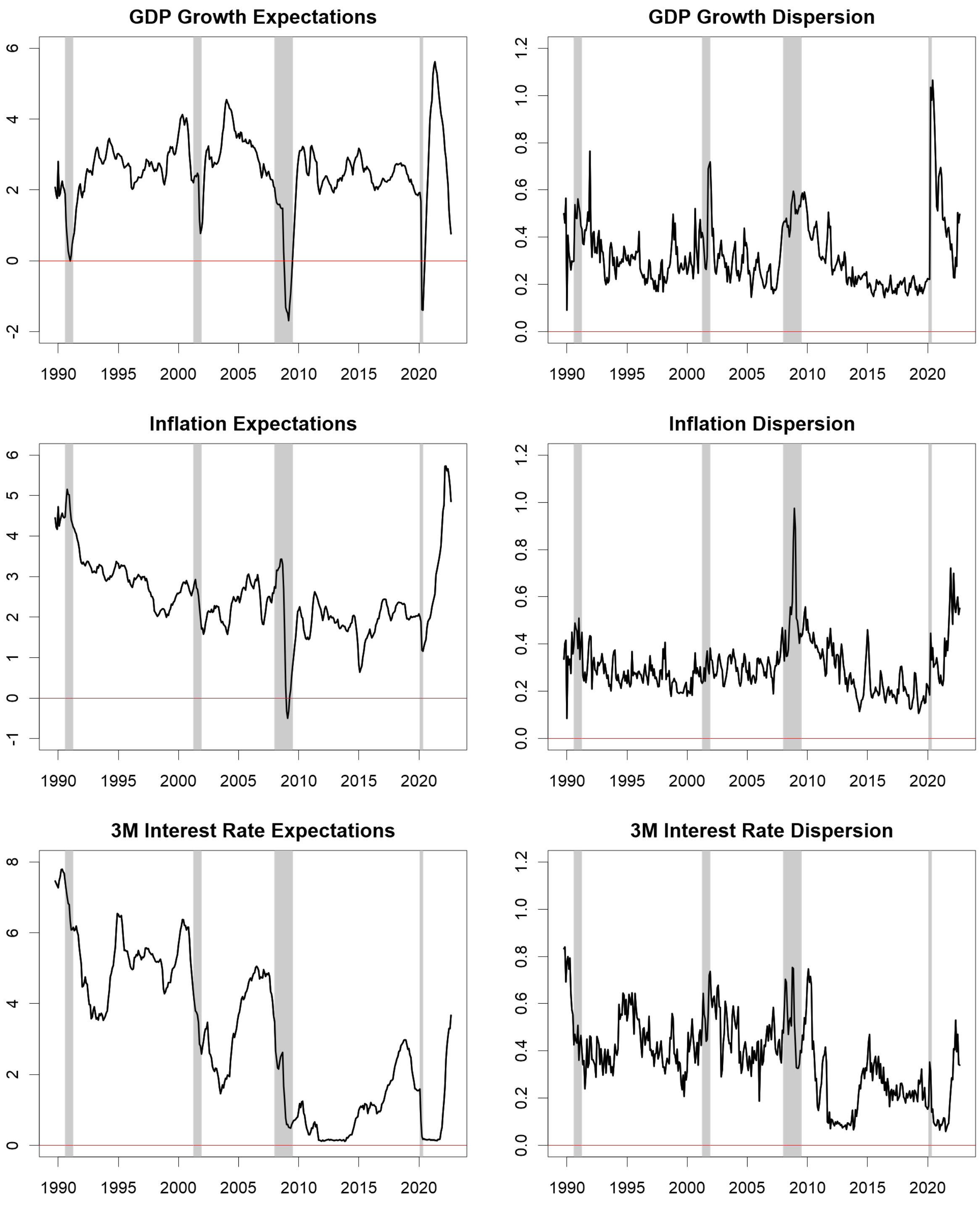
Table 3: Average Pricing and Premium Errors of Test Assets

	RMSE			RMSPE		
	GDP	CPI	SR	GDP	CPI	SR
Linear_C	1.963	2.032	1.986	5.788	5.788	5.788
Linear_F	**1.922**	**1.904**	**1.911**	**5.771**	**5.742**	**5.761**
Linear_FC	**1.910**	**1.894**	**1.904**	**5.770**	**5.742**	**5.760**
Normal_C	1.999	2.137	1.939	5.797	5.801	5.794
Normal_F	**1.912**	**1.917**	**1.917**	5.788	5.825	**5.775**
Normal_FC	**1.899**	**1.908**	**1.909**	**5.787**	5.822	**5.775**
Crisis_C	2.457	2.971	2.622	5.860	5.862	5.824
Crisis_F	2.428	2.421	2.275	5.931	6.082	5.893
Crisis_FC	2.378	2.384	2.241	5.912	6.049	5.872
Mixture_C	2.071	2.260	2.078	5.788	5.788	5.788
Mixture_F	2.031	2.147	2.007	**5.771**	**5.742**	**5.761**
Mixture_FC	2.021	2.138	2.000	**5.770**	**5.742**	**5.760**
Benchmark		1.933			5.788	

Notes: Table shows the average root mean square pricing error (RMSE) and the average root mean square premium error (RMSPE) of different specifications of the DAPM using OLS and constant betas. Benchmark model uses T10Y, TS, and DY as price of risk factors (F) and MKT, SMB, HML, and MOM as pricing factors (C). Survey forecasts (EXP) of GDP, inflation (CPI), and the short-term interest rate (SR) and their dispersion (DISP) act as additional risk factors and additional price of risk factors. Rows represent different models that vary in the pricing specification and the modelling of innovations in the state variables. The pricing specification depends on whether survey forecasts and their dispersion are used as pricing variable (C), price of risk variable (F), or both (FC). The contemporaneous innovations are extracted from a linear VAR model (Linear) or from an LMVAR model (Normal state, Crisis state, or state-weighted Mixture). Test assets are 25 value-weighted equity portfolios sorted on size and value and 25 value-weighted portfolios sorted on size and prior performance. Bold entries indicate an outperformance of the benchmark.

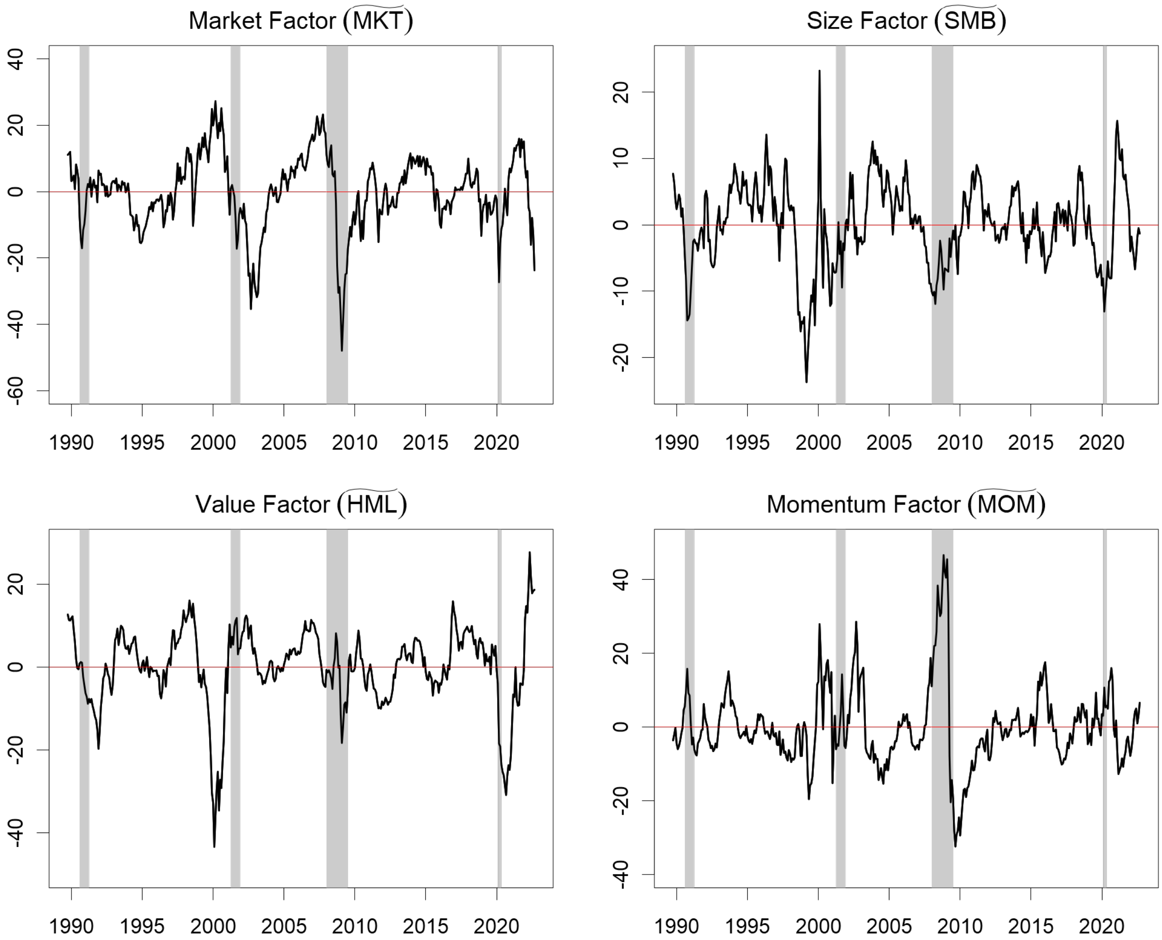
Appendix A: Background on Dataset

Figure A1: Macroeconomic Expectations



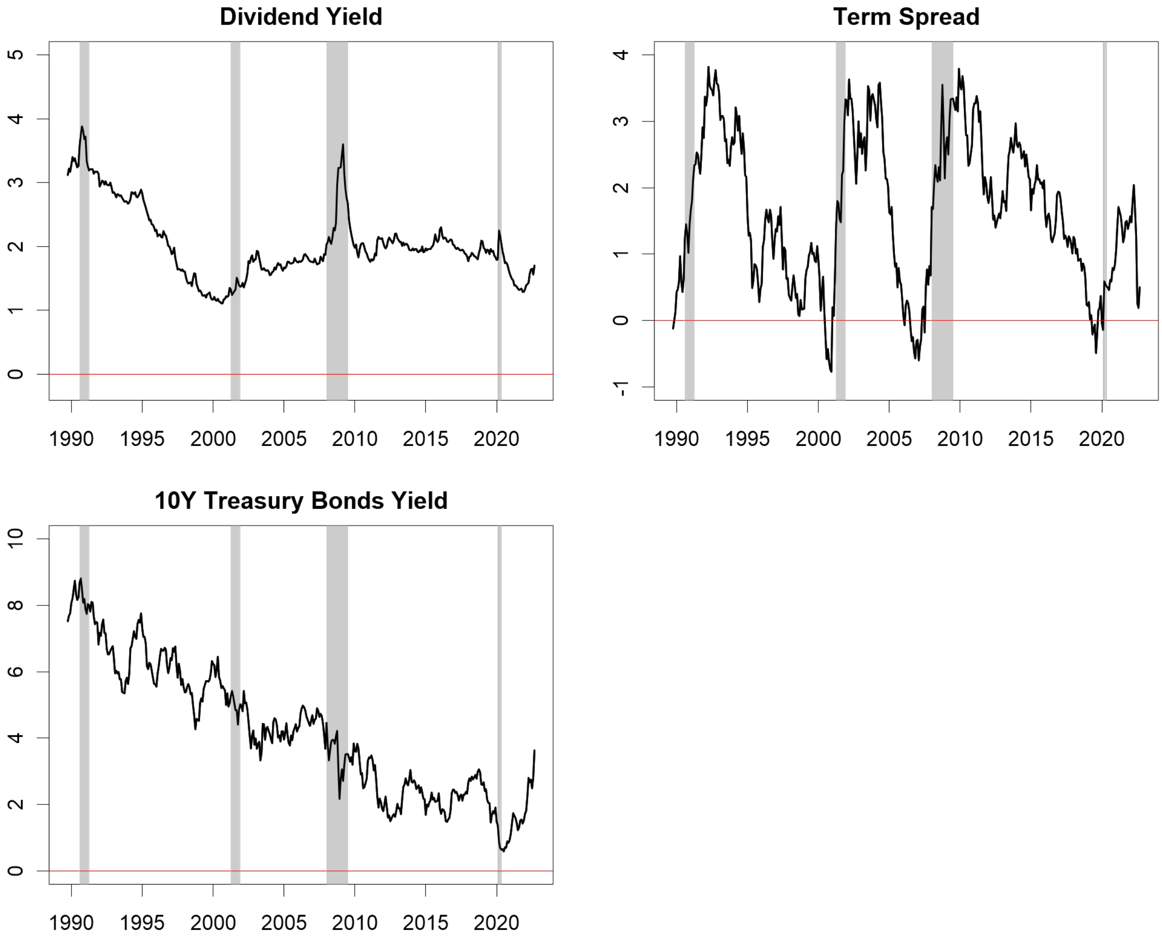
Source: Consensus Economics. Gray-shaded areas indicate NBER recessions.

Figure A2: Cyclical Stock Market Factors



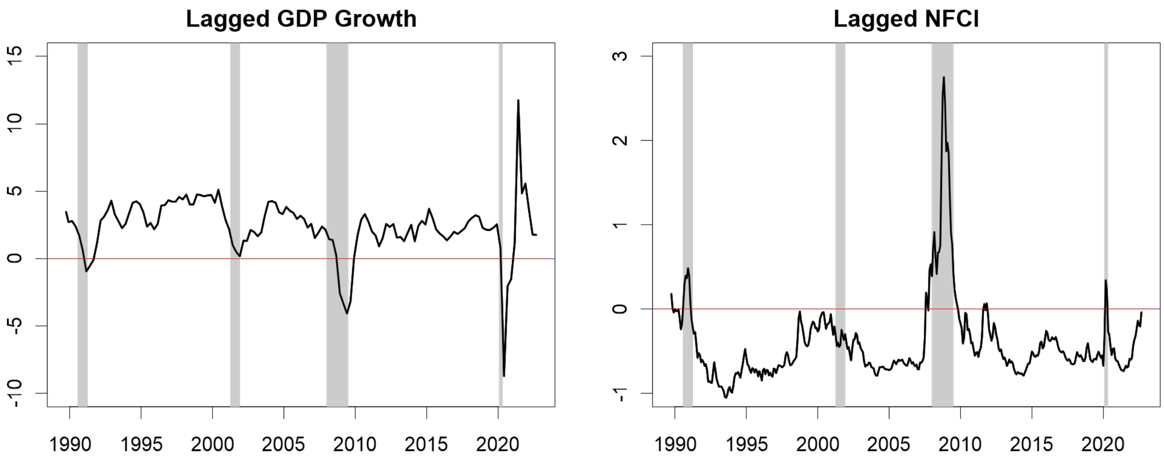
Source: Kenneth French's website. Log cumulative return series are de-trended using the Hodrick-Prescott filter. Gray-shaded areas indicate NBER recessions.

Figure A3: DAPM Predictors



Source: Federal Reserve Bank of St. Louis and Nasdaq Data Link. Gray-shaded areas indicate NBER recessions.

Figure A4: State Drivers for Logit-Mixture Weights



Source: Federal Reserve Bank of St. Louis. Gray-shaded areas indicate NBER recessions.

Table A1: Descriptive Statistics

	GDP^E	CPI^E	SR^E	GDP^D	CPI^D	SR^D	MKT	SMB	HML	MOM	DY	TS	$T10Y$	GDP	$NFCI$
Mean	2.53	2.51	3.07	0.32	0.30	0.37	0.65	0.09	0.14	0.50	0.68	1.65	4.21	2.37	–0.41
Std	1.04	0.94	2.16	0.14	0.11	0.17	4.43	3.15	3.22	4.68	0.27	1.12	2.00	2.00	0.49
Skewness	–1.00	0.66	0.18	1.81	1.69	0.18	–0.57	0.63	0.24	–1.45	0.27	–0.01	0.29	–1.13	3.14
Exc. Kurt.	3.68	1.84	–1.19	5.01	5.74	–0.29	1.11	7.14	2.51	10.40	–0.27	–0.98	–0.89	5.77	13.53
Minimum	–1.69	–0.50	0.12	0.09	0.09	0.06	–17.23	–17.23	–13.97	–34.30	0.10	–0.77	0.59	–8.72	–1.05
Maximum	5.62	5.73	7.79	1.06	0.97	0.84	13.65	21.42	12.75	18.20	1.36	3.82	8.81	11.74	2.75

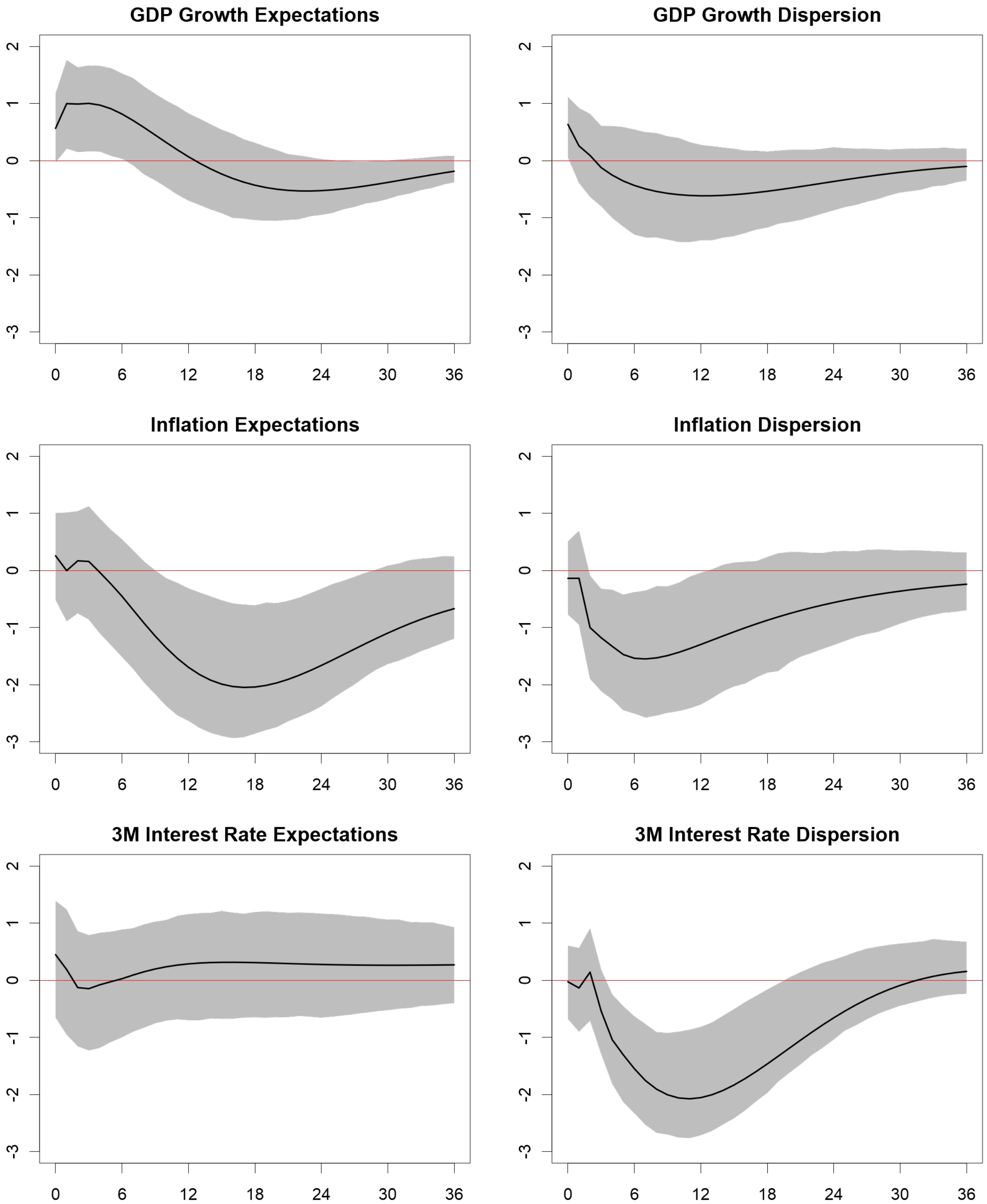
Source: Consensus Economics, Kenneth French's website, Federal Reserve Bank of St. Louis, and Nasdaq Data Link. E: 12-month ahead expectations, D: dispersion of 12-month ahead expectations, GDP: gross domestic product, CPI: inflation, SR: 3M Treasury bill rate, MKT: market risk premium, SMB: size premium, HML: value premium, MOM: momentum premium, DY: log dividend yield, TS: term spread, $T10Y$: 10Y Treasury bonds yield, $NFCI$: National Financial Conditions Index.

Table A2: Correlation Matrix

	GDP^E	CPI^E	SR^E	GDP^D	CPI^D	SR^D	MKT	SMB	HML	MOM	DY	TS	$T10Y$	GDP	$NFCI$
GDP^E	1.00														
CPI^E	0.12	1.00													
SR^E	0.05	0.60	1.00												
GDP^D	–0.40	0.02	–0.11	1.00											
CPI^D	–0.34	0.16	–0.12	0.49	1.00										
SR^D	–0.07	0.29	0.55	0.11	0.21	1.00									
MKT	–0.04	–0.13	–0.08	0.12	–0.09	–0.13	1.00								
SMB	–0.06	–0.07	–0.08	0.09	0.02	–0.01	0.24	1.00							
HML	0.18	0.10	0.03	–0.02	0.00	–0.02	–0.12	–0.22	1.00						
MOM	0.13	0.15	0.13	–0.09	–0.05	0.08	–0.28	0.00	–0.22	1.00					
DY	–0.51	0.22	0.15	0.12	0.19	0.18	–0.00	–0.04	–0.11	–0.07	1.00				
TS	–0.03	–0.15	–0.38	0.16	0.22	0.10	0.00	0.12	0.06	–0.06	0.32	1.00			
$T10Y$	–0.01	0.56	0.89	–0.01	–0.02	0.60	–0.06	–0.02	0.06	0.10	0.35	0.04	1.00		
GDP	0.75	0.28	0.31	–0.54	–0.28	0.02	–0.04	–0.12	0.06	0.16	–0.35	–0.17	0.23	1.00	
$NFCI$	–0.61	–0.11	–0.08	0.41	0.56	0.23	–0.20	–0.01	–0.14	–0.06	0.21	0.03	–0.06	–0.46	1.00

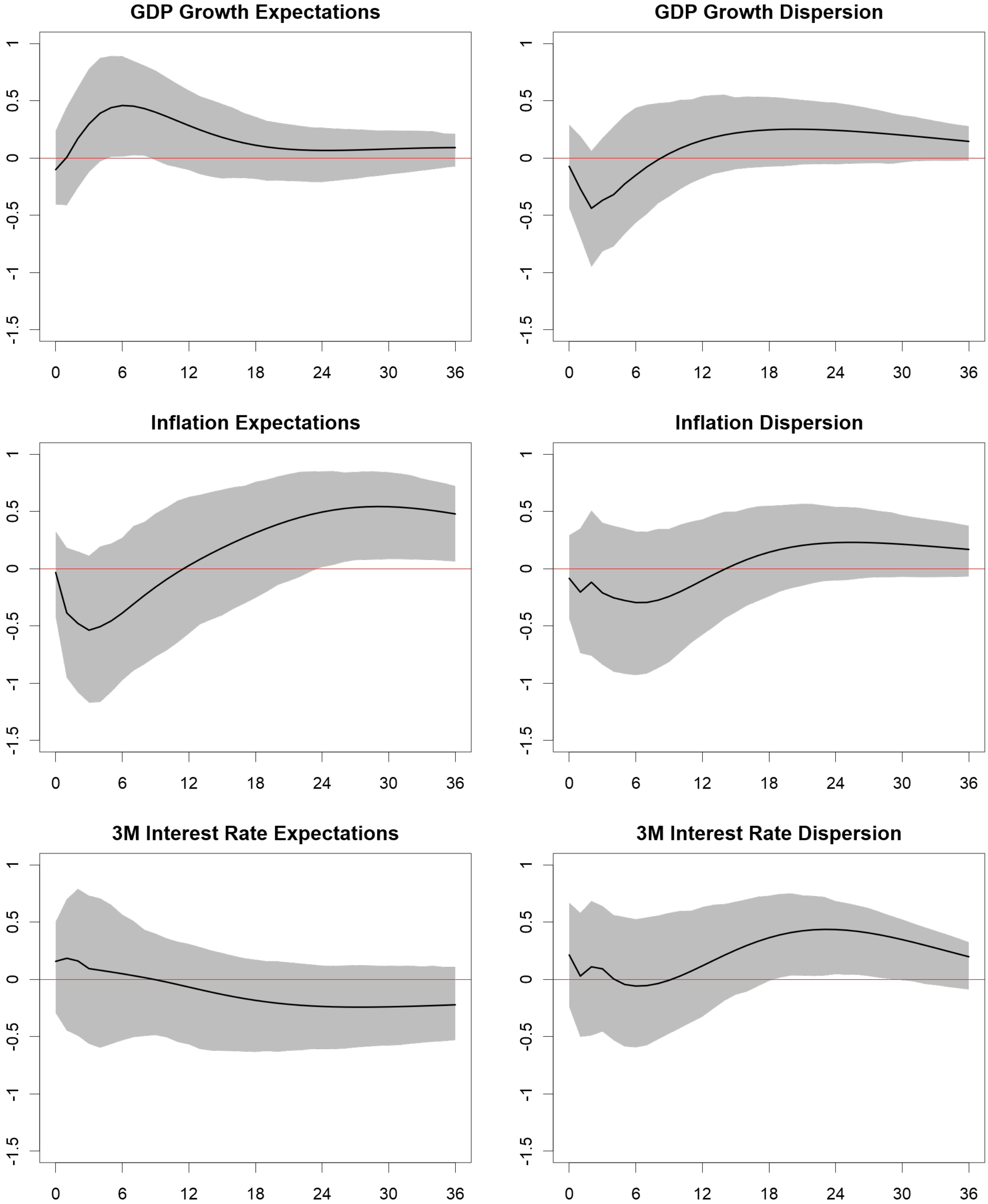
Appendix B: IRFs of Linear VAR Models

Figure B1: IRFs for Cyclical Market Factor ($\widetilde{MKT}$)



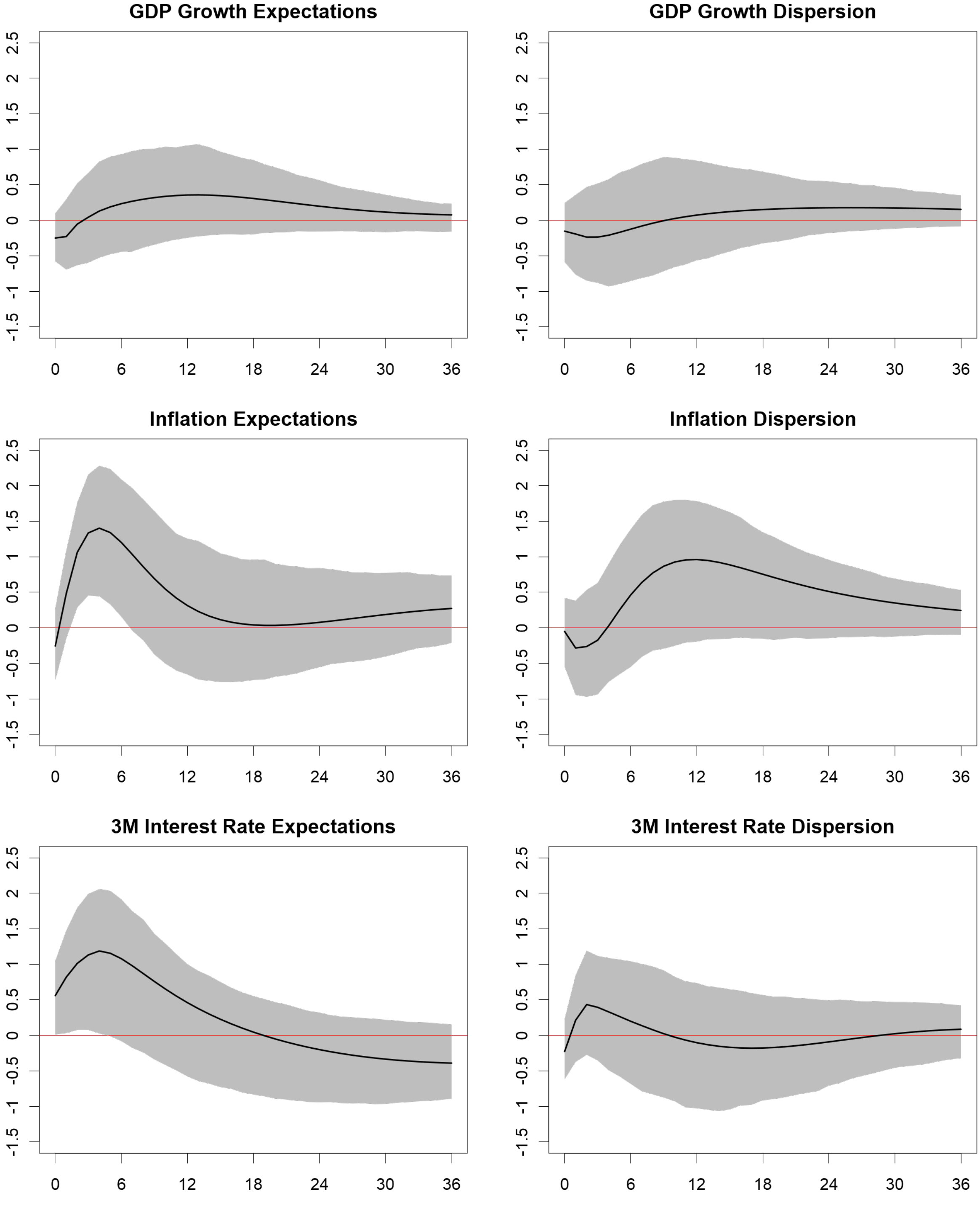
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel). Gray-shaded areas indicate 90% confidence bands. Full set of impulse responses is available on request. The corresponding IRFs for an LMVAR can be found in Figure 2.

Figure B2: IRFs for Cyclical Size Factor ($\widetilde{SMB}$)



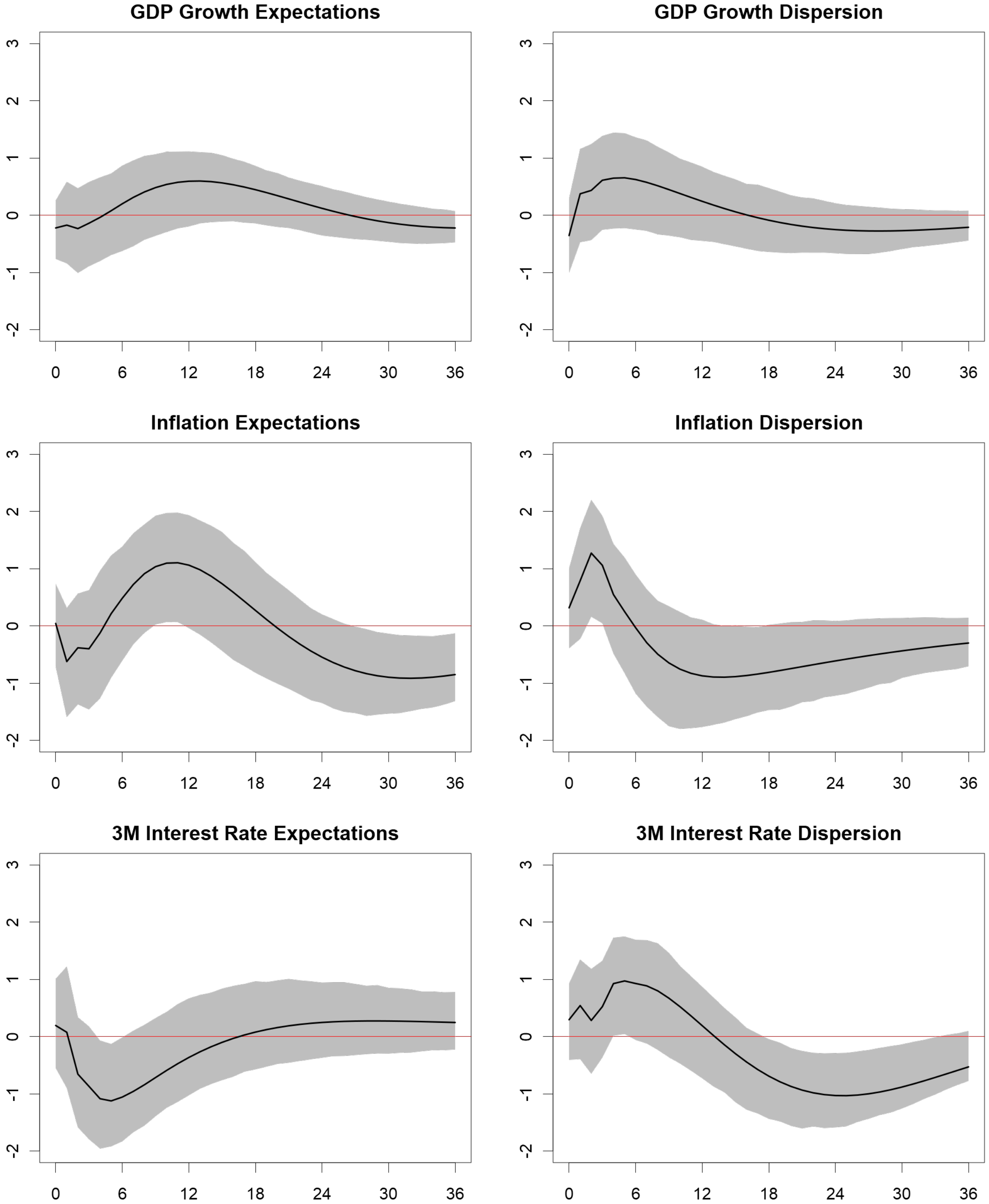
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel). Gray-shaded areas indicate 90% confidence bands. Full set of impulse responses is available on request. The corresponding IRFs for an LMVAR can be found in Figure 3.

Figure B3: IRFs for Cyclical Value Factor ($\widetilde{HML}$)



Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel). Gray-shaded areas indicate 90% confidence bands. Full set of impulse responses is available on request. The corresponding IRFs for an LMVAR can be found in Figure 4.

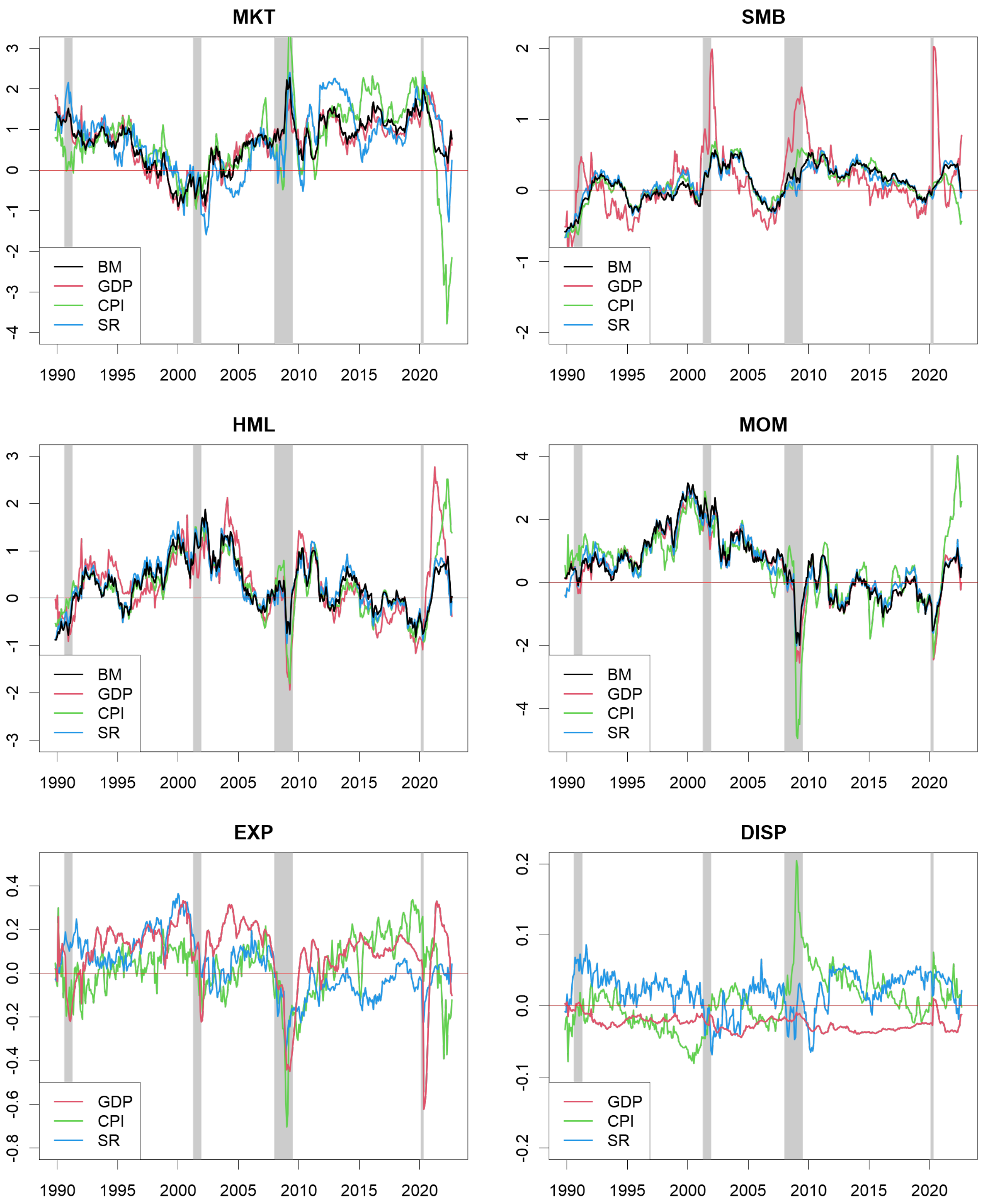
Figure B4: IRFs for Cyclical Momentum Factor ($\widetilde{MOM}$)



Notes: Solid black lines show mean impulse responses of a 25 bps shock in the first moment of macroeconomic expectations (left panel) and of a 10 bps shock in their second moment (right panel). Gray-shaded areas indicate 90% confidence bands. Full set of impulse responses is available on request. The corresponding IRFs for an LMVAR can be found in Figure 5.

Appendix C: Time Variation in the Price of Risk

Figure C1: Dynamics of Price of Risk with Survey Forecasts

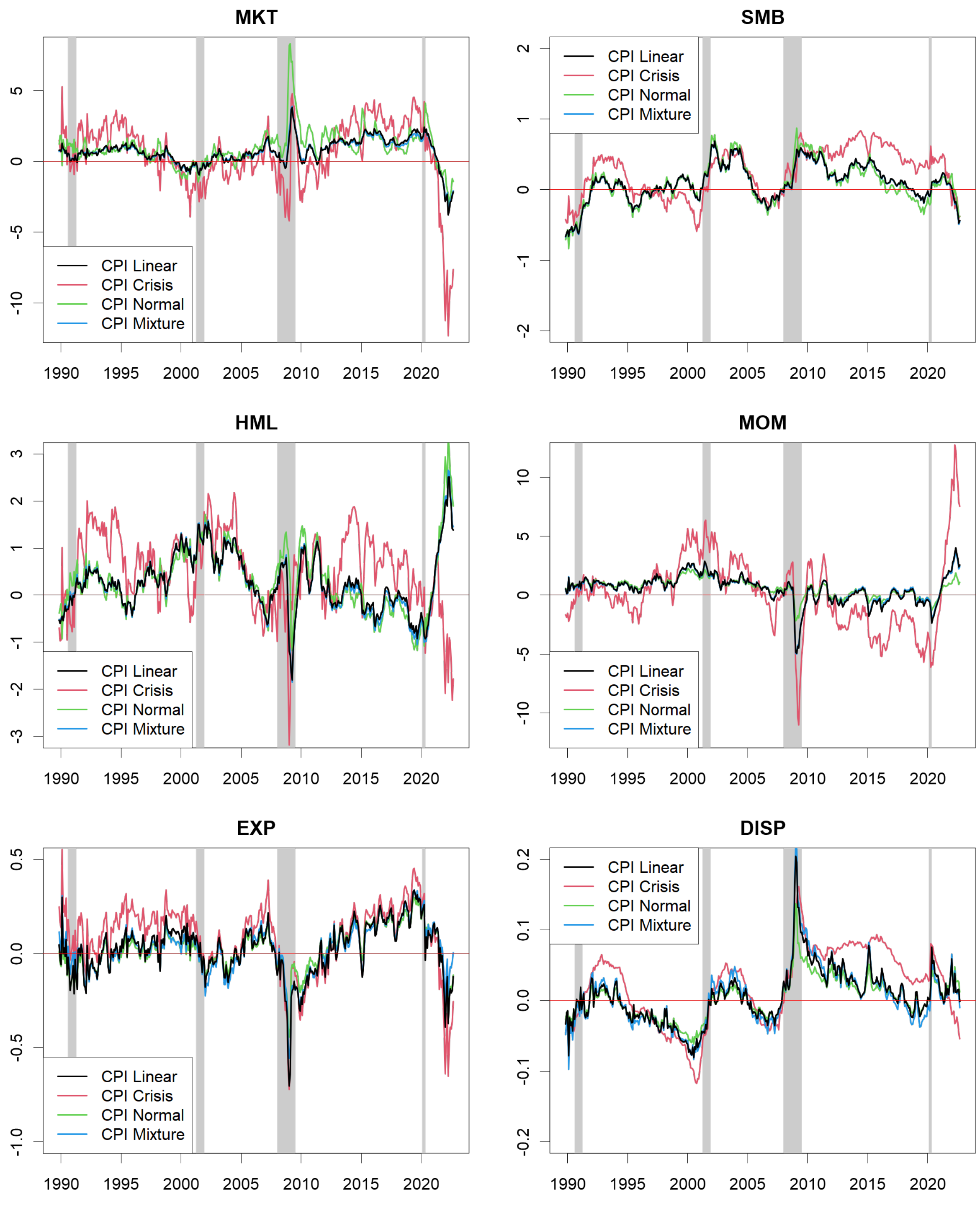


Notes: Figure shows the dynamics of the price of risk estimated with the DAPM for the risk factors MKT, SMB, HML, MOM, EXP, and DISP. Benchmark model (BM) assumes that the price of risk is only driven by T10Y, TS, and DY. The three other specifications extend the price of risk factors by GDP, inflation (CPI), or interest rate (SR) expectations and their dispersion. State variable innovations are estimated using linear VARs in all cases. Gray-shaded areas indicate NBER recessions.

Figure C2: State-Dependent Dynamics of Price of Risk with GDP Forecasts

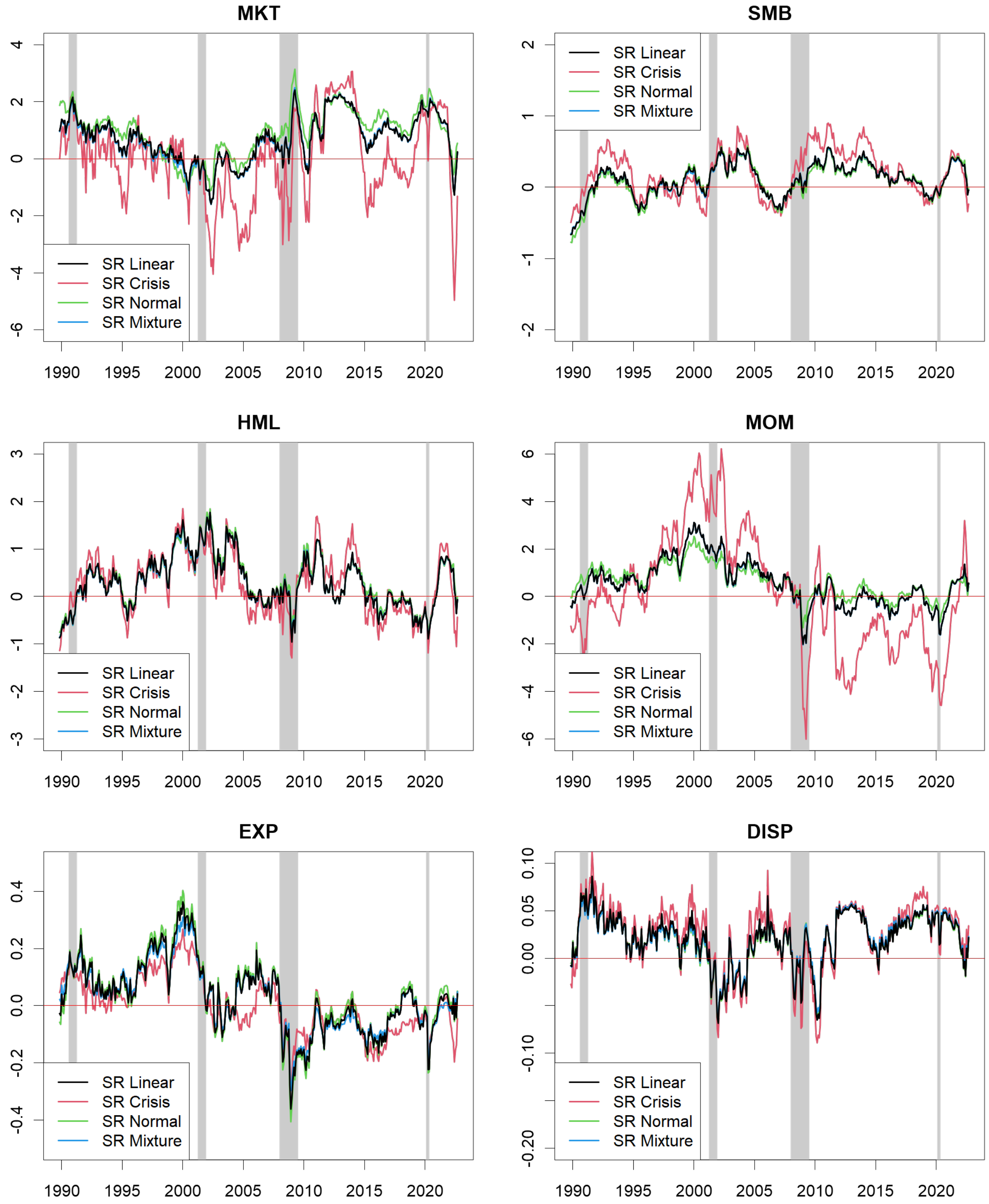
Notes: Figure shows the dynamics of the price of risk estimated with the DAPM for the risk factors MKT, SMB, HML, MOM, EXP, and DISP. The price of risk is driven by T10Y, TS, DY, and GDP expectations and their dispersion. State variable innovations are estimated using linear VARs and two-state LMVARs. Gray-shaded areas indicate NBER recessions.

Figure C3: State-Dependent Dynamics of Price of Risk with Inflation Forecasts



Notes: Figure shows the dynamics of the price of risk estimated with the DAPM for the risk factors MKT, SMB, HML, MOM, EXP, and DISP. The price of risk is driven by T10Y, TS, DY, and inflation expectations and their dispersion. State variable innovations are estimated using linear VARs and two-state LMVARs. Gray-shaded areas indicate NBER recessions.

Figure C4: State-Dependent Dynamics of Price of Risk with Interest Rate Forecasts



Notes: Figure shows the dynamics of the price of risk estimated with the DAPM for the risk factors MKT, SMB, HML, MOM, EXP, and DISP. The price of risk is driven by T10Y, TS, DY, and short-term interest rate expectations and their dispersion. The state variable innovations are estimated using linear VARs and two-state LMVARs. Gray-shaded areas indicate NBER recessions.