TRACKING THE RELATIVE IMPORTANCE OF DEMAND AND SUPPLY SHOCKS USING THE SURVEY OF PROFESSIONAL FORECASTERS

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ABSTRACT. This paper proposes a novel measure that tracks changes in the relative importance of demand and supply shocks in the economy. This measure is model-free, forward-looking, and available in real time. It is based on data from individual professional forecasters and is therefore available at a quarterly frequency. In each period, it is computed as the correlation between GDP and inflation forecasts (across forecasters). We rationalize it in the context of a synthetic model: if individual forecasters use imperfectly correlated private information about demand and supply factors to derive GDP and inflation forecasts, then the relationship, across forecasters, between expected changes in GDP and inflation is informative about the relative importance of demand over supply shocks in the economy. Regression results suggest that (i) this measure can capture, ex ante, changes in the covariance between GDP and inflation, and (ii) it is negatively related to changes in bond term premiums.

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1. Introduction

Disentangling the effects of demand and supply factors on the economy is at the heart of business cycle research. An economy driven predominantly by supply shocks operates fundamentally differently from one driven by demand shocks. Policymakers must tailor their responses to the specific type of shock. Fiscal stimulus is appropriate for demand-driven issues, while structural reforms or targeted investments are needed to address supply-side constraints.

Traditional macroeconomic models often assume that shock variances are constant over long periods of time. This is however a strong assumption as fundamental changes in technology, politics, and the economy, may affect the relative importance of demand and supply shocks over time. The present paper proposes a measure of such changes. It is defined as the correlation between individual forecasters' GDP and inflation forecasts, as provided by the Survey of Professional Forecasters (SPF). This measure is model-free, based on publicly available data, and computed in real time. Being based on predictions of future GDP and inflation, it is forward-looking by construction and does not rely on realized shocks.

To obtain measures of the relative importance of demand and supply shocks, a standard approach is to compute the rolling correlation between aggregate GDP and inflation. Such a measure has several drawbacks: GDP data is only published with a significant lag, and the measure becomes meaningful only for a certain window size. Unfortunately, the longer the window size, the more backward-looking the measure becomes. Our approach is not subject to these limitations.

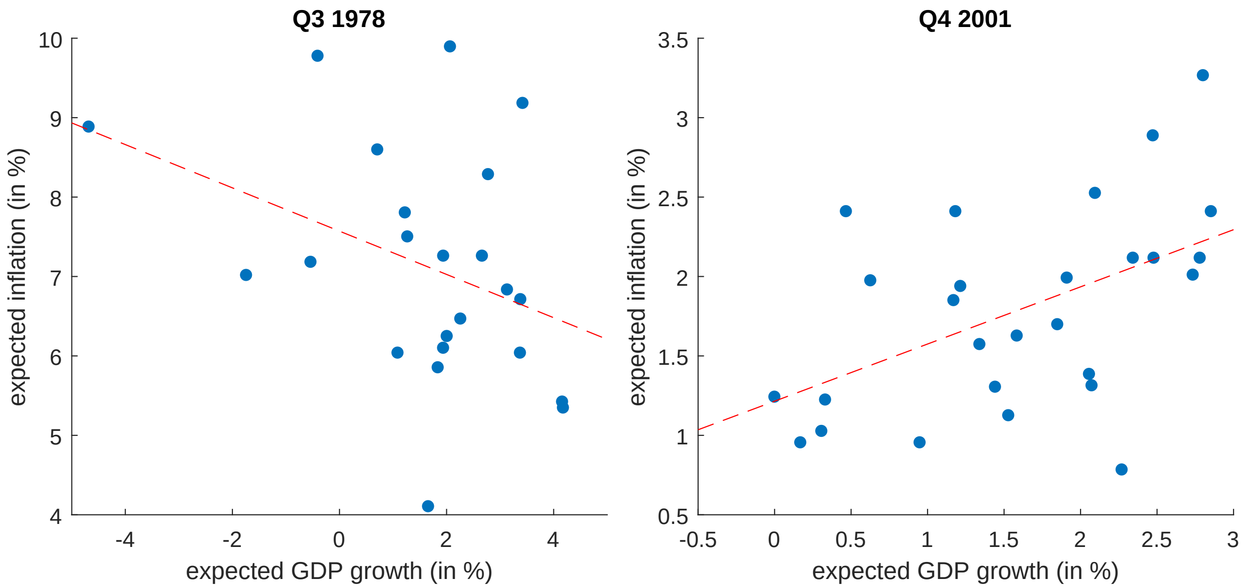
A stylized model with heterogeneous and imperfect information motivates our measure. In the context of our model, the dispersion of GDP and inflation forecasts—across a set of professional forecasters—can be informative about the relative importance of demand and supply shocks in the economy. To grasp the rationale behind this, let's consider an extreme situation where the economy is driven entirely by demand shocks. Specifically, let's assume that both inflation and GDP growth are positively influenced by one persistent factor—a demand factor—and additional volatile, non-persistent shocks. When forecasters are tasked with predicting inflation and GDP, they must first filter out the impact of volatile shocks. With their estimate of the persistent component in hand, they proceed to compute forecasts for GDP and inflation. Since both inflation and GDP positively depend on the latent factor, that is also true for the forecasts they produce. If all forecasters possess identical information, resulting in the same estimation of the latent factor (and assuming they are aware of the model's parameterization), their GDP and inflation forecasts will align. In contrast, if forecasters possess private information about the latent factor, their inferences will lead to divergent GDP and inflation forecasts.

To fix ideas, if a forecaster obtains a particularly high (respectively low) estimate of the latent factor, both her inflation forecast and her GDP forecast will be higher (lower) compared to other forecasters. That is, the correlation of inflation and GDP forecasts—across forecasters—will be positive. Alternatively, it is easy to check that the correlation between inflation and GDP forecasts would be negative in an economy where only a supply factor persistently affects inflation and GDP. As our stylized model illustrates, in intermediate cases, the correlation of inflation and GDP forecasts (across forecasters) depends on the relative importance of demand and supply factors in explaining the joint dynamics of inflation and GDP.

Consistent with this theoretical framework, our measure—which we call the Individual Forecast Slope (IFS) Index or just Slope Index—is computed as the cross-forecaster correlation between expected changes in GDP and inflation. On each date on which it is computed, it aims to capture the relative importance of demand and supply shocks. Figure 1 shows two examples of this measure in two different quarters.

The left-hand panel shows 4-quarter-ahead forecasts for GDP and inflation in the third quarter of 1978, just before the second oil price crisis, when heightened political turmoil in Iran, and increased uncertainty about crude oil production and prices dominated the news. The right-hand panel, in contrast, shows Q4 2001. The economy was in a recession due to the dot-com bubble. Also, the terrorist attacks of September 11, 2001, lead to additionally increased uncertainty. This mostly depressed demand, accompanied by a fall in consumption,

Figure 1. Individual Forecast Correlation for Two Exemplary Dates



Notes: This figure depicts the SPF point forecasts for inflation and GDP growth for all available forecasters at two exemplary dates, along with the regression line. It shows the 4-quarters-ahead forecasts of real GDP and the GDP deflator, respectively. Both variables are in year-on-year growth rates.

stock prices, and interest rates. The first episode is a clear example of large uncertainty about supply, while the second one is a typical case of large negative demand shocks.[1] The respective dominance of either supply or demand is reflected in the slope between GDP and inflation forecasts (see Figure 1).

The empirical analysis, supported by regression results, demonstrates that the proposed measure effectively captures changes in the realized covariance between GDP and inflation surprises. Moreover, it is informative about the covariance of ex-post mean forecast errors.

Another validation comes from asset prices. It is well-known that term premiums—i.e. risk premiums extracted from bond yields— are negatively correlated with the importance of demand shocks in the economy (e.g., Piazzesi and Schneider, 2007; Rudebusch and Swanson, 2012; Gurkaynak and Wright, 2012; Campbell, Pflueger, and Viceira, 2014; Bekaert, Engstrom,

[1] Blinder and Rudd (2013) and Blomberg, Hess, and Orphanides (2004) discuss the two periods and their dominant macroeconomic drivers in great detail.

and Ermolov, 2021). In a supply-driven economy, recessions tend to be inflationary. The portfolios of nominal bondholders experience a decline in value during recessions because the real returns of nominal bonds decline with inflation. As the bond returns decline in value during recessions, they exhibit bad hedging properties. Accordingly, bondholders demand an average excess return (called term premium) to carry nominal long-term bonds in this supply-driven economy. Naturally, the logic is reversed in a demand-driven economy, where term premiums tend to be negative. Consistent with these arguments, our measure—which is higher when demand shocks are more important—is negatively correlated with standard term premium measures (namely, those estimated by Adrian, Crump, and Moench, 2013).

Our research is also related to several other strands of the literature. First, our study is related to the empirical macroeconomic literature dealing with the differentiation of demand and supply shocks. Some examples of influential early work include Shapiro and Watson (1988), Blanchard and Quah (1989), and Gali (1992). Since then, Structural Vector Auto-Regressive (SVAR) models have been commonly used to identify demand and supply shocks (see Fry and Pagan, 2011, for an overview). Recent contributions on the subject include works by Wolf (2020) and Eickmeier and Hofmann (2022). Specifically, Eickmeier and Hofmann (2022) use a factor model on sector-level data that allows them to extract indicators that suggest varying levels of demand or supply dominance over time. Exploiting the term-premium mechanism described above, researchers have also used asset prices to identify demand and supply factors (e.g. Breach, D'Amico, and Orphanides, 2020; Bekaert, Engstrom, and Ermolov, 2022).

An emerging strand of the literature focuses on inflation and examines the differing effects of policy depending on whether inflation is driven by supply or demand (e.g., Shapiro, 2022; Boissay et al., 2023). It is important to emphasize that the primary objective of the above papers is to estimate demand and supply shocks or factors. In contrast, we aim to measure the time variation in the relative importance of demand and supply shocks, which is a different undertaking to ours.

Second, we contribute to the literature that explores and exploits surveys of professional forecasters (SPFs), which provide valuable insights into expectations and expectation formation. Coibion and Gorodnichenko (2015) use SPFs to study the expectation formation process and to test for informational rigidities. Abel et al. (2016), Aruoba (2016), and Grishchenko, Mouabbi, and Renne (2019) estimate the uncertainty around inflation expectations, relying on the SPF.

Rather than examining forecasts for different variables in isolation, additional insight can be gained by examining forecasts for multiple variables simultaneously. Banternghansa and McCracken (2009) and Clements (2022) take into account the covariance between forecasts and produce multivariate disagreement measures to test for forecast efficiency and contrarianism.

Focusing specifically on GDP and inflation forecasts, allows us to learn about (expected) demand and supply shocks. Herbst and Winkler (2021) employ a dynamic factor model on SPF forecasts and find two persistent factors corresponding to disagreement on aggregate demand and supply shocks. Benhima and Poilly (2021) use sign restrictions on inflation and GDP forecasts to measure demand and supply noise and point out that demand noise in particular has a negative effect on output and output volatility. Geiger and Scharler (2021) and Bekaert, Engstrom, and Ermolov (2020) use survey revisions and higher-order moments to identify demand and supply shocks.

The paper is structured as follows: Section 2 presents a synthetic model that explains the relationship between demand or supply dominance and survey data. Section 3 introduces the Slope Index, a forecast-based measure of supply or demand dominance. Then, Section 4 examines the implications of the new measure. Finally, Section 5 concludes.

2. Model

In this section, we propose a stylized model that rationalizes our measure of supply or demand dominance. It describes a situation in which the distribution of expected changes in GDP and inflation (across forecasters) reflects the relative importance of demand versus supply shocks in the economy. It is important to note that, in the context of this stylized homoskedastic model, the relationship between expected changes in GDP and inflation is constant. Our empirical analysis, however, assumes that this relationship is time-varying.[2] One way to reconcile these two observations is to assume that the parameterization of the present model moves over time, but that the agents do not take these changes into account when they compute one-year-ahead forecasts. In other words, we consider the present model to serve as a local approximation of the forecasting process. Having a more realistic modeling approach (that could be brought to the data) would require a model featuring heteroskedastic GDP-inflation dynamics. This is left for further research.

2.1. **The Model and its Implications.**

Inflation, GDP and their determinants We denote by $\Delta y_{t-1,t}$ and $\pi_{t-1,t}$ the quarterly GDP growth rate and inflation rate, defined as

$$\pi_{t-1,t} = p_t - p_{t-1}$$

$$\Delta y_{t-1,t} = gdp_t - gdp_{t-1},$$

where $p_t = \log(P_t)$ and $gdp_t = \log(GDP_t)$.

Without loss of generality, we assume that the long-run mean of both GDP growth and inflation is zero. We also make the hypothesis that the dynamics of quarterly inflation and GDP growth rate are linear combinations of demand and supply factors collected in the 2×1 vector $\xi_t = [d_t, s_t]'$. Importantly, the dynamics of ξ_t is such that its marginal mean is zero. The dynamics of ξ_t can thus be captured by the VAR(1) model

$$\xi_t = F\xi_{t-1} + v_t, \tag{1}$$

with

$$F = \begin{bmatrix} \rho_d & 0 \\ 0 & \rho_s \end{bmatrix} \qquad \text{and} \qquad \mathbb{E}(v_t v_t') = Q = \begin{bmatrix} \sigma_d^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix},$$

[2] Our measure aims to capture changes in the relative importance of demand and supply shocks.

and where the eigenvalues of F lie within the unit circle. σ_d^2 and σ_s^2 denote the variance of demand and supply shocks, respectively, and thus determine the relative importance between demand and supply shocks.

Given the dynamics specified above, the joint model for inflation and GDP growth can be expressed as a linear combination of factors plus measurement errors:

$$S_t = \begin{bmatrix} \Delta y_{t-1,t} \\ \pi_{t-1,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \end{bmatrix} \begin{bmatrix} d_t \\ s_t \end{bmatrix} + \begin{bmatrix} \eta_{y,t} \\ \eta_{\pi,t} \end{bmatrix}, \tag{2}$$

where $\alpha_d > 0$ and $\alpha_s > 0$ determine the effects of demand and supply factors on inflation. For the sake of simplicity, both parameters are normalized to have a unit effect on GDP.

Private information. While the elements contained in S_t can be considered as a public signal for all forecasters, a given forecaster (i) also has private and imperfect information about the factors d_t and s_t on which she relies to form her forecast. We call these private signals $p_{d,t}^{(i)}$ and $p_{s,t}^{(i)}$, which can be viewed as the demand and supply factors, as perceived by a given forecaster (i):

$$\begin{bmatrix} p_{d,t}^{(i)} \\ p_{s,t}^{(i)} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} d_t \\ s_t \end{bmatrix} + \begin{bmatrix} \eta_{d,t}^{(i)} \\ \eta_{s,t}^{(i)} \end{bmatrix}. \tag{3}$$

Combining all elements mentioned above, forecaster (i) observes a total of two public signals, along with two private signals. This results in the following system:

$$Z_t^{(i)} = H'\xi_t + \eta_t^{(i)}, \tag{4}$$

where,

$$Z_t^{(i)} = \begin{bmatrix} \Delta y_{t-1,t} \\ \pi_{t-1,t} \\ p_{d,t}^{(i)} \\ p_{s,t}^{(i)} \end{bmatrix}, \quad H' = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \xi_t = \begin{bmatrix} d_t \\ s_t \end{bmatrix}, \quad \eta_t^{(i)} = \begin{bmatrix} \eta_{y,t} \\ \eta_{\pi,t} \\ \eta_{d,t}^{(i)} \\ \eta_{s,t}^{(i)} \end{bmatrix},$$

and where the signal variance is given by $\mathbb{E}(\eta_t^{(i)}\eta_t'^{(i)}) = R$.

Kalman algorithm. Assuming that forecasters have a substantial history of observed signals and exhibit consistent behavior, it is reasonable to infer that they employ the Kalman algorithm to formulate their individual conditional expectations, i.e. $\xi_{t|t-1}^{(i)} = \mathbb{E}_{t-1}^{(i)}\left(\xi_t\right)$, where $\mathbb{E}_{t-1}^{(i)}\left(\bullet\right)$, denotes the expectation conditional on $\underline{Z_{t-1}^{(i)}} = \{Z_{t-1}^{(i)}, Z_{t-2}^{(i)}, \cdots\}$. The Kalman filter allows us to derive these conditional expectations and leads to the following recursive law of motion for $\xi_{t|t}^{(i)}$ (see Appendix A.1 for the derivation):

$$\xi_{t|t}^{(i)} = F\xi_{t-1|t-1}^{(i)} + K\left(Z_t^{(i)} - H'F\xi_{t-1|t-1}^{(i)}\right),$$

where K is the steady-state Kalman gain.

Combining all aspects, we end up with the following VAR representation:[3]

$$X_t^{(i)} = \Phi X_{t-1}^{(i)} + \Sigma\epsilon_t^{(i)}, \tag{5}$$

where,

$$X_t^{(i)} = \left[d_t,\ s_t,\ \Delta y_{t-1,t},\ \pi_{t-1,t},\ p_{d,t}^{(i)},\ p_{s,t}^{(i)},\ d_{t|t}^{(i)},\ s_{t|t}^{(i)}\right],$$

and $\epsilon_t^{(i)} = \left[\nu_t, \quad \eta_t^{(i)}\right]$.

Note that equation (5) includes the state variables, observables, as well as the private expectations of the factors, i.e. $\xi_{t|t}^{(i)} = [d_{t|t}^{(i)}, \quad s_{t|t}^{(i)}]'$. In particular, it enables the computation of GDP and inflation expectations for any horizon h:

$$\mathbb{E}_t^{(i)}\begin{bmatrix}\Delta y_{t+h-1,t+h}\\ \pi_{t+h-1,t+h}\end{bmatrix} = H_{[1:2,1:2]}F^h\xi_{t|t}^{(i)} = H_{[1:2,1:2]}F^h\Pi X_t^{(i)},$$

where $\Pi X_t^{(i)} = \xi_{t|t}^{(i)}$, and Π is a selection matrix.

[3]See Appendix A.2 for the derivation of the VAR representation.

Joint Distribution between forecasters. This model contains the whole information set of forecaster (i). Since there are variations in the private signals $p_{d,t}^{(i)}$ and $p_{s,t}^{(i)}$, there will also be variations in individual expectations between forecasters. The unconditional distribution of $X_t^{(i)}$ is

$$X_{\mathrm{t}}^{(i)} \sim N\left(0, \Sigma_X\right), \tag{6}$$

where $\Sigma_X = (I_8 - \Phi)^{-1}\left(\Sigma \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \Sigma'\right)(I_8 - \Phi)'^{-1}$.

Finally, We can derive the forecaster's expected changes[4] in GDP growth and inflation, which can be expressed as a function of $X_t^{(i)}$ (see Appendix A.3 for more details):

$$\Gamma_{t,h}^{(i)} = \mathbb{E}_t^{(i)} \begin{bmatrix} \Delta y_{t+h-1,t+h} - \Delta y_{t-1,t} \\ \pi_{t+h-1,t+h} - \pi_{t-1,t} \end{bmatrix} = \Lambda_h X_t^{(i)}, \tag{7}$$

where

$$\Lambda_h = \begin{bmatrix} 0_2 & -I_2 & 0_2 & H'_{[1:2,1:2]} F^h \end{bmatrix}.$$

Since we know the (Gaussian) distribution of $X_t^{(i)}$, we can compute the conditional distribution of $\Gamma_{t,h}^{(i)} | \xi_t$:

$$\Gamma_{t,h}^{(i)} \mid \xi_t \sim N\left(\widetilde{\Lambda_h} \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \xi_t \;,\; \widetilde{\Lambda_h}\left(\Sigma_{X_{22}} - \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \Sigma_{X_{12}}\right) \widetilde{\Lambda_h}'\right), \tag{8}$$

with $\widetilde{\Lambda_h} = \left[-I_2 \;,\; 0_2 \;,\; H'_{[1:2,1:2]} F^h \right]$ and $\Sigma_{X_{11}}, \Sigma_{X_{12}}, \Sigma_{X_{21}}, \Sigma_{X_{22}}$ are sub-matrices of Σ_X, such that,

$$\Sigma_X = \begin{bmatrix} \Sigma_{X_{11}} & \Sigma_{X_{12}} \\ \Sigma_{X_{21}} & \Sigma_{X_{22}} \end{bmatrix}.$$

Equation (8) shows the joint distribution of expected changes in GDP and inflation across forecasters. Figure 1 is its empirical counterpart. It is important to note that while the expected value of the distribution in equation (8) depends on ξ_t, the variance-covariance matrix does

[4]For the sake of simplicity, we use the difference between the expectations and current values of inflation and GDP. We focus on the forecaster's expected changes, as they exhibit a mean of zero. In addition, we focus on the slope of the scatter plot, as shown in Figure 1, which is contingent on the second-order moment of the distribution. Notably, this slope remains unaffected by the aforementioned change.

not. Thus, in the context of this simple model, the distribution (across forecasters) of expected changes in inflation and GDP moves over time only because the coordinates of the "center" of the distribution depend on ξ_t. In particular, in this model, the slope of the regression line in the regression of expected changes in GDP on expected changes in inflation (which relate to our measure) is not time-varying.[5] However, this is not the case in the data (as illustrated by Figure 1). To reconcile the present model with the data, one can think of the model as a "local" approximation of reality. A model that accounts for changes in the regression line—which could then be amenable to the data—would require heteroskedastic demand and supply shocks (i.e., a time-varying Σ_X). However, this is beyond the scope of the present paper.

2.2. **Demand and Supply-Dominant Economies.** As mentioned above, the model developed in the last subsection lacks dynamic changes in the relative importance of demand and supply, since σ_d^2 and σ_s^2 remain constant over time. Nevertheless, this model is useful for elucidating the relationship between the distribution of expected changes in inflation and GDP growth (across forecasters) and the relative importance of demand and supply shocks in the economy, which can be measured by σ_d/σ_s.

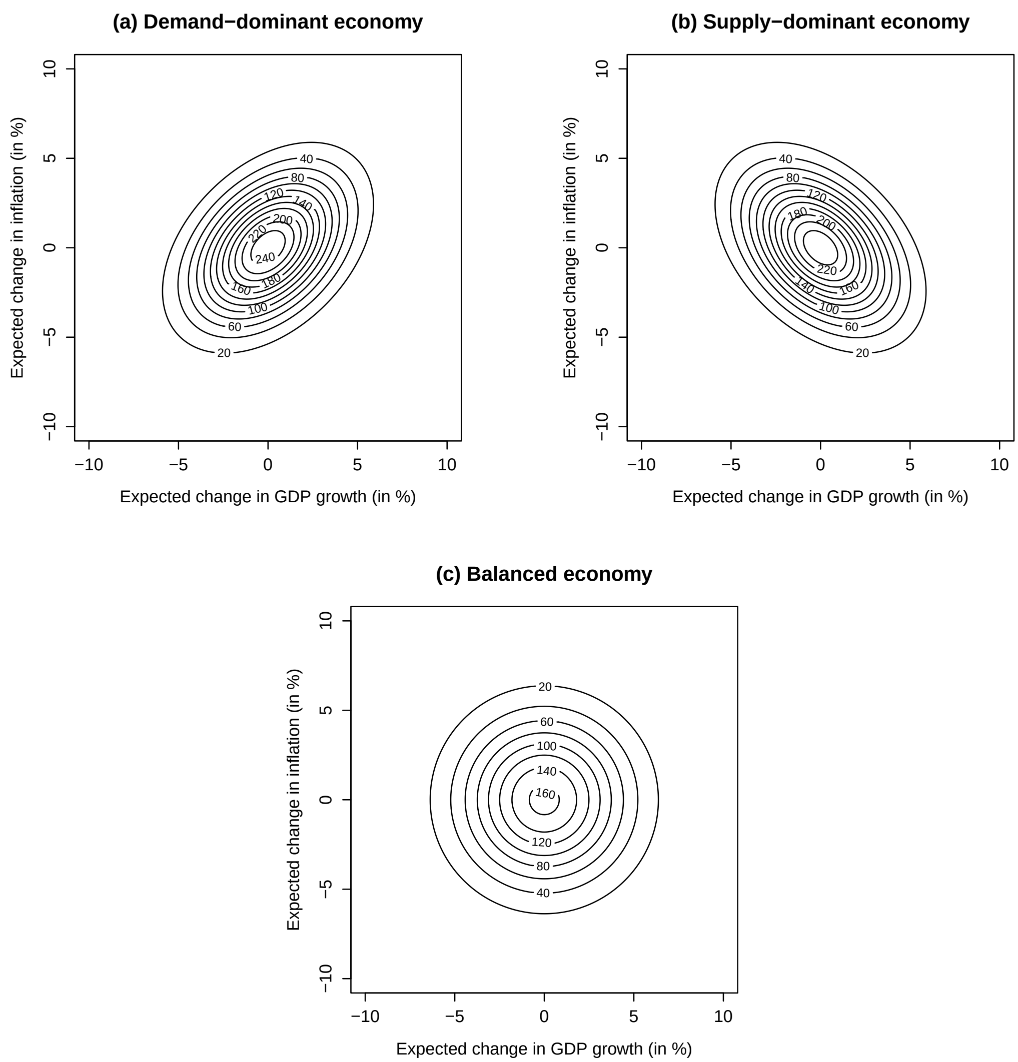
For this purpose, we consider three calibrations of the model that differ substantially with respect to σ_d/σ_s. The first scenario is a "balanced" economy with two shocks of equal magnitude, i.e., $\sigma_d = \sigma_s$. The second scenario represents a demand-dominant economy where $\sigma_d = 10\sigma_s$. The third scenario corresponds to a supply-dominant economy, where $\sigma_s = 10\sigma_d$. Appendix A.4 presents the model calibration.

Figure 2 shows the joint distributions—across forecasters—of expected changes in inflation and GDP growth for the three different scenarios: demand-dominant economy (top left chart), supply-dominant economy (top right chart), and balanced economy (bottom chart). As shown in (8), these distributions depend on the value of ξ_t. For simplicity, we consider the case where ξ_t equals zero (its long-run mean), such that the distribution is centered around zero as

[5]Note that this is the case in the population (of forecasters). That is, this is only if an infinite number of forecasts were included in the regression (and under the model assumptions) that we would have a constant regression slope.

well. This is without loss of generality since the second-order moments of the distribution—in which we are primarily interested—do not depend on ξ_t.

Figure 2. Demand versus Supply-Dominant Economy

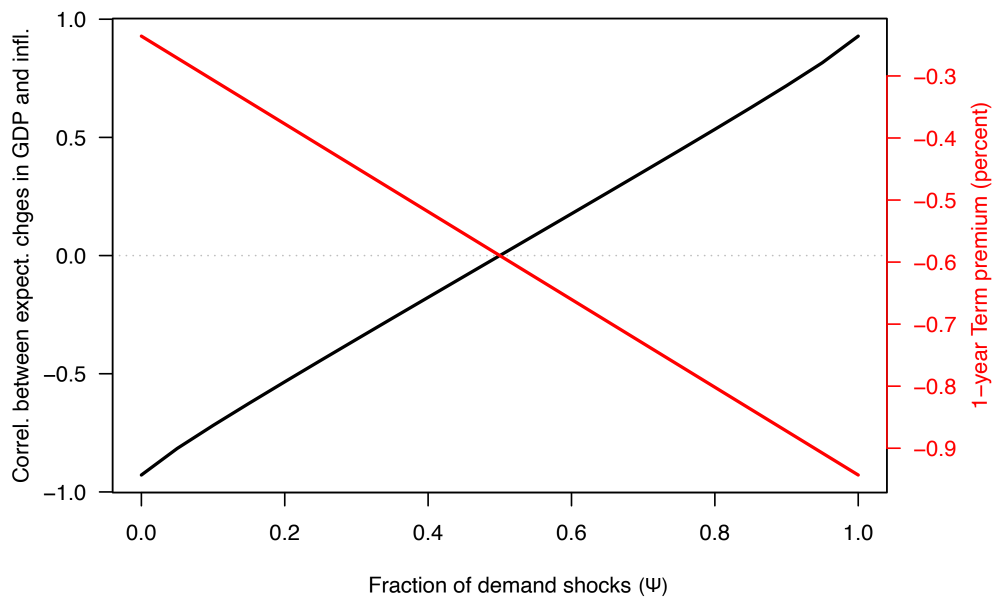


Notes: This figure shows joint distributions of expected change in inflation and GDP growth (across forecasters) under three distinct scenarios: one characterized by the dominance of demand shocks (upper left chart with $(\sigma_d, \sigma_s) = (0.5\%, 0.05\%)$), another by the prevalence of supply shocks (upper right chart with $(\sigma_d, \sigma_s) = (0.05\%, 0.5\%)$), and the last representing the balanced situation (bottom center chart with $(\sigma_d, \sigma_s) = (0.5\%, 0.5\%)$). The calibration of other coefficients is symmetric and outlined in Appendix A.4.

For the demand-dominant economy, the contour plot reveals elongated ellipses. The positive correlation across forecasters between inflation and GDP growth is evident as the ellipses are stretched in one direction—from northeast to southwest. Conversely, the supply-dominant economy exhibits a negative correlation. For the balanced economy, we see no correlation between the expected changes in inflation and GDP growth. This is consistent with Figure 1, which shows different types of slopes depending on the type of shock prevailing in the economy.

The previous results suggest that the shape of the joint distribution of expected changes in GDP and inflation is informative about the relative importance of demand shocks in the economy. This is further illustrated by Figure 3, where the black line plots the correlation of expected changes in GDP and inflation as a function of the relative importance of demand shocks.[6]

Figure 3. Term Premium and the Relative Importance of Demand Shocks



Notes: This figure illustrates the evolution of the correlation between expected changes in GDP and inflation on the left y-axis, and the evolution of the term premium on the right y-axis, as the fraction of demand shocks varies. See Section 4.3 for details regarding the term premium. σ_d^2 and σ_s^2 are set depending on the fraction of demand shocks ψ. The specifications are such that the total variance in the model remains constant when ψ varies. See Appendix A.4 for details on the model calibration.

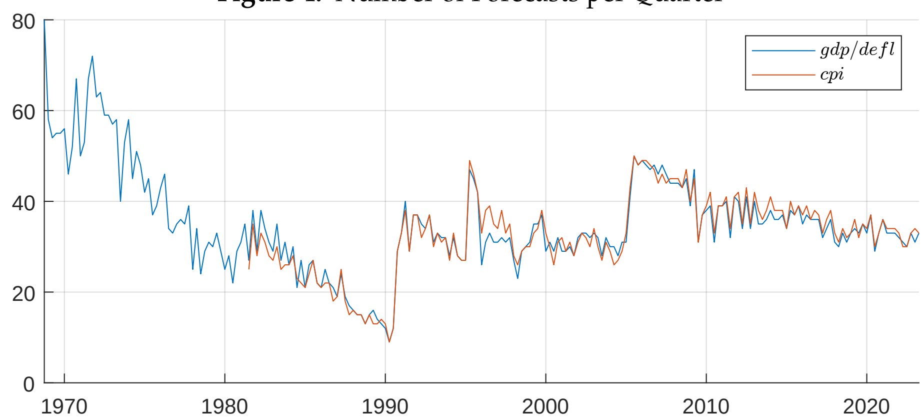
[6] This section focuses on the correlation between the expected changes in GDP and inflation (black line). The relationship with the term premium (red line) is discussed in Section 4.3.

3. Construction of the Indicator

This section presents the data and the computation of the Individual Forecaster Slope Index.

3.1. **Data.** The Survey of Professional Forecasters (SPF) is a quarterly survey of forecasts from financial and research institutions. It provides forecasts for a multitude of variables and horizons. We make use of quarterly point forecasts of real GDP, the implicit GDP deflator, and CPI inflation, covering all forecasts with horizons from current-quarter to four quarters ahead. Participating institutions also provide forecasts for calendar years with a changing forecast horizon each quarter [7]. The fixed-horizon forecasts (from current-quarter to 4 quarters ahead) are more homogeneous, comparable, and thus better suited for our purposes.[8]

Figure 4. Number of Forecasts per Quarter



Notes: This figure depicts the number of forecasts for each quarter. The blue line depicts both the number of observations for GDP and the GDP deflator, as the two numbers are equal for every quarter. The red line depicts forecasts for CPI inflation, which starts in 1981Q3, only. The smallest number of observations is 9 forecasts, which is recorded for 1990Q2.

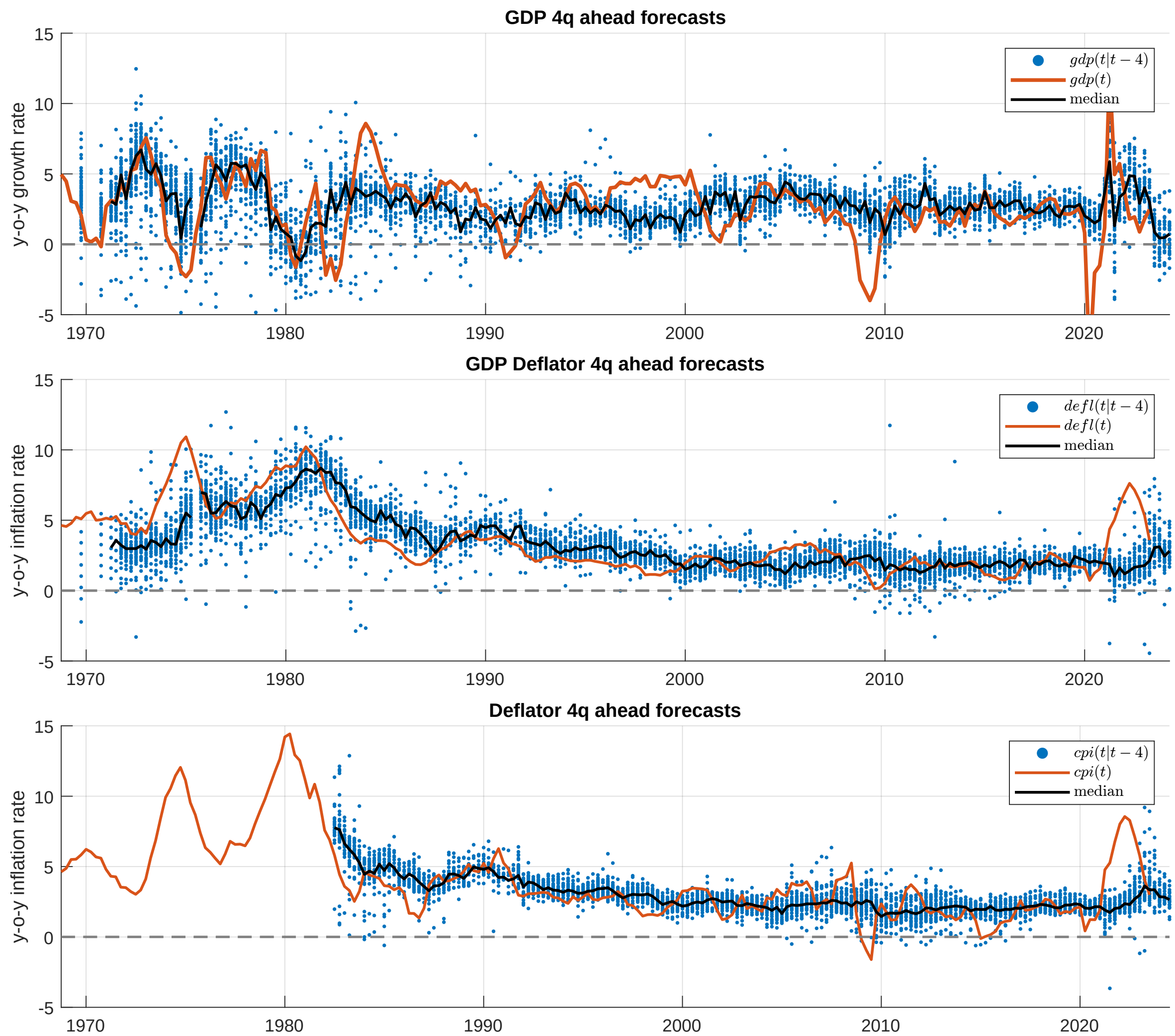
All variables are expressed as year-on-year percentage changes, henceforth referred to as growth rates for GDP and inflation rates for the GDP deflator and the CPI. The sample period starts in 1968Q4 for GDP and the GDP deflator forecasts, and in 1981Q3 for CPI forecasts. The last observation is in 2023Q3.[9]

[7] e.g. every quarter in 2022, forecasters make forecasts for the calendar years 2022, 2023, and 2024

[8] Notably, forecasts are sampled mid-quarter, prior to the release of official GDP and GDP deflator figures, giving rise to current-quarter forecasts.

[9] For more information on the SPF, and the construction and transformation of the forecast data, see Appendix C.

Figure 5. Individual 4-Quarter-Ahead Forecasts and Realizations



Notes: This figure shows individual 4-quarter-ahead forecasts for year-on-year growth rates of GDP, the GDP deflator, and the CPI. The red line denotes the last vintage of official data for the three series. The black line denotes the median forecast and the blue dots denote the individual forecasts. Forecasts are displayed at the date which is targeted by the forecast, not the date when the forecast was made.

Each forecaster has a unique identification number that allows them to be tracked over time. However, it is important to note that ID numbers are not always unique, as there are instances where the IDs of leaving institutions have been reassigned to new entrants. Due to this, and because of constant changes in the composition of forecasters, we do not exploit the time series dimension of individual forecasters. In the cross-section, the number of forecasters per quarter was quite volatile before 1990, when the Federal Reserve Bank of Philadelphia took over the survey from the National Bureau of Economic Research. The average number of respondents in the sample is about 36, and the minimum is 9 observations in 1990Q1 (see Figure 4).

Table 1. Descriptive Statistics SPF

Mean Forecast Errors: $MFE_t = \mu_t \left(x_t - x^{(i)}_{t\|t-h} \right)$, where $x_t = \{gdp_t, defl_t, cpi_t\}$	gdp_t			$defl_t$			cpi_t		
	$h=0$	$h=1$	$h=4$	$h=0$	$h=1$	$h=4$	$h=0$	$h=1$	$h=4$
$\mu(MFE_t)$	0.17	0.17	−0.01	0.11	0.14	0.19	0.06	0.05	−0.09
$\sigma(MFE_t)$	0.62	1.27	2.19	0.32	0.60	1.68	0.33	0.72	1.56
$\rho(MFE_t)$	0.02	0.19	0.78	0.60	0.79	0.96	0.15	0.49	0.84
Disagreement: $D_t = \sigma_t \left(x^{(i)}_{t\|t-h} \right)$, where $x_t = \{gdp_t, defl_t, cpi_t\}$									
$\mu(D_t)$	0.37	0.59	1.16	0.28	0.44	0.93	0.23	0.37	0.64
$\sigma(D_t)$	0.28	0.42	0.76	0.16	0.25	0.59	0.13	0.21	0.34
$corr(MFE_t, D_t)$	0.62	0.41	0.34	0.62	0.50	0.46	0.75	0.60	0.41

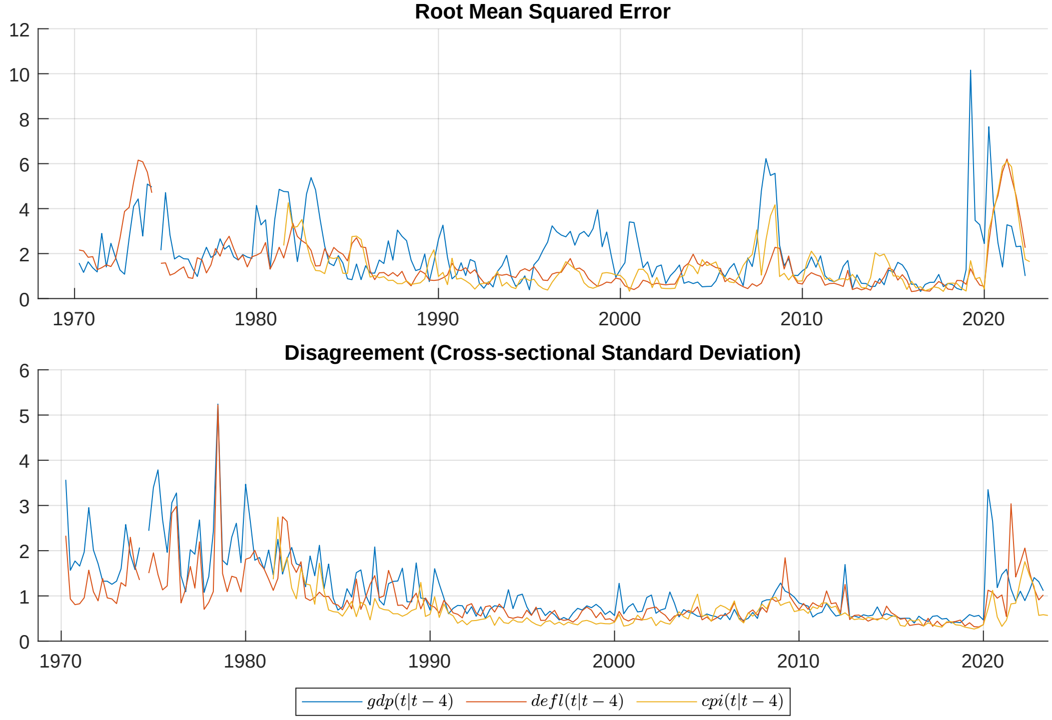
Notes: This table reports common descriptive statistics for the SPF data from 1968 - 2023. μ_t and σ_t denote the cross-sectional mean and standard deviation across forecasters, whereas μ and σ depict the mean and standard deviation across time. $\rho(MFE_t)$ depicts the sample autoregressive coefficient of MFE_t for $lag = 1$, and $corr(MFE_t, D_t)$ stands for the correlation coefficient between mean forecast errors and disagreement. x_t stands for the respective variable $x_t = \{gdp_t, defl_t, cpi_t\}$, which is transformed into year-on-year growth rates.

Table 1 reports descriptive statistics. The statistics are presented for the three variables of interest and for three horizons: $h = \{0, 1, 4\}$.[10] Both the forecast error variance, as well as the disagreement increase with the length of the horizon. The statistics shown in Table 1 average over both the time and forecaster dimensions. Figure 6, however, shows that mean forecast errors and disagreement vary over time, with both variables increasing in periods of distress (e.g., during the great financial crisis or during the COVID period). The same statistics for forecasts of shorter horizons ($h = 0$ and $h = 1$) are available in Appendix C.

3.2. **Constructing the Individual Forecast Slope Index.** Our Slope Index is based on individual SPF forecasts. This data being available at the forecaster level, we can exploit it to operationalize the insights of Section 2, according to which the correlation (across forecasters) of expected changes in GDP and inflation is informative about the relative importance of

[10]Note that the forecasts for the current quarter $h = 0$ (or nowcasts) are submitted before any official figures are published. This is with the exception of CPI inflation, which is partially known (see Appendix C for details).

Figure 6. Accuracy and Disagreement for Horizon $h = 4$



Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x_t = \{gdp_t, defl_t, cpi_t\}$. The bottom figure displays the disagreement between forecasts, which means the dispersion between point forecasts. It is measured by the cross-sectional standard deviation. The horizon for both plots is $h = 4$. For other horizons, the same plots can be found in Appendix C.

demand shocks in the economy. Importantly, this correlation can be computed on each date when SPFs are released (at the quarterly frequency).

There are roughly 36 forecasts submitted, on average, per date. Given this relatively small number, and taking into account the fact that in our methodology, a single forecaster can significantly change the Slope Index, we proceed in three steps to construct the indicators:

- Taking all forecasts for horizons $h \in \{0, 1, ..., 4\}$, we winsorize the data at the 95th percentile.
- We calculate the Pearson correlation coefficient for each horizon separately:

$$Corr^{gdp,\pi}_{t,t+h} = corr(y^{(i)}_{t,t+h}, \pi^{(i)}_{t,t+h}), \tag{9}$$

with horizons $h \in \{0, 1, ..., 4\}$ and $\pi \in \{defl, cpi\}$ indicating the price index used to compute inflation.

- We collect the Slope Indices for each horizon by extracting the first principal component. Depending on the measure for inflation, this yields three different *Individual Forecast Slope* (IFS) indices, or just Slope Indices, in short.

In graphs and tables, $IFS_t(defl)$, $IFS_t(cpi)$, and $IFS_t(all)$ denote the three Slope Indices for the rest of the paper. The first two use the respective inflation measure to construct the Slope Index, and the last index combines the Slope Indices of both inflation measures. Thus, for $IFS_t(defl)$ and $IFS_t(cpi)$ we use 5 data series ($Corr^{gdp,defl}_{t,t+h}$ or $Corr^{gdp,cpi}_{t,t+h}$, respectively, for all h), while for $IFS_t(all)$ we have 10 series ($Corr^{gdp,defl}_{t,t+h}$ and $Corr^{gdp,cpi}_{t,t+h}$, combined, for all h) that are used to draw the principal component.

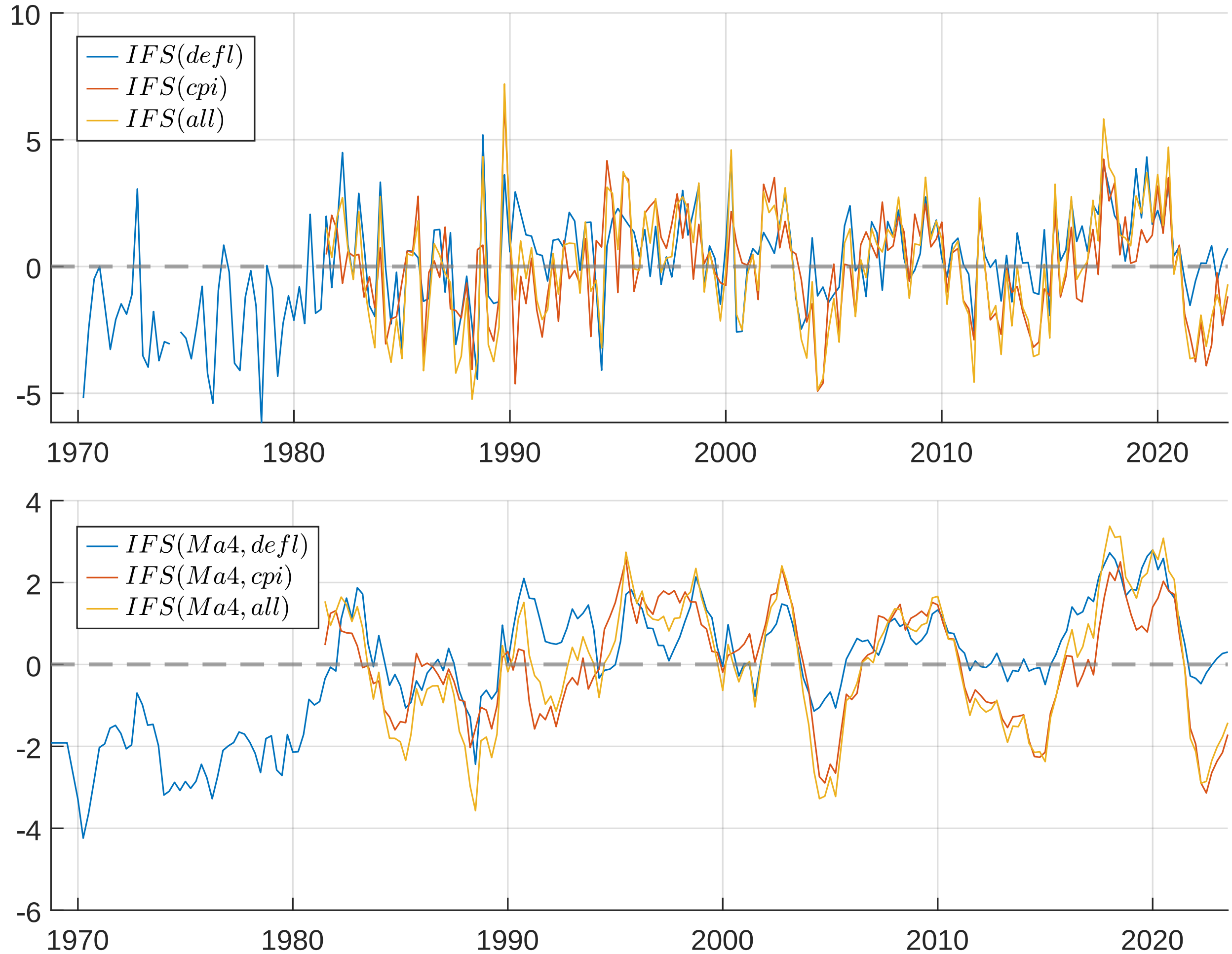
Because the three IFS (top graph in Figure 7) are quite noisy, and since we view the Slope Index as a measure that captures slow-moving changes in demand or supply dominance in the economy, we apply a 4-quarter moving average filter to the three IFS. These smoothed indices are denoted $IFS_t(Ma4, defl)$, $IFS_t(Ma4, cpi)$, and $IFS_t(Ma4, all)$, respectively. Our outputs (tables and figures) report the results for the original Slope Indices and for the smoothed versions. Let us reiterate that the *cpi* forecasts are only available starting in 1981. Table 2 reports the correlation between different Slope Indices.

Table 2. Correlations between Slope Indices

	IFS_{defl}	IFS_{cpi}	IFS_{all}	IFS^{Ma4}_{defl}	IFS^{Ma4}_{cpi}	IFS^{Ma4}_{all}
$IFS(defl)$	1.00					
$IFS(cpi)$	0.42	1.00				
$IFS(all)$	0.84	0.85	1.00			
$IFS(Ma4, defl)$	0.69	0.40	0.55	1.00		
$IFS(Ma4, cpi)$	0.37	0.65	0.60	0.63	1.00	
$IFS(Ma4, all)$	0.50	0.60	0.65	0.87	0.92	1.00

Notes: This table reports the Pearson correlation coefficient between the six different Slope Indices. They are calculated using the maximum sample size per pair of data series, which is 169 observations when CPI data is used, and 220 observations otherwise.

Figure 7. Original and Smoothed Slope Indices



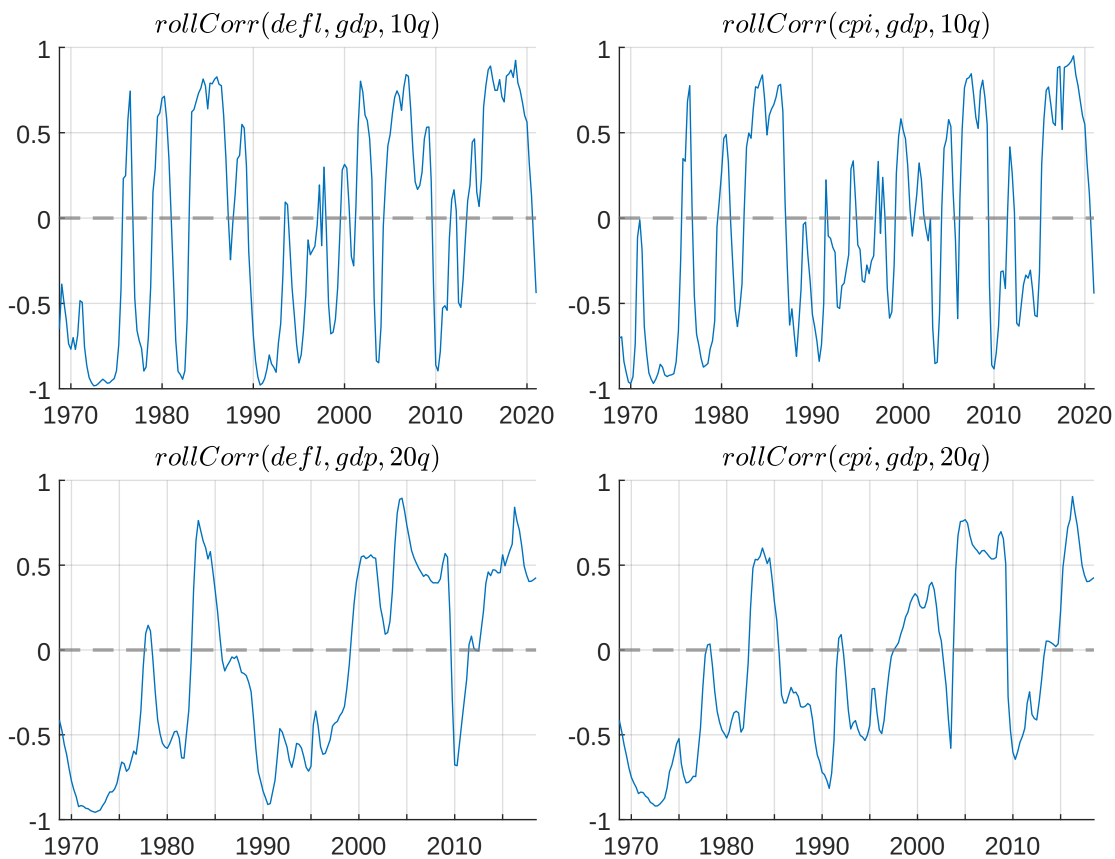
Notes: This figure depicts the 3 principal components, as derived from the Slope Indices from the three inflation measures (always combined with gdp). The top plot depicts the original series, and the bottom plot the smoothed series (smoothed by a 4-quarter moving-average filter).

Because it is based on SPF data, our Slope Index is a forward-looking measure, in the sense that it is based on how forecasters see the future dynamics of GDP and inflation. It is model-free, and available in real time, even if the *Ma*4 versions are based only on forecast data published over the last four quarters. These properties are not shared by alternative approaches. In particular, those approaches relying on rolling windows to compute time-varying correlations between GDP and inflation are backward-looking; to produce a reasonable correlation estimate, they must rely on windows longer than one year. However, they can provide good *ex-post* measures of the GDP-inflation correlation. In the next subsection, we examine the relationship between our Slope Indices and such *ex-post* correlation measures.

4. Regression Analysis

4.1. **Slope Index and Aggregate Correlations.** We consider rolling correlations between real GDP and inflation, using a sliding window of 10 and 20 quarters, and call them aggregate correlations, where aggregate refers to official and realized macroeconomic variables, as opposed to the survey-based correlations underlying the Slope Index.

Figure 8. Rolling Correlation of GDP and Inflation



Notes: This figure shows the evolution of the rolling correlation coefficient across time. The left column uses the GDP deflator ($defl$) as an inflation measure, the right column uses CPI (cpi). The top row uses a 10-quarter $(10q)$, the bottom row a 20-quarter $(20q)$ rolling window to calculate correlations. The X-axis denotes the first observation of the rolling window, i.e. for the bottom row (20 quarters the value at $t = 2018Q1$ uses observations from $2018Q1$ to $2022Q4$.

These rolling correlations are displayed in Figure 8 using both the GDP deflator ($defl$) and CPI inflation (cpi) as the inflation measure. The results indicate considerable co-movement between GDP and Inflation. While there are some fast-moving changes in these series, there is also a slow-moving part that drives the series. This simple measure is roughly in line with the dominant economic forces in the U.S. economic development since 1968: In the 1970s and 1990s, inflation and GDP co-moved negatively in the vast majority of quarters, suggesting a larger role for supply shocks. The 1970s are known as a stagflationary period, where high inflation coincided with low growth rates. The 1990s were characterized by accelerating globalization and deregulation; two changes that directly influence supply.

On the other hand, the 1980s were characterized by Reagonomics, i.e. a strong expansion due to fiscal policy (through tax cuts and expenditure increases) and a more active monetary policy. Both affect aggregate demand. The 2000s and 2010s were characterized by the Great Moderation. Impulses came mainly from expansionary monetary policy. Supply factors played a smaller role. These historical findings are consistent with other research on the importance of demand and supply, see e.g. Eickmeier and Hofmann (2022). At the same time, the Slope Indices (Figure 7), as well as the ex-post correlations (Figure 8) fit these observations reasonably well.

We now examine whether professional forecasters capture the changes in the correlation structure of GDP and inflation in real time. To do this, we use the Slope Index, as derived in Subsection 3.2, and we set up the following regression:

$$rollCorr_{t,q}(gdp, \pi) = \beta_0 + \beta_1 IFS_t(i) + \varepsilon_t, \tag{10}$$

where $\pi = \{defl, cpi\}$ depicts the aggregate inflation measure, $i = \{defl, cpi, all\}$ denotes the Slope Index used. $rollCorr_{t,q}(gdp, \pi)$ denotes the *ex-post* rolling correlation coefficient between GDP and inflation measure π for the time window $(t : t + q - 1)$. For the following regressions, we set $q = 10$ and $q = 20$.

Table 3. Rolling Correlation Regressions

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(defl)$	0.065*			0.058**		
	(0.033)			(0.027)		
$IFS(cpi)$		0.019			−0.035	
		(0.032)			(0.031)	
$IFS(all)$			0.013			−0.032
			(0.026)			(0.023)
Observations	205	159	159	195	149	149
R^2	0.046	0.004	0.003	0.046	0.017	0.021
F-test (robust)	3.831*	0.345	0.261	4.476**	1.274	1.914
	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(defl)$	0.085***			0.077***		
	(0.029)			(0.023)		
$IFS(cpi)$		0.053**			0.001	
		(0.027)			(0.025)	
$IFS(all)$			0.041*			0.006
			(0.025)			(0.020)
Observations	205	159	159	195	149	149
R^2	0.094	0.037	0.033	0.101	0.000	0.001
F-test (robust)	8.710***	4.005**	2.778*	11.567***	0.003	0.085

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top regressions: GDP deflator used as the inflation measure. Bottom regressions: CPI is used as the measure of inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parentheses. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

The results are displayed in Table 3. They portray a positive relationship between the Slope Index and the rolling correlation, providing evidence in support of the hypothesis that a positive Slope Index at time t (indicating a demand-dominant economy) coincides with a positive correlation between aggregate GDP and inflation in the 10 or 20 quarters following period t. More generally, the observed positive relationship substantiates the claim that GDP and inflation are not forecast in isolation and that we can derive information on the underlying shock structure.

The additional results in Appendix D confirm the robustness of these findings across various subsamples, including the earliest and most recent periods. However, significance diminishes for the intermediate period (1986-2008), possibly due to fewer observations or challenges in disentangling demand and supply shocks amidst low inflation rates.

4.2. **Regressing Mean Forecast Errors.** This subsection presents the results of a related regression exercise based on a simpler measure of GDP and inflation covariance. Let $MFE^{v}_{t,t+h}$ denote the aggregate forecast error made by forecasters for variable v between dates t and $t+h$, that is $MFE^{v}_{t,t+h} = v_{t+h} - \mathbb{E}_t(v_{t+h})$. Considering GDP and inflation as v variables, we can compute the ex-post forecast errors using SPF data. By definition, we have

$$\mathbb{E}_t(MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h}) = \mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h}),$$

which implies

$$MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h} = \mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h}) + \varepsilon_{t+h},$$

where $\mathbb{E}_t(\varepsilon_{t+h}) = 0$. By the law of iterated expectations, we also have $\mathbb{E}(\varepsilon_{t+h}) = 0$. Since the Slope Index can be seen as a proxy for $\mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h})$, what precedes suggests that the regression of $MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h}$ on the date-t Slope Index should result in a positive coefficient. To test for the potential forward-looking nature of the Slope Index, we include the rolling covariance between GDP and inflation over the past 10 quarters ($rollCov_t(gdp, \pi)$, say) as a control in some of the regressions.[11] Formally, our regressions are as follows:

$$MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h} = \beta_0 + \beta_1 IFS_t(i) + \beta_2 rollCov_t(gdp, \pi) + \varepsilon_t, \tag{11}$$

where $i = \{defl, cpi, all\}$, $\pi = \{defl, cpi\}$, and $h = \{0, 1, 4\}$. Tables 4 and 5 show the regression results for $h = 4$.[12] This shows the relationship between the Slope Index and the product of the one-year-ahead mean forecast errors, which confirms the ability of our measure to capture changes in the relative importance of demand shocks in real time.

[11]It is important to note that $rollCov_t(gdp, \pi)$ is backward-looking (as opposed to $rollCorr_{t,q}(gdp, \pi)$ in Subsection 4.1, which is forward-looking.)

[12]We get very similar results for $h = 1$ and $h = 0$ (see Appendix D.2).

Table 4. MFE Product (gdp-$defl$) Regressions, for $h = 4$

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	1.078*			0.689		
	(0.597)			(0.611)		
$IFS(Ma4, cpi)$		0.844*			0.466	
		(0.455)			(0.658)	
$IFS(Ma4, all)$			0.749**			0.435
			(0.334)			(0.677)
$rollCov(gdp, defl)$				0.588	0.904*	0.776**
				(0.550)	(0.483)	(0.356)
Observations	210	168	168	208	168	168
R^2	0.094	0.077	0.085	0.173	0.115	0.119
F-test (robust)	3.263*	3.433*	5.037**	2.097	4.026**	4.961***

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5. MFE Product (gdp-cpi) Regressions, for $h = 4$

	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.798**			0.254		
	(0.400)			(0.723)		
$IFS(Ma4, cpi)$		0.930*			0.335	
		(0.485)			(0.651)	
$IFS(Ma4, all)$			0.716**			0.297
			(0.351)			(0.675)
$rollCov(gdp, defl)$				0.797*	0.976*	0.737**
				(0.411)	(0.502)	(0.363)
Observations	164	164	164	164	164	164
R^2	0.025	0.065	0.054	0.033	0.079	0.065
F-test (robust)	3.976**	3.680*	4.167**	2.538*	2.685*	2.979*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4.3. **Relationship with the Term Premium.** In this subsection, we study the relationship between our Slope Index and term premium measures. The latter are deviations from the expectation hypothesis (EH). More specifically, they are the difference between the interest paid on a long-term bond and the expected return associated with the strategy that consists of rolling over a portfolio by investing the entire portfolio, at each period, in short-term bonds. (Under the EH, the yield-to-maturity of a long-term bond would be equal to the expected average of future short-term rates until the maturity of the bond.) As discussed in the introduction, the theory predicts that supply shocks pose a greater risk to holders of long-term bonds than demand shocks which implies that term premiums are higher in an economy driven by supply shocks (e.g., Piazzesi and Schneider, 2007; Gurkaynak and Wright, 2012).

This can be illustrated in the context of the model presented in Section 2. Appendix B extends this model by introducing a representative investor who consumes the output and features time-separable power-utility preferences. In that context, one can derive the term premiums in closed form. Figure 3 shows how, in this framework, term premiums depend on the relative importance of demand shocks. In contrast to the correlation between expected changes in inflation and GDP (in black), term premiums depend negatively on the importance of demand shocks.

We now turn to the empirical evaluation of this model prediction. Since the Slope Index increases with demand dominance, we expect a negative relationship with the term premium. To test this hypothesis, we run the following linear regressions:

$$TP_{k,t} = \beta_0 + \beta_1 IFS_t(i) + \varepsilon_t, \tag{12}$$

where $i = \{defl, cpi, all\}$, and $k = \{10Y, 2Y\}$. As a positive Slope Index coincides with a demand-dominant economy, we expect term premiums to be lower in this case. Therefore, we expect the regression coefficients to be negative.

Table 6. Term Premium Regressions (10Y TP)

	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(defl)$	−0.052			−0.015***		
	(0.032)			(0.006)		
$IFS(cpi)$		−0.026			−0.000	
		(0.041)			(0.007)	
$IFS(all)$			−0.050			−0.010*
			(0.035)			(0.005)
Observations	214	168	168	210	167	167
R^2	0.028	0.005	0.028	0.029	0.000	0.020
F-test (robust)	2.649	0.392	1.996	7.390***	0.001	3.895*

	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(Ma4, defl)$	−0.089			−0.078***		
	(0.058)			(0.021)		
$IFS(Ma4, cpi)$		−0.037			0.009	
		(0.081)			(0.029)	
$IFS(Ma4, all)$			−0.083			−0.052**
			(0.073)			(0.021)
Observations	220	169	169	219	168	168
R^2	0.042	0.005	0.035	0.035	0.001	0.032
F-test (robust)	2.388	0.202	1.319	13.321***	0.096	6.322**

Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. The term premiums data is from Adrian, Crump, and Moench (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

For this empirical exercise, we use the term premiums derived from the Adrian, Crump, and Moench (2013) term structure model. Their estimates go back to 1961 and are continuously updated by the Federal Reserve Bank of New York.[13]

As there is a slight linear trend in the regressor and regressand, we want to make sure that our results are not driven by spurious correlation. For this, we include regressions of first

[13]The term premium data, as calculated by Adrian, Crump, and Moench (2013), is plotted in Figure 12 in the appendix.

Table 7. Term Premium Regressions (Different Time Periods)

	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	-0.110	0.276^{***}	-0.079	-0.218^{**}
	(0.068)	(0.057)	(0.059)	(0.103)
Observations	214	64	89	62
R^2	0.027	0.244	0.022	0.076
F-test (robust)	2.638	23.142^{***}	1.771	4.456^{**}

	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(cpi)$	-0.059	-0.030	-0.119^{**}	-0.008
	(0.091)	(0.064)	(0.055)	(0.125)
Observations	168	18	89	62
R^2	0.006	0.019	0.067	0.000
F-test (robust)	0.418	0.220	4.738^{**}	0.004

	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(all)$	-0.106	-0.047^{**}	-0.100^{**}	-0.070
	(0.077)	(0.021)	(0.046)	(0.089)
Observations	168	18	89	62
R^2	0.027	0.102	0.063	0.021
F-test (robust)	1.929	5.074^{**}	4.779^{**}	0.620

Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

differences. The first three columns of Table 6 contain the standard regression, while the last three columns contain the regression in first differences. Consistent with the theory, the table shows that term premiums are negatively related to the Slope Index. While all coefficients are negative, only a third are statistically significant. Results for the 2-year maturity, shown in Appendix D, are qualitatively equivalent.

Table 7 reports the results of the same regressions run on three subperiods. It shows that the negative correlation between the different periods does not come from any particular subset of the sample. Rather, it holds for both low and high-inflation environments, and for periods where demand dominates, as well as for periods where supply shocks are dominant.

5. Concluding Remarks

This article focuses on the time variation in the relative importance of demand and supply shocks in the U.S. economy. To do so, it proposes a simple metric that is computed each quarter, namely the correlation between GDP and inflation forecasts across individual forecasts in the Survey of Professional Forecasters. We call this metric Slope Index, as it resembles a regression of expected changes in GDP and inflation (for each date, across forecasters). Unlike standard measures based on rolling correlations between realized GDP and inflation data, our measure is forward-looking and available in real time. This can be particularly useful in periods of rapid changes and uncertainties, such as the COVID era, when capturing the nature of the underlying shocks was crucial for devising suitable policy responses.

Building a synthetic model in which forecasters use imperfectly correlated private information about demand and supply, we show that the relationship between expected changes in GDP and inflation across forecasters is informative about the relative importance of demand over supply shocks. We find that when the model is calibrated such that demand shocks dominate, the correlation of GDP and inflation expectations across forecasters is more positive and term premiums are lower when compared to a calibration where supply shocks dominate.

Several empirical exercises suggest that our Slope Index is able to track, ex ante, part of the co-movement between GDP and inflation (as measured ex post). We also find a negative relationship between the Slope Index and bond term premiums, consistent with the latter, in theory, being negatively related to the importance of demand shocks in the economy.

To summarize, this paper shows that the importance of demand and supply varies over time and provides a novel way to track these changes. Further research is needed to uncover the drivers and the repercussions of these changes.

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APPENDIX A. MODEL DERIVATIONS

The derivations in this appendix complement the model in Section 2.

A.1. **Kalman algorithm.** Given equations (1) and (4), we take expectations of ξ_t conditional on forecaster (i)'s information set, which yields:

$$\mathbb{E}_{t-1}^{(i)}\Big(\xi_t\Big) = \xi_{t|t-1}^{(i)} = F\xi_{t-1|t-1}^{(i)}$$

and

$$\mathbb{E}_{t-1}^{(i)}\Big(Z_t^{(i)}\Big) = Z_{t|t-1}^{(i)} = H'\xi_{t|t-1}^{(i)}$$

, where $\mathbb{E}_{t-1}^{(i)}\Big(\bullet\Big)$, denote the expectation conditional on $\underline{Z_{t-1}^{(i)}} = \{Z_{t-1}^{(i)}, Z_{t-2}^{(i)}, \cdots\}$. To simplify notation, we denote $X_{t|t-1}^{(i)} = \mathbb{E}_{t-1}^{(i)}(X_t)$ for a generic variable $X_t^{(i)}$.

This derivation closely follows Hamilton (1994). We denote the mean squared error matrix $P_{t|t-1} = \mathbb{E}_{t-1}\left[(\xi_t - \xi_{t|t-1})(\xi_t - \xi_{t|t-1})'\right]$. The Kalman Filter is given by:

$$K_t = P_{t|t-1}H\left[H'P_{t|t-1}H + R\right]^{-1} \tag{13}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q \tag{14}$$

and hence

$$\xi_{t|t}^{(i)} = \xi_{t|t-1}^{(i)} + K_t\left(Z_t^{(i)} - Z_{t|t-1}^{(i)}\right) \tag{15}$$

$$P_{t|t} = P_{t|t-1} - K_tH'P_{t|t-1}. \tag{16}$$

As the sample size increases, $P_{t|t-1}$ and K_t converge to its steady-state values P and K, respectively.[14] Equations (13) and (14) become:

$$P = F\Big(P - PH(H'PH+R)^{-1}H'P\Big)F' + Q$$

$$K = PH\left[H'PH + R\right]^{-1}.$$

[14]Proposition 13.1 in Hamilton (1994) shows that $P_{t|t-1}$ and K_t converge under the given assumptions.

Hence, equation (15) can be rewritten as

$$\xi^{(i)}_{t|t} = F\xi^{(i)}_{t-1|t-1} + K\left(Z^{(i)}_t - H'F\xi^{(i)}_{t-1|t-1}\right).$$

To simplify the reading, we rename $\xi^{(i)}_{t|t}$ by $U^{(i)}_t$, i.e. the signal reflecting the demand and supply shocks captured by the forecaster (i) and taking into account all the information available (public and private) at time t:

$$U^{(i)}_t = -KA + KZ^{(i)}_t + (I_2 - KH')FU^{(i)}_{t-1}. \tag{17}$$

A.2. **Towards a VAR model.** Combining equations (1), (4), and (17), we get the following VAR(1) representation:

$$\widetilde{A_0}X^{(i)}_t = \widetilde{\Phi}X^{(i)}_{t-1} + \widetilde{\Sigma}\epsilon^{(i)}_t, \tag{18}$$

where,

$$X^{(i)}_t = \begin{bmatrix} \xi_t \\ Z^{(i)}_t \\ U^{(i)}_t \end{bmatrix}, \quad \widetilde{A_0} = \begin{bmatrix} I_2 & 0 & 0 \\ -H' & I_4 & 0 \\ 0 & -K & I_2 \end{bmatrix}, \quad \widetilde{\Phi} = \begin{bmatrix} F & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & (I_2 - KH')F \end{bmatrix}$$

and

$$\widetilde{\Sigma} = \begin{bmatrix} I_2 & 0 \\ 0 & I_4 \\ 0 & 0 \end{bmatrix}, \quad \epsilon^{(i)}_t = \begin{bmatrix} v_t \\ \eta^{(i)}_t \end{bmatrix}.$$

This equation can be transformed to:

$$X^{(i)}_t = \Phi X^{(i)}_{t-1} + \Sigma\epsilon^{(i)}_t, \tag{19}$$

where,

$$\Phi = \widetilde{A_0}^{-1}\widetilde{\Phi} \quad \text{and} \quad \Sigma = \widetilde{A_0}^{-1}\widetilde{\Sigma},$$

with,

$$\widetilde{A_0}^{-1} = \begin{bmatrix} I_2 & 0 & 0 \\ H' & I_4 & 0 \\ KH' & K & I_2 \end{bmatrix}, \quad \Phi = \begin{bmatrix} F & 0 & 0 \\ H'F & 0 & 0 \\ KH'F & 0 & (I_2 - KH')F \end{bmatrix}, \quad \Sigma = \begin{bmatrix} I_2 & 0 \\ H' & I_4 \\ KH' & K \end{bmatrix}.$$

Given the assumption of normally distributed innovations, the unconditional distribution of $X_t^{(i)}$ is:

$$\mathrm{X}_{\mathrm{t}}^{(i)} \sim N\left(0, \Sigma_X\right), \tag{20}$$

where $\Sigma_X = (I_8 - \Phi)^{-1}\left(\Sigma \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \Sigma'\right)(I_8 - \Phi)'^{-1}$ denotes the long-run variance of the model.

A.3. **Forecasting Inflation and GDP.** Given the dynamics of ξ_t in (1), the best forecast of period h for forecaster (i) is $\xi_{t+h|t}^{(i)} = F^h \xi_{t|t}^{(i)}$. Combined with the observation equations (2), we get the forecast for inflation and GDP at time $t+h$ with the information set at time t:

$$S_{t+h|t}^{(i)} = \mathrm{E}_{\mathrm{t}}^{(i)}\left(S_{t+h}\right) = H'_{[1:2,1:2]} F^h \xi_{t|t}^{(i)}, \tag{21}$$

where $H_{[1:2,1:2]}$ denotes the top left $2x2$ matrix of H'.

Of particular interest, especially given its zero mean, is the difference between the expected and current, realized values of inflation and GDP. These measures are referred to as the expected change in GDP growth and the expected change in inflation, expressed by the following formula:

$$\Gamma_{t,h}^{(i)} = S_{t+h|t}^{(i)} - S_t = \Lambda_h X_t^{(i)}, \tag{22}$$

where,

$$\Lambda_h = \begin{bmatrix} 0_2 & -I_2 & 0_2 & H'_{[1:2,1:2]}F^h \end{bmatrix}.$$

Another notable aspect is the distribution of $\Gamma_{t,h}^{(i)}$ given ξ_t. This distribution serves as the basis for drawing the individual perceptions of forecasters, as shown in Figure 1. To construct this distribution, we start by formulating the joint distribution of $W_t^{(i)}$ and ξ_t, where $W_t^{(i)} = \left[Z_t^{(i)}, U_t^{(i)}\right]'$. To do this, we need to rewrite equation (21) as:

$$\Gamma_{t,h}^{(i)} = \widetilde{\Lambda_h} W_t^{(i)},$$

where

$$\widetilde{\Lambda_h} = \begin{bmatrix} -I_2 & 0_2 & H'_{[1:2,1:2]}F^h \end{bmatrix}.$$

The joint distribution of $W_t^{(i)}$ and ξ_t is therefore:

$$\begin{bmatrix} \xi_t \\ W_t^{(i)} \end{bmatrix} \sim N\left(\begin{bmatrix} 0_2 \\ 0_6 \end{bmatrix}, \begin{bmatrix} \Sigma_{X_{11}} & \Sigma_{X_{12}} \\ \Sigma_{X_{21}} & \Sigma_{X_{22}} \end{bmatrix} \right), \tag{23}$$

with $\Sigma_{X_{11}}$ refering to the upper-left 2×2 submatrix of Σ_X, $\Sigma_{X_{22}}$ representing the lower-right 6×6 submatrix of Σ_X, while $\Sigma_{X_{12}}$ and $\Sigma'_{X_{21}}$ both denote the upper-left 2×6 submatrix of Σ_X. Hence, the conditional distribution of $W_t^{(i)}$ given ξ_t, can be written as:

$$W_t^{(i)} \mid \xi_t \sim N\left(\Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \xi_t \, , \, \Sigma_{X_{22}} - \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \Sigma_{X_{12}} \right).$$

The conditional distribution of $\Gamma_{t,h}^{(i)}$ given ξ_t is hence given by:

$$\Gamma_{t,h}^{(i)} \mid \xi_t \sim N\left(\widetilde{\Lambda_h} \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \xi_t \, , \, \widetilde{\Lambda_h} \left(\Sigma_{X_{22}} - \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \Sigma_{X_{12}} \right) \widetilde{\Lambda_h}' \right). \tag{24}$$

A.4. **Baseline Calibration.** In this subsection, we provide a simple calibration to illustrate the properties of the model. The goal, as already emphasized in the main text, is not to bring the model to the data. Rather, the guiding principle of this calibration, as well, is to keep the model as simple as possible. This calibration is used in Sections 2.2 and 4.3.

The coefficient matrices are

$$F = \begin{bmatrix} \rho_d & 0 \\ 0 & \rho_s \end{bmatrix} = \begin{bmatrix} 0.8 & 0 \\ 0 & 0.8 \end{bmatrix}, \; H' = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix},$$

and the covariance of the measurement equations are

$$R = \mathbb{E}(\eta_t^{(i)} \eta_t'^{(i)}) = \begin{bmatrix} 0.02^2 & 0 & 0 & 0 \\ 0 & 0.02^2 & 0 & 0 \\ 0 & 0 & 0.02^2 & 0 \\ 0 & 0 & 0 & 0.02^2 \end{bmatrix}.$$

These values remain the same for all calibrations. What changes is the covariance matrix of the demand and supply factors, given by

$$Q = \mathbb{E}(v_t v_t') = \begin{bmatrix} \sigma_d^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix}.$$

For the different economies, we set it to

$$Q_{bal} = \begin{bmatrix} 0.005^2 & 0 \\ 0 & 0.005^2 \end{bmatrix}, \; Q_{dem} = \begin{bmatrix} 0.05^2 & 0 \\ 0 & 0.005^2 \end{bmatrix}, \text{and } Q_{sup} = \begin{bmatrix} 0.005^2 & 0 \\ 0 & 0.05^2 \end{bmatrix},$$

where Q_{bal}, Q_{dem}, and Q_{sup} depict the balanced, the demand-dominant, and the supply-dominant economy, respectively. Finally we choose $\gamma = 3$, and $\beta = 0.99$ in the calculation of the term premium.

The fraction of demand shocks spans the interval $\psi = (0, 1)$. It is used for calculating Figure 3. The demand and supply shock variances then equal

$$\sigma_d^2 = \psi \left(\sigma_{d,bal}^2 + \sigma_{s,bal}^2 \right)$$
$$\sigma_s^2 = (1 - \psi) \left(\sigma_{d,bal}^2 + \sigma_{s,bal}^2 \right),$$

where $\sigma_{d,bal}^2 + \sigma_{s,bal}^2$ is the sum of the variances in the balanced model. This way, the total variance in the model remains constant independently of ψ.

APPENDIX B. TERM PREMIUM - DERIVATION

B.1. **Fundamental Asset Pricing Equation.** The structural model outlined here is based on a simplified version of the representative agent models of asset returns developed by Breeden (1979) and Lucas (1978). For the sake of clarity, we assume an economy without frictions, characterized by a singular representative household. We consider a discrete-time model with an infinite horizon so that the representative investor has a utility function of the form:

$$U_t = \mathbb{E}_t \left[\sum_{h=0}^{\infty} \beta^h u(c_{t+h}) \right], \tag{25}$$

where c_t represents the consumption of period t, $u(c_t)$ an increasing, continuously differentiable concave utility function, β the time discount factor and $\mathbb{E}_t()$ the expectation operator conditional on information available at time t.

The utility function is of the constant relative risk aversion class. This preference function is scale-invariant and independent of the initial distribution of endowments.

$$u(c_{t+h}) = \frac{c_{t+h}^{1-\gamma}}{1-\gamma} \qquad \text{(CRRA)},$$

where the parameter γ is positive for risk-averse agents and measures the curvature of the utility function. The elasticity of intertemporal substitution is the inverse of the coefficient of relative risk aversion.

The first-order condition for maximizing the utility function under the resource constraint requires that the price, in real terms, of a one-period zero-coupon bond be:

$$P_{t,1} = \exp(-i_{t,1}) = \mathbb{E}_t \left[\beta \left(\frac{c_{t+1}}{c_t} \right)^{-\gamma} \cdot \exp(-\pi_{t,t+1}) \cdot \underbrace{1}_{=P_{t+1,0}} \right], \tag{26}$$

where $\pi_{t,t+1}$ denotes the inflation rate between t and $t+1$ and $i_{t,1}$ the nominal yield of a zero coupon bond. This finally gives us:

$$\begin{aligned} P_{t,1} &= \beta \mathbb{E}_t \left\{ \exp \left[-\gamma \ln \left(\frac{c_{t+1}}{c_t} \right) \right] \cdot \exp(-\pi_{t,t+1}) \right\} \\ &= \mathbb{E}_t \left\{ \beta \exp \left[-\gamma \Delta c_{t,t+1} - \pi_{t,t+1} \right] \right\} = \mathbb{E}_t (M_{t,t+1}), \end{aligned}$$

where $\Delta c_{t,t+1} = \ln \left(\frac{c_{t+1}}{c_t} \right)$[15] and $M_{t,t+1} = \beta \exp \left[-\gamma \Delta c_{t,t+1} - \pi_{t,t+1} \right]$ is the Representative Agent's Stochastic Discount Factor (SDF, henceforth) in nominal terms.

Knowing the SDF allows us to relate current prices to those of the following period. In particular, if we denote by $P_{t,h}$ the price of a nominal zero-coupon bond with residual maturity h, we obtain:

$$P_{t,h} = \exp(-i_{t,h} \cdot h) = \mathbb{E}_t \left[M_{t,t+1} \cdot P_{t+1,h-1} \right]. \tag{27}$$

This outcome is recognized as the fundamental asset pricing equation. Its validity extends to all bonds, which inherently prevents arbitrage opportunities across maturities.

B.2. **Bond Prices as a Function of State Vector.** In the interest of streamlining our model and aligning with its structure, where the GDP growth rate is a component of the state vector $X_t^{(i)}$, we adopt the GDP growth rate as a proxy for the consumption growth rate. Moreover, in our model, the equation governing the term premium is not affected by $X_t^{(i)}$, rendering individual components irrelevant. As a result, we omit the (i) index for the remaining portion of the derivation. This implies that the SDF can be rewritten as:

$$M_{t,t+1} = \beta \exp \left[-\gamma \Delta y_{t,t+1} - \pi_{t,t+1} \right] = \beta \exp \left[G' X_{t+1} \right], \tag{28}$$

[15] $\Delta c_{t,t+1}$ can also be thought of as the growth rate of consumption in period $t+1$ when $g_{c_{t+1}}$ is small.

where $G = [0,\ 0,\ -\gamma,\ -1,\ 0,\ \cdots,\ 0]$.

Hence, the fundamental pricing equation given by equation (27) for $h = 1$ can be rewritten as:

$$\begin{aligned} P_{t,1} &= \mathbb{E}_t\left[\beta \exp\left(G' X_{t+1}\right)\right] = \mathbb{E}_t\left[\beta \exp\left(G'(B + \Phi X_t + \Sigma \epsilon_t)\right)\right] \\ &= \beta \exp\left(G'B + G'\Phi X_t + \frac{G'\Sigma \mathbb{V}(\epsilon_t)\Sigma' G}{2}\right) = \exp\left(A_1 + B_1 X_t\right), \end{aligned} \tag{29}$$

where $A_1 = \log(\beta) + G'B + \frac{G'\Sigma\mathbb{V}(\epsilon_t)\Sigma' G}{2}$ and $B_1 = \Phi' G$.

Since the nominal yield of maturity h is given by $-1/h \log P_{t,h}$, we get the one-period zero-coupon interest rate:

$$i_{t,1} = \overline{A_1} + \overline{B_1'} X_t, \tag{30}$$

with $\overline{A_1} = -A_1$ and $\overline{B_1} = -B_1$.

Considering equation (27) and assuming $P_{t,h-1} = \exp(A_{h-1} + B'_{h-1} X_t)$, the price of h-period zero-coupon bond can be rewritten as:

$$\begin{aligned} P_{t,h} &= \mathbb{E}_t\left[\beta \exp\left(G' X_{t+1}\right) \cdot \exp(A_{h-1} + B'_{h-1} X_{t+1})\right] \\ &= \mathbb{E}_t\left[\beta \exp\left(A_{h-1} + (G + B_{h-1})' X_{t+1}\right)\right] \\ &= E_t\left[\beta \exp\left(A_{h-1} + (G + B_{h-1})'(B + \Phi X_t + \Sigma \epsilon_t)\right)\right] \\ &= \beta \exp\left[A_{h-1} + (G + B_{h-1})' B + (G + B_{h-1})' \Phi X_t + \frac{(G + B_{h-1})' \Sigma \mathbb{V}(\epsilon_t) \Sigma' (G + B_{h-1})}{2}\right] \\ &= \exp(A_h + B'_h X_t), \end{aligned} \tag{31}$$

where the coefficients are:

$$\begin{cases} A_h &= \log(\beta) + A_{h-1} + (G + B_{h-1})' B + \frac{(G+B_{h-1})'\Sigma\mathbb{V}(\epsilon_t)\Sigma'(G+B_{h-1})}{2} \\ B_h &= \Phi'(G + B_{h-1}). \end{cases}$$

We have therefore shown that $P_{t,h} = \exp(A_h + B_h' X_t)$ for all maturities h. Denoting by $i_{t,h}$ the nominal zero-coupon bond of maturity h, we have:

$$i_{t,h} = -\frac{\log(P_{t,h})}{h} = \overline{A_h} + \overline{B_h'} X_t, \tag{32}$$

where $\overline{A_h} = -\frac{A_h}{h}$ and $\overline{B_h'} = -\frac{B_h}{h}$.

B.3. **Derivation of the Term Premium.** By definition:

$$\text{Term Premium} = i_{t,h} - \frac{1}{h}\mathbb{E}_t(i_{t,1} + i_{t+1,1} + \cdots + i_{t+h-1,1}). \tag{33}$$

Considering equations (30) and (32), we obtain the expression for the term premium for maturity h:

$$\begin{aligned} TP_{t,h} &= \overline{A_h} + \overline{B_h'} X_t - \frac{1}{h}\mathbb{E}_t\left(\overline{A_1} + \overline{B_1'} X_t + \overline{A_1} + \overline{B_1'} X_{t+1} + \cdots + \overline{A_1} + \overline{B_1'} X_{t+h}\right) \\ &= \overline{A_h} + \overline{B_h'} X_t - \overline{A_1} - \frac{1}{h}\overline{B_1'}\mathbb{E}_t\left(X_t + X_{t+1} + \cdots + X_{t+h}\right) \\ &= \overline{A_h} + \overline{B_h'} X_t - A_1 - \frac{1}{h}\overline{B_1'}\Big((h-1)B + (h-2)\Phi B + \cdots + 2\Phi^{h-3}B + \Phi^{h-2}B \\ &\quad + (I + \Phi + \cdots + \Phi^{h-1})X_t\Big). \end{aligned}$$

It is then easy to show that B_h can also be written as:

$$B_h = \Phi'(G + B_{h-1}) = (I + \Phi' + \cdots + \Phi'^{(h-1)})B_1.$$

Hence, as stated above, the term premium for maturity h is independent of X_t:

$$TP_{t,h} = \overline{A_h} - \overline{A_1} - \frac{1}{h}\overline{B_1'}\Big((h-1)B + (h-2)\Phi B + \cdots + 2\Phi^{h-3}B + \Phi^{h-2}B\Big),$$

that we can simplify as :

$$TP_{t,h} = \overline{A_h} - \overline{A_1} - \frac{1}{h}\overline{B_1'}\widetilde{A}_h, \tag{34}$$

where $\widetilde{A}_h = \Phi \widetilde{A}_{h-1} + (h-1)B$. Therefore, our model indicates that the term premium varies with respect to h, but remains constant over time.

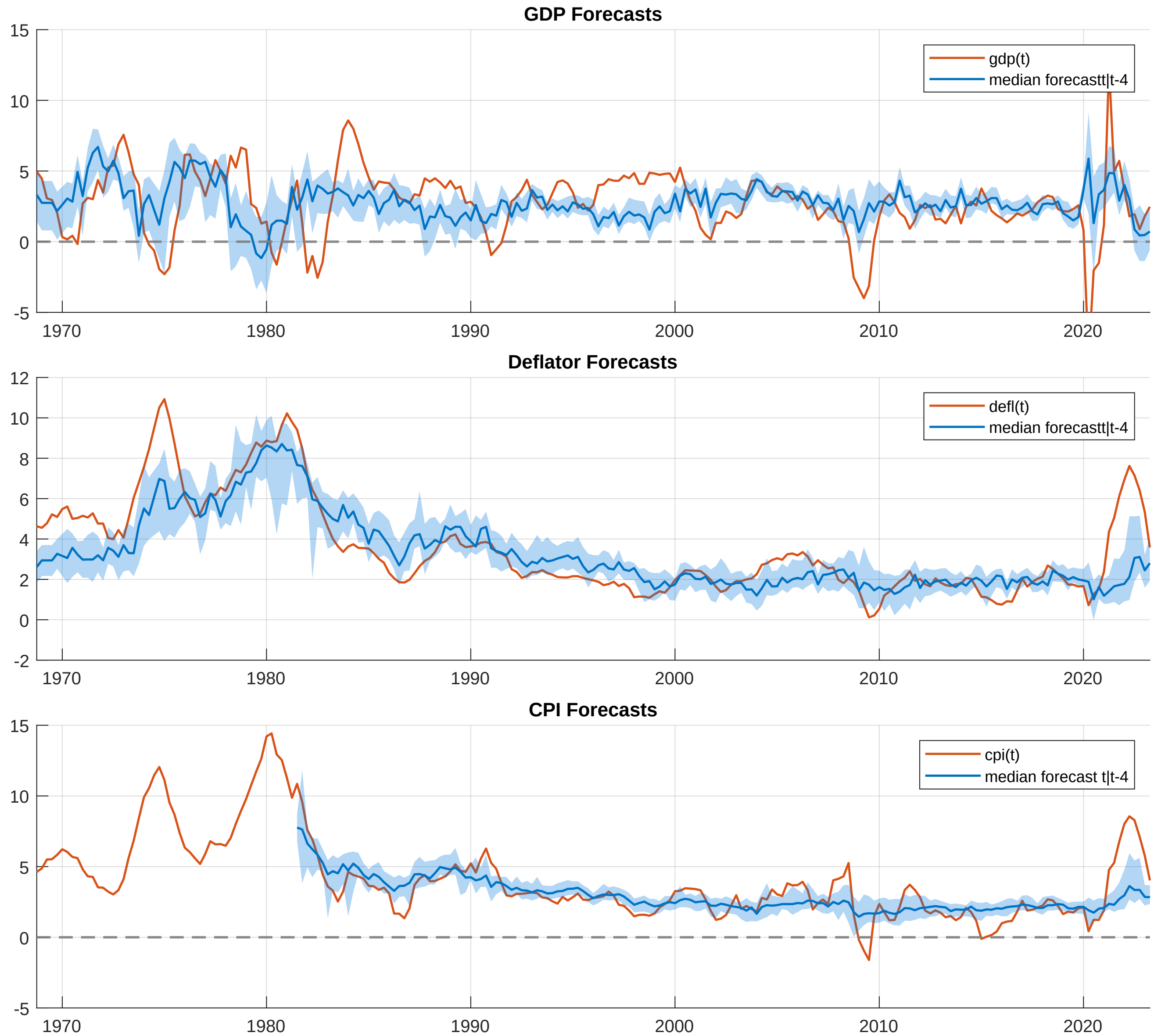
Appendix C. Survey of Professional Forecasters

The Survey of Professional Forecasters (SPF) is conducted quarterly, with a deadline for forecasters in the middle of February, May, August, and November. This deadline for the survey precedes the release of the official GDP and GDP deflator data, allowing a forecast for the current quarter to be made before the official data is released. GDP and the GDP deflator are forecast in levels. They are seasonally adjusted, with different base years, which is irrelevant, since we convert these variables to year-on-year growth rates.

Prior to 1992Q1, forecasters targeted GNP and the GNP deflator. After that date, they switched to fixed-weight GDP data, and later to chain-weighted GDP data. For analytical consistency, and because the series are very similar, no distinction is made between the slightly different variables and they are treated as equivalent.

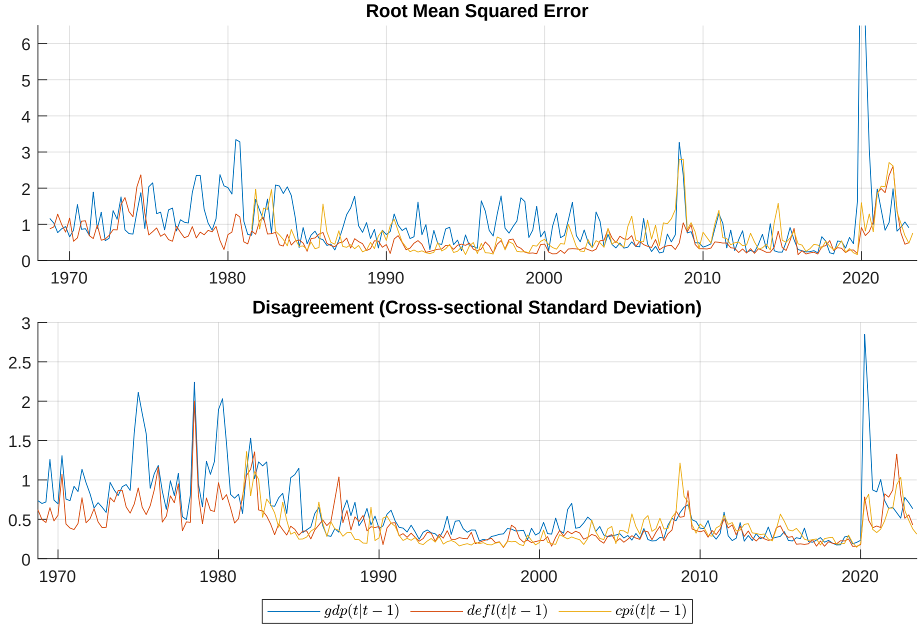
Official CPI data is monthly. The quarterly CPI forecasts in the SPF aim to predict the average of the three monthly CPI releases published each quarter. These releases typically occur around the middle of each month. In most quarters (though not always), the CPI release precedes the SPF deadline. In fact, forecasters typically have data from two of the three monthly CPI releases for the current quarter when they submit their forecasts. Forecasters provide quarter-on-quarter growth rates, which are seasonally adjusted annual rates. We then convert these forecasts to year-on-year growth rates (i.e., in the case of CPI forecasts, year-on-year inflation rates). The median and the 10th and 90th percentiles of the forecasts are displayed for each date in Figure 9.

Figure 9. Median, 1st and 9th Decile of 4-Quarter-Ahead Forecasts



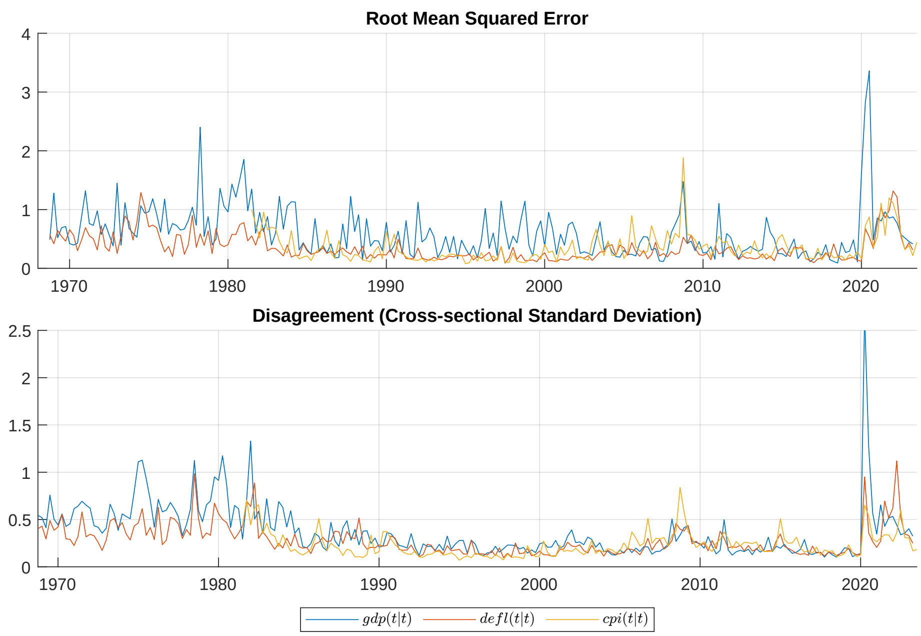
Notes: This figure shows scatter plots of individual 4-quarter-ahead forecasts for year-on-year growth rates of GDP, the GDP deflator, and CPI. The red line indicates the most recent vintage of official data for the three series. Forecasts are displayed on the date which is targeted by the forecast, not the date when the forecast was made.

Figure 10. Accuracy and Disagreement for Horizon $h = 1$



Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x = \{gdp, defl, cpi\}$. The bottom figure displays the disagreement between forecasts, meaning the cross-sectional standard deviation between point forecasts.

Figure 11. Accuracy and Disagreement for Horizon $h = 0$



Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x = \{gdp, defl, cpi\}$. The bottom figure displays the disagreement between forecasts, meaning the cross-sectional standard deviation between point forecasts.

APPENDIX D. FURTHER REGRESSION RESULTS

In this section, we present further regression results that include the Slope Index and its relation with the measures presented in Section 3.

D.1. **Rolling Correlation.** In subsection 4.1, we display that there is a significant co-movement between the Slope Index and the rolling correlation between aggregate GDP and inflation. In this part of the appendix, we show that the results do not depend on a specific time period. it is positive and significant for the period before 1985, and also highly significant after 2008. Table 8 corresponds to Table 3 in the main text, with the regressors here being the smoothed version of the Slope Index (smoothed with a 4 quarter moving average filter).

Next, we want to make sure that the results are valid for different time periods independently. For this, we repeat the same regressions for different subsamples. We also show the same regressions, using the smoothed Slope Indices. While these results are less significant than for the original Slope Indices, they are qualitatively similar.

Table 8. Rolling Correlation Regressions (MA-filtered Slope Indices)

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(Ma4, defl)$	0.102*			0.146***		
	(0.056)			(0.044)		
$IFS(Ma4, cpi)$		−0.049			−0.094	
		(0.064)			(0.058)	
$IFS(Ma4, all)$			−0.048			−0.081
			(0.053)			(0.050)
Observations	210	159	159	200	149	149
R^2	0.059	0.010	0.015	0.146	0.051	0.053
F-test (robust)	3.348*	0.571	0.800	11.071***	2.642	2.666
	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(Ma4, defl)$	0.151***			0.164***		
	(0.048)			(0.037)		
$IFS(Ma4, cpi)$		0.041			−0.034	
		(0.059)			(0.053)	
$IFS(Ma4, all)$			0.036			−0.019
			(0.052)			(0.048)
Observations	210	159	159	200	149	149
R^2	0.150	0.009	0.011	0.222	0.008	0.004
F-test (robust)	9.888***	0.482	0.487	19.635***	0.413	0.152

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top Regressions: The GDP deflator is used as the inflation measure. Bottom Regressions: CPI is used as the measure for inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9. Rolling Correlation Regressions (Different Time Periods)

	rollCorr gdp - defl (10q)			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	0.065*	0.048	−0.030	0.160***
	(0.033)	(0.050)	(0.037)	(0.037)
Observations	205	64	89	53
R^2	0.046	0.023	0.009	0.203
F-test (robust)	3.831*	0.932	0.645	19.150***

	rollCorr gdp - cpi (10q)			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	0.085***	0.090**	−0.005	0.195***
	(0.029)	(0.041)	(0.037)	(0.037)
Observations	205	64	89	53
R^2	0.094	0.096	0.000	0.240
F-test (robust)	8.710***	4.950**	0.019	27.829***

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure for rolling correlation between aggregate output and GDP. Top regression: GDP deflator used as inflation measure. Bottom regressions: CPI is used as a measure of inflation. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

D.2. **Mean Forecast Errors.** In the following, we do the same regressions as in the main text, but using the unchanged Slope Indices as regressors.

Table 10. MFE Regressions ($h = 4$)

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(defl)$	0.400			0.707		
	(0.289)			(0.568)		
$IFS(cpi)$		0.160			0.435	
		(0.242)			(0.741)	
$IFS(all)$			0.177			0.423
			(0.183)			(0.755)
$rollCov(gdp, defl)$				0.190	0.219	0.207
				(0.192)	(0.189)	(0.149)
Observations	209	168	168	207	168	168
R^2	0.030	0.006	0.011	0.135	0.039	0.043
F-test (robust)	1.909	0.440	0.937	1.464	1.766	1.758
	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(defl)$	0.187			0.258		
	(0.220)			(0.755)		
$IFS(cpi)$		0.270			0.312	
		(0.267)			(0.723)	
$IFS(all)$			0.213			0.289
			(0.211)			(0.739)
$rollCov(gdp, defl)$				0.192	0.313	0.236
				(0.210)	(0.227)	(0.187)
Observations	164	164	164	164	164	164
R^2	0.004	0.012	0.011	0.013	0.024	0.021
F-test (robust)	0.719	1.018	1.019	0.489	1.412	1.047

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

In the main text, we only display the results for $h = 4$ with the goal of being concise. Here, we display the same results for $h = 1$ and $h = 0$, meaning for 1-quarter-ahead forecast errors and for nowcasts.[16]

Table 11. MFE Regressions ($h = 1$)

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	0.099			−0.044		
	(0.074)			(0.078)		
$IFS(Ma4, cpi)$		0.185*			−0.060	
		(0.100)			(0.100)	
$IFS(Ma4, all)$			0.170*			−0.065
			(0.091)			(0.099)
$rollCov(gdp, defl)$				0.141	0.177*	0.166*
				(0.100)	(0.096)	(0.089)
Observations	218	168	168	210	168	168
R^2	0.020	0.059	0.070	0.029	0.069	0.082
F-test (robust)	1.789	3.377*	3.477*	1.002	2.069	2.196
	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.322			−0.075		
	(0.227)			(0.115)		
$IFS(Ma4, cpi)$		0.280**			−0.053	
		(0.142)			(0.108)	
$IFS(Ma4, all)$			0.243*			−0.062
			(0.133)			(0.106)
$rollCov(gdp, defl)$				0.322	0.273*	0.240*
				(0.228)	(0.145)	(0.134)
Observations	167	167	167	167	167	167
R^2	0.032	0.047	0.049	0.037	0.050	0.053
F-test (robust)	2.020	3.900**	3.371*	1.705	2.700*	2.613*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[16] We define nowcasts to be all forecasts with horizon $h = 0$.

Table 12. MFE Regressions ($h = 0$)

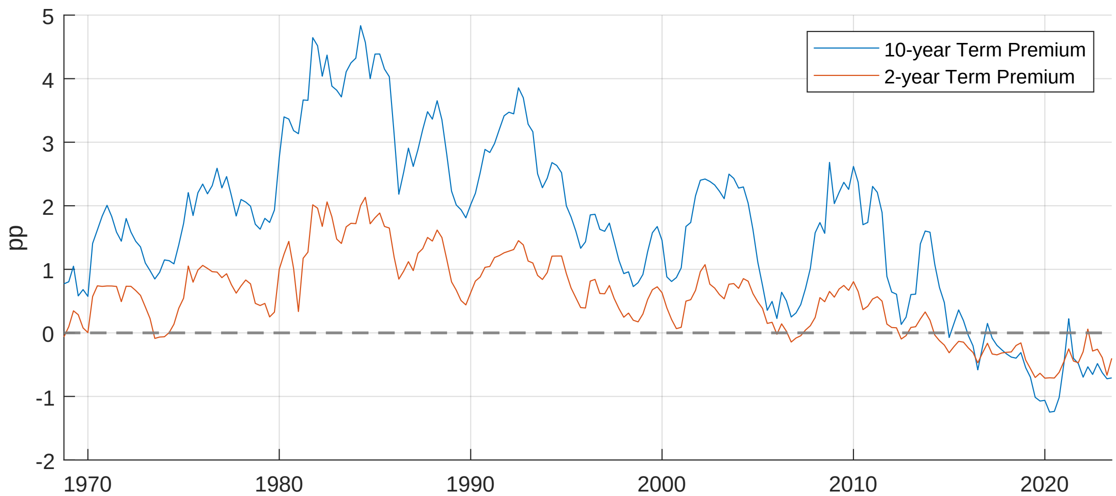
	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	−0.001			−0.016		
	(0.013)			(0.013)		
$IFS(Ma4, cpi)$		0.026			−0.013	
		(0.017)			(0.018)	
$IFS(Ma4, all)$			0.026*			−0.014
			(0.015)			(0.018)
$rollCov(gdp, defl)$				0.009	0.024	0.026*
				(0.017)	(0.016)	(0.014)
Observations	219	168	168	210	168	168
R^2	0.000	0.025	0.037	0.014	0.035	0.048
F-test (robust)	0.002	2.338	3.288*	0.748	1.459	1.985

	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.040			−0.006		
	(0.029)			(0.016)		
$IFS(Ma4, cpi)$		0.035*			−0.003	
		(0.020)			(0.015)	
$IFS(Ma4, all)$			0.037**			−0.004
			(0.018)			(0.014)
$rollCov(gdp, defl)$				0.040	0.035*	0.036**
				(0.030)	(0.020)	(0.018)
Observations	168	168	168	168	168	168
R^2	0.014	0.021	0.031	0.015	0.021	0.031
F-test (robust)	1.867	3.140*	4.176**	1.180	1.768	2.420*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

D.3. **Term Premiums.** For term premiums, we use the data from Adrian, Crump, and Moench (2013). They derive term premiums from a model based on Treasury yields for maturities from one to ten years. We choose to work with their set of term premiums because of the large sample length, which goes from 1961 to today. Figure 12 shows the term premium data that is used in the regressions in the main text and this appendix.

Figure 12. Term Premium over Time



Notes: This figure denotes the term premium data, as it is calculated by Adrian, Crump, and Moench (2013). It is quarterly, and continuously updated by the Federal Reserve Bank of New York.

We present additional regression results on term premiums. In the main text, we presented the results for 10-year term premiums. In the following, we display the same regressions for 2-year term premiums.

The results between the 2-year and the 10-year term premium regressions are very similar. While the significance of the original slope Index is slightly higher for the 10-year term premiums, the 2-year term premiums have a slightly stronger relationship with the smoothed Slope Indices. However, the differences are very small.

Table 13. Term Premium Regressions (2Y TP)

	ACM Term Premia 2 years					
$IFS(defl)$	−0.110			−0.017*		
	(0.068)			(0.009)		
$IFS(cpi)$		−0.059			0.004	
		(0.091)			(0.013)	
$IFS(all)$			−0.106			−0.011
			(0.077)			(0.010)
Observations	214	168	168	210	167	167
R^2	0.027	0.006	0.027	0.013	0.001	0.007
F-test (robust)	2.638	0.418	1.929	3.722*	0.104	1.169
	ACM Term Premia 2 years					
$IFS(Ma4, defl)$	−0.186			−0.094***		
	(0.127)			(0.032)		
$IFS(Ma4, cpi)$		−0.065			0.031	
		(0.187)			(0.044)	
$IFS(Ma4, all)$			−0.163			−0.055
			(0.165)			(0.035)
Observations	220	169	169	219	168	168
R^2	0.039	0.003	0.028	0.019	0.002	0.010
F-test (robust)	2.132	0.120	0.979	8.403***	0.480	2.492

We regress term premiums on the different measures of the Slope Index. The term premiums data is from Adrian, Crump, and Moench (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.