Forecaster Inattention: Measurement, Determinants and Policy Implications

Zidong An, American University
Xuguang (Simon) Sheng, American University
Jonathan Wallen, Stanford University

Abstract: Using individual forecasts from the U.S. Survey of Professional Forecasters during 1968-2014 and Consensus Economics for G7 countries during 1990-2014, we provide direct econometric estimates of time varying inattention, defined as the common component in forecasters' inattentiveness when predicting many economic variables. Based on this measure, we find that professional forecasters update their information sets every four months on average, and they are less inattentive in periods of recession and high economic uncertainty. Through the time varying structural vector autoregression model, we show that the same sized monetary shock has more persistent real effects when the degree of inattention is high. Our findings contribute to the literature on the transmission of monetary policy shocks and suggest inattention as an additional explanation why policy might become less effective during recessions.

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1. Introduction

The current resurgence of interest in the expectations formation process builds upon a long tradition of research on imperfect information. These informational limitations play an important role in explaining why economic agents may be inattentive to news and disagree. Both of these characteristics are prominent within the literature: information limitations were modeled by Phelps (1968) and Lucas (1972); differences in agent beliefs herald back to as early as Keynes (1936) and Pigou (1937). However, most modern macroeconomic models assume full-information and rational expectations. In response, a recent reemergence of interest in information frictions and limitations have yielded two prominent models: the sticky information model of Mankiw and Reis (2002) and Reis (2006) and the noisy information model of Sims (2003) and Woodford (2003). The sticky information model explains rational inattentiveness in terms of limited resources and the cost of updating information sets. In contrast, the noisy information model emphasizes the limited ability of economic agents to process new information from noisy signals. Regardless of their differences, both models agree on the existence and importance of information rigidities in how economic agents form expectations, as evidenced by the comprehensive surveys in Mankiw and Reis (2010) and Sims (2010).

Despite this strong theoretical coverage of imperfect information models within the literature, empirical studies vary substantially. For example, Andrade and Le Bihan (2013) find an information rigidity of 4 months using ECB Survey of Professional Forecasters (SPF) data. Coibion and Gorodnichenko (2013) identify an information rigidity of 6 to 7 months using U.S. SPF data. Mankiw, Reis, and Wolfers (2004) find an information rigidity of about 10 months from the Livingston survey. The variation in empirical findings reflects the challenges and differing methodologies for measuring information rigidity. In response, we propose a micro-data based measure of information rigidity defined in terms of observable proxies of information set updates: forecast revision and size.

Using this measure, we identify a set of stylized facts that characterize information rigidity. We use data from *Consensus Forecasts* on professional forecasts of inflation and GDP, covering G7 countries from 1990-2012. The major advantages of this dataset are the multi-economy and micro-data structure of individual forecasts at a monthly frequency. Through this dataset, we find that professional forecasters have an information rigidity of two to three months.

We may interpret this finding through the sticky information model to mean that the average duration between information update is two to three months. However, the degree of inattentiveness is not constant. Professional forecasters are most inattentive at very long or very short horizons, but pay attention at middle horizons (15- to 6-month ahead). Similarly, we observe different levels of information rigidity for countries, reflecting their different economic environments and levels of policy transparency. Finally, information rigidities vary over time in relation to the business cycle.

We explore potential determinants of information rigidities: the target variable, business cycle, market levels and volatility, central bank transparency, and economic policy uncertainty. After controlling for characteristics of the target variable, we find commonalities in the behavior of information rigidities. Inattentiveness rises during stable, expansionary periods and fall during uncertain, recession periods. Inattentiveness of professional forecasters declines with market volatility, but rises with the market level. The inverse relationship between central bank transparency and information rigidity highlights how clear communication of monetary policy may decrease inattentiveness. These findings about the determinants of information rigidity highlight how the economic context surrounding professional forecasters directly impacts their ability to obtain and process new information.

Our paper is closely related to the literature that studies imperfect information through survey data, including Carroll (2003), Mankiw et al. (2004), and Coibion and Gorodnichenko (2012, 2013). These papers use the aggregate survey forecasts together with a set of auxiliary assumptions about the economy to estimate the degree of information rigidity. By contrast, we exploit the sequences of individual forecasts for a fixed event to construct a direct, arguably more reliable, micro-data estimate of the frequency of information updating. Recent contributions that have also explored the expectations formation process based on individual survey data include Andrade and Le Bihan (2013), Dräger and Lamla (2012, 2013), and Dovern et al. (2015). Our approach differs from those four papers in that we measure the degree of information rigidity by (i) using monthly, rather than quarterly or semi-annual, survey data; (ii) capturing the two elements of forecast revisions (size and frequency), rather than focusing on the frequency element only; and (iii) separating meaningful revisions from superfluously small revisions possibly due to strategic behavior.

Our paper is also closely linked to the literature that examines the impact of monetary policy on expectations among professional forecasters. Recent contributions include Capistrán and Ramos-Francia (2010), Crowe (2010), Cecchetti and Hakkio (2010), Beechey et al. (2011), Dovern et al. (2012), Ehrmann et al. (2012) and Hubert (2014). All of these papers explore the role of central banks in professional forecaster disagreement. Our paper complements these studies by providing new evidence on how enhanced central bank transparency decreases forecaster inattentiveness. This finding illuminates an additional channel through which monetary policies affect the expectations formation process.

The analysis of the dynamics of information rigidity and its determinants contributes to the recent literature that explores the effect of uncertainty shocks on economic activity (Bloom, 2009; Jurado et al., 2014). Over forecasting horizons, we find evidence of a wait-and-see effect. At long horizons (about 2 years ahead), information rigidities tend to be higher, reflecting how professional forecasters more heavily weight priors and wait to see more decisive economic news. For intermediate horizons (about 1 year ahead), professional forecasters pay close attention and actively revise their forecasts as more high quality information becomes available. Over time, we find that professional forecasters are less inattentive during uncertain periods when using stock market volatility, economic policy uncertainty, and forecast disagreement as indicators of uncertainty. These findings uphold the sticky information model of Reis (2006) that more volatile shocks lead to more frequent updating since inattention is more costly in a world that is rapidly changing. These findings are also consistent with the state-dependent models of information updating as in Gorodnichenko (2008) and Woodford (2009).

The paper is organized as follows. Section 2 describes information rigidity through a comprehensive measure and characteristics. Section 3 identifies key determinants of information rigidities. Section 4 explores if inattention alters the real effect of monetary policy. Section 5 concludes.

2. Measuring Information Rigidity and Some Stylized Facts

2.1 A New Measure of Information Rigidity

Within the literature, we have two prominent measures of information rigidity with exceptionally different approaches. Based on the aggregate survey forecasts, Coibion and Gorodnichenko (2013, CG hereafter) suggest regressing mean forecast error on mean forecast revision. The coefficient on mean forecast revisions, β, maps one to one into the underlying degree of information rigidity. In the sticky information model, $\beta = \frac{\lambda}{1-\lambda}$, where λ is the proportion of forecasters who do not update information in each period and interpreted as information rigidity. The strength of the CG measure lies in its need for the mean forecast only and structural interpretation. However, the measure provides an aggregated information rigidity over the entire time span, instead of showing how information rigidity may change over time.

Alternatively, the Andrade and Le Bihan's (2013, AL hereafter) measure allows for variation in information rigidity over time. AL measures information rigidity non-parametrically by counting the proportion of forecasters who make any revision within a given period. By looking at individual level data and considering the binary choice between revising and not revising a forecast, AL focuses on the cost for professional forecasters in updating their information sets, a feature of the sticky information model. Complementing the measure's simplicity is its insensitivity to outliers and no need for actual values. However, the limitation of this simple approach is the focus on the frequency component of forecast revisions only, excluding revision size. Large, sharp revisions at economically meaningful turning points are treated equally to that of the smallest revisions.

When we observe a forecast revision, the forecaster may have updated his information set or behaved strategically. Professional forecasters are motivated to make small revisions because of "peer pressure" and pressure from clients. Their strategic behavior was modelled by Ehrbeck and Waldman (1996), in which forecasters are incentivized to make small, superfluous revisions in an environment of noisy signals so that clients perceive their forecasts as new. At very long horizons, where news tends to be noisier and more costly to acquire, Lahiri and Sheng (2008) find that forecasters make unnecessary revisions. Clements (1997) provides additional evidence of forecasters making random adjustments in the absence of news. These superfluous revisions do not accurately reflect updates to the information sets of professional forecasters. Thus, an appropriate measure of inattentiveness needs to distinguish between information-driven revisions and strategic revisions.

To capture both features of forecast revisions, frequency and size, we propose a new measure of information rigidity. Let F_{ith} be the forecast made by individual i for the target year t and at h-period ahead, and forecast revision $R_{ith} = F_{ith} - F_{it,h+1}$. We define an indicator function,

$$I_{ith} = \begin{cases} 1, if\ |R_{ith}| \leq \tau \\ 0, \quad otherwise \end{cases} \tag{1}$$

Using this indicator, our measure of information rigidity, IR_{th}, can be expressed as

$$IR_{th} = \frac{1}{N} \sum_{i=1}^{N} I_{ith}. \tag{2}$$

By controlling for the horizon effect, we estimate the degree of information rigidity over time for each country and each variable. Our measure of information rigidity incorporates both the frequency and size of revisions through a flexible threshold. When $\tau = 0$, our measure is reduced to the non-parametric measure of inattentiveness used in Andrade and Le Bihan (2013), Dräger and Lamla (2012, 2013), and Dovern et al. (2015). In line with this literature, we interpret no forecast revision as no updating of information set. However, it is possible that a forecaster updates information set and nevertheless keeps expectation constant. We cannot verify this possibility. This is an inherent limitation to measuring information rigidity because the closest proxy to information updates is forecast revisions. When $\tau > 0$, the proposed measure distinguishes between information updates and strategic behavior because strategic forecast revisions tend to be small and fall under the threshold. The specification of the threshold is a feature that provides flexibility of application to a variety of target variables and research questions.

2.2 Empirical Estimates of Information Rigidity

To estimate information rigidities, we use professional forecasts of GDP and inflation from *Consensus Forecasts*, published by Consensus Economics Inc. We focus on professional forecast data to study information rigidities due to a variety of strengths. Professional forecasters have access to a wide range of macroeconomic news and data, and they have a comparative advantage in allocating resources to process this news, relative to other economic agents. Furthermore, Carroll (2003) describes how the expectations of professional forecasts impact those of households. More particular to our data, *Consensus Forecasts* are not anonymous, providing strong incentives for forecasters to be accurate and minimally inattentive. Due to these characteristics, we expect information rigidities to be lowest in professional forecasters. Consequently, our findings represent conservative estimates of information rigidities in the formation of expectations for the broad economy. The *Consensus Forecasts* dataset is extraordinarily rich in its coverage: monthly forecasts, multiple countries, 23 target years (1990-2012), horizons of 24- to 1-month ahead, and a large number of forecasters (about 30) per country.[1] This fixed-event structure of the forecasts enables us to assess how forecasts develop not only over time, but also over various forecasting horizons. The dataset covers forecasts made for seven major, industrialized countries: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States (the G7). The coverage of many countries offers a unique opportunity to compare forecasting characteristics across countries and protects our general findings from any country-specific shocks that could dominate the results. Finally, the detail of the micro-data yields insight into information rigidities on the individual level.[2]

Most empirical studies find information rigidity ranging from 4 months to 12 months. These contrasting results reflect the challenges in measuring information rigidity: (i) low survey frequencies and (ii) capturing both elements of forecast revisions (size and frequency).

First of all, most surveys of professional forecasters are conducted at low frequencies, such as quarterly or semi-annually. However, forecasters may update their information sets at much more regular intervals. As a result, professional forecasters have good reason to be more attentive than quarterly or semi-annual data would suggest. However, the frequency of the survey forms a lower bound on the measure of inattentiveness. We show the lower bound effect in Figure 1 by subsampling our monthly dataset to quarterly and semi-annual frequencies. On average, the duration between forecast revisions monotonically increases as the survey frequency decreases. The difference is economically meaningful: the semi-annual frequencies yield information rigidities about five months longer than that of the monthly frequencies.

[1] To illustrate, in January of year 1990, a forecaster will provide GDP and inflation forecasts for the current (12 months ahead) and next year (24 months ahead). Similarly, in February, the same individual will make forecasts for the current (11 months ahead) and next year (23 months ahead).

[2] Despite the richness, using this dataset presents several challenges, especially forecaster name changes, mergers and acquisitions. We developed our dataset by tracking name changes, mergers and acquisitions of over 300 professional forecasters from 1990 to 2012, extending the earlier work by Dovern et al. (2012) that ends in 2006.

Consequently, empirical studies of information rigidities based on quarterly and semi-annual data may overestimate the inattentiveness of professional forecasters.

The size component of forecast revisions provides insight to the motivation behind the forecast revision. We illustrate the variation in forecast revision size within Table 1. Although professional forecasters make no revision approximately 53-55% of periods, the other revisions vary from 0.1% to as much as above 0.5%. Of note is that revisions of inflation forecasts are not highly correlated with revisions of GDP forecasts. Conditional on a forecaster revising her GDP forecast, she only revises her inflation forecast 60% of the time. The finding that forecast revisions are not independent across macroeconomic variables is consistent with Andrade and Le Bihan's (2013).

Applying our measure, we specifically define the threshold as 5% of the average magnitude of the macroeconomic variable over the past five years. Since our dataset provides forecasts rounded to the first decimal point, we choose 5% of the historical level, which yields a threshold comparable to that of a 0.1% forecast revision on average. This threshold naturally fits the distribution of forecast revisions within our dataset as shown by Table 1. We use the five-year historical average rather than the previous year to avoid spurious jumps in the threshold.[3]

At this threshold, we find the information rigidity of professional forecasters to be on average two to three months. Our finding of two to three months of information rigidity is comparable to those of other measures. The Andrade and Le Bihan's (2013) measure yields an average of about two to three months of inattentiveness as well (Table 2). As expected, the estimates by AL are persistently smaller than that of our measure across all countries, which is due to our measure including a time-varying threshold. Alternatively, the Coibion and Gorodnichenko's (2013) measure indicates the level of information rigidity to be two to three months for inflation and two to four months for GDP. The differences between CG and our measure reflect varying methodologies: the CG measure is based on parametric regression and aggregate survey data, while our measure is non-parametric in nature and utilizes individual survey data.

[3] For robustness, we also consider fixed thresholds from the set {0, 0.1%, 0.2% and 0.3%}, and the core regression results described in Section 3 are qualitatively similar.

Empirically, special surveys conducted by the U.S. and ECB SPF directly corroborate our findings of information rigidities for professional forecasters. In a November 2009 special survey of the U.S. SPF, question 11 asks, "How often do you update your forecast?" About 95% of responding professional forecasters claim to update their forecasts at least quarterly, see Stark (2013). Similarly, in a special survey of the ECB SPF in the autumn of 2008, question 1b asks, "If it is calendar driven, how often do you update your forecasts?" About 90% of professional forecasters responded that they update at least quarterly, see Meyler and Rubene (2009). Of note is that these surveys followed the financial crisis, a period when macroeconomic uncertainty was high and information rigidities were low. Consequently, a post-crisis information rigidity of less than or equal to one quarter according to the special surveys corresponds well with our finding of an average two to three months of information rigidity from 1990 to 2012.

2.3 Characteristics of Information Rigidity

In terms of the sticky information model, this finding implies professional forecasters on average update information sets every two to three months. Beyond this aggregation, we present three characteristics about information rigidity observed within our dataset in relation to forecasting horizon, country, and time. While some of these findings have been documented in recent studies of expectation formation, other findings, such as the dynamics of information rigidity over forecasting horizons and over time, are not well articulated in the macroeconomics literature.

First, information rigidities vary over forecasting horizons. The *Consensus Forecasts* are for fixed events, rather than fixed horizons, giving us the opportunity to study how information rigidities evolve over forecasting horizons. In contrast, much of the literature analyzes fixed horizons, e.g. 1-year-ahead forecasts, as reported in U.S. SPF, Livingston Survey, and Michigan Survey of Consumers. Coibion and Gorodnichenko (2013) and Dovern et al. (2015) are two notable exceptions. They studied the evolution of information rigidity over horizon at a quarterly frequency and found that information rigidity tends to increase with forecast horizon. However, at the monthly frequency, Figure 2 clearly indicates a U-shaped trend for information rigidity over horizon for both inflation and GDP. At very long horizons, professional forecasters receive noisier signals and prefer a wait-and-see approach by sticking to priors. As long as there is no substantial evidence that would dramatically surprise them, forecasters tend not to revise their forecasts at long horizons. At the medium term, professional forecasters are the least inattentive and make the most frequent revisions. Finally, in the near term forecasters are more inattentive because they have already observed the majority of the news for the year to be forecasted. Since they predict the current-year inflation and output growth, when nearing the end of a year, even a big shock can only have a limited effect.

Second, information rigidities vary across countries, cf. Table 2. For inflation forecasts, we find a high information rigidity of 3.28 months (Canada) and a low of 2.56 months (Italy). For GDP forecasts, we observe a high information rigidity of 3.1 months (UK) and a low of 2.29 months (Japan). The differences in mean information rigidity among countries may reflect country specific phenomenon. For instance, Japan suffered from a series of economic recessions over the sample period and the UK experienced high and volatile inflation in the early 1990's. Comparable cross-country differences have also been documented by Dovern et al. (2015) for emerging and developed economies. Of note is the closeness of information rigidities for France and Germany. This similarity implies that there may be regional commonalities underlying information rigidities within the Eurozone. The geographical similarity makes intuitive sense due to the synchronization of Eurozone economic data releases and news. Complementing these findings, Loungani, Stekler, and Tamirisa (2013) find significant cross-country relations in GDP growth forecasts, such as news in China impacting India and Japan.

Third, information rigidities vary over time. To extract this time variation from the fixed-event forecast structure, we perform a seasonal adjustment by X12.[4] These time-varying information rigidities are well illustrated in Figure 3. Periods of low and high inattentiveness differ depending on the idiosyncratic economic conditions of each country. For example, information rigidities declined sharply for Germany during the reunification of West and East Germany in the fall of 1990. Similarly, after the terrorist attacks of 9/11, inattentiveness virtually disappeared in the U.S. In all countries, information rigidities tend to decline during their respective recession periods. In particular, inattentiveness declined in all countries during the Great Recession, reflecting its global impact. These findings suggest the state dependency in information rigidities, which is explored in detail in the following section.

[4] As an alternative, we removed the seasonality by regressing information rigidity on horizon dummies. These two approaches yield highly correlated seasonally adjusted series (correlation of 0.94 on average).

3. Determinants of Information Rigidity over Time

3.1. Hypothesis Development

Earlier, we observed that the inattentiveness of professional forecasters varies over time, after controlling for horizon effects. In this section, we explore the potential determinants of information rigidity.

Professional forecasters tend to have the smallest of information rigidities in crises and periods of volatile economic condition. This effect may be captured through the business cycle. As suggested by Gorodnichenko (2008) who covers the theory of state dependency in terms of information acquisition, we consider that information rigidity may rise and fall inversely to the business cycle. We measure this effect through a recession dummy for each country of the G7 with data from the Economic Cycle Research Institute. Since recession periods are more uncertain and less stable, we expect professional forecasters to have lower information rigidities.

Similarly, the macroeconomic news received by professional forecasters may be reflected in the financial markets. Consequently, we measure the volatilities of major market indices for each country to identify economic news reflected in market price changes.[5] The use of financial market volatility as a proxy for uncertainty has been recently advocated by Bloom (2009). In periods of high market volatility, we expect professional forecasters, especially those associated with financial institutions, to be less inattentive. Market impacting news related to the target variable may impact both level and volatility. The level of market indices may reflect information on expectations of future economic conditions not contained within market volatility. In periods of high market levels, we expect professional forecasters to be more complacent and inattentive.

We expect greater uncertainty to decrease information rigidities in professional forecasters. This uncertainty may materialize in financial markets, economic sentiment, and forecast disagreement. Similar to the expected negative relation between financial market

[5] We compute a 30 day standard deviation in the price levels of the following market index and country pairs: S&P/TSX Composite index for Canada, CAC 40 index for France, the DAX index for Germany, the FTSEMIB Index for Italy, the Nikkei index for Japan, the FTSE 100 index for the UK, and the S&P 500 for the U.S. Due to the limited time series coverage of the FTSEMIB Index for Italy (goes back to 1998), we use one year yields on Italian sovereign debt to compute a longer time series of market level and volatility.

volatility and inattentiveness, broad economic uncertainty may motivate professional forecasters to pay more attention to news. To measure economy-wide uncertainty, we use the news-based economic policy uncertainty (EPU) by Baker et al. (2013).[6] The index is measured as the frequency of news media references to economic policy uncertainty. Complementing these market and economy based measures of uncertainty, forecast disagreement captures perceived uncertainty by forecasters; see Lahiri and Sheng (2010). To avoid a potentially mechanical relationship between forecast revisions and disagreement, we lag forecast disagreement by one period. When forecasters perceive greater uncertainty, we anticipate lower inattentiveness.

Since monetary policy directly affects inflation and GDP growth, we consider the impact of policy on information rigidity. We focus on metrics that assess the communication of monetary policy. We expect more frequent and credible communication by central banks to decrease information rigidities in professional forecasters. More credible announcements and information from central banks make information more dependable. Increased quality of information would decrease information rigidities in terms of the noisy information model. Similarly, increased availability of information decreases the cost to updating information sets, which explains lower information rigidities in terms of the sticky information model. We use the measure by Dincer and Eichengreen (2014), which covers central bank policy objectives, policy decisions, economic analyses, and the decision making process. From these criteria, the measure yields a quantitative score, ranging from 0 to 15 (least to most transparent).[7]

Besides the core variables, we also need to control for the stickiness of inattentiveness and characteristics of the macroeconomic variable of interest. Notice how, despite the variability of inattentiveness, it tends to persist over time at different levels for various countries of the G7. Overall, professional forecasters have an inattentiveness level of 0.6 to 0.8, meaning that they require 2 to 3 months on average to fully incorporate new information. We account for the stickiness of information rigidity across countries by including country fixed effects and lagged values of information rigidity.

[6] We use the news based EPU data series, instead of the aggregate series, because the news based series is unique for each of the G7 countries. Furthermore, Baker et al. (2013) stopped using forecast disagreement as a component of the EPU index.

[7] Despite the strong theoretical connection, we note practical limitations of this measure: incomplete sample coverage, 1998-2010. To not lose a large portion of our sample, we extend back the 1998 central bank transparency score to 1990 and forward the 2010 score to 2012. This is consistent with the methodology of the literature, such as Ehrmann et al. (2012).

When analyzing the macroeconomic variables of interest, inflation and GDP, we expect their volatility to impact information rigidity. The volatility of the macroeconomic series directly impacts the frequency at which professional forecasters receive news related to the variable, cf. Dräger and Lamla (2013). Following Capistrán and Timmermann (2009), we estimate GARCH(1,1) models for inflation and GDP to extract conditional volatilities of the respective variables.[8] Since higher conditional volatilities imply a more difficult variable to forecast, we control for this characteristics of macroeconomic variable of interest.

3.2 Empirical Results

Since our dependent variable, IR, is a fractional variable, we use the quasi-maximum likelihood method in Papke and Wooldridge (1996) to estimate the nonlinear model:

$$E(IR_{jt} \mid X_{jt}) =$$

$$\mathrm{G}(\gamma_j + \alpha_1 IR_{j,t-1} + \alpha_2 \sigma_{jt} + \beta_1 rec_{jt} + \beta_2 EPU_{jt} + \beta_3 PFD_{jt} + \beta_4 CBT_{jt} + \beta_5 ML_{jt} + \beta_6 MV_{jt}), \qquad (3)$$

where G(·) is the logistic function. In equation (3), IR_{jt} denotes information rigidity for country *j* at time *t* and is bounded between 0 and 1, γ_j is country fixed effect, σ_{jt} is the conditional volatility of the target variable, rec_{jt} is the recession dummy, EPU_{jt} is economic policy uncertainty, PFD_{jt} is professional forecaster disagreement, CBT_{jt} is central bank transparency, ML_{jt} is market level and MV_{jt} is market volatility. As outlined in detail in Section 3.1, our hypotheses for the core determinants are that professional forecasters are less inattentive during recessions ($\beta_1 < 0$), periods of high economic uncertainty ($\beta_2 < 0$) and periods of high perceived uncertainty ($\beta_3 < 0$). Similarly, we expect more transparent monetary policy to be associated with lower information rigidity ($\beta_4 < 0$). We anticipate professional forecasters to be inattentive in periods of high market levels ($\beta_5 > 0$), but attentive in periods of high market volatility ($\beta_6 < 0$). As for control variables, information rigidities are persistent ($\alpha_1 > 0$); higher variable-specific volatility decreases information rigidity ($\alpha_2 < 0$). We calculate panel-corrected standard errors to address possible heteroskedasticity and cross-country correlation.

[8] We control for the serial correlation by fitting an AR(*p*) model, with the optimal lag order, *p*, selected according to the Akaike Information Criterion.

Panel (a) and (b) of Table 3 presents the results for inflation. For current year (i.e. short-term) inflation forecasts, the regression results (Column 1) tend to yield statistically significant results in the expected direction for most of the variables. We find slightly stronger coefficients for next year (i.e. medium-term) forecasts. More specifically, we observe negative coefficients on the business cycle, confirming our economic condition hypothesis. Although the coefficient on market level is positive and significant for next year inflation forecast, market volatility coefficients tend not to be significant. Furthermore, both economy-wide uncertainty and perceived uncertainty are negatively related to information rigidity. These findings support the state-dependent model of information updating as in Gorodnichenko (2008) and Woodford (2009). The coefficient on central bank transparency is negative, but only marginally significant for current year and not significant for next year inflation forecasts. The weakness of this impact may be due to the stabilizing effects of a credible and transparent central bank. In such a case, professional forecasters may be more confident in median-term inflation forecasts and pay less attention. As for the inflation specific variables, we find information rigidities to be persistent for both near and medium term inflation forecasts. The difficulty of forecasting inflation may motivate professional forecasters to pay more attention as shown by the negative coefficient on conditional volatility.

Panel (a) and (b) of Table 4 presents the results for GDP forecasts. Similar to inflation, we find the determinants to generally yield statistically significant results in the expected direction for most cases as shown by Column (1). Unlike for inflation, central bank transparency is significantly negatively related to information rigidities in GDP forecasts. This difference may be due to increased confidence in inflation targets from credible, transparent central banks. Consequently, professional forecasters may expect deviations in inflation to be short-term and temporary. Another difference with inflation is how periods of high market volatility correspond to significantly lower levels of information rigidity for medium term GDP forecasts. Furthermore, we find that professional forecasters are more inattentive in periods of higher market levels. Of note is that we find lower levels of persistence within information rigidities for GDP forecasts, but the impact of economic policy uncertainty is comparable in levels. Overall, our regression results confirm theoretical predictions about the determinants of inattentiveness in professional forecasters.

3.3 Robustness Checks

We find consistent results when we narrow the sample to only the years for which we have variation in the measure of central bank transparency (1998-2010), cf. Column (2). Similarly, in Columns (3-9) of Table 3 and 4, we show the regression results for subsamples excluding each country. The broad consistency of the coefficients excluding any one of the G7 countries confirms the robustness of the relations among the determinants and information rigidity.

Beyond these determinants of information rigidity, we considered surprise indices, inflation targeting, and fiscal illusion index. We considered measures of news surprise, such as differences between unemployment data expectations and announcements. However, the short time span of expectations data of many macroeconomic variables limited the sample to 2003 onward, excluding more than half of our sample. As a competing measure of central bank communication, we compare inflation targeting against the measure of central bank transparency. Inflation targeting is well covered in the literature as an impactful means of communicating central bank policy; see Cecchetti and Hakkio (2010). However, of the G7, only Canada and the UK implemented inflation targeting policies and this occurred early within our sample period: February 1991 and October 1992, respectively. We considered the fiscal illusion index by Mourao (2008) that measures the opacity of fiscal policy.[9] However, we ran across similar data problems. Due to limited time span and small yearly variation, the index did not significantly explain inattentiveness at a monthly frequency.

4. Inattention and the Effectiveness of Monetary Policy

This section explores if inattentiveness alters the effectiveness of monetary policy. The intuition is straightforward. When agents pay less attention, it takes a longer time for them to incorporate new information into their decisions, which makes the monetary policy to have a slower but more persistent effect. Motivated by Aastveit et al. (2013), we use the time-varying parameter structural autoregressive model with stochastic volatility (TVP-VAR):

$$y_t = \Phi_{0,t} + \Phi_{1,t} y_{t-1} + \Phi_{2,t} y_{t-2} + \cdots + \Phi_{p,t} y_{t-p} + \varepsilon_t, \;\; \varepsilon_t \sim i.i.d\; N(0, \Omega_t), \qquad (4)$$

[9] We are grateful to Paulo Mourao for the fiscal illusion index.

where y_t is the n ×1 vector of endogenous variables; $\Phi_{i,t}$, i = 0, 1, ... p, are n ×1 matrix of time varying intercept and coefficients; ε_t are heteroscedastic shocks with the variance-covariance matrix Ω_t, defined as $\Omega_t = (A_t)^{-1}\Sigma_t\Sigma_t'(A_t')^{-1}$, where A_t is the lower triangular matrix

$$A_t = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ a_{n1,t} & \cdots & 1 \end{bmatrix}$$

and Σ_t is the diagonal matrix

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_{n,t} \end{bmatrix}$$

All the time-varying coefficients evolve as random walks or geometric random walks, specified as follows

$$\Phi_t = \Phi_{t-1} + u_t,\ u_t \sim i.i.d\ N(0, U),$$

$$a_t = a_{t-1} + v_t,\ v_t \sim i.i.d\ N(0, V),$$

$$\log(\sigma_t) = \log(\sigma_{t-1}) + w_t,\ w_t \sim i.i.d\ N(0, W).$$

The TVP-VAR approach allows the coefficients, consequently the effectiveness of monetary policy, to vary over time. We include four variables of interest, in the order of inflation, growth rate of industrial production, measure of inattentiveness based on the SPF data, and federal funds rate. Following Primiceri (2005), we use the first 10 years (40 quarters, from 1971Q1 to 1980Q4) to calibrate the prior distribution. The simulations are based on 110,000 draws of Gibbs sample, where the first 10,000 draws were discarded and thereafter every tenth draw was selected to avoid correlation. In order to compare policy impact on the inflation and industrial production during high and low inattentiveness periods, we compute the average impulse responses when inattentiveness was in the top and bottom deciles. The results are shown in Figure 4, and the dashed lines are the 68% error bands.

The response of industrial production is consistent with the conventional monetary theory. The effect of monetary shock reaches its maximum after one quarter. During the low inattention scenarios, the same sized monetary shock has double initial effect compared to the high inattention scenarios. However, the impact decays quickly during the low inattention scenario. In contrast, during the high inattention scenarios, the impact of monetary policy is very persistent.

The response of inflation displays the "price puzzle", that is, a positive shock in federal funds rate results in a sustained increase in the inflation rate. The effect of monetary shock reaches its maximum at the third quarter. During the low inattention scenarios, the monetary impact decays quickly; while during the high inattention scenarios, the impact tends to be persistent.

5. Conclusion

We propose a micro-data based measure of information rigidity that takes into account (i) frequency by measuring the proportion of forecasters who revise and (ii) size by setting a threshold to the revision. This design directly responds to two major challenges in measuring information rigidity: low survey frequencies and capturing both elements of forecast revisions (size and frequency). The use of simple proportions, but meaningful weighting schemes, allows the proposed measure to most effectively capture the inattentiveness of forecasters. From this measure, we find the degree of information rigidity to be 2 to 3 months among professional forecasters. Forecasters display wait-and-see behavior in that they are more inattentive at very long horizons and less inattentive at medium horizons. Due to differing economic conditions and policies, the G7 countries have contrasting levels of information rigidity. Finally, inattentiveness is state dependent: information rigidities rise in stable periods, but fall sharply during crises. These findings are particularly important because they help us better understand the expectations formation process and calibrate imperfect information models.

Using our measure, we investigate the possible determinants of information rigidity. The inattentiveness of professional forecasters is significantly negatively related to economic policy uncertainty, forecast disagreement and market volatility. Similarly, information rigidities are low during recessions and positively related to market level. Furthermore, more credible announcements and information from central banks decrease information rigidities. By highlighting the determinants of information rigidity, we inform economic agents on when expectations of professional forecasters tend to be most up to date. These determinants provide insight into how policy makers may directly impact the expectations formation process of key macroeconomic variables.

The measure of information rigidities, stylized facts, and their determinants offer much potential for future research. One worthwhile application is to estimate the degrees of information rigidity for different variables and different sectors of the economy. Does the sector that adjusts less often have a disproportionate effect on the aggregate dynamics than the sectors that adjust more frequently? Another potential extension is to investigate time-varying characteristics of information rigidity and the effectiveness of monetary policy.

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Table 1: Proportion of forecast revisions

Revision Size	Inflation	GDP	Inflation | GDP	GDP | Inflation
0%	54.6%	52.6%	NA	NA
0.1%	20.1%	16.9%	59.7%	62.4%
0.2%	10.7%	11.0%	62.2%	64.5%
0.3%	5.7%	6.5%	64.2%	66.5%
0.4%	2.9%	3.7%	65.5%	68.5%
0.5%+	6.0%	9.3%	66.5%	68.9%

Note: Columns Inflation and GDP show the proportion of unconditional forecast revisions by the given size in predicting inflation and GDP, respectively. Inflation | GDP shows the proportion of inflation forecast revision conditional on the professional forecaster having revised her GDP forecast by the given size. GDP | Inflation shows the proportion of GDP forecast revision conditional on the professional forecaster having revised her inflation forecast by the given size.

Table 2: Summary statistics of information rigidity across countries

a) Inflation

Country	IR	AL	CG
Canada	3.28	2.26	2.09
France	3.16	2.37	2.48
Germany	2.96	2.58	2.40
Italy	2.56	2.39	1.95
Japan	3.19	2.71	1.95
UK	2.83	1.91	2.44
US	3.11	1.79	1.79

b) GDP

Country	IR	AL	CG
Canada	2.88	2.15	2.68
France	2.83	2.31	2.39
Germany	2.88	2.70	3.84
Italy	2.54	2.35	3.54
Japan	2.29	2.05	2.19
UK	3.10	2.20	4.19
US	2.56	1.53	2.26

Note: The tables show the number of months between information updates as measured by our measure (IR), Andrade and Le Bihan (2013, AL), and Coibion and Gorodnichenko (2013, CG).

Table 3: Determinants of information rigidity in inflation forecasts

a) Current-year inflation forecasts

Variables	1	2	3	4	5	6	7	8	9
Own Lag	1.791***	1.622***	1.862***	1.680***	1.788***	1.833***	1.795***	1.768***	1.687***
	(0.162)	(0.198)	(0.177)	(0.162)	(0.200)	(0.183)	(0.218)	(0.196)	(0.127)
Conditional Volatility	-0.619*	-0.727**	-0.669*	-0.559	-0.528	-0.617*	-0.965***	-0.372	-0.675
	(0.331)	(0.297)	(0.344)	(0.352)	(0.325)	(0.333)	(0.366)	(0.272)	(0.931)
Recession	-0.102	-0.124	-0.120	-0.127	-0.129	-0.057	-0.154	-0.047	-0.104
	(0.078)	(0.105)	(0.094)	(0.079)	(0.082)	(0.069)	(0.105)	(0.063)	(0.093)
EPU	-0.165**	-0.135*	-0.132	-0.229**	-0.189**	-0.181**	-0.180**	-0.099	-0.160*
	(0.081)	(0.081)	(0.087)	(0.091)	(0.093)	(0.088)	(0.082)	(0.068)	(0.085)
Disagreement	-0.344***	-0.550***	-0.273***	-0.341***	-0.359***	-0.334**	-0.404**	-0.285**	-0.440***
	(0.119)	(0.163)	(0.100)	(0.126)	(0.123)	(0.132)	(0.160)	(0.139)	(0.093)
CB Transparency	-1.292*	-1.130	-1.237	-1.514	-1.665**	-1.281	-0.325	-1.719**	-0.974
	(0.772)	(0.724)	(0.771)	(0.928)	(0.748)	(0.848)	(0.672)	(0.695)	(0.784)
Market Level	0.027	-0.079	0.050	0.015	0.039	-0.007	-0.067	0.039	0.064
	(0.052)	(0.077)	(0.057)	(0.053)	(0.043)	(0.057)	(0.057)	(0.038)	(0.039)
Market Volatility	0.202	0.143	0.175	0.301	0.278	0.164	0.378	0.012	0.163
	(0.220)	(0.234)	(0.259)	(0.240)	(0.247)	(0.232)	(0.231)	(0.155)	(0.217)
Observations	1,590	1,176	1,316	1,398	1,398	1,398	1,316	1,398	1,316

Note: Column (1) presents the results for the full sample. Column (2) limits the sample to 1998-2010, covering the years for which central bank transparency data is available. Column (3) shows the panel data regression result without Canada. Similarly, columns (4-9) show the regression results by removing one country at a time in the following order: France, Germany, Italy, Japan, U.K., and U.S. The numbers in parentheses are panel corrected standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

b) Next-year inflation forecasts

Variables	1	2	3	4	5	6	7	8	9
Own Lag	1.964***	2.099***	2.059***	1.788***	2.004***	2.017***	2.029***	1.857***	1.915***
	(0.209)	(0.195)	(0.230)	(0.153)	(0.242)	(0.245)	(0.231)	(0.215)	(0.233)
Conditional Volatility	-0.717**	-0.676***	-0.725**	-0.682**	-0.632**	-0.709**	-0.983***	-0.503*	-0.564
	(0.299)	(0.245)	(0.293)	(0.339)	(0.291)	(0.308)	(0.256)	(0.291)	(0.883)
Recession	-0.150**	-0.167**	-0.139*	-0.186***	-0.150**	-0.128*	-0.199**	-0.100*	-0.166**
	(0.069)	(0.079)	(0.080)	(0.063)	(0.076)	(0.069)	(0.095)	(0.052)	(0.077)
EPU	-0.165***	-0.157***	-0.155**	-0.224***	-0.170***	-0.165***	-0.160***	-0.123***	-0.172***
	(0.053)	(0.047)	(0.062)	(0.048)	(0.062)	(0.058)	(0.050)	(0.037)	(0.058)
Disagreement	-0.214***	-0.241**	-0.210***	-0.211***	-0.259***	-0.204***	-0.203***	-0.171***	-0.248***
	(0.056)	(0.099)	(0.064)	(0.062)	(0.044)	(0.059)	(0.065)	(0.066)	(0.070)
CB Transparency	-0.575	-0.433	-0.536	-0.866	-0.756	-0.608	0.041	-0.967**	-0.351
	(0.578)	(0.546)	(0.583)	(0.695)	(0.665)	(0.656)	(0.577)	(0.461)	(0.578)
Market Level	0.089***	0.048	0.091***	0.091***	0.098***	0.062**	0.076**	0.094***	0.099***
	(0.021)	(0.043)	(0.025)	(0.026)	(0.021)	(0.027)	(0.033)	(0.011)	(0.019)
Market Volatility	-0.210	-0.167	-0.283	-0.204	-0.191	-0.222	-0.050	-0.330**	-0.167
	(0.166)	(0.182)	(0.173)	(0.193)	(0.179)	(0.169)	(0.145)	(0.145)	(0.182)
Observations	1,503	1,176	1,242	1,323	1,323	1,323	1,242	1,323	1,242

Table 4: Determinants of information rigidity in GDP forecasts

a) Current-year GDP forecasts

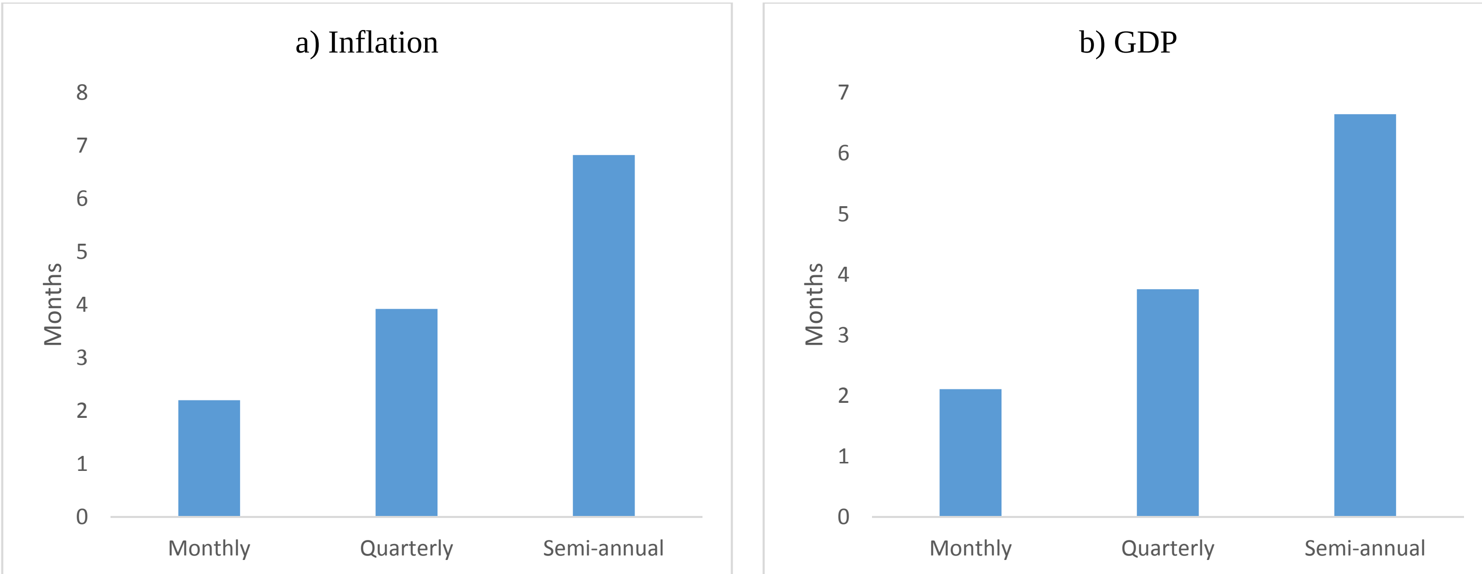
Variables	1	2	3	4	5	6	7	8	9
Own Lag	1.118***	1.093***	1.147***	1.057***	1.077***	1.163***	1.159***	0.997***	1.111***
	(0.123)	(0.159)	(0.154)	(0.124)	(0.143)	(0.140)	(0.117)	(0.108)	(0.163)
Conditional Volatility	-0.049*	-0.061***	-0.046	-0.036	-0.045	-0.045	-0.102***	-0.038	-0.051*
	(0.027)	(0.021)	(0.029)	(0.026)	(0.031)	(0.032)	(0.023)	(0.025)	(0.028)
Recession	-0.121**	-0.130*	-0.135**	-0.114*	-0.104*	-0.116*	-0.139**	-0.075*	-0.141**
	(0.053)	(0.073)	(0.061)	(0.060)	(0.058)	(0.066)	(0.056)	(0.045)	(0.058)
EPU	-0.166*	-0.152*	-0.145	-0.259***	-0.176*	-0.167*	-0.182**	-0.102	-0.144
	(0.089)	(0.081)	(0.105)	(0.063)	(0.103)	(0.098)	(0.088)	(0.083)	(0.091)
Disagreement	-0.187**	-0.234**	-0.139*	-0.215***	-0.190**	-0.155*	-0.181	-0.229***	-0.171*
	(0.079)	(0.103)	(0.074)	(0.081)	(0.088)	(0.079)	(0.138)	(0.072)	(0.101)
CB Transparency	-1.975***	-1.496**	-2.039***	-2.197***	-2.101***	-2.054**	-1.189***	-2.431***	-1.904**
	(0.693)	(0.582)	(0.772)	(0.791)	(0.815)	(0.798)	(0.416)	(0.636)	(0.803)
Market Level	0.187**	0.058	0.201*	0.217**	0.220**	0.195**	0.098***	0.212***	0.204**
	(0.077)	(0.045)	(0.109)	(0.091)	(0.088)	(0.093)	(0.030)	(0.080)	(0.091)
Market Volatility	0.077	-0.008	0.041	0.056	0.083	0.064	0.200**	-0.011	0.121
	(0.127)	(0.199)	(0.123)	(0.107)	(0.143)	(0.138)	(0.082)	(0.155)	(0.147)
Observations	1,590	1,176	1,316	1,398	1,398	1,398	1,316	1,398	1,316

Note: Column (1) presents the results for the full sample. Column (2) limits the sample to 1998-2010, covering the years for which central bank transparency data is available. Column (3) shows the panel data regression result without Canada. Similarly, columns (4-9) show the regression results by removing one country at a time in the following order: France, Germany, Italy, Japan, U.K., and U.S. The numbers in parentheses are panel corrected standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

b) Next-year GDP forecast

Variables	1	2	3	4	5	6	7	8	9
Own Lag	1.512***	1.450***	1.517***	1.457***	1.462***	1.551***	1.533***	1.434***	1.577***
	(0.102)	(0.116)	(0.118)	(0.103)	(0.115)	(0.119)	(0.108)	(0.094)	(0.106)
Conditional Volatility	-0.009	-0.011	-0.009	-0.002	-0.007	-0.009	-0.020	-0.000	-0.012
	(0.010)	(0.008)	(0.010)	(0.008)	(0.013)	(0.014)	(0.019)	(0.010)	(0.010)
Recession	-0.151***	-0.154**	-0.161***	-0.158***	-0.128**	-0.135***	-0.194***	-0.121**	-0.157***
	(0.049)	(0.061)	(0.057)	(0.055)	(0.050)	(0.051)	(0.055)	(0.049)	(0.056)
EPU	-0.180***	-0.188***	-0.173***	-0.228***	-0.180***	-0.184***	-0.187***	-0.159***	-0.159***
	(0.044)	(0.044)	(0.052)	(0.037)	(0.051)	(0.050)	(0.045)	(0.046)	(0.036)
Disagreement	-0.238***	-0.310***	-0.290***	-0.228***	-0.257***	-0.213***	-0.251**	-0.234***	-0.190***
	(0.073)	(0.098)	(0.074)	(0.076)	(0.086)	(0.073)	(0.103)	(0.083)	(0.067)
CB Transparency	-1.755***	-1.438***	-1.773***	-1.822***	-1.872***	-1.853***	-1.425***	-2.146***	-1.541***
	(0.402)	(0.478)	(0.407)	(0.484)	(0.524)	(0.476)	(0.421)	(0.320)	(0.450)
Market Level	0.162***	0.091	0.151***	0.163***	0.213***	0.157***	0.148***	0.193***	0.153***
	(0.035)	(0.070)	(0.045)	(0.039)	(0.031)	(0.056)	(0.039)	(0.038)	(0.039)
Market Volatility	-0.904***	-1.045***	-0.921***	-0.900***	-1.003***	-0.893***	-0.894***	-0.894***	-0.837***
	(0.098)	(0.146)	(0.108)	(0.132)	(0.117)	(0.093)	(0.140)	(0.095)	(0.082)
Observations	1,503	1,176	1,242	1,323	1,323	1,323	1,242	1,323	1,242

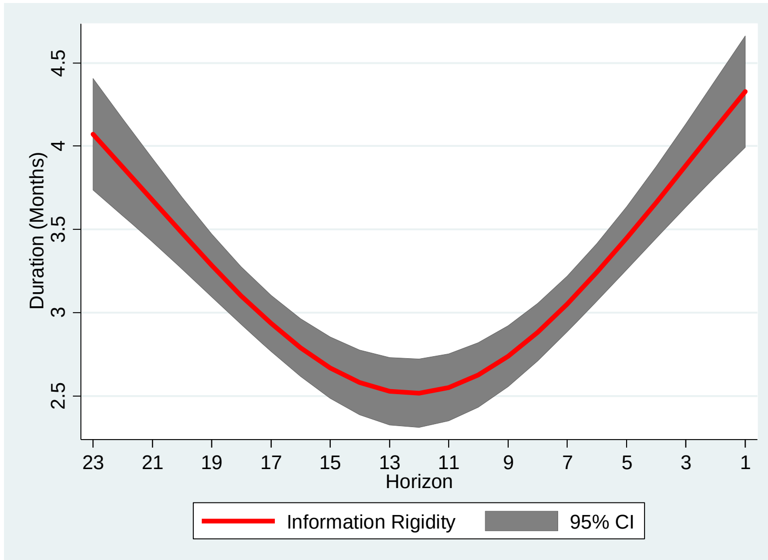
Figure 1: Information rigidity at varying survey frequencies



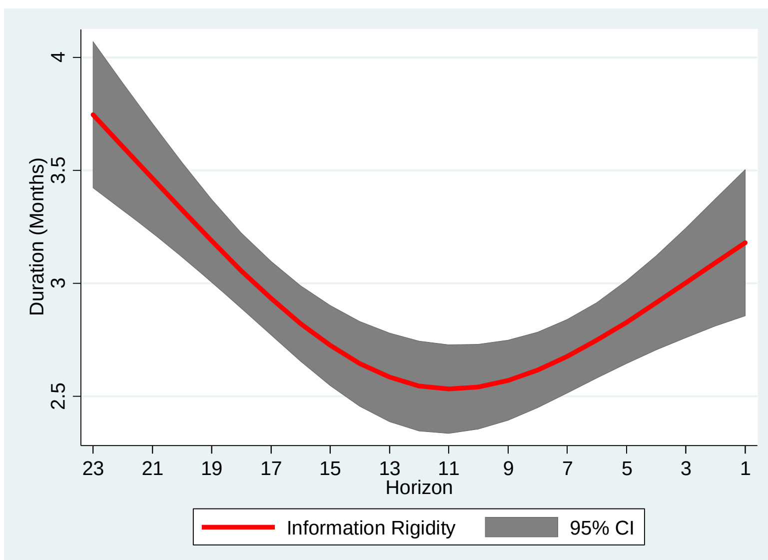
Note: The graphs show the number of months between information updates derived from various survey frequencies.

Figure 2: Information rigidity over horizon

a) Inflation



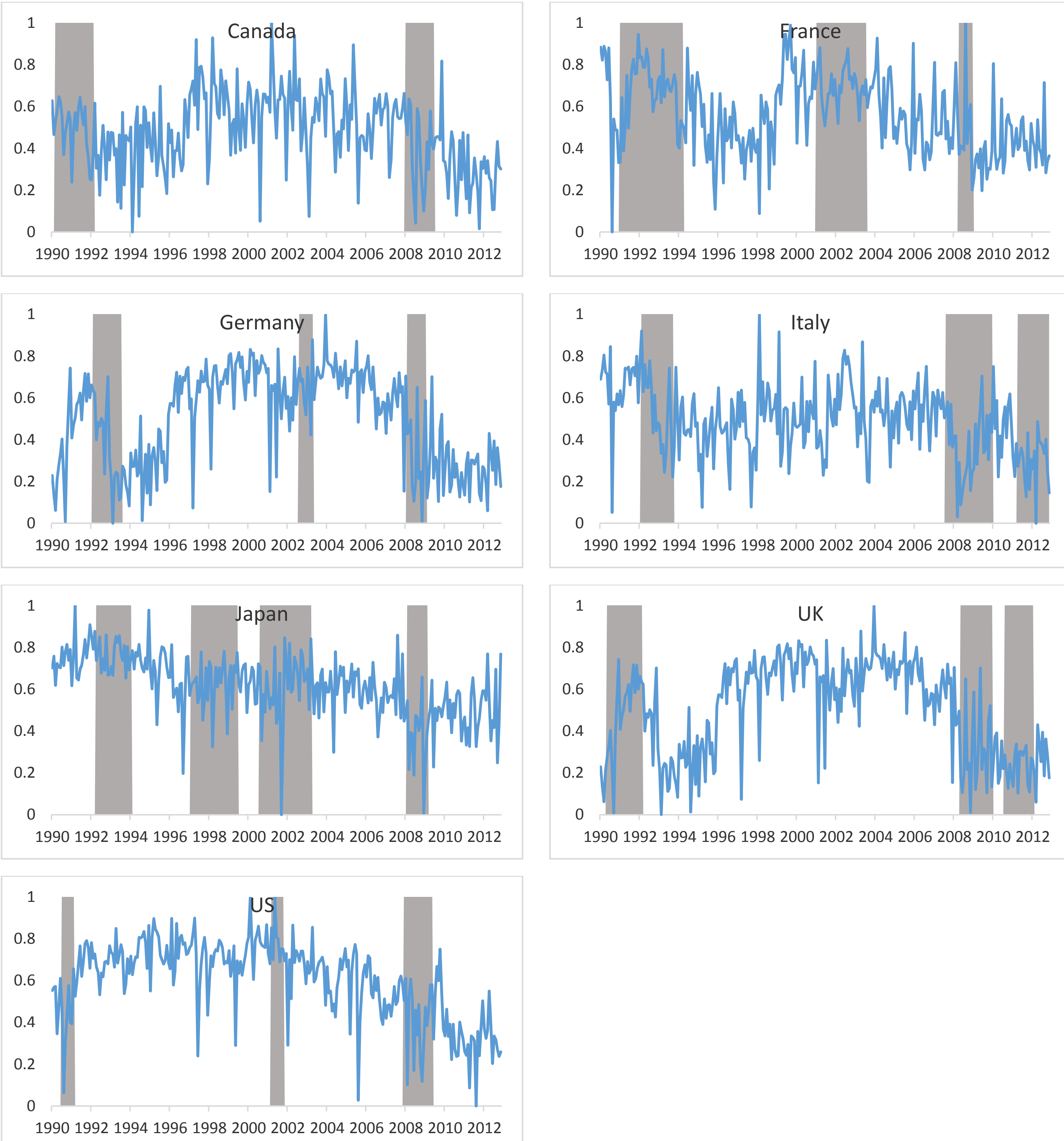
b) GDP



Note: To estimate the trends of information rigidity over horizon, we fit a smooth line using a cubic spline with three bands to pooled rigidities over 23 years and G7 countries. Information rigidity and horizon both have units of months.

Figure 3: Information rigidity over time

a) Inflation



b) GDP

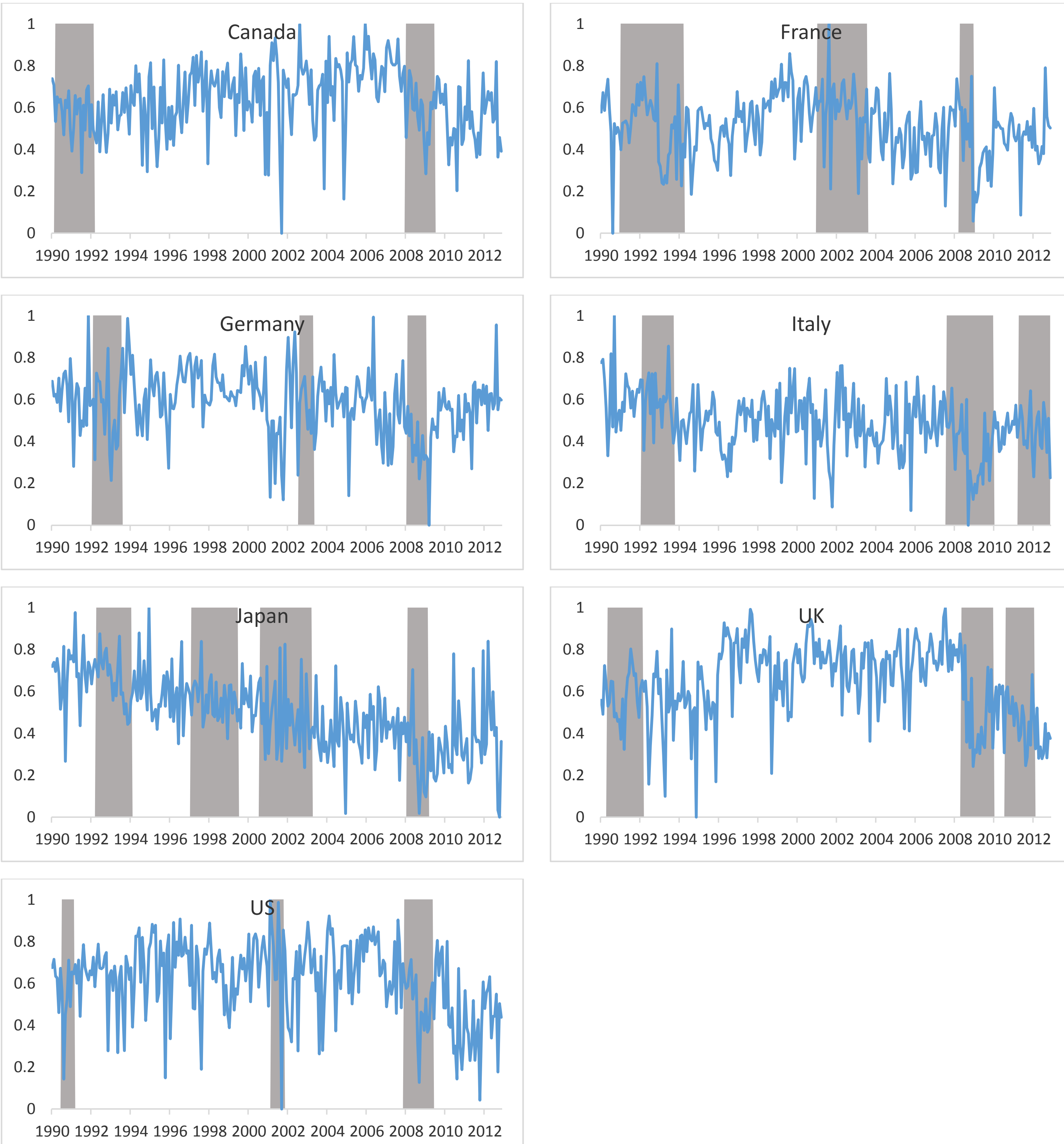

Canada
France
Germany
Italy
Japan
UK
US
1
0.8
0.6
0.4
0.2
0
1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012

Figure 4: Inattention and the Effectiveness of Monetary Policy