Information Rigidity in Macroeconomic Forecasts:
An International Empirical Investigation[*]

Xuguang (Simon) Sheng[&] and Jonathan Wallen
Department of Economics, American University

Abstract: Using *Consensus Forecasts* data across the G7 countries, we investigate information rigidities in professional forecasts of inflation and GDP. We develop a micro-data based measure of information rigidity, which we interpret under both the sticky and noisy information models. Based on this measure, we find that professional forecasters update their information sets every two to three months, and information rigidities vary across forecasting horizons, individuals, countries and time. Our regression analysis shows that professional forecasters are less inattentive in periods of high market volatility, recession, and economic uncertainty. Furthermore, policy makers may decrease information rigidity through better communication of monetary policy.

JEL Classification: E3, E5
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[&] Corresponding author. Address: Department of Economics, American University, 4400 Massachusetts Avenue NW, Washington, DC 20016. Tel: (202) 885-3782. Email: sheng@american.edu.

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 contrasting methodologies of measuring information rigidity. In response, we propose a micro-data based measure of information rigidity as the proportion of forecasters who revise above a given threshold within a period.

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. Similarly, through the lens of the noisy information model, this finding implies that professional forecasters require two to three months to fully incorporate new information. 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). Information rigidities vary across professional forecasters, indicating that some may be better at processing new information. Similarly, we observe different levels of information rigidity for countries, reflecting their different economic environments and levels of policy transparency. Finally, information rigidities are state dependent and respond strongly to crises.

We explore potential determinants of information rigidities: the business cycle, market volatility, central bank transparency, and economic policy uncertainty. We document that information rigidities rise during stable, expansionary periods and fall during uncertain, recession periods. Similarly, inattentiveness of professional forecasters declines in response to market volatility. The inverse relationship between central bank transparency and information rigidity highlights how clear communication of monetary policy may decrease inattentiveness. Contrasting with this monetary policy relationship, information rigidities tend to fall during periods of high economic policy uncertainty. In particular, uncertainty about fiscal policy motivates forecasters to revise their forecasts more frequently. Complementing these core determinants, we include a series of control variables related to the persistence of information rigidity and characteristics of the macroeconomic variable of interest. 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. (2014). 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 (2013). 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; Bachmann et al, 2013; Baker et al, 2013). Over the term structure of forecasts at long horizons, we find evidence of a wait-and-see effect. At long horizons, information rigidities tend to be higher, reflecting how professional forecasters more heavily weight priors and wait to see more decisive economic news. Over time, we assess potential determinants of information rigidity. Using stock market volatility and economic policy uncertainty as indicators of macroeconomic uncertainty, we find that professional forecasters are less inattentive during periods of high economic 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 characterizes information rigidity through a comprehensive measure and establishes some stylized facts. Section 3 identifies key determinants of information rigidities across the G7 countries. Section 4 concludes.

2. Measuring Information Rigidity and Some Stylized Facts

2.1 Data

To study 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. 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). 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. Supplementing the cross-country coverage is the relatively long period from January 1990 to December 2012, spanning volatile and stable periods. The sample period allows us to analyze the effect of changing economic conditions on the expectations formation process. Finally, the detail of the micro-data yields insight into information rigidities on the individual level.

Despite the richness, using this dataset presents several challenges, especially forecaster name changes, mergers and acquisitions.[1] We developed the *Consensus Forecasts* 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. Furthermore, we document significant country-level changes, such as the reunification of Germany and the United Kingdom's transition from a Retail to a Consumer Price Index.

2.2 Challenges in Measuring Information Rigidity

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. For example, in the U.S., the Bureau of Labor Statistics releases important macroeconomic information every month, and the Federal Reserve makes frequent announcements. 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. Consequently, empirical studies of information rigidities based on quarterly and semi-annual data may overestimate the inattentiveness of professional forecasters.

Second, the previous non-parametric measures of information rigidity focus only on frequency. However, forecast revisions have two components: size and frequency. Both

[1] For example, Warburg Dillon Read, the forecasting subsidiary of the Swiss Bank Corporation, underwent a name change to UBS Warburg because of Swiss Bank Corporation's merger with UBS in 1998; later, UBS Warburg was shortened to UBS. See the Online Appendix for the detailed documentation on over 300 professional forecasters from 1990 to 2013.

components tell a story as illustrated by Figure 2. There are four different scenarios characterized by different frequencies and sizes. The case of (a) high frequency and high size of revisions captures easy-to-identify events of low forecaster inattentiveness, such as the 9/11 terrorist attacks and the Great Recession. In direct contrast, the (d) "run-of-the-mill period" does not correspond to historic events. The set of low frequency and low size revisions contains periods of no meaningful new information and high forecaster inattentiveness. The two mixed cases are more difficult to characterize. In the case of (b) high frequency, but low size in revisions, we have many professional forecasters fine-tune their forecasts based on news with little added value. The other mixed case (c), low frequency, but high size in revisions, indicates disagreement among forecasters. While the majority remain inattentive, a small subset of the professional forecasters are making substantial revisions, which is of particular interest in assessing macroeconomic uncertainty. These four different relations between frequency and size of revisions show how both of these characteristics are essential for understanding the inattentiveness of forecasters.

The size component of forecast revisions provides insight to the motivation behind the forecast revision. We illustrate the variation in forecast revisions size within Figure 3. Although professional forecasters make no revision approximately 50% of periods, the other revisions vary from 0.1% to as much as above 0.5%. 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.

2.3 Measures 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. In the noisy information model, $\beta = \frac{1-G}{G}$, where G is the Kalman gain and measures the weight given to the new information. Information rigidity in this model is defined as $1 - G$, the weight on agents' prior beliefs relative to new information. The strength of the CG measure lies in its need for the mean forecast only and structural interpretation. However, the interpretation is only meaningful in cases where the coefficient is positive. As shown by Lahiri and Sheng (2008), forecasters sometimes overreact to new information, resulting in a negative coefficient. Furthermore, the measure provides an aggregated information rigidity over the entire time span, instead of showing how information rigidity may change over time.

In contrast, 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 cost of this simple approach is the limited focus on the frequency component of forecast revisions only, but not the size. Large, sharp revisions at economically meaningful turning points are treated equally to that of the smallest of revisions.

Since we are interested in studying the determinants of information rigidity over time, we need a time-varying measure of information rigidity. We earlier noted the importance of capturing both features of forecast revisions: frequency and size. Furthermore, we are interested in using a measure with strong ties to the theory of information rigidity: a measure that is interpretable under both the noisy and sticky information models. To address these challenges, 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 can find a 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. (2014). 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.

We define the threshold in terms of the historical level of the macroeconomic variable of interest. This approach is targeted in that the threshold is variable and country specific, but also easily generalizable as it only depends on the knowledge of historical realizations of the target variable. Furthermore, the threshold is flexible in that it varies over time to reflect the dynamic nature of forecasting. The intuition behind the approach is that the economic significance of a revision depends on the historical level of macroeconomic variable of interest. We specifically define the threshold as 5% of the average magnitude of the macroeconomic variable of interest over the past five years.[2]

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

[2]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. We use the five-year historical average rather than the previous year to avoid spurious jumps in the threshold.

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 1). However, the estimates by AL is persistently smaller than that of our measure across all countries. This is not unexpected because our measure includes 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.

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.

2.4 The IR measure in terms of the sticky and noisy information models

We may interpret our findings in terms of the noisy information model as professional forecasters take two to three months to fully incorporate new information into their forecasts. In terms of the sticky information model, this finding implies professional forecasters on average update information sets every two to three months. Going beyond the empirical results, we perform a simulation study to connect our measure of information rigidity with models of noisy and sticky information.

Our data generating process follows from Coibion and Gorodnichenko (2012). We assume a simple AR(1) process for the target variable π_t, that is, $\pi_t = \rho\pi_{t-1} + \omega_t,\ \omega_t \sim iid\ N(0, \sigma_w^2)$. At time *t*, each agent *i* observes two signals about π_t: public signal (s_t) and private signal (y_{it}):

$$s_t = \pi_t + \eta_t,\ \eta_t \sim iid\ N(0, \sigma_\eta^2),$$

$$y_{it} = \pi_t + v_{it},\ v_{it} \sim iid\ N(0, \sigma_v^2).$$

According to the noisy information model, agent *i* makes forecast $\hat{\pi}_{it}$ given his information sets via the Kalman filter

$$\hat{\pi}_{it} = (1 - PH)\rho\hat{\pi}_{i,t-1} + PH\pi_t + P[v_{it}\ \eta_t]', \tag{3}$$

where $H = [1\ 1]'$, $P = [P_\eta \quad P_v] = \left[\frac{\Psi\sigma_v^2}{\Psi(\sigma_v^2+\sigma_\eta^2)+\sigma_v^2\sigma_\eta^2} \quad \frac{\Psi\sigma_\eta^2}{\Psi(\sigma_v^2+\sigma_\eta^2)+\sigma_v^2\sigma_\eta^2}\right]$ is the Kalman gain, and $\Psi = \rho\left[\Psi - \Psi\mathrm{H}'\left(\mathrm{H}\Psi\mathrm{H}' + \mathrm{diag}\{\sigma_v^2, \sigma_\eta^2\}\right)^{-1} H\Psi\right]\rho + \sigma_w^2$ is the variance-covariance matrix of the one-step ahead forecast error. In equation (3), $(1 - PH)$ represents the relative weight placed on previous forecasts relative to new information and can be interpreted as the degree of information rigidity. We use the half-life metric $\ln(0.5)/\ln(1 - PH)$ to calculate the average number of months for agents to incorporate 50% of new information in their forecasts, based on the noisy information model.

In our simulation, we round the forecasts to the first decimal, corresponding to our dataset structure. For simplicity, we omit the horizon subscript and assume that the forecast horizon is fixed at one-step ahead. Using these forecasts, we compute information rigidity as the proportion of forecasts with a revision size less than or equal to a threshold τ, $\mathrm{IR}(\tau)_\mathrm{t}$, as in equation (2). According to the sticky information model, $0.5/(1 - \mathrm{IR}(\tau)_t)$ can be interpreted as half of the average duration between information updates. Consequently, we compare $0.5/(1 - \mathrm{IR}(\tau)_t)$ implied by the sticky information model with $\ln(0.5)/\ln(1 - PH)$ implied by the noisy information theory. Across a wide range of parameter values, our simulation experiments show that our selected threshold, that is, 5% of the average magnitude of the macroeconomic variable over the past five years, leads to a minimum of differences between $0.5/(1 - \mathrm{IR}(\tau)_t)$ and

$\ln(0.5)/\ln(1-PH)$.[3] Of note is how well integrated the noisy and sticky information models are within the proposed measure, IR, through the threshold determination.

2.5 Stylized Facts about Information Rigidity

We present four stylized facts about information rigidity with relation to forecasting horizon, individuals, 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 across individuals, 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. (2014) 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 4 clearly indicates a U-shaped trend for information rigidity over horizon for both inflation and GDP. This trend in the inattentiveness of forecasters over horizon lends credence to the noisy information model. At very long horizons (18-23 months ahead), 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 (10-17 months ahead), professional forecasters are the least inattentive and make the most frequent revisions. Finally, in the near term (1-9 months ahead) 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.

[3] For the data generating process considered here, we choose $\sigma_w^2 = \{0.2,1\}$, $\sigma_v^2 = \{0.2,1\}$, $\sigma_\eta^2 \in \{0.2, 1\}$, $\rho \in \{0.2, 0.5\}$, $N \in \{50, 100\}$ and $T \in \{50, 100\}$ after the initial burn-in period of 50 observations. The results are obtained with Matlab using 5,000 simulations.

Second, information rigidities vary across individuals. Since the survey data provides individual forecasts, we are able to assess the heterogeneity of information rigidity across characteristics of professional forecasters. As shown in Table 2, we consider the following characteristics: domicile (foreign vs. domestic), internationality (global vs. local), industry (financial vs. non-financial), and participation (veteran vs. newcomer). Professional forecasters who have the foreign, global, and financial characteristics have significantly lower information rigidities. Furthermore, new forecasters tend to have lower information rigidities than veterans. We interpret these findings along the lines of two themes: resources and priors. The foreign, global, and financial characteristics are good proxies for greater access to resources to update information sets and process news from noise. We expect multinational financial firms with the confidence to forecast in foreign markets have lower information rigidities because of greater access to information and the manpower to process the news. Firms with a long history of participation, may have higher information rigidities due to more ingrained priors. These characteristics reflect the differences in ability of professional forecasters to process information and distinguish news from noise.

Third, information rigidities vary across countries. We note differences in mean information rigidity across countries in Table 1. For GDP forecasts, we observe a high information rigidity of 3.1 months (US) and a low of 2.29 months (Japan). For inflation forecasts, we find a high information rigidity of 3.28 months (Canada) and a low of 2.56 months (Italy). 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. (2014) 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.

Fourth, 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 5. 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.

3. Determinants of Information Rigidity over Time

3.1. The Core Determinants

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. We categorize these determinants in the following groups: (i) the business cycle and market volatility, and (ii) monetary and fiscal policy.

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 and market volatility. 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: a negative coefficient.

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

[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).

each country to identify economic news reflected in market price changes. 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.[5] The use of financial market volatility as a proxy for uncertainty has been recently advocated by Bloom (2009) and Bachmann et al. (2013). In periods of high market volatility, we expect professional forecasters, especially those associated with financial institutions, to be less inattentive: a negative coefficient.

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. Through both models, we expect a negative coefficient on central bank transparency and independence. We use the measure by Minegishi and Cournède (2009), 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 100 (least to most transparent).[6]

In terms of fiscal policy, we expect greater uncertainty related to fiscal policy to decrease information rigidities in professional forecasters. To capture fiscal policy uncertainty, we consider a broad index of economic policy uncertainty (EPU) by Baker et al. (2013).[7] The index is built on three components: the frequency of news media references to economic policy uncertainty, the number of federal tax code provisions set to expire, and the extent of forecaster disagreement over

[5] 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.

[6] Despite the strong theoretical connection, we note practical limitations of this measure: incomplete sample coverage, 1999-2009, and rather small yearly variation. To not lose a large portion of our sample, we extend back the 1999 central bank transparency score to 1990. This is consistent with the methodology of the literature, such as Ehrmann et al. (2012).

[7] The EPU data series span the entire sample period for the Canada, Japan, and the U.S. but the series for the France, Germany, Italy, and the U.K. begin in January of 1997, corresponding to the year the Eurozone formed.

future inflation and government purchases. The EPU index primarily reflects fiscal uncertainty, especially in the recent years where increases are primarily driven by tax, spending and healthcare policy uncertainty. Furthermore, fiscal policy uncertainty is more long term so we consequently expect the EPU index to impact on longer term information rigidity; see Baker et al. (2013). We expect forecasters to be less inattentive in periods with high macroeconomic policy uncertainty: a negative coefficient.

3.2. The Control Variables

Although the core determinants of information rigidity may provide a strong indication as to how information rigidity may vary over time, we 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. This persistence is well described by theoretical models. The sticky information model explains how the costs to updating information sets create this stickiness to information. Similarly, the noisy information model explains this inertia in terms of the continued challenge of distinguishing news from noise. We account for the stickiness of information rigidity across countries by including country fixed effects and lagged values of information rigidity.

When analyzing the macroeconomic variables of interest, inflation and GDP, we expect their volatility to impact information rigidity.[8] 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.[9] Since higher conditional volatilities imply a more difficult variable to forecast, we control for this characteristics of macroeconomic variable of interest.

[8] We obtain quarterly GDP growth and monthly inflation data from the OECD for each country of the G7.
[9] 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.

3.3 Results

To assess the impact of the aforementioned factors on information rigidity, we run the following panel data regression:

$$IR_{jt} = \alpha_j + \beta_1 rec_{jt} + \beta_2 MV_{jt} + \beta_3 EPU_{jt} + \beta_4 CBT_{jt} + C_1 IR_{j,t-1} + C_2 \sigma_{jt} + u_{jt}, \quad (4)$$

where IR_{jt} denotes information rigidity for country *j* at time *t*, α_j is the county fixed effects, rec_{jt} is the recession dummy, MV_{jt} is market volatility, EPU_{jt} is economic policy uncertainty, CBT_{jt} is central bank transparency and σ_{jt} is the conditional volatility of the target variable. 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 market volatility ($\beta_2 < 0$) and fiscal policy uncertainty ($\beta_3 < 0$). More transparent monetary policy decreases information rigidity ($\beta_4 < 0$). In Section 3.2, we discussed important control variables and their expected relation to information rigidity: information rigidities are persistent ($C_1 > 0$); higher variable-specific volatility decreases information rigidity ($C_2 < 0$). We estimate equation (4) by ordinary least squares with panel-corrected standard errors to address possible heteroskedasticity and cross-country correlation.

Panel (a) of Table 3 presents the results for inflation forecasts. For current year (i.e. short-term) information rigidity, the core regression results (Column 1) tend to yield statistically significant results in the expected direction. We find similarly significant coefficients for next year (i.e. medium-term) information rigidity. More specifically, we observe negative coefficients on the business cycle, confirming our economic condition hypothesis. These findings are consistent with the intuition that professional forecasters are less inattentive during periods of high economic uncertainty. However, market volatility tends not to be significant. Furthermore, these findings support the state-dependent model of information updating as in Gorodnichenko (2008) and Woodford (2009). More transparency of central banks tends to decrease information rigidity in predicting inflation in short-term forecasts. Similarly, fiscal policy uncertainty is negatively related to information rigidity. As for the control variables, we find information rigidities to be persistent for both near and medium term inflation forecasts. The difficulty of forecasting inflation (conditional volatility) may motivate professional forecasters to pay more attention in the near term as shown by the lower information rigidity.

Panel (b) of Table 3 presents the results for GDP forecasts. Similar to inflation, we find the determinants to generally yield statistically significant results in the expected direction (Column 1). Unlike for inflation, periods of high market volatility correspond to significantly lower levels of information rigidity for medium term GDP forecasts. Of further note is that we find lower levels of persistence within information rigidities for GDP forecasts, but the impact of central bank transparency and policy uncertainty is comparable in levels. Overall, our regression results confirm theoretical predictions about the determinants of inattentiveness in professional forecasters.

3.4 Robustness Checks

We assess the robustness of market volatility and economic policy uncertainty by extending the regression specification in equation (4) to include two additional explanatory variables: market level and disagreement. Market impacting news related to the macroeconomic variable of interest may impact both level and volatility: first and second moments. The level of market indices may reflect information on expectations of future economic conditions not contained within market volatility. To address the potential problem of market volatility only capturing part of the picture, we include the market level in the model specification. We find that market levels is positively related to information rigidity and significant in all cases, except for near term inflation forecasts (Table 3, Column 2). This may reflect how during periods of economic prosperity market levels tend to be high and professional forecaster may be complacent and less attentive to news. We use the economic policy uncertainty index as a proxy for uncertainty related to fiscal policy. However, a potential concern with EPU is the forecast disagreement component of the index. There may be a mechanical relationship between forecast disagreement and our measure of information rigidity. To assess whether EPU contains information about fiscal policy uncertainty beyond that of forecast disagreement, we include both in the model specification (Column 2).[10] Not surprisingly, information rigidity and disagreement is significantly inversely related, reflecting how periods of greater attentiveness also correspond to periods when forecasters

[10] We measure disagreement as the interquartile range of forecasts in our dataset.

revise away from the consensus. However, even when including forecast disagreement, EPU continues to remain significant and negatively related to information rigidity.

Beyond these robustness checks, we considered other potential determinants of information rigidity: surprise indices, inflation targeting, and fiscal illusion. 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. 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. 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, less inattentive at medium horizons, and more inattentive at very short horizons. Furthermore, inattentiveness varies across professional forecasters, reflecting characteristics related to resources and experience. Due to differing economic conditions and policies, the G7 countries have contrasting levels of information rigidity. Supporting this finding is similarity in the information rigidities of France and Germany, reflecting geographic and Eurozone commonalities. 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 business cycle, market volatility, monetary and fiscal policy. The inattentiveness of professional forecasters is significantly negatively related to the business cycle or market volatility. Furthermore, more credible announcements and information from central banks decrease information rigidities and fiscal policy uncertainty decreases longer-term information rigidity. 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. Some key areas of exploration include the application of our new measure to a larger set of countries. Do geographic regions tend to have similar levels of information rigidity? Another 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? The stylized facts, in particular the state dependence of information rigidities, raise the question of how information rigidities respond to structural changes in the economy. We leave these areas for future research.

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Table 1: 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 in between information updates as measured by our measure (IR), Andrade and Le Bihan (2013, AL), and Coibion and Gorodnichenko (2013, CG).

Table 2: Information rigidity across professional forecasters

Inflation	Information Rigidity		Significance
Foreign/Domestic	2.44	3.03	***
Global/Local	2.56	3.13	***
Financial/Non Financial	2.78	3.23	***
Veteran/Newcomer	3.03	2.86	*

GDP	Information Rigidity		Significance
Foreign/Domestic	2.27	2.78	***
Global/Local	2.38	2.78	***
Financial/Non Financial	2.56	2.78	**
Veteran/Newcomer	2.78	2.50	***

Note: the symbols ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively for the test of differences in means.

Table 3: Determinants of information rigidity

a) Inflation

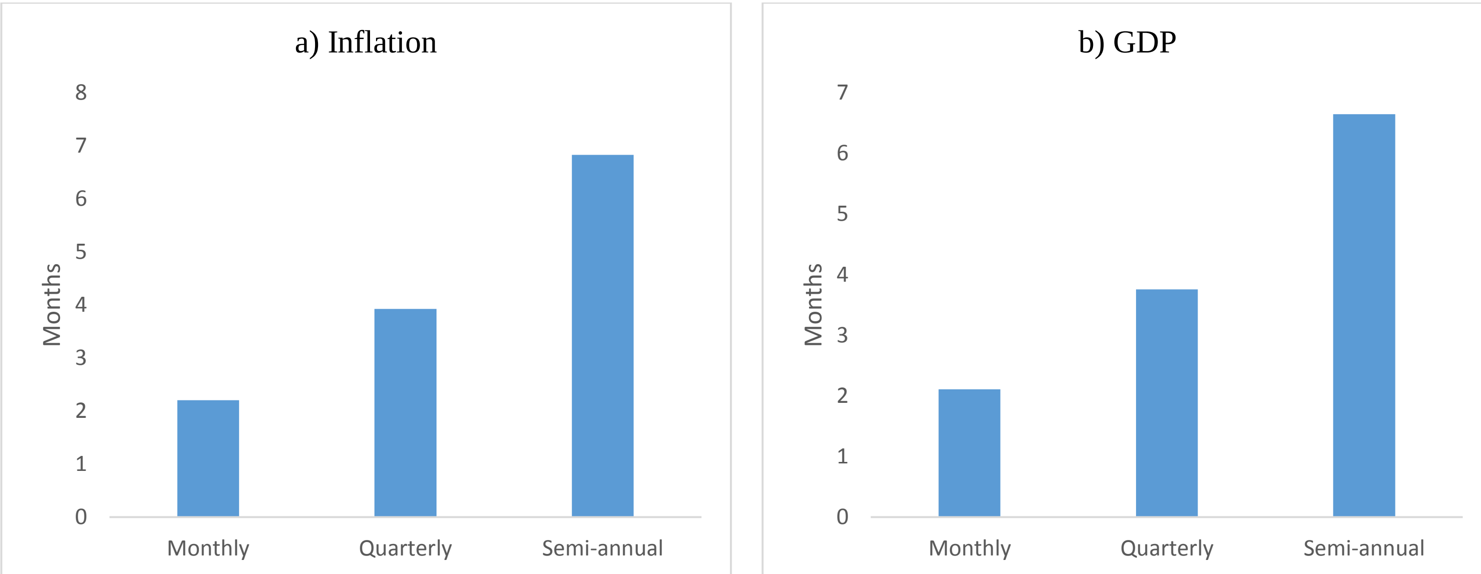
	Current Year		Next Year	
Variables	1	2	1	2
Recession	-0.031***	-0.025**	-0.040***	-0.036***
	(0.011)	(0.011)	(0.011)	(0.011)
CB Transparency	-0.308***	-0.334***	-0.205***	-0.229***
	(0.045)	(0.045)	(0.044)	(0.044)
Market Volatility	0.003	0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Policy Uncertainty	-0.026***	-0.024***	-0.028***	-0.027***
	(0.005)	(0.005)	(0.005)	(0.005)
Own Lag	0.411***	0.404***	0.452***	0.441***
	(0.025)	(0.025)	(0.024)	(0.025)
Conditional Volatility	-0.011***	-0.010**	-0.005	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Market Level		0.004		0.009*
		(0.005)		(0.005)
Disagreement		-0.016***		-0.009**
		(0.005)		(0.005)
Observations	1,590	1,590	1,503	1,503
R-squared	0.934	0.935	0.946	0.946

b) GDP

	Current Year		Next Year	
Variables	1	2	1	2
Recession	-0.034***	-0.024**	-0.042***	-0.035***
	(0.011)	(0.011)	(0.010)	(0.010)
CB Transparency	-0.328***	-0.409***	-0.211***	-0.265***
	(0.048)	(0.048)	(0.045)	(0.045)
Market Volatility	0.006	0.007	-0.018***	-0.018***
	(0.005)	(0.004)	(0.005)	(0.005)
Policy Uncertainty	-0.025***	-0.027***	-0.026***	-0.026***
	(0.004)	(0.004)	(0.005)	(0.005)
Own Lag	0.266***	0.237***	0.373***	0.346***
	(0.026)	(0.026)	(0.025)	(0.026)
Conditional Volatility	-0.017***	-0.012***	-0.004	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Market Level		0.023***		0.017***
		(0.005)		(0.005)
Disagreement		-0.018***		-0.013***
		(0.004)		(0.004)
Observations	1,590	1,590	1,503	1,503
R-squared	0.940	0.942	0.955	0.956

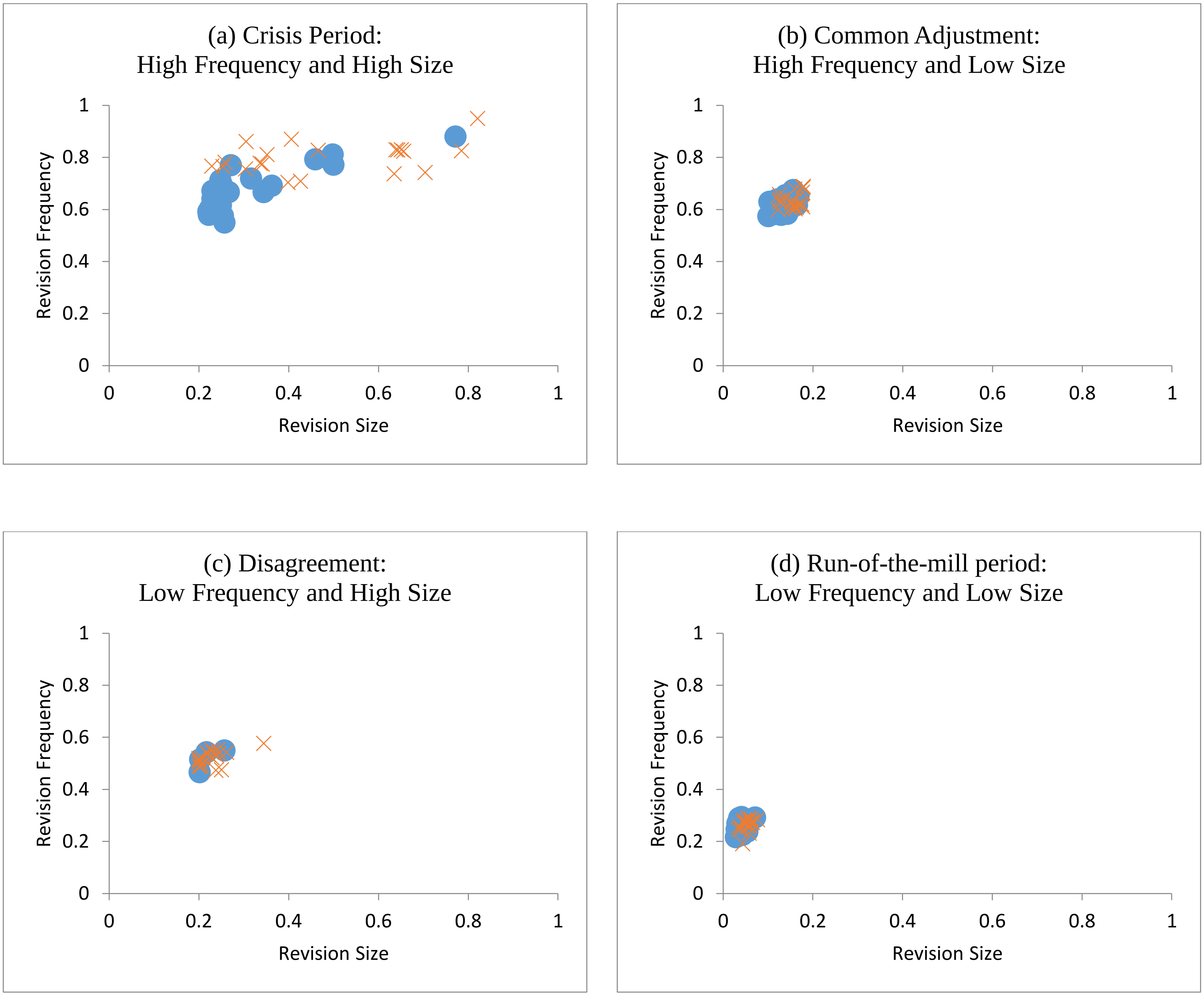
Note: the numbers in parentheses are panel corrected standard errors; ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

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: The frequency and size of forecast revisions



Note: The four cases illustrate the various combinations of frequency and size within the forecast revisions of our sample. We measure frequency as the proportion of forecasters who revise in any given period and size as the magnitude of the forecast revision. The crosses represent the forecast revisions of GDP expectations and circles for that of inflation.

Figure 3: Proportion of forecast revisions

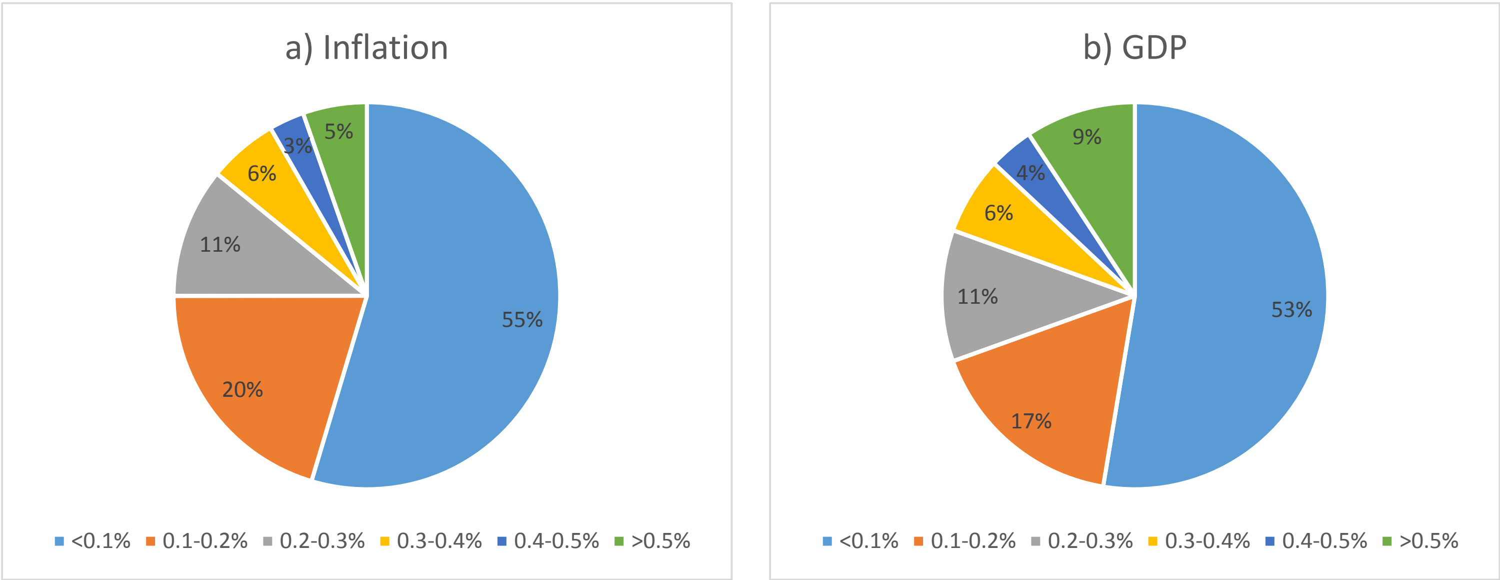
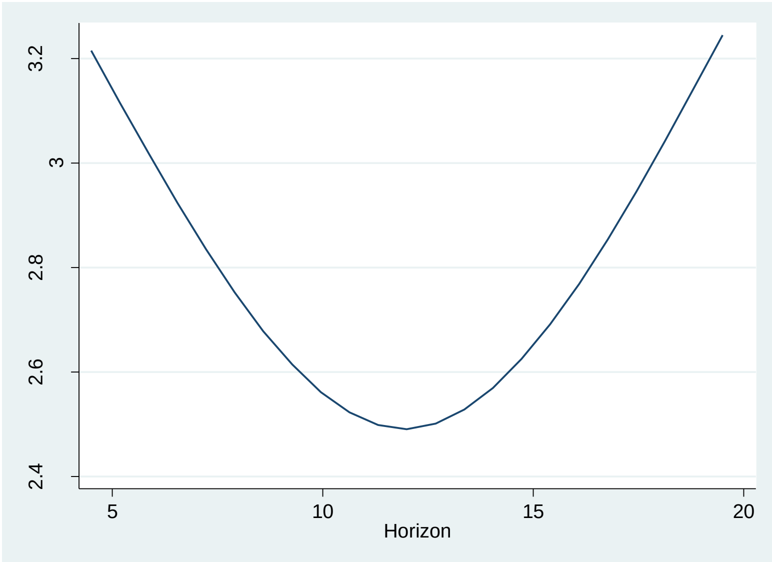
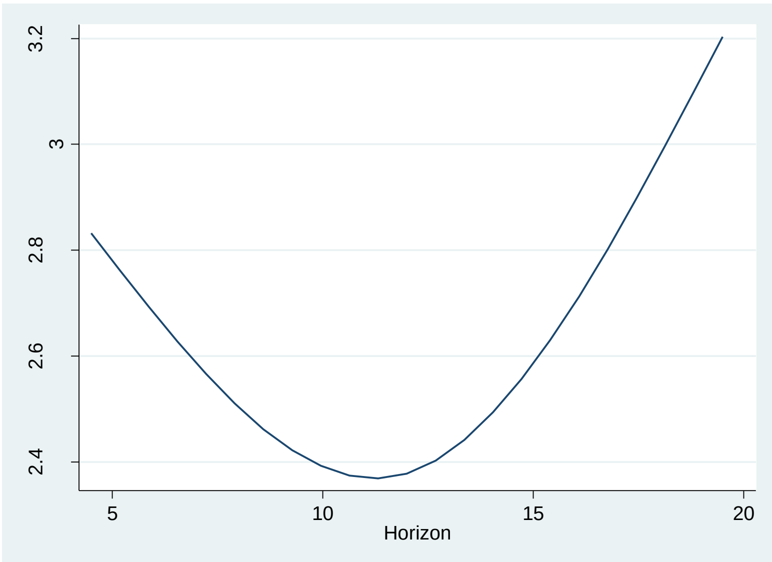


Figure 4: Information rigidity over horizon

(a) Inflation



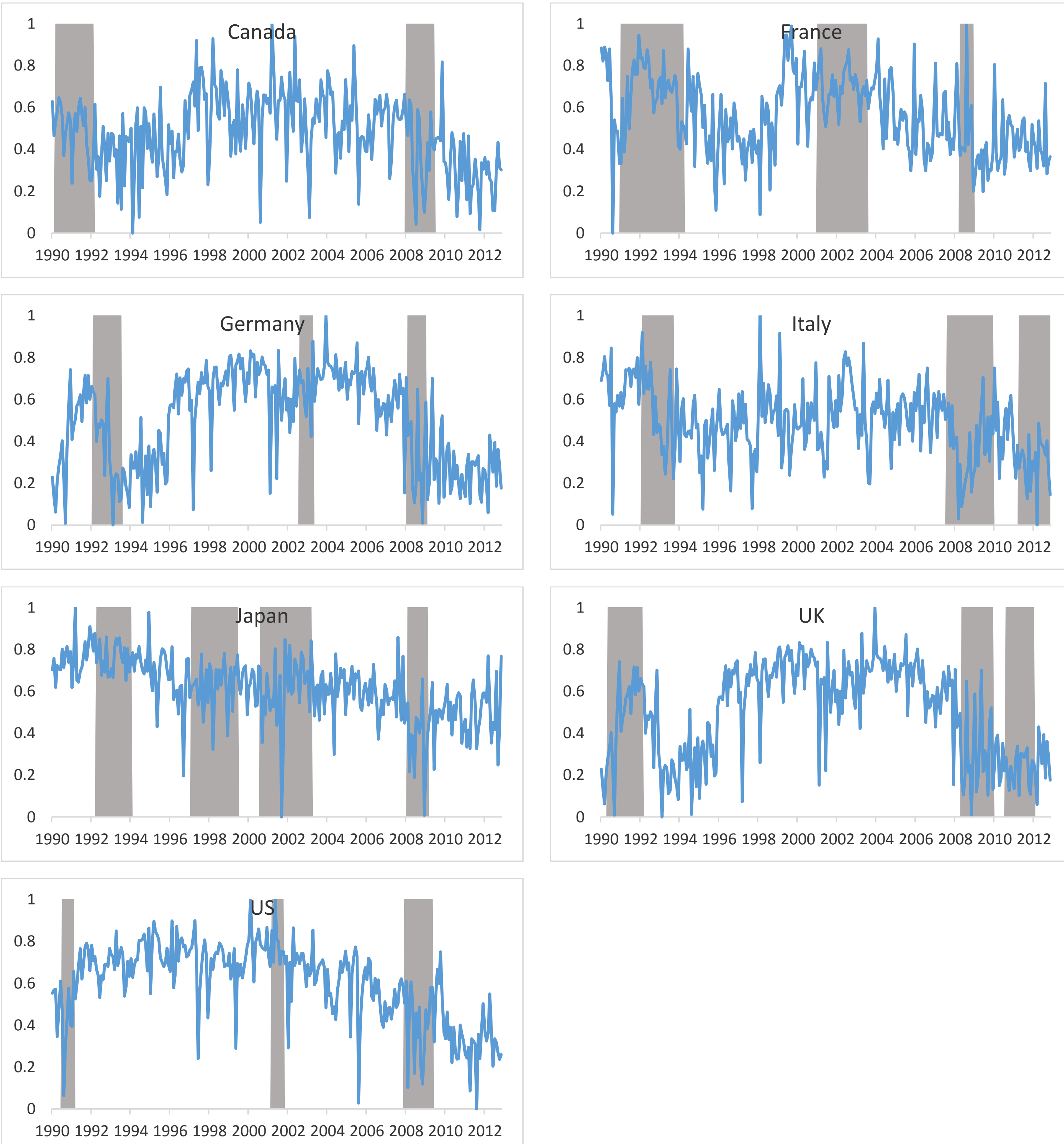
(b) GDP



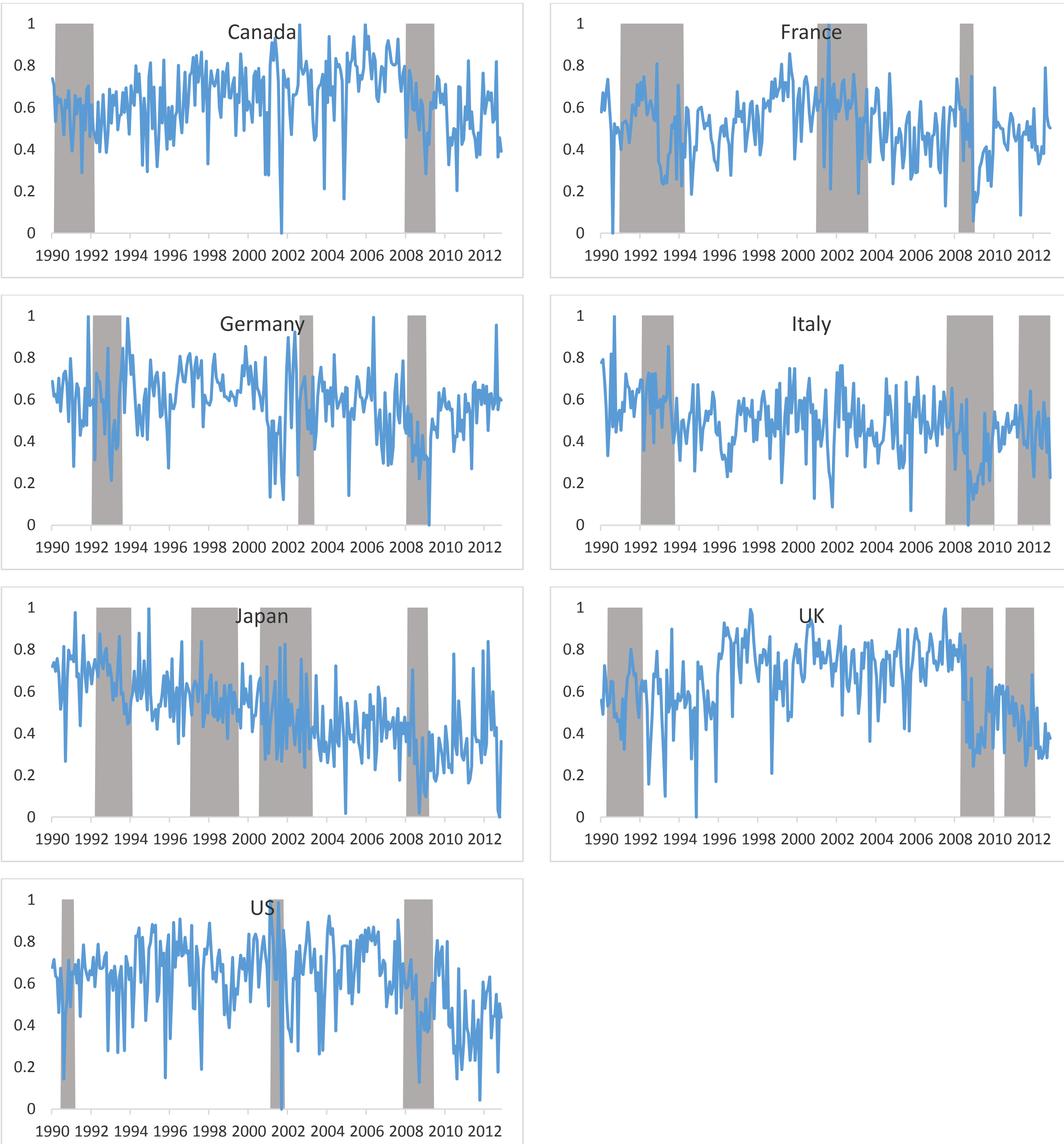
Note: To observe the trends of information rigidity over horizon, we use non-seasonalized information rigidity measured by IR by horizon (23 months ahead to 1 month ahead) and pooled over the G7 countries. We fit a smooth line using a cubic spline with three bands, corresponding to the long, medium, and short term in forecast horizons. Information rigidity and horizon both have units of months.

Figure 5: Information rigidity over time

(a) Inflation



(b) GDP


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