Forecaster Inattention: Measurement, Determinants, and Policy Implications*

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Abstract

Abstract: Building from the theoretical groundwork on imperfect information, we develop a novel measure of inattention as the common component in professional forecasters' inattentiveness to many economic variables. Applying this measure to survey forecasts of the U.S. and G7, we find forecaster inattention of about three to four months on average, with procyclical variation and negative relation to various indicators of uncertainty. The level of inattention has economically significant effects: monetary policy shocks have more persistent real effects when inattention is high, and financial analyst inattention is positively associated with post-earnings-announcement drift.

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1. Introduction

The current resurgence of interest in the expectation 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). Despite these findings, many modern macroeconomic models assume full-information rational expectations. In response, a number of papers explore the potential for frictions to improve macroeconomic models. From this literature, we draw two prominent models of information frictions: 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 inattention 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 limitations 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 four months of inattentiveness using ECB Survey of Professional Forecasters (SPF) data. Coibion and Gorodnichenko (2012) identify an information lag of six to seven months using U.S. SPF data. Mankiw, et al. (2004) find about ten months of inattentiveness from the Livingston survey. The variation in empirical findings reflects the challenges and differing methodologies for measuring information frictions. In response, we propose a micro-data based measure of forecaster inattention defined as the common component in professional forecasters' inattentiveness to many economic variables. Using this measure, we find that forecasters update their information set about three to four months on average. This result follows from two typical surveys of professional forecasters: the U.S. SPF and Consensus Forecasts. We include both surveys to capture long time series and cross-sectional variation. Over time, we find inattention to vary with the business cycle: inattention tends to be low during recessions, periods of financial market volatility, and economic policy uncertainty. Across countries, we find similar effects and small variation in the level of inattention.

This paper is closely related to the literature that estimates information rigidity through survey data, including Carroll (2003), Mankiw et al. (2004) and Coibion and Gorodnichenko (2015). These papers use the aggregate survey forecasts together with a set of auxiliary assumptions about the economy to estimate a structural parameter of information friction. By contrast, we use micro-level data on individual forecasts for a large set of macroeconomic variables to non-parametrically measure inattention and its variation over time and across countries. 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 inattention by (i) using monthly and quarterly, not 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) studying the overall inattention of forecasters, not their inattentiveness in predicting a single variable. Accordingly, our measure of inattention helps avoiding the overestimation of inattentiveness due to low survey frequencies, separating meaningful revisions from superfluously small revisions possibly due to strategic behavior, and capturing the overall inattention rather than the idiosyncratic inattention specific to a particular variable.

The analysis of the dynamics of inattention and its determinants contributes to our understanding of how monetary policy and uncertainty shocks help shape expectations among professional forecasters. Our paper provides new evidence on how enhanced central bank transparency decreases forecaster inattention. This finding illuminates an additional channel through which monetary policies affect the expectations formation process and complements the recent studies that explore the role of central banks in guiding private sector forecasts, e.g. Beechey et al. (2011), Dovern et al. (2012), Ehrmann et al. (2012) and Hubert (2014). Furthermore, 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).

Finally, our paper is closely related to the long literature on the impact of monetary policy on real economy. For example, Woodford (2003) finds that the highly persistent response of real activity to monetary policy can be predicted by the imperfect-information model. Mankiw and Reis (2002) demonstrate that the response of inflation to monetary policy is readily matched by the sticky-information model. Using a dynamic stochastic general equilibrium model with sticky information (SIGE), Reis (2009) shows that the responses of inflation and output to monetary shock implied by the SIGE model match the empirical results very well. In this context, our results from a time-varying structural vector autoregression model show that the same-sized monetary policy shock has more persistent real effects when the degree of inattention is high. In the similar spirit, we find that in the financial markets analyst inattention amplifies the post-earnings-announcement drift and deteriorates market efficiency.

The rest of the paper is organized as follows. Section 2 proposes the measure of forecaster inattention and empirically estimates it using two surveys of professional forecasters. Section 3 explores the potential determinants of the variation in inattention over time and across countries. Section 4 demonstrates how forecaster inattention (i) alters the effect of monetary policy on real activity and (ii) contributes to the drift of stock prices for a long period after earnings announcements. Section 5 concludes.

2. Measuring Forecaster Inattention

2.1. A New Measure of Inattention

Within the literature, we have two prominent measures of inattentiveness with exceptionally different approaches. Based on the aggregate survey forecasts, Coibion and Gorodnichenko (2015, CG hereafter) suggest regressing mean forecast errors on mean forecast revisions. The coefficient on mean forecast revisions, β, maps one to one into the underlying degree of inattentiveness. 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 the degree of 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 friction over the entire time span, instead of showing how inattentiveness may change over time.

Alternatively, the Andrade and Le Bihan's (2013, AL hereafter) measure allows for variation in inattentiveness over time. AL measures the inattention non-parametrically by counting the proportion of forecasters who do not 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.

Ideally, a measure of inattentiveness should directly measure information set updates. However, these information sets are unobservable. Survey forecasts offer an observable proxy for information set updates: forecast revisions. Figure 1 illustrates the mapping from information set to forecast revision. In line with the literature, we interpret no forecast revision as no update to the 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 frictions because forecast revision is the closest proxy to information update. Another complication in using forecast revision as a proxy for information update arises when 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. Finally, the current literature including both CG and AL measures the degree of inattention when forecasting a single variable. However, information friction in predicting any one series does not represent the overall inattentiveness of forecasters. This is important because imperfect information theories of the business cycle typically require the existence of inattention for consumers, firms and workers, not their inattention to a single variable, such as inflation.

To address these challenges, we propose a new measure of forecaster inattention. Let $F_{j,i,t}$ be the forecast made for target variable j by individual i at time t, and forecast revision $R_{j,i,t} = F_{j,i,t} - F_{j,i,t+1}$. We define an indicator function,

$$I_{j,i,t} = \begin{cases} 1 & \text{if } |R_{j,i,t}| \leq \tau_{j,t}; \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Using this indicator, our measure of inattention, IR_t, can be expressed as

$$IR_t = \frac{1}{MN} \sum_{j=1}^{M} \sum_{i=1}^{N} I_{j,i,t} \tag{2}$$

We emphasize two features of these definitions. First, the flexible threshold in the indicator function (1) incorporates both the frequency and size of revisions. When $\tau_{j,t} = 0$, our estimation of inattention to a single variable 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). When $\tau_{j,t} > 0$, the proposed measure distinguishes between information updates and strategic behavior because strategic 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.

Second, forecaster inattention is not equal to the inattention to any single series. Instead, it is a measure of the common variation in inattention to many series. This common variation is critical for the study of business cycles because imperfect information theories typically require the existence of inattention for economic agents, not their inattention to any single variable. As far as the underlying information processes of these economic variables have commonalities, we expect professional forecasters to have common time variation in information rigidities. This feature of definition is supported by the recent studies that emphasize the multivariate nature of expectation formation, such as Banternghansa and McCracken (2009), Andrade et al. (2014) and Dovern (2015).

2.2. *Estimation of Forecaster Inattention*

To estimate the degree of forecaster inattention, we use the datsets from U.S. SPF and Consensus Forecasts (CF) published by Federal Reserve Bank of Philadelphia and Consensus Economics Inc., respectively. We focus on professional forecaster data to study inattentiveness 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 the news, relative to other economic agents. Furthermore, Carroll (2003) describes how the expectations of professional forecasters impact those of households. Due to these characteristics, we expect inattention to be lowest in professional forecasters. Consequently, our findings represent conservative estimates of inattention in the formation of expectations for other economic agents.

The SPF and CF surveys vary across important features, despite the substantial overlap in participants. The SPF survey is anonymous, while the CF is not. The lack of anonymity in the CF survey provides strong incentives for forecasters to be accurate and minimally inattentive. The SPF survey covers a longer time period (1968 to 2015) than the CF survey (1990-2015). However, the CF survey samples at a higher frequency, monthly, compared to the quarterly SPF survey and covers many countries. For the SPF survey, we use two sets of target variables, spanning a wide range of U.S. macroeconomic variables and different time horizons.[1] Similarly, for the CF survey we have a series of macroeconomic variables for the G7.[2] Whether our findings are robust to these differences in survey characteristics is an important test of the consistency of how we measure inattentiveness.

Most empirical studies find information frictions ranging from 4 months to 12 months. These contrasting results reflect the challenges in measuring the unobservable inattentiveness of economic agents: (i) low survey frequencies and (ii) capturing both elements of forecast revisions (size and frequency). First, most surveys of professional forecasters are conducted at low frequencies, such as semi-annually or annually. However, forecasters may update their information sets at much more regular intervals. The frequency of the survey forms an artificial lower bound on the measure of inattentiveness, motivating the use of higher frequency surveys: monthly and quarterly. Second, the size component of forecast revisions provides insight to the motivation behind the forecast revision. Although professional forecasters on average make no revision in half of the periods, the

[1]Spanning from 1968 to 2015, we have seven target variables: nominal GDP, price index of GDP, after-tax corporate profits, civilian unemployment, industrial production, housing starts, and real GDP. From 1981 to 2015, we have an additional ten target variables: three-month treasury bill rate, real personal consumption expenditures, real non-residential fixed investment, real residential fixed investment, real federal government consumption expenditures and gross investment, real state and local consumption expenditures and gross investment, real change in private inventories, real net exports of goods and services, and the CPI inflation rate. More information on each of these variables is available from the Federal Reserve Bank of Philadelphia.

[2]Spanning from 1990 to 2015, we have seven target variables: real GDP, consumption, investment, industrial production, CPI, unemployment, and short and long term interest rates

average revision size is about 2.3%.

Applying our measure, we specifically define the threshold as 5% of the average magnitude of the macroeconomic variable over the past five years. Since surveys often provide forecasts rounded to the first decimal point, we choose 5% of the historical growth level, which yields a threshold comparable to that of a 0.1% forecast revision on average.[3] Furthermore, some variables in the SPF survey are forecasted as levels and have periods with forecast revisions of less than 0.001%; further motivating our threshold approach. Table 1 shows the variation of forecaster inattention across countries and threshold levels. We use the five-year historical average rather than the previous year to avoid spurious jumps in the threshold. [4]

At this threshold, we find the inattentiveness of professional forecasters to be on average about three to four months for both surveys. These findings are 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 expected, the estimates by AL are persistently smaller than that of our measure across all countries and all variables, which is due to our measure including a time-varying threshold. Alternatively, as shown in Table 2, the Coibion and Gorodnichenko's (2015) measure provides a much wider range of inattention across countries: 1.9 to 4.6 months. 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 inattention for professional forecasters. In a January 2014 special survey of the ECB SPF, question 1a asks, "When do you update your forecasts?" About 95% of responding professional forecasters claim to update their forecasts at least quarterly. This frequency is consistent with a

[3]We further restrict the threshold between [0.1%, 0.5%] to ensure that the threshold is not trivially 0 or extraordinarily large.

[4]For robustness, we also consider 1% and 10% of historical average as well as fixed thresholds from the set 0, 0.1%, 0.2% and 0.3%, and the regression results described in Section 3 are qualitatively similar.

November 2009 special survey of the U.S. SPF, see Stark (2013). Of note is that the self-reported level of inattentiveness is consistent over a time span of about four years, indicating a high level of persistence in information frictions. The responses to the special surveys correspond well with our finding of an average of three to four months of inattentiveness.

3. Determinants of Forecaster Inattention

3.1. Hypotheses

Our measure of forecaster inattention allows for cross country and time variation, as illustrated in Figure 2. In this section, we explore the potential determinants of inattentiveness. Inattention tends to be low 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 frictions may rise and fall inversely to the business cycle. We measure this effect through a country specific recession dummy using data from the Economic Cycle Research Institute. Since macroeconomic variables are more volatile in recession periods, we expect inattention to be more costly for professional forecasters during economic downturns.

Similarly, the macroeconomic news received by professional forecasters may be reflected in 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

[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.

institutions, to be less inattentive. Market impacting news related to the target variable may impact both level and volatility. The growth rate in the level of market indices may reflect information on expectations of future economic conditions not contained within market volatility. In periods of high market returns, we expect greater complacency and forecaster inattentiveness to be high.

We expect greater uncertainty to decrease forecaster inattentiveness. This uncertainty may materialize in financial markets, economic sentiment, and forecast disagreement. Similar to the expected negative relation between financial market volatility and inattentiveness, the policy uncertainty may motivate professional forecasters to pay more attention to news. We use the news-based economic policy uncertainty (EPU) by Baker et al. (2013), measured as the frequency of news media references to economic policy uncertainty.[6] Complementing these market and policy 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 affect the economy, we consider the impact of policy on forecaster inattentiveness. 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

[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.

(least to most transparent).[7] We use the change in this measure to capture the effect of monetary policy communication on inattentiveness among economic agents.

Besides the core variables, we also need to control for the stickiness of inattentiveness over time. Notice how in Figure 2, despite the variability of inattentiveness, it tends to persist over time. Overall, professional forecasters require about three to four months to fully incorporate new information. We correct the standard errors for the autocorrelation of inattentiveness.

3.2. Empirical Results

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

$$E(IA_{th}|X_{th}) = G(\gamma + \beta_1 rec_{th} + \beta_2 EPU_{th} + \beta_3 PFD_{th} + \beta_4 CBT_{th} + \beta_5 ML_{th} + \beta_6 MV_{th}) \qquad (3)$$

where $G(\cdot)$ is the logistic function. In equation (3), IA_{th} denotes inattentiveness at time t for country h and is bounded between 0 and 1, γ is a constant, rec_{th} is the recession dummy, EPU_{th} is economic policy uncertainty, PFD_{th} is professional forecaster disagreement, CBT_{th} is central bank transparency, ML_{th} is market level and MV_{th} is market volatility. Based on our hypotheses described in section 3.1, we anticipate negative coefficients on macroeconomic fundamentals related to uncertainty: shown in the predicted sign column of Table 3.

Table 3 presents the regression results for the U.S. using SPF survey data and panel regression results for the G7 using CF survey data. Of note is that despite the differences in survey methodologies, time span, and variable coverage, the magnitude and direction of the coefficients

[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 2015. This is consistent with the methodology of the literature, such as Ehrmann et al. (2012). For the SPF dataset, we use a proxy of central bank communication: the absolute value of the quarterly change in the Federal Fund rate.

are highly comparable. More specifically, we observe negative coefficients on the business cycle, confirming our economic condition hypothesis. Furthermore, both policy uncertainty (EPU) and perceived uncertainty (forecast disagreement) are negatively related to inattention. On average for the G7 countries, entering into a recession ceteris paribus decreases the proportion of forecasters who do not update by 4.5 percentage points. Furthermore, a one standard deviation of perceived uncertainty and policy uncertainty ceteris paribus decreases inattentiveness by 2.2 and 2.7 percentage points, respectively. 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 and significant across all specifications. We interpret this as evidence of inattentiveness falling in tandem with increases to transparency in central bank communication. Although the growth in market level is insignificantly related to inattentiveness, professional forecasters update their information sets in response to market volatility. The similarity of the determinants' effects on inattentiveness across the surveys reflects the robustness of our findings. Overall, the regression results confirm our predictions about the determinants of inattentiveness in professional forecasters.

3.3. Robustness Checks

We perform a series of robustness checks in the choice of specification. For the CF panel regression, we narrow the sample to only the years for which we have variation in the measure of central bank transparency (1998-2010) and find consistent results. Similarly, the findings are not driven by any one country: relations are broadly consistent to excluding each country iteratively. For the marginal effects, we do not find significant non-linear effects for both the SPF and CF survey: the marginal effects are not statistically different across the interquartile range. Supporting this finding, the marginal effects coefficients are comparable to coefficients from a simple OLS regression.

Beyond these determinants of inattention, we considered surprise indices, inflation targeting, and fiscal illusion index. We considered a measure of macroeconomic news surprise, such as Scotti (2013). 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. Furthermore, the correlation between the inattention measure and the Scotti Surprise Index is low, illustrating the differences between forecaster inattention and macro surprise. 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. Policy Implications of Forecaster Inattention

4.1. Time-varying inattention and the impact of monetary policy

In the classical sticky information model, inattention is assumed to be exogenous and constant. However, in the previous sections we find empirical evidence that the probability of agents updating information is time-varying and affected by economic condition. To capture this feature of inattention, we include our measure of inattention into the VAR model using the data from the third quarter of 1970 to the first quarter of 2015.[8] The other variables include CPI inflation rate, industrial production and the Federal funds rate. We place the funds rate the last and inattention before the funds rate to capture the response of inflation and industrial production to monetary policy shock through inattention.

[8] Here we use the measure of inattention based on the SPF 7 variables with long time span from 1970Q3 to 2015Q1.

We use the time-varying parameter structural vector autoregressive model with stochastic volatility (TVP-VAR) originally proposed by Primiceri (2005):

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

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

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ a_{n1,t} & \cdots & a_{nn-1,t} & 1 \end{bmatrix}$$

and Σ_t is the diagonal matrix

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}$$

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

$$\Phi_t = \Phi_{t-1} + u_t, u_t \sim i.i.d.N(0, U) \tag{5}$$

$$a_t = a_{t-1} + v_t, v_t \sim i.i.d.N(0, V) \tag{6}$$

$$log(\sigma_t) = log(\sigma_{t-1}) + w_t, w_t \sim i.i.d.N(0, W) \tag{7}$$

We use the first 10 years to calibrate the prior distribution. The simulations are based on the 110,000 draws of Gibbs sample, where we delete the first 10,000 draws and thereafter select every tenth draw to avoid correlation.

The TVP-VAR approach allows the coefficients and consequently the responses to monetary policy to vary over time. In order to compare the policy impact on inflation and industrial production during high and low inattentiveness periods, we compute the average impulse responses when inattention falls into its top and bottom 10th percentiles. Figure 3 plots the impulse responses together with the 68% error bands. During the low inattention scenario, industrial production immediately drops and then gets back to its original level after four years following a one standard deviation monetary policy shock. During the high inattention scenario, however, the same-sized monetary policy shock has a smaller initial effect on industrial production, but its effect is more persistent, lasting for more than six years. The response of inflation to monetary policy shock displays the usual "price puzzle". Consistent with Reis (2009), the response of inflation reaches its peak after that for industrial production. Similarly, we see that monetary policy shocks have more persistent effect on inflation during the high than low inattention scenarios.[9]

4.2. Financial Analyst Inattention and Post Earnings Announcement Drift

We apply our measure of inattention to financial analysts: professional forecasters of firm earnings. Through our measure, we find a persistent decline in financial analyst inattentiveness in the 1990's. This downward trend flattened in the early 2000's with approximately a quarter of financial analysts remaining inattentive following a firm's earnings announcement as of 2014. This trend may be

[9] To address the impact of zero lower bound for the funds rate after December 2008, we perform the sub-sample analysis for the period from the third quarter of 1970 to the third quarter of 2008. In addition, we replace the funds rate with the shadow rate of Wu and Xia (2015). We find similar results in both exercises.

thought of as a decrease in the cost of financial analysts updating their forecasts, following the sticky information model. Alternatively, we may interpret this decline as an increase in the ability of financial analysts to process the news contained in earnings announcements, following the noisy information model.

To measure financial analyst inattentiveness, we identify the proportion of analysts who do not revise annual EPS estimates after a quarterly earnings announcement. We use I/B/E/S data for individual analyst forecasts for all firms between 1990 and 2014. To measure inattention we require that the analyst continually covers the firm for a fiscal year. Of the analysts covering the firm, we measure the proportion who revise within a five day window following a quarterly earnings announcement. To stably define the proportion, we require that at least five analysts follow the firm.

We apply our measure of financial analyst inattentiveness to study a canonical financial market inefficiency: post earnings announcement drift (PEAD). This well documented anomaly, e.g. Ball and Brown (1968) and Fama (1998), is directly related to the responsiveness of financial markets to earnings announcements. The inattentiveness of financial analysts reflects the inefficiency of the market in response to the information content of earnings announcements. We measure PEAD as the cumulative abnormal return in the 60 trading days following the earnings announcement. Additionally, we define earnings surprise as the percentage difference between the earnings announcement and consensus forecast. We expect firms with surprising earnings and high financial analyst inattentiveness to also have larger PEAD. Table 4 shows the regression results. For all specifications, the coefficients on the interaction term, Inattention*Surprise, are positive and statistically significant at the 1% level. These findings support our hypothesis that PEAD is particularly high for firms with surprising earnings and high analyst inattention. These results are robust to the inclusion of firm fixed effects and other control variables. In addition, the coefficients on all control variables have the correct sign. Specifically, the coefficients on Bad News and Q4 are all statistically significant and negative, implying that analysts are more likely to be responsive to negative earnings surprise and earnings announcements for the fourth quarter of a fiscal year. The coefficient on the number of analysts is negative, implying that when there is greater competition among analysts, they have a higher incentive to revise promptly after earnings announcements, e.g. Cooper et al. (2001).

In sum, a large literature studies the informational content of prices in the context of insiders with private information (see Kyle (1985)) and the release of public information (see Busse and Green (2002)). Within this literature, financial analysts and their forecasts are a focal point of interest. Gleason and Lee (2003) find that price adjustments to analyst revisions are faster and more complete for firms with greater analyst coverage. We contribute to this literature by applying our measure of inattention to financial analysts. After surprising earnings announcements, firms with higher inattentiveness experience much PEAD: a market inefficiency. This effect dominates that of the number of analysts covering the firm. Consequently, not only does the number of analyst covering an equity matter, but also the inattentiveness of the analysts matters for the informational efficiency of markets.

5. Conclusion

We propose a micro-data based measure of inattention that captures the common component in professional forecasters' inattentiveness to many economic variables and takes into account both frequency and size of forecast revisions. From this measure, we find the degree of inattentiveness to be three to four months among professional forecasters. Due to differing economic conditions and policies, the G7 countries have contrasting levels of information frictions. 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 inattentiveness for the U.S.

and the G7. 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. These findings are robust to different surveys, countries and time spans. By highlighting the determinants of inattentiveness, 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 inattention and its characteristics and determinants offer much potential for future research. We demonstrate this by applying our measure to financial analysts and finding a positive relation between PEAD and surprising earnings announcements with inattentive analysts. In the similar spirit, we find that monetary policy shocks have more persistent effects on industrial production and inflation when the degree of inattention is high. Another worthwhile application is to estimate the degrees of information frictions for 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? We leave this for future research.

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Table 1: Forecaster Inattention: Months between Information Update

	SPF		Consensus Forecasts						
Threshold	IR7var	IR17var	Canada	France	Germany	Italy	Japan	UK	US
0.01	3.575	3.572	1.854	2.035	2.182	2.013	2.181	1.871	1.499
0.05	3.581	3.601	2.659	2.758	2.911	2.731	2.545	2.782	2.296
0.1	3.643	3.651	3.532	3.773	3.706	3.381	3.058	3.482	3.234

Table 2: Coibion and Gorodnichenko (2015) Measure of Inattentiveness

	SPF		Consensus Forecasts						
	7var	17var	Canada	France	Germany	Italy	Japan	UK	US
Forecast	0.479***	0.542	0.942***	2.256***	3.603***	1.671***	2.541***	1.744***	1.664***
revision	(0.078)	(0.42)	(0.186)	(0.192)	(0.256)	(0.195)	(0.175)	(0.178)	(0.178)
Months	4.437	4.626	1.942	3.256	4.603	2.671	3.541	2.744	2.664

* p<0.1; ** p<0.05; *** p<0.01

Table 3: Determinants of Inattention

Variable		SPF 7		SPF 17		CF	
	Predicted Sign	Coefficient	Marginal Effect (1 SD)	Coefficient	Marginal Effect (1 SD)	Coefficient	Marginal Effect (1 SD)
Recession	-	-0.216** (0.100)	-3.10%	-0.243*** (0.083)	-3.59%	-0.197** (0.083)	-4.51%
EPU	-	-0.19* (0.105)	-1.08%	-0.132 (0.094)	-0.78%	-0.201*** (0.024)	-2.74%
Forecaster Disagreement	-	-0.372*** (0.053)	-3.09%	-0.423*** (0.079)	-3.31%	-0.122*** (0.045)	-2.22%
Central Bank Policy	-	-0.078* (0.047)	-0.67%	-0.16** (0.063)	-1.41%	-0.246** (0.106)	-0.94%
Market Returns	+	-0.268 (0.461)	-0.31%	-0.151 (0.436)	-0.18%	0.330* (0.184)	0.37%
Market Volatility	-	-0.962* (0.501)	-1.12%	-0.55 (0.53)	-0.66%	-0.306 (0.199)	-0.62%
Constant		-0.44** (0.123)		-0.439*** (0.157)		1.638*** (0.07)	
Observations		177		134		1,752	

* p<0.1; ** p<0.05; *** p<0.01

Table 4: Financial Analyst Inattention and PEAD

PEAD	(1)	(2)	(3)	(4)
Inattention	-0.0443**	-0.0166	-0.0611***	-0.0377**
	(-2.51)	(-0.94)	(-3.20)	(-1.98)
Inattention Surprise	0.0669***	0.0649***	0.0729***	0.0701***
	(3.43)	(3.34)	(3.61)	(3.49)
Surprise	0.0147	-0.0351***	0.0132	-0.0363***
	(1.52)	(-3.55)	(1.33)	(-3.56)
Bad News		-0.2035***		-0.2055***
		(-27.58)		(-25.87)
Q4		-0.0406***		-0.0438***
		(-5.26)		(-5.40)
Analyst Number		-0.0008**		-0.0043***
		(-2.08)		(-8.28)
Year Dummies	Y	Y	Y	Y
Firm Fixed Effects	N	N	Y	Y
N	49370	49370	49370	49370

* p<0.1; ** p<0.05; *** p<0.01

Figure 1: Information update vs. forecast revision

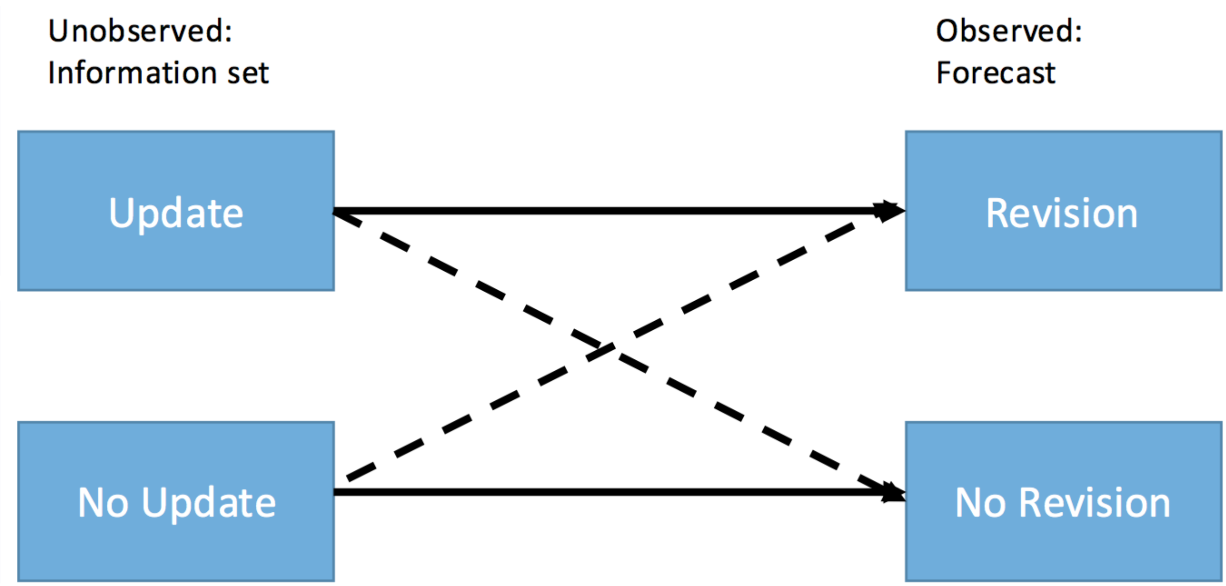
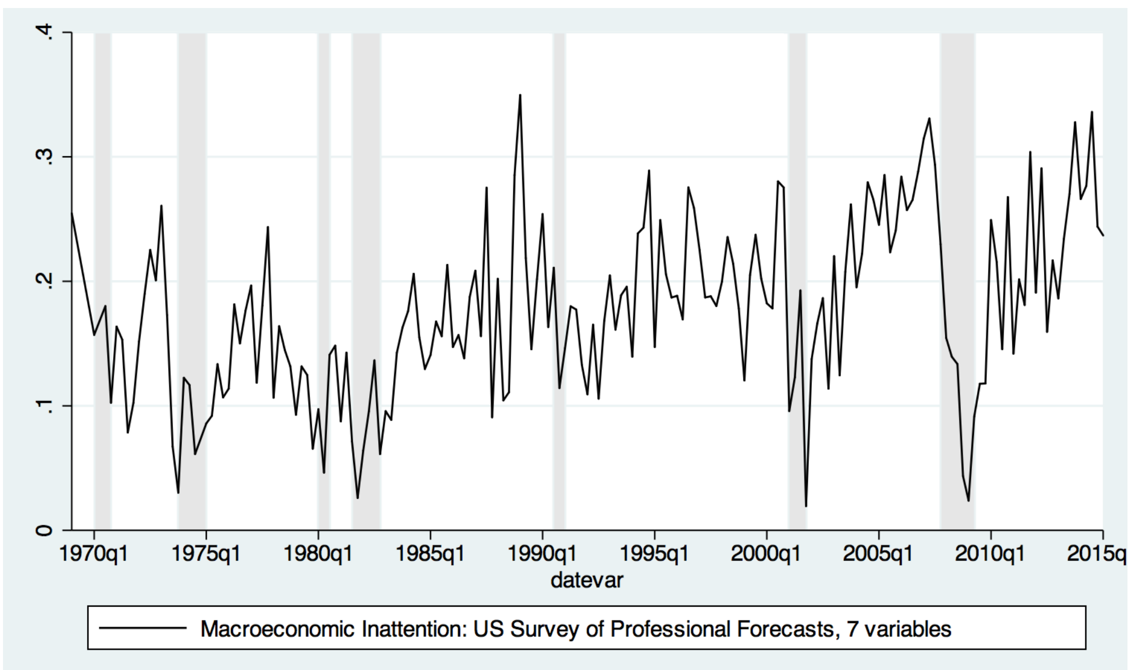
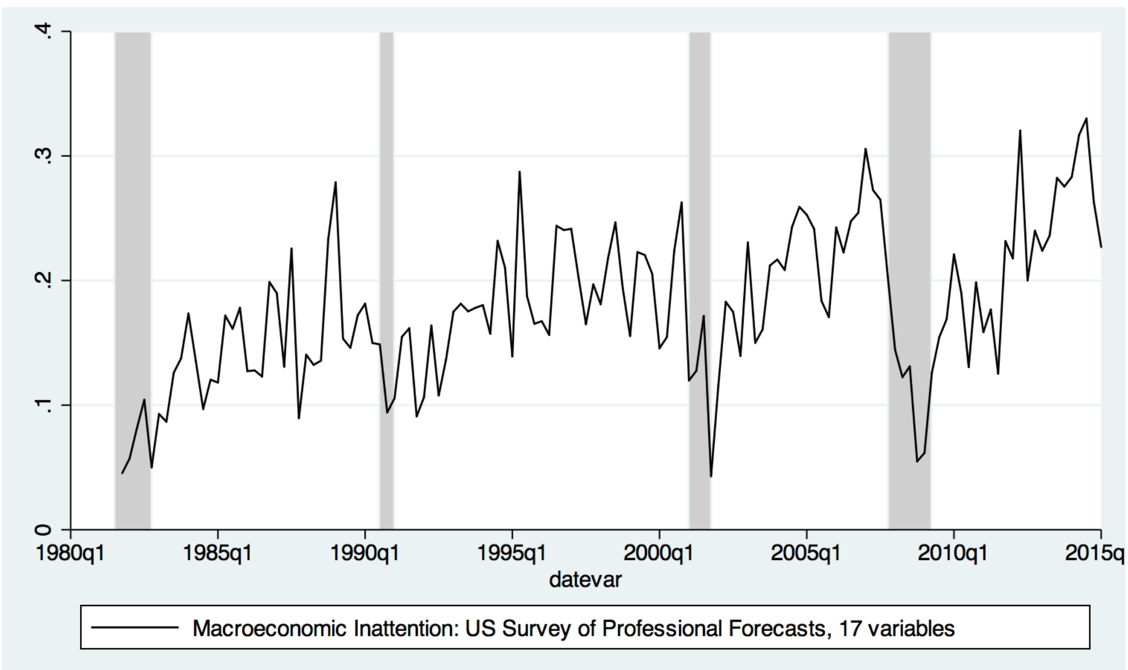


Figure 2: Forecaster inattention over time

Panel A: Survey of Professional Forecasters: 7 variables



Panel B: Survey of Professional Forecasters: 17 variables



Panel C: Consensus Forecasts

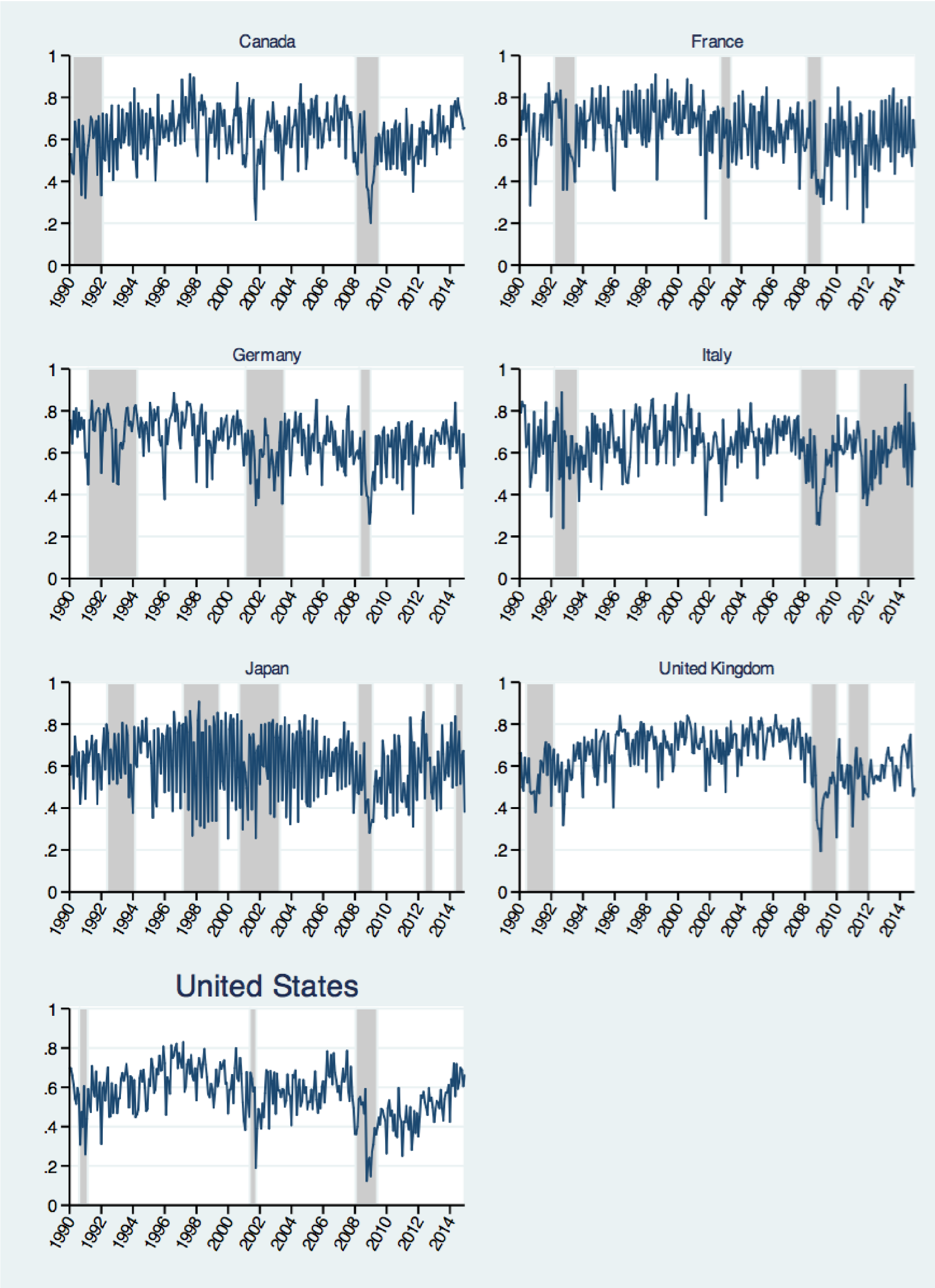


Figure 3: Impulse response function under high and low inattention scenarios