Time-Varying Attention and the Business Cycle*

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Abstract

This paper estimates time-varying information flows/attention to unemployment using cross-sectional variability in the SPF. We use this series of attention along with a standard set of macro time series and three measures of macroeconomic volatility computed by Jurado et al. (2015) to estimate a BVAR. We use this model to identify autonomous movements in attention and study their macroeconomic consequences. We find that these consequences are important and explain a large chunk of macro volatility at business-cycle frequencies. An exogenous increase in attention to unemployment triggers a persistent economic boom. Shocks to the private sector's attention lower macro volatility and, in fact, explain most of the fluctuations in uncertainty at longer horizons. Consistent with rational inattention theory, the private sector's attention rises following an exogenous increase in macroeconomic volatility.

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*The views in this paper are soley those of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of Chicago or any other person associated with the Federal Reserve System.

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1 Introduction

Central banks and policymakers care about the economic expectations of agents in the economy as the actions of these agents directly affect policy objectives. For this reason, there is a growing interest in how economic agents approach the problem of collecting information and using it to form beliefs. Amid this growing interest is an interest in rational inattention models, where rather than facing exogenous constraints on information, agents optimally choose some level of attention to assign to a target variable subject to a capacity constraint. Rationally inattentive agents choose the degree of attention they pay to a variable in response to economic dynamics. Therefore, this degree of attention is likely be subject to changes given different monetary policy actions and underlying economic conditions.

This paper proposes a framework for estimating attention that tracks time variation using subjective expectations. This allows us to view changes in the expectations formation process in light of changes to macroeconomic processes over time. We find that forecasters' degree of attention to unemployment exhibits considerable time-variation and further that attention is highest in times where forecasters are anticipating a downturn. Attention is higher in periods where the labor market is very tight and lower in periods where the labor market has a high degree of slack. Furthermore, the anxious index, or agents' subjective belief in recession is positively correlated with the level of attention in a period.

This result is, on its own, somewhat counterintuitive. Using a 10-variable quarterly BVAR, we show that an exogenous shock that increases attention results in a decline in macroeconomic uncertainty and a persistent economic boom. This means that the increase in attention that precedes a recession must be correlated with underlying macroeconomic conditions that create recessionary outcomes. Using the same BVAR, we show that a contemporaneous shock to macroeconomic uncertainty as defined in Jurado, Ludvigson, and Ng 2015 and attention to unemployment will generate a bust.

With these stylized facts in mind, we propose a model of endogenous attention in which agents allocate attention to learning about *current* shocks. Agents have diminishing payoffs and are rationally more concerned about shocks that negatively affect them. A negative shock results in an uptick in attention which in turn generates a stronger response to the shock. As increased attention increases the response of agents' actions to shocks, agents' behavior more strongly affects macroeconomic outcomes in high attention period. Accordingly, high attention periods are linked to an increased the likelihood of recession.

To construct our time-varying measure of inattention, we exploit heterogeneity in responses to information across forecasters. There is a large literature considering heterogeneity in both expectations and the way that agents learn about a process. Armantier et al. 2016 find differential responses to a price information experiment embedded in the Survey of Consumer Expectations across demographic groups. Madeira and Zafar 2015 document heterogeneity in both inflation expectations and learning. Malmendier and Nagel 2016 argues that consumers overweight their own inflation experiences in forming their inflation expectations. The current paper differs from these papers mostly in that it considers the response to information about *unemployment* rather than inflation. We further assume that heterogeneity in expectations and learning comes primarily from the macroeconomic and business cycle conditions at play during the period in which agents form their forecasts. We further consider professional forecasters rather than consumers.

This paper further relates to a literature on rational inattention initiated by Sims 2003 and Mackowiak and Wiederholt 2009. Within this literature, the current paper is most similar to Kamdar 2018, who finds that beliefs about inflation and unemployment are linked and largely driven by sentiment, or optimism or pessimism. She explains this by developing a model in which rationally inattentive consumers learn about both prices and labor market slack. Empirically, this paper is similar to Afrouzi 2017 who calibrates a rational inattention model and backs out estimates of noisy information parameters, which is the approach of our paper in reverse. Theorhetically, this paper relates to Carroll 2003 and Mackowiak and Wiederholt 2015.

Our approach begins with the empirical estimation of a noisy information model making this paper similar to Andrade and Le Bihan 2013, Coibion and Gorodnichenko 2015, Coibion and Gorodnichenko 2012, and Ryngaert 2018. It further relates to extensions of imperfect information models such as Melosi 2017.

The paper is organized as follows. Section 2 discusses our approach for estimating time variation in attention and presents our results. Section 3 describes the Bayesian VAR and desSection 4 presents our rational inattention model to explain the stylized facts we observe. Section 5 explores the robustnest of our empirical results. Section 6 concludes.

2 Time-Varying Attention

In this section we develop an approach for estimating the amount of attention, given by the information flow, in a specific period. We estimate a noisy information model on individual forecaster data and aggregate individual-level parameters to form estimates for each period. We then transform this parameter into a measure of information flow.

2.1 Model and Estimation

We begin with a simple Kalman filter model in which agents predict a fundamental, x_t, according to a linear combination of the their past beliefs about the fundamental and a private signal that they receive. While signal processing via methods like the Kalman filter commonly appear in noisy information models, these same methods can be used in a rational inattention framework. In noisy information models, agents receive exogenously imperfect signals. As their information is imperfect, they cannot fully trust their signals and place a portion of the weight of their new expectation on prior beliefs. On the other hand, rationally inattentive agents face a capacity constraint on processing information and therefore view attention to any particular variable as costly. The precision of agent signals in rational inattention models is, therefore, endogenously generated and left up to agent choice.

Mackowiak, Wiederholt, and Matejka 2017 show that, given a fundamental that evolves according to an AR(1) process, the optimal signal chosen by a rationally inattentive agent has the same structure as a basic noisy information signal. Accordingly, we allow the fundamental to follow an AR(1) and follow Sims 2003 and Woodford 2002 in specifying the following noisy information model.

$$x_t = \mu + \rho x_{t-1} + w_t. \tag{1}$$

Agents optimally select signals of the form:

$$z_t(i) = x_t + v_t(i) \tag{2}$$

where $w_t \sim N(0, \sigma_w^2)$ and $v_{it} \sim N(0, \sigma_v^2(i))$. Each forecaster chooses their signal noise variance, $\sigma_v^2(i)$, consistent with rational inattention models over noisy information models. The constant in the transition equation, μ, allows the fundamental to converge to a non-zero long run mean. The agent forms her time-t expectation of x_t according to the following equation:

$$\begin{aligned}\tilde{x}_{t|t}(i) &= k_i(z_t) + (1-k_i)\tilde{x}_{t|t-1} \\ &= k_i(\pi_t + v_{it}) + (1-k_i)\tilde{x}_{t|t-1} \\ &= k_i\pi_t + (1-k_i)\tilde{x}_{t|t-1} + k_i v_{it}\end{aligned} \tag{3}$$

The steady state Kalman gain, k_i has the following representation:

$$k_i = \frac{P_{t|t-1}(i)}{\sigma_{v,x}(i)^2 + P_{t|t-1}(i)}$$

The a priori covariance of the estimate, $P_{t|t-1}(i)$, represents the forecaster's perceived variance, or uncertainty, of the time-t state conditioned on signals received up to period t-1. As she enters time t and receives signal z_t(i), she updates this uncertainty estimate to $P_{t|t}(i) = (1-k_i)P_{t|t-1}(i)$. A forecaster can reduce her uncertainty about a particular variable by allocating attention to it. Models of rational inattention rely on placing constraints on information flow or the reduction in uncertainty that results from attention; forecaster can generate information flow up to a specified capacity constraint and will therefore optimally choose to limit attention.

Using entropy as a measure of uncertainty, as in Mackowiak and Wiederholt 2009, it is possible to define information flow as the difference between the entropy of a random variable, $\mathbf{x}$, prior to receiving the signal z_{it} and the conditional entropy of $\mathbf{x}$ given the signal $z_t(i)$. The entropy of $\mathbf{x}$ prior to receiving $z_t(i)$, given that x_t is normally distributed with conditional variance $\sigma^2_{x|z_{t-1}(i)}$ is:

$$H(x|z_{t-1}(i)) = \frac{1}{2}log_2(2xe\sigma^2_{x|z_{t-1}(i)}). \tag{4}$$

The conditional entropy given signal $z_t(i)$ is:

$$H(x|z_{it}) = \frac{1}{2}log_2(2xe\sigma_{x|z_t}(t)^2). \tag{5}$$

Given these two terms, the information flow for a univariate process is equal to the mutual information between the two, defined as:

$$I(x; z_t(i)) = H(x|z_{t-1}(i)) - H(x|z_t(i)). \tag{6}$$

As the a priori estimate covariance establishes the agent's uncertainty about the state before realizing her signal, let $\sigma^2_{x|z_{t-1}(i)}$ take the value of the a priori variance of the state estimate, $P_{t|t-1}(i)$. Following the observation of the signal, the agent's estimate covariance updates to $P_{t|t}(i)$. Therefore, we can consider $P_{t|t}(i)$ an estimate of the conditional variance $\sigma_{x|z_t(i)}$. Each individual's information flow now takes the form:

$$\begin{aligned} I(x; z_t(i)) &= \frac{1}{2} log_2(2xeP_{t|t-1}(i)) - \frac{1}{2} log_2(2xeP_{t|t}(i)) \\ &= \frac{1}{2}\left[log_2(P_{t|t-1}) - log_2(P_{t|t})\right] \end{aligned}$$

Using the relationship between the two uncertainty estimates, $P_{t|t}(i) = (1 - k_i)P_{t|t-1}(i)$, it is possible to rewrite this as:

$$\begin{aligned} I(x; z_t(i)) &= \frac{1}{2}\left[log_2(P_{t|t-1}(i)) - log_2((1 - k_i)P_{t|t-1}(i))\right] \\ &= \frac{1}{2}\left[log_2(P_{t|t-1}(i)) - log_2(1 - k_i) - log_2(P_{t|t-1}(i))\right] \\ &= -\frac{1}{2} log_2((1 - k_i)). \end{aligned} \tag{7}$$

As k_i is bounded between 0 and 1, this term is guaranteed to be nonnegative. Information flow is also greater than zero as long as $k_i > 0$ or as long as agent signals contain some informative content.

Changing underlying economic conditions over time will induce a different choice of signal noise variance, $\sigma^2_v(i)$. This choice leads to a different Kalman gain, k_i, and a different information flow, $I(x|z_t(i))$. We should accordingly expect information flow to differ across agents based on the time periods that they participate in the sample.

From Equation 7, it is clear that one only needs an estimate of the individual-specific Kalman gain to obtain an estimate of the individual's information flow. I estimate k_i for the individuals in the sample by running a constrained regression of the agent's forecast of x_t on her lagged forecast of the same event and on the realization of x_t, which is the observable part of her signal.

$$\tilde{x}_{t|t} = \beta_0(i) + \beta_1(i)x_t + \beta_2(i)\tilde{x}_{t|t-1} + \epsilon_t \tag{8}$$

We impose the constraint $\beta_1 + \beta_2 = 1$ as $\beta_1 = \hat{k}_i$ and $\beta_2 = (1 - \hat{k}_i)$. The errors in the above equation have a structural interpretation as signal noise terms, scaled by each agent's Kalman gain. I expect that the agents forecasting equation will not include a constant term and therefore want to check that the regression constants do not differ from 0.

The information flow for each individual is a monotonic transformation of $\hat{k}_i$, $\hat{I}(x; z_t(i)) = -\frac{1}{2}log_2((1 - \hat{k}_i))$. The aggregate information flow is calculated using the same transformation of the *aggregate* Kalman gain for the period: $\overline{k_t} = \frac{\sum_i \hat{k}_i 1_t(i)}{\sum_i 1_t(i)}$, where $1_t(i)$ is an indicator equal to one if forecaster i is present in period t. While changes in the time-average of attention occur due to changes in the composition of sample, it remains the case that, over time, the sample may transition to higher or lower attention individuals. As rationally inattentive forecasters will respond to changing underlying economic conditions with adjustments to attention, observing forecasters present in different periods will give estimates of inattention in those periods.

2.2 Data

The data for this estimation comes from the Survey of Professional Forecasters, a quarterly survey conducted by the Federal Reserve Bank of Philadelphia.[1]. Several design features of this survey make it desireable for this estimation. First, the survey began in 1968 tracking several macroeconomic variables. This allows for the examination of attention across several influential periods in monetary policy including the high inflation of the 1970s followed by the Volcker Disinflation and Great Moderation. Second, the survey consists of a highly unbalanced panel, meaning that not all forecasters are observed for all periods. This allows us to estimate the information flow for individuals who are present in different periods and therefore differentially exposed to different policy regimes and underlying conditions.

The survey includes several macroeconomic variables since its inception in 1968. These variables include the GDP price deflator, unemployment, real GDP. I form each of these variables except for unemployment into projected growth rates. I use the quarterly nowcast of each variable as $\tilde{x}_{t|t}(i)$ and use the final release measure of each as variable to represent the realization or the observable part of the signal. Each forecaster's lagged expectation of time-t x is proxied by the lag of the quarter-ahead forecast.

[1]The American Statistical Organization and the National Bureau of Economic Research conducted the survey prior to 1990.

2.3 Results

Figure 1 shows the average information flow to in each period. Figure 2 shows the aggregate information flow to real GDP and inflation over the same period. Information flow to unemployment shows considerable time variation and is on average higher than the information flow to other variables. Information flow to real GDP and inflation declines slightly over the sample period.

We focus the remainder of our analysis on attention to unemployment and explore the relationship between aggregate attention and forecasters' perception of the business cycle. We further focus on the the period 1984 - present. Figure 3 shows the relationship between attention (information flow) and the unemployment gap.[2] Attention is presented deviations from the average information flow across the period. There is a negative relationship between slack in the labor market. When unemployment is well above the natural rate, agents allocate relatively little attention to unemployment. As the labor market tightens, attention increases.

Forecasters may direct attention to the labor market as slack diminishes because they anticipate a negative shock and a business cycle downturn. The Survey of Professional Forecasters includes a measure of the expected probability of recession. Survey participants are asked to report the probability of a recession both in the current quarter and over the next four quarters. The anticipated probability of recession in the next quarter is known as the anxious index. Figure 4 plots the relationship between the average expected probability of recession both in the current period and one to four quarters from the forecasting period and the aggregate information flow or level of attention.

This figure shows that expectations of a *current* recession are actually decreasing in information flow. This reflects that the labor market and that forecasters understand that the current period includes exhibits very low unemployment and, accordingly, tightness in the labor market. This relationship changes as we look at periods further away from the current forecasting period. While no significant relationship exists between the anxious index and the attention level, the expected probability of recession in periods two to four is significantly increasing in information flow. The relationship further becomes steeper for periods further away from the forecasting period. This means that forecasters anticipate that a recession becomes more likely as more

[2]The unemployment gap is calculated as the difference between the quarterly long run natural rate of unemployment and the current quarterly unemployment rate. Both of these are pulled from the Federal Reserve Bank of St. Louis FRED.

time goes passes. This is consistent in a model in which agents believe that a contraction will inevitably follow a period of such labor market tightness.

3 Evidence from Bayesian VAR

We run our BVAR estimate using quarterly data. The data are ordered in the VAR model as follows:

1. Real Gross Domestic Product (SAAR, Bil.Chn.2012$). Log levels. Source BEA
2. Real Personal Consumption Expenditures (SAAR, Bil.Chn.2012$). Log levels. Source BEA
3. Real Gross Private Domestic Investment (SAAR, Bil.Chn.2012$). Log levels. Source BEA
4. CPI-U: All Items Less Food and Energy (SA, 1982-84=100). Quarterly growth rate annualized and in percent. Source: BLS
5. Civilian Unemployment Rate: 16 yr + (SA, percentage). Percentage. Source: BLS.
6. Federal Funds [effective] Rate (percentage p.a.). Average of daily figures. Annualized rates in percent.Source: FRB
7. Macro Volatility at one-month horizon. Percentage. Source: Jurado, Ludvigson, and Ng 2015.
8. Macro Volatility at one-quarter horizon. Percentage. Source: Jurado, Ludvigson, and Ng 2015.
9. Macro Volatility at one-year horizon. Percentage. Source: Jurado, Ludvigson, and Ng 2015.
10. Attention to current unemployment rate. Percentage quarter-over-quarter growth rate.

The sample period ranges from 1971Q1-2019Q1. We estimate a BVAR with four lags. [3] We adopt a unit-root prior Sims and Zha 1998 for the parameters of this empirical model with a

[3] Compared to the frequentist approach the Bayesian methodology allows us to more reliably estimate VAR models with a larger number of observables because of the prior shrinkage. Furthermore, this approach does not lead to spurious estimates when non-cointegrated data are used (Sims and Uhlig 1991).

presample of eight quarters. As is standard, the number of lags and the hyperparameters pinning down the prior are chosen so as to maximize the marginal likelihood. We perform Bayesian estimation of this VAR model with four lags and the ten observable variables described earlier.

Once the posterior distribution for the parameter of the VAR model is computed with the Gibbs sampler, we use the Cholesky factorization to identify two shocks of interest. The tenth shock is a shock that moves only attention contemporaneously. We interpret this shock as changes in attention that are orthogonal to any current and past changes in the macro variables included in the VAR model. As such, these variations in attention can be interpreted as autonomous changes in people's ability to process information. This changes may occur as a result of the media industry (newspapers, social network etc) focusing more on labor-market developments and producing more news about it, which arguably help the private sector get a to get cleaner signals about the unemployment rate. In addition, these exogenous changes in attention can be interpreted as shock to the parameter that controls the maximum amount of information rationally inattentive agents can process in the model introduced byMackowiak and Wiederholt 2009. The impulse responses to this shock can be seen in Figure 5.

The second shock we want to identify is a shock to the macroeconomic volatility. We shock the seventh column of the Cholesky representation of the estimated variance and covariance matrix. This is a shock that moves the three measures of volatility as well as the private sector's attention contemporaneously. From the rational inattention theory we know that agents pay more attention to macro aggregates when the macroeconomy becomes more volatile (Mackowiak and Wiederholt 2009). These shocks do not move the other six macro variables in our VAR model. The impulse responses to this shock can be seen in Figure 6.

4 Model of Limited Attention

We develop a simple non-linear model in which agents can pay only limited attention to current shocks. In every period, agents decide how much "bandwidth" (i.e., their total level of attention) to use to learn about the shocks that have hit the economy today. Using more bandwidth lowers their utility. For simplicity, we assume that there is only one aggregate shock. Since agents' objective function is characterized by diminishing payoffs, agents are relatively more concerned about the consequences of shocks that negatively affect their payoffs. As a result, agents will respond to negative shocks by buying more bandwidth. As this bandwidth expands, the shocks turn out to have stronger and stronger effects on agents' behavior and hence on macroeconomic outcomes, raising the probability of a recession in the near future. While this model is stylized because of the complexity of solving nonlinear models with endogenous attention, it explains the earlier stylized facts: Agents tend to pay more attention to aggregate conditions, which are proxied by the unemployment gap, before a recession occurs.

5 Robustness

We consider two alternative estimations for the measure of unemployment. The first alternative approach includes all three states in the equation estimating the noisy information model. The second estimates time-variation using a rolling window approach.

5.1 Multi-State Updating

In this section, we allow forecasters to update their expectations considering multiple variables at once. Allow n states, $\mathbf{x}_t = [x_1 \dots x_n]'$ and a $n \times 1$ signal vector, $\mathbf{z}_t$.

We assume each state evolves according to an AR(1) and each signal contains information about only one state.

$$\mathbf{x}_t = \begin{bmatrix} \rho_1 & 0 & \dots & 0 \\ 0 & \rho_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \rho_n \end{bmatrix} \mathbf{x}_{t-1} + \mathbf{w}_t$$

In this case, the Kalman gain, K_i is a $n \times n$ matrix and forecasters update according to :

$$\tilde{\mathbf{x}}_{t|t}(i) = K_i z_t + (I_n - K_i H)\tilde{x}_{t|t-1} = K_i z_t + (I_n - K_i)\tilde{\mathbf{x}}_{t|t-1} \quad (9)$$

The estimation equation for the l-th elecment of vector $\mathbf{x}_t$ then becomes:

$$\tilde{x}_{l,t|t}(i) = \beta_0(i) + \sum_{j=1}^{n}[\beta_{1,j}(i)x_{j,t} + \beta_{2,j}(i)\tilde{x}_{j,t|t-1}(i)] + \epsilon_t(i) \quad (10)$$

The coefficients in the above equation have the following mapping to the Kalman filter model:

$$\beta_{1,j}(i) = \begin{cases} 1 - k_{l,j}(i) & j = l \\ -k_{l,j}(i) & j \neq l \end{cases}$$

$$\beta_{2,j}(i) = k_{l,j}(i)$$

Accordingly, we impose the following constraints on the individual level regressions:

$$\beta_{1,j}(i) + \beta_{1,j}(i) = \begin{cases} 1 & j = l \\ 0 & j \neq l \end{cases}$$

The results of an estimation that includes all three variables at once is presented in Table 7. The blue series present the estimates from the single state model that appears in Section 2. The red series present estimates from a model estimated with all three states included, as in Equation 10. For each variables estimates - unemployment, real GDP, and GDP inflation, both series look similar. We therefore focus our analysis on the series estimated from a single-state model for simplicity.

5.2 Rolling Window

As the survey of professional forecasters includes entry and exit, we may worry that the aggregates are sensitive to periods in which many forecasters enter the survey at once. To check for this, we estimate the Equation 8 for unemployment using a rolling window of 20 quarters. We would like to keep the window small to get a feeling for time-variation. However, because the realized unemployment rate is used as a proxy for the unemployment rate, this value does not vary across forecasters within a period. Therefore, we must include a sufficiently large number of periods to ensure that there is sufficient variation in the value of x_t across individuals.

Figure 8 shows the estimates from Section 2 alongside the rolling window estimates. The estimate for each date is the estimate obtained from the window in which the given date falls in the middle. The rolling window estimates show greater fluctuations in aggregate attention, but the pattern of declines and increases is the same as our baseline estimates.

6 Conclusion

Rational inattention models are useful for modeling a rational limited response to information and for modeling the slow propagation of shocks through the economy. What is not as well understood is how attention actually changes in response to macroeconomic conditions and business cycles. This paper uses survey data to answer that question. We propose a new method for measuring the average degree of attention paid to macroeconomic variables. We note time-variation in attention to unemployment and, strikingly, that attention to unemployment increases in time periods likely to be followed by recession. We further consider a model of limited attention in which agents rational decide to pay more attention following negative shocks. Their increased attention to negative shocks in generates a behavioral response which actually increases the probability of recession. This link between attention and perceived business cycles can prove informative for policymakers structuring their communications.

References

Afrouzi, Hassan (2017). "Strategic Inattention, Inflation Dynamics and the Non-Neutrality of Money". Mimeo.

Andrade, Philippe and Hervé Le Bihan (2013). "Inattentive Professional Forecasters". In: *Journal of Monetary Economics* 60.8, pp. 967–982.

Armantier, Olivier et al. (2016). "The Price is Right: Updating Inflation Expectations in a Randomized Price Information Experiment". In: *Review of Economics and Statistics* 98.3, pp. 506–523.

Carroll, Christopher D. (2003). "Macroeconomic Expectations of Households and Professional Forecasters". In: *Quarterly Journal of Economics* 118.1, pp. 269–298.

Coibion, Olivier and Yuriy Gorodnichenko (2012). "What Can Survey Forecasts Tell Us About Informational Rigidities?" In: *Journal of Political Economy* 120.1, pp. 116–159.

— (2015). "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts". In: *American Economic Review* 105.8, pp. 2644–2678.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng (2015). "Measuring Uncertainty". In: *American Economic Review* 105.3, pp. 1177–1216.

Kamdar, Rupal (2018). "The Inattentive Consumer: Sentiment and Expectations". Mimeo.

Mackowiak, Bartosz and Mirko Wiederholt (2009). "Optimal Sticky Prices under Rational Inattention". In: *American Economic Review* 99.3, pp. 769–803.

— (2015). "Business Cycle Dynamics under Rational Inattention". In: *Review of Economic Studies* 82.4, pp. 1502–1532.

Mackowiak, Bartosz, Mirko Wiederholt, and Filip Matejka (2017). "Strategic Inattention, Inflation Dynamics and the Non-Neutrality of Money". Mimeo.

Madeira, Carlos and Basit Zafar (2015). "Heterogeneous Inflation Expectations and Learning". In: *Journal of Money, Credit and Banking* 47.5, pp. 867–896.

Malmendier, Ulrike and Stefan Nagel (2016). "Learning from Inflation Experiences". In: *Quarterly Journal of Economics* 131.1, pp. 53–87.

Melosi, Leonardo (2017). "Signaling Effects of Monetary Policy". In: *Review of Economic Studies* 84.2, pp. 853–884.

Ryngaert, Jane (2018). "What Do (and Don't) U.S. Forecasters Know about Inflation?" Mimeo.

Sims, Christopher A. (2003). "Implications of Rational Inattention". In: *Journal of Monetary Economics* 50.3, pp. 665–690.

Sims, Christopher A. and Harald Uhlig (1991). "Understanding Unit Rooters: A Helicopter Tour". In: *Econometrica* 59.6, pp. 1591–1599.

Sims, Christopher A. and Tao Zha (1998). "Bayesian Methods for Dynamic Multivariate Models". In: *International Economic Review* 39.4, pp. 949–968.

Woodford, Michael (2002). "Imperfect Common Knowledge and the Effects of Monetary Policy". In: *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund Phelps*. Princeton Univ. Press.

Table 1: Individual Kalman Gains

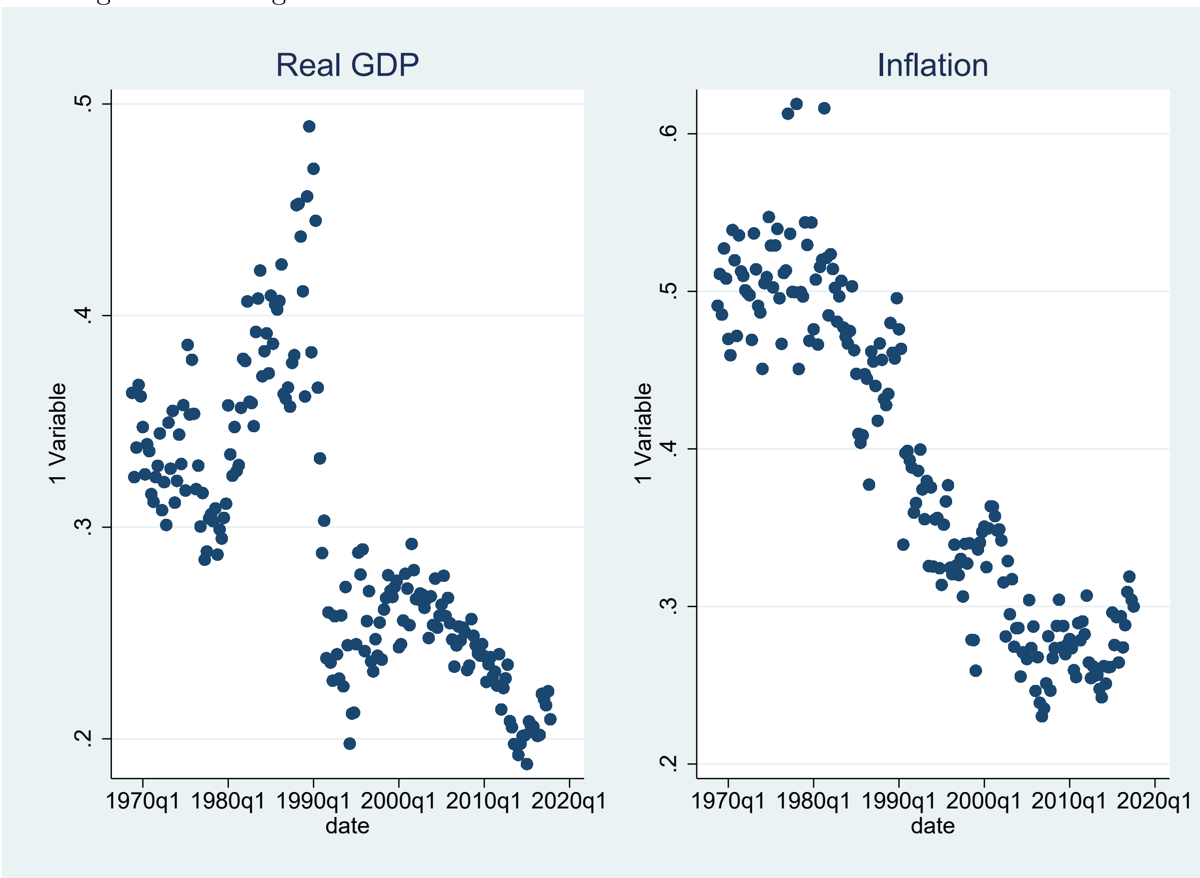
	GDP Inflation	Unemployment	Real GDP
Mean	0.41	0.73	0.33
Median	0.39	0.73	0.31
Standard Deviation	0.21	0.12	0.16
Interquartile Range	0.24	0.14	0.17

Notes: This table provides descriptive statistics of the distributions of individual Kalman gains for each of the following variables: GDP deflator inflation, unemployment, and real GDP. Each variable is approximately normally distributed with a median value close to the mean. There is variation in the average Kalman gain across variables, with forecasters showing a high degree of attention to unemployment and a relatively low degree of attention to real GDP. Variables with average Kalman gains closer to the center of the acceptable interval $(0, 1)$ also show greater dispersion across individuals. See Section 2.3 for more information.

Figure 1: Average Information Flow in Unemployment Forecasts over Time

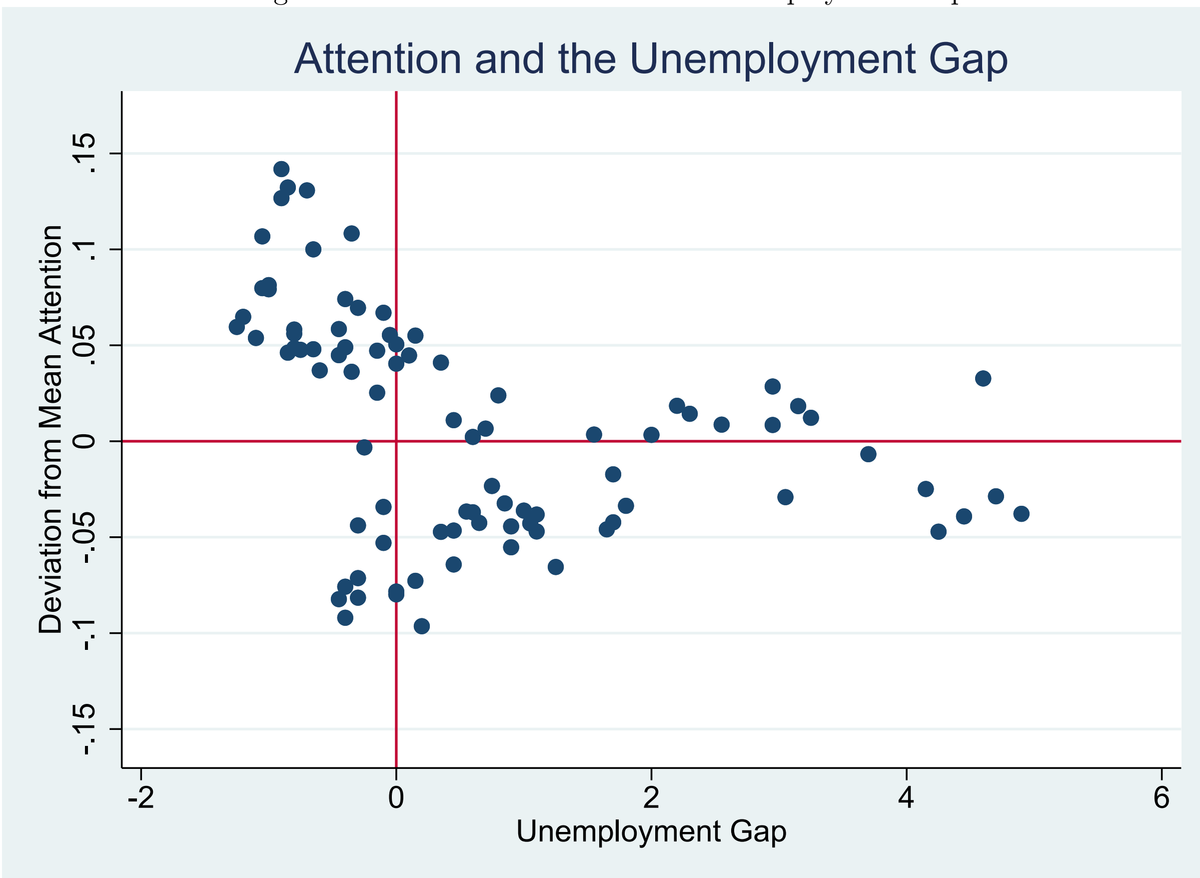
Notes: This figure shows the aggregate information flow to unemployment since the survey's initial release in 1968. Attention to unemployment exhibits time-variation. See Section 2.3 for more information.

Figure 2: Average Information Flow in Real GDP and Inflation Forecasts over Time



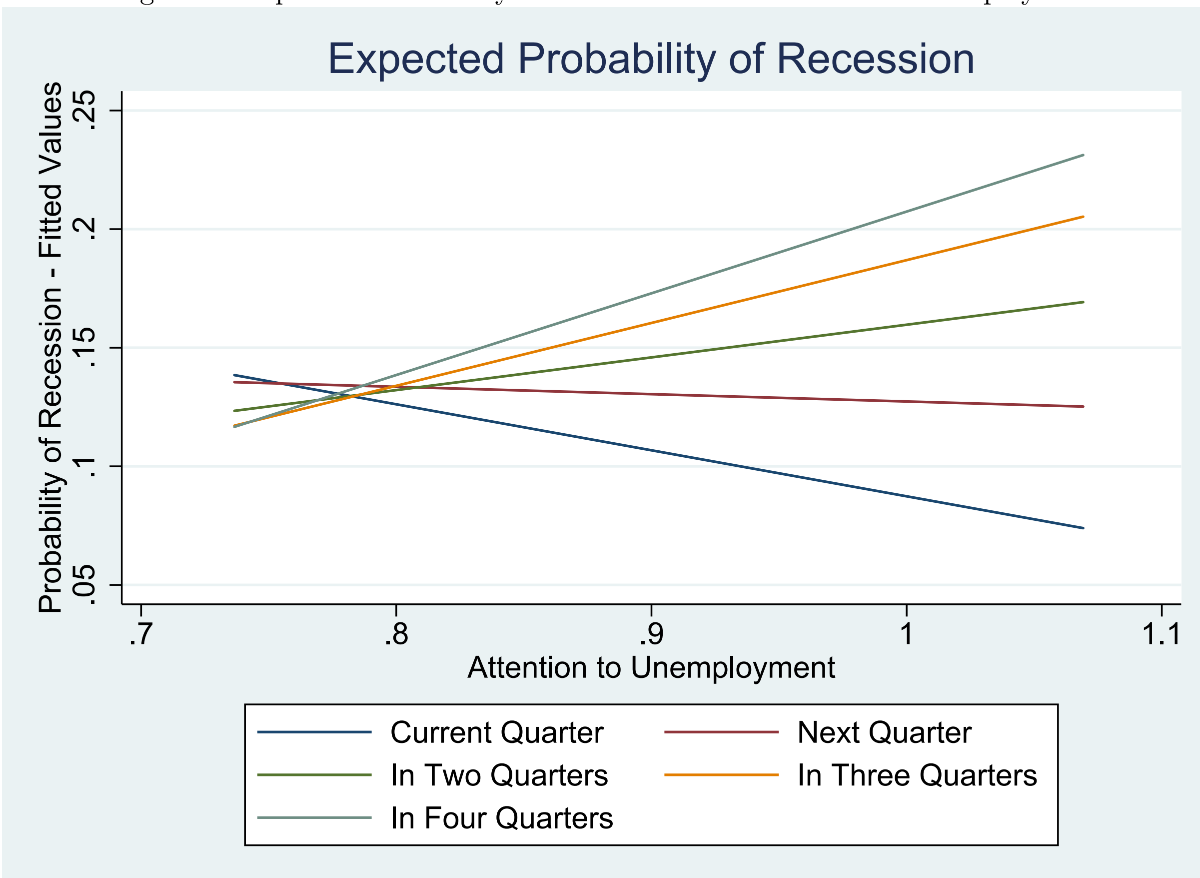
Notes: This figure shows the aggregate information flow to inflation and GDP since the survey's initial release in 1968. Attention to these two variables declines slightly over time. See Section 2.3 for more information.

Figure 3: Information Flow and the Unemployment Gap



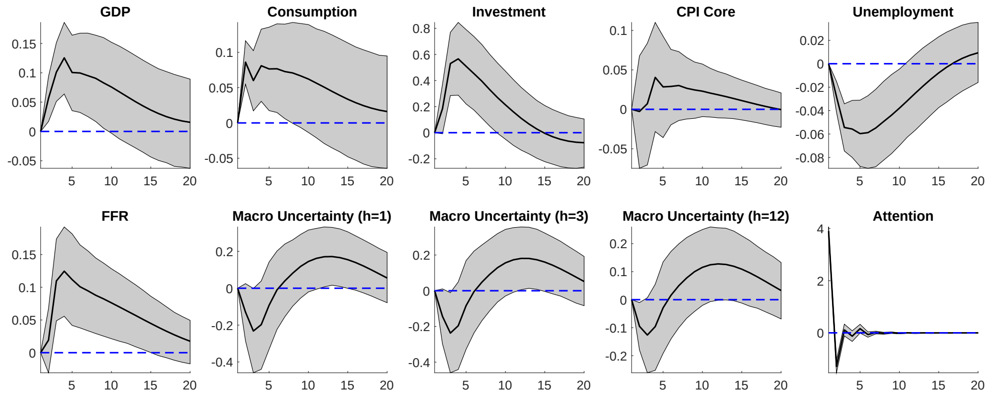
Notes: This figure shows the deviation of the aggregate information flow from its mean plotted against the unemployment gap. When there is a large amount of slack in the labor market (indicated by a large, positive unemployment gap), attention falls below its mean. As the slack dissipates and the unemployment gap becomes negative, attention rises above its mean. This means that attention is higher in periods when the labor market is tight. See Section 2.3 for more information.

Figure 4: Expected Probability of Recession and Attention to Unemployment



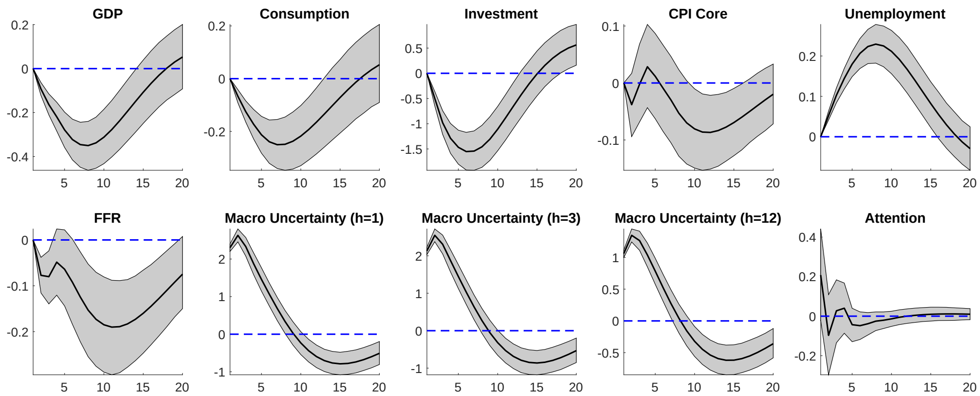
Notes:This figure shows fitted values for the average expected probability of recession plotted against the aggregate information flow. The expected probability of recession comes from from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The dark blue line shows the probability of recession in the current period. The red line the probability of recession next quarter or the "anxious index". The green, yellow, and light blue lines show the probability of recession in two, three, and four quarters, respectively. The expected probability of current recession is decreasing in the aggregate attention level. There is no apparent relationship between the anxious index and the attention level. The expected probability of recession in the future is increasing in the aggregate attention level and this relationship is more pronounced for expectations of a recession in periods further away from the forecasting period. See Section 2.3 for more information.

Figure 5: Impulse Responses to Shock to Attention



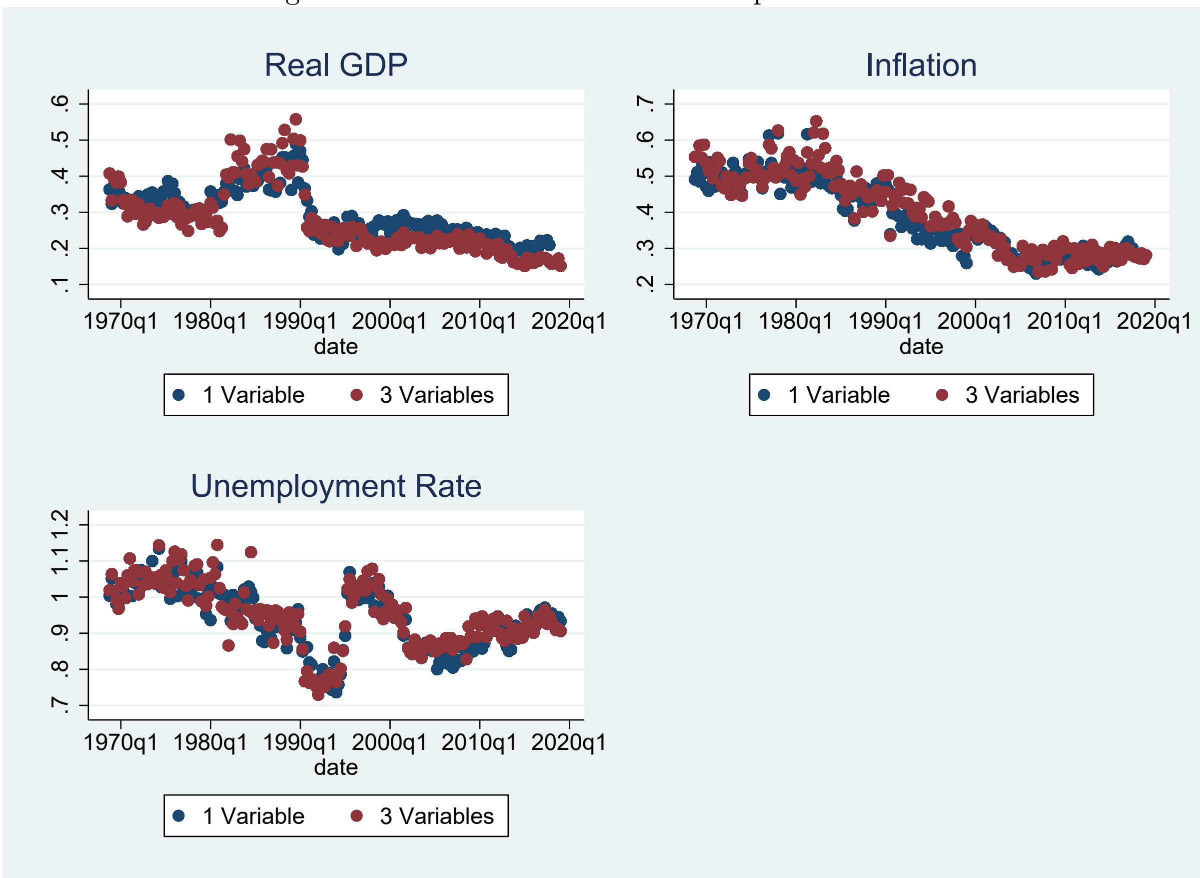
Notes: This figure shows the impulse responses of a shock to the tenth column of the Cholesky decomposition as described in Section 3. A shock to attention creates a large and persistent boom in business cycle variables as well as a decrease in macroeconomic volatility.

Figure 6: Impulse Responses to Shock to Attention



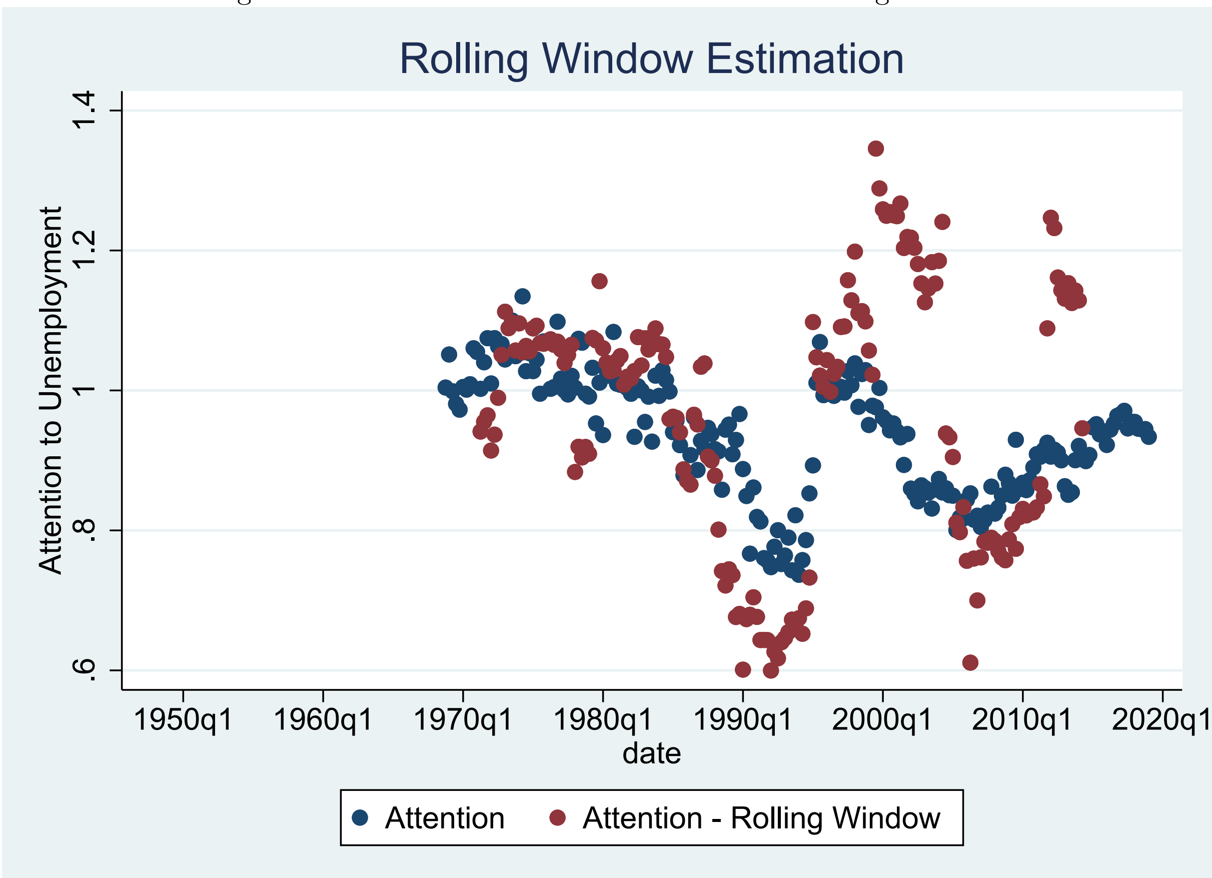
Notes: This figure shows the impulse responses of a shock to the seventh column of the Cholesky decomposition as described in Section 3. This shocks the three measures of macroeconomic volatility and attention contemporaneously. Macroeconomic volatility increases and attention both increase, creating a persistent recessionary shock.

Figure 7: Information Flow with Multiple State Model



Notes: This figure shows the aggregate information flow to unemployment, inflation, and GDP by including all three variables in the state space model simultaneously as in Section 5. Expanding the state space does not dramatically change the results from the single state version of the model. See Section 5 for more information.

Figure 8: Information Flow Estimated with a Rolling Window



Notes: This figure shows the aggregate information flow to unemployment calculated as in Section **??** and via rolling window. The blue series is the information flow from our approach. The red series are estimated using Equation 10. The estimate for aggregate information flow for each date is associated with the date in which that observation is in the middle of the rolling window. See Section 5 for more information.