Why Do Certain Macroeconomic News Announcements Have a Big Impact on Asset Prices?*

Thomas Gilbert† Chiara Scotti‡ Georg Strasser§
Clara Vega¶

PRELIMINARY

This Draft: July 14, 2010

Abstract

Previous literature documents a heterogenous asset price response to macroeconomic announcements. Some announcements have a strong impact on asset prices and others do not. The most common explanation is that timing matters - announcements released earlier in the cycle affect asset prices more. We define in a novel way the relevance or information content of a macroeconomic announcement as its ability to forecast FOMC decisions, to nowcast GDP growth and inflation; and investigate to what extent the information content, timeliness, and revision noise of macroeconomic announcements help explain the differential impact of news on asset prices. We find that a significant fraction of the variation in price impact can be explained by differences in information content. The timeliness of a news release is even slightly more important for its price impact. Revision noise of an announcement, in contrast, is less important, it has only about half of the impact of the other two properties.

*For comments and suggestions, we thank Torben Andersen, Tim Bollerslev, Dean Croushore, Michael McCracken, Barbara Rossi, Jonathan Wright, the participants of the 2009 $(EC)^2$ Conference, of the Forecasting and Real-Time Data session at the 2009 Joint Statistical Meeting, and of the 6^{th} ECB Workshop on Forecasting Techniques. We thank Domenico Giannone, Lucrezia Reichlin, and David Small for sharing their computer code with us, and Margaret Walton for outstanding research assistance. The views expressed are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve System, or the Board of Governors.

†Foster School of Business, Finance Dept., University of Washington (*gilbertt@u.washington.edu*)
‡Board of Governors, Federal Reserve System, Washington D.C. (*chiara.scotti@frb.gov*)
§Department of Economics, Boston College (*georg.strasser@bc.edu*)
¶Board of Governors, Federal Reserve System, Washington D.C. (*clara.vega@frb.gov*)

The primary source of information content is the ability to forecast FOMC decisions.

Keywords: Central bank policy, public information, macroeconomic forecasting, learning, price discovery, coordination role of public information
JEL classification: C53, D83, E27, E37, E44, E47, E5, G1

1 Introduction

How is news about macroeconomic fundamentals incorporated into asset prices? This question is of basic importance to financial economics. Unfortunately, we still do not have a satisfactory answer. There is extensive literature on *whether* asset prices respond to macroeconomic news announcements. This literature documents a heterogeneous response to news announcements. For example, two seemingly similar announcements released at the same time, nonfarm payroll and the unemployment rate, affect asset prices very differently. In this paper we investigate *why* certain announcements have a very strong impact on asset prices and others do not.

To answer this question we focus on the U.S. Treasury bond market response to macroeconomic news announcements.[1] We explore three announcement characteristics that may affect their impact on asset prices: (i) information content, (ii) revision noise, and (iii) timeliness. Previous literature has analyzed the latter two characteristics, revision noise, defined as the difference between the preliminary data release and its final revised value, and timeliness, defined as the difference between the announcement date and the period the announcement refers to. To the best of our knowledge we are the first to consider the information content of macroeconomic announcements and to evaluate the importance of all three characteristics simultaneously.

We define the information content of an announcement as its ability to forecast FOMC target rate decisions, nowcast GDP and inflation. The logic behind our definition is as follows. U.S. Treasury bond prices are a function of discount rates and discount rates are mainly determined by FOMC target rate decisions. Thus the information content of an

[1] We focus on the U.S. Treasury bond market as opposed to the equity or foreign exchange market because Treasury market price movements are driven by macroeconomic news much more than price movements in, say, equity and foreign exchange markets. For example, the average R^2 when regressing 5-minute price changes on 25 macroeconomic news announcements from 1998 to 2002 is 12 percent in the U.S. Treasury market compared to 7 percent in the foreign exchange market and 3 percent in the equity market (these numbers are estimated using Table 5A in the NBER working paper version of Andersen, Bollerslev, Diebold and Vega (2007)). Consistent with this evidence, Fleming and Remolona (1997) find that all of their 25 largest 5-minute U.S. Treasury price changes are linked to news releases, while Andersen and Bollerslev (1998) find that only 15 of their 25 largest moves are linked to news releases, and Cutler, Poterba and Summers (1989) find it difficult to attribute sharp daily movements in the stock market to important news.

announcement is naturally related to its ability to forecast FOMC target rate decisions. We also consider GDP and inflation as the primitives because, according to the Taylor rule, FOMC target rate decisions are a function of GDP and inflation.[2] More generally, one could define the information content of a macroeconomic announcement as its ability to forecast some other primitives, including other central bank decisions, term premia, risk premia, liquidity premia. Furthermore, these primitives depend on the asset class one studies. For example, when analyzing the impact of macroeconomic announcements on foreign exchange markets the primitive should be both home country and foreign country policy rates. We leave these extensions to future research.

According to standard Bayesian learning models, all three characteristics affect the price response to news because all three characteristics affect the precision of the posterior beliefs or the uncertainty surrounding the market's expectation of the state of the economy following the release of the announcement. Consistent with theory, we find that more timely announcements, announcements with less revision noise, and announcements with higher information content affect asset prices more. Empirically, we show that the information content and timeliness of the announcement are more important in explaining the price response to announcements than revision noise. We also find that information content related to the ability to forecast FOMC decisions and nowcast GDP are more important than the information content related to inflation. The fact that nowcasting GDP rather than inflation is more important may be an artifact of the sample period we analyze. During our sample period inflation has been relatively low and the FOMC has not been particularly worried about inflation.

In general our empirical findings are consistent with the Bayesian learning model we discuss in 2, however the three characteristics we consider do not perfectly explain the data. In particular, we find that the NAPM/ISM index has more information content than the nonfarm payroll announcement, it is released earlier, and it is less noisy, yet it does not affect bond prices as much as the nonfarm payroll announcement, the "king "of the announcements.[3] As we mention above, our information content variable does not consider all the primitives (e.g., it ignores risk premia, term premia, liquidity premia) and it could be that nonfarm payroll contains more information regarding those primitives we do not consider than the NAPM/ISSM index. Alternatively, agents may have decided to

[2]In reality, the FOMC takes into consideration many variables, including asset prices and the individual announcements we consider in this paper. Thus the announcement's ability to forecast FOMC target rate decisions may be the best way to define information content. Ideally, however, we want our information content definition to be independent of the timing and revision noise of the announcement, and this definition is not. Using GDP and inflation as the primitives helps us estimate information content independent of the timing and revision noise. We discuss in detail these considerations in Section X.

[3]Andersen and Bollerslev (1998), among others, refer to the Nonfarm Payroll report as the "king"of announcements because of the significant sensitivity of most asset markets to its release.

coordinate on the nonfarm payroll signal and they may be overreacting as in the Morris and Shin (2002)'s model.

Our paper is related to two different areas of research. The first examines the links between asset prices and macroeconomic fundamentals; the second forecasts the state of the economy and FOMC decisions. Our contribution to the former area of research is threefold. First, we extend Bayesian learning models to explicitly incorporate the information content of news announcements, in addition to the timing and revision noise (or precision) of the announcement, which previous literature has analyzed. Second, we show that the price response to a particular type of announcement cannot be analyzed in isolation. The effect announcements have on asset prices crucially depends on the information environment. When studying the link between asset prices and macroeconomic fundamentals, researchers not only need to take into account the surprise component of an announcement, but they also need to account for the timing of the announcement relative to other announcements and the information content relative to other announcements. For example, studies that chose to only analyze the effect final GDP announcements have on a particular asset price may wrongly conclude that there is a disconnect between asset prices and macroeconomic fundamentals. In this paper we show that asset prices do not react to final GDP announcements because the information content of this announcement relative to other announcements is minimal and it is the last announcement released in a given announcement cycle. Conversely, a study that estimates the effect multiple macroeconomic announcements have on a particular asset price may wrongly conclude that there macroeconomic announcements affect asset prices. In this paper we show that asset prices should only react to a few announcements, only those announcements with information content and timely release. If a study finds that asset prices do not react to these important announcements, but react to other announcements, the authors should worry about data mining. Third, we raise the possibility that there may be a rational overreaction to certain announcements because of the coordination value of public information beyond its intrinsic value (Morris and Shin (2002)), although we do not offer direct evidence to support this claim. Our contribution to the latter area of research is to show that the nowcast of GDP and inflation, which serve as summary statistics, lose useful information in forecasting FOMC decisions. In other words, the nowcast of GDP and inflation do not forecast FOMC decisions as well as considering key individual announcements separately.

The remainder of this paper is organized as follows. In section 2 we first describe the theoretical motivation for the hypothesis tested, based on a Bayesian learning model. We then provide evidence that the theoretical set-up may be relevant to the real world. Next, we describe the data and define two measures of the information content of macroeconomic announcements. In Section 6 we formally investigate to what extent the information content, timeliness, and revision noise of macroeconomic announcements help explain the differential impact of news on asset prices. In Section 6 we conclude and discuss directions for future research.

2 Theory

In order to illustrate the relative importance of timing, information content, and revision noise (or precision) of macroeconomic announcements, we construct a three-date model of a pure exchange economy where investors receive two sequential public announcements about a risky asset's value. Bayesian models of the type we derive have been used in the literature only to analyze the impact of public announcements by looking at their timing and their revision noise (see, among others, Grundy and McNichols (1989), Kim and Verrecchia (1991a), Kim and Verrecchia (1991b), Kandel and Pearson (1995), Veronesi (2000), Hautsch and Hess (2007), Niessen and Hess (2009)). We extend those models by explicitly incorporating the information content of news announcements.

2.1 Model Setup

In our model, trading of a risky asset occurs at $t = 1$ and 2, and consumption happens at $t = 3$. Before observing any information, i.e. at $t = 0$, agents assume the risky asset's payoff $\tilde{X}$ at $t = 3$ to be normally distributed with mean μ_{X0} and precision (inverse of variance) ρ_{X0}. In the context of this paper, the risky asset should be interpreted as the underlying state of the economy (e.g. GDP) about which investors receive public (macroeconomic) announcements.

At $t = 1$, investors observe a first signal of $\tilde{X}$ labeled as $\tilde{A}_1 = \beta_1 \tilde{X} + \tilde{\varepsilon}_1$ where β_1 is a fixed constant and $\tilde{\varepsilon}_1$ is normally distributed with mean 0 and precision ρ_{A1}. Similarly, at $t = 2$, investors observe a second signal of $\tilde{X}$ labeled as $\tilde{A}_2 = \beta_2 \tilde{X} + \tilde{\varepsilon}_2$ where β_2 is a fixed constant and $\tilde{\varepsilon}_2$ is normally distributed with mean 0 and precision ρ_{A2}. In this setup, the timing of macroeconomic announcements is trivially taken into account by the fact that A_1 and A_2 occur at different times. The revision noise of each announcement is modeled by the precision (inverse of the variance) of the noise terms in the signals, ρ_{A1} and ρ_{A2}.

The novel part of this Bayesian model is that we explicitly take into account the fact that two announcements can have different information content. Indeed, the covariance between each announcement and the underlying state of the economy is $Cov(\tilde{A}_1, \tilde{X}) = \beta_1 Var(\tilde{X})$ and $Cov(\tilde{A}_2, \tilde{X}) = \beta_2 Var(\tilde{X})$, which are allowed to be different if $\beta_1 \neq \beta_2$.[4]

[4] To the best of our knowledge, in all previous Bayesian models of public announcements in the literature, including Niessen and Hess (2009), public signals have the same covariance with the risky asset's payoff:

One can interpret the β coefficients as "loadings" on the latent state variable, i.e. on the underlying state of the economy. For instance, it may be that nonfarm payroll is a good signal of the state variable (high loading) whereas construction spending is not (low loading). Economically, we would then identify nonfarm payroll as having a higher information content than industrial production and nonfarm payroll announcements would therefore be more useful to investors than releases of industrial production. Note that the loadings can be negative if the signals are counter-cyclical.[5]

Because the focus of the model is on the impact of the characteristics of public announcements on price changes, we abstract from private information and hence investor heterogeneity. There is one representative investor who maximizes her expected utility of wealth $\tilde{W}$ at $t = 3$ by choosing to hold an amount $\tilde{D}$ of the risky asset in that period:

$$E[U(\tilde{W})] = E[-e^{-\gamma \tilde{D}\tilde{X}}] \tag{1}$$

where γ is the investor's coefficient of absolute risk aversion. For simplicity, we assume that $\gamma = 1$. Since all payoffs and signals are normally distributed and i.i.d., it is well known that the negative exponential utility function above is consistent with the investor's demand at date t being a simple function of the asset's price p_t at date t:

$$\tilde{D}_t = \frac{E_t[\tilde{X}] - \tilde{p}_t}{Var_t[\tilde{X}]} \tag{2}$$

where both the mean and the variance of X are conditional on all information available at time t. It is worth pointing out that since this is a competitive rational expectations equilibrium, prices will move without any trading. Heterogenous priors are required so as to generate volume, but this is not the focus of this paper.

2.2 Equilibrium Returns

In each period, the rational investor assesses the conditional expectation and variance of the risky asset's payoff based on all available information. However, since all signals are public, there is nothing additional to learn from the price and hence the agent only needs to condition on the signals themselves. Using Bayes' rule, it is easy to show that the asset's conditional expected payoff at date 1 is given by:

$$E[\tilde{X}|\tilde{A}_1] \equiv \mu_{X1} = \rho_{X1}^{-1}(\rho_{X0}\mu_{X0} + \beta_1 \rho_{A1} \tilde{A}_1) \tag{3}$$

$Cov(\tilde{A}_t, \tilde{X}) = Var(\tilde{X})$ since $\tilde{A}_t = \tilde{X} + \tilde{\varepsilon}_t$ and therefore have the same information content.

[5]Qualitatively similar results can be derived in a model with two states, say $\tilde{X} = \tilde{X}_1 + \tilde{X}_2$, and each signal gives about one of the states: $\tilde{A}_1 = \tilde{X}_1 + \tilde{\varepsilon}_1$ and $\tilde{A}_1 = \tilde{X}_1 + \tilde{\varepsilon}_2$.

where $\rho_{X1} = \rho_{X0} + \beta_1^2 \rho_{A1}$ is the asset's conditional precision at date 1. Similarly, the conditional expected payoff at date 2 is:

$$E[\tilde{X}|\tilde{A}_1, \tilde{A}_2] \equiv \mu_{X2} = \rho_{X2}^{-1}(\rho_{X0}\mu_{X0} + \beta_1 \rho_{A1}\tilde{A}_1 + \beta_2 \rho_{A2}\tilde{A}_2) \quad (4)$$

$$= \rho_{X2}^{-1}(\rho_{X1}\mu_{X1} + \beta_2 \rho_{A2}\tilde{A}_2) \quad (5)$$

where $\rho_{X2} = \rho_{X0} + \beta_1^2 \rho_{A1} + \beta_2^2 \rho_{A2} = \rho_{X1} + \beta_2^2 \rho_{A2}$ is the asset's conditional precision at date 2.

In each period, by using the linear demand functions (2) and imposing the market clearing condition that demand must be equal to an exogenous supply $\tilde{S}$ of the risky asset (normally distributed), we obtain the following price functions:

$$\tilde{p}_0 = \mu_{X0} - \rho_{X0}^{-1}\tilde{S} \quad (6)$$

$$\tilde{p}_1 = \mu_{X1} - \rho_{X1}^{-1}\tilde{S} \quad (7)$$

$$\tilde{p}_2 = \mu_{X2} - \rho_{X2}^{-1}\tilde{S} \quad (8)$$

We can then derive expressions for the price change around both macroeconomic announcements:

$$\tilde{p}_1 - \tilde{p}_0 = \frac{\beta_1 \rho_{A1}}{\rho_{X1}}(\tilde{A}_1 - \beta_1 \mu_{X0}) + \tilde{S}\left(\frac{1}{\rho_{X0}} - \frac{1}{\rho_{X1}}\right) \quad (9)$$

$$\tilde{p}_2 - \tilde{p}_1 = \frac{\beta_2 \rho_{A2}}{\rho_{X2}}(\tilde{A}_2 - \beta_2 \mu_{X1}) + \tilde{S}\left(\frac{1}{\rho_{X1}} - \frac{1}{\rho_{X2}}\right) \quad (10)$$

Equilibrium price changes are thus proportional to the surprise component of the announcement, $\tilde{S}_t = \tilde{A}_t - \beta_t \mu_{X(t-1)}$, as well as the precision of the data release relative to the precision of the market's posterior belief, ρ_{Xt} with $t = 1, 2$.

Note that, in the following, we will ignore the supply terms in the above return equations. As is explained in Kim and Verrecchia (1991b), these terms can be viewed as noise terms that stem from the exogenous supply of the risky asset used to make the equilibrium partially revealing in the presence of private information. However, since all information is public in our setup, we will disregard them for clarity of the algebra even though the results are unchanged if they are included.

2.3 Relative Importance of Timing, Information Content, and Revision Noise

We will now use the above setup to analyze the relative contribution of the timing, information content, and precision of announcements on their price impact. To do so, we will mute two of the channels, for instance value and precision, and analyze the impact of the third alone, for instance timing.

2.3.1 Timing

Let us first clarify the impact of timing on the return surrounding the public signals (Niessen and Hess (2009)). Assume that the two sequential announcements release exactly the same (independent) signal $\tilde{A}_1 = \tilde{A}_2$, that they both have exactly the same information content $\beta_1 = \beta_2$, and that they are both equally precise $\rho_{A1} = \rho_{A2}$. The return equations (9) and (10) can therefore be written as:

$$\tilde{p}_1 - \tilde{p}_0 = \frac{\beta_1 \rho_{A1}}{\rho_{X1}}(\tilde{A}_1 - \beta_1 \mu_{X0}) \tag{11}$$

$$\tilde{p}_2 - \tilde{p}_1 = \frac{\beta_2 \rho_{A2}}{\rho_{X2}}(\tilde{A}_2 - \beta_2 \mu_{X1}) \tag{12}$$

$$= \frac{\beta_1 \rho_{A1}}{\rho_{X2}}(\tilde{A}_2 - \beta_1 \rho_{X1}^{-1}(\rho_{X0}\mu_{X0} + \beta_1 \rho_{A1}\tilde{A}_1)) \tag{13}$$

$$= \frac{\beta_1 \rho_{A1}}{\rho_{X1} + \beta_2^2 \rho_{A2}}(\tilde{A}_1 - \beta_1 \mu_{X0})\rho_{X1}^{-1}\rho_{X0} \tag{14}$$

As a result, it is unambiguous that the first announcement has a higher price impact that the second, i.e. $\tilde{p}_1 - \tilde{p}_0 > \tilde{p}_2 - \tilde{p}_1$.[6] This effect is partly due to the fact that the surprise component of the second announcement is smaller:

$$\tilde{A}_1 - \beta_1 \mu_{X0} > (\tilde{A}_1 - \beta_1 \mu_{X0})\rho_{X1}^{-1}\rho_{X0} \tag{15}$$

and it is also partly due to the fact that the relative precision of the second announcement is smaller:

$$\frac{\beta_1 \rho_{A1}}{\rho_{X1}} > \frac{\beta_1 \rho_{A1}}{\rho_{X1} + \beta_2^2 \rho_{A2}} \tag{16}$$

The first effect is driven by the fact that the representative investor uses the first announcement to update its conditional expectation. As a result, the second release of the same signal provides a much smaller surprise. Similarly, her beliefs after the first signal are more

[6] As stated above, the inclusion of the supply terms does not change the results since it is easy to show that $\tilde{S}\left(\frac{1}{\rho_{X0}} - \frac{1}{\rho_{X1}}\right) = \tilde{S}\frac{\beta_1^2 \rho_{A1}}{\rho_{X0}^2 + \rho_{X0}\beta_1^2 \rho_{A1}} > \tilde{S}\left(\frac{1}{\rho_{X1}} - \frac{1}{\rho_{X2}}\right) = \tilde{S}\frac{\beta_1^2 \rho_{A1}}{\rho_{X0}^2 + 3\rho_{X0}\beta_1^2 \rho_{A1} + 2\beta_1^4 \rho_{A1}^2}$.

precise, leading to a smaller price impact of the second release. Since U.S. macroeconomic announcements follow a fairly rigid release schedule every month, one would expect, everything else held equal, the early releases, such as consumer confidence and nonfarm payroll, to have a much higher price impact than the later releases, such as factory orders and business inventories.

2.3.2 Information Content

To analyze the impact of information content while holding timing and revision noise fixed, we assume that both announcements A_1 and A_2 are released simultaneously at $t = 1$. We can therefore combine both return equations (9) and (10) to yield:

$$\tilde{p}_1' - \tilde{p}_0 = \frac{\beta_1 \rho_{A1}(\tilde{A}_1 - \beta_1 \mu_{X0}) + \beta_2 \rho_{A2}(\tilde{A}_2 - \beta_2 \mu_{X0})}{\rho_{X2}} \tag{17}$$

This equation allows us to analyze the contribution of each announcement on the price impact if the timing is fixed, if they have the same precision $\rho_{A1} = \rho_{A2} \equiv \rho_A$, but if their intrinsic value is allowed to differ $\beta_1 \neq \beta_2$. As before, let us assume that each announcement releases the same signal, $\tilde{A}_1 = \tilde{A}_2 \equiv \tilde{A}$, which gives us:

$$\tilde{p}_1' - \tilde{p}_0 = \frac{\beta_1 \rho_A(\tilde{A} - \beta_1 \mu_{X0}) + \beta_2 \rho_A(\tilde{A} - \beta_2 \mu_{X0})}{\rho_{X0} + \beta_1^2 \rho_A + \beta_2^2 \rho_A} \tag{18}$$

It becomes straightforward to observe that if announcement 1 has higher intrinsic value than announcement 2, i.e. $\beta_1 > \beta_2$, then announcement 1 contributes more to the price impact then announcement 2:

$$\frac{\beta_1 \rho_A(\tilde{A} - \beta_1 \mu_{X0})}{\rho_{X0} + \beta_1^2 \rho_A + \beta_2^2 \rho_A} > \frac{\beta_2 \rho_A(\tilde{A} - \beta_2 \mu_{X0})}{\rho_{X0} + \beta_1^2 \rho_A + \beta_2^2 \rho_A} \tag{19}$$

since the denominator of both fractions is the same. As a result, if two announcements are released simultaneously and they have the same precision, then the one that has the highest information content will move prices the most. Practically, it could be that nonfarm payroll is more highly correlated with the underlying state of the economy than the unemployment rate and its impact on returns would therefore be higher, assuming that they are both equally precise.

2.3.3 Revision Noise

To analyze the impact of revision noise while holding timing and information content fixed, we assume that both announcements are releasing the same signal A simultaneously and that their information content is equal, $\beta_1 = \beta_2 \equiv \beta$, while the precision of the two announcements is allowed to differ, $\rho_{A1} \neq \rho_{A2}$. We therefore have:

$$\tilde{p}_1'' - p_0 = \frac{\beta\rho_{A1}(\tilde{A} - \beta\mu_{X0}) + \beta\rho_{A2}(\tilde{A} - \beta\mu_{X0})}{\rho_{X0} + \beta^2\rho_{A1} + \beta^2\rho_{A2}} \tag{20}$$

From this equation, it is easy to observe that if announcement 1 has higher precision than announcement 2, i.e. $\rho_{A1} > \rho_{A2}$, then announcement 1 contributes more to the price impact than announcement 2:

$$\frac{\beta\rho_{A1}(\tilde{A} - \beta\mu_{X0})}{\rho_{X0} + \beta^2\rho_{A1} + \beta^2\rho_{A2}} > \frac{\beta\rho_{A2}(\tilde{A} - \beta\mu_{X0})}{\rho_{X0} + \beta^2\rho_{A1} + \beta^2\rho_{A2}} \tag{21}$$

since the denominator of both fractions is equal. Consequently, if nonfarm payroll is more precise than unemployment, then it will have a higher price impact if they are releasing simultaneously and they have equal information content. Note that in our model, the precision coefficient ρ_A is an ex-ante variable that gives investors a measure of expected revision, hence the term revision noise.

2.3.4 Single Announcement versus Concurrent Announcements

Lastly, we analyze how an announcement's price impact if affected by the release of a concurrent announcement. For instance, nonfarm payroll and unemployment are always released simultaneously by the Bureau of Labor Statistics and it is possible that nonfarm payroll's price impact would be higher if it were released on its own. Using our modeling setup, this amounts to comparing the contribution to price impact of each announcement using the following return equations:

$$\tilde{p}_1 - \tilde{p}_0 = \frac{\beta\rho_A}{\rho_{X0} + \beta^2\rho_A}(\tilde{A} - \beta\mu_{X0}) \tag{22}$$

$$\tilde{p}_1''' - \tilde{p}_0 = \frac{\beta\rho_A(\tilde{A} - \beta\mu_{X0}) + \beta\rho_A(\tilde{A} - \beta\mu_{X0})}{\rho_{X0} + \beta^2\rho_A + \beta^2\rho_A} \tag{23}$$

where timing is fixed (as in equation (17), both announcements in equation (23) are released simultaneously), the information content of both announcements is equal to β, the precision of both announcements is equal to ρ_A, and both announcements are releasing the same signal $\tilde{A}$. As a result, it is clear that, when there is a simultaneous announcement, the impact is reduced:

$$\frac{\beta\rho_A}{\rho_{X0} + \beta^2\rho_A} < \frac{\beta\rho_A}{\rho_{X0} + 2\beta^2\rho_A} \tag{24}$$

Holding everything else constant, it is therefore possible that the simultaneous release of unemployment and nonfarm payroll makes the latter have a lower price impact than it otherwise would if it were released as a stand-alone piece of information.

2.4 Model Summary

The simple Bayesian model used here leads to clear predictions about why the release of a particular macroeconomic variable may have a higher price impact than others:

- If all variables have equal information content and are equally precise, then the earlier a variable is released, the higher its price impact.
- If all variables are released at the same time and are equally precise, then the higher the information content of a variable, the higher its price impact.
- If all variables are released at the same time and have the equal information content, then the higher the precision of a variable, the higher its price impact.
- Multiple simultaneous releases decrease the price impact of each individual release compared to a case where each release is done separately (assuming equal information content and precision).

Of course, it is possible to analyze cases where two of the three characteristics are allowed to vary. For instance, one can imagine a situation where a sufficiently precise signal that is released second actually has a higher price impact than the first release, holding their information content fixed. Similarly, a signal that is less precise but has a higher information content than another simultaneous signal may have a higher price impact. While such an analysis is interesting in its own right, it would detract from the main predictions of the model highlighted above.

3 Data and Preliminary Analysis

There is significant evidence that indicates that the timing of releases matters. Andersen, Bollerslev, Diebold and Vega (2003) observe that the announcement timing matters because within a general category of macroeconomic indicators, news on those released earlier tends to have greater impact than those released later. Niessen and Hess (2009) show that the impact of the German IFO business indicator on German bond futures prices diminished substantially when the German ZEW business indicator was created. The ZEW index is highly correlated with the IFO index and the former is released before the latter. However, timing cannot fully explain the impact of macroeconomic news on asset prices because among the announcements that are released contemporaneously (such as nonfarm payroll and the unemployment rate, CPI and core CPI, retail sales and retail sales less autos), there is invariably one announcement that affects asset prices much more than the other. This is what leads us to examine two other characteristics that may determine the importance of an announcement: its information content and revision noise. Below we describe the data we use to estimate the impact of announcements on asset prices and we provide evidence that each of these three characteristics, information content, revision noise, and timing, affects the impact of news on asset prices. In Section 5 we formally investigate their importance.

3.1 Macroeconomic Data

We analyze the value of 32 U.S. macroeconomic variables during the period from January 1994 to December 2008. Four observations guided our choice of the sample period. First, the FOMC started announcing its Federal Funds Target rate explicitly in January 1994. Second, equity futures trading data at 8.30am EST is only available since January 1994. Third, NAICS-based revised data for all macroeconomic series published by the Census Bureau is available since 1992. And, fourth, Bloomberg and Money Market Services (MMS) real-time data on the expectations and realizations of the announcements is only available for all 32 series as of 1992.[7]

In Table I we provide a brief description of the most salient characteristics of these announcements: the announcement unit used in both the agency's report and the Bloomberg and MMS expectations, the time of the announcement release, the median reporting lag which is defined as the number of days between the end of the reference period (end of the quarter, month, or week) and the actual announcement, as well as the revision noise (RN^k), and the information content, both of which are defined in Section 4. The median reporting lag matches the announcement calendar shown in Figure 1 where the consumer confidence index is released first, followed by the NAPM/ISM index and then the employment report (unemployment, nonfarm payroll, and average hourly earnings).

The real-time nature of the dataset allows us to define announcement surprises as the difference between announcement realizations and their corresponding expectations. Because units of measurement vary across macroeconomic variables, we standardize the

[7]Because Bloomberg provides similar market expectations data, we use their data for the most recent period and for certain variables not covered by MMS. For a more detailed description of the MMS data we refer the reader to Andersen et al. (2003). According to Hess (2001) the forecasts of GDP, employment cost index, construction spendings, business inventories, and industrial production are not efficient. We find that (?)

resulting surprises by dividing each of them by their sample standard deviation. The standardized news associated with the macroeconomic indicator A^k at time t referring to period p is therefore computed as:

$$S^k_{p,t} = \frac{A^k_{p,t} - E^k_{p,t}}{\sigma^k_S}, \tag{25}$$

where $A^k_{p,t}$ is the announced value of indicator A^k, and $E^k_{p,t}$ is the MMS or Bloomberg median forecast. The denominator, σ^k_S, is the sample standard deviation of $A^k_{p,t} - E^k_{p,t}$ estimated using the full sample period of expectations and announcements. Equation (25) facilitates meaningful comparisons of responses of different asset price changes to different pieces of news. Operationally, we estimate the responses by regressing asset price changes on standardized news. Because σ^k_S is constant for any indicator A^k, the standardization affects neither the statistical significance of the response estimates nor the fit of the regressions.[8]

In order to assess the precision of each macroeconomic variable, we add to the above dataset the final revised values of each announcement that were obtainable from each reporting agency's website in July 2009. The revision, i.e. the *im*precision, of an announcement is then defined as the difference between the final available value and the initial announced value. This definition is the most parsimonious because it includes both sample and benchmark revisions and assumes that the last available value is the "truth." As a robustness check, we also use the first and second available sample revisions for the variables available in the Federal Reserve Bank of Philadelphia's Real-Time Data Set.[9]

3.2 Asset Price Response to Macroeconomic Announcements

We estimate the impact of macroeconomic announcements on asset prices by regressing the 5-minute log price change of different interest rate futures contracts on macroeconomic news surprises. Specifically, we estimate the following equation:

$$r_t = \alpha_k + \beta_k S^k_{p,t} + \varepsilon_t \tag{26}$$

denotes r_t the 5-minute continuously compounded return of the following futures contracts: eurodollar, 2-year, 5-year, 10-year, and 30-year U.S. Treasury bond. The intercept α_k is

[8]Rigobon and Sack (2006) refine the econometric approach to measuring announcement surprises, by using identification through censoring they estimate the share of the survey-based surprise due to noise. We choose to not follow their procedure because (?)

[9]These variables are GDP, GDP price deflator, unemployment, nonfarm payroll, housing starts, CPI, PPI, industrial production, and capacity utilization.

a time-invariant, variable-specific announcement return, the standardized announcement surprise $S^k_{p,t}$ is defined by (25), and $\varepsilon_t \overset{iid}{\approx} (0, \sigma^2)$. We obtained tick-by-tick transaction prices from Tick Data Inc. for all of the contracts. As a result, we have a balanced sample with trading beginning at 8.20am EST on all contracts. The contracts all have high liquidity and low transaction costs, which make them optimal to uncover the price discovery process over short intervals.[10]

Table II reports the results of the above univariate regression for each of the 32 macroeconomic variables across these four asset.[11] The variables are presented in the order of their release time within each class (see Table I). We use two measures of impact, the slope coefficient on the standardized surprise and the adjusted R^2. These two measures are highly correlated, indicating that a sizable part of explanatory power of variables stems from their big absolute impact. In agreement with the prior literature, we find large differences between the variables in terms of impact coefficient and adjusted R^2.

The slope coefficient on the standardized surprise are, for the most part, comparable across announcements, but we need to bear in mind two caveats. First, the variance of the 5-minute return is higher in the early morning (8:30 am, when most announcements are released) than at other times, say 10:00 am. Second, we need to be cautious when comparing the impact of an announcement that is released in isolation (like the NAPM/ISM index) with the impact of an announcement that is released along with others (like the nonfarm payroll and the unemployment rate, CPI and core CPI etc.). In order to address the time-varying volatility during the day, we model the response of exchange rates to news according to the approach of Andersen et al. (2003). [Explain more on the model] Results are presented in Table III. Results are very similar to those in Table II.

3.2.1 Timeliness

Consistent with Andersen et al. (2003), the results in Tables II and III provide supportive evidence to the claim that timing matters because within a general category of macroeconomic indicators, those news released earlier tends to have greater impact than those released later. The most obvious example is that of GDP. The BEA releases three GDP figures: advanced, preliminary, and final figures. The first figure is released one month after the quarter the figure refers to is over (e.g., the Q1 advance GDP figure is generally announced at the end of April), the preliminary figure is released one month afterward

[10] See Andersen et al. (2007) for details on the contracts and statistical properties of the data.

[11] The results in Table II are reported in percentage terms: $\log(p_t/p_{t-1}) \times 100$ where p_t is the price of the last trade in the t^{th} five-minute interval. If there are no trades in a given five-minute interval, we use the price from the previous interval, as long as the previous price was quoted within the last 30 minutes. We always use the most actively traded nearest-to-maturity contract, switching to the next-maturity contract five days before expiration.

(e.g., in May), and the final figure one month after (e.g., in June). The revision noise of these figures is decreasing over time and the information content of these announcements is potentially increasing (to the extent that the final GDP figure is more highly correlated with the state of the economy), however the GDP advance figure has the highest impact on the eurodollar futures and U.S. Treasury bond price futures (regardless of whether we measure the impact by the R^2 or the slope coefficient).

3.2.2 Information Content and Revision Noise

As we show in Table I there are several announcements that are released simultaneously. For example, nonfarm payroll and the unemployment rate. Across all assets we find that nonfarm payroll has a bigger impact (higher adjusted r^2 and higher absolute slope coefficient) on asset prices than the unemployment rate. This result can not be explained by revision noise because the nonfarm payroll figure is more heavily revised than the unemployment rate as shown in Table I and according to theory and our empirical results in Section 5 the larger the revision noise the smaller the impact of the macroeconomic announcement. In contrast, the information content of nonfarm payroll, as shown in the last column, is higher than that of the unemployment rate and this characteristic of the nonfarm payroll announcement would explain its higher impact on asset prices consistent with theory and our empirical results in section 5. For other announcements that are also released contemporaneously, results are mixed: retail sales has a bigger impact than retail sales less autos, despite having the least amount of noise and the smaller information content; CPI core has a bigger impact on prices than CPI, consistently with having the least amount of noise and the highest information content.

In the next section we describe in detail how we estimate the information content of these 32 announcement and subsequently evaluate which characteristic matters the most.

4 Methodology

As shown in the previous section, some announcements have a significantly larger price impact than others due to the diversified amount of information they convey to market participants about the current and future state of the economy. In this section we describe in more details the factors driving the price impact: Timeliness, Precision, and Intrinsic Value. For each of the factors we describe how we compute a summary statistic for the entire sample and a time-varying statistic.

4.1 Timeliness

Measuring the timeliness of an announcement is straightforward in our framework. A summary statistics for timeliness is the median reporting lag as shown in column five of Table I. The reporting lag is the median of the difference between the end of the reference month and the announcement date over our sample period. For example, the median reporting lag of the consumer confidence index is -3 days because it is almost always released before the end of the month p. Announcements which are usually labeled "forward looking," such as the consumer confidence index and the NAPM index, are released at the end of the reference month, whereas business inventories are released not until at least five weeks later. The ordering of the announcements throughout the month has been fairly constant over the last two decades, with idiosyncratic deviations happening due to release mistakes, government shutdowns, strikes, holidays, etc. Note in particular that the NAPM index is on average released before the nonfarm payroll report. It is therefore important to note that there is a difference between the reporting lag as we define it and the difference between the end of the survey period and the announcement date. At the Bureau of Labor Statistics, "employment data refer to persons on establishment payrolls who received pay for any part of the pay period that includes the 12^{th} of the month."[12] This means that taking the end of the month as the end of the reference period is not exact, because the surveying stopped much earlier in the month. Because of the way we set up our tests, however, we do not think that this biases our tests in any systematic way.

The timeliness of each announcement is calculated as the difference between the end of the reference month the announcement refers to and the announcement date.

Previous work on timeliness includes the study by Hess (2001), which shows that for a given reference period, within a class of announcements, later announcements have a smaller impact on prices of T-bond futures. More recently, the importance of the timing of an announcement for the asset price response has been considered in the work of Hautsch and Hess (2007) and Andersson, Ejsing and von Landesberger (2008).[13]

[12] http://www.bls.gov/web/cestn1.htm

[13] For Germany, Andersson et al. (2008) show that the reason for the small reaction of German bond prices to the aggregate German CPI announcement lies in the earlier release of CPI data for German states. Bond prices react significantly to surprises in the CPI of the two largest German states, effectively trading off the lower precision (by sampling only a part of Germany), with timing (by receiving the state figures four hours before the national figure).

4.2 Precision/Noise

Macroeconomic announcements undergo significant revisions during the months and years following their initial release. A summary statistics for the noise of an announcement is

$$\frac{1}{P}\sum_{p}\frac{\left|F_p^k - A_{p,t(p)}^k\right|}{\sigma_{\left|F_p^k - A_{p,t(p)}^k\right|}}. \tag{27}$$

Column 6 in Table I shows that macroeconomic announcements differ considerably in the amount of revisions they undergo. On the one end of the spectrum are government budget deficit, the consumer confidence index, and the trade balance, which are barely revised at all, meaning their announcements are essentially free of noise. On the other end of the spectrum are average hourly earnings and the core producer price index, which are both dominated by noise. The revisions of both vary more strongly than the underlying macroeconomic variable. Note in particular that the NAPM index is less noisy than the nonfarm payroll report.

A time-varying measure of the noise of each release is given by $\frac{\left|F_p^k - A_{p,t(p)}^k\right|}{\sigma_{\left|F_p^k - A_{p,t(p)}^k\right|}}$.

Among previous work, only Hautsch and Hess (2007) consider noise in the context of revision variance. They define the expected precision of a nonfarm payroll announcement at date t as the size of the most recent sample revisions of the previous two announcements, both released concurrently at time t.

[we should show and discuss a time-series regression for this variable].

4.3 Information content

The existing literature largely ignores information content as a separate channel of the asset price response to an announcement. It typically focuses on the direct link between announcements and asset prices, without disentangling the link from the announcement to the underlying state of the economy, which in turn determines the asset price response.

4.3.1 Ex-post Information Content

As shown in our theoretical model, a first definition of information content or intrinsic value relates to the correlation between a macroeconomic variable and the state of the economy. Asset prices can, in principle, respond to any signal, and thus also to any macroeconomic news announcement. These responses can be self-fulling, in that investors react to a certain signal because they anticipate that other investors will react in the same way (Morris and Shin (2002)). Albeit most fashions and fads in asset markets are shortlived, they can convey the impression that some macroeconomic variables have forecasting power. A natural first question to ask is therefore whether a given macroeconomic variable is significantly correlated with the main fundamental determinants of asset prices, namely GDP growth and FOMC decisions, which we call target variables.

We index announcements by underlying macroeconomic variable and time. The announcement $A^k_{p,t}$, for example, is released at time t and refers to the value of the macroeconomic variable A^k, listed with index number k in Table I, in period p. With this notation, we define the *ex-post information content* of a macroeconomic variable A^k with respect to a target variable F^j as the underlying "true" relationship measured by the correlation coefficient between the values of the announcement series and a target variable (say GDP or GDP price deflator). The ex-post information content measures how well a macroeconomic variable alone explains the target variable without taking into consideration the announcements release calendar. Because the FOMC takes real-time decisions looking at real-time variables, we are interesting in knowing how well news announcements can explain the real-time state of the economy as represented by advance GDP (or advance GDP deflator - results omitted). The ex-post measure of information content, contrary to its real-time counterpart, disregards the timing of the announcements. The last column in Table I shows the in-sample correlation between the first release of each of the 32 macroeconomic announcements and advance GDP. IP and change in nonfarm payrolls have the highest correlations, followed by retail sales less autos, NAPM, construction spending, and personal consumption.

A *time-varying measure of ex-post information content* is represented by the ten-year rolling correlations between the first release of each of the 32 macroeconomic announcements and advance GDP (or advance DDP price deflator). [Figure MISSING]

4.3.2 Real-Time Information Content

In contrast to the ex-post information content, the *real-time information content* of a macroeconomic variable A^k with respect to a target variable F^j is measured by the additional information that all its announcements $A^k_{p,t}$ carry in nowcasting or forecasting the target variable (FOMC decisions, advance GPD or advance GDP price deflator), given all the information that has been released until time t.

We start with measuring the Real-Time Information Content of macroeconomic variables for forecasting FOMC decisions. Our metric for Information Content is the additional forecasting power that variable A^k provides, given all the other variables $A^j, j \neq k$. Conditioning on all other variables released until the time of the announcement of A^k allows us to extract the information content of A^k itself, and separating it from information that has been released by other, earlier announcements. The empirical measure used as proxy for the conditioning information set at a particular announcement time is the GDP nowcast at that time, which excludes the pending announcement. We discuss the methodology for nowcast in the next section.

We measure the Real-Time Information Content by the likelihood ratio (LR) between Model M2 and Model M1. Model 1 (M1) is an ordered probit regression of FFTR changes on the GDP nowcast based on information which has been released prior to the release of variable A^k. Model 2 (M2) is also an ordered probit regression of FFTR changes on the GDP nowcast based on information which has been released prior to the release of variable A^k, but additionally the variable A^k itself is included.

$$M1 : y_t^* = \beta_k' \cdot Now_{p,t-1}^{\Delta GDP} + \gamma_k' \cdot Now_{p,t-1}^{GDPDef} + \varepsilon_t' \tag{28}$$

versus

$$M2 : y_t^* = \beta_k \cdot Now_{p,t-1}^{\Delta GDP} + \gamma_k \cdot Now_{p,t-1}^{GDPDef} + \delta_k \cdot A_{p,t}^k + \varepsilon_t \tag{29}$$

where Now stands for the GDP or GDP Deflator nowcasts.

Table IV shows that the NAPM index has the highest Information Content, which goes a long way towards explaining why it has such a big impact on asset prices. We can further compare announcements that are released at the same time. For instance, nonfarm payroll, unemployment and average hourly earnings. Nonfarm payroll has the biggest information content, closely followed by unemployment, while average hourly earnings has insignificant value. This ordering is consistent with the ordering of the asset price impact results.

Our second measure of real-time information content is the propensity to forecast GDP growth and the GDP deflator. The tests are very similar to the FOMC ones, where we compare the log-likelihoods of two models, one that contains the announcement variable of interest A^k (M2) and one that does not (M1):

$$M1 : \Delta GDP_{p,t+\tau} = \alpha_k' + \beta_k' \cdot Now_{p,t-1}^{\Delta GDP} + \varepsilon_p' \tag{30}$$

versus

$$M2 : \Delta GDP_{p,t+\tau} = \alpha_k + \beta_k \cdot Now_{p,t-1}^{\Delta GDP} + \gamma_k \cdot A_{p,t}^k + \varepsilon_p \tag{31}$$

The results are shown in Table V and Table VI. For the GDP channel in Table V, NAPM has again the highest Information Content. Only for the GDP Deflator channel nonfarm payroll outperforms NAPM, but is itself - unsurprisingly - dominated by price variables such as CPI.

In Table VII, we report multivariate asset return impact regressions where the independent variables are grouped together if they are released exactly at the same time. This allows us to control for timing and assess whether the variable with the highest information content does move asset prices the most.

For instance, nonfarm payroll, the unemployment rate, and average hourly earnings are all released within the same report by the BLS. Nonfarm payroll has the highest information content and moves prices the most between the three of them. Likewise, Core PPI and Core CPI matter more than their respective broader definition. The results confirm that, conditional on timing, information content matters for all our assets. [TO BE COMPLETED]

A *time-varying measure of real-time information content* for a macroeconomic announcement is the absolute value of the nowcasting weight put on the respective macroeconomic variable one instant before the announcement is released. The weight is the product of the coefficient on the factors from the Kalman forecasting regression, multiplied with the respective factor weights, thus effectively the weight of the variable in the estimation of the nowcast of $GDP_{adv.}$ (or $GDPdefl_{adv.}$ respectively) at time t. Real-time information content can be thought of as the eagerness with which a nowcaster awaits the new announcement, assuming that the weights in the new nowcast will be close to the weights from his previous nowcast. Table [MISSING] reports the average Real-time information content for each macroeconomic variable.

In the next sections, we describe our nowcasting procedure, which forms the basis of our measures of Real-time Information Content, and we also describe the ordered Probit model that we use for FFTR change forecasts.

4.3.3 Nowcasting GDP Growth and Inflation

Our approach is to estimate the hidden state of the economy from observable macroeconomic variables, and use the hidden state vector for nowcasting GDP, GDP deflator, and the FFTR. Market participants are assumed to nowcast these variables in a similar way, and thus respond to all macroeconomic announcements. Figure 3 illustrates this underlying information model and estimation sequence.

We generate nowcasts of GDP Advance and the GDP Deflator Advance many times during each quarter, at each macroeconomic announcement time. The set of variables available for any given month becomes more and more complete from one announcement time to the next. Our approach to nowcasting is related to the one presented in Evans (2005) and Giannone, Reichlin and Small (2008). In contrast to these papers, we account for seasonality and cyclicality in the state vector process. We do not modify published data, e.g. by removing or replacing outliers with fitted values. Instead we treat them as features of the data that our estimates should capture. Further, we apply our approach to a large set of time series, including information that is released at frequencies shorter than one month.

We first calculate three factors by principal component analysis from all 31 macroeconomic announcement series, which we consider as capturing the state of the economy. Assuming that the state vector of the economy $\Phi_{p,t} = \left[\phi^1_{p,t}, \phi^2_{p,t}, \phi^3_{p,t}\right]$ follows a VAR(1) process, a possible state equation is

$$\Phi_{p,t} = B_t \Phi_{p-1,t} + C_t \nu_{p-1,t}, \tag{32}$$

where $\nu_{p,t} \sim WN(0, Q^q_t)$. Note that there are two time indices, p and t. The index p identifies the state of the economy at time p. We model the state of the economy as evolving at monthly frequency, which dictates that p is measured in months. The index t governs how much information is available about the current and past state vectors. This setup naturally maps the ever-evolving information set, with its missing values, revisions, and irregular announcement dates into our data structure, illustrated by figure 4. B_t is the transition matrix, and C_t translates q structural shocks into factor innovations. As the information set grows with t, the estimates of B_t and C_t change as well.

State equation (32), however, imposes the unrealistic restriction that the transition of announcements is constant over time. In reality, announcements follow calendar-based patterns over the year. In addition to potential seasonality in announced values, there is cyclicality in announcement times. For these reasons we use month-specific transition matrices. The factor process follows therefore the modified VAR(1)

$$\Phi_{p,t} = B_{m(p-1),t} \Phi_{p-1,t} + C_{m(p-1),t} \nu_{p-1,t}, \tag{33}$$

where $m(p) \in \{1, \ldots, 12\}$ denotes the calendar month at time p, and $\nu_{p,t} \sim WN(0, I_2)$.

The corresponding observation equation for a given information set t is

$$A_{p,t} = D_t \Phi_{p,t} + \varepsilon_t, \tag{34}$$

where $\varepsilon_t \sim WN(0, R_{31})$, and $A_{p,t} = \left[A^1_{p,t}, \ldots, A^N_{p,t}\right]$ is the monthly vector of macroeconomic variables containing the values announced on or before time t. We follow Giannone et al. (2008) in muting missing observations by setting the observation variance of missing announcements to a very large number. In contrast to previous work, we apply this method consistently both within-sample and out-of-sample.

Using this setup we refine the in-sample estimates of the (latent) factors by Kalman smoothing, which improves estimates of past factors by updating them based on subsequently revealed information until time t. Using the estimates of $B_{m(t),T}$ and $C_{m(t),T}$ for $t > T$, we can forecast the factors (or states) out-of-sample. Next, we regress the in-sample announcements of GDP growth and of the GDP deflator available at time t on the factor estimates at time t, that is

$$A^k_{\bar{p},t} = \alpha_t + \beta_t \tilde{\Phi}_{\bar{p},t}, \tag{35}$$

where $\bar{p}$ indices the reference periods of A^k and is restricted to the periods for which the values of $A^k_{\bar{p},t}$ and $\tilde{\Phi}_{\bar{p},t}$ are already known at time t. The independent variable $\tilde{\Phi}_{\bar{p},t} = \left[\tilde{\Phi}^1_{\bar{p},t}, \tilde{\Phi}^2_{\bar{p},t}, \tilde{\Phi}^3_{\bar{p},t}\right]$ is the arithmetic average of each estimated factor $\tilde{\Phi}^i_{p,t}$ during period $\bar{p}$. For this regression we use a rolling 30-quarter estimation window, to reduce overweighting of observations early in the sample. The out-of-sample nowcast for an announcement $A^k_{p,t}$ released at time $t > T$ based on information until time t is then

$$\hat{A}^k_{\bar{p},T} = \hat{\alpha}_t + \hat{\beta}_t \tilde{\Phi}^f_{\bar{p},T}, \tag{36}$$

where $\tilde{\Phi}^f_{\bar{p},t}$ is the average Kalman smoother forecast for period $\bar{p}$ based on information until time T.

Repeating this procedure for each announcement time in our sample gives us a sequence of nowcasts $\hat{A}^k_{p(t),t}$, where $p(t)$ is the reference period of the very next announcement of variable k after time t.

Figure 2 shows the nowcasts for GDP Advance growth and the GDP Deflator Advance. The root mean squared forecasting error (RMSFE) of our nowcast of GDP growth is 1.58, much lower than the RMSFE of a random walk forecast of 2.20. The RMSFE for the GDP deflator is 0.95, also lower than that of a random walk forecast with 1.15.

4.3.4 Forecasting FOMC Interest Rate Decisions

To evaluate how well these announcements can predict FFTR changes we estimate an ordered conditional probit model similar to the specification in Hamilton and Jordà (2002). We hypothesize the existence of an unobserved latent variable y^*_τ that depends on $w_{\tau-1}$ according to

$$y^*_t = w'_{t-1}\beta + \varepsilon_t \tag{37}$$

where $\epsilon_t | w_{t-1} \overset{iid}{\sim} N(0,1)$. With our notation we can also rewrite it as

$$y^*_{p(t)} = \beta_0 + \beta_1 A^k_{p,t} + \beta_2 y^f_{p(t)} + \varepsilon_t \tag{38}$$

We assume that the Fed can choose among 5 discrete changes of the target. Conditional on a target rate change occurring on FOMC dates, we hypothesize that the observed discrete target change y_t measured in basis points is related to the latent continuous variable y_τ^* according to

$$\begin{aligned}
y_t &= -50 \quad \text{if} \quad y_t^* \leq c_1 \\
y_t &= -25 \quad \text{if} \quad c_1 < y_t^* < c_2 \\
y_t &= 0 \quad \text{if} \quad c_2 < y_t^* < c_3 \\
y_t &= 25 \quad \text{if} \quad c_3 < y_t^* < c_4 \\
y_t &= 50 \quad \text{if} \quad y_t^* \geq c_4
\end{aligned} \tag{39}$$

where $c_1, \ldots, c_4$ reflect the FOMC decision thresholds. We estimate the above conditional ordered probit using the equally weighted sum of each macro series from time $t-1$ to t, where t corresponds to a FOMC meeting date or to an inter-meeting target rate change.[14]

5 What Matters Most?

So far in this paper we have looked separately at each of the three factors: information content, timeliness, or precision. Our main goal in this paper is to show which of these three factors, if any, is the main determinant of asset price impact of a macroeconomic variable. To achieve this, we expand the event study regression (equation 26) by including our three proxies for information content, timeliness, and precision as independent variables as well as interaction terms between each proxy and the announcement surprise.

We estimate the following asset market response:

$$r_t = \beta_0 + \beta_S S_t + \beta_T T_t + \beta_N N_t + \beta_I I_t + \beta_{ST} S_t T_t + \beta_{SN} S_t N_t + \beta_{SI} S_t I_t + \varepsilon_t. \tag{40}$$

where $\varepsilon_t | w_{t-1} \overset{iid}{\approx} N(0,1)$. r_t is the 5-minute continuously compounded return of the Eurodollar futures contract at time t computed as $\log(p_t/p_{t-1}) \times 10000$, where p_t is the price of the last trade in the Eurodollar futures contract at the t^{th} five-minute interval. The surprise S_t is defined by (25), T_t is the time lag of the announcement at time t relative to the end of the reference month in days. N_t is the standardized noise of the announcement at time t defined as the absolute value of the actual announcement minus the final revised figure divided by its standard deviation, and I_t is the Real-time information content of the announcement at time t.

[14] In February 1994, the Federal Reserve began announcing FFTR on the FOMC meeting day at 2:15 pm EST. Consequently, the majority of FFTR changes after April 1994 take place on FOMC meeting days. The target rate changes are dated according to the day on which they became known. Until 1994, this corresponded to the day after the decision to change rates, when the new target rate became effective.

In this regression we effectively constrain all announcement surprises to have the same effect on the Eurodollar 5-minute return, and we only allow this surprise to be different depending on the timing of the announcement, its precision and information content. This allows us to determine which characteristic of the announcement affects the asset price response the most. Because some announcements are released at the same time we estimate equation 40) only taking into account the announcement with the highest information content when two or more announcements are released simultaneously (e.g., in the case of nonfarm payroll and the unemployment report, we only take into account the nonfarm payroll announcement, in the case of the CPI core and CPI, we only take into account CPI core etc.). Alternatively, we also estimate 40) using all the announcements and repeating the 5-minute continuously compounded return whenever two or more announcements are released simultaneously. In other words, we stack 5-minute observations one on top of the other whenever two or more announcements are released at the same time.

We report the coefficient estimates in Table VIII for data from 2003 until 2009, where we condition on the size of the surprise by including only interaction terms. The table reveals that announcements impact the Eurodollar due to their ability of forecasting GDP (left column), and not due to their ability of forecasting GDP Deflator (right column). This extends the known fact that the GDP deflator itself hard to forecast in general. Figure 5 illustrates the impact of these characteristics on asset prices. The graph assumes a unit-size surprise, and average values of information content, timeliness, and noise. The impact of information content and timeliness is similar, whereas the impact of noise is only about half. As the graph suggests, very late announcements, i.e. very bad timeliness, can completely mute the surprise effect.

Next, we calculate the marginal effect each of these characteristics on the 5-minute continuously compounded return conditional on a one standard deviation surprise shock.[15] This marginal effect is computed as follows:

$$\bar{r}_t = \hat{\beta}_0 + \hat{\beta}_S \bar{S}_t + \hat{\beta}_T \bar{T}_t + \hat{\beta}_P \bar{P}_t + \hat{\beta}_I \bar{I}_t + \hat{\beta}_{ST} \bar{S}_t \bar{T}_t + \hat{\beta}_{SP} \bar{S}_t \bar{P}_t + \hat{\beta}_{SI} \bar{S}_t \bar{I}_t \tag{41}$$

$$\begin{aligned} r_t^S &= \hat{\beta}_0 + \hat{\beta}_S \times \left(\sigma_S + \bar{S}_t\right) + \hat{\beta}_T \bar{T}_t + \hat{\beta}_P \bar{P}_t + \hat{\beta}_I \bar{I}_t + \hat{\beta}_{ST} \times \left(\sigma_S + \bar{S}_t\right) \times \bar{T}_t \\ &+ \hat{\beta}_{SP} \times \left(\sigma_S + \bar{S}_t\right) \times \bar{P}_t + \hat{\beta}_{SI} \times \left(\sigma_S + \bar{S}_t\right) \times \bar{I}_t \end{aligned} \tag{42}$$

[15] Because the mean of the surprise is zero it is not very informative to compute the marginal effect evaluated at the mean of the surprise. Mean and standard deviation of all characteristics are reported in Table IX.

The one standard deviation surprise effect is:

$$r_t^S - \bar{r}_t = \hat{\beta}_S \times \sigma_S + \hat{\beta}_{ST} \times \sigma_S \times \bar{T}_t + \hat{\beta}_{SP} \times \sigma_S \times \bar{P}_t + \hat{\beta}_{SI} \times \sigma_S \times \bar{I}_t \tag{43}$$

We compute the marginal effect of e.g. the timing of the announcement by first calculating the Eurodollar return after a one-standard deviation shock to timing:

$$\begin{aligned} r_t^{ST} &= \hat{\beta}_0 + \hat{\beta}_S \times \left(\sigma_S + \bar{S}_t\right) + \hat{\beta}_T \left(\sigma_T + \bar{T}_t\right) + \hat{\beta}_P \bar{P}_t + \hat{\beta}_I \bar{I}_t \\ &+ \hat{\beta}_{ST} \times \left(\sigma_S + \bar{S}_t\right) \times \left(\sigma_T + \bar{T}_t\right) + \hat{\beta}_{SP} \times \left(\sigma_S + \bar{S}_t\right) \times \bar{P}_t \\ &+ \hat{\beta}_{SI} \times \left(\sigma_S + \bar{S}_t\right) \times \bar{I}_t \end{aligned} \tag{44}$$

The marginal effect of the timing of the announcement is therefore:

$$r_t^{ST} - r_t^S = \hat{\beta}_T \times \sigma_T + \hat{\beta}_{ST} \times \left(\sigma_S + \bar{S}_t\right) \times \sigma_T \tag{45}$$

The marginal effects for all variables for the GDP channel are reported in Table X. All variables have the correct sign relative to the surprise: The later an announcement, the less the surprise has impact. The more intrinsice value, the stronger the surprise impact. The noisier an announcement, the smaller the surprise impact. Timeliness has the largest marginal effect, followed closely by information content. The marginal effect of noise is only about half.

Table XI reports the same coefficients for the GDP channel for real activity variables only, i.e. for all announcements except average hourly earnings, PPI and Core PPI, CPI and Core CPI. Now information content ranks slightly ahead of timeliness. The higher marginal effect of information content is not surprising, because price variables are less important for GDP than real activity variables, and the average information content of an announcement increases therefore if we exclude price variables. The smaller impact of timeliness might indicate that the time ordering between PPI and CPI matters a lot, and with these variables missing in the real-activity-only regression timeliness of the remaining variables is less relevant. [Same analysis with rolling correlations]

6 Future Work and Conclusion

We summarize our results by three key findings: First, information content and timeliness dominate the price impact, whereas noise less important. Bad timing can completely mute the surprise effect. Second, bond markets respond more strongly to information which explains GDP, than to information which explains the GDP deflator. Third, the most valuable announcement in terms of information content, timeliness, and noise is NAPM, not Nonfarm Payroll. In this sense NAPM might be the true "king of announcements."

Our findings raise a number of interesting questions for future work. First, it is well known that foreign markets react more strongly to U.S. macro announcements than to their own. Is this asymmetric response due to differences in information content, or due to the fact that U.S. data is usually released first? Second, the strong reaction of asset markets to NFP and the somewhat smaller response to NAPM might be due to another announcement value beyond the ones considered. For example, a rational overreaction to NFP instead of NAPM could be due to the value of coordination (Morris and Shin 2002). Third, the impact of news on equity markets is known to change along the business cycle. In expansions, on average, good real activity news tends to push prices down, and vice versa in recessions. It might be that this differential impact of real activity variables on equity returns in recessions versus expansions biases news impact estimates in equity markets. Further, revisions are known to be smaller in recessions than during expansions. If this is true, then we expect noisy variables to improve their ranking in recessions.

References

Andersen, T. G. and Bollerslev, T., 1998, "Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies," *Journal of Finance*, 53(2), 219–265.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C., 2003, "Micro effects of macro announcements: Real-time price discovery in foreign exchange," *American Economic Review*, 93(1), 38–62.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C., 2007, "Real-time price discovery in global stock, bond and foreign exchange markets," *Journal of International Economics*, 73(2), 251–277.

Andersson, M., Ejsing, J. W. and von Landesberger, J., 2008, "How do Euro area inflation expectations evolve over time?," European Central Bank.

Cutler, D. M., Poterba, J. and Summers, L. H., 1989, "What moves stock prices," *Journal of Portfolio Management*, 15, 4–12.

Evans, M., 2005, "Where are we now? Real-time estimates of the macroeconomy," *International Journal of Central Banking*, 1(2), 127–175.

Fleming, M. J. and Remolona, E. M., 1997, "What moves the bond market?," *Economic Policy Review*, 3(4), 31–50.

Giannone, D., Reichlin, L. and Small, D. H., 2008, "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 55, 665–676.

Grundy, B. D. and McNichols, M., 1989, "Trade and the revelation of information through prices and direct disclosure," *Review of Financial Studies*, 2, 495–526.

Hamilton, J. D. and Jordà, O., 2002, "A model of the federal funds rate target," *Journal of Political Economy*, 110(5), 1135–1167.

Hautsch, N. and Hess, D., 2007, "Bayesian learning in financial markets: Testing for the relevance of information precision in price discovery," *Journal of Financial and Quantitative Analysis*, 42(1), 189–208.

Hess, D., 2001, Surprises in U.S. macroeconomic releases: Determinants of their relative impact on T-bond futures, *Discussion Paper 01-01*, CoFE, University of Konstanz.

Kandel, E. and Pearson, N. D., 1995, "Differential interpretation of public signals and trade in speculative markets," *Journal of Political Economy*, 103, 831–872.

Kim, O. and Verrecchia, R. E., 1991a, "Market reaction to anticipated announcements," *Journal of Financial Economics*, 30, 273–309.

Kim, O. and Verrecchia, R. E., 1991b, "Trading volume and price reactions to public announcements," *Journal of Accounting Research*, 29, 302–321.

Morris, S. and Shin, H. S., 2002, "Social value of public information," *American Economic Review*, 92, 1521–1534.

Niessen, A. and Hess, D., 2009, "The early news catches the attention: On the relative price impact of similar economic indicators,".

Rigobon, R. and Sack, B., 2006, Noisy macroeconomic announcements, monetary policy, and asset prices, *Working Paper 12420*, NBER.

Veronesi, P., 2000, "How does information quality affect stock returns?," *Journal of Finance*, 55, 807–837.

A Macroeconomic Variable Transformations

We transform the dependent variables, i.e. the macroeconomic series, in order to approximate a linear relationship with the forecasting object.

A.1 GDP Regression

For the dependent variable *real GDP growth rate* we derive the appropriate transformation from the definition of GDP, $GDP = C+I+G+(EX-IM)$, where C denotes consumption, I investment, G government expenditures, and $EX-IM$ the trade balance. Replacing each variable by its growth rate, denoted by Δ, and using suitable coefficients $\alpha_1 ... \alpha_4$, we can write:

$$\Delta GDP = \alpha_1 \Delta C + \alpha_2 \Delta I + \alpha_3 \Delta G + \alpha_4 \Delta(EX - IM) \tag{46}$$

The components of GDP themselves depend on other macroeconomic variables. For example, a component of the change in consumption, ΔC, is the change in retail sales. Likewise, a change in the inflation rate affects consumers' willingness to consume, and thus changes consumption as well. We include both variables therefore as percentage changes in our regression. A different type of variable are mean-reverting (confidence) indices. If confidence exceeds its neutral level, the economy expands, as a high confidence level leads to increases in consumption and investment. We therefore include confidence indices as levels in our regression.

A.2 FOMC Regression

For the dependent variable *absolute FFTR change* we derive the transformation from the Fed's goals defined in the Federal Reserve Act. We specify the FFTR accordingly as a function of the deviation of unemployment u, inflation π, long-term interest rate i, and output growth ΔGDP from its respective natural level:

$$FFTR = f(u - u_0, \pi - \pi_0, i - i_0, \Delta GDP - \Delta GDP_0) \tag{47}$$

If the Fed attempted to reach the goals specified in that act by a Taylor rule, it would respond fully and immediately as in $\Delta FFTR = f(\Delta u, \Delta \pi, \Delta i, \Delta^2 GDP)$. This full response would require the Fed to be certain about the impact of its policies, which may not be the case in reality, especially not with real-time data. Thus we assume that the Fed changes the FFTR gradually, then observes the effect, and then changes FFTR again in response to the remaining deviation of the macro variables from their target level, assuming the new level is a steady state:

$$\Delta FFTR = f(u - u_0, \pi - \pi_0, i - i_0, \Delta GDP - \Delta GDP_0) \tag{48}$$

As a result of this gradual adjustment hypothesis for FFTR decisions, the transformations are usually the same for GDP, GDP deflator, and FOMC forecasts. The main difference are employment variables, because the Fed is to target the level of employment directly, whereas the GDP growth rate responds to changes in employment.[16] Another difference stems from that fact that FOMC decisions are based on expectations beyond the current quarter. Because in the GDP regression we focus on the contemporaneous GDP change, we use the information of capacity utilization and business inventories about the same period GDP, and therefore include them as percentage change in the GDP regression. For the FOMC, however, the effect of idle capacity and excess inventory on future growth dominates, which is why we include them as levels in the FFTR regression.[17]

[16]Some macroeconomic variables are expressed a percentages of some aggregate. We assume that the aggregate does not change noticeably during the forecasting period. For example, we consider percentage changes in the unemployment rate to approximate changes in the headcount of unemployed persons, thereby assuming that the population is more or less constant over the horizon of interest.

[17]The Archival Federal Reserve Economic Data (ALFRED) database provides realtime level data for business inventories starting in October 1996. We use the realtime level data reported by ALFRED from 10/31/1996 until today, and construct the level series for the years 1994 to 1996 using the percentage change from Bloomberg.

Figure 1
Macroeconomic Announcement Calendar

This figure shows the usual calendar timing of U.S. macroeconomic announcements across the month. The reference month is labeled as p with most variables released in the subsequent month and some released up to six weeks later. Each GDP series (advance, preliminary, or final) is released on a quarterly basis. The only variable not represented in the figure is initial jobless claims, which is released on the Thursday of every week and refers to the week ended ten days prior.

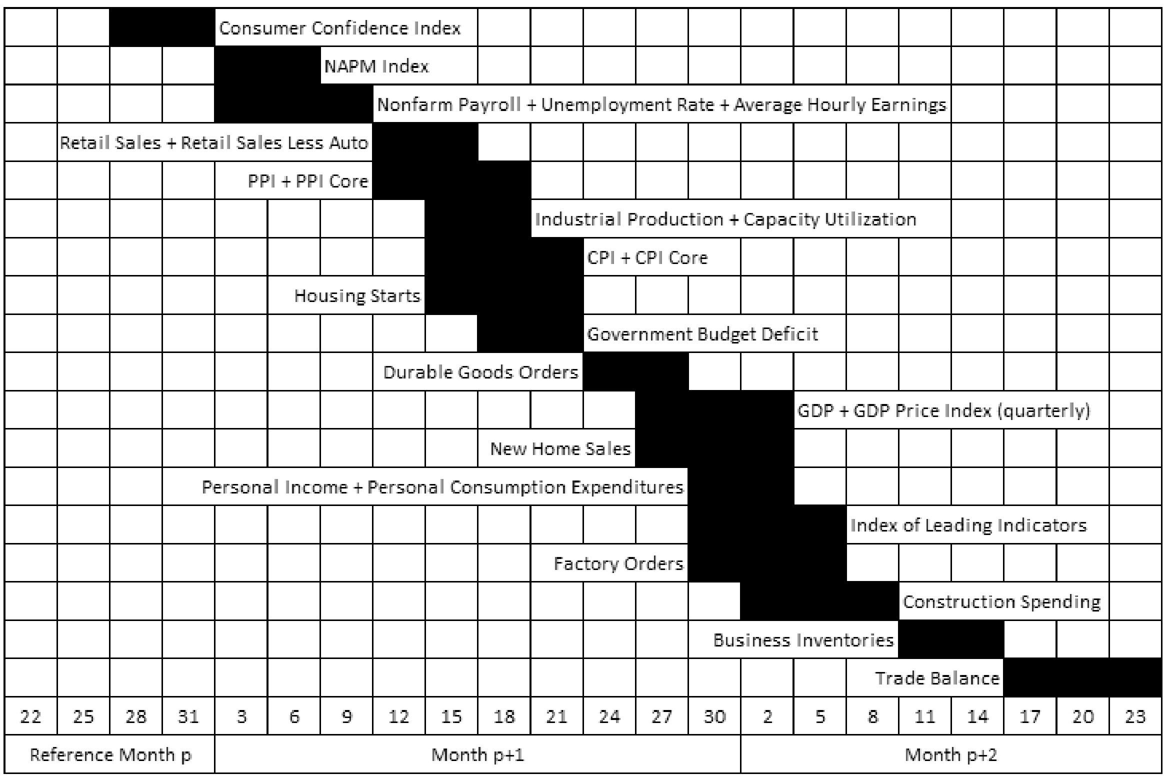

Figure 2
Nowcasts and Realizations

The upper panel shows the GDP Advance (Growth) Nowcast for the most recent unreleased annualized quarterly GDP Advance value based on public information available at each point in time. The step function represents the GDP Advance realization corresponding to the release to be forecast. The lower panel shows the GDP Deflator Advance Nowcast for the most recent unreleased annualized quarterly GDP Deflator Advance value based on public information available at each point in time. The step function represents the GDP Deflator Advance realization corresponding to the release to be forecast. Note that the values of the step functions in both panels are released at the right end of each step, that is, the forecasts should converge to the step function value during each interval.

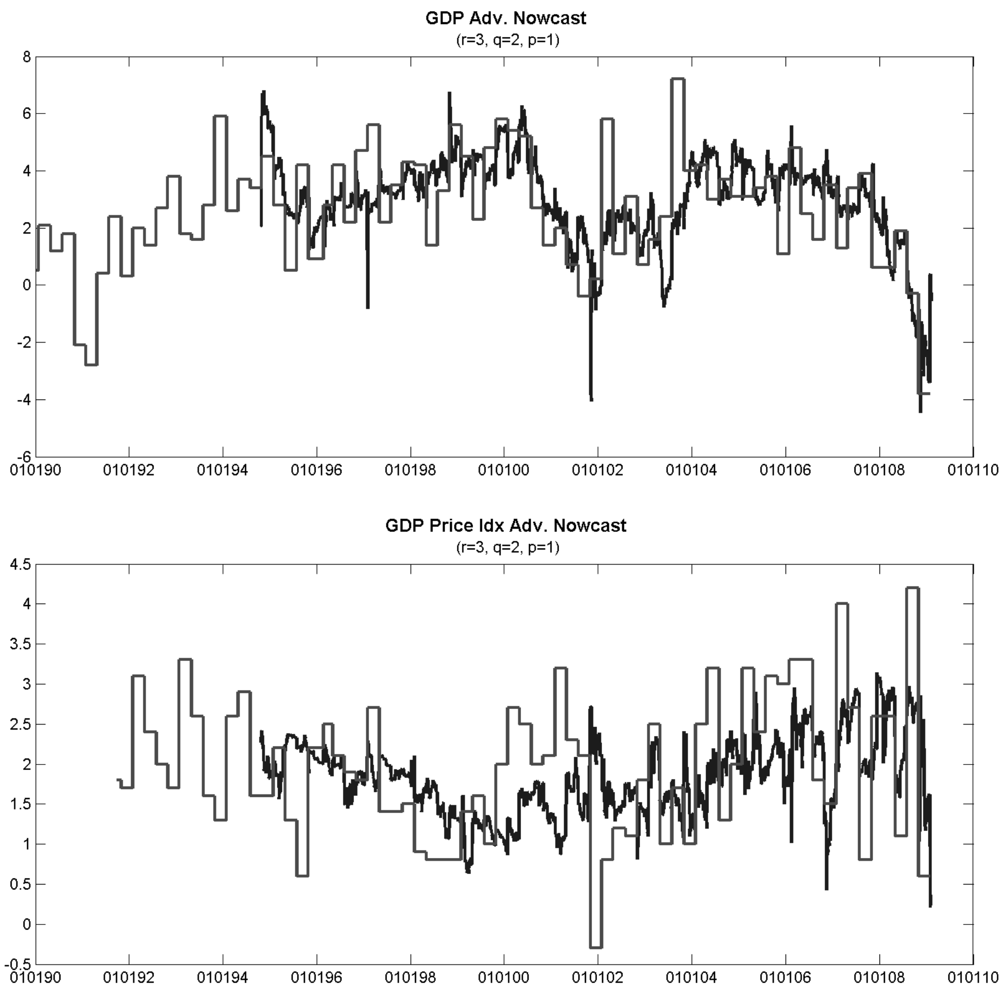

Figure 3
Information Model

The figure shows our information model and sequence of estimation.

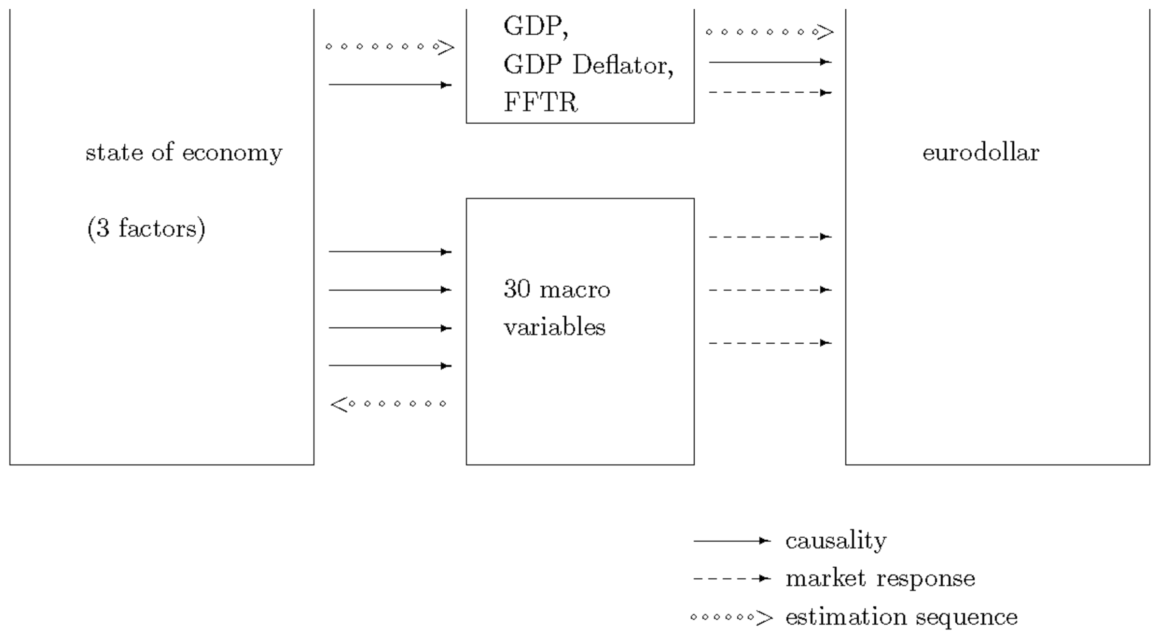

Figure 4
Nowcasts: Data Structure

The figure shows the data structure based on which nowcasts are calculated using the Kalman Filter.

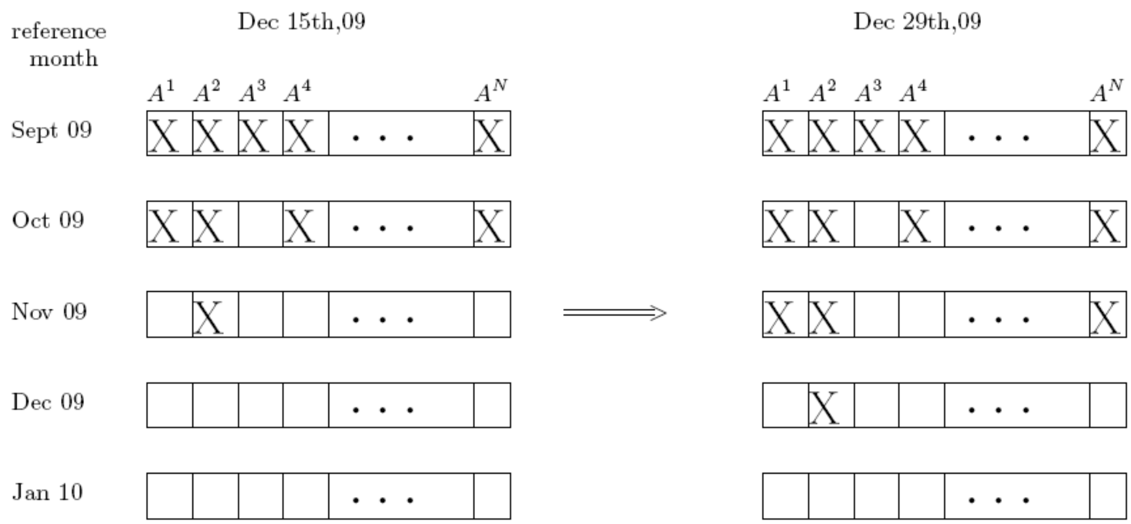

Figure 5
Composition of Announcement Impact

The graph shows the impact on eurodollar prices of a unit surprise. information content, timeliness, and noise are evaluated at the sample mean of their absolute values.

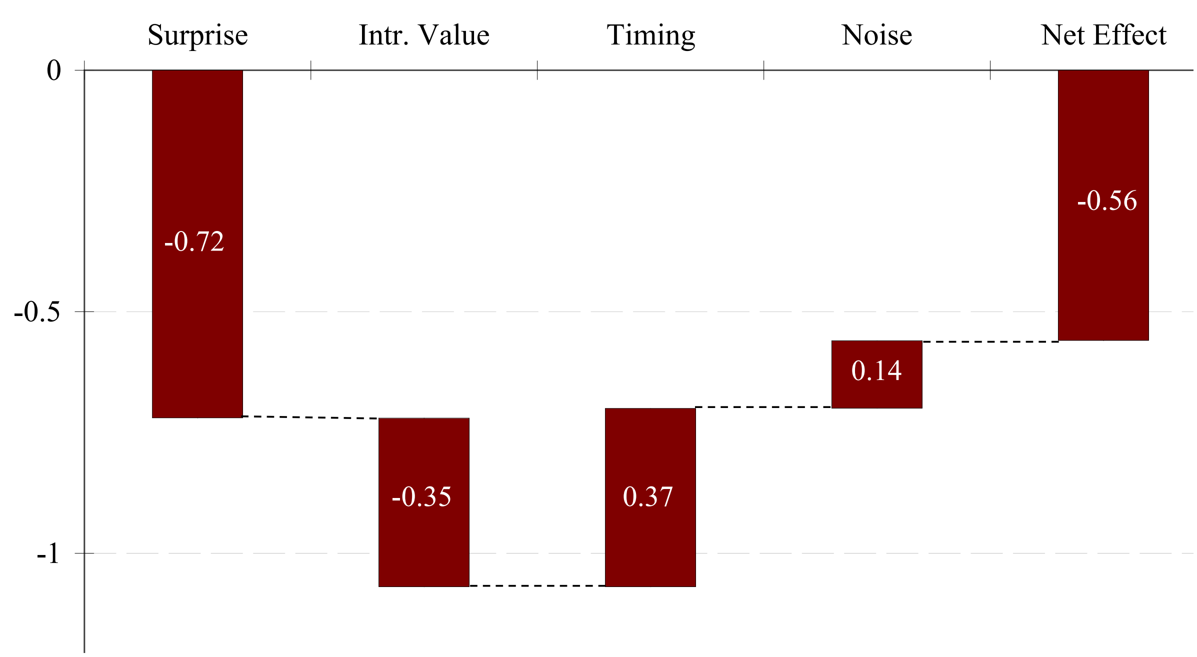

Table I
Characteristics of Macroeconomic Announcements

The reporting lag is the difference between the announcement date and the date of the period the announcement refers to. Revision noise is defined as the absolute value of the difference between the final revised figure and the initial announced figure, divided by the standard deviation of the absolute value of this difference. [CHANGE: Information content is the announcements ability to forecast FOMC decisions defined as. We need to change the information content to be the announcement's ability to forecast FOMC decisions rather than GDP.] The data sample is from January 1994 to December 2008.

k	**Announcement**	**Unit**	**Release Time** (ET)	**Reporting Lag** (median days)	**Revision Noise** (average)	**Information Content**
			Quarterly Announcements			
			Real Activity			
1	GDP Advance (A)	% change	8:30	29	1.15	
2	GDP Preliminary (P)	% change	8:30	59	1.22	
3	GDP Final (F)	% change	8:30	87	1.16	
			Prices			
4	GDP Price Index/Deflator A	% change	8:30	29	1.19	
5	GDP Price Index/Deflator P	% change	8:30	59	1.24	
6	GDP Price Index/Deflator F	% change	8:30	87	1.31	
			Monthly Announcements			
			Real Activity			
7	Unemployment Rate	%	8:30	5	0.76	-0.09
8	Nonfarm Payroll	net change	8:30	5	1.28	0.55
9	Retail Sales	% change	8:30	13	1.33	0.34
10	Retail Sales Less Autos	% change	8:30	13	1.27	0.52
11	Industrial Production	% change	9:15	16	1.30	0.60
12	Capacity Utilization	%	9:15	16	1.81	0.13
13	Personal Income	% change	8:30/10:00	30	0.63	0.27
			Consumption			
14	Personal Consumption	% change	8:30	29	1.21	0.35
15	New Home Sales	level	10:00	29	1.24	0.05
			Investment			
16	Durable Goods Orders	% change	8:30/9:00/10:00	26	1.07	0.18
17	Construction Spending	% change	10:00	32	1.21	0.38
18	Factory Orders	% change	10:00	33	1.06	0.32
19	Business Inventories	% change	8:30/10:00	45	1.18	0.20
			Government Purchases			
20	Government Budget Deficit	level	14:00	21	0.20	0.09
			Net Exports			
21	Trade Balance	level	8:30	48	1.02	0.01
			Prices			
22	Average Hourly Earnings	% change	8:30	5	0.96	-0.12
23	Producer Price Index (PPI)	% change	8:30	13	1.04	0.01
24	Core PPI	% change	8:30	13	0.92	-0.10
25	Consumer price index (CPI)	% change	8:30	16	1.03	0.10
26	Core CPI	% change	8:30	16	0.65	-0.15
			Forward Looking			
27	Consumer Confidence Index	index	10:00	-3	1.21	0.32
28	NAPM/ISM Index	index	10:00	1	1.13	0.45
29	Housing Starts	level	8:30	17	1.24	0.33
30	Index of Leading Indicators	% change	8:30/10:00	30	1.22	-0.08
			Weekly Announcements			
31	Initial Unemployment Claims	level	8:30	5	0.84	-0.30

Table II
Effect of Macroeconomic Surprises on Asset Prices

This table reports the result of individual regressions of 5-minute asset returns around announcement times on the announcement surprises. The sample period is from January 1994 to December 2008. White standard errors are used and ***, **, and * represent a 1, 5, and 10% level of significance, respectively.

k	Announcement	Eurodollar		Two-Year Bond		Five-Year Bond		Ten-Year Bond		Thirty-Year Bond	
		Coeff.	R^2	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2
1	GDP Advance	-0.012***	21.7	-0.042***	30.1	-0.091***	28.0	-0.122***	27.0	-0.146***	21.0
2	GDP Preliminary	-0.009***	15.2	-0.012***	10.2	-0.036***	11.4	-0.045**	10.7	-0.069**	10.9
3	GDP Final	-0.001	0.2	-0.002	1.1	0.000	0.0	0.002	0.0	-0.012	0.9
4	GDP Price Index/Deflator A	0.004	2.2	0.000	0.0	-0.003	0.0	-0.006	0.1	-0.028	0.8
5	GDP Price Index/Deflator P	-0.005***	6.0	-0.005	2.3	-0.020*	4.1	-0.030**	5.4	-0.046**	5.6
6	GDP Price Index/Deflator F	0.000	0.0	0.001	0.3	-0.002	0.2	-0.007	0.8	-0.022	4.4
7	Unemployment Rate	0.023***	15.5	0.049***	9.6	0.116***	11.2	0.133***	8.9	0.167***	8.4
8	Nonfarm Payroll	-0.037***	42.4	-0.099***	40.5	-0.210***	38.3	-0.270***	38.5	-0.314***	30.9
9	Retail Sales	-0.011***	24.1	-0.029***	20.3	-0.063***	20.3	-0.085***	18.7	-0.103***	14.9
10	Retail Sales Less Autos	-0.011***	21.6	-0.032***	21.7	-0.067***	20.5	-0.096***	21.6	-0.120***	18.0
11	Industrial Production	-0.004***	12.4	-0.011***	18.3	-0.023***	14.2	-0.032***	13.2	-0.038***	8.8
12	Capacity Utilization	-0.006***	20.7	-0.016***	28.7	-0.034***	24.9	-0.048***	24.8	-0.065***	21.2
13	Personal Income	-0.001	0.4	0.000	0.0	-0.003	0.2	-0.008	0.5	-0.016	1.2
14	Personal Consumption	-0.001	0.3	-0.006*	3.1	-0.012	2.3	-0.011	1.0	-0.022	2.2
15	New Home Sales	-0.006***	18.6	-0.016***	24.7	-0.036***	26.0	-0.047***	21.9	-0.062***	19.0
16	Durable Goods Orders	-0.001	1.1	-0.001	0.2	-0.006	1.2	-0.008	1.1	-0.016**	2.4
17	Construction Spending	0.000	0.0	-0.001	0.1	-0.007	0.3	-0.007	0.2	-0.013	0.3
18	Factory Orders	-0.003***	5.1	-0.008***	6.1	-0.018***	7.2	-0.027***	7.6	-0.036***	6.5
19	Business Inventories	0.002	1.6	0.003	0.3	0.005	0.2	0.014	0.6	0.022	0.8
20	Government Budget Deficit	0.000	0.2	0.001*	0.8	0.000	0.0	0.002	0.2	0.004	0.4
21	Trade Balance	-0.001	0.4	-0.001	0.1	-0.003	0.2	-0.002	0.0	-0.006	0.3
22	Average Hourly Earnings	-0.004	0.5	-0.018	1.2	-0.041	1.3	-0.050	1.1	-0.092	2.3
23	Producer Price Index (PPI)	-0.006***	10.0	-0.019***	13.4	-0.039***	10.9	-0.055***	11.0	-0.082***	11.8
24	Core PPI	-0.009***	15.7	-0.024***	18.2	-0.054***	16.7	-0.075***	16.9	-0.111***	17.6
25	Consumer Price Index (CPI)	-0.004***	3.4	-0.015***	6.2	-0.030***	5.5	-0.043***	5.4	-0.065***	6.4
26	Core CPI	-0.011***	22.2	-0.036***	32.0	-0.071***	28.2	-0.095***	25.5	-0.138***	26.9
27	Consumer Confidence Index	-0.010***	39.3	-0.024***	41.8	-0.052***	40.7	-0.070***	40.2	-0.090***	34.8
28	NAPM/ISM Index	-0.014***	46.8	-0.038***	46.9	-0.089***	48.0	-0.118***	43.0	-0.157***	39.9
29	Housing Starts	-0.002**	2.7	-0.009***	7.8	-0.019***	6.6	-0.021***	4.5	-0.032***	5.3
30	Index of Leading Indicators	-0.001	0.4	-0.006	1.3	-0.012*	1.3	-0.017**	2.0	-0.028	2.7
31	Initial Unemployment Claims	0.004***	6.8	0.012***	10.0	0.022***	6.8	0.027***	5.2	0.037***	5.0

Table III
Joint Effect of Macroeconomic Surprises on Asset Prices – NOT UPDATED – TO BE DECIDED!

This table reports the result of single pooled regressions relating 5-minute asset returns around announcement times and the announcement surprises. The sample period is from January 1994 to December 2008. ***, **, and * represent a 1,5,and 10% level of significance.

k		Eurodollar	Two-Year Bond	Five-Year Bond	Ten-Year Bond	Thirty-Year Bond
1	GDP Advance	-0.0109***	-0.0234***	-0.0954***	-0.1287***	-0.1602***
2	GDP Preliminary	-0.0072***	-0.0092**	-0.0293***	-0.0364***	-0.0531***
3	GDP Final	-0.0011*	-0.0017	-0.0044	-0.0038	-0.0173***
4	GDP Price Deflator Adv.	-0.0006	-0.0142***	-0.0323***	-0.0454***	-0.0744***
5	GDP Price Deflator Prel.	-0.0038***	-0.004	-0.0135***	-0.0215***	-0.0324***
6	GDP Price Deflator Final	-0.0007	0.0036	-0.0067***	-0.0135***	-0.0283***
7	Unemployment Rate	0.0199***	0.0345***	0.1037***	0.1184***	0.1478***
8	Nonfarm Payroll	-0.0368***	-0.0648***	-0.2094***	-0.2687***	-0.3208***
9	Retail Sales	-0.0064***	-0.0089***	-0.042***	-0.0662***	-0.0839***
10	Retail Sales Less Autos	-0.0073***	-0.0063**	-0.036***	-0.0421***	-0.048***
11	Industrial Production	0.0001	0.0023	0.0023	0.0067**	0.0222***
12	Capacity Utilization	-0.0064***	-0.0122***	-0.0368***	-0.0553***	-0.0857***
13	Personal Income	0.0002	0.0029	0.0023	-0.0005	-0.0068**
14	Personal Consumption	0.0002	-0.0017	-0.0059***	-0.0033	-0.0107***
15	New Home Sales	-0.0056***	-0.0079***	-0.0337***	-0.0445***	-0.0595***
16	Durable Goods Orders	-0.0012***	-0.0024	-0.0061***	-0.0082***	-0.0156***
17	Construction Spending	0.0004	0.0038*	-0.003**	-0.0014	-0.0062**
18	Factory Orders	-0.0026***	-0.0051**	-0.0181***	-0.0277***	-0.0378***
19	Business Inventories	0.0022***	0.0007	0.0045***	0.0129***	0.0213***
20	Government Budget Deficit	0.0002	0.0005	0.0003	0.0018	0.0042
21	Trade Balance	-0.002***	-0.0016	-0.0114***	-0.0112***	-0.0144***
22	Average Hourly Earnings	-0.0136***	-0.0317***	-0.0918***	-0.1141***	-0.169***
23	Producer Price Index (PPI)	-0.0016***	-0.0028	-0.0107***	-0.0137***	-0.0251***
24	Core PPI	-0.0075***	-0.0112***	-0.0456***	-0.0658***	-0.0934***
25	Consumer Price Index (CPI)	0.0013***	-0.0016	0.005***	0.0041*	0.0022
26	Core CPI	-0.0116***	-0.0185***	-0.0757***	-0.1003***	-0.1424***
27	Consumer Confidence Index	-0.0096***	-0.0122***	-0.0511***	-0.0682***	-0.0879***
28	NAPM/ISSM Index	-0.0135***	-0.021***	-0.0895***	-0.1189***	-0.1575***
29	Housing Starts	-0.0019***	-0.0066***	-0.0178***	-0.02***	-0.031***
30	Index of Leading Indicators	0.0002***	0.0004	0.0011***	0.0014***	0.0025***
31	Initial Unemployment Claims	0.0039***	0.0071***	0.023***	0.0281***	0.0387***
R^2	2.43%	0.13%	3.83%	3.16%	2.33%	
Obs.	1174950	1372981	1169478	1169478	1169478	

Table IV
Information Content for FOMC Decisions Forecasts

We measure the Information Content by the Likelihood Ratio (LR) between Model M2 and Model M1. Model 1 (M1): Ordered probit regression of FFTR changes on the GDP nowcast based on information which has been released prior to the release of variable A^k. Model 2 (M2): Ordered probit regression of FFTR changes on the GDP nowcast based on information which has been released prior to the release of variable A^k and on the variable A^k itself. The right column reports the p-value of the likelihood ratio test based on LR.

Variable A^k	**LR**	**p(LR)**
NAPM	39.97	0.00
Housing Starts	29.13	0.00
New Home Sales	27.06	0.00
Retail Sales Less Auto	5.03	0.02
Nonfarm Payroll	4.70	0.03
Capacity Utilization	3.66	0.06
CPI	3.39	0.07
Unemployment	3.04	0.08
Advance Retail Sales	2.20	0.14
Consumer Credit	2.12	0.15
Factory Orders	1.84	0.18
Construction Spending	1.50	0.22
Durable Goods Orders	1.27	0.26
Industrial Production	0.95	0.33
Budget Deficit	0.85	0.36
Average Hourly Earnings	0.54	0.46
Business Inventory	0.49	0.48
Trade Balance	0.44	0.51
Leading Indicators	0.39	0.53
Personal Income	0.33	0.57
Consumer Confidence	0.12	0.73
CPI Core	0.07	0.79
PPI Core	0.03	0.86
PPI	0.02	0.88
Personal Consumption	0.01	0.92

Table V
Information Content for GDP Growth Forecast

Information Content is defined as in table IV. The table shows the Likelihood Ratio (LR) and its p-value at the first, second, and – where applicable – third announcement A^k during a given quarter. The rightmost column reports the p-value of the aggregate null hypothesis that all three likelihood ratios are zero.

Variable A^k	**First Announcement**		**Second Announcement**		**Third Announcement**		**All Announcements**
	LR_1	$p(LR_1)$	LR_2	$p(LR_2)$	LR_3	$p(LR_3)$	$p(Aggregate)$
NAPM	7.49	0.01	4.38	0.04	4.56	0.03	0.00
Housing Starts	2.26	0.13	1.63	0.20	0.14	0.71	0.26
New Home Sales	0.23	0.63	0.15	0.70	0.07	0.79	0.93
Retail Sales Less Auto	2.99	0.08	1.72	0.19	10.17	0.00	0.00
Nonfarm Payroll	2.01	0.16	4.45	0.03	3.64	0.06	0.02
Capacity Utilization	0.05	0.82	2.84	0.09	3.22	0.07	0.11
CPI	0.13	0.71	2.37	0.12	3.01	0.08	0.14
Unemployment	4.29	0.04	1.87	0.17	1.30	0.25	0.06
Advance Retail Sales	3.76	0.05	1.57	0.21	1.18	0.28	0.09
Consumer Credit	4.15	0.04	1.95	0.16	n.a.	n.a.	0.05
Factory Orders	2.53	0.11	0.10	0.75	n.a.	n.a.	0.27
Construction Spending	4.85	0.03	5.49	0.02	5.91	0.02	0.00
Durable Goods Orders	2.27	0.13	0.02	0.89	0.02	0.90	0.51
Industrial Production	0.80	0.37	2.08	0.15	4.83	0.03	0.05
Budget Deficit	0.09	0.77	1.12	0.29	0.14	0.71	0.72
Average Hourly Earnings	0.09	0.76	1.34	0.25	0.01	0.94	0.70
Business Inventory	0.00	0.99	1.87	0.17	n.a.	n.a.	0.39
Trade Balance	0.10	0.75	0.48	0.49	n.a.	n.a.	0.75
Leading Indicators	3.69	0.05	1.22	0.27	0.02	0.90	0.18
Personal Income	0.22	0.64	1.55	0.21	n.a.	n.a.	0.41
Consumer Confidence	4.46	0.03	0.57	0.45	0.00	0.99	0.17
CPI Core	2.73	0.10	0.00	0.99	0.00	0.98	0.43
PPI Core	3.36	0.07	0.18	0.67	0.02	0.88	0.31
PPI	0.13	0.71	0.36	0.55	3.42	0.06	0.27
Personal Consumption	1.34	0.25	0.83	0.36	n.a.	n.a.	0.34

Table VI
Information Content for GDP Deflator Forecast

Information Content is defined as in table IV. The table shows the Likelihood Ratio (LR) and its p-value at the first, second, and – where applicable – third announcement A^k during a given quarter. The rightmost column reports the p-value of the aggregate null hypothesis that all three likelihood ratios are zero.

Variable A^k	**First Announcement**		**Second Announcement**		**Third Announcement**		**All Announcements**
	LR_1	$p(LR_1)$	LR_2	$p(LR_2)$	LR_3	$p(LR_3)$	$p(Aggregate)$
NAPM	2.67	0.10	2.12	0.15	0.60	0.44	0.15
Housing Starts	2.52	0.11	3.84	0.05	2.19	0.14	0.04
New Home Sales	4.31	0.04	2.36	0.12	2.74	0.10	0.02
Retail Sales Less Auto	0.54	0.46	1.41	0.24	1.29	0.26	0.36
Nonfarm Payroll	5.55	0.02	2.44	0.12	1.25	0.26	0.03
Capacity Utilization	3.22	0.07	0.42	0.52	0.43	0.51	0.25
CPI	15.51	0.00	4.56	0.03	5.85	0.02	0.00
Unemployment	0.77	0.38	0.20	0.66	5.34	0.02	0.10
Advance Retail Sales	3.28	0.07	2.52	0.11	0.06	0.80	0.12
Consumer Credit	1.26	0.26	0.60	0.44	n.a.	n.a.	0.39
Factory Orders	9.89	0.00	2.24	0.13	n.a.	n.a.	0.00
Construction Spending	0.01	0.93	2.30	0.13	9.62	0.00	0.01
Durable Goods Orders	15.56	0.00	1.68	0.20	1.62	0.20	0.00
Industrial Production	0.81	0.37	0.09	0.76	0.35	0.55	0.74
Budget Deficit	1.20	0.27	0.04	0.85	6.19	0.01	0.06
Average Hourly Earnings	0.79	0.37	0.04	0.85	0.08	0.78	0.82
Business Inventory	8.74	0.00	7.06	0.01	n.a.	n.a.	0.00
Trade Balance	0.51	0.47	0.30	0.58	n.a.	n.a.	0.66
Leading Indicators	7.07	0.01	2.39	0.12	0.95	0.33	0.02
Personal Income	0.09	0.76	0.08	0.78	n.a.	n.a.	0.92
Consumer Confidence	0.17	0.68	1.00	0.32	0.21	0.65	0.71
CPI Core	4.21	0.04	0.01	0.94	2.77	0.10	0.07
PPI Core	8.65	0.00	0.68	0.41	0.05	0.82	0.02
PPI	12.29	0.00	4.44	0.04	2.31	0.13	0.00
Personal Consumption	1.24	0.27	0.77	0.38	n.a.	n.a.	0.37

Table VII
Tests on Simultaneous Announcements

[TO BE COMPLETED]

Announcement	Eurodollar			Ten-year Gov't Bond			British Pound			S&P500			
	Coeff	t-stat	Adj R^2	Coeff	t-stat	Adj R^2	Coeff	t-stat	Adj R^2	Coeff	t-stat	Adj R^2	Obs
Unemployment Rate	0.0120	4.64	46.12%	0.1089	4.46	45.95%	0.0295	2.05	21.03%	-0.0246	-0.67	5.71%	175
Nonfarm Payroll	-0.0282	-10.60		-0.2634	-10.56		-0.0943	-6.40		-0.0589	-1.56		175
Average Hourly Earnings	-0.0097	-3.71		-0.1033	-4.22		-0.0158	-1.09		-0.1282	-3.46		175
Retail Sales	-0.0066	-4.01	26.42%	-0.0448	-2.66	23.90%	-0.0273	-3.22	26.65%	0.0065	0.26	-0.47%	177
Retail Sales Less Autos	-0.0047	-2.83		-0.0634	-3.75		-0.0314	-3.68		0.0162	0.65		177
Capacity Utilization	-0.0032	-2.93	15.48%	-0.0526	-5.42	24.86%	0.0014	0.19	6.62%	0.0116	1.18	-0.23%	176
Industrial Production	-0.0008	-0.78		0.0085	0.89		-0.0178	-2.48		-0.0118	-1.21		176
PPI	-0.0027	-1.82	13.86%	-0.0315	-2.30	18.23%	-0.0063	-0.75	0.02%	-0.0322	-1.53	16.28%	178
Core PPI	-0.0054	-3.72		-0.0571	-4.19		-0.0060	-0.71		-0.0923	-4.40		178
CPI	0.0008	0.56	19.68%	0.0065	0.49	25.36%	0.0047	0.60	4.38%	-0.0343	-1.55	28.17%	178
Core CPI	-0.0090	-6.04		-0.0934	-6.99		-0.0234	-2.98		-0.1398	-6.31		178
GDP Advance	-0.0116	-3.60	16.98%	-0.1350	-4.85	27.41%	-0.0981	-5.95	36.94%	0.1065	1.99	5.55%	58
GDP Price Index/Deflator A	-0.0003	-0.09		-0.0364	-1.30		-0.0219	-1.32		-0.0359	-0.67		58
GDP Preliminary	-0.0044	-3.02	15.22%	-0.0367	-2.48	12.82%	-0.0197	-2.03	4.64%	-0.0381	-1.51	7.25%	54
GDP Price Index/Deflator P	-0.0021	-1.44		-0.0265	-1.82		-0.0058	-0.61		-0.0472	-1.91		54
GDP Final	-0.0015	-1.46	0.32%	-0.0017	-0.15	-3.78%	0.0011	0.15	-1.18%	0.0206	1.30	6.39%	55
GDP Price Index/Deflator F	-0.0001	-0.05		-0.0010	-0.08		-0.0088	-1.17		-0.0359	-2.14		55
GDP All	-0.0070	-5.58	15.31%	-0.0778	-6.90	21.71%	-0.0545	-7.67	25.65%	0.0498	2.36	3.30%	166
GDP Price Index/Deflator All	-0.0006	-0.48		-0.0224	-1.98		-0.0153	-2.14		-0.0179	-0.85		166

Table VIII
GDP Channel versus GDP Deflator Channel

Result of master regression. The left column uses intrinsic values based on GDP weights, whereas the right column uses GDP deflator weigths. Data is for 2003–2009. If several announcements are released at the same time, only the announcement with the largest effect is kept (e.g. keep NFP, drop unemployment).

Variable	**GDP Channel**	**GDP Deflator Channel**
$\bar{S}$	-0.72***	-1.25***
	(0.16)	(0.14)
$\bar{S} \times \bar{T}$	0.02***	0.03***
	(0.00)	(0.01)
$\bar{S} \times \bar{I}$	-3.24***	-0.88
	(0.83)	(1.11)
$\bar{S} \times \bar{N}$	0.14***	0.13***
	(0.04)	(0.04)
const.	-0.00	-0.01
	(0.05)	(0.05)

Table IX
Mean and Standard Deviation of Variables in master regression

The table reports mean and standard deviation of the variables used in the master regression.

Variable	mean	s.d.
Surprise $\bar{S}$	-0.05	1.00
Timing $\bar{T}$	18.51	12.23
Real-time Intrinsic Value $\bar{I}$	0.11	0.07
Noise $\bar{N}$	0.98	0.96

Table X
Marginal Effects

The table reports the marginal effect on the eurodollar of a one-standard-deviation shock via the GDP channel for all variables in our sample. (No main effects, no overlap, GDP channel only) Marginal effects are evaluated at mean.

Variable	Effect	Wald test	p(W)
Surprise	-0.53	108.4	0.00
Timing	0.25	22.0	0.00
Real-time Intrinsic Value	-0.20	15.2	0.00
Noise	0.13	12.6	0.00

Table XI
Marginal Effects for Real Activity Variables

The table reports the marginal effect of a one-standard-deviation shock on the eurodollar via the GDP channel for real activity variables only. (No main effects, no overlap, GDP channel only) Marginal effects are evaluated at mean.

Variable	Effect	Wald test	p(W)
Surprise	-0.44	75.8	0.00
Timing	0.18	10.6	0.00
Real-time Intrinsic Value	-0.31	30.6	0.00
Noise	0.14	14.1	0.00