Informed and Strategic Order Flow in the Bond Market

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Abstract

We analyze the role private and public information play in the U.S. Treasury bond price discovery process. To guide our analysis, we develop a parsimonious model of speculative trading in the presence of two realistic market frictions, information heterogeneity and imperfect competition among informed traders. We test its equilibrium implications by studying the response of 2-year, 5-year, and 10-year U.S. bond yields to order flow and real-time U.S. macroeconomic news. Consistent with the stylized model, we find that unanticipated order flow explains a bigger portion of bond yield changes when the dispersion of beliefs across informed traders is high and public announcements are noisy.

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1 Introduction

Researchers can successfully associate bond price movements to macroeconomic fundamentals when they focus on announcement days.[1] Yet, the poor performance of public news in explaining day to day bond price changes outside announcement days has motivated a search for alternative explanatory variables.[2] One possible candidate, analyzed in Brandt and Kavajecz (2004), is order flow. When sophisticated agents trade, their private information is (partially) revealed to the market causing revisions in bond prices even in the absence of public announcements.

The goal of this paper is to theoretically identify and empirically measure the effect of these two complementary mechanisms responsible for daily bond price changes: aggregation of public news and aggregation of order flow. In particular, we investigate the relevance of each mechanism conditional on the dispersion of beliefs among investors and the public signals' noise.

To guide our analysis, we first construct a parsimonious one-shot version of Foster and Viswanathan's (1996) multiperiod model à la Kyle (1985) with imperfectly competitive and heterogeneously informed investors. In this setting, greater asymmetric sharing of information among investors leads to lower equilibrium market liquidity (i.e., unanticipated order flow has a larger effect on bond yield changes). We then introduce a public signal and derive the implications for equilibrium prices and trading strategies on announcement and non-announcement days. In particular, we show that the availability of a public signal improves market liquidity (the more so the lower the signal's noise) since its presence mitigates the quasi-monopolistic behavior of the informed traders.

This model is not asset-specific, i.e., it applies to stock, bond, and foreign exchange markets, but we test its implications for the U.S. government bond market for two reasons. First, Treasury market data contains signed trades, thus we do not rely on algorithms, e.g. Lee and Ready's (1991), which introduce measurement error to our estimates of order flow. Second, govern-

[1] See, for example, Fleming and Remolona (1997, 1999), Balduzzi, Elton and Green (2001), Kuttner (2001), Andersen, Bollerslev, Diebold, and Vega (2004).

[2] Most of the "non-event" term structure literature ignores macroeconomic fundamentals and builds models around a few latent state variables, e.g. Vasicek (1977), Cox, Ingersoll and Ross (1985), Litterman and Scheinkman (1991), Dai and Singleton (2000). Recent papers explicitly incorporate macroeconomic fundamentals into these multi-factor yield curve models, e.g. Ang and Piazzesi (2003), Hördahl, Tristani, and Vestin (2002), Wu (2002), and Diebold, Rudebusch and Aruoba (2004). However, these studies focus on monthly data and show that macro factors explain up to 30% of the variation in bond yields (Ang and Piazzesi, 2003). For a survey of this literature, see Diebold, Piazzesi and Rudebusch (2005).

ment bond markets represent the simplest trading environment to decompose price changes while avoiding omitted variable biases. For example, most theories predict an unambiguous link between macroeconomic fundamentals and bond yield changes, with unexpected increases in real activity and inflation raising nominal bond yields.[3] In contrast, there is a regime switch in the effect macroeconomic fundamentals have on stock market movements (Boyd et al., 2005, and Andersen et al., 2004).

The empirical results strongly support the main implications of the model. First, on non-announcement days, adverse selection costs are higher when the dispersion of beliefs is high.[4] An average shock to abnormal order flow decreases 2-year, 5-year and 10-year bond yields by 6.51%, 10.19% and 6.04%, respectively, on high dispersion days compared to 3%, 3.3% and 2.86% on low dispersion days.[5] These differences are economically and statistically significant. Intuitively, when information heterogeneity is high, the investors' quasi-monopolistic trading behavior leads to a "cautious" equilibrium where changes in unanticipated order flow have a greater impact on bond yields.

Mechanically, higher adverse selection costs translate into higher correlation between order flow changes and bond yield changes, but the magnitude of the differences in the adjusted R^2 is striking. For example, during non-announcement days order flow explains 40.55% of the variation in 5-year bond yield changes when the dispersion of beliefs is high, compared to 5.84% of the variation when the dispersion of beliefs is low.

The release of a public signal, a trade-free source of information about fundamentals, induces informed traders to trade more aggressively on their private information. Consistently, the importance of unanticipated order flow in explaining yield changes declines during announcement days. For example, comparing non-announcement days with Nonfarm Payroll Employment announcement days, the explanatory power of order flow decreases from 21.13% to 5.50%, 20.57% to 19.92%, and 9.06% to 1.50% for the 2-year, 5-year, and 10-year bonds, respectively. Yet, when the dispersion of beliefs is high and the public information signal is noisy, the importance of order flow in setting bond prices increases.[6]

[3] This unambiguous relationship is shown, for example, in Lucas' (1982) general equilibrium model and has been confirmed empirically by Fleming and Remolona (1997) and Balduzzi, Elton, and Green (2001), among others.

[4] We measure the dispersion of beliefs among sophisticated market participants using the standard deviation of professional forecasts of macroeconomic announcements. We then classify the resulting measures as high or low according to three alternative procedures. We provide more details about these classification schemes in Section 4.1.

[5] We define an average shock as one standard deviation change from the mean.

[6] As specified in Section 3, we measure the public signal's noise as the absolute difference between the actual announcement and the latest announcement revision.

Our paper is most closely related to two recent studies of order flow in the U.S. Treasury market. Brandt and Kavajecz (2004) find that order flow imbalances account for up to 26% of the variation in yields on days without major macroeconomic announcements. Green (2004) examines the effect of order flow on intraday bond price changes surrounding macroeconomic news announcements. We extend both studies by identifying a theoretical and empirical link between the price discovery role of order flow and the degree of information heterogeneity among informed traders and the quality of macroeconomic data releases. By documenting the important role of dispersion of beliefs, our results contradict the weak relation reported by Green (2004). This contradiction is due to the difference in time horizons. Green (2004) focuses on 30-minute intervals surrounding macroeconomic news events, while we analyze daily data. Since the econometrician does not observe the arrival of private information signals, narrowing the estimation window may lead to an underestimation of the interaction between dispersion of beliefs and order flow.

Our work also belongs to the literature bridging the gap between asset pricing and market microstructure. Evans and Lyons (2003) find that signed order flow is a good predictor of subsequent exchange rate movements; Brandt and Kavajecz (2004) show that this is true for bond market movements; Easley, Hvidkjaer, and O'Hara (2002) argue that the probability of informed trading (PIN), a function of order flow, is a priced firm characteristic in stock returns. These studies conjecture that order flow conveys information about fundamentals, yet it can be the case that these studies are picking up a *liquidity* effect unrelated to fundamentals. Evans and Lyons (2004) address this issue by showing that foreign exchange order flow predicts future macroeconomic surprises; so at least foreign exchange order flow conveys information about fundamentals. We go a step further in linking the impact of order flow on bond prices to macroeconomic uncertainty (i.e., public signal noise) and the heterogeneity of beliefs about real shocks.

We proceed as follows. In Section 2, we construct a stylized model of trading and identify the implications of public information shocks for the resulting equilibrium. This theoretical benchmark provides useful guidance for developing the subsequent empirical analysis. In Section 3, we describe the three data sets we use. In Section 4, we present the empirical results. Section 5 concludes.

2 Theoretical Model

In this section we motivate the analysis of the impact of the release of macroeconomic news on bond prices and order flow. We first describe a one-shot version of the multi-period model of trading with heterogeneously informed traders of Foster and Viswanathan (1996). Then, we consider the effect of introducing a public signal on the equilibrium price and trading strategies. All proofs are in the Appendix unless otherwise noted.

2.1 Benchmark: No Public Signal

The basic model is a two-date, one-period economy in which a single risky asset is exchanged. Trading occurs only at the end of the first period ($t = 1$), after which the asset payoff, a normally distributed random variable v with mean p_0 and variance σ_v^2, is realized. The economy is populated by three types of risk-neutral traders: A discrete number (M) of informed traders, liquidity traders, and perfectly competitive market-makers (MMs). All traders know the structure of the economy and the decision process leading to order flow and prices.

At time $t = 0$ there is no information asymmetry about v, and the price of the risky asset is p_0. Sometime between $t = 0$ and $t = 1$, each informed trader k receives a private and noisy signal of $v - p_0$, S_{vk}. In the spirit of Foster and Viswanathan (1996), it is assumed that the resulting signal vector S_v is drawn from a multivariate normal distribution (MND) with mean zero and covariance matrix Σ_s such that $var\left(S_{vk}\right) = \sigma_s^2$ and $cov\left(S_{vk}, S_{vj}\right) = \sigma_{ss}$. We further impose that the informed traders together know the liquidation value of the risky asset: $\sum_{k=1}^{M} S_{vk} = v - p_0$; therefore, $cov\left(v, S_{vk}\right) = \frac{1}{M}\sigma_v^2$.[7]

These assumptions imply that $E\left(v - p_0 | S_{vk}\right) = \delta_k = \psi S_{vk}$, where $\psi = \frac{\sigma_v^2}{M\sigma_s^2}$, and that $E\left(\delta_j | \delta_k\right) = \gamma\delta_k$, where $\gamma = \frac{\sigma_{ss}}{\sigma_s^2}$ is the correlation between any two information endowments δ_k and δ_j. We parametrize the degree of precision of, and diversity among informed investors' signals by requiring that $\sigma_s^2 - \sigma_{ss} = \chi \geq 0$.[8] If $\chi = 0$, then agents' information is *homogeneous*: all informed traders receive the same signal $S_{vk} = \frac{v-p_0}{M}$, for all k, such that $\sigma_s^2 = \sigma_{ss} = \frac{\sigma_v^2}{M^2}$ and $\gamma = 1$. If $\chi = \frac{\sigma_v^2}{M}$, then agents' information is *heterogeneous*: $\sigma_s^2 = \chi$, $\sigma_{ss} = 0$, and $\gamma = 0$. Otherwise, agents' signals are only partially

[7] This specification makes the total amount of information available to informed traders independent from the correlation of their private signals, albeit still implying the most general structure up to rescaling by a constant (see Foster and Viswanathan, 1996).

[8] This restriction ensures that the covariance matrix Σ_s is positive definite.

correlated, $\gamma \in (0,1)$ if $\chi \in \left(0, \frac{\sigma_v^2}{M}\right)$ and $\gamma \in \left(-\frac{1}{M-1}, 0\right)$ if $\chi > \frac{\sigma_v^2}{M}$.[9]

At time $t = 1$, both informed traders and liquidity traders submit their orders to the MMs, before the equilibrium price p_1 has been set. We define the market order of the k^{th} informed trader to be x_k. Thus, his profit is given by $\pi_k(x_k, p_1) = (v - p_1)\, x_k$. Liquidity traders generate a random, normally distributed demand u, with mean zero and variance σ_u^2. For simplicity, we assume that u is independent from all other random variables. MMs do not receive any information, but observe the aggregate order flow $\omega_1 = \sum_{k=1}^{M} x_k + u$ from all market participants and set the market-clearing price $p_1 = p_1(\omega_1)$.

2.1.1 Equilibrium

Consistently with Kyle (1985), we define a Bayesian Nash equilibrium as a set of $M + 1$ functions $x_1(\cdot), \ldots, x_M(\cdot)$, and $p_1(\cdot)$ such that the following two conditions hold:

1. *Profit maximization*: $x_k(\delta_k) = \arg\max E(\pi_k|\delta_k)$;

2. *Semi-strong market efficiency*: $p_1(\omega_1) = E(v|\omega_1)$.

We restrict our attention to linear equilibria. We first conjecture general linear functions for the pricing rule and informed traders' demands. Then we solve for their parameters satisfying conditions 1 and 2. And finally we show that these parameters and those functions represent a rational expectations equilibrium. The following proposition accomplishes this task.

Proposition 1 *There exists a unique linear equilibrium given by the price function*

$$p_1 = p_0 + \lambda\omega_1 \tag{1}$$

and by the k^{th} informed trader's demand strategy

$$x_k = \frac{\lambda^{-1}\psi}{2 + (M-1)\gamma} S_{vk}, \tag{2}$$

where $\lambda = \frac{\sigma_v \psi^{\frac{1}{2}}}{\sigma_u[2+(M-1)\gamma]} > 0$.

[9] Note that the assumption that the total amount of information available to investors is fixed ($\sum_{k=1}^{M} S_{vk} = v - p_0$) implies that $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$. Furthermore, the absolute bound to the largest negative correlation γ across agents' private signals, $\left|-\frac{1}{M-1}\right|$, is compatible with a positive definite variance-covariance matrix, Σ_s, and it is a decreasing function of the number of informed traders, M.

The optimal trading strategy of each informed trader depends on the information he receives about the intrinsic asset value, v, and on the depth of the market, λ^{-1}. If $M = 1$, Eqs. (1) and (2) reduce to the well-known equilibrium of Kyle (1985). The informed traders, albeit risk-neutral, exploit their private information cautiously ($|x_k| < \infty$), to avoid dissipating their informational advantage with their trades. Thus, the equilibrium market liquidity in p_1 reflects the MMs' attempt to be compensated for the losses they anticipate from trading with informed traders, as it affects their profits from liquidity trading.

2.1.2 Testable Implications

The parsimonious equilibrium of Eqs. (1) and (2) displays many of the properties of the multi-period model of Foster and Viswanathan (1996).[10] In both models the optimal market orders x_k depend on the number of informed traders (M) and the correlation among their information endowments (γ). The intensity of competition among informed traders affects their ability to maintain the informativeness of the order flow as low as possible. A greater number of informed agents trade more aggressively, since (imperfect) competition among them precludes any collusive trading strategy. This behavior makes less serious the adverse selection problem for the MMs and the market more liquid (lower λ). The heterogeneity of informed investors' signals attenuates their trading aggressiveness. When information is less correlated (low γ), each informed trader has some monopoly power over his private signal because at least part of it is only known to him. And so he trades more cautiously to reveal less of his private information and attain higher profits. This "quasi-monopolistic" behavior makes the MMs more vulnerable to adverse selection and the market less liquid (higher λ). The following corollary summarizes the first set of empirical implications of our model.

Corollary 1 *Equilibrium market liquidity is increasing in the number of informed traders and decreasing in the heterogeneity of their information endowments.*

To gain further insight on this result, we construct a simple numerical example by setting $\sigma_v = \sigma_u = 1$. We then vary the parameter χ to study the liquidity of this market with respect to a broad range of signal correlations γ (from very highly negative to very highly positive) when $M = 1$, 2, 4, and 8. We plot the resulting λ in Figure 1a. Multiple, perfectly heterogeneously

[10] Similar results and intuition have also been provided by Back et al. (2000) in a continuous-time setting.

informed agents ($\gamma = 0$) collectively trade as cautiously as a monopolist informed investor. Under these circumstances, adverse selection is at its highest, and market liquidity at its lowest ($\lambda = \frac{\sigma_v}{2\sigma_u}$). A greater number of competing informed traders improves market depth, but significantly so only if accompanied by more correlated private signals. Along the same lines, the ensuing greater competition among informed traders raises the unconditional volatility of the equilibrium price, $var(p_1) = \frac{M\sigma_v^4}{\sigma_v^2(M+1)+M(M-1)\chi} < \sigma_v^2$, i.e., its informativeness (plotted in Figure 1b).[11] However, ceteris paribus, the improvement in market liquidity is more pronounced (and informed trading less cautious) when informed traders' signals are negatively correlated. When $\gamma < 0$, each informed trader expects his competitors' trades to be negatively correlated to his own (pushing p_1 against his signal), and trading on his own signal becomes more profitable. Consistently, $var(p_1)$ is low (and lower so for higher M), since negatively correlated trades, x_k, tend to offset each other in aggregate order flow, ω_1.

2.2 Extension: A Public Signal

We now amend the basic setting of Section 2.1 by providing each player with an additional common source of information about the risky asset's intrinsic value. According to Kim and Verrecchia (1994, p. 43), "Public disclosure has received little explicit attention in theoretical models whose major focus is understanding market liquidity."[12] More specifically, we assume that, sometime between $t = 0$ and $t = 1$, both the informed traders and the MMs also observe a public and noisy signal, S_p, of the intrinsic value of the asset, v, which is normally distributed with mean p_0 and variance $\sigma_p^2 > \sigma_v^2$. We can think of S_p as any public announcement (e.g., macroeconomic news) released simultaneously to all market participants. We further impose that $cov(S_p, v) = \sigma_v^2$, so that the parameter σ_p^2 controls for the quality of the public signal and $cov(S_p, S_{vk}) = \frac{\sigma_v^2}{M}$. The information endowment of each informed trader is then given by $\delta_k = E(v - p_0 | S_{vk}, S_p) = \alpha S_{vk} + \beta(S_p - p_0)$,

[11] Proposition 1 implies that $var(p_1) = \frac{\sigma_v^4}{M\sigma_s^2+\sigma_v^2}$, where $\sigma_s^2 = \frac{\sigma_v^2+M(M-1)\chi}{M^2}$ because $\sum_{k=1}^{M} S_{vk} = v - p_0$ and $\sigma_s^2 - \sigma_{ss} = \chi$.

[12] Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) consider dynamic models in which the private information of either perfectly competitive insiders or a monopolistic insider is either fully or partially revealed by the end of the trading period. Diamond and Verrecchia (1991) argue that the disclosure of public information may reduce the volatility of the order flow, leading some market makers to exit. Kim and Verrecchia (1994) show that in the presence of better information processors the arrival of a public signal leads to greater information asymmetry and market liquidity.

where $\alpha = \frac{M\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_p^2[\sigma_v^2+M(M-1)\chi]-\sigma_v^4} > 0$ and $\beta = \frac{\sigma_v^2 M(M-1)\chi}{\sigma_p^2[\sigma_v^2+M(M-1)\chi]-\sigma_v^4} \geq 0$. Thus, $E\left(\delta_j|\delta_k\right) = \gamma_p\delta_k$, where $\gamma_p = \frac{M\alpha^2\sigma_{ss}+2\alpha\beta\sigma_v^2+M\beta^2\sigma_p^2}{M\alpha^2\sigma_s^2+2\alpha\beta\sigma_v^2+M\beta^2\sigma_p^2} > 0$ even when investors' information is heterogeneous ($\chi = \frac{\sigma_v^2}{M}$ and $\gamma = 0$).

2.2.1 Equilibrium

Again we search for linear equilibria. The following proposition summarizes our results.

Proposition 2 *There exists a unique linear equilibrium given by the price function*

$$p_1 = p_0 + \lambda_p\omega_1 + \lambda_s\left(M+1\right)\left(S_p - p_0\right) \tag{3}$$

and by the k^{th} informed trader's demand strategy

$$x_k = \frac{\lambda_p^{-1}\alpha}{2+\left(M-1\right)\gamma_p}S_{vk} + \lambda_p^{-1}\left[\frac{\beta}{2+\left(M-1\right)\gamma_p} - \lambda_s\right]\left(S_p - p_0\right), \tag{4}$$

where $\lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]} > 0$, $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2}\left\{\frac{\sigma_v^2\left[2+(M-1)\gamma_p-\alpha\right]-\beta M\sigma_p^2}{\sigma_v^2\left[2+(M-1)\gamma_p\right]}\right\}$, *and* $\Gamma > 0$ *is defined in the Appendix.*

The optimal trading strategy of each informed trader in Eq. (4) depends now on three terms. The first one represents the cautious use of the private signal, S_{vk}, as in Proposition 1. The last two instead represent the use of the surprise portion of the public signal. The former, of the same sign as the public surprise, $S_p - p_0$, is driven by the informed trader's belief update about the intrinsic value of the asset, v, stemming from S_p. The latter, possibly of the opposite sign of the publis surprise, $S_p - p_0$, is a strategic component driven by the informed trader's attempt to make trading on his private signal, S_{vk}, more profitable.

Indeed, the MMs extract information about the intrinsic value of the asset, v, from two noisy sources of information, order flow and the public signal, in order to set the market-clearing price, p_1. However, the public signal, S_p, does not generate any adverse selection concern, hence, if precise (low σ_p^2), it pushes the equilibrium price, p_1, closer to the intrinsic value of the asset, v, making investors' private information less valuable. It therefore becomes imperative for them to steer the equilibrium price, p_1, away from the public signal, S_p, with *contrarian* trades. For example, each informed trader would sell (or buy less) on a positive surprise to mislead the MMs into believing that he received bad private news about the intrinsic value of the asset, v, in order to induce them to revise p_1 downward.

We can re-write Eq. (3) as,

$$p_1 = p_0 + \frac{\alpha (v - p_0)}{2 + (M-1)\gamma_p} + \lambda_p u + \frac{\sigma_v^2}{\sigma_p^2}\left[\frac{2 + (M-1)\gamma_p - \alpha}{2 + (M-1)\gamma_p}\right](S_p - p_0). \quad (5)$$

According to Eq. (5), the public signal affects the equilibrium price, p_1, through two channels, which (in the spirit of Evans and Lyons, 2003) we call *direct*, related to MMs' belief updating process $(2+(M-1)\gamma_p)$, and *indirect*, via the informed investors' trading activity (α).[13] Since $2 + (M-1)\gamma_p > \alpha$, the former always dominates the latter. Therefore, public news always enter the equilibrium price with the "right" sign.

2.2.2 Additional Testable Implications

The following corollary summarizes the impact of a public signal on the sensitivity of the price to an order flow shock.

Corollary 2 *A public signal of v increases equilibrium market liquidity.*

The availability of the public signal, S_p, reduces the adverse selection risk for the MMs, thus increasing the depth of this stylized market, for two reasons. First, the public signal represents an additional, trade-free source of information about the intrinsic value of the asset, v. Second, informed investors have to trade more aggressively to extract rents from their private information. In Figure 2a we plot the ensuing gain in market liquidity, $\lambda - \lambda_p$, as a function of the private signals' correlation, γ, (similar to Figure 1) when the public signal's standard deviation, σ_p, equals 1.25. The increase in market depth is greater when γ is negative *and* the number of informed traders, M, is high. In those circumstances, the introduction of a public signal reinforces the informed investors' existing incentives to place market orders on their own private signals, S_{vk}, less cautiously. However, greater public signal noise, σ_p^2, ceteris paribus, increases the adverse selection cost, λ_p, since the poorer quality of the public signal, S_p, (lower information-to-noise ratio $\frac{\sigma_v^2}{\sigma_p^2}$) induces the MMs to rely more heavily on aggregate order flow, ω_1, to set market-clearing prices. Hence informed investors trade more cautiously.

[13] Kim and Verrecchia (1997) also suggest that pre-announcement information unrelated to fundamentals may still be used by perfectly competitive information processors after the arrival of a public signal, if their prior beliefs are nonconcordant.

Remark 1 *(The increase in) market liquidity is decreasing in the volatility of the public signal.*

In the scenario where a public signal is available, the dispersion of beliefs among informed investors plays a more ambiguous role. If the volatility of the public signal is low, heterogeneously informed investors put less weight on their private signals when updating their beliefs (lower α in δ_k) than homogeneously informed investors (since the information held by homogeneously informed investors is less noisy), thus inducing less adverse selection risk for the MMs. Vice versa, when the public signal noise, σ_p, is high, informed traders rely more heavily on their private signals, but more cautiously so if the correlation of their signals, γ, is low, leading to lower equilibrium market depth.

Remark 2 *Information heterogeneity decreases market liquidity only when the volatility of the public signal is "high."*

Competition among informed traders and their inability to act collusively also affect the impact of the public signal, S_p, on the equilibrium price of Eq. (3). The more numerous informed traders are, the more aggressive is their trading activity and the more fully revealing their aggregate actions are. In this setting, MMs do not need to rely so heavily on the public signal to set equilibrium prices. This pattern is obvious in Figure 2b.

Corollary 3 *The absolute sensitivity of the equilibrium price to the public signal is decreasing in the number of informed traders.*

Interestingly, when the volatility of the public signal is high and the private signals' correlation, γ, is low, the public surprise impact, λ_s, may be negative. In our example, $\lambda_s = -0.017$ if, for example, $\gamma = 0$ and $\sigma_p = 2.5$. In those circumstances, the public signal, S_p, is too weakly correlated to the investors' aggregate information set (v) to shield against adverse selection; thus, in equilibrium, the MMs reduce market depth (see Remark 2) and use the public signal mainly to offset the strategic component of the informed investors' trading activity. A negative λ_s may then arise. This effect may explain apparently incongruous price changes in response to macroeconomic news. Yet, poorer quality of S_p eventually leads investors to rely solely on their private information signal, S_{vk}, (and the MMs on ω_1) to infer the intrinsic value of the asset, v: $\lim_{\sigma_p \to \infty} \lambda_s = 0$.

Finally, the introduction of a public signal has a significant impact on the volatility of the equilibrium price. It can be shown that the variance of the equilibrium price, $var\,(p_1)$, is greater when a public signal is available than in the equilibrium of Proposition 1, when no public signal is available. Intuitively, the availability of an additional source of information about the intrinsic value of the asset, v, as well as informed agents' more aggressive trading have a destabilizing effect on the price of the risky asset.

Corollary 4 *A public signal increases unconditional price volatility.*

Figure 2c plots this increase as a function of γ and for different M. The upsurge in price volatility is generally greater when informed traders are more numerous or when their private signals are highly (positively or negatively) correlated, i.e., when informed traders place their orders with the least caution. Nonetheless, the power of S_p in explaining price fluctuations is decreasing in γ. Figure 2d shows that $R^2_{S_p}$, the percentage of the variance in equilibrium prices, $var(p_1)$, explained by public information, S_p, for an average public signal noise, $\sigma_p = 1.25$, is low, consistent with empirical evidence in both fixed income and exchange rate markets. This $R^2_{S_p}$ is rapidly declining in the correlation of the informed traders' private signals, S_{vk}. When the private signal's correlation, γ, is negative, informed traders' market orders are more likely to cancel each other out in equilibrium, preserving the importance of the public signal, S_p, in the price discovery process. For greater private signal's correlation, γ, those orders reinforce each other and the order flow becomes the MMs' dominant information source, so $R^2_{S_p}$ falls.

3 Data Description

We test the implications of the model presented in the previous section using macroeconomic announcement data and US Treasury bond market data. As mentioned in the Introduction, this choice is motivated not only by the quality and availability of data on U.S. government bond order flow, but also by the clear theoretical link between macroeconomic fundamentals and bond yield changes.

3.1 Bond Market Data

We use intraday U.S. Treasury security yields, quotes, transactions, and signed trades for the most recently issued, "on-the-run," two-year, five-year, and ten-year Treasury notes. We use "on-the-run" notes because, according to Fleming (1997) and Brandt and Kavajecz (2004), those are the securities where the majority of interdealer trading and informed trading takes place. We are interested in studying the impact of informed trading related to macroeconomic fundamentals on yield changes. Therefore, we focus on the intermediate to long maturities, since the corresponding bond yields are the most responsive to macroeconomic fundamentals (see, Balduzzi, Elton, and Green, 2001).

We obtain the data from GovPX, a firm that collects quote and trade information from six of the seven main inter-dealer brokers (with the notable exception of Cantor Fitzgerald).[14] Fleming (1997) argues that these six brokers account for approximately two-thirds of the inter-dealer broker market, which in turn translates into approximately 45% of the trading volume in the secondary market for Treasury securities. Our sample includes every transaction taking place within "regular trading hours," from 7:30 a.m. to 5:00 p.m. Eastern Standard Time (EST), between January 1992 and December 2000.[15] Strictly speaking, the U.S. Treasury market is open 24 hours a day; yet, 95% of the trading volume occurs during those hours. Thus, to remove fluctuations in bond yields due to illiquidity, we ignore trades outside that narrower interval. Finally, the data contains some interdealer brokers' posting errors not previously filtered out by GovPX. We eliminate these errors following the procedure described in Fleming's (2003) appendix.

In Figure 3, we compare the resulting daily yield changes during days when one of the most closely observed U.S. macroeconomic announcement, the Nonfarm Payroll Employment report, is released to daily yield changes during non-announcement days.[16] Bond yield changes are clearly more volatile on days when the Payroll numbers are announced, but yield changes during non-announcement days are economically significant as well. These dynamics, together with the notoriously poor performance of public macroeconomic surprises in explaining fluctuations in bond yields on non-announcement days, further motivate our study of the price discovery role of order flow even when no public news arrive to the bond market.

[14] The major interdealer brokers in the U.S. Treasury market are Cantor Fitzgerald Inc., Garban Ltd., Hilliard Farber & Co. Inc., Liberty Brokerage Inc., RMJ Securities Corp., and Tullet and Tokyo Securities Inc.

[15] Our sample period ends in December 2000 because GovPX stopped recording daily aggregate volume in December 2000, preventing us from accurately identifying the exact timing of transactions.

[16] 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.

3.2 Macroeconomic Data

3.2.1 Expected and Announced Fundamentals

We use the International Money Market Services (MMS) Inc. real-time data on the expectations and realizations of 25 of the most relevant U.S. macroeconomic fundamentals to estimate announcement surprises. Table 1 provides a brief description of the most salient characteristics of U.S. economic news announcements in our sample: The total number of observations in our sample, the agency reporting each announcement, the time of the announcement release, and whether the standard deviation across professional forecasts is available.[17]

We define announcement surprises as the difference between announcement realizations and their corresponding expectations. More specifically, since units of measurement vary across macroeconomic variables, we standardize the resulting surprises by dividing each of them by their sample standard deviation. The standardized news associated with the macroeconomic indicator p at time t is therefore computed as

$$S_{pt} = \frac{A_{pt} - E_{pt}}{\widehat{\sigma}_p}, \tag{6}$$

where A_{pt} is the announced value of indicator p, E_{pt} is its MMS median forecast, as a proxy for its market expected value, and $\widehat{\sigma}_p$ is the sample standard deviation of $A_{pt} - E_{pt}$. Eq. (6) facilitates meaningful comparisons of responses of different bond yield changes to different pieces of news. Operationally, we will estimate those responses by regressing bond yield changes on news. However, since $\widehat{\sigma}_p$ is constant for any indicator p, the standardization will affect neither the statistical significance of response estimates nor the fit of the regressions.

3.2.2 Information Heterogeneity

We use the MMS standard deviation across professional forecasts as a measure of dispersion of beliefs across investors. This measure of information heterogeneity is widely adopted in the literature on investors' reaction to information releases in the stock market (e.g. Diether et al., 2002; Kallberg and Pasquariello, 2004); Green (2004) recently uses it in a bond market context. As indicated in Table 1, this variable is only available for 18 out of the 25 macroeconomic news in our sample.

[17] For a more detailed description of the data we refer the reader to Andersen, Bollerslev, Diebold, and Vega (2003)

Overall, the dispersion of beliefs is positively correlated across macroeconomic announcements. To conserve space, we do not show the correlation matrix of all the announcements, but only report the pairwise correlation between each announcement and arguably the most important announcement, the Payroll report. This correlation, shown in Table 2a, is positive, albeit not statistically significant for most of the announcements. Thus, dispersion of beliefs in Nonfarm Payroll forecasts is not necessarily a good measure of information heterogeneity about the state of the economy, which is ultimately what we are interested in. So as a robustness check, we use three different measures of dispersion of beliefs during announcement and non-announcement days: one based exclusively on the Payroll announcement, another based on 7 "influential" announcements, defined below, and in the last measure we use all 18 announcements.

We face two caveats when calculating monthly measures of dispersion of beliefs: (i) the announcements listed in Table 2a are released at different frequencies and (ii) the professional forecasts' standard deviation only measures heterogenous beliefs at the time of the announcement. We solve these two caveats under the assumption that the dispersion of beliefs remains constant in between announcements. This assumption is justified because the first order autocorrelation in the standard deviation of professional forecasts is positive and most of the time statistically significant, as shown in Table 2a. Hence, if the dispersion of beliefs across investors is high in one month (week or quarter), it is likely to remain high in the next month (week or quarter).

To convert weekly and quarterly dispersions to a monthly frequency we use the following procedure. For the weekly announcement, Initial Unemployment Claims, we average the dispersion of beliefs across four weeks. For the quarterly announcements, GDP Advance, Preliminary, and Final, we assume that the dispersion of beliefs in the first month of the quarter is constant throughout the quarter. Naturally, the dispersion of beliefs of monthly announcements are left unchanged and assumed to be constant in between announcements.[18]

We define our monthly proxy for the aggregate degree of information heterogeneity about macroeconomic fundamentals as a weighted sum of monthly dispersions across announcements,

$$SD_t = \sum\nolimits_{p=1}^{P} \frac{SD_{pt}}{\widehat{\sigma}(SD_{pt})}, \tag{7}$$

[18] Sometimes, New Home Sales, Factory Orders, and the Index of Leading Indicators are released twice in the same month, at the beginning and at the end of the month. When this happens, we move the announcement that occurred at the end of the month to the next month.

where SD_{pt} is the standard deviation of announcement p across professional forecasts and $\sigma(SD_{pt})$ is the sample standard deviation of the dispersion of beliefs across time. P is equal to 1 when we only use the Nonfarm Payroll Employment report. P is equal to 7 when we use "influential" macroeconomic announcements: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims.[19] P is equal to 18 when we use all the announcements for which the measure SD_{pt} is available (i.e., those in Table 2a). The standardization in Eq. (7) is necessary because, as we mentioned earlier, units of measurement differ across economic variables. As an example of the dynamics of these measures, we display the variable SD_{1t}, our proxy for the dispersion of beliefs surrounding the Nonfarm Payroll announcement, in the top left panel of Figure 4.

We use the monthly dispersion estimates from these three methodologies to classify days in which the corresponding monthly variable SD_t is above (below) the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution as days with high (low) information heterogeneity. In the remaining three panels of Figure 4, we plot the resulting time series of high (+1) and low (−1) dispersion days. The three series appear to be positively correlated: In the bottom table of Figure 4, their correlations range from 0.37 (between the Payroll-based series, $P = 1$, and the series constructed with the influential announcements, $P = 7$) to 0.70 (between the series using all announcements, $P = 18$, and the one based only on the influential news releases, $P = 7$).

In Table 2b we report the differences in the mean daily number of transactions in the two, five, and ten-year Treasury bond markets across days with high (b_h) and low (b_l) dispersion of beliefs measured with those three alternative methodologies. We report Newey-West standard errors, because Table 3 shows that the number of transactions is positively autocorrelated.

Consistent with Griffith, Smith, Turnbull, and White (2000) and Ranaldo (2004), among others (but also with the spirit of the model of Section 2), we interpret a big (small) number of daily transactions as a proxy for a high (low) degree of trading aggressiveness. The ensuing differences are economically and statistically significant: high dispersion days have a lower number of transactions than low dispersion days (i.e., $b_h - b_l < 0$). This evidence provides support for the basic intuition of our model and gives us further confidence in the heterogeneity proxies of Eq. (10), since it suggests that, in the government bond market, periods of greater dispersion of beliefs among

[19] In Section 4.2, we show that these announcements represent the most important information events for the Treasury market, consistent with Fleming and Remolona's (1997) findings, among others.

market participants are accompanied by more cautious speculative trading activity, as argued in Section 2.1.1.

3.2.3 News or Noise?

To measure public news noise, we use the Federal Reserve Bank of Philadelphia "Real Time Data Set" (RTDS), which records real-time macroeconomic announcements and subsequent revisions to the announcements.[20] The RTDS contains monthly data on Capacity Utilization, Industrial Production and Nonfarm Payroll Employment report.[21] Aruoba (2004) differentiates between "informative" and "uninformative" data revisions, the latter being identified as due to definitional changes (such as changes in the base-year or changes in seasonal weights). Since, our three variables do not undergo any "uninformative" changes, we simply measure public news noise as the difference between the actual announcement and the latest revision. What matters in our model is the magnitude of the noise (σ_p^2 of Section 2.2), not its direction, so we use the absolute value of this difference in our empirical analysis.

In Figure 5 we plot the simple and absolute difference between the real-time announcement and the latest revision for Capacity Utilization, Industrial Production, and Nonfarm Payroll Employment. Interestingly, macroeconomic data revisions display a few spikes and are often negative, revealing a tendency for the government to be overly optimistic in its initial announcements. The absolute value of the measurement error tends to be positively correlated with the volatility of the underlying announcement. This suggests that the measurement error is related to macroeconomic uncertainty. In our theoretical model, σ_p^2 arises from either uncertainty about the macroeconomy or noise of the public signal. In the ensuing empirical analysis, we will consider both possibilities.

4 Empirical Analysis

The model of Section 2 generates several implications that we test in this section. In the database described in Section 3, we are able to directly

[20] See Croushere and Stark (1999, 2001) for details of the data set and examples of empirical applications. The data set is publicly available on the internet at http://www.phil.frb.org/econ/forecast/reaindex.html. A bibliography of relevant papers, as well as detailed documentation about the data, is also available from the same source.

[21] RTDS also includes quarterly data for major National Income and Product Account (NIPA) variables. However, we only use these three variables in our analysis because of their exact correspondence with the MMS data.

observe price changes, $P_t - P_{t-1}$, as a proxy for $p_1 - p_0$, public news surprises S_{pt}, as a proxy for $S_p - p_0$, and aggregate order flow Ω_t. Yet, in our setting, it is only the unexpected portion of aggregate order flow that affects the equilibrium prices of Eqs. (1) and (3): $E(\omega_1) = 0$ in both Propositions 1 and 2. Furthermore, although ω_1 is assumed to depend only on informed and liquidity trading, many microstructure imperfections can cause lagged and intraday seasonality effects in the observed order flow (see, Hasbrouck, 2004). Therefore, to implement our model, we need to estimate Ω_t^*, the unanticipated portion of aggregate order flow.

We use the linear autoregressive model of Hasbrouck (1991) with intraday seasonal dummies,

$$x_i = a_x + b(L)r_i + c(L)x_i + D_{1i} + \ldots + D_{19i} + v(x)_i, \tag{8}$$

where x_i is the half-hour net order flow in the market (purchases take a $+1$ and sales take a -1), r_i is the half-hour quote revision on the asset, $b(L)$ and $c(L)$ are polynomials in the lag operator, and $D_{1i}, \ldots, D_{19i}$ are intraday seasonal dummy variables for the 19 half-hour intervals from 7:30 a.m. to 5:00 p.m. EST.[22,23]

The residual in this equation, $v(x)_i$, includes two components. The first one is unanticipated trading due to liquidity shocks: investors trade in an asset market in response to random shocks to their wealth. The second component is unanticipated trading due to new private information: investors trade when their private assessment of the asset's value is different from the prevailing market quote. Hasbrouck (1991) identifies these two effects by assuming that the *permanent* impact on trades is due to information shocks and the *transitory* impact is due to liquidity shocks.[24] In our model, the market-maker is unable to distinguish the former from the latter, and so both have a permanent effect on prices. However, the former may facilitate the estimation of the price impact parameter λ and the testing of our model's implications, since it is less noisy by construction and less likely to be driven by liquidity traders' hedging demands in response to the disclosure of public

[22] Our results are robust to different specifications of Eq. (8): we sample bonds each time there is a transaction, rather than at 30-minute intervals; we sample bonds at the optimal frequency according to Bandi and Russell (2005); and we use different lag polynomial lengths. Independent of the specification, the R^2 associated with these regressions is lower than 1%, so the robustness of the results reflect the fact that aggregate unanticipated order flow, Ω_t^*, is very closely related to aggregate raw order flow Ω_t.

[23] we use different lag length polynomials and settle on 19 lags (one day) because these many lags are sufficient to eliminate all the serial correlation in the data.

[24] In the microstructure literature (see Hasbrouck, 2004 for a review), a transitory trade impact lasts for an hour or two, while permanent trade impacts last for a day or longer.

information. Therefore, we focus on daily horizons and compute the aggregate unanticipated net order flow over each day t, $\Omega_t^* = \sum_{i=1}^{19} v(x)_{it}$, as a proxy for ω_1.

In Table 3 we show summary statistics for unanticipated daily aggregate order flow, Ω_t^* and daily raw order flow, Ω_t, among other variables used in the empirical tests. Note that Eq. (8) succesfully eliminates the first-order autocorrelation in aggregate daily order flow.

To be consistent with the term-structure literature, we estimate the impact of unanticipated order flow and public information arrivals on daily yield changes, rather than price changes.[25] More specifically, we translate the equilibrium prices of Propositions 1 and 2 into the following estimable equations:

$$(y_t - y_{t-1}) \times 100 = a + \lambda\Omega_t^* + \varepsilon_t \tag{9}$$

when no public signal is released (Eq. (1)), and

$$(y_t - y_{t-1}) \times 100 = a_p + \lambda_p\Omega_t^* + \lambda_s S_{pt} + \varepsilon_{pt} \tag{10}$$

when a public signal S_{pt} becomes available to all market participants on day t (Eq. (3)). According to our model, we expect, λ and λ_p to be negative, while, according to the Lucas (1982) model, we expect λ_s to be positive for positive real activity and inflationary shocks.

4.1 Non-Announcement Days

We test Corollary 1 by amending Eq. (9) as follows:

$$\begin{aligned}(y_t - y_{t-1}) \times 100 &= a + \lambda_h\Omega_t^* D_{ht} + \lambda_l\Omega_t^* D_{lt} + \\ &\quad + \lambda_m\Omega_t^*(1 - D_{ht} - D_{lt}) + \varepsilon_t,\end{aligned} \tag{11}$$

where D_{ht} (D_{lt}) is a dummy variable equal to one on days with high (low) heterogenous beliefs defined as in Section 3.2.2. We report the resulting estimates in Table 4 using the three proxies for information heterogeneity, $P = 1$, $P = 7$, and $P = 18$.[26] Since higher dispersion days are also associated with more volatile bond yields, the standard errors are adjusted

[25] Naturally, our results are robust to whether we use price changes or yield changes. GovPX calculates bond yields using transaction prices, so there is a mechanical inverse relation between the two quantities.

[26] When we assume that $P = 1$ to measure the degree of asymmetric sharing of private information among insiders, we also control for the day-of-the-week effect. More specifically, since all of the Nonfarm Payroll announcements, except for one, are released on Friday, we estimate Eq. (11) using Fridays only.

for heteroskedasticity. We also correct for serial correlation, given the mild, though statistically significant, daily bond yield autocorrelation.

The results in Table 4 provide strong evidence in favor of Corollary 1, especially for the 5-year bond, the most liquid U.S. Treasury note. Regardless of whether we only use the Nonfarm Payroll announcement to measure dispersion of beliefs or whether we aggregate dispersion of beliefs across macroeconomic announcements, we cannot reject the null hypothesis that $\lambda_h - \lambda_l < 0$. This evidence is consistent with the basic intuition of the benchmark model of Section 2.1: in the absence of a public signal, greater information heterogeneity among informed traders in the bond market translates into greater adverse selection risk for the market-makers, hence into lower market liquidity. The difference in market liquidity is economically significant. Focusing on the 5-year bond market, an average shock, i.e. one standard deviation shock, to abnormal order flow decreases bond yields by 10.19%, on high dispersion days compared to 3.3% on low dispersion days. This magnitude is significant, since daily bond yield changes one standard deviation away from the mean are close to 6%, as shown in Table 3.

We also show that the adjusted R^2 of the above regression during high dispersion days ($R^2_{ha} = 40.55\%$) is significantly higher than during low dispersion days ($R^2_{la} = 5.84\%$). In future research, it would be interesting to see how macroeconomic fundamentals and order flow are related to affine term structure latent factors. Whether these factors can explain bond yield changes best when the dispersion of beliefs is low and there are no macroeconomic announcements, i.e. when our model has the lowest explanatory power.

We also find evidence in favor of Corollary 1 in the 2-year and 10-year bond markets, although only when we use the dispersion of analysts' forecasts about either Nonfarm Payroll Employment or the "influential" announcements as a proxy for information heterogeneity. This may be due to the fact that not all macroeconomic announcements are equally important ex ante, thus making the aggregate dispersion of beliefs across announcements a noisy measure of such heterogeneity.[27]

4.2 Announcement Days

When we introduce a public signal in the model (Proposition 2), market liquidity increases (Corollary 2), because the presence of a trade-free source of information and more aggressive trading by the informed traders mitigates the adverse selection risk for the market-makers. In our empirical analysis,

[27] We explore this issue in greater depth in the next subsection.

this translates into testing the difference between, λ and λ_p in the following regression,

$$(y_t - y_{t-1}) \times 100 = a + \lambda \Omega_t^* (1 - D_p) + \lambda_p \Omega_t^* (1 - D_p) + \varepsilon_t, \qquad (12)$$

where D_p is a dummy variable equal to one if an announcement is released on that day according to the three different announcement day definitions described above: Nonfarm Payroll, "influential" announcements and all "announcements." Table 5 shows that, in general, the difference between λ and λ_p is not statistically significant. If we focus on the Nonfarm Payroll announcement, the evidence is favorable towards Corollary 2, since the adjusted R^2 is always higher on non-announcement days. This means that dealers rely more heavily on unanticipated order flow to set bond prices during non-announcement days than during announcement days. This result is consistent with the findings in Brandt and Kavajecz (2004), but contradicts the evidence reported in Green (2004). Green (2004) shows that asymmetric information increases when public announcements are released. It is not surprising that the literature finds contradictory evidence, since Table 5 shows that the result is not robust to different announcement day classifications.

According to the extended model of Section 2.2, a public signal can impact yield changes through two channels, which we called *direct* and *indirect* (through order flow). Intuitively, the latter, of opposite sign than the former, is driven by the informed traders' strategic attempt to move the equilibrium price away from the fundamental information revealed by the public signal in order to profit from their private signals. Yet, in the model, the direct channel is always more important than the indirect one. To test this implication we estimate the following representation of Eq. (10), conditional on announcement days:

$$\begin{aligned}(y_t - y_{t-1}) \times 100 &= a + \sum_{j=1}^{P} \lambda_{sj} S_{jt} + \lambda_{ph} \Omega_t^* D_{ht} + \\ &\quad \lambda_{pl} \Omega_t^* D_{lt} + \lambda_{pm} \Omega_t^* (1 - D_{ht} - D_{lt}) + \varepsilon_t,\end{aligned} \qquad (13)$$

which accounts for multiple signals arriving on the same day. The evidence presented in Table 6 confirms this result: the direct channel is always more important than the indirect one. The adjusted R^2 of the fully specified regressions of Eq. (13), R_a^2, is between 2 and 19 times bigger than the adjusted R^2 of the regressions estimated using only order flow, R_{fa}^2. The results in Table 6 also allow us to test whether higher dispersion of beliefs increase adverse selection costs during announcement days. The implications of the model are ambiguous: given sufficiently high public signal noise, adverse selection costs are higher on high dispersion announcement days than on low dispersion announcement days. For the most part, the difference between λ_{ph} and λ_{pl} is statistically significant, so in reality the public signal noise is sufficiently high.

As previously mentioned, many of the above results are generally weaker in correspondence with the aggregate proxies for information heterogeneity described in Eq. (7). In particular, the difference between R_a^2 of Table 4 and R_{fa}^2 of Table 6 appears to be declining in P. For example, the adjusted R^2 for the 5-year bond when $P = 18$ is actually higher, rather than lower, during announcement days than non-announcement days: $R_{fa}^2 = 20.60\%$ compared to $R_{fna}^2 = 19.67\%$ in Table 6. These exceptions may be explained by a potentially mistaken classification of certain macroeconomic releases as important public announcements. Eq. (7) assumes that the dispersion of analysts' forecasts for each announcement in our sample contributes equally to the aggregate intensity of information heterogeneity. It is however possible that not all public information is equally important ex ante.

In Tables 7 to 9 we show estimates of Eq. (10) for all 25 macroeconomic announcements in the sample when we ignore the degree of information heterogeneity among informed traders. In particular, we provide adjusted R^2 from regressing yield changes only on order flow, R_{fa}^2 and from regressing yield changes only on the public announcement surprise, R_{sa}^2. These results indeed reveal that not all public information is equally important. Indeed, only the announcements labeled in Section 4.1 as "influential" have a statistically significant impact $(\widehat{\lambda}_s)$ on two, five, and ten-year bond yield changes over the sample period 1992-2000. When the public news announcement is not important — the public news surprise alone has very low explanatory power, i.e. R_{sa}^2 is very low — unanticipated order flow plays a bigger role in the price discovery process. This can be due to several factors: The dispersion of beliefs could be higher for certain announcements than for others, some announcements could be noisier than others, or some announcements do not reveal any useful information to price bonds (i.e., the days in which they occur are effectively non-announcement days).

Finally, Remark 1 states that adverse selection costs are higher, and the reaction to the public announcement surprise is lower, when the public signal noise is high. Intuitively, when the public signal is noisy, the market-makers rely more heavily on the order flow than on the public signal, thus requiring greater compensation for providing liquidity. The evidence in Table 10 supports this claim. There we report estimates of the following regression:

$$\begin{aligned}(y_t - y_{t-1}) \times 100 \;=\;& a + \lambda_{snh}\, S_{pt} D_{nht} + \lambda_{snl}\, S_{pt} D_{nlt} + \\ & \lambda_s\, S_{pt}(1 - D_{nht} - D_{nlt}) + \lambda_{pnh}\, \Omega_t^* D_{nht} + \\ & + \lambda_{pnl}\, \Omega_t^* D_{nlt} + \lambda_p\, \Omega_t^* (1 - D_{nht} - D_{nlt}) + \varepsilon_t,\end{aligned} \tag{14}$$

where D_{nht} (D_{nlt}) is a dummy variable equal to one on days with high (low) public signal noise, defined as the absolute value of the difference between the actual announcement minus the latest revision of the announcement being on the top (bottom) 70^{th} (30^{th}) percentile of their empirical distribution, and zero otherwise. Consistent with Section 3.2.3, we focus only on Nonfarm Payroll Employment, Industrial Production, and Capacity Utilization announcements, i.e. the only news releases in our sample included in the RTDS database of announcement revisions.

Most of the public news surprise coefficients λ_{snh} and λ_{snl} are significant when the public signal noise is low, and insignificant when the public noise is of high or medium intensity.[28] The order flow coefficients are significant when the public signal is high or of medium magnitude, while the order flow's incremental adjusted R^2 is higher when the public signal noise is high than when the public signal noise is low, i.e., $R^2_{fnha} > R^2_{fnla}$ in Table 10. Hence, the impact of the release of macroeconomic data on the process of price formation in the U.S. Treasury market is decreasing in the quality of the public signals, as argued in the model of Section 2.2.

Our model further predicts that the most liquid market (i.e., with the greatest number of informed traders), arguably the one for the 5-year U.S. Treasury bond, should have the weakest reaction to public announcements. Intuitively, more numerous informed traders compete more aggressively in their trading activity, thus reducing the perceived adverse selection risk for the market-makers and increasing the weight of the order flow in the equilibrium price. Unfortunately, this hypothesis cannot be tested directly, since the reaction of bond yield changes to macroeconomic announcements depends on the maturity of the asset. For example, a positive real activity shock today contains more relevant information for determining the state of the economy in a 2-year period than in a 5-year period, hence it has a stronger effect on the 2-year bond than on the 5-year bond, regardless of the liquidity of the markets.

5 Conclusions and Future Research

The main goal of this paper is to deepen our understanding of the links between daily bond yield movements, news about fundamentals, and order flow conditional on the informed traders' dispersion of beliefs and the public signals' noise. To that end, we theoretically identify and empirically document

[28]Incidentally, we observe that the positive correlation between our measure of public news noise and the announcement's volatility (see Figure 4) does not affect the surprise coefficients, λ_{snh} and λ_{snl}, since the news surprises are standardized.

important news and order flow effects in the U.S. Treasury bond market. To guide our analysis, we first develop a parsimonious model of speculative trading in the presence of asymmetric sharing of information among imperfectly competitive informed traders. We then test its equilibrium implications by studying the response of 2-year, 5-year, and 10-year U.S. bond yields to unanticipated order flow and real-time U.S. macroeconomic news releases. Our evidence suggest that announcement and order flow surprises produce conditional mean jumps, i.e., that the process of price formation in the bond market is linked to fundamentals and agents' beliefs. The nature of this linkage is sensitive to the intensity of investors' dispersion of beliefs and the noise of the public announcement. In particular, and consistently with our model, unanticipated order flow explains a bigger portion of bond yield changes when the dispersion of beliefs across informed traders is high and the public announcement is noisy.

These findings allow us to draw several implications for future research. Existing term structure models are notorious for their poor out-of-sample forecast performance (Duffee, 2002). Recently, Diebold and Li (2003) use a variation of the Nelson and Siegel (1987) exponential components framework to forecast yield curve movements at short and long horizons, finding encouraging results at short horizons. We show here that U.S. Treasury bond order flow is related to future macroeconomic surprises and is contemporaneously correlated with daily yield changes. In future work, we intend to include order flow information to forecast the term structure.

Finally, our results indicate that the reaction of bond yield changes and order flow is most sensitive to Nonfarm Payroll Employment announcements. Nominal bond yields depend on future inflation and future capital productivity, hence naturally react to employment announcement surprises. The importance of this announcement should however depend on its predictive power. Yet, to the best of our knowledge, no study has shown that the Nonfarm Payroll Employment has the best predictive power for future activity and inflation out of the 25 macroeconomic announcements in our sample.[29] Thus, we suspect that its importance goes beyond its predictive power for real activity. Morris and Shin (2002) provide an interesting theoretical explanation for this *overreaction* to Nonfarm Payroll news. They argue that

[29] The NBER's Business-Cycle Dating Committee mentions that no single macroeconomic variable is the most important predictor of recessions and expansions (e.g., see http://www.nber.org/cycles/recessions.html). The committee takes into account real GDP, real income, employment, industrial production, and wholesale and retail sales to determine whether the U.S. is in a recession or in an expansion. When running a horse race between macroeconomic variables and financial variables to predict the business cycle, Estrella and Mishkin (1998) do not even consider Nonfarm Payroll announcements.

bond yields will be most reactive to the types of news emphasized by the press. In their model, this overreaction to news is rational and reflects the coordination role of public information. We look forward to future research that further investigates this possibility.

6 Appendix

Proof of Proposition 1. As noted in Section 2.1.1, the proof is by construction. We start by guessing that equilibrium p_1 and x_k are given by $p_1 = A_0 + A_1\omega_1$ and $x_k = B_0 + B_1\delta_k$, respectively, where $A_1 > 0$. Those expressions and the definition of ω_1 imply that, for the k^{th} informed trader,

$$E(p_1|\delta_k) = A_0 + A_1 x_k + A_1 B_0 (M-1) + A_1 B_1 (M-1)\gamma\delta_k. \qquad \text{(A-1)}$$

Using Eq. (A-1), the first order condition of the maximization of the k^{th} informed trader's expected profit $E(\pi_k|\delta_k)$ is given by

$$p_0 + \delta_k - A_0 - (M+1) A_1 B_0 - 2A_1 B_1 \delta_k - (M-1) A_1 B_1 \gamma \delta_k = 0. \qquad \text{(A-2)}$$

The second order condition is satisfied, since $2A_1 > 0$. For Eq. (A-2) to be true, it must be that

$$\begin{aligned} p_0 - A_0 &= (M+1) A_1 B_0 && \text{(A-3)} \\ 2A_1 B_1 &= 1 - (M-1) A_1 B_1 \gamma. && \text{(A-4)} \end{aligned}$$

The distributional assumptions of Section 2.1 imply that the order flow ω_1 is normally distributed with mean $E(\omega_1) = MB_0$ and variance $var(\omega_1) = \sigma_u^2 + MB_1^2\psi^2[\sigma_s^2 + (M-1)\sigma_{ss}]$. Since $cov(v, \omega_1) = B_1\psi\sigma_v^2$, it ensues that

$$E(v|\omega_1) = p_0 + \frac{B_1\psi\sigma_v^2}{\sigma_u^2 + MB_1^2\psi^2[\sigma_s^2 + (M-1)\sigma_{ss}]}(\omega_1 - MB_0). \qquad \text{(A-5)}$$

According to the definition of a Bayesian-Nash equilibrium in this economy (Section 2.1.1), $p_1 = E(v|\omega_1)$. Therefore, our conjecture for p_1 implies that

$$\begin{aligned} A_0 &= p_0 - A_1 M B_0 && \text{(A-6)} \\ A_1 &= \frac{B_1\psi\sigma_v^2}{\sigma_u^2 + MB_1^2\psi^2[\sigma_s^2 + (M-1)\sigma_{ss}]}. && \text{(A-7)} \end{aligned}$$

The expressions for A_0, A_1, B_0, and B_1 in Proposition 1 must solve the system made of Eqs. (A-3), (A-4), (A-6), and (A-7) to represent a linear equilibrium. Defining A_1B_0 from Eq. (A-3) and plugging it into Eq. (A-6) leads us to $A_0 = p_0$. Thus, it must be that $B_0 = 0$ to satisfy Eq. (A-3). We are left with the task of finding A_1 and B_1. Solving Eq. (A-4) for A_1, we get

$$A_1 = \frac{1}{B_1 \left[2 + (M-1)\gamma\right]}. \tag{A-8}$$

Equating Eq. (A-8) to Eq. (A-7), and using the definition of $\psi = \frac{\sigma_v^2}{M\sigma_s^2} > 0$ and $\gamma = \frac{\sigma_{ss}}{\sigma_s^2}$, it follows that $B_1^2 = \frac{\sigma_u^2}{\psi\sigma_v^2}$, i.e. that $B_1 = \frac{\sigma_u}{\sigma_v\psi^{\frac{1}{2}}}$, where $\psi^{\frac{1}{2}} = \frac{\sigma_v}{\sigma_s\sqrt{M}}$ is the unique square root of ψ. Substituting this expression back into Eq. (A-8) implies that $A_1 = \frac{\sigma_v\psi^{\frac{1}{2}}}{\sigma_u[2+(M-1)\gamma]}$. Finally, we observe that Proposition 1 is equivalent to a symmetric Cournot equilibrium with M informed traders. Therefore, the "backward reaction mapping" introduced by Novshek (1984) to find n-firm Cournot equilibria proves that, given any linear pricing rule, the symmetric linear strategies x_k of Eq. (2) indeed represent the unique Bayesian Nash equilibrium of the Bayesian game among informed traders. ■

Proof of Corollary 1. Market liquidity is increasing in the number of informed traders, since $\frac{\partial\lambda}{\partial M} = -\frac{(M-1)\sigma_v^2\left[M^3\chi^2 - M(M+1)\chi\sigma_v^2 + \sigma_v^4\right]}{2M^{\frac{1}{2}}\sigma_u[\sigma_v^2+M(M-1)\chi]^{\frac{1}{2}}[M(M-1)\chi+(M+1)\sigma_v^2]^2} < 0$ under reasonable parameters. Moreover, $\lim_{M\to\infty}\lambda = 0$. Market liquidity is decreasing in the heterogeneity of informed traders' S_{vk} since $\lambda = \frac{\sigma_v^2\sqrt{M}\left[\sigma_v^2+M(M-1)\chi\right]^{-\frac{1}{2}}}{\sigma_u[\sigma_v^2(M+1)+M(M-1)\chi]}$ is a concave function of χ with its maximum at $\chi = \frac{\sigma_v^2}{M}$, i.e., when $\sigma_{ss} = 0$. Indeed, $\frac{\partial\lambda}{\partial\chi} = -\frac{M^{\frac{3}{2}}(M+1)^2\sigma_v^2\left(M\chi-\sigma_v^2\right)}{2\sigma_u[\sigma_v^2+M(M-1)\chi]^{\frac{1}{2}}[M(M-1)\chi+(M+1)\sigma_v^2]^2}$, implying that $\frac{\partial\lambda}{\partial\chi} > 0$ for $\chi < \frac{\sigma_v^2}{M}$ (i.e., when $\gamma > 0$), $\frac{\partial\lambda}{\partial\chi} < 0$ for $\chi > \frac{\sigma_v^2}{M}$ (i.e., when $\gamma < 0$), and finally $\frac{\partial\lambda}{\partial\chi} = 0$ for $\chi = \frac{\sigma_v^2}{M}$ (i.e., when $\gamma = 0$). ■

Proof of Proposition 2. This proof is similar to the proof of Proposition 1 above, hence we only sketch its outline. Here we start by guessing that equilibrium p_1 and x_k are given by $p_1 = A_0 + A_1\omega_1 + A_2S_p$ and $x_k = B_0 + B_1\delta_k$, respectively, where $A_1 > 0$. Those expressions imply the following first order condition of the maximization of $E(\pi_k|\delta_k)$:

$$\begin{aligned} &p_0 + \delta_k + (M-1)\,A_1B_1\gamma_p\delta_k - A_0 + \\ &-(M+1)\,A_1B_0 - 2A_1B_1\delta_k - A_2S_p = 0. \end{aligned} \tag{A-9}$$

For Eq. (A-9) to be true, it must be that

$$p_0 - A_0 = (M+1)\,A_1B_0 + A_2S_p \tag{A-10}$$

$$2A_1B_1 = 1 - (M-1)\,A_1B_1\gamma_p. \tag{A-11}$$

The distributional assumptions of Section 2.1 imply that

$$E(v|\omega_1) = p_0 + \frac{B_1 \alpha \sigma_v^2 \left(\sigma_p^2 - \sigma_v^2\right)}{\sigma_u^2 \sigma_p^2 + B_1^2 \left(C\sigma_p^2 - D^2\right)} (\omega_1 - MB_0) + + \frac{\sigma_v^2 \left\{B_1^2 \left[C - (\alpha + \beta M) D\right] + \sigma_u^2\right\}}{\sigma_u^2 \sigma_p^2 + B_1^2 \left(C\sigma_p^2 - D^2\right)} (S_p - p_0), \quad \text{(A-12)}$$

where $C = \alpha^2\sigma_v^2 + \beta^2 M^2 \sigma_p^2 + 2\alpha\beta M \sigma_v^2$ and $D = \alpha\sigma_v^2 + \beta M \sigma_p^2$. Since $p_1 = E(v|\omega_1)$ in equilibrium, our conjecture for p_1 implies that

$$A_0 = p_0 - A_1 M B_0 - A_2 p_0 \quad \text{(A-13)}$$

$$A_1 = \frac{B_1 \alpha \sigma_v^2 \left(\sigma_p^2 - \sigma_v^2\right)}{\sigma_u^2 \sigma_p^2 + B_1^2 \left(C\sigma_p^2 - D^2\right)} \quad \text{(A-14)}$$

$$A_2 = \frac{\sigma_v^2 \left\{B_1^2 \left[C - (\alpha + \beta M) D\right] + \sigma_u^2\right\}}{\sigma_u^2 \sigma_p^2 + B_1^2 \left(C\sigma_p^2 - D^2\right)}. \quad \text{(A-15)}$$

The expressions for A_0, A_1, A_2, B_0, and B_1 in Proposition 2 must solve the system made of Eqs. (A-10), (A-11), (A-13), (A-14), and (A-15) to represent a linear equilibrium. Defining $A_0 - p_0$ from Eq. (A-10) and plugging it into Eq. (A-13) leads us to $A_0 = p_0 (1 - A_2) + MA_2 (S_p - p_0)$ and $B_0 = -\frac{A_2}{A_1} (S_p - p_0)$. Then, we solve Eq. (A-11) for A_1 and equate the resulting expression to Eq. (A-14) to get $A_1^2 = \frac{\Gamma}{\sigma_u^2 \sigma_p^2 \left[2 + (M-1)\gamma_p\right]^2}$, where $\Gamma = \alpha\sigma_v^2 \left(\sigma_p^2 - \sigma_v^2\right) \left[2 + (M-1)\gamma_p - \alpha\right] > 0$ since $2 + (M-1)\gamma_p - \alpha = 1 + \frac{M^2(M-1)}{\sigma_p^2 - \sigma_v^2 + M(M-1)\chi} > 1$ for $\chi \geq 0$ and $\sigma_p^2 > \sigma_v^2$. This implies that $A_1 = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p \left[2 + (M-1)\gamma_p\right]} > 0$, where $\Gamma^{\frac{1}{2}}$ is the unique square root of Γ. Substituting this expression into Eq. (A-11) implies that $B_1 = \sigma_u \sigma_p \Gamma^{-\frac{1}{2}}$. Finally, we plug B_1^2 into Eq. (A-15) to get $A_2 = \frac{\sigma_v^2}{\sigma_p^2} \left\{\sigma_v^2 \left[2 + (M-1)\gamma_p - \alpha\right] - \beta M \sigma_p^2\right\}$. ■

Proof of Corollary 2. To prove this statement, we compare λ and λ_p under all possible scenarios for M and γ. When $M = 1$, $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \frac{\sigma_v}{2\sigma_p\sigma_u} \left(\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}$ since $\sigma_p^2 > \sigma_v^2$. Along the same lines, when $M = 1$ and $\chi = 0$ ($\gamma = 1$), $\lambda = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u} > \lambda_p = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_p\sigma_u} \left(\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}$. When $M > 1$ and $\chi = \frac{\sigma_v^2}{M}$ ($\gamma = 0$), $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p \left[2 + (M-1)\gamma_p\right]}$ since $\sigma_p^2 > \sigma_v^2$, $\alpha = \frac{M\left(\sigma_p^2 - \sigma_v^2\right)}{M\sigma_p^2 - \sigma_v^2}$, and $\beta = \frac{\sigma_v^2 (M-1)}{M\sigma_p^2 - \sigma_v^2}$ imply that $\gamma_p = \frac{\sigma_v^2 (M-1) \left[\sigma_p^2 (M+1) - 2\sigma_v^2\right]}{\left(M\sigma_p^2 - \sigma_v^2\right)\left[\sigma_p^2 + (M-2)\sigma_v^2\right]} > 0$ and $\left[2 + (M-1)\gamma_p\right]^2 > 4\left[2 + (M-1)\gamma_p\right]$. Finally, it can be shown that, when $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right)$ ($\gamma \in (0,1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in \left(-\frac{1}{M-1}, 0\right)$), $\lambda = \frac{\sigma_v^2\sqrt{M}\left[\sigma_v^2+M(M-1)\chi\right]^{-\frac{1}{2}}}{\sigma_u[\sigma_v^2(M+1)+M(M-1)\chi]} > \lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]}$ with $\gamma_p = 1 + \frac{M^2\chi}{\sigma_p^2+M(M-1)\chi-\sigma_v^2} - \frac{\sigma_p^2 M^2\chi}{\sigma_p^2[\sigma_v^2+M(M-1)\chi]-\sigma_v^4}$, given the expressions for α and β in Section 2.2 . In addition, $\lim_{M\to\infty} \lambda - \lambda_p = 0$, since both variables converge to zero at the limit. ■

Proof of Remark 1. We prove this remark under all possible scenarios for M and γ. When $M = 1$, $\frac{\partial\lambda_p}{\partial\sigma_p} = \frac{\sigma_v^3}{2\sigma_p^2\sigma_u}\left(\sigma_p^2 - \sigma_v^2\right)^{-\frac{1}{2}} > 0$. When $M > 1$ and $\chi = 0$ ($\gamma = 1$), $\frac{\partial\lambda_p}{\partial\sigma_p} = \frac{\sqrt{M}\sigma_v^3}{(M+1)\sigma_p^2\sigma_u}\left(\sigma_p^2 - \sigma_v^2\right)^{-\frac{1}{2}} > 0$. When $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right]$ ($\gamma \in [0,1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in \left(-\frac{1}{M-1}, 0\right)$), it can be shown that $\frac{\partial\lambda_p}{\partial\sigma_p}$ yields a positive function of σ_p, σ_v, M, and χ under the assumptions of Sections 2.1 and 2.2. Finally, in all the above scenarios, $\lim_{\sigma_p\to\infty} \lambda_p = \lambda$. ■

Proof of Remark 2. We prove this remark by comparing the equilibrium λ_p when either $\gamma = 1$ or $\gamma = 0$. If informed traders' signals are perfectly correlated, then $\lambda_p = \frac{\left[M\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)\right]^{\frac{1}{2}}}{\sigma_u\sigma_p(M+1)}$; if informed traders' private signals are uncorrelated, then $\lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]}$ with $\Gamma = \frac{M\left[\sigma_p^2+\left(M^2-2\right)\sigma_v^2\right]\left(\sigma_v^3-\sigma_v\sigma_p^2\right)^2}{\left(M\sigma_p^2-\sigma_v^2\right)\left[\sigma_p^2+(M-2)\sigma_v^2\right]}$ and the expression for γ_p in the proof of Corollary 2. It then follows that it exists a unique $\sigma_p^* > \sigma_v > 0$ such that $\lambda_p > \frac{\left[M\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)\right]^{\frac{1}{2}}}{\sigma_u\sigma_p(M+1)}$; if $M = 2$, $\sigma_p^* = \frac{1}{2}\sqrt{\sigma_v^2\left(7+\sqrt{33}\right)}$, while if $M \geq 3$, $\sigma_p^* = \frac{1}{\sqrt{2}}\left\{3\sigma_v^2 + \frac{\sigma_v^2}{M}\left[1 + (4M^3 + M^2 - 2M + 1)^{\frac{1}{2}}\right]\right\}^{\frac{1}{2}}$. ■

Proof of Corollary 3. We prove this statement under all possible scenarios for M and γ. When $M = 1$, $\lambda_s = \frac{\sigma_v^2}{2\sigma_p^2}$ and $\frac{\partial\lambda_s}{\partial\sigma_p} = -\frac{\sigma_v^2}{\sigma_p^3} < 0$. When $M > 1$ and $\chi = 0$ ($\gamma = 1$), $\lambda_s = \frac{\sigma_v^2}{(M+1)\sigma_p^2}$ and $\frac{\partial\lambda_s}{\partial\sigma_p} = -\frac{2\sigma_v^2}{(M+1)\sigma_p^3} < 0$. When $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right]$ ($\gamma \in [0,1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in \left(-\frac{1}{M-1}, 0\right)$), $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2}\left\{\frac{\sigma_v^2\left[2+(M-1)\gamma_p-\alpha\right]-\beta M\sigma_p^2}{\sigma_v^2\left[2+(M-1)\gamma_p\right]}\right\}$. Given the expressions for γ_p (in the proof of Corollary 2) and α (see Section 2.2), $\lambda_s < 0$ for "high" public signal volatility and less than perfectly correlated private signals, i.e., for $\sigma_p^2 > \frac{M^2(M-1)\chi\left[(M-1)\chi+2\sigma_v^2\right]}{2M(M+1)^2\chi-2\sigma_v^2} + \frac{M^2(M-1)^{\frac{3}{2}}\chi^{\frac{3}{2}}\sqrt{4\sigma_v^2+(M-1)\chi}-2\sigma_v^4}{2M(M+1)^2\chi-2\sigma_v^2}$ and $\chi > \frac{\sigma_v^2}{M(M-1)^2}$. Yet, regardless of χ and the sign of λ_s, $\lim_{\sigma_p\to\infty} \lambda_s = 0$. ■

Proof of Corollary 4. We prove this remark under all possible scenarios for M and γ. When $M = 1$, $var\,(p_1) = \frac{3\sigma_v^2\left(\sigma_v^2+2\sigma_p^2\right)}{4\sigma_p^2} > \frac{1}{2}\sigma_v^2$, the unconditional variance of p_1 in the absence of S_p, since $\sigma_p^2 > \sigma_v^2$. Along the same lines, when $M > 1$ and $\chi = 0$ ($\gamma = 1$), $var\,(p_1) = \frac{(2M+1)\sigma_v^2\left(\sigma_v^2+2\sigma_p^2\right)}{(M+1)^2\sigma_p^2} > \frac{M}{M+1}\sigma_v^2$, the variance of p_1 in Eq. (1). When $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right]$ ($\gamma \in [0, 1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in \left(-\frac{1}{M-1}, 0\right)$), it can be shown that $var\,(p_1) = \frac{\sigma_v^2\left[2+(M-1)\gamma_p-\alpha\right]^2}{\left[2+(M-1)\gamma_p\right]^2} + \frac{\alpha\sigma_v^2\left[\sigma_p^2\left(\sigma_p^2-\sigma_v^2\right)+2\sigma_v^2\right]}{\left[2+(M-1)\gamma_p\right]} + \frac{\alpha^2\sigma_v^2\left[1-\sigma_p^2\left(\sigma_p^2-\sigma_v^2\right)\right]}{\left[2+(M-1)\gamma_p\right]^2} > \frac{M\sigma_v^4}{(M+1)\sigma_v^2+M(M-1)\chi}$, the corresponding variance of p_1 of Proposition 1, since $\sigma_p^2 > \sigma_v^2$ and given the expressions for γ_p (derived in the proof of Corollary 2) and α (see Section 2.2). ■

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Table 1. Macroeconomic News Announcements

Announcements	Obs[1]	Source[2]	Time[3]	Stdev[4]
	Quarterly Announcements			
1- GDP Advance	36	BEA	8:30	Yes
2- GDP Preliminary	34	BEA	8:30	Yes
3- GDP Final	35	BEA	8:30	Yes
	Monthly Announcements			
Real Activity				
4- Nonfarm Payroll	108	BLS	8:30	Yes
5- Retail Sales	108	BC	8:30	Yes
6- Industrial Production	107	FRB	9:15	Yes
7- Capacity Utilization	107	FRB	9:15	No
8- Personal Income	105	BEA	10:00/8:30[5]	No
9- Consumer Credit	108	FRB	15:00[6]	No
Consumption				
10- New Home Sales	106	BC	10:00	Yes
11- Personal Consumption Expenditures	107	BEA	10:00/8:30[7]	No
Investment				
12- Durable Goods Orders	106	BC	8:30/9:00/10:00[8]	Yes
13- Factory Orders	105	BC	10:00	Yes
14- Construction Spending	105	BC	10:00	Yes
15- Business Inventories	106	BC	10:00/8:30[9]	
Government Purchases				
16- Government Budget	107	FMS	14:00	No
Net Exports				
17- Trade Balance	107	BEA	8:30	Yes
Prices				
18- Producer Price Index	108	BLS	8:30	Yes
19- Consumer Price Index	107	BLS	8:30	Yes
Forward-Looking				
20- Consumer Confidence Index	106	CB	10:00	Yes
21- NAPM Index	107	NAPM	10:00	Yes
22- Housing Starts	106	BC	8:30	Yes
23- Index of Leading Indicators	108	CB	8:30	Yes
	Six-Week Announcements			
24- Target Federal Funds Rate	71	FRB	14:15[10]	No
	Weekly Announcements			
25- Initial Unemployment Claims	459	ETA	8:30	Yes

Notes to Table 1

We partition the U.S. monthly news announcements into seven groups: real activity, GDP components (consumption, investment, government purchases and net exports), prices, and forward-looking. Within each group, we list U.S. news announcements in chronological order of their release.

Footnotes:

1. Total number of observations in our announcements and expectations data sample.

2. Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), National Association of Purchasing Managers (NAPM), Conference Board (CB), Financial Management Office (FMO), Employment and Training Administration (ETA).

3. Eastern Standard Time. Daylight savings time starts on the first Sunday of April and ends on the last Sunday of October.

4. The standard deviation across professional forecasters is available.

5. In 01/94, the personal income announcement time moved from 10:00 a.m. to 8:30 a.m.

6. Beginning in 01/96, consumer credit was released regularly at 3:00 p.m. Prior to this date the release times varied.

7. In 12/93, the personal consumption expenditures announcement time moved from 10:00 a.m. to 8:30 a.m.

8. Whenever GDP is released on the same day as durable goods orders, the durable goods orders announcement is moved to 10:00 a.m. On 07/96 the durable goods orders announcement was released at 9:00 a.m.

9. In 01/97, the business inventory announcement was moved from 10:00 a.m. to 8:30 a.m.

10. Beginning in 3/28/94, the fed funds rate was released regularly at 2:15 p.m. Prior to this date the release times varied.

Table 2a. Dispersion of Beliefs: Summary Statistics

This table presents summary statistics for the standard deviation across professional forecasts, our proxy for dispersion of beliefs among market participants. We report the mean, standard deviation, maximum, minimum, Spearman rank correlation with the nonfarm payroll standard deviation, and the first-order autocorrelation coefficient. A " * ", " ** ", or " *** " indicate the latter two measures' significance at 10%, 5%, or 1% level, respectively. The dispersion of beliefs for Capacity Utilization, Personal Income, Consumer Credit, Personal Consumption Expenditures, Business Inventories, Government Budget, and Target Federal Funds Rate (announcements 7, 8, 9, 11, 15, 16, and 24 in Table 1) is not available.

	Mean	Stdev.	Max.	Min	ρ(Payroll)	$\rho(1)$
	Quarterly Announcements					
1- GDP Advance	0.452	0.145	0.320	1.100	0.162*	0.820***
2- GDP Preliminary	0.298	0.188	0.120	1.290	0.014	0.880***
3- GDP Final	0.118	0.051	0.040	0.240	0.083	0.819***
	Monthly Announcements					
Real Activity						
4- Nonfarm Payroll	41.675	14.905	17.496	103.190	1.000	0.391***
5- Retail Sales	0.243	0.079	0.106	0.650	0.109	0.011
6- Industrial Production	0.172	0.066	0.087	0.439	0.236**	0.438***
Consumption						
10- New Home Sales	19.168	10.285	7.840	96.225	0.151	0.079
Investment						
12- Durable Goods Orders	0.944	0.305	0.501	2.583	0.077	0.348***
13- Factory Orders	0.579	0.677	0.239	7.249	0.219**	0.029
14- Construction Spending	0.432	0.202	0.158	1.139	0.176*	0.282**
Net Exports						
17- Trade Balance	0.815	1.058	0.423	11.480	0.122	0.004
Prices						
18- Producer Price Index	0.120	0.034	0.060	0.301	0.186*	0.324***
19- Consumer Price Index	0.066	0.014	0.040	0.115	0.146	0.207*
Forward-Looking						
20- Consumer Conf. Index	1.645	0.587	0.663	4.026	0.079	0.258*
21- NAPM Index	0.939	0.257	0.441	1.840	0.242**	0.301***
22- Housing Starts	0.031	0.009	0.016	0.082	0.16	0.282***
23- Index of Leading Ind.	0.127	0.058	0.044	0.345	0.134	0.302***
	Weekly Announcements					
25- Initial Unemp. Claims	7.807	4.158	3.428	33.010	0.069	0.189**

Table 2b. Dispersion of Beliefs and Traders Aggressiveness

This table reports estimates of the following equation:

$$NT_t = b_h D_{ht} + b_l D_{lt} + b_m (1 - D_{ht} - D_{lt}) + \varepsilon_t,$$

where NT_t is the number of transactions on day t, D_{ht} (D_{lt}) is a dummy variable equal to one on days with high (low) dispersion of beliefs defined as the forecasts' standard deviation to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution, and zero otherwise. We measure the degree of heterogeneity of beliefs in a given month using three different methodologies. First, we only use the standard deviation of the Nonfarm Payroll Employment report. Second, we aggregate the standard deviation across seven "influential" macroeconomic announcements: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims. Third, we aggregate the forecasts' standard deviation across all macroeconomic news announcements listed in Table 2a. R_a^2 is the adjusted R^2. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	b_h	b_l	b_m	$b_h - b_l$	R_a^2
			2-Year		
Nonfarm Payroll Employment	366.687	374.983	362.978	-8.296	0.860
Influential Announcements	317.836	409.360	372.472	-91.524***	0.868
All Announcements	321.120	421.500	362.468	-100.38***	0.869
			5-Year		
Nonfarm Payroll Employment	603.503	648.080	570.535	-44.576***	0.857
Influential Announcements	562.774	599.127	626.650	-36.353***	0.855
All Announcements	534.212	657.696	607.237	-123.484***	0.859
			10-Year		
Nonfarm Payroll Employment	530.563	570.922	505.908	-40.359***	0.855
Influential Announcements	496.024	527.157	554.288	-31.132***	0.855
All Announcements	452.617	584.260	546.248	-131.643***	0.862

Table 3. Summary Statistics

This table presents summary statistics for the variables used in our empirical tests, daily yields, daily yield changes, number of buys, number of sells, order flow, abnormal order flow and the number of transactions. We report the mean, standard deviation, maximum, minimum and the first-order autocorrelation coefficient. A " * ", " ** ", or " *** " indicates the first-order autocorrelation is statistically significant at 10%, 5%, or 1% level.

	Mean	Stdev.	Max.	Min.	$\rho(1)$
			2-Year		
Daily Yield	5.486	0.885	7.728	3.67	0.998***
Daily Yield Change×100	0.054	6.101	35.100	-31.1	0.041*
Number of Buys	202.067	79.996	604	25	0.559***
Number of Sells	170.770	69.892	640	17	0.533***
Order Flow	31.297	37.377	204	-89	0.088***
Abnormal Order Flow	0.000	33.737	187.580	-102.494	0.032
Number of Transactions	372.836	145.504	1244	44	0.578***
			5-Year		
Daily Yield	5.965	0.739	7.898	3.978	0.996***
Daily Yield Change×100	-0.005	6.389	35.100	-29.3	0.044**
Number of Buys	324.699	127.360	816	34	0.633***
Number of Sells	289.412	114.465	737	33	0.631***
Order Flow	35.287	49.534	278	-127	0.128***
Abnormal Order Flow	0.000	47.845	262.719	-129.443	-0.007
Number of Transactions	614.111	237.048	1423	88	0.654***
			10-Year		
Daily Yield	6.263	0.736	8.033	4.164	0.997***
Daily Yield Change×100	-0.044	5.994	33.6	-23	0.044**
Number of Buys	281.696	109.034	693	34	0.710***
Number of Sells	260.554	102.438	553	22	0.692***
Order Flow	21.142	36.447	153	-105	0.160***
Abnormal Order Flow	0.000	40.294	142.984	-105.377	0.038
Number of Transactions	542.250	208.412	1246	73	0.718***

Table 4. No Public Signal

This table reports estimates of the following representation of Eq. (9):

$$(y_t - y_{t-1}) \times 100 = a + \lambda_h \Omega_t^* D_{ht} + \lambda_l \Omega_t^* D_{lt} + \lambda_m \Omega_t^* (1 - D_{ht} - D_{lt}) + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields, Ω_t^* is unanticipated order flow, D_{ht} (D_{lt}) is a dummy variable equal to one on days with high (low) dispersion of beliefs defined as the forecasts' standard deviation to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution, and zero otherwise. We measure the degree of heterogeneity of beliefs in a given month using three different methodologies. First, we only use the standard deviation of the Nonfarm Payroll Employment report. Second, we aggregate the standard deviation across seven "influential" macroeconomic announcements: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims. Third, we aggregate the forecasts' standard deviation across all macroeconomic news announcements listed in Table 2a. R^2_{ha} (R^2_{la}) is the adjusted R^2 conditional on high (low) dispersion days, while R^2_a is the adjusted R^2 including all observations. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	λ_h	λ_l	λ_m	$\lambda_h - \lambda_l$	R^2_{ha}	R^2_{la}	R^2_a
				2-Year			
Nonfarm Payroll Employment	-0.193***	-0.089***	-0.181***	-0.104***	28.21%	8.19%	22.42%
Influential Announcements	-0.133***	-0.077***	-0.105***	-0.028***	13.15%	13.16%	15.54%
All Announcements	-0.131***	-0.100***	-0.084***	-0.031	14.85%	19.04%	15.97%
				5-Year			
Nonfarm Payroll Employment	-0.213***	-0.069***	-0.143***	-0.144***	40.55%	5.84%	23.14%
Influential Announcements	-0.151***	-0.087***	-0.120***	-0.064***	19.32%	13.12%	20.31%
All Announcements	-0.160***	-0.106***	-0.102***	-0.053***	22.16%	20.48%	21.21%
				10-Year			
Nonfarm Payroll Employment	-0.150***	-0.071***	-0.140***	-0.056	10.78%	2.14%	9.14%
Influential Announcements	-0.079***	-0.077***	-0.095***	-0.002	3.78%	5.38%	6.49%
All Announcements	-0.081***	-0.071***	-0.085***	-0.010	3.25%	4.82%	5.58%

Table 5. Comparison of Announcement vs Non-announcement Days

This table reports estimates of the following representation of Eq. (12):

$$(y_t - y_{t-1}) \times 100 = a + \lambda\Omega_t^*(1 - D_p) + \lambda_p\Omega_t^*(1 - D_p) + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields, Ω_t^* is unanticipated order flow, D_p is a dummy variable equal to one on days an announcement is released. We define announcement days using three different methodologies. First, we only consider days when the Nonfarm Payroll Employment report is released. Second, we clasify as announcement days any day one of the seven "influential" macroeconomic announcements is released: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims. Third, we classify as announcement days any day a macroeconomic news announcement listed in Table 2a is released. R_f^2 (R_{fp}^2) is the adjusted R^2 using non-announcement (announcement) days only, and R_a^2 is the adjusted R^2 of the fully specified regression above. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	λ	λ_p	$\lambda - \lambda_p$	R_f^2	R_{fp}^2	R_a^2
			2-Year			
Nonfarm Payroll Employment	-0.157***	-0.103***	-0.054*	21.13%	5.50%	14.05%
Influential Announcements	-0.106***	-0.110***	0.004	15.06%	11.96%	13.44%
All Announcements	-0.100***	-0.106***	0.006	15.70%	12.81%	13.42%
			5-Year			
Nonfarm Payroll Employment	-0.139***	-0.175***	0.036	20.57%	19.92%	20.40%
Influential Announcements	-0.130***	-0.137***	0.007	19.67%	20.61%	20.25%
All Announcements	-0.116***	-0.13***	0.014	20.60%	20.03%	20.17%
			10-Year			
Nonfarm Payroll Employment	-0.125***	-0.086***	-0.039	9.06%	1.50%	6.05%
Influential Announcements	-0.089***	-0.087***	-0.002	6.57%	4.64%	5.51%
All Announcements	-0.079***	-0.089***	0.01	5.84%	5.45%	5.53%

Table 6. Public Signal

This table reports estimates of the following representation of Eq. (10):

$$(y_t - y_{t-1}) \times 100 = a + \sum_{j=1}^{P} \lambda_{sj} S_{jt} + \lambda_{ph} \Omega_t^* D_{ht} + \lambda_{pl} \Omega_t^* D_{lt} + \lambda_{pm} \Omega_t^* (1 - D_{ht} - D_{lt}) + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields, Ω_t^* is unanticipated order flow, D_{ht} (D_{lt}) is a dummy variable equal to one on days with high (low) dispersion of beliefs defined as the forecasts' standard deviation to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution, and zero otherwise. We measure the degree of heterogeneity of beliefs in a given month using three different methodologies. First, we only use the standard deviation of the Nonfarm Payroll Employment report. Second, we aggregate the standard deviation across seven "influential" macroeconomic announcements: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims. Third, we aggregate the forecasts' standard deviation across all macroeconomic news announcements listed in Table 2a. We estimate the above equation using only those observations when an announcement was made. The coefficient $\overline{\lambda_{sp}}$ is either the average estimated coefficient across some ($P = 7$) or all ($P = 18$) macroeconomic announcements or the estimated coefficient for the impact of Nonfarm Payroll announcements alone. R^2_{fha} (R^2_{fla}) is the adjusted R^2 conditional on high (low) dispersion days and only using order flow, R^2_{fa} is the adjusted R^2 when we regress only order flow on yield changes, and R^2_a is the adjusted R^2 of the fully specified regression above. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Table 6 (*Continued*).

Announcements	$\overline{\lambda_{sp}}$	λ_{ph}	λ_{pl}	λ_{pm}	$\lambda_{ph}-\lambda_{pl}$	R^2_{fha}	R^2_{fla}	R^2_{fa}	R^2_{a}
				2-Year					
Nonfarm Payroll Employment	6.577***	-0.122***	-0.097*	-0.150***	-0.025	1.12%	2.77%	4.34%	42.02%
Influential Announcements	2.991***	-0.174***	-0.108***	-0.079***	-0.067***	14.96%	13.87%	13.01%	29.37%
All Announcements	1.530***	-0.162***	-0.092***	-0.092***	-0.070***	15.77%	13.71%	12.96%	25.71%
				5-Year					
Nonfarm Payroll Employment	5.600***	-0.217***	-0.120**	-0.175***	-0.097	19.10%	3.07%	17.30%	46.40%
Influential Announcements	2.856***	-0.179***	-0.126***	-0.111***	-0.053**	23.57%	19.89%	21.51%	33.27%
All Announcements	1.264***	-0.178***	-0.122***	-0.111***	-0.056***	23.76%	22.72%	21.34%	30.29%
				10-Year					
Nonfarm Payroll Employment	4.448***	-0.192**	0.052	-0.039	-0.244**	4.81%	-3.18%	1.28%	23.52%
Influential Announcements	2.644***	-0.102***	-0.082***	-0.062***	-0.020	4.04%	5.22%	4.53%	15.35%
All Announcements	1.327***	-0.112***	-0.066***	-0.080***	-0.052**	5.00%	4.03%	5.34%	13.66%

Table 7. Public Signal: 2-Year Bonds

This table reports estimates of the following equation:

$$(y_t - y_{t-1}) \times 100 = a_p + \lambda_s S_{pt} + \lambda_p \Omega_t^* + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields for the 2-year bond, Ω_t^* is the unanticipated order flow, and S_{pt} is the standardized macroeconomic news surprise estimated using MMS data. We estimate the above equation using only those observations when an announcement was made. R^2_{sa} (R^2_{fa}) is the adjusted R^2 we obtain when we estimate the above equation only using macroeconomic news surprise (order flow), while R^2_a is the adjusted R^2 when we include both variables. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	λ_s	λ_p	R^2_{sa}	R^2_{fa}	R^2_a
	Quarterly Announcements				
1- GDP Advance	0.431	-0.180***	-2.30%	18.67%	16.42%
2- GDP Preliminary	0.871	-0.218***	0.41%	26.16%	25.33%
3- GDP Final	0.087	-0.065	-2.90%	0.16%	-2.94%
	Monthly Announcements				
Real Activity					
4- Nonfarm Payroll	6.621***	-0.129***	33.90%	4.64%	42.84%
5- Retail Sales	3.500***	-0.174***	14.39%	28.88%	36.08%
6- Industrial Production	1.213**	-0.099***	3.28%	14.64%	17.53%
7- Capacity Utilization	1.694***	-0.089***	9.80%	14.64%	20.92%
8- Personal Income	1.408**	-0.099***	4.29%	9.58%	13.50%
9- Consumer Credit	0.129	-0.105***	-0.71%	13.13%	12.33%
Consumption					
10- New Home Sales	2.255***	-0.105***	19.14%	17.73%	34.58%
11- Personal Cons. Exp.	1.006	-0.094***	2.48%	9.48%	10.36%
Investment					
12- Durable Goods Orders	0.840	-0.104***	-0.10%	7.39%	7.68%
13- Factory Orders	0.386	-0.043	-0.78%	0.38%	-0.32%
14- Construction Spending	1.193	-0.09***	-0.25%	7.88%	8.33%
15- Business Inventories	0.878	-0.107***	-0.30%	13.20%	13.57%
Government Purchases					
16- Government Budget	-1.216	-0.137***	0.12%	14.99%	15.38%
Net Exports					
17- Trade Balance	-0.138	-0.069***	-0.95%	8.54%	7.75%

Table 7 (*Continued*).

Announcements	λ_s	λ_p	R^2_{sa}	R^2_{fa}	R^2_a
	Monthly Announcements				
Prices					
18- Producer Price Index	-0.017	-0.117***	-0.94%	14.93%	14.12%
19- Consumer Price Index	2.325***	-0.136***	4.17%	16.61%	21.77%
Forward-Looking					
20- Consumer Confidence Index	1.875***	-0.054**	9.28%	4.28%	12.12%
21- NAPM Index	3.743***	-0.097***	26.28%	9.37%	35.59%
22- Housing Starts	1.023	-0.101***	-0.47%	12.40%	12.33%
23- Index of Leading Indicators	3.366*	-0.029	2.70%	0.74%	3.07%
	Six-Week Announcements				
24- Target Federal Funds Rate	32.383***	-0.015	19.62%	-0.50%	18.69%
	Weekly Announcements				
25- Initial Unemployment Claims	-0.622**	-0.107***	0.45%	13.72%	14.26%

Table 8. Public Signal: 5-Year Bonds

This table reports estimates of the following equation:

$$(y_t - y_{t-1}) \times 100 = a_p + \lambda_s S_{pt} + \lambda_p\, \Omega_t^* + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields for the 5-year bond, Ω_t^* is the unanticipated order flow, and S_{pt} is the standardized macroeconomic news surprise estimated using MMS data. We estimate the above equation using only those observations when an announcement was made. R_{sa}^2 (R_{fa}^2) is the adjusted R^2 we obtain when we estimate the above equation only using macroeconomic news surprise (order flow), while R_a^2 is the adjusted R^2 when we include both variables. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	λ_s	λ_p	R_{sa}^2	R_{fa}^2	R_a^2
	Quarterly Announcements				
1- GDP Advance	-1.612	-0.147**	-0.09%	13.70%	14.02%
2- GDP Preliminary	0.643	-0.134***	3.56%	28.02%	26.64%
3- GDP Final	0.525	-0.165***	-3.03%	18.15%	16.11%
	Monthly Announcements				
Real Activity					
4- Nonfarm Payroll	5.644***	-0.171***	28.02%	17.53%	46.59%
5- Retail Sales	4.463***	-0.165***	12.32%	27.51%	40.07%
6- Industrial Production	0.875	-0.127***	3.40%	24.77%	25.67%
7- Capacity Utilization	1.487***	-0.123***	7.90%	24.77%	28.77%
8- Personal Income	1.095*	-0.083***	4.00%	9.97%	11.88%
9- Consumer Credit	0.201	-0.143***	-0.88%	23.96%	23.30%
Consumption					
10- New Home Sales	2.083***	-0.091***	18.17%	20.52%	34.06%
11- Personal Cons. Exp.	1.426**	-0.097***	2.00%	10.74%	13.45%
Investment					
12- Durable Goods Orders	1.241*	-0.165***	1.77%	24.12%	26.17%
13- Factory Orders	0.157	-0.177***	-0.20%	25.50%	24.81%
14- Construction Spending	0.724	-0.114***	0.19%	15.65%	15.37%
15- Business Inventories	0.466	-0.108***	-0.49%	18.07%	17.56%
Government Purchases					
16- Government Budget	-0.481	-0.131***	1.09%	21.02%	20.44%
Net Exports					
17- Trade Balance	-0.368	-0.087***	-0.95%	12.30%	11.95%

Table 8 (*Continued*).

Announcements	λ_s	λ_p	R^2_{sa}	R^2_{fa}	R^2_a
	Monthly Announcements				
Prices					
18- Producer Price Index	-0.429	-0.147***	-0.93%	25.76%	25.32%
19- Consumer Price Index	1.103	-0.150***	1.96%	29.29%	29.83%
Forward-Looking					
20- Consumer Confidence Index	1.453***	-0.148***	9.94%	40.38%	44.27%
21- NAPM Index	2.971***	-0.132***	23.29%	28.01%	41.35%
22- Housing Starts	0.390	-0.123***	-0.95%	13.20%	12.45%
23- Index of Leading Indicators	3.764**	-0.089***	3.29%	8.67%	11.87%
	Six-Week Announcements				
24- Target Federal Funds Rate	23.424***	-0.106***	9.41%	10.52%	19.46%
	Weekly Announcements				
25- Initial Unemployment Claims	-0.652**	-0.116***	0.50%	16.48%	17.07%

Table 9. Public Signal: 10-Year Bonds

This table reports estimates of the following equation:

$$(y_t - y_{t-1}) \times 100 = a_p + \lambda_s S_{pt} + \lambda_p \, \Omega_t^* + \varepsilon_t,$$

where $y_t - y_{t-1}$ is the daily change in bond yields for the 10-year bond, Ω_t^* is the unanticipated order flow, and S_{pt} is the standardized macroeconomic news surprise estimated using MMS data. We estimate the above equation using only those observations when an announcement was made. R^2_{sa} (R^2_{fa}) is the adjusted R^2 we obtain when we estimate the above equation only using macroeconomic news surprise (order flow) as the explanatory variable, while R^2_a is the adjusted R^2 when we include both variables. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

Announcements	λ_s	λ_p	R^2_{sa}	R^2_{fa}	R^2_a
	Quarterly Announcements				
1- GDP Advance	-1.392	-0.129*	-1.13%	6.03%	5.79%
2- GDP Preliminary	1.228	-0.077	1.90%	0.02%	1.55%
3- GDP Final	-0.003	-0.130**	-3.02%	9.15%	6.31%
	Monthly Announcements				
Real Activity					
4- Nonfarm Payroll	4.348***	-0.048	21.98%	0.81%	22.01%
5- Retail Sales	3.908***	-0.130***	11.48%	12.31%	23.93%
6- Industrial Production	1.213**	-0.072**	3.50%	3.24%	6.21%
7- Capacity Utilization	1.643***	-0.060*	7.78%	3.24%	9.35%
8- Personal Income	1.163**	-0.079**	3.96%	5.04%	7.82%
9- Consumer Credit	-0.109	-0.146***	-0.94%	8.44%	7.59%
Consumption					
10- New Home Sales	2.024***	-0.086***	17.51%	6.32%	22.35%
11- Personal Cons. Exp.	1.387**	-0.097***	1.87%	5.03%	7.99%
Investment					
12- Durable Goods Orders	1.409**	-0.085**	2.61%	3.04%	6.07%
13- Factory Orders	0.425	-0.145***	0.07%	10.60%	10.08%
14- Construction Spending	1.500*	-0.064*	2.08%	2.23%	4.14%
15- Business Inventories	0.490	-0.108***	-0.85%	7.48%	6.94%
Government Purchases					
16- Government Budget	-1.049	-0.068**	0.48%	3.60%	3.71%
Net Exports					
17- Trade Balance	-0.129	-0.101***	-0.90%	8.17%	7.35%

Table 9 (*Continued*).

Announcements	λ_s	λ_p	R^2_{sa}	R^2_{fa}	R^2_a
	Monthly Announcements				
Prices					
18- Producer Price Index	-0.006	-0.097***	-0.93%	7.22%	6.34%
19- Consumer Price Index	1.399	-0.109***	1.22%	6.34%	7.83%
Forward-Looking					
20- Consumer Confidence Index	2.204***	-0.046	11.29%	0.56%	11.88%
21- NAPM Index	3.199***	-0.052	21.07%	4.16%	21.83%
22- Housing Starts	0.047	-0.101***	-0.89%	6.96%	6.06%
23- Index of Leading Indicators	3.046*	-0.090***	2.63%	6.50%	8.92%
	Six-Week Announcements				
24- Target Federal Funds Rate	13.211*	-0.067	4.48%	3.57%	6.40%
	Weekly Announcements				
25- Initial Unemployment Claims	-0.634**	-0.093***	0.54%	6.00%	6.61%

Table 10. Public Signal Noise

This table reports estimates of the following equation:

$$\begin{aligned}(y_t - y_{t-1}) \times 100 &= a + \lambda_{snh}\, S_{pt} D_{nht} + \lambda_{snl}\, S_{pt} D_{nlt} + \lambda_{snm}\, S_{pt}(1 - D_{nht} - D_{nlt}) + \\ &\quad + \lambda_{pnh}\, \Omega_t^* D_{nht} + \lambda_{pnl}\, \Omega_t^* D_{nlt} + \lambda_{pnm}\, \Omega_t^*(1 - D_{nht} - D_{nlt}) + \varepsilon_t,\end{aligned}$$

where $y_t - y_{t-1}$ is the daily change in bond yields, D_{nht} (D_{nlt}) is a dummy variable equal to one on days with high (low) public noise signals defined as the absolute value of the difference between the actual announcement minus the latest revision of the announcement to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution, and zero otherwise. We estimate the above equation using the Nonfarm Payroll Employment, Industrial Production, and Capacity Utilization announcement days, i.e., using the only news releases in our sample for which announcement revisions are available. The revision data is from the Philadelphia Federal Reserve Bank Real Time Data Set. R^2_{sa} is the adjusted R^2 only using the public news surprises as the explanatory variables. R^2_{fnha} (R^2_{fnla}) is the incremental adjusted R^2 of order flow conditional on high (low) public signal noise days defined as the adjusted R^2 of the above equation estimated only using the public surprise variables and $\Omega_t^* D_{nht}$ ($\Omega_t^* D_{nlt}$). R^2_a is the adjusted R^2 of the fully specified model. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using heteroskedasticity and autocorrelation consistent standard errors.

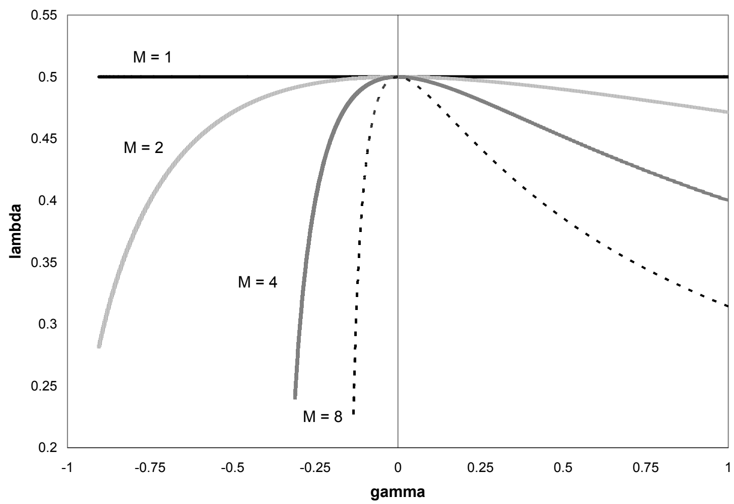
Table 10 (*Continued*).

Announcements	λ_{snh}	λ_{snl}	λ_{snm}	λ_{pnh}	λ_{pnl}	λ_{pnm}	R^2_{sa}	R^2_{fnha}	R^2_{fnla}	R^2_a
					2-Year					
Nonfarm Payroll Emp.	6.166***	6.576***	6.893***	-0.136*	-0.105	-0.146***	32.67%	39.24%	39.00%	40.82%
Industrial Production	1.149	1.225	1.297	-0.105***	-0.133**	-0.082***	2.38%	10.93%	9.50%	14.83%
Capacity Utilization	1.312	2.667***	1.798**	-0.056	-0.087	-0.101***	9.01%	18.20%	18.80%	19.23%
					5-Year					
Nonfarm Payroll Emp.	5.672***	5.359***	5.879***	-0.168***	-0.165***	-0.183***	26.77%	39.16%	38.21%	44.56%
Industrial Production	0.901	1.067	0.652	-0.094**	-0.096	-0.156***	2.44%	22.80%	20.82%	24.12%
Capacity Utilization	1.648*	2.688**	0.972	-0.095**	-0.064	-0.149***	7.66%	27.80%	24.85%	27.97%
					10-Year					
Nonfarm Payroll Emp.	4.397**	5.167***	3.810***	-0.141	0.028	-0.055***	20.88%	21.29%	19.84%	20.61%
Industrial Production	0.330	2.096**	2.045**	-0.006	-0.097	-0.124**	3.70%	5.47%	7.69%	6.78%
Capacity Utilization	1.500	3.530***	1.086	0.002	-0.125*	-0.057***	8.15%	7.44%	10.64%	9.75%

Figure 1. Equilibrium without a Public Signal

Figure 1a plots the inverse of the market liquidity parameter defined in Proposition 1, $\lambda = \frac{\sigma_v^2}{\sigma_u \sigma_s \sqrt{M}[2+(M-1)\gamma]}$, and Figure 1b plots the unconditional variance of the equilibrium price, $var\left(p_1\right) = \frac{\sigma_v^4}{M\sigma_s^2+\sigma_v^2}$, as a function of the degree of correlation of the informed traders' signals, γ, in the presence of $M = 1$, 2, 4, or 8 informed traders, when $\sigma_v^2 = \sigma_u^2 = 1$. Since $\sigma_s^2 = \frac{\sigma_v^2+M(M-1)\chi}{M^2}$, $\sigma_{ss} = \frac{\sigma_v^2-M\chi}{M^2}$, and $\gamma = \frac{\sigma_v^2-M\chi}{\sigma_v^2+M(M-1)\chi}$, the range of correlations compatible with an equilibrium is obtained by varying the parameter $\chi = \sigma_s^2 - \sigma_{ss}$ within the interval $[0, 10]$ when $M = 2$, the interval $[0, 5]$ when $M = 4$, and the interval $[0, 2.5]$ when $M = 8$.

a) λ



b) $var\left(p_1\right)$

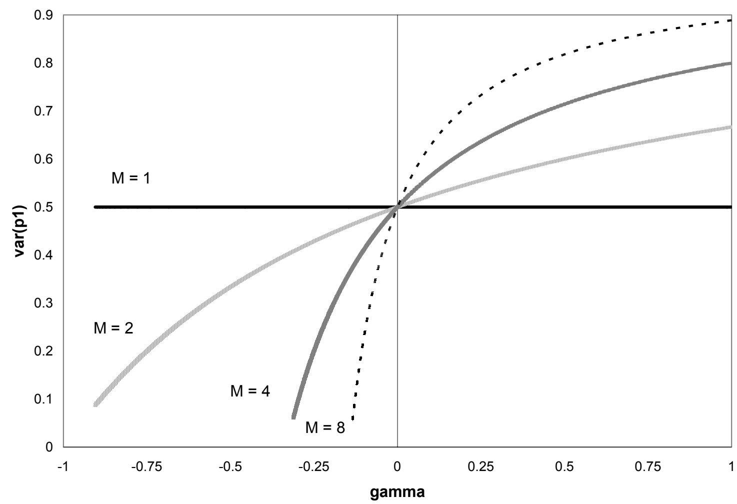
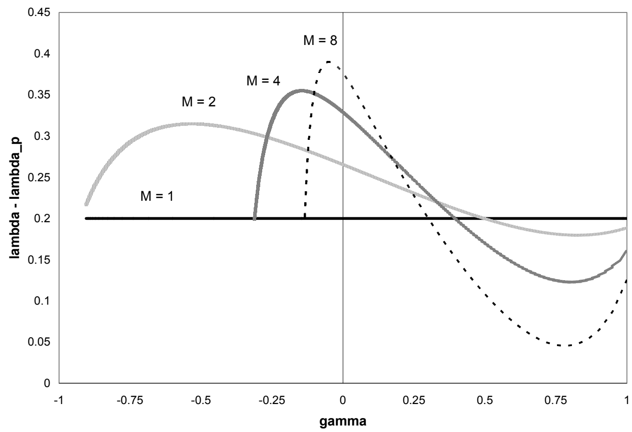


Figure 2. Equilibrium with a Public Signal

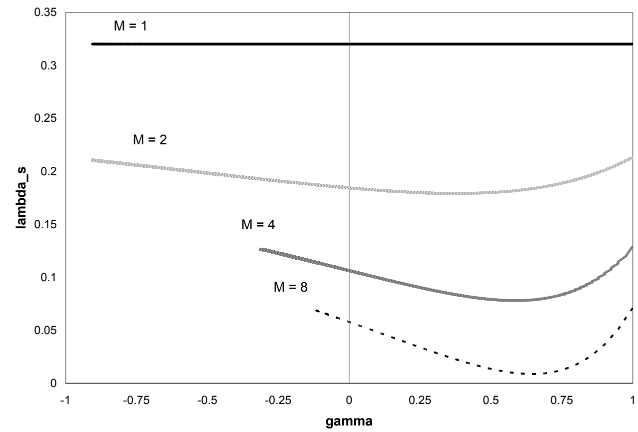
These figures plot the difference between the sensitivity of the equilibrium price to the order flow in the absence and in the presence of a public signal S_p, i.e., $\lambda - \lambda_p$ (Figure 2a), the impact of S_p on the equilibrium price p_1, λ_s (Figure 2b), the difference between the unconditional variance of the equilibrium price p_1 in Propositions 1 and 2, i.e., $dvar\left(p_1\right) = \frac{\sigma_v^4}{M\sigma_s^2+\sigma_v^2} - var\left(p_1\right)$, and the percentage of $var\left(p_1\right)$ explained by S_p, $R^2_{S_p} = \frac{\left[\lambda_s + \frac{M\beta}{2+(M-1)\gamma}\right]^2 \sigma_p^2}{var(p_1)}$, as a function of the degree of correlation of the informed traders' signals, γ, when $M = 1$, 2, 4, or 8 informed traders, $\sigma_v = \sigma_u = 1$, and $\sigma_p = 1.25$. According to Proposition 1, $\lambda = \frac{\sigma_v^2}{\sigma_u \sigma_s \sqrt{M}[2+(M-1)\gamma]}$, while $\lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p \left[2+(M-1)\gamma_p\right]}$ and $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2}\left\{\frac{\sigma_v^2\left[2+(M-1)\gamma_p-\alpha\right]-\beta M\sigma_p^2}{\sigma_v^2\left[2+(M-1)\gamma_p\right]}\right\}$ in Proposition 2. Finally, $var\left(p_1\right) = \frac{\sigma_v^2\left[2+(M-1)\gamma_p-\alpha\right]^2}{\left[2+(M-1)\gamma_p\right]^2} + \frac{\alpha\sigma_v^2\left[\sigma_p^2\left(\sigma_p^2-\sigma_v^2\right)+2\sigma_v^2\right]}{\left[2+(M-1)\gamma_p\right]} + \frac{\alpha^2\sigma_v^2\left[1-\sigma_p^2\left(\sigma_p^2-\sigma_v^2\right)\right]}{\left[2+(M-1)\gamma_p\right]^2}$. Since $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2+M(M-1)\chi}$, $\gamma_p = 1 + \frac{M^2\chi}{\sigma_p^2+M(M-1)\chi-\sigma_v^2} - \frac{\sigma_p^2 M^2\chi}{\sigma_p^2[\sigma_v^2+M(M-1)\chi]-\sigma_v^4}$, and $\sigma_s^2 = \frac{\sigma_v^2+M(M-1)\chi}{M^2}$, the range of correlations compatible with an equilibrium is obtained by varying the parameter $\chi = \sigma_s^2 - \sigma_{ss}$ within the interval $[0, 10]$ when $M = 2$, the interval $[0, 5]$ when $M = 4$, and the interval $[0, 2.5]$ when $M = 8$.

Figure 2 (*Continued*).

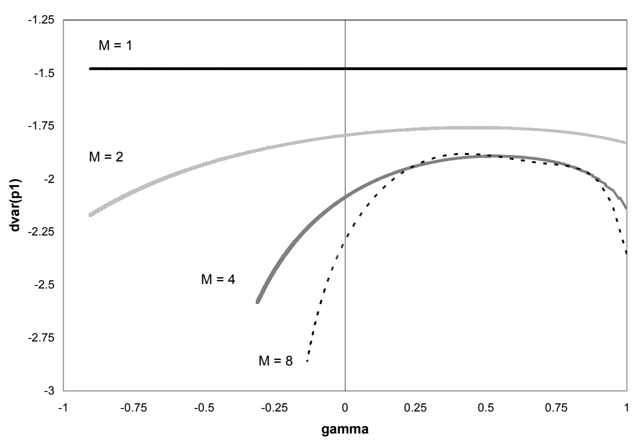
a) $\lambda - \lambda_p$



b) λ_s



c) $dvar\,(p_1)$



d) $R^2_{S_p}$

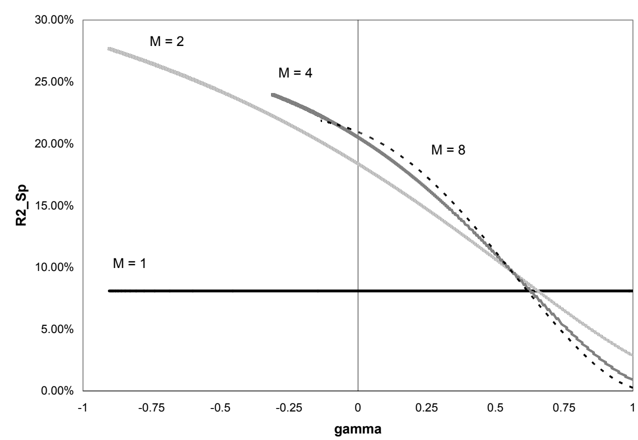


Figure 3. Daily Bond Yield Changes

In this figure, we compare 2-year, 5-year and 10-year daily bond yield changes on Nonfarm Payroll Employment announcement days (left-hand panels) to daily yield changes on non-announcement days (right-hand panels). Non-announcement days are defined as days the week before the Nonfarm Payroll Employment is released and none of the 25 announcements listed in Table 1 were released.

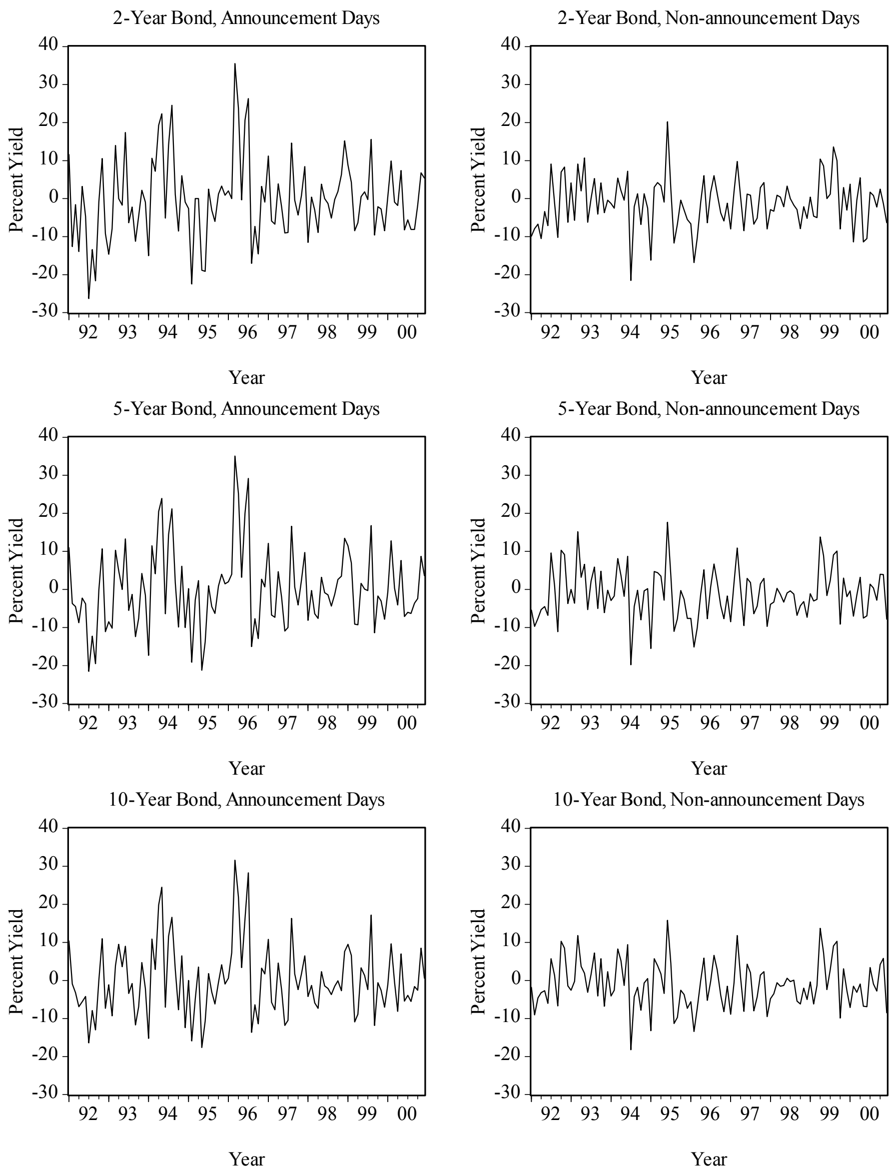
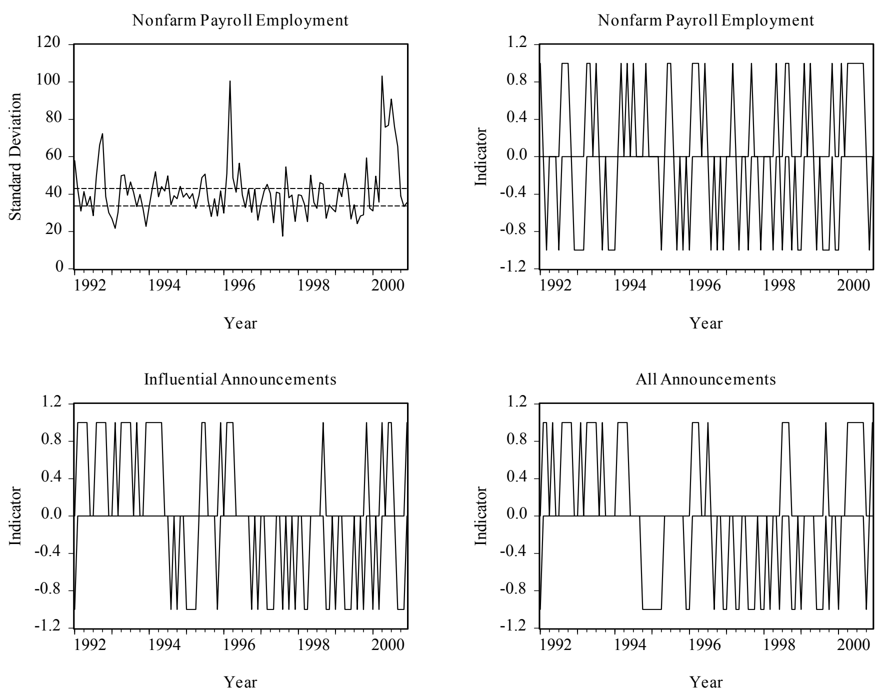


Figure 4. Aggregate Proxies for Dispersion of Beliefs

The top left panel of this figure shows the time series of the Nonfarm Payroll Employment forecasts' standard deviation, SD_{1t}. The top right panel plots the corresponding series of months with high, $+1$ (low, -1), dispersion of beliefs defined as SD_{1t} to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution (e.g., the dotted lines in the top left panel). The bottom panels of the figure plot the series of months with high, $+1$ (low, -1), dispersion of beliefs defined as SD_t for influential announcements ($P = 7$, left panel) or for all announcements ($P = 18$, right panel) to be on the top (bottom) 70^{th} (30^{th}) percentile of its empirical distribution. The seven "influential" macroeconomic announcements are Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims, i.e., those announcements having a statistically significant impact on two, five, and ten-year bond yield changes over the sample period 1992-2000 (in Tables 5 to 7). Finally, we report the correlation matrix for the three resulting sequences of high and low information heterogeneity periods.



	Correlation Matrix		
Announcements	Nonfarm	Influential	All
Nonfarm	1.000	0.378	0.362
Influential	0.378	1.000	0.698
All	0.362	0.698	1.000

Figure 5. Public Signal Noise and Public Signal Volatility

In the left-hand panel of this figure, we plot the actual announcement minus the latest revision of the announcement according to the Federal Reserve Bank of Philadelphia "Real Time Data Set" (RTDS). In the right-hand panel of the figure, we plot the absolute value of the public signal noise and the public announcement volatility. The solid line is the volatility of the actual public announcement, the dashed line is the absolute value of the actual announcement minus the revision. The number in the box is the correlation between the two. April 1995 Industrial Production and Capacity Utilization data is missing.