

Informed and Strategic Order Flow in the Bond Markets

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Abstract

We study the role played by private and public information in the process of price formation in the U.S. Treasury bond market. 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 — and a public signal. We test its equilibrium implications by analyzing the response of two-year, five-year, and ten-year U.S. bond yields to order flow and real-time U.S. macroeconomic news. We find strong evidence of informational effects in the U.S. Treasury bond market: unanticipated order flow has a significant and permanent impact on daily bond yield changes during both announcement and non-announcement days. Our analysis further shows that, consistent with our stylized model, the contemporaneous correlation between order flow and yield changes is higher when the dispersion of beliefs among market participants is high and public announcements are noisy.

JEL classification: E44; G14

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Résumé

L'étude traite du rôle que jouent l'information publique et privée dans le processus de formation des prix sur le marché des obligations du Trésor américain. Pour guider leur analyse, les auteurs élaborent un modèle parsimonieux qui formalise les activités de spéculation en présence de deux frictions réalistes (hétérogénéité de l'information et situation de concurrence imparfaite entre opérateurs informés) et d'un signal public. Ils testent les implications du modèle pour l'équilibre en analysant la réaction des rendements d'obligations américaines à deux, cinq et dix ans au flux d'ordres et à la publication en temps réel de données macroéconomiques. Ils constatent l'existence d'effets informationnels sur le marché de ces obligations : les variations inattendues du flux d'ordres ont une incidence significative et permanente sur les fluctuations quotidiennes des rendements obligataires, que des données macroéconomiques aient ou non été publiées ce jour-là. Les auteurs montrent également que, comme le prévoit leur modèle stylisé, la corrélation contemporaine entre le flux d'ordres et l'évolution des rendements est plus élevée lorsque les points de vue des acteurs du marché sont très variés et que les signaux publics sont entachés de bruit.

1 Introduction

Identifying the causes of daily asset price movements remains a puzzling issue in finance. In a frictionless market, asset prices should immediately adjust to public news surprises. Hence, we should observe price jumps only during announcement times. However, asset prices fluctuate significantly during non-announcement days as well. This fact has motivated the introduction of various market frictions to better explain the behavior of asset prices. One possible friction is asymmetric information.¹ When sophisticated agents trade, their private information is (partially) revealed to the market, via order flow, causing revisions in asset 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 price changes: aggregation of public news and aggregation of order flow. In particular, we assess the relevance of each mechanism conditional on the dispersion of beliefs among traders and the public signals' noise.

To guide our analysis, we develop a parsimonious model of speculative trading in the spirit of Kyle (1985). The model builds upon two realistic market frictions: information heterogeneity and imperfect competition among informed traders (henceforth, speculators). In this setting, more diverse information among speculators leads to lower equilibrium market liquidity, since their trading activity is more cautious than if they were homogeneously informed, thus making the market-makers more vulnerable to adverse selection. We then introduce a public signal and derive equilibrium prices and trading strategies on announcement and non-announcement days. The contribution of the model is twofold. To our knowledge, it provides a novel theoretical analysis of the relationship between the trading activity of heterogeneously informed, imperfectly competitive speculators, the availability and quality of public information, and market liquidity. Furthermore, its analytically tractable closed-form solution, in terms of elementary functions, generates several explicit and empirically testable implications on the nature of that relationship.²

¹According to Goodhart and O'Hara (1997, p. 102), "one puzzle in the study of asset markets, either nationally or internationally, is that so little of the movements in such markets can be ascribed to identified public 'news'. In domestic (equity) markets this finding is often attributed to private information being revealed." This friction has been recently studied by Brandt and Kavajecz (2004) and Green (2004) in the U.S. Treasury bond market, by Andersen and Bollerslev (1998) and Evans and Lyons (2002, 2003, 2004) in the foreign exchange market, by Berry and Howe (1994) in the U.S. stock market, and by Brenner, Pasquariello, and Subrahmanyam (2005) in the U.S. corporate bond market, among others.

²Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) extend Kyle (1985) to analyze the impact of competition among heterogeneously informed traders on market liquidity and price volatility in discrete-time and continuous-time models of intraday trading, respectively. Foster and Viswanathan (1993) show that, when

In particular, we show that the availability of a public signal improves market liquidity (the more so the lower that signal’s volatility) since its presence reduces the adverse selection risk for the market-makers and mitigates the quasi-monopolistic behavior of the speculators.

This model is not asset-specific, i.e., it applies to stock, bond, and foreign exchange markets. In this study, we test its implications for the U.S. government bond market for three reasons. First, Treasury market data contains signed trades; thus, we do not need to rely on algorithms (e.g., Lee and Ready, 1991) which add measurement error to our estimates of order flow. Second, government bond markets represent the simplest trading environment to analyze 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 bond yields (e.g., Fleming and Remolona (1997) and Balduzzi, Elton, and Green (2001), among others). In contrast, the link between macroeconomic fundamentals and the stock market is less clear (e.g., Andersen, Bollerslev, Diebold, and Vega, 2004; Boyd, Hu, and Jagannathan, 2005). Third, the market for Treasury securities is interesting in itself since it is among the largest, most liquid U.S. financial markets.

Our empirical results strongly support the main implications of our model. During non-announcement days, adverse selection costs of unanticipated order flow are higher when the dispersion of beliefs — measured by the standard deviation of professional forecasts of macroeconomic news releases — is high. For instance, we estimate that a one standard deviation shock to abnormal order flow decreases two-year, five-year, and ten-year bond yields by 7.19, 10.04, and 6.84 basis points, respectively, on high dispersion days compared to 4.08, 4.07, and 2.86 basis points on low dispersion days. These differences are economically and statistically significant. Consistently, these higher adverse selection costs translate into higher contemporaneous correlation between order flow changes and bond yield changes. For example, the adjusted R^2 of regressing daily five-year Treasury bond yield changes on unanticipated order flow is 41.38% on high dispersion days compared to 9.65% on low dispersion days. Intuitively, when information heterogeneity is high, the speculators’ quasi-monopolistic trading behavior leads to a “cautious” equilibrium where changes in unanticipated order flow have a greater impact on bond yields.

the beliefs of perfectly informed traders are represented by elliptically contoured distributions, price volatility and trading volume depend on the surprise component of public information. Yet, neither model’s equilibrium is in closed-form, except the (analytically intractable) inverse incomplete gamma function in Back et al. (2000). Hence, their implications are sensitive to the chosen calibration parameters. Further, neither model, by its dynamic nature, generates unambiguous comparative statics for the impact of information heterogeneity or the availability of public information on market liquidity. Finally, neither model can be easily generalized to allow for both a public signal of the traded asset’s payoff and less than perfectly correlated private information.

The release of a public signal, a trade-free source of information about fundamentals, induces the speculators to trade more aggressively on their private information. Accordingly, we find that the correlation between unanticipated order flow and day-to-day bond yield changes is lower during announcement days. For example, comparing non-announcement days with Nonfarm Payroll Employment release dates, the explanatory power of order flow decreases from 15.31% to 6.47%, 21.03% to 19.61%, and 6.74% to 3.59% for the two-year, five-year, and ten-year bonds, respectively. Yet, when both the dispersion of beliefs and the noise of the public signal — measured as the absolute difference between the actual announcement and its last revision — are high, the importance of order flow in setting bond prices increases. All of the above results are robust to alternative measures of the dispersion of beliefs among market participants, as well as to different regression specifications and the inclusion of different control variables. Lastly, our evidence cannot be attributed to transient inventory or portfolio rebalancing considerations, since the unanticipated government bond order flow has a permanent impact on yield changes during both announcement and non-announcement days in the sample.

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 accounts 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 U.S. 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 investors and the quality of macroeconomic data releases. In particular, we document important effects of both dispersion of beliefs and public signal noise on the correlation between daily bond yield changes and order flow during announcement and non-announcement days. This evidence complements the weak effects reported by Green (2004) over thirty-minute intervals around news releases. Since the econometrician does not observe the precise arrival time of private information signals, narrowing the estimation window may lead to underestimating the effect of dispersion of beliefs on market liquidity.³

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

³For instance, heterogeneously informed investors may not trade immediately after public news are released but instead wait to preserve (and exploit) their informational advantage as long (and as much) as possible, as in Foster and Viswanathan (1996).

informed trading (PIN), a function of order flow, is a priced firm characteristic in stock returns. These studies enhance our understanding of the determinants of asset price movements, but do not provide any evidence on the determinants of order flow. Evans and Lyons (2004) address this issue by showing that foreign exchange order flow predicts future macroeconomic surprises, i.e., it conveys information about fundamentals. We go a step further in linking the impact of order flow on bond prices to macroeconomic uncertainty (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 to guide our empirical analysis. In Section 3, we describe the data. In Section 4, we present the empirical results. We conclude in Section 5.

2 Theoretical Model

In this section we motivate our investigation of the impact of the dispersion of beliefs among sophisticated market participants and the release of macroeconomic news on the informational role of trading. We first describe a one-shot version of the multi-period model of trading of Foster and Viswanathan (1996) and derive closed-form solutions for the equilibrium market depth and trading volume. Then, we enrich the model by introducing a public signal and consider its implications for 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 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 (which we label speculators), 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 speculator k receives a private and noisy signal of $v - p_0$, S_{vk} . We assume 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 $var(S_{vk}) = \sigma_s^2$ and $cov(S_{vk}, S_{vj}) = \sigma_{ss}$. We also impose that the speculators together know the liquidation value

of the risky asset: $\sum_{k=1}^M S_{vk} = v - p_0$; therefore, $cov(v, S_{vk}) = \frac{1}{M}\sigma_v^2$. This specification makes the total amount of information available to the speculators independent from the correlation of their private signals, albeit still implying the most general information structure up to rescaling by a constant (see Foster and Viswanathan, 1996).

These assumptions imply that $E(v - p_0 | S_{vk}) = \delta_k = \psi S_{vk}$, where $\psi = \frac{\sigma_v^2}{M\sigma_s^2}$, and that $E(\delta_j | \delta_k) = \gamma \delta_k$, where $\gamma = \frac{\sigma_{ss}}{\sigma_s^2}$ is the correlation between any two information endowments δ_k and δ_j . As in Foster and Viswanathan (1996), we parametrize the degree of diversity among speculators' signals by requiring that $\sigma_s^2 - \sigma_{ss} = \chi \geq 0$. This restriction ensures that Σ_s is positive definite. If $\chi = 0$, then speculators' private information is *homogeneous*: All speculators receive the same signal $S_{vk} = \frac{v-p_0}{M}$ such that $\sigma_s^2 = \sigma_{ss} = \frac{\sigma_v^2}{M^2}$ and $\gamma = 1$. If $\chi = \frac{\sigma_v^2}{M}$, then speculators' information is *heterogeneous*: $\sigma_s^2 = \chi$, $\sigma_{ss} = 0$, and $\gamma = 0$. Otherwise, speculators' signals are only partially correlated: Indeed, $\gamma \in (0, 1)$ if $\chi \in \left(0, \frac{\sigma_v^2}{M}\right)$ and $\gamma \in \left(-\frac{1}{M-1}, 0\right)$ if $\chi > \frac{\sigma_v^2}{M}$.⁴

At time $t = 1$, both speculators 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} speculator to be x_k . Thus, her 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 $x_1(\cdot), \dots, x_M(\cdot)$, 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 speculators' demands. We then solve for their parameters satisfying conditions 1 and 2. Finally, we show that these parameters and those functions represent a rational expectations equilibrium. The following proposition accomplishes this task.

⁴The assumption that the total amount of information available to speculators is fixed ($\sum_{k=1}^M S_{vk} = v - p_0$) implies that $\sigma_s^2 = \frac{\sigma_v^2 + M(M-1)\chi}{M^2}$ and $\sigma_{ss} = \frac{\sigma_v^2 - M\chi}{M^2}$, hence $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$. Further, the absolute bound to the largest negative private signal correlation γ compatible with a positive definite Σ_s , $\left|-\frac{1}{M-1}\right|$, is a decreasing function of M .

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} speculator's demand strategy

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

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

The optimal trading strategy of each speculator depends on the information she receives about the asset payoff (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 speculators, 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 MMs' attempt to be compensated for the losses they anticipate from trading with speculators, as it affects their profits from liquidity trading.

2.1.2 Testable Implications

The intuition behind the parsimonious equilibrium of Eqs. (1) and (2) is similar to that in the multi-period models of Foster and Viswanathan (1996) and Back et al. (2000). Yet, its closed-form solution (in Proposition 1) translates that intuition into unambiguous predictions on the impact of information heterogeneity on market depth.⁵ The optimal market orders x_k depend on the number of speculators (M) and the correlation among their information endowments (γ). The intensity of competition among speculators affects their ability to maintain the informativeness of the order flow as low as possible. A greater number of speculators trade more aggressively — i.e., their aggregate amount of trading is higher — since (imperfect) competition among them precludes any collusive trading strategy. For instance, when $M > 1$ speculators are homogeneously informed ($\gamma = 1$), then $x_k = \frac{\sigma_u}{\sigma_v \sqrt{M}} (v - p_0)$, which implies that $\frac{\partial M x_k}{\partial M} = \frac{\sigma_u}{\sigma_v 2\sqrt{M}} (v - p_0) > 0$. This behavior reduces the adverse selection problem for the MMs, thus leading to greater market liquidity (lower λ).

The heterogeneity of speculators' signals attenuates their trading aggressiveness. When information is less correlated (γ closer to zero), each speculator has some monopoly power on her signal, because at least part of it is known exclusively to her. Hence, as a group, they trade

⁵This contrasts with the numerical examples of the dynamics of market depth reported in Foster and Viswanathan (1996, Figure 1C) and Back et al. (2000, Figure 3A).

more cautiously — i.e., their aggregate amount of trading is lower — to reveal less of their own information endowments δ_k . For example, when $M > 1$ speculators are heterogeneously informed ($\gamma = 0$), then $x_k = \frac{\sigma_u}{\sigma_v} S_{vk}$, which implies that $\sum_{k=1}^M x_k = \frac{\sigma_u}{\sigma_v} (v - p_0) < \frac{\sigma_u M}{\sigma_v \sqrt{M}} (v - p_0)$, i.e., lower than the aggregate amount of trading by $M > 1$ homogeneously informed speculators ($\gamma = 1$) but identical to the trade of a monopolistic speculator ($M = 1$). This “quasi-monopolistic” behavior makes the MMs more vulnerable to adverse selection, thus 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 speculators 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 . By construction, both the private signals’ variance (σ_s^2) and covariance (σ_{ss}) change with χ and M , yet the total amount of information available to the speculators is unchanged. We plot the resulting λ in Figure 1. Multiple, perfectly heterogeneously informed speculators ($\gamma = 0$) collectively trade as cautiously as a monopolist speculator. 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 speculators improves market depth, but significantly so only if accompanied by more correlated private signals. However, ceteris paribus, the improvement in market liquidity is more pronounced (and informed trading less cautious) when speculators’ private signals are negatively correlated. When $\gamma < 0$, each speculator expects her competitors’ trades to be negatively correlated to her own (pushing p_1 against her signal), hence trading on it to be more profitable.

2.2 Extension: A Public Signal

We now extend the basic model of Section 2.1 by providing each player with an additional, common source of information about the risky asset before trading takes place. 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.”⁶ More specifically, we assume that,

⁶Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) consider dynamic models of intraday trading 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. McKelvey and Page (1990) provide experimental evidence that individuals make inferences from publicly available information using Bayesian updating. Diamond

sometime between $t = 0$ and $t = 1$, both the speculators and the MMs also observe a public and noisy signal S_p of the asset payoff v . This signal 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 $\text{cov}(S_p, v) = \sigma_v^2$, so that the parameter σ_p^2 controls for the quality of the public signal and $\text{cov}(S_p, S_{vk}) = \frac{\sigma_v^2}{M}$. The information endowment of each speculator is then given by $\delta_k = E(v - p_0 | S_{vk}, S_p) = \alpha S_{vk} + \beta (S_p - p_0)$, where $\alpha = \frac{M\sigma_v^2(\sigma_p^2 - \sigma_v^2)}{\sigma_p^2[\sigma_v^2 + M(M-1)\chi] - \sigma_v^4} > 0$ 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, $E(\delta_j | \delta_k) = \gamma_p \delta_k$, 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 speculators' 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*

$$p_1 = p_0 + \lambda_p \omega_1 + \lambda_s (M + 1) (S_p - p_0) \quad (3)$$

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

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

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

The optimal trading strategy of each speculator 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 S_p . The former, of the same sign as $S_p - p_0$, is driven by the speculator's belief update about v stemming from S_p . The latter, possibly of the opposite sign as $S_p - p_0$, is driven by the MMs' belief update about v stemming from S_p , which makes speculators' private information less valuable. The resulting equilibrium price p_1 in Eq. (3) can be rewritten as

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

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 absence of better informed agents but in the presence of better information processors with homogeneous priors, the arrival of a public signal leads to greater information asymmetry and lower market liquidity.

According to Eq. (5), the public signal impacts 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 speculators' trading activity (α). 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

Foster and Viswanathan (1993) generalize the trading model of Kyle (1985) to distributions of the elliptically contoured class (ECC) and show that, in the presence of a discrete number of identically informed traders, the unexpected realization of a public signal has no impact on market liquidity regardless of the ECC used. This is the case for the equilibrium of Proposition 2 as well.⁷ Nonetheless, Proposition 2 allows us to study the impact of the availability of noisy public information on equilibrium market depth in the presence of imperfectly competitive and heterogeneously informed speculators. To our knowledge, this analysis is novel to the financial literature. We start with the following result.

Corollary 2 *The availability of 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 v . Second, speculators have to trade more aggressively to extract rents from their private information. In Figure 2a we plot the ensuing gain in liquidity, $\lambda - \lambda_p$, as a function of private signal correlations γ when the public signal's noise $\sigma_p = 1.25$, i.e., by varying χ and M (so σ_s^2 and σ_{ss} as well, but not the total amount of information available to the speculators) as in Figure 1. The increase in market depth is greater when γ is negative and the number of speculators (M) is high. In those circumstances, the availability of a public signal reinforces speculators' existing incentives to place market orders on their private signals S_{vk} more aggressively. However, greater σ_p^2 , ceteris paribus, increases λ_p , since the poorer quality of S_p (lower information-to-noise ratio $\frac{\sigma_v^2}{\sigma_p^2}$) induces the MMs to rely more heavily on ω_1 to set market-clearing prices, hence the speculators to trade less aggressively.

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

⁷Specifically, it can be shown that the one-shot equilibrium in Foster and Viswanathan (1993, Proposition 1) is a special case of our Proposition 2 when private signal correlations $\gamma = 1$ for any ECC.

In the presence of a public signal, information heterogeneity among speculators plays a more ambiguous role on market liquidity. If the volatility of the public signal is low, heterogeneously informed (thus more cautious) speculators put less weight on their private signals S_{vk} (lower α in δ_k) and more weight on the public signal S_p (higher β in δ_k) when updating their beliefs than homogeneously informed (thus more aggressive) speculators. Hence, the ensuing trading behavior leads to *less* adverse selection risk for the MMs (lower λ_p). Vice versa, when σ_p is high, speculators rely more heavily on their private signals, but more cautiously so if gamma is low, leading to lower equilibrium market depth (higher λ_p), as in Corollary 1.

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

The volatility of the public signal S_p also affects its direct impact (λ_s) on the equilibrium price of Eq. (3). Everything else equal, the poorer is the quality of the public signal (higher σ_p), the more the speculators rely on their private signals S_{vk} (see Remark 1) and the MMs rely on the aggregate order flow ω_1 to infer the asset payoff v . Consequently, the MMs put less weight on S_p and more weight on ω_1 in setting the market-clearing price p_1 , toward the benchmark of Eq. (1): $\lim_{\sigma_p \rightarrow \infty} \lambda_s = 0$ and $\lim_{\sigma_p \rightarrow \infty} \lambda_p = \lambda$.

Corollary 3 *The absolute sensitivity of the equilibrium price to the public signal is decreasing in that signal’s volatility.*

In Figure 2b, we plot λ_s , the impact of the public signal on p_1 , as a function of γ , the correlation of speculators’ private signals. That impact is generally decreasing in the absolute value of γ since then, ceteris paribus, speculators are collectively more aggressive and the market’s liquidity is greater (lower λ_p).⁸

3 Data Description

We test the implications of the model presented in the previous section using U.S. Treasury bond market data and U.S. macroeconomic announcements. As mentioned in Section 1, this

⁸Yet, Figure 2b also suggests that if $|\gamma|$ is “high,” so is λ_s . Intuitively (and consistent with Remark 2), more homogeneously informed (thus more aggressive) speculators also rely less heavily on the public signal S_p and more heavily on their private signals S_{vk} in their trading activity (lower β and higher α , respectively, in δ_k). When $|\gamma|$ is large enough, this effect is sufficient to lead to greater (and not lower) perceived adverse selection risk for the MMs, hence to lower reliance on the aggregate order flow ω_1 (lower market’s liquidity) and greater reliance on their trade-free source of information S_p (higher λ_s) in setting the equilibrium price p_1 .

choice is motivated not only by the quality and availability of data on U.S. government bond transactions, 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 bond 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 these “on-the-run” notes because, according to Fleming (1997), Brandt and Kavajecz (2004), and Goldreich, Hanke, and Nath (2005), those are the securities with the greatest liquidity and where the majority of informed trading takes place. We are interested in studying the informational role of bond trading related to macroeconomic fundamentals. Therefore, we focus on the intermediate to long maturities, since these are the most responsive to macroeconomic aggregates (e.g., Balduzzi et al., 2001). Consistently, when we perform the analysis that follows on the remaining “on-the-run” and “off-the-run” Treasury securities in our database, we find that (i) the resulting inference for the former is weaker than the one described in the paper, and (ii) order flow has no impact on yield changes for the latter. These results are available upon request from the authors.

We obtain the data from GovPX, a firm that collects quote and trade information from six of the seven main interdealer brokers (with the notable exception of Cantor Fitzgerald).⁹ Fleming (1997) argues that these six brokers account for approximately two-thirds of the interdealer-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 during “regular trading hours,” from 7:30 a.m. to 5:00 p.m. Eastern Standard Time (EST), between January 2, 1992 and December 29, 2000. GovPX stopped recording intraday volume afterward. 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.

⁹In our sample period, 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. Cantor Fitzgerald’s share of the interdealer Treasury market is about 30% over our sample period (Goldreich et al., 2005). Nevertheless, Cantor Fitzgerald is a dominant player only in the “long end” of the Treasury yield curve, which we do not study in depth in this paper.

We report summary statistics for the daily raw yield and transaction data in Table 1. Bond yields are in percentage, i.e., were multiplied by 100; bond yield changes are in basis points, i.e., were multiplied by 10,000. Not surprisingly, mean Treasury bond yields are increasing with maturity and display large positive first-order autocorrelation ($\rho(1) > 0$). Mean daily yield changes are small or zero; yet, their sample variability suggests that economically important fluctuations of the yield curve took place over the sample period. Five-year Treasury notes are characterized by the largest mean daily number of transactions (roughly 614), hence by the highest liquidity, consistent with the findings of Fleming (2003), among others.

In Figure 3, we compare daily bond yield changes during days when one of the most closely observed U.S. macroeconomic announcement, the Nonfarm Payroll Employment report, is released to daily bond yield changes during non-announcement days.¹⁰ 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 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 when no public news arrive to the bond market.¹¹

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 2 provides a brief description of the most salient characteristics of U.S. economic news announcements in our sample: the total number of observations, the agency reporting each announcement, the time of the announcement release, and whether the standard deviation across professional forecasts is available.

We define announcement surprises as the difference between announcement realizations and

¹⁰Andersen 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.

¹¹Most of the “non-event” term structure literature ignores macroeconomic variables 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). More recent studies explicitly incorporate macroeconomic fundamentals into these multi-factor yield curve models (e.g., Hördahl, Tristani, and Vestin, 2002; Wu, 2002; Ang, Piazzesi, and Wei, 2003; Diebold, Rudebusch, and Aruoba, 2004). However, these studies focus on monthly data and show that macro factors can explain only up to 30% of the variation in bond yields (Ang et al., 2003). For a survey of this literature, see Diebold, Piazzesi, and Rudebusch (2005).

their corresponding expectations.¹² 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 j at time t is therefore computed as

$$S_{jt} = \frac{A_{jt} - E_{jt}}{\hat{\sigma}_j}, \quad (6)$$

where A_{jt} is the announced value of indicator j , E_{jt} is its MMS median forecast, as a proxy for its market expected value, and $\hat{\sigma}_j$ is the sample standard deviation of $A_{jt} - E_{jt}$. Eq. (6) facilitates meaningful comparisons of responses of different bond yield changes to different pieces of news. Operationally, we estimate those responses by regressing bond yield changes on news. However, since $\hat{\sigma}_j$ is constant for any indicator j , the standardization affects 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 sophisticated 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, Malloy, and Scherbina, 2002; Kallberg and Pasquariello, 2004); Green (2004) recently uses it in a bond market context. As indicated in Table 2, this variable is only available for 18 of the 25 macroeconomic news in our sample. These announcements are listed in Table 3a.

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 (in Table 3a) the pairwise correlation between each announcement and arguably the most important of them, the Nonfarm Payroll report (e.g., Andersen and Bollerslev, 1998; Andersen et al., 2004; Brenner et al., 2005). This correlation 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. This motivates us to construct three alternative measures of dispersion of beliefs during announcement and non-announcement days:

¹²It is reasonable to assume that, at each point in time, the professional forecasters surveyed by MMS use all information available to them (including other, most recent macroeconomic announcements) to formulate their expectations. Consistently, Balduzzi et al. (2001) show that MMS forecasts are not stale. Therefore, each announcement surprise can be interpreted with respect to all previously available information, regardless of its timing. For a further discussion of the properties of MMS expectations, see Fleming and Remolona (1997) and Andersen, Bollerslev, Diebold, and Vega (2003).

one based exclusively on the Payroll announcement, another based on 7 “influential” announcements (defined below), and the last one based on the 18 announcements in Table 3a.

The use of the MMS database to calculate monthly measures of dispersion of beliefs raises two issues: (i) the announcements in Table 3a are released at different frequencies and (ii) the standard deviation of professional forecasts only measures heterogeneous beliefs at the time of the announcement. We address these issues by assuming that the dispersion of beliefs remains constant between announcements. This assumption is empirically justified since the first order autocorrelation in the standard deviation of professional forecasts ($\rho(1)$ in Table 3a) is positive and mostly statistically significant. 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 single weekly announcement in the sample, Initial Unemployment Claims, we average the dispersion of beliefs across four weeks. For the three quarterly announcements in the sample, GDP Advance, Preliminary, and Final, we assume that the dispersion of beliefs in the first month of the quarter is constant throughout the quarter. The dispersion of beliefs of monthly announcements is instead left unchanged and assumed to be constant between announcements.

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

$$SD_{Pt} = \sum_{j=1}^P \frac{SD_{jt} - \hat{\mu}(SD_{jt})}{\hat{\sigma}(SD_{jt})}, \quad (7)$$

where SD_{jt} is the standard deviation of announcement j across professional forecasts and $\hat{\mu}(SD_{jt})$ and $\hat{\sigma}(SD_{jt})$ are its sample mean and standard deviation, respectively. P is equal to 1 when we only use the Nonfarm Payroll Employment to compute our measure of dispersion of beliefs. P is equal to 7 when we use the following “influential” macroeconomic announcements: Nonfarm Payroll Employment, Retail Sales, New Home Sales, Consumer Confidence Index, NAPM Index, Index of Leading Indicators, and Initial Unemployment Claims.¹³ Lastly, P is equal to 18 when we use all the announcements for which the measure SD_{Pt} is available in our sample (i.e., those in Table 3a). 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.

¹³In Section 4.2.2, we show that these announcements represent the most important information events in the U.S. Treasury Market, i.e., the only ones having a statistically significant impact on day-to-day bond yield changes, consistent with Fleming and Remolona (1997), among others.

We use the monthly dispersion estimates from these three methodologies to classify days in which the corresponding monthly variable SD_{Pt} is above (below) the top (bottom) 70th (30th) 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 are 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, $P = 7$).

Finally, we report in Table 3b 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 the three alternative methods described above. The corresponding t statistics are computed using Newey-West standard errors, because Table 1 shows that the number of daily transactions is positively autocorrelated. Consistent with Griffith, Smith, Turnbull, and White (2000) and Rinaldo (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: fewer transactions take place in high dispersion days than in 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. (7), since it suggests that, in the government bond market, periods of greater dispersion of beliefs among market participants are accompanied by more cautious speculative trading activity, as argued in Section 2.1.1.

3.2.3 News or Noise?

The U.S. government often revises previously released macroeconomic information. Aruoba (2004) identifies these data revisions as either “informative,” i.e., due to newly available information, or “uninformative,” i.e., due to definitional changes (such as changes in the base-year or changes in seasonal weights). In this paper, we use the former revisions to measure public signal noise. Specifically, we use the Federal Reserve Bank of Philadelphia “Real Time Data Set” (RTDS), which records not only real-time macroeconomic announcements but also their subsequent revisions.¹⁴ Of the 18 announcements in Table 3a for which MMS forecasts are available, the RTDS contains monthly data on Capacity Utilization, Industrial Production, and Nonfarm Payroll Employment report. The only variable undergoing “uninformative” changes over the

¹⁴See Croushore and Stark (1999, 2001) for details of this database and examples of empirical applications. The database is publicly available on the internet at <http://www.phil.frb.org/econ/forecast/reaindex.html>.

sample period is Industrial Production, whose base-year was revised in February 1998. According to extant literature (e.g., Mork, 1987; Faust, Rogers, and Wright, 2003; Aruoba, 2004), (i) the final published revision of each actual announcement represents the most accurate measure for the corresponding macroeconomic variable, and (ii) those revisions should be interpreted as noise, for they are predictable (based on past information).¹⁵ Hence, we measure public news noise as the difference between each initial announcement and its last revision. Since what matters in our model is the magnitude of the noise (σ_p^2 of Section 2.2), not its direction, 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 final revision for Capacity Utilization, Industrial Production, and Nonfarm Payroll Employment. Consistent with Aruoba (2004), macroeconomic data revisions display a few spikes and are often negative, revealing a tendency for the government to be overly conservative in its initial announcements. Interestingly, 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 the quality of the public signal. In the ensuing empirical analysis, we consider both possibilities.

4 Empirical Analysis

The model of Section 2 generates several implications that we now test in this section. In the database described in Section 3, we are able to directly observe price changes, $P_t - P_{t-1}$, as a proxy for $p_1 - p_0$, public news surprises S_{jt} , as a proxy for $S_p - p_0$, and aggregate order flow Ω_t , as a proxy for ω_1 . Yet, in our setting, it is only the unexpected portion of aggregate order flow that affects the equilibrium prices of Eqs. (1) and (3).¹⁶ Furthermore, ω_1 is assumed to depend only on informed and liquidity trading. Yet, in reality, many additional microstructure imperfections can cause lagged effects in the observed order flow (see Hasbrouck, 2004). Therefore, to implement

¹⁵Much of this evidence stems from the analysis of either GDP or the RTDS variables listed above. The evidence is more controversial for money stock announcements. For instance, Mankiw, Runkle, and Shapiro (1984) and Mork (1990) find that the preliminary growth rates of several Federal Reserve's money aggregates are not efficient predictors of the growth rates of finally-revised data. Yet, according to Kavajecz and Collins (1995), the bias in preliminary monetary data may be attributed either to the specific seasonal adjustment procedure used by the Federal Reserve or to a different temporal aggregation than for finally-revised, not-seasonally adjusted data. Monetary aggregates are not included in our database.

¹⁶Indeed, the distributional assumptions in Section 2.1 imply that $E(\omega_1) = 0$ in both Propositions 1 and 2.

our model, we estimate Ω_t^* , the unanticipated portion of aggregate order flow.

For that purpose, we use the linear autoregressive model of Hasbrouck (1991),

$$x_{t_{in}} = a_x + b(L)r_{t_{in}} + c(L)x_{t_{in}} + v(x)_{t_{in}}, \quad (8)$$

where $x_{t_{in}}$ is the half-hour net order flow in the market (purchases take a +1 and sales take a -1) for interval t_{in} , $r_{t_{in}}$ is the half-hour quote revision, and $b(L)$ and $c(L)$ are polynomials in the lag operator. We estimate Eq. (8) separately for two-year, five-year, and ten-year Treasury notes using 19 lags (one day) because they are sufficient to eliminate all the serial correlation in the data. The results that follow are robust to different lag-length polynomials.¹⁷ As previously mentioned, we focus on daily horizons, for narrower intervals (e.g., as in Green, 2004) may lead to underestimate the impact of information heterogeneity on investors' trading activity. Therefore, we compute aggregate unanticipated (or "abnormal") net order flow over each day t by simply summing the 19 residuals of Eq. (8) within each day, $\Omega_t^* = \sum_{t_{in}=1}^{19} v(x)_{t-1+\frac{t_{in}}{19}}$, as a proxy for ω_t . As shown in Table 1, this procedure successfully eliminates the first-order autocorrelation in the aggregate raw order flow series Ω_t .

GovPX calculates bond yields using transaction prices, so there is a mechanical inverse relation between the two quantities. To be consistent with the term-structure literature, we estimate the impact of unanticipated order flow and public information arrivals on daily yield changes ($r_t = (y_t - y_{t-1}) \times 100$) rather than on price changes. Nonetheless, our results are robust to either specification. We translate the equilibrium prices of Propositions 1 and 2 into the following estimable equations:

$$r_t = a + \lambda\Omega_t^* + \varepsilon_t \quad (9)$$

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

$$r_t = a_p + \lambda_p\Omega_t^* + \lambda_{sj}S_{jt} + \varepsilon_{pt} \quad (10)$$

when a public signal S_{jt} 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_{sj} to be positive for positive real activity and inflationary shocks.

¹⁷Our results are also robust to different specifications of Eq. (8). For example, we sample bond yields each time there is a transaction, rather than at thirty-minute intervals. We also sample bond yields at an "optimal" frequency determined according to the procedure of Bandi and Russell (2005). The evidence presented below is qualitatively and quantitatively similar to that obtained using these alternative sampling procedures, as well as using the aggregate raw (rather than unanticipated) order flow, Ω_t . The robustness of our results reflects the fact that aggregate unanticipated order flow, Ω_t^* , is very closely related to Ω_t . Indeed, regardless of the selected specification, the resulting R^2 from Eq. (8) are lower than 4%.

Even in the absence of the information effects of our model, inventory considerations (first formalized by Garman, 1976) may explain, either in full or in part, any significant correlation between price changes and order flow. Yield changes may in fact react to net order flow imbalances, to compensate market participants for providing liquidity, even when the order flow has no information content. To assess the relevance of this alternative hypothesis, we follow Hasbrouck (1991) and include lagged values of unanticipated order flow and yield changes in both Eqs. (9) and (10). As in Hasbrouck (1991), we assume the permanent impact of trades is due to information shocks and the transitory impact is due to noninformation (e.g., liquidity) shocks. Hence, negative and significant estimates for λ and λ_p are driven by transitory inventory control effects when accompanied by a positive and significant impact of lagged unanticipated net order flow on yield changes. In other words, significant contemporaneous order flow effects are *transient* if they are later reversed. On the other hand, negative and significant estimates for λ and λ_p are driven by permanent information effects (consistent with our model) when accompanied by negative and significant, or statistically insignificant, impact of lagged unanticipated net order flow on yield changes.

4.1 Non-Announcement Days

We start by estimating Eq. (9) across non-announcement days and then testing the main implication of Proposition 1, namely that market liquidity (λ^{-1}) is decreasing in the heterogeneity of speculators' information endowments. First, we define non-announcement days consistently with our procedures to measure such heterogeneity (in Section 3.2.2). When $P = 1$, we define non-announcement days as all trading Fridays in the sample in which no Nonfarm Payroll Employment report is released, to control for potential day-of-the-week effects. When $P = 7$ or 18, we define non-announcement days as all trading days when none of the corresponding announcements (either the influential ones or those listed in Table 3a) take place. We then test Corollary 1 by amending Eq. (9) as follows:

$$r_t = a + \sum_{i=0}^N \lambda_{hi} \Omega_{t-i}^* D_{ht} + \sum_{i=0}^N \lambda_{li} \Omega_{t-i}^* D_{lt} + \sum_{i=0}^N \lambda_{mi} \Omega_{t-i}^* (1 - D_{ht} - D_{lt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t, \quad (11)$$

where D_{ht} (D_{lt}) is a dummy variable equal to one on non-announcement days with high (low) heterogeneity of beliefs, as defined in Section 3.2.2, and equal to zero otherwise. Motivated by the discussion above, we estimate both the contemporaneous and lagged effects of unanticipated order flow on yield changes. Specifically, we define the impact of order flow on yield changes as permanent (i.e., driven by information effects) when lasting for at least five trading days. Hence,

we set $N = 5$ in Eq. (11).¹⁸ We report the resulting estimates in Table 4 using the three proxies for information heterogeneity, $P = 1$, $P = 7$, and $P = 18$. Since higher dispersion days are also associated with more volatile bond yields, the standard errors are adjusted for heteroskedasticity. We also correct for serial correlation, given the mild, though statistically significant, first-order autocorrelation in daily bond yield changes.

The results in Table 4 provide strong evidence for information effects of order flow on bond yield changes and no evidence for inventory control effects. For all maturities and nearly all measures of dispersion of beliefs, the estimated contemporaneous correlation between unanticipated order flow and yield changes (λ_0) is negative and significant. The coefficients for one-period lagged unanticipated order flow (λ_1), not reported here, are instead often negative, always statistically insignificant at the 5% level, and about ten times smaller in magnitude than the contemporaneous coefficients λ_0 . Lastly, the resulting cumulated impact of unanticipated order flow on yield changes ($\sum_{i=0}^5 \lambda_i$ in Table 4) is mostly statistically significant, albeit more weakly so on non-announcement days with low heterogeneity of beliefs. In other words, we find no evidence that the impact of unanticipated U.S. Treasury bond order flow on yield changes is reversed in the next five trading days, except in correspondence with low dispersion of beliefs about Nonfarm Payroll announcements ($P = 1$). Consistently, the plots of cumulative impulse-response functions in Figure 6 — computed as average cumulative yield changes stemming from a one standard deviation shock to unanticipated order flow (as in Hasbrouck, 2003) — reveal that the simultaneous impact of unanticipated order flow on yield changes is always persistent, unless when estimated during low dispersion days.

The results in Table 4 also provide strong evidence in favor of Corollary 1, especially for the five-year bond, the most liquid U.S. Treasury note. Regardless of whether we use only 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 $\lambda_{h0} - \lambda_{l0} < 0$. 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 investors translates into greater adverse selection risk for the market-makers, hence into lower market liquidity ($|\lambda_{h0}| > |\lambda_{l0}|$).

The increase in adverse selection costs in correspondence with high dispersion of beliefs among market participants is not only statistically but also economically significant. For example, when classifying trading days according to SD_{1t} (i.e., only with respect to the volatility of Nonfarm Payroll forecasts), we find that a one standard deviation shock to unanticipated order flow in

¹⁸Nonetheless, the inference that follows is robust to smaller or bigger values for N .

five-year bonds decreases their yields by 10.03 basis points on high dispersion days ($D_{ht} = 1$) and just 4.06 basis points on low dispersion days ($D_{lt} = 1$), as compared to a daily yield change one standard deviation from its mean of roughly 6.4 basis points (in Table 1) over the entire sample. Consistently, the correlation between daily five-year bond yield changes and unanticipated daily net order flow (the adjusted R^2 of the above regression) is much greater during high dispersion days ($R_{ha}^2 = 41.38\%$) than during low dispersion days ($R_{la}^2 = 9.65\%$).

We also find evidence in favor of Corollary 1 in the two-year bond market, although only when we use the dispersion of analysts' forecasts about Nonfarm Payroll Employment ($P = 1$) and Influential announcements ($P = 7$) as proxies for information heterogeneity, and in the ten-year bond market when we use the Nonfarm Payroll announcement alone. 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. We explore this issue in greater depth in Section 4.2.

4.1.1 Omitted Variable Biases

In the model of Section 2, equilibrium market liquidity (λ^{-1} and λ_p^{-1}) is a function of several parameters beyond the one determining the intensity of information heterogeneity among speculators (χ). For example, in the benchmark equilibrium with no public signal (Proposition 1), λ also depends on the intensity of noise trading (σ_u^2), the number of informed traders (M), and the volatility of the intrinsic value of the asset (σ_v^2). The regression model of Eq. (11), whose estimates are reported in Table 4, does not explicitly control for any of these parameters. These omissions have the potential to bias our inference.

To begin with, in our model the parameters σ_u^2 , σ_v^2 , and M are unrelated to the dispersion of beliefs. If this were true, the estimation of Eq. (11) would in principle be unbiased. Nevertheless, omitted variable biases may arise from relaxing some of the model's most stringent assumptions. For example, if we allowed for endogenous entry of informed traders, the equilibrium number of market participants might be correlated with their dispersion of beliefs, since the latter would affect investors' potential profits from trading. In addition, misspecification biases may arise from the intertemporal dynamics of either speculators' participation, intensity of noise trading, or fundamental uncertainty. It is difficult to control for these variables. In this section, we do our best to gauge the robustness of the results presented above to their inclusion. The analysis that follows indicates that these results are indeed robust.

Specifically, we conduct several robustness checks. First, the inclusion of lagged unanticipated order flow in Eq. (11) allows us to assess the relevance of any transient, noninformation

effect (hence not just inventory control effects but also those due to noise trading, σ_u^2) on the relationship between trades and price changes (see Hasbrouck, 1991). As previously mentioned, the estimation of Eq. (11) in Table 4 indicates that the impact of unanticipated government bond order flow on yield changes is permanent, i.e., cannot be explained by transitory noise effects. Alternatively, we determine the importance of noise trading by computing order flow and yield changes over disjoint intervals of each day in our sample, as in Brandt and Kavajecz (2004), rather than concurrently. In particular, we aggregate unanticipated order flow in the morning (from 7:30 a.m. to 12:00 p.m.), labeled as time t , and average yields from 12:00 p.m. until the end of each trading day (5:00 p.m.), labeled as time $t + 1$. We then regress bond yield changes at time $t + 1$ on unanticipated order flow at time t . This procedure not only prevents non-synchronous measurement errors (as argued by Brandt and Kavajecz, 2004) but also allows us to identify the long run or permanent effect of order flow on prices. The resulting estimates of market liquidity, not reported here, are qualitatively similar to those from Eq. (11) presented in Table 4.

We also control for the number of informed traders (M) and the volatility of the intrinsic value of the asset (σ_v^2). We do so by including in Eq. (11) additional variables capturing the interaction between (i.e., the product of): (i) order flow and daily realized volatility,¹⁹ (ii) order flow and the number of transactions, and (iii) order flow and a weight linearly increasing as the announcement date approaches.²⁰ In our model, the degree of information heterogeneity affects both equilibrium price volatility and the aggressiveness of informed trading (proxied by the number of transactions, as in Section 3.2.2). Depending on the strength of these effects, the inclusion of those cross terms in Eq. (11) may reduce the statistical significance of the relation between market liquidity and dispersion of beliefs. Instead, we find no evidence that order flow interacts with either the number of transactions or the proximity to the announcement date. The product of order flow and daily realized volatility is statistically significant only in the five-year Treasury bond market.²¹ This is not surprising, since we expect informed investors to be more

¹⁹We estimate realized volatility applying the procedure of Andersen, Bollerslev, Diebold, and Labys (2003) to yield mid-quotes sampled at an “optimal” frequency determined according to Bandi and Russel (2005).

²⁰Presumably, the number of informed traders might increase as the public announcement date approaches. We do not include this product term when measuring dispersion of beliefs only with forecasts of Nonfarm Payroll announcements (i.e., SD_{1t}), since then we only use the Fridays before the announcement dates to control for potential day-of-the-week effects.

²¹The resulting adjusted R^2 from the introduction of this cross term in Eq. (8) for five-year bond yield differentials increases from 23.30%, 20.31%, and 19.40% (i.e., R_a^2 of Table 4) to 30.05%, 23.18%, and 23.22% when measuring the dispersion of beliefs with the standard deviation of professional forecasts of Nonfarm Payroll ($P = 1$), “influential” ($P = 7$), and all available macroeconomic news announcements ($P = 18$), respectively.

active in the most liquid trading venues (e.g., Chowdhry and Nanda, 1991), as so the five-year bond market is generally deemed (e.g., Fleming, 2003). It is therefore possible that our proxy for realized volatility is successfully capturing the time-varying participation of informed traders only in the market where such participation is probably most important. Nonetheless, neither the economic nor the statistical significance of the dispersion of beliefs dummies in Table 4 are affected by the inclusion of these interaction terms in Eq. (11).²²

Lastly, we control for variables outside our model that might spuriously affect our results. For example, Treasury auction dates might have a liquidity effect on the secondary bond market. Thus, if our proxies for dispersion of beliefs were spuriously correlated with auction dates, an additional omitted variable bias might arise. We account for this eventuality by including the interaction between order flow and dummies for these dates in Eq. (11).²³ The liquidity of U.S. Treasury bonds may also be affected by their repurchase agreement (repo) rates, i.e., by their *specialness*. According to Moulton (2004), the relative repo specialness of on-the-run Treasury securities (such as those in our database) generally increases in proximity of auction dates. Hence, the inclusion of auction dummies in Eq. (11) may control for spurious liquidity shocks induced by time-varying specialness as well. Similarly, we include day-of-the-week and annual effects to control for weekly seasonality and temporal trends in the order flow and/or the dispersion of beliefs. None of these effects are statistically significant.

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 speculators mitigates the adverse selection risk for the market-makers. In our empirical analysis, this translates into observing a negative difference (since we work with yields)

²²These considerations could also affect the correlation between yield changes and unanticipated order flow indirectly, via their impact on the bid-ask spread. Specifically, we control for this possibility by estimating Eq. (11) for the subset of days in our sample characterized by high bid-ask spreads (i.e., when the average spread in the corresponding U.S. Treasury market is greater than its daily median). The resulting estimates (available on request from the authors) are consistent in sign and magnitude with the inference described above: the contemporaneous correlation between order flow and yield changes is higher when the dispersion of beliefs among market participants is high, even after accounting for time-varying bid-ask spreads.

²³The history of auction dates we use in the analysis is available on the U.S. Treasury website, at <http://www.publicdebt.treas.gov/of/ofaicqry.htm>.

between λ (of Eq. (1)) and λ_p (of Eq. (3)) in the following regression:

$$r_t = a + \sum_{i=0}^N \lambda_i \Omega_{t-i}^* (1 - D_{Pt}) + \sum_{i=0}^N \lambda_{pi} \Omega_{t-i}^* D_{Pt} + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t, \quad (12)$$

where D_{Pt} is a dummy variable equal to one if either the Nonfarm Payroll Employment report ($P = 1$), any of the 7 influential announcements listed in Section 3.2.2 ($P = 7$), or any of the 18 announcements listed in Table 3a ($P = 18$) is released on day t and equal to zero otherwise. As in Eq. (11), we set $N = 5$ to assess the relevance of permanent (i.e., information) versus temporary (i.e., inventory control) effects of unanticipated order flow on yield changes. We estimate Eq. (12) for each announcement type $P = 1, 7, \text{ or } 18$ and either two-year, five-year, or ten-year bond yield changes, and report the resulting estimates in Table 5.

Consistent with Table 4, the evidence in Table 5 indicates that, even during announcement days, both the contemporaneous and cumulative impact of unanticipated order flow on yield changes (λ_{p0} and $\sum_{i=0}^5 \lambda_{pi}$, respectively) are negative and statistically significant (often at the 1% level).²⁴ Hence, the correlation between unanticipated order flow and yield changes during announcement days does not appear to be driven by inventory control effects. Table 5 also shows that, in most cases, the difference between λ_0 and λ_{p0} is not statistically significant (except for the five-year Treasury notes when $P = 1$ or 7). Our model suggests that this would be the case if the public news surprises in our sample ($S_p - p_0$ in Eq. (3)) were noisy, since $\lim_{\sigma_p \rightarrow \infty} \lambda_p = \lambda$. Yet, our model (Corollary 3) also implies that noisy public signals should have little or no impact on price changes (i.e., $\lim_{\sigma_p \rightarrow \infty} \lambda_s = 0$ as well). This interpretation, although intriguing, is not exhaustive since in Section 4.2.2 below we find that seven of the macroeconomic news releases in our sample (the “influential” ones) do have a statistically significant impact on day-to-day bond yield changes between 1992 and 2000 (i.e., at least some λ_s are statistically significant).

An alternative interpretation of the statistically indistinguishable estimates for λ and λ_p in Table 5 is that the release of public macroeconomic signals may increase investors’ information heterogeneity (as argued in Kim and Verrecchia, 1994, 1997), hence compensating the reduction in adverse selection costs due to the availability of trade-free sources of information (as in our model). This interpretation is consistent with the evidence reported by Green (2004), who finds that the estimated half-hour price impact of order flow in the Treasury bond market is actually higher during the thirty-minute interval immediately after an announcement than during the thirty-minute interval immediately before the announcement or on non-announcement days.

²⁴In addition, the coefficients for one-period lagged unanticipated order flow (λ_{p1}), not reported here, are either negative, statistically insignificant at the 1% level, or of significantly smaller magnitude than the corresponding estimates for λ_{p0} .

However, the analysis of both the estimated correlation between bond yield changes and unanticipated net order flow and the average cumulative impact of the latter on the former provides stronger support for Corollary 2. Indeed, the adjusted R^2 of Eq. (12) is always higher for non-announcement days than for announcement days (i.e., $R_f^2 > R_{fp}^2$ in Table 5), with the sole exception of five-year notes when $P = 7$. Furthermore, the estimated impulse-response functions plotted in Figure 7 reveal that the impact of one standard deviation shocks to unanticipated order flow in either the two-year or the ten-year Treasury notes on the corresponding yield changes is permanent during non-announcement days, but only transitory during Nonfarm Payroll announcement days (in conformity with the estimates for $\sum_{i=0}^5 \lambda_{pi}$ in Table 5). This suggests that dealers rely more heavily on unanticipated order flow to set bond prices during non-announcement days than on announcement days, consistent with our model and the findings in Brandt and Kavajecz (2004).

Overall, the evidence reported in Table 5 and Figure 7 indicates (albeit not as strongly as in Section 4.1) that the release of public signals either reduces or does not increase adverse selection costs and either improves or does not deteriorate market liquidity. Nonetheless, both the above discussion and the comparative statics of Figure 2a also indicate that any such liquidity gain may crucially depend on the quality of the public signal (σ_p^2) and on the degree of information heterogeneity among market participants (γ). We explore these issues next, starting with the latter.

4.2.1 Heterogeneous Information on Announcement Days

In this section, we analyze the effect of information heterogeneity on market liquidity during announcement days. For that purpose, we estimate the following representation of Eq. (10):

$$r_t = a + \sum_{j=1}^P \lambda_{sj} S_{jt} + \sum_{i=0}^N \lambda_{phi} \Omega_{t-i}^* D_{ht} + \sum_{i=0}^N \lambda_{pli} \Omega_{t-i}^* D_{lt} \quad (13)$$

$$+ \sum_{i=0}^N \lambda_{pmi} \Omega_{t-i}^* (1 - D_{ht} - D_{lt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where D_{ht} (D_{lt}) is the high (low) dispersion of beliefs dummy defined in Section 4.1, to account for multiple signals arriving on the same day, and $N = 5$. We report the resulting estimates in Table 6, and assess their significance after correcting the standard errors for heteroskedasticity and serial correlation.

According to our model (Remark 2), greater dispersion of beliefs among speculators reduces market liquidity during announcement days (i.e., $\lambda_{ph0} - \lambda_{pl0} < 0$ in Eq. (13)) only when the public signal is noisy, since the latter induces those heterogeneously informed speculators to use cautiously their private signals, thus increasing adverse selection risks for the market-makers.

Vice versa, if the quality of the public signal is high (σ_p^2 is low), more heterogeneously informed speculators display their caution by relying less on their private signals (and more on the public signal) in their trading activity, thus lowering the perceived adverse selections risk for the market-makers and improving market liquidity (i.e., $\lambda_{ph0} - \lambda_{pl0} > 0$ in Eq. (13)).

Table 6 reveals that the difference between λ_{ph0} and λ_{pl0} is always negative and, in most cases, both economically and statistically significant. For instance, when we measure dispersion of beliefs using the Nonfarm Payroll announcement, a one standard deviation shock to unanticipated order flow decreases ten-year bond yields by 9.62 basis points during high dispersion days, while it *increases* bond yields by 3.06 basis points during low dispersion days. This evidence suggests that the dispersion of beliefs among market participants has an important impact on Treasury bond market liquidity, in the direction predicted by our model, even in the presence of public signals of macroeconomic fundamentals. This evidence is also (indirectly) consistent with the conjecture made in Section 4.2 that public signal noise is “sufficiently” high in our sample. In Section 4.2.3 below, we gauge more explicitly the potential role of public signal noise on market liquidity.

We now turn to the impact of public signals on yield changes. According to the extended model of Section 2.2, a public signal can induce price (and yield) changes through two channels, which in the spirit of Evans and Lyons (2003) we call direct (through market-makers’ belief updating process) and indirect (through speculators’ trades in the order flow). Yet, in the model, the direct channel is always more important than the indirect one. The evidence presented in Table 6 confirms this latter result: The adjusted R^2 of the fully specified regressions of Eq. (13), i.e., including both the unanticipated order flow and the public signal(s), R_a^2 , is between 2 and 84 times bigger than the adjusted R^2 of the regressions estimated using only unanticipated order flow, R_{fa}^2 .

4.2.2 Disaggregated Results

Many of the results in Section 4.2.1 above are generally weaker in correspondence with the aggregate proxies for information heterogeneity described in Eq. (7). In particular, the relevance of public signals for bond yield changes (i.e., the difference between R_a^2 and R_{fa}^2 in Table 6) is declining in P , the number of announcements used in the analysis. This may be explained by a potentially mistaken classification of certain macroeconomic releases as important public announcements. Indeed, both Eq. (7) and the corresponding classification of announcement days implicitly assume that all U.S. macroeconomic news releases listed in Table 3a are equally important. However, the literature (e.g., Fleming and Remolona, 1997) suggests that not all

public information may be equally relevant ex ante to participants in the U.S. Treasury bond markets.

To address this possibility, we report estimates of Eq. (10) for each of the 25 macroeconomic announcements in our sample (listed in Table 2) for two-year, five-year, and ten-year bond yield changes in Tables 7 to 9, respectively, when we ignore the degree of information heterogeneity among investors. There we also 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 reveal that, as expected, not all public information is equally important. In particular, and by definition, only the announcements labeled in Section 3.2.2 as “influential” have a statistically significant impact ($\lambda_{sj} \neq 0$) on all 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 and often more permanent role in the price discovery process (i.e., $\sum_{i=0}^5 \lambda_{pi}$ is often statistically significant).

As previously mentioned, the estimation of Eq. (11) suggests that the correlation between bond yield changes and unanticipated order flow during non-announcement days (R_a^2 in Table 4) is the lowest in the ten-year Treasury bond market. The above analysis provides a possible interpretation for this result. Tables 7 to 9 show in fact that the impact of macroeconomic news releases on ten-year bond yield changes (λ_{sj} in Eq. (10)) is not as economically significant as in the two-year and five-year bond markets. For instance, the correlation between those yield changes and Nonfarm Payroll surprises (R_{sa}^2 in Tables 7 to 9) is 33.90%, 28.02%, and 21.98%, respectively.²⁵ In our model, both public and private signals are positively correlated, and the latter drive unanticipated order flow. Therefore, if the former have the lowest information content in the ten-year bond market, hence the lowest impact on yield changes, so might unanticipated order flow driven by the latter.

4.2.3 Public Signal Noise

The evidence presented so far indicates that not all announcements are equally important in the U.S. Treasury bond market. This can be due to several factors: The dispersion of beliefs might be higher for certain announcements than for others, some announcements may not reveal any useful information to price bonds (i.e., the days in which they occur are effectively non-announcement days), or some announcements might be noisier than others. According to our

²⁵Consistently, $\hat{\lambda}_s = 6.459, 5.286, \text{ and } 3.870$ for two-year, five-year, and ten-year bond yield changes, in Tables 7 to 9 respectively, in correspondence with Nonfarm Payroll announcements.

model, the availability of a public signal of higher (lower) quality implies a higher (lower) impact of order flow on equilibrium price changes during announcement days. In this section, we examine the effect of public signal noise directly.

Specifically, Remark 1 and Corollary 3 state that adverse selection costs are higher and the price reaction to public announcement surprises 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 equation:

$$\begin{aligned}
r_t = & a + \lambda_{snh}S_{pt}D_{nht} + \lambda_{snl}S_{pt}D_{nlt} + \lambda_{snm}S_{pt}(1 - D_{nht} - D_{nlt}) + \\
& \sum_{i=0}^N \lambda_{pnh} \Omega_{t-i}^* D_{nht} + \sum_{i=0}^N \lambda_{pnl} \Omega_{t-i}^* D_{nlt} + \\
& \sum_{i=0}^N \lambda_{pnm} \Omega_{t-i}^* (1 - D_{nht} - D_{nlt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,
\end{aligned} \tag{14}$$

where D_{nht} (D_{nlt}) is a dummy variable equal to one on announcement days with high (low) public signal noise, defined in Section 3.2.3 as the absolute value of the difference between the actual announcement minus the last revision of the announcement being on the top (bottom) 70th (30th) percentile of their empirical distribution, and equal to zero otherwise, and $N = 5$. We limit our analysis to Nonfarm Payroll, Industrial Production, and Capacity Utilization news releases, since those are the only announcements in our MMS database for which RTDS revision data is available.

Table 10 shows that the impact of these public signals on bond yield changes is generally more significant when their noise is lower (columns λ_{snm} and λ_{snl}). Accordingly, we also find that (i) the coefficients measuring the contemporaneous and permanent impact of unanticipated order flow on bond yield changes are generally insignificant on announcement days when the public signal noise is low (columns λ_{pnl0} and $\sum_{i=0}^5 \lambda_{pnl}i$ in Table 10), and (ii) the adjusted R^2 of order flow alone is generally higher on days with high public signal noise ($D_{nht} = 1$) than on days with low public signal noise ($D_{nlt} = 1$), i.e., $R_{fnha}^2 > R_{fnla}^2$; yet, these differences are not large. These results suggest that 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, albeit not importantly so.²⁶

²⁶Interestingly, neither information heterogeneity (as suggested by Figures 2b and 2d) nor public signal noise (as implied by $\lim_{\sigma_p \rightarrow \infty} \lambda_s = 0$) appear to explain why Nonfarm Payroll surprises are the most influential on day-to-day bond yield changes among the three announcements listed above (according to Tables 7 to 9). Indeed, we find that both the intertemporal dynamics of their estimated noise (in Figure 5) and dispersion of beliefs (e.g., Figure 4), as well as their empirical distributions (not reported here) are very similar over the sample period 1992-2000. We leave further analysis of this issue to future research.

Finally, we amend all the regression models specified above to account for the potential omitted variable biases described in Section 4.1.1. Many of these biases are in fact more likely to arise when analyzing the impact of both information heterogeneity and public signal noise on market liquidity during announcement days. For example, the number of informed market participants is likely to be endogenously higher during announcement days regardless of their dispersion of beliefs, if they expect the Treasury bond market to be more liquid then (e.g., Chowdhry and Nanda, 1991). In addition, as observed in Section 3.2.3, public signal noise may stem not only from the signal’s intrinsic quality but also from fundamental uncertainty (σ_v^2 in our model), which affects market liquidity directly as well (Proposition 2). Yet, we find that all our conclusions are robust to the inclusion of the same control variables employed for our analysis of non-announcement days.

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 investors’ dispersion of beliefs and the public signals’ noise. To that end, we theoretically identify and empirically document important news and order flow effects in the U.S. Treasury bond market. To guide our analysis, we develop a parsimonious model of speculative trading in the presence of asymmetric sharing of information among imperfectly competitive traders and a public signal of the terminal value of the traded asset. We then test its equilibrium implications by studying the relation between daily two-year, five-year, and ten-year U.S. Treasury bond yield changes and unanticipated order flow and real-time U.S. macroeconomic news releases.

Our evidence suggests that announcement and order flow surprises produce conditional, persistent mean jumps, i.e., that the process of price formation in the bond market is linked to information about 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 (albeit more weakly so). In particular, and consistent with our model, unanticipated order flow is more highly correlated with 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 (e.g., 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 contemporaneously correlated with daily yield changes and that the significance of this relation depends on the degree of information heterogeneity about macroeconomic fundamentals among market participants. In future work, we intend to include order flow information to forecast the term structure.

Our results also indicate that day-to-day bond yield changes and order flow are 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. Previous studies observe that Nonfarm Payroll Employment is the first news release for a given month (e.g., Fleming and Remolona, 1997; Andersen et al., 2003). However, our analysis implicitly accounts for the timing of the announcements, by focusing exclusively on their surprise content. Hence, the importance of this announcement should depend on its predictive power. Yet, to the best of our knowledge, no study has shown that the Nonfarm Payroll Employment is the best predictor for future activity and inflation out of the 25 macroeconomic announcements in our sample.²⁷ 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 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} speculator,

$$E(p_1|\delta_k) = A_0 + A_1x_k + A_1B_0(M-1) + A_1B_1(M-1)\gamma\delta_k. \quad (\text{A-1})$$

²⁷The 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.

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

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

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

$$p_0 - A_0 = (M + 1) A_1 B_0 \quad (\text{A-3})$$

$$2A_1 B_1 = 1 - (M - 1) A_1 B_1 \gamma. \quad (\text{A-4})$$

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

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

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

$$A_0 = p_0 - A_1 MB_0 \quad (\text{A-6})$$

$$A_1 = \frac{B_1 \psi \sigma_v^2}{\sigma_u^2 + MB_1^2 \psi^2 [\sigma_s^2 + (M - 1) \sigma_{ss}]}. \quad (\text{A-7})$$

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 $A_1 B_0$ 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

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

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 speculators. 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 speculators. ■

Proof of Corollary 1. Market liquidity is increasing in the number of speculators, since $\frac{\partial \lambda}{\partial M} = -\frac{(M-1)\sigma_v^2 [M^3\chi^2 - M(M+1)\chi\sigma_v^2 + \sigma_v^4]}{2\sqrt{M}\sigma_u[\sigma_v^2 + M(M-1)\chi]^{\frac{1}{2}}[\sigma_v^2(M+1) + M(M-1)\chi]^2} < 0$ under most parametrizations (except in the small region of $\{\sigma_v^2, M, \chi\}$ where $\sigma_v^2 > \frac{M^3\chi^2}{M(M+1)\chi - \sigma_v^2}$). Moreover, $\lim_{M \rightarrow \infty} \lambda = 0$. Market liquidity is decreasing in the heterogeneity of speculators' S_{vk} since $\lambda = \frac{\sigma_v^2\sqrt{M}[\sigma_v^2 + M(M-1)\chi]^{\frac{1}{2}}}{\sigma_u[\sigma_v^2(M+1) + M(M-1)\chi]}$ is a concave function of χ with its maximum at $\chi = \frac{\sigma_v^2}{M}$, i.e., when $\sigma_{ss} = 0$. Indeed, $\frac{\partial \lambda}{\partial \chi} = -\frac{M^{\frac{3}{2}}(M-1)^2\sigma_v^2(M\chi - \sigma_v^2)}{2\sigma_u[\sigma_v^2 + M(M-1)\chi]^{\frac{1}{2}}[\sigma_v^2(M+1) + M(M-1)\chi]^2}$, 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 $E(\pi_k|\delta_k)$:

$$p_0 + \delta_k + (M-1)A_1B_1\gamma_p\delta_k - A_0 - (M+1)A_1B_0 - 2A_1B_1\delta_k - A_2S_p = 0. \quad (\text{A-9})$$

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

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

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

The distributional assumptions of Section 2.1 imply that

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

where $C = \alpha^2\sigma_v^2 + \beta^2M^2\sigma_p^2 + 2\alpha\beta M\sigma_v^2$ 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

$$A_0 = p_0 - A_1MB_0 - A_2p_0 \quad (\text{A-13})$$

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

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

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 $A_1^2 = \frac{\Gamma}{\sigma_u^2 \sigma_p^2 [2 + (M-1)\gamma_p]^2}$, where $\Gamma = \alpha \sigma_v^2 (\sigma_p^2 - \sigma_v^2) [2 + (M-1)\gamma_p - \alpha] > 0$ 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 $A_1 = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p [2 + (M-1)\gamma_p]} > 0$, 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 $A_2 = \frac{\sigma_v^2}{\sigma_p^2} \{ \sigma_v^2 [2 + (M-1)\gamma_p - \alpha] - \beta M \sigma_p^2 \}$. ■

Proof of Corollary 2. To prove this statement, we compare λ and λ_p under all possible scenarios for M and γ . When $M = 1$, $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \frac{\sigma_v}{2\sigma_p \sigma_u} (\sigma_p^2 - \sigma_v^2)^{\frac{1}{2}}$ since $\sigma_p^2 > \sigma_v^2$. Along the same lines, when $M > 1$ and $\chi = 0$ ($\gamma = 1$), $\lambda = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u} > \lambda_p = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_p \sigma_u} (\sigma_p^2 - \sigma_v^2)^{\frac{1}{2}}$. When $M > 1$ and $\chi = \frac{\sigma_v^2}{M}$ ($\gamma = 0$), $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p [2 + (M-1)\gamma_p]}$ since $\sigma_p^2 > \sigma_v^2$, $\alpha = \frac{M(\sigma_p^2 - \sigma_v^2)}{M\sigma_p^2 - \sigma_v^2}$, and $\beta = \frac{\sigma_v^2(M-1)}{M\sigma_p^2 - \sigma_v^2}$ imply that $\gamma_p = \frac{\sigma_v^2(M-1)[\sigma_p^2(M+1) - 2\sigma_v^2]}{(M\sigma_p^2 - \sigma_v^2)[\sigma_p^2 + (M-2)\sigma_v^2]} > 0$ and $[2 + (M-1)\gamma_p]^2 > 4[2 + (M-1)\gamma_p]$. Finally, it can be shown that, when $M > 1$ and $\chi \in (0, \frac{\sigma_v^2}{M})$ ($\gamma \in (0, 1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in (-\frac{1}{M-1}, 0)$), $\lambda = \frac{\sigma_v \sqrt{M} [\sigma_v^2 + M(M-1)\chi]^{-\frac{1}{2}}}{\sigma_u [\sigma_v^2(M+1) + M(M-1)\chi]} > \lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p [2 + (M-1)\gamma_p]}$ 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, $\lim_{M \rightarrow \infty} \lambda - \lambda_p = 0$, 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 $M = 1$, $\frac{\partial \lambda_p}{\partial \sigma_p} = \frac{\sigma_v^3}{2\sigma_p^2 \sigma_u} (\sigma_p^2 - \sigma_v^2)^{-\frac{1}{2}} > 0$. When $M > 1$ and $\chi = 0$ ($\gamma = 1$), $\frac{\partial \lambda_p}{\partial \sigma_p} = \frac{\sqrt{M}\sigma_v^3}{(M+1)\sigma_p^2 \sigma_u} (\sigma_p^2 - \sigma_v^2)^{-\frac{1}{2}} > 0$. When $M > 1$ and $\chi \in (0, \frac{\sigma_v^2}{M})$ ($\gamma \in [0, 1)$) or $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in (-\frac{1}{M-1}, 0)$), 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 of the above scenarios, $\lim_{\sigma_p \rightarrow \infty} \lambda_p = \lambda$. ■

Proof of Remark 2. We prove this remark by comparing the equilibrium λ_p when either $\gamma = 1$ or $\gamma = 0$. If speculators' signals are perfectly correlated, then $\lambda_p = \frac{[M\sigma_v^2(\sigma_p^2 - \sigma_v^2)]^{\frac{1}{2}}}{\sigma_u \sigma_p (M+1)}$; if speculators' private signals are uncorrelated, then $\lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p [2 + (M-1)\gamma_p]}$ by $\Gamma = \frac{M[\sigma_p^2 + (M^2 - 2)\sigma_v^2](\sigma_v^3 - \sigma_v \sigma_p^2)^2}{(M\sigma_p^2 - \sigma_v^2)[\sigma_p^2 + (M-2)\sigma_v^2]}$ 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 $\lambda_p > \frac{[M\sigma_v^2(\sigma_p^2 - \sigma_v^2)]^{\frac{1}{2}}}{\sigma_u \sigma_p (M+1)}$ if $\sigma_p > \sigma_p^*$; if $M = 2$, $\sigma_p^* = \frac{1}{2} \sqrt{\sigma_v^2 (7 + \sqrt{33})}$, while if $M \geq 3$, it can be shown that $\sigma_p^* = \frac{1}{\sqrt{2}} \left\{ 3\sigma_v^2 + \frac{\sigma_v^2}{M} \left[1 + (4M^3 + M^2 - 2M + 1)^{\frac{1}{2}} \right] \right\}^{\frac{1}{2}}$. ■

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 $\chi > \frac{\sigma_v^2}{M}$ ($\gamma \in \left(-\frac{1}{M-1}, 0\right)$), $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2} \left\{ \frac{\sigma_v^2 [2+(M-1)\gamma_p - \alpha] - \beta M \sigma_p^2}{\sigma_v^2 [2+(M-1)\gamma_p]} \right\}$. 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 $\sigma_p^2 > \frac{M^2(M-1)\chi[(M-1)\chi+2\sigma_v^2]}{2M(M+1)^2\chi-2\sigma_v^2} + \frac{M^2(M-1)^{\frac{3}{2}}\chi^{\frac{3}{2}}\sqrt{4\sigma_v^2+(M-1)\chi-2\sigma_v^4}}{2M(M+1)^2\chi-2\sigma_v^2}$ and $\chi > \frac{\sigma_v^2}{M(M-1)^2}$. Yet, regardless of χ and the sign of λ_s , $\lim_{\sigma_p \rightarrow \infty} \lambda_s = 0$. ■

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Table 1. GovPX Transaction Data: Summary Statistics

This table presents summary statistics for the following variables in the GovPX database of transactions in two-year, five-year, and ten-year on-the-run Treasury bonds between January 2, 1992 and December 29, 2000: Daily yields (in percentage, i.e., multiplied by 100), daily yield changes (in basis points, i.e., multiplied by 10,000), number of buys, number of sells, daily net order flow Ω_t (number of buys minus number of sells), daily abnormal order flow, and the daily number of transactions. The daily abnormal, or unanticipated order flow (defined in Section 4 as Ω_t^*) is computed by aggregating over each day t all half-hour intraday residuals from the estimation of the linear autoregressive model of Hasbrouck (1991) in Eq. (8). We report the mean, standard deviation, maximum, minimum, and first-order autocorrelation coefficient ($\rho(1)$). A “ * ”, “ ** ”, or “ *** ” indicates that $\rho(1)$ is statistically significant at 10%, 5%, or 1% level.

	Mean	Stdev.	Max.	Min.	$\rho(1)$
Two-Year					
Daily Yield×100	5.486	0.885	7.728	3.670	0.998***
Daily Yield Change×10,000	0.054	6.101	35.100	-31.100	0.041*
Number of Buys	202.07	79.996	604	25	0.559***
Number of Sells	170.77	69.892	640	17	0.533***
Order Flow	31.30	37.38	204	-89	0.088***
Abnormal Order Flow	0.00	33.74	187.58	-102.49	0.032
Number of Transactions	372.84	145.50	1244	44	0.578***
Five-Year					
Daily Yield×100	5.965	0.739	7.898	3.978	0.996***
Daily Yield Change×10,000	-0.005	6.389	35.100	-29.300	0.044**
Number of Buys	324.70	127.36	816	34	0.633***
Number of Sells	289.41	114.47	737	33	0.631***
Order Flow	35.29	49.53	278	-127	0.128***
Abnormal Order Flow	0.00	47.85	262.72	-129.44	-0.007
Number of Transactions	614.11	237.05	1423	88	0.654***
Ten-Year					
Daily Yield×100	6.263	0.736	8.033	4.164	0.997***
Daily Yield Change×10,000	-0.044	5.994	33.600	-23.000	0.044**
Number of Buys	281.70	109.03	693	34	0.710***
Number of Sells	260.55	102.44	553	22	0.692***
Order Flow	21.14	36.45	153	-105	0.160***
Abnormal Order Flow	0.00	40.29	142.98	-105.38	0.038
Number of Transactions	542.25	208.41	1246	73	0.718***

Table 2. Macroeconomic News Announcements

Announcement	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				
<u>Real Activity</u>				
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
<u>Consumption</u>				
10- New Home Sales	106	BC	10:00	Yes
11- Personal Consumption Expenditures	107	BEA	10:00/8:30 ⁷	No
<u>Investment</u>				
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	No
<u>Government Purchases</u>				
16- Government Budget	107	FMS	14:00	No
<u>Net Exports</u>				
17- Trade Balance	107	BEA	8:30	Yes
<u>Prices</u>				
18- Producer Price Index	108	BLS	8:30	Yes
19- Consumer Price Index	107	BLS	8:30	Yes
<u>Forward-Looking</u>				
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 2

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 (EST). 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 3a. 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 ($\rho(\text{Payroll})$), and the first-order autocorrelation coefficient ($\rho(1)$). 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 2) is not available.

	Mean	Stdev.	Max.	Min	$\rho(\text{Payroll})$	$\rho(1)$
Quarterly Announcements						
1- GDP Advance	0.480	0.170	1.100	0.320	0.162*	-0.181
2- GDP Preliminary	0.313	0.178	1.290	0.120	0.014	0.192
3- GDP Final	0.128	0.051	0.240	0.040	0.083	0.250
Monthly Announcements						
<u>Real Activity</u>						
4- Nonfarm Payroll	41.814	14.212	103.190	17.496	1.000	0.424***
5- Retail Sales	0.302	0.158	1.390	0.106	0.109	0.047
6- Industrial Production	0.183	0.135	1.700	0.087	0.236**	0.358***
<u>Consumption</u>						
10- New Home Sales	19.270	10.235	96.225	7.840	0.151	0.099
<u>Investment</u>						
12- Durable Goods Orders	1.034	0.333	2.583	0.450	0.077	0.412***
13- Factory Orders	0.587	0.577	7.249	0.239	0.219**	0.015
14- Construction Spending	0.499	0.253	1.270	0.158	0.176*	0.192***
<u>Net Exports</u>						
17- Trade Balance	0.790	0.851	11.480	0.400	0.122	0.018
<u>Prices</u>						
18- Producer Price Index	0.130	0.049	0.380	0.060	0.186*	0.287***
19- Consumer Price Index	0.086	0.051	0.580	0.040	0.146	0.221**
<u>Forward-Looking</u>						
20- Consumer Conf. Index	1.646	0.609	4.026	0.663	0.079	0.230**
21- NAPM Index	0.961	0.303	2.680	0.441	0.242**	0.382***
22- Housing Starts	0.045	0.038	0.430	0.016	0.160	0.246***
23- Index of Leading Ind.	0.202	0.137	0.920	0.044	0.134	0.480***
Weekly Announcements						
25- Initial Unemp. Claims	7.973	5.440	53.400	2.100	0.069	0.578***

Table 3b. 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) 70th (30th) 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 3a. R_a^2 is the adjusted R^2 . A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using Newey-West standard errors.

Announcement	b_h	b_l	b_m	$b_h - b_l$	R_a^2
Two-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
Five-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
Ten-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 4. Market Liquidity on Non-announcement Days

This table reports estimates of the following regression model (Eq. (11)):

$$r_t = a + \sum_{i=0}^N \lambda_{hi} \Omega_{t-i}^* D_{ht} + \sum_{i=0}^N \lambda_{li} \Omega_{t-i}^* D_{lt} + \sum_{i=0}^N \lambda_{mi} \Omega_{t-i}^* (1 - D_{ht} - D_{lt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields, Ω_t^* is unanticipated order flow (defined in Section 4), D_{ht} (D_{lt}) is a dummy variable equal to one on non-announcement days (defined in Section 4.1) with high (low) dispersion of beliefs, defined as the forecasts' standard deviation to be on the top (bottom) 70th (30th) percentile of its empirical distribution, and zero otherwise, and $N = 5$. We measure the dispersion of beliefs in each trading day of a given month using three different methodologies. In the first, we only use the standard deviation of professional forecasts of the Nonfarm Payroll Employment report. In the second, we aggregate the standard deviations of forecasts of seven "influential" macroeconomic announcements (listed in Section 3.2.2). In the third, we aggregate the standard deviations of forecasts across all macroeconomic news announcements listed in Table 3a. R_{ha}^2 (R_{la}^2) is the adjusted R^2 conditional on high (low) dispersion days, while R_a^2 is the adjusted R^2 including all observations. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using Newey-West standard errors.

Announcement	λ_{h0}	λ_{m0}	λ_{l0}	$\lambda_{h0} - \lambda_{l0}$	Two-Year					R_{ha}^2	R_{la}^2	R_a^2
					$\sum_{i=0}^5 \lambda_{hi}$	$\sum_{i=0}^5 \lambda_{mi}$	$\sum_{i=0}^5 \lambda_{li}$	$\sum_{i=0}^5 \lambda_{hi}$	$\sum_{i=0}^5 \lambda_{li}$			
Nonfarm Payroll	-0.213***	-0.182***	-0.121***	-0.092***	-0.161**	-0.182***	-0.072	28.54%	6.66%	21.69%		
Influential	-0.140***	-0.108***	-0.080***	-0.060***	-0.106	-0.096***	-0.049**	14.61%	10.65%	15.52%		
All	-0.122***	-0.093***	-0.098***	-0.024	-0.152***	-0.086***	-0.086***	15.46%	16.92%	15.83%		
Five-Year												
Nonfarm Payroll	-0.210***	-0.153***	-0.085***	-0.125***	-0.285***	-0.136***	0.019	41.38%	9.65%	23.30%		
Influential	-0.151***	-0.122***	-0.087***	-0.064***	-0.142***	-0.106***	-0.050**	19.14%	11.97%	20.31%		
All	-0.155***	-0.097***	-0.102***	-0.053***	-0.167***	-0.079***	-0.083***	21.37%	18.76%	19.40%		
Ten-Year												
Nonfarm Payroll	-0.170***	-0.129***	-0.071	-0.099	-0.192**	-0.269***	-0.017	15.10%	1.02%	10.29%		
Influential	-0.081***	-0.093***	-0.079***	-0.002	-0.075**	-0.109***	-0.053	2.83%	4.72%	6.05%		
All	-0.075***	-0.086***	-0.071***	-0.004	-0.109**	-0.119***	-0.097**	3.82%	4.43%	6.16%		

Table 5. Market Liquidity in Announcement and Non-announcement Days

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

$$r_t = a + \sum_{i=0}^N \lambda_i \Omega_{t-i}^* (1 - D_{Pt}) + \sum_{i=0}^N \lambda_{pi} \Omega_{t-i}^* D_{Pt} + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields, Ω_t^* is unanticipated order flow (defined in Section 4), D_{Pt} is a dummy variable equal to one if either the Nonfarm Payroll Employment report ($P = 1$), any of the 7 “influential” announcements listed in Section 3.2.2 ($P = 7$), or any of the 18 announcements listed in Table 3a ($P = 18$) is released on day t and equal to zero otherwise, and $N = 5$. R_f^2 (R_{fp}^2) is the adjusted R^2 from the estimation of Eq. (12) over just non-announcement (announcement) days, while R_a^2 is the adjusted R^2 from the estimation of the fully specified regression above. A “*” , “**” , or “***” indicate significance at the 10%, 5%, or 1% level, respectively, using Newey-West standard errors.

Announcement	λ_0	λ_{p0}	$\lambda_0 - \lambda_{p0}$	$\sum_{i=0}^5 \lambda_i$	$\sum_{i=0}^5 \lambda_{pi}$	R_f^2	R_{fp}^2	R_a^2
Two-Year								
Nonfarm Payroll	-0.108***	-0.087***	-0.021	-0.131***	-0.013	15.31%	6.47%	14.72%
Influential	-0.103***	-0.112***	0.009	-0.075***	-0.059***	15.34%	12.29%	13.98%
All	-0.102***	-0.109***	0.007	-0.096***	-0.059***	16.00%	13.24%	13.99%
Five-Year								
Nonfarm Payroll	-0.124***	-0.168***	0.044**	-0.121***	-0.242***	21.03%	19.61%	21.37%
Influential	-0.117***	-0.137***	0.020*	-0.095***	-0.137***	19.88%	20.88%	20.76%
All	-0.115***	-0.131***	0.016	-0.107***	-0.115***	20.29%	20.48%	20.70%
Ten-Year								
Nonfarm Payroll	-0.087***	-0.053*	-0.034	-0.181***	-0.020	6.74%	3.59%	7.07%
Influential	-0.086***	-0.086***	0.000	-0.083***	-0.086***	6.73%	5.73%	6.52%
All	-0.077***	-0.090***	0.013	-0.103***	-0.076***	7.08%	5.99%	6.49%

Table 6. Public Signals and Market Liquidity

This table reports estimates of the following regression model (Eq. (14)):

$$r_t = a + \sum_{j=1}^P \lambda_{sj} S_{jt} + \sum_{i=0}^N \lambda_{phi} \Omega_{t-i}^* D_{ht} + \sum_{i=0}^N \lambda_{phi} \Omega_{t-i}^* D_{lt} + \sum_{i=0}^N \lambda_{pmi} \Omega_{t-i}^* (1 - D_{ht} - D_{lt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields, Ω_t^* is unanticipated order flow (defined in Section 4), D_{ht} (D_{lt}) is a dummy variable equal to one on days with high (low) dispersion of beliefs (defined in Section 3.2.2), and zero otherwise, and $N = 5$. We estimate the above equation using only announcement days (defined in Section 4.2). The coefficient $\overline{\lambda_{sp}}$ is the estimated price impact of the Nonfarm Payroll announcement ($P = 1$) or the average estimated impact either across the “influential” ($P = 7$) or all ($P = 18$) macroeconomic announcements listed in table 3a. R_{fha}^2 (R_{fa}^2) is the adjusted R^2 conditional on high (low) dispersion days and only using Ω_t^* , R_{fa}^2 is the unconditional adjusted R^2 using only Ω_t^* , 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 Newey-West standard errors.

Announcement	$\overline{\lambda_{sp}}$	λ_{ph0}	λ_{pm0}	λ_{p0}	$\lambda_{ph0} - \lambda_{p0}$	$\sum_{i=0}^5 \lambda_{phi}$	$\sum_{i=0}^5 \lambda_{pmi}$	$\sum_{i=0}^5 \lambda_{phi}$	R_{fha}^2	R_{fa}^2	R_a^2	
Two-Year												
Nonfarm Pay.	6.279***	-0.141**	-0.117**	-0.116	-0.025*	0.087	-0.301***	-0.055	7.81%	-8.04%	8.51%	40.87%
Influential	2.805***	-0.179***	-0.08***	-0.106***	-0.073***	-0.152***	-0.063**	-0.040	15.86%	9.57%	13.54%	30.27%
All	1.490***	-0.165***	-0.092***	-0.093***	-0.072***	-0.130***	-0.030	-0.055**	16.65%	14.50%	13.79%	26.70%
Five-Year												
Nonfarm Pay.	6.028***	-0.220***	-0.179***	-0.117**	-0.103***	-0.209	-0.253***	-0.087	11.45%	-4.37%	14.46%	46.68%
Influential	2.670***	-0.184***	-0.111***	-0.124***	-0.060***	-0.202***	-0.129***	-0.083**	24.16%	15.27%	21.45%	34.00%
All	1.259***	-0.183***	-0.111***	-0.124***	-0.059***	-0.192***	-0.100***	-0.083***	23.94%	24.78%	21.83%	31.27%
Ten-Year												
Nonfarm Pay.	4.195***	-0.239**	-0.017	0.076	-0.315**	-0.157	0.040	0.109	-10.27%	-3.53%	0.26%	22.81%
Influential	2.445***	-0.103***	-0.068***	-0.072***	-0.031	-0.130**	-0.064*	-0.038	3.55%	5.33%	5.58%	16.95%
All	1.329***	-0.117***	-0.079***	-0.068***	-0.049**	-0.120**	-0.070**	-0.014	4.26%	6.71%	6.31%	15.04%

Table 7. Disaggregate Influence of Public Signal: Two-Year Bonds

This table reports estimates of the following equation:

$$r_t = a_p + \lambda_{sj}S_{jt} + \sum_{i=0}^N \lambda_{pi}\Omega_{t-i}^* + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields for the two-year bond, Ω_t^* is the unanticipated order flow (defined in Section 4), S_{jt} is the standardized macroeconomic news surprise j estimated using MMS data, and $N = 5$. 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 Newey-West standard errors.

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^5 \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Quarterly Announcements						
1- GDP Advance	0.538	-0.223***	-0.100	-2.30%	3.00%	-0.91%
2- GDP Preliminary	1.366	-0.218***	-0.181	0.41%	34.44%	35.53%
3- GDP Final	-0.332	-0.120	-0.066	-2.90%	-11.64%	-16.49%
Monthly Announcements						
Real Activity						
4- Nonfarm Payroll	6.459***	-0.125***	-0.173**	33.90%	5.83%	41.83%
5- Retail Sales	3.321***	-0.161***	-0.143**	14.39%	31.37%	38.15%
6- Industrial Production	1.279**	-0.103***	0.038	3.28%	22.71%	26.15%
7- Capacity Utilization	1.607***	-0.097***	0.063	9.80%	22.71%	28.75%
8- Personal Income	1.458**	-0.085***	-0.014	4.29%	6.03%	10.55%
9- Consumer Credit	0.075	-0.106***	-0.137*	-0.71%	6.91%	5.93%
Consumption						
10- New Home Sales	2.459***	-0.109***	-0.017	19.14%	16.25%	37.26%
11- Personal Cons. Exp.	1.049	-0.082***	-0.011	2.48%	6.65%	7.60%
Investment						
12- Durable Goods Orders	0.847	-0.109***	-0.054	-0.10%	3.52%	3.75%
13- Factory Orders	0.891	-0.095***	-0.063	-0.25%	10.94%	10.63%
14- Construction Spending	0.076	-0.053	0.168*	-0.78%	4.22%	3.18%
15- Business Inventories	0.566	-0.099***	-0.025	-0.30%	20.77%	20.44%
Government Purchases						
16- Government Budget	-1.384	-0.137***	-0.196***	0.12%	22.42%	23.22%
Net Exports						
17- Trade Balance	0.096	-0.079***	-0.100**	-0.95%	7.31%	6.36%

Table 7 (*Continued*).

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^N \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Monthly Announcements						
Prices						
18- Producer Price Index	0.140	-0.112***	-0.087	-0.94%	7.24%	6.28%
19- Consumer Price Index	2.392***	-0.118***	-0.120*	4.17%	18.16%	23.54%
Forward-Looking						
20- Consumer Confidence Index	1.885***	-0.070**	0.061	9.28%	10.35%	18.25%
21- NAPM Index	3.911***	-0.098***	-0.011	26.28%	8.73%	35.93%
22- Housing Starts	0.059	-0.089***	0.054	-0.47%	21.72%	20.88%
23- Index of Leading Indicators	3.334*	-0.036	0.080	2.70%	2.21%	4.42%
Six-Week Announcements						
24- Target Federal Funds Rate	39.923***	-0.037	0.102	19.62%	-5.50%	24.08%
Weekly Announcements						
25- Initial Unemployment Claims	-0.416	-0.110***	-0.065**	0.45%	18.41%	18.55%

Table 8. Disaggregate Influence of Public Signal: Five-Year Bonds

This table reports estimates of the following equation:

$$r_t = a_p + \lambda_{sj}S_{jt} + \sum_{i=0}^N \lambda_{pi}\Omega_{t-i}^* + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields for the five-year bond, Ω_t^* is the unanticipated order flow (defined in Section 4), S_{jt} is the standardized macroeconomic news surprise j estimated using MMS data. We estimate the above equation using only those observations when an announcement was made, and $N = 5$. 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 Newey-West standard errors.

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^5 \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Quarterly Announcements						
1- GDP Advance	-1.400	-0.224***	-0.308	-0.09%	3.70%	1.52%
2- GDP Preliminary	0.487	-0.102*	-0.102	3.56%	28.31%	25.48%
3- GDP Final	0.434	-0.198**	-0.051	-3.03%	-3.62%	-7.95%
Monthly Announcements						
Real Activity						
4- Nonfarm Payroll	5.286***	-0.181***	-0.287***	28.02%	20.85%	46.81%
5- Retail Sales	4.19***	-0.159***	-0.162**	12.32%	27.48%	38.80%
6- Industrial Production	0.836	-0.126***	0.010	3.40%	28.95%	29.72%
7- Capacity Utilization	1.130*	-0.125***	-0.003	7.90%	28.95%	31.03%
8- Personal Income	1.046	-0.075***	-0.053	4.00%	8.69%	10.35%
9- Consumer Credit	0.358	-0.146***	-0.159**	-0.88%	22.24%	21.60%
Consumption						
10- New Home Sales	2.019***	-0.091***	-0.088	18.17%	21.55%	34.33%
11- Personal Cons. Exp.	1.543**	-0.094***	-0.035	2.00%	8.97%	12.11%
Investment						
12- Durable Goods Orders	1.233*	-0.169***	-0.133*	1.77%	21.10%	23.17%
13- Factory Orders	0.414	-0.112***	-0.139*	0.19%	17.35%	16.60%
14- Construction Spending	0.000	-0.178***	-0.272***	-0.20%	23.82%	22.98%
15- Business Inventories	0.356	-0.112***	0.008	-0.49%	18.91%	18.21%
Government Purchases						
16- Government Budget	-0.904	-0.109***	-0.155***	1.09%	28.81%	28.70%
Net Exports						
17- Trade Balance	-0.319	-0.101***	-0.087	-0.95%	13.40%	12.85%

Table 8 (*Continued*).

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^N \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Monthly Announcements						
Prices						
18- Producer Price Index	0.015	-0.161***	-0.202***	-0.93%	27.46%	26.69%
19- Consumer Price Index	1.231	-0.147***	-0.079	1.96%	28.84%	29.58%
Forward-Looking						
20- Consumer Confidence Index	1.637***	-0.153***	-0.064	9.94%	38.85%	43.52%
21- NAPM Index	3.456***	-0.113***	-0.157**	23.29%	30.66%	48.83%
22- Housing Starts	0.465	-0.117***	-0.060	-0.95%	15.85%	15.08%
23- Index of Leading Indicators	4.280**	-0.094***	-0.049	3.29%	15.36%	19.91%
Six-Week Announcements						
24- Target Federal Funds Rate	30.606***	-0.110***	-0.046	9.41%	9.24%	25.79%
Weekly Announcements						
25- Initial Unemployment Claims	-0.549*	-0.115***	-0.084***	0.50%	19.70%	20.07%

Table 9. Disaggregate Influence of Public Signal: Ten-Year Bonds

This table reports estimates of the following equation:

$$r_t = a_p + \lambda_{sj}S_{jt} + \sum_{i=0}^N \lambda_{pi}\Omega_{t-i}^* + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields for the five-year bond, Ω_t^* is the unanticipated order flow (defined in Section 4), S_{jt} is the standardized macroeconomic news surprise j estimated using MMS data. We estimate the above equation using only those observations when an announcement was made, and $N = 5$. 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 Newey-West standard errors.

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^N \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Quarterly Announcements						
1- GDP Advance	-1.394	-0.185**	0.069	-1.13%	13.11%	12.62%
2- GDP Preliminary	0.868	-0.150	-0.209	1.90%	-8.18%	-10.53%
3- GDP Final	-1.645	-0.086	-0.370*	-3.02%	-1.56%	-0.34%
Monthly Announcements						
Real Activity						
4- Nonfarm Payroll	3.870***	-0.047	-0.002	21.98%	5.44%	22.12%
5- Retail Sales	3.562***	-0.107***	-0.181**	11.48%	14.71%	24.42%
6- Industrial Production	1.219*	-0.068*	-0.024	3.50%	0.68%	3.64%
7- Capacity Utilization	1.577***	-0.056	-0.017	7.78%	0.68%	6.51%
8- Personal Income	1.213**	-0.065	-0.009	3.96%	1.02%	4.27%
9- Consumer Credit	0.011	-0.126**	-0.161*	-0.94%	4.70%	3.69%
Consumption						
10- New Home Sales	2.239***	-0.109***	-0.074	17.51%	1.22%	21.12%
11- Personal Cons. Exp.	1.285*	-0.09**	0.002	1.87%	0.91%	3.28%
Investment						
12- Durable Goods Orders	1.149	-0.116***	0.029	2.61%	4.47%	6.17%
13- Factory Orders	1.072	-0.061	-0.077	2.08%	3.33%	3.58%
14- Construction Spending	0.632	-0.133***	-0.104	0.07%	7.87%	7.66%
15- Business Inventories	0.221	-0.073*	-0.181**	-0.85%	12.42%	11.56%
Government Purchases						
16- Government Budget	-1.753*	-0.048	-0.071	0.48%	15.26%	17.25%
Net Exports						
17- Trade Balance	-0.156	-0.115***	-0.043	-0.90%	7.35%	6.47%

Table 9 (*Continued*).

Announcement	λ_{sj}	λ_{p0}	$\sum_{i=0}^N \lambda_{pi}$	R_{sa}^2	R_{fa}^2	R_a^2
Monthly Announcements						
Prices						
18- Producer Price Index	-0.008	-0.081**	-0.134	-0.93%	9.50%	8.53%
19- Consumer Price Index	1.943**	-0.073*	-0.067	1.22%	3.45%	6.70%
Forward-Looking						
20- Consumer Confidence Index	2.269***	-0.059	0.001	11.29%	-4.69%	7.70%
21- NAPM Index	3.356***	-0.064	-0.051	21.07%	1.78%	22.60%
22- Housing Starts	0.230	-0.091**	0.019	-0.89%	16.94%	16.09%
23- Index of Leading Indicators	3.106*	-0.088***	-0.084	2.63%	8.91%	11.38%
Six-Week Announcements						
24- Target Federal Funds Rate	23.226***	-0.091*	0.099	4.48%	4.70%	15.08%
Weekly Announcements						
25- Initial Unemployment Claims	-0.683**	-0.093***	-0.127***	0.54%	11.52%	12.26%

Table 10. Public Signal Noise and Market Liquidity

This table reports estimates of the following regression model (Eq. (14)):

$$r_t = a + \lambda_{snh} S_{pt} D_{nht} + \lambda_{snl} S_{pt} D_{nlt} + \lambda_{smm} S_{pt} (1 - D_{nht} - D_{nlt}) + \sum_{i=0}^N \lambda_{pnh} \Omega_{t-i}^* D_{nht} + \sum_{i=0}^N \lambda_{pnl} \Omega_{t-i}^* D_{nlt} + \sum_{i=1}^N \lambda_{pnm} \Omega_{t-i}^* (1 - D_{nht} - D_{nlt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields, Ω_t^* is the unanticipated order flow (defined in Section 4), D_{nht} (D_{nlt}) is a dummy variable equal to one on days with high (low) public signal noise (defined in Section 3.2.3 using news revisions), and zero otherwise, and $N = 5$. We estimate Eq. (14) just for Nonfarm Payroll, Industrial Production, and Capacity Utilization, since no other revisions (from RTDS) are available. R_{sa}^2 is the adjusted R^2 using public news as the only explanatory variable. R_{faha}^2 (R_{fnla}^2) is the adjusted R^2 of using contemporaneous order flow alone in high (low) public signal noise days. R_c^2 is the adjusted R^2 of the fully specified model above. A “*” , “**” , or “***” indicate significance at the 10%, 5%, or 1% level, respectively, using Newey-West standard errors.

Ann.	λ_{snh}	λ_{smm}	λ_{snl}	λ_{pnh0}	λ_{pnm0}	λ_{pnl0}	Two-Year					R_{faha}^2	R_{fnla}^2	R_{sa}^2	R_c^2
							$\sum_{i=0}^5 \lambda_{pnh}$	$\sum_{i=0}^5 \lambda_{pnm}$	$\sum_{i=0}^5 \lambda_{pnl}$	$\sum_{i=0}^5 \lambda_{pnh}$	$\sum_{i=0}^5 \lambda_{pnl}$				
Non. P.	6.861***	7.569***	5.205***	-0.132*	-0.164***	-0.108*	-0.105	-0.378***	0.041	32.67%	39.24%	39.00%	46.88%		
In. P.	1.672*	1.468	0.820	-0.075*	-0.106***	-0.130**	0.037	0.154*	-0.008	2.38%	10.93%	9.50%	23.40%		
Cap. U.	1.643	1.399	2.123	-0.072	-0.092***	-0.097	0.113	0.075	0.052	9.01%	18.20%	18.80%	25.73%		
Five-Year															
Non. P.	5.959***	5.513***	4.267***	-0.196***	-0.212***	-0.210***	-0.411**	-0.343***	-0.290***	26.77%	39.16%	38.21%	51.06%		
Ind P.	1.251	0.233	0.916	-0.099**	-0.157***	-0.122*	-0.035	0.048	-0.096	2.44%	22.80%	20.82%	23.05%		
Cap. U.	1.466	0.152	1.956	-0.128**	-0.152***	-0.085	-0.053	0.065	-0.135	7.66%	27.80%	24.85%	28.06%		
Ten-Year															
Non. P.	3.702**	3.165**	4.225**	-0.139	-0.078	0.036	-0.566**	0.267	0.116	20.88%	21.29%	19.84%	27.62%		
Ind. P.	0.281	2.025*	1.940	0.059	-0.117	-0.131*	0.020	-0.071	0.036	3.70%	5.47%	7.69%	-0.96%		
Cap. U.	1.365	1.174	2.456*	-0.013	-0.057	-0.148**	0.013	-0.022	-0.09	8.15%	7.44%	10.64%	6.03%		

Figure 1. Equilibrium without a Public Signal

Figure 1 plots the inverse of the market liquidity parameter defined in Proposition 1, $\lambda = \frac{\sigma_v^2}{\sigma_u \sigma_s \sqrt{M} [2 + (M-1)\gamma]}$, as a function of the degree of correlation of the speculators' signals, γ , in the presence of $M = 1, 2, 4,$ or 8 speculators, when $\sigma_v^2 = \sigma_u^2 = 1$. Since $\sigma_s^2 = \frac{\sigma_v^2 + M(M-1)\chi}{M^2}$, $\sigma_{ss} = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$, 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 $M = 8$.

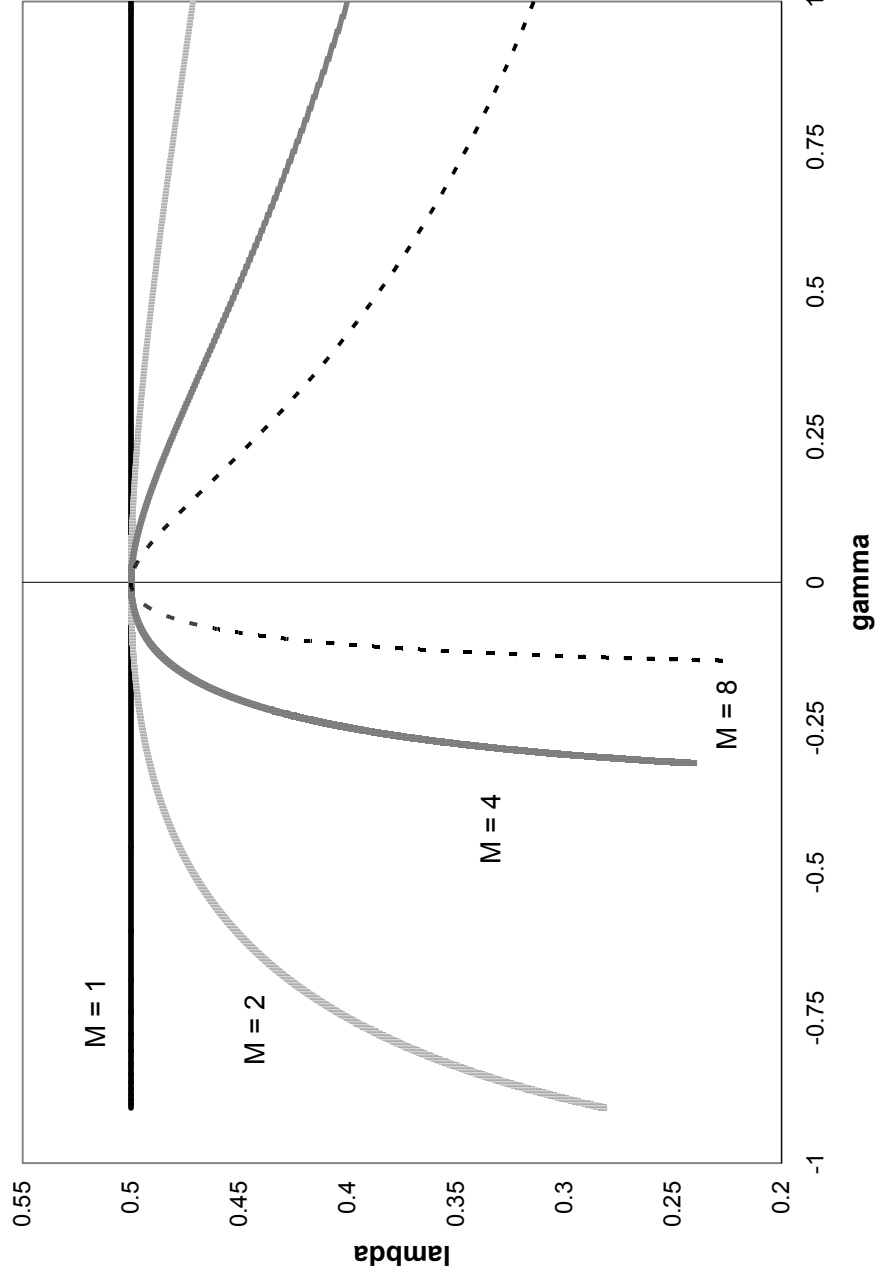


Figure 2. Equilibrium with a Public Signal

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), and the impact of S_p on the equilibrium price p_1 , λ_s (Figure 2b), as a function of the degree of correlation of the speculators' signals, γ , when $M = 1, 2, 4$, or 8 speculators, $\sigma_v = \sigma_u = 1$, 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 $\lambda_p = \frac{\Gamma^{\frac{1}{2}}}{\sigma_u \sigma_p [2 + (M-1)\gamma_p]}$ and $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2} \left\{ \frac{\sigma_v^2 [2 + (M-1)\gamma_p - \alpha] - \beta M \sigma_p^2}{\sigma_v^2 [2 + (M-1)\gamma_p]} \right\}$ in Proposition 2. Since $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$, $\gamma_p = 1 + \frac{M^2\chi}{\sigma_p^2 + M(M-1)\chi - \sigma_v^2} - \frac{\sigma_v^2 M^2\chi}{\sigma_v^2 [\sigma_v^2 + M(M-1)\chi] - \sigma_v^4}$, 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 $M = 8$.

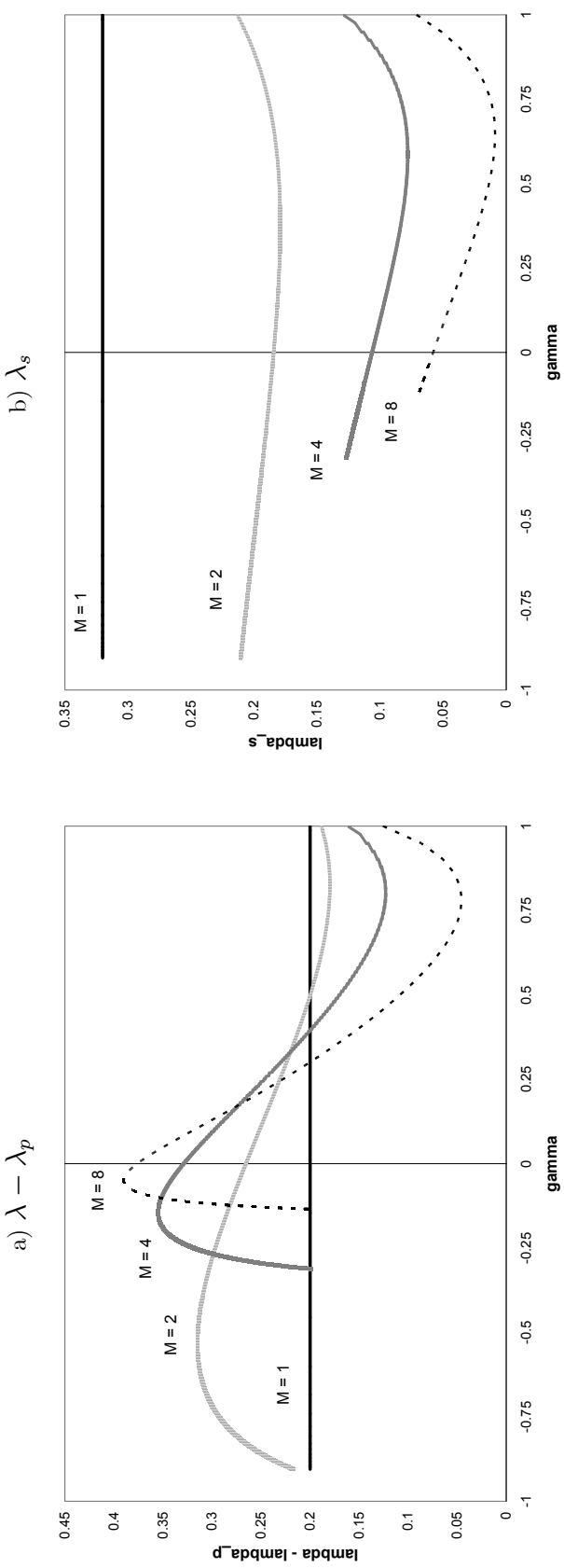


Figure 3. Daily Bond Yield Changes

In this figure, we compare two-year, five-year and ten-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). In these figures, 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 2 were released.

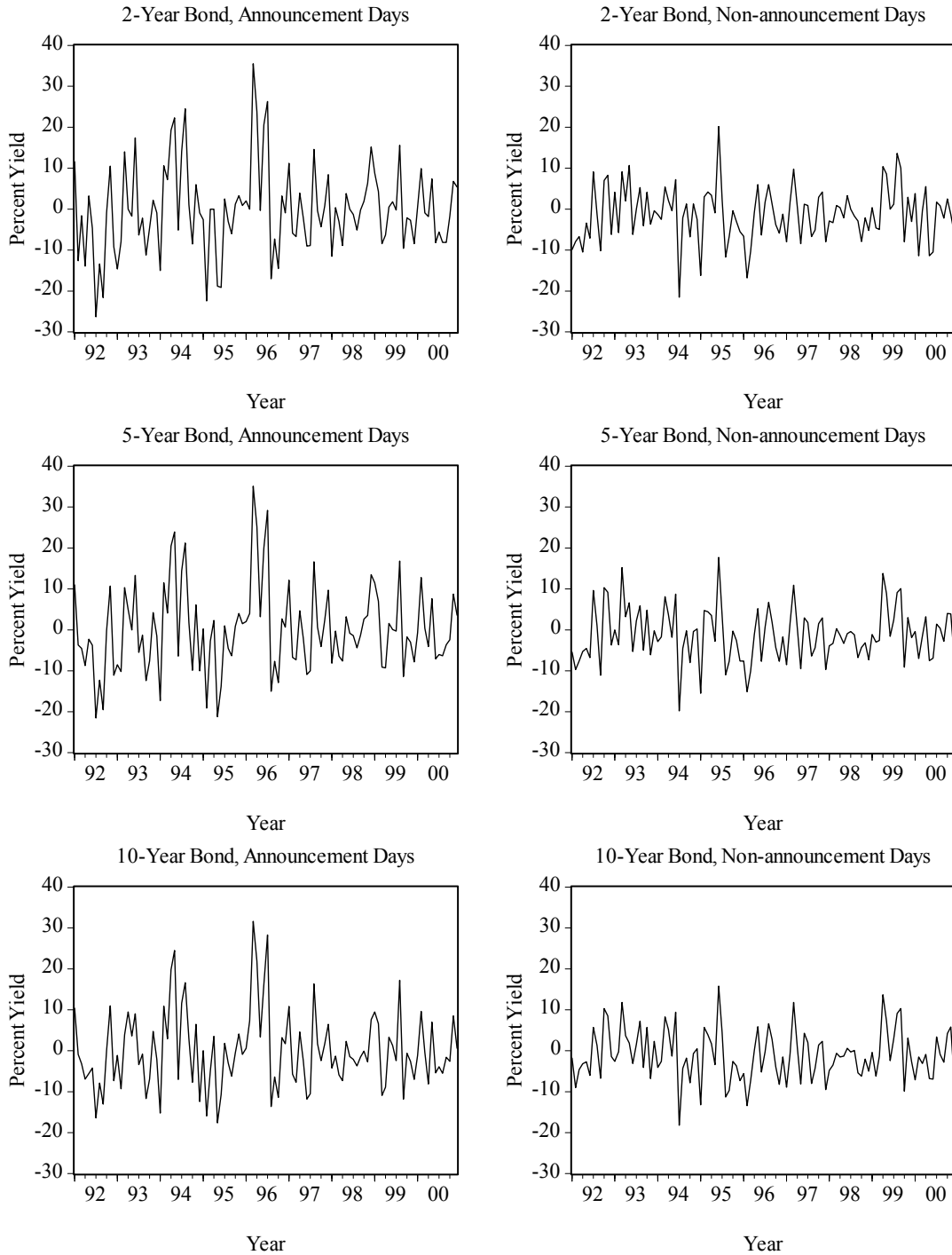
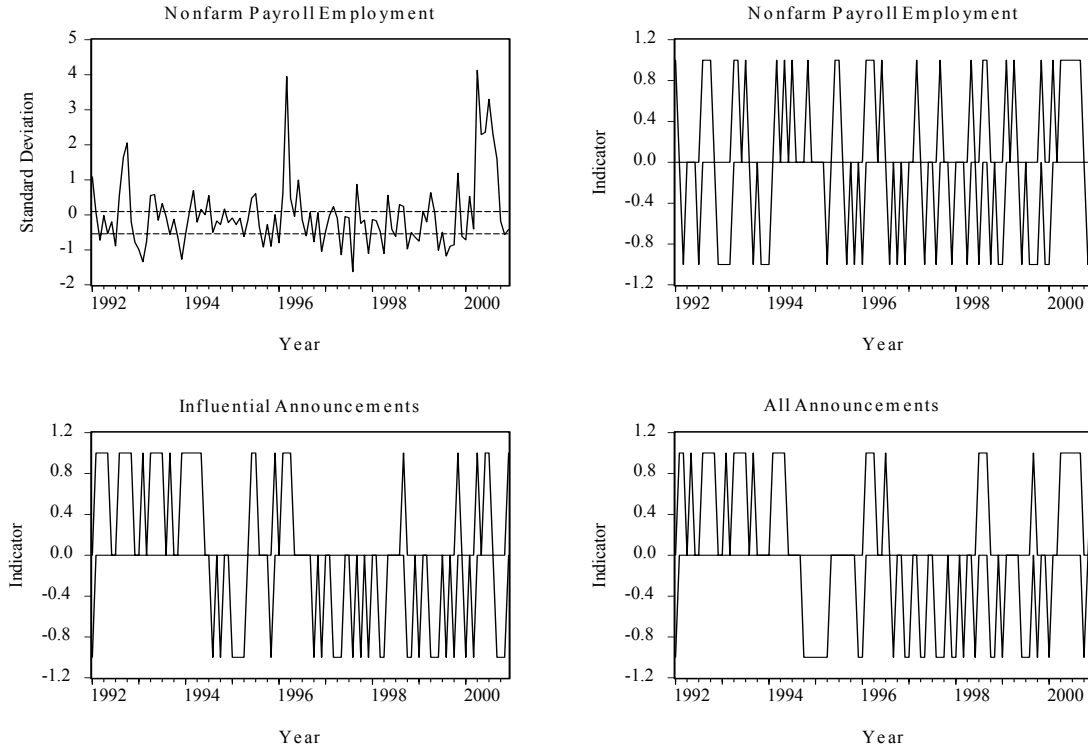


Figure 4. Aggregate Proxies for Dispersion of Beliefs

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) 70th (30th) 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) 70th (30th) 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 7 to 9). Finally, we report the correlation matrix for the three resulting sequences of high and low information heterogeneity periods.



Correlation Matrix			
Announcement	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 final published 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 are missing.

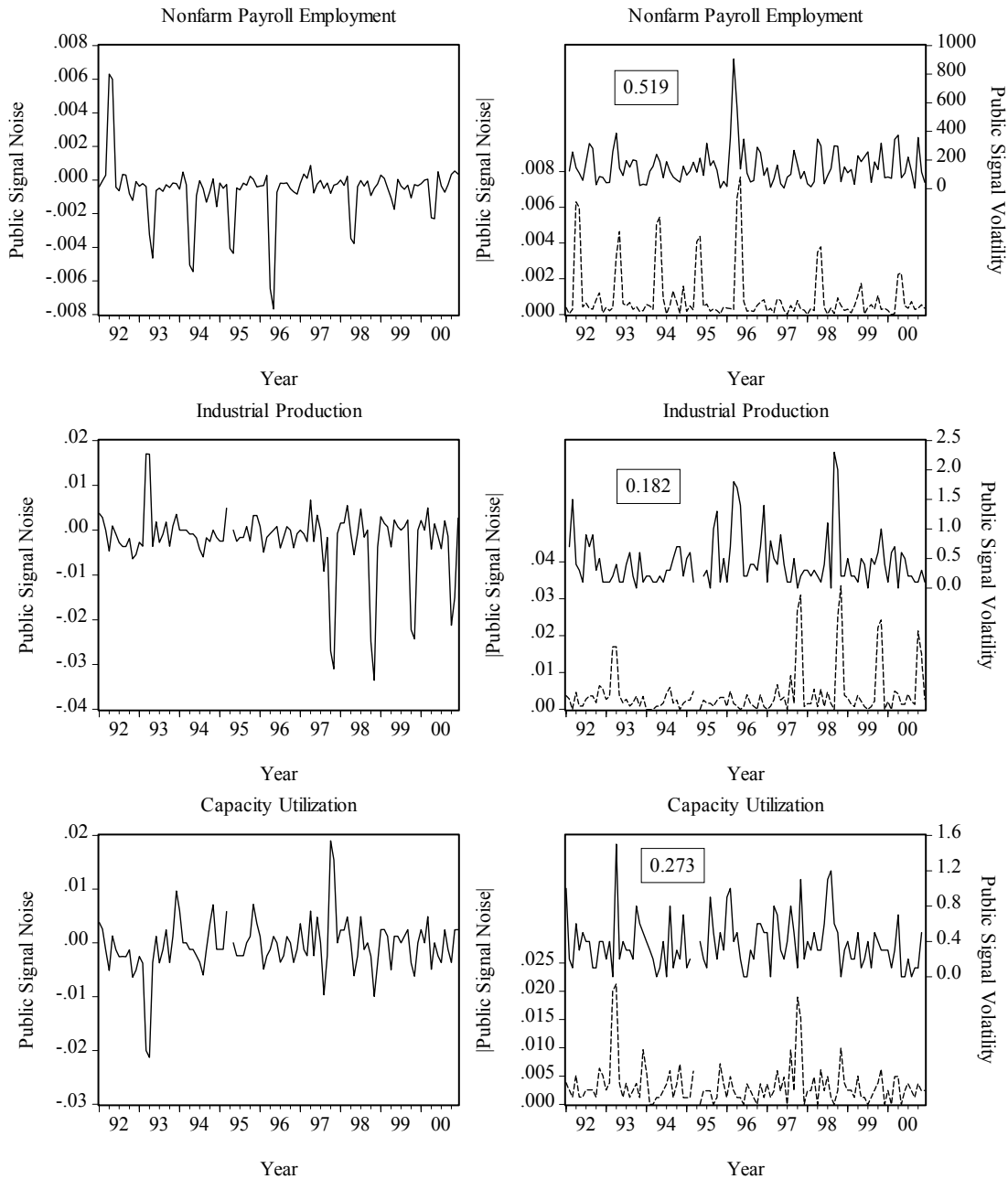


Figure 6. Impulse-Response Function for Non-announcement Days

In this figure, we plot the impulse-response functions (solid line) stemming from one standard deviation shocks to unanticipated order flow during days of high, medium, and low dispersion of beliefs. The impulse response functions are calculated from the estimation of the following regression model (Eq. (11)):

$$r_t = a + \sum_{i=0}^N \lambda_{hi} \Omega_{t-i}^* D_{ht} + \sum_{i=0}^N \lambda_{li} \Omega_{t-i}^* D_{lt} + \sum_{i=0}^N \lambda_{mi} \Omega_{t-i}^* (1 - D_{ht} - D_{lt}) + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in bond yields, in either two-year, five-year, or ten-year bond yields, Ω_t^* is the corresponding unanticipated order flow (defined in Section 4), D_{ht} (D_{lt}) is a dummy variable equal to one on non-announcement days (defined in Section 4.1) with high (low) dispersion of beliefs, defined as the standard deviation of professional forecasts of the Nonfarm Payroll Employment report ($P = 1$) to be on the top (bottom) 70th (30th) percentile of its empirical distribution, and zero otherwise, and $N = 5$. The dashed lines are 95% confidence intervals, under the null hypothesis of a zero response, computed with Newey-West standard errors.

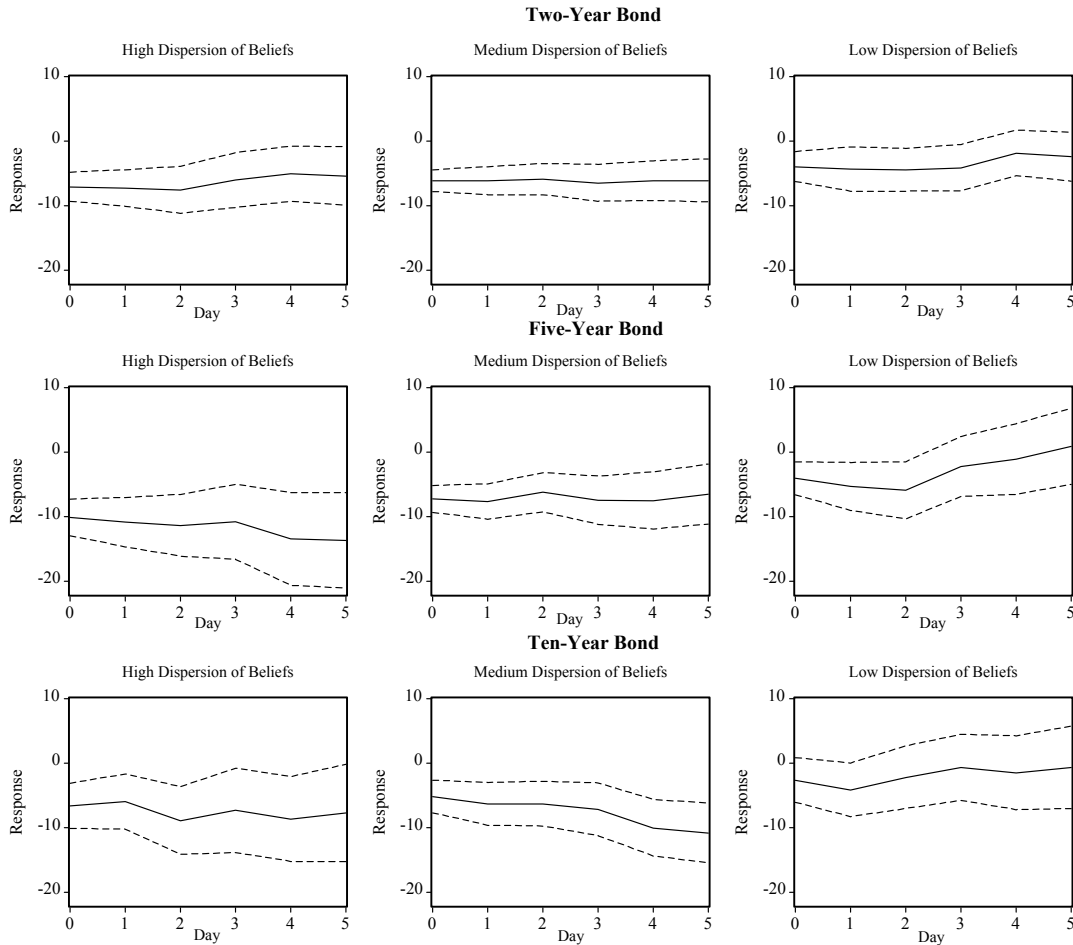


Figure 7. Impulse-Response Function for Announcement and Non-announcement Days

In this figure, we plot the impulse-response functions (solid line) stemming from one standard deviation shocks to unanticipated order flow during Nonfarm Payroll announcement days and non-announcement days. The impulse-response functions are calculated from the estimation of the following regression model (Eq. (12)):

$$r_t = a + \sum_{i=0}^N \lambda_i \Omega_{t-i}^* (1 - D_{Pt}) + \sum_{i=0}^N \lambda_{pi} \Omega_{t-i}^* D_{Pt} + \sum_{i=1}^N \beta_i r_{t-i} + \varepsilon_t,$$

where $r_t = (y_t - y_{t-1}) \times 100$ is the daily change in either two-year, five-year, or ten-year bond yields, Ω_t^* is the corresponding unanticipated order flow (defined in Section 4), D_{Pt} is a dummy variable equal to one if the Nonfarm Payroll Employment report ($P = 1$) is released on day t and equal to zero otherwise, and $N = 5$. The dashed lines are 95% confidence intervals, under the null hypothesis of a zero response, computed with Newey-West standard errors.

