Informed and Strategic Order Flow in the Bond Markets

Paolo Pasquariello
Ross School of Business, University of Michigan

Clara Vega
Simon School of Business, University of Rochester and FRBG

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 nonannouncement 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* E44, G14)

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 nonannouncement days as well. This fact has motivated the introduction of various market frictions to better explain the behavior

The authors are affiliated with the Department of Finance at the Ross School of Business, University of Michigan (Pasquariello) and the University of Rochester, Simon School of Business and the Federal Reserve Board of Governors (Vega). We are grateful to the Q Group for financial support. We benefited from the comments of an anonymous referee, Sreedhar Bharath, Michael Brandt, Michael Fleming, Michael Goldstein, Clifton Green, Joel Hasbrouck (the editor), Nejat Seyhun, Guojun Wu, Kathy Yuan, and other participants in seminars at the 2005 European Finance Association meetings in Moscow, the 2006 Bank of Canada Fixed Income Markets conference in Ottawa, the 2007 American Finance Association meetings in Chicago, Federal Reserve Board of Governors, George Washington University, the University of Maryland, the University of Michigan, the University of Rochester, and the University of Utah. Any remaining errors are our own. Address correspondence to Paolo Pasquariello, Ross School of Business, University of Michigan, 701 Tappan Street, Room E7602, Ann Arbor, MI 48109-1234, or e-mail: ppasquar@bus.umich.edu and Clara.Vega@frb.gov.

doi:10.1093/rfs/hhm034 Advance Access publication August 27, 2007

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 article 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 (MMs) more vulnerable to adverse selection. We then introduce a public signal and derive equilibrium prices and trading strategies on announcement and nonannouncement days. The contribution of the model is two-fold. 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] 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 MMs and mitigates the quasimonopolistic behavior of the speculators.

[1] According 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 Fleming and Remolona (1997, 1999), Brandt and Kavajecz (2004) and Green (2004) in the US 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 US stock market, and by Brenner et al. (2005) in the US corporate bond market, among others.

[2] Foster and Viswanathan (1996) and Back et al. (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 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.

This model is not asset-specific, that is, it applies to stock, bond, and foreign exchange markets. In this study, we test its implications for the US 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)] that 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 et al. (2001), among others]. In contrast, the link between macroeconomic fundamentals and the stock market is less clear [e.g. Andersen et al. (2004) and Boyd et al. (2005)]. Third, the market for Treasury securities is interesting in itself since it is among the largest, most liquid US financial markets.

Our empirical results strongly support the main implications of our model. During nonannouncement 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' quasimonopolistic trading behavior leads to a "cautious" equilibrium where changes in unanticipated order flow have a greater impact on bond yields.

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 nonannouncement 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 nonannouncement days in the sample.

Our article 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 nonannouncement days. This evidence complements the weak effects reported by Green (2004) over 30-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; and Easley et al. (2002) argue that the probability of 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 1, we construct a stylized model of trading to guide our empirical analysis. In Section 2, we describe the data. In Section 3, we present the empirical results. We conclude in Section 4.

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

1. 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 multiperiod 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.

1.1 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 zero 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 (that we label speculators), liquidity traders, and perfectly competitive 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 neither information asymmetry about v nor trading. Sometime between $t = 0$ and $t = 1$, each speculator k receives a private and noisy signal of v, 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 $cov\left(S_{vk}, S_{vj}\right) = \sigma_{ss}$. We also impose that the speculators together know the liquidation value of the risky asset: $\sum_{k=1}^{M} S_{vk} = v$; therefore, $cov\,(v, S_{vk}) = \frac{\sigma_v^2}{M}$. 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 $\delta_k \equiv E\,(v|S_{vk}) = \frac{\sigma_v^2}{M\sigma_s^2} S_{vk}$ and $E\left(\delta_j|\delta_k\right) = \gamma\delta_k$, where $\gamma = \frac{\sigma_{ss}}{\sigma_s^2}$ is the correlation between any two private 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 $S_{vk} = \frac{v}{M}$ 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, that speculator's 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 $p_1 = p_1(\omega_1)$.

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

1. *Profit maximization*: $x_k(S_{vk}) = \arg\max E(\pi_k | S_{vk})$; and
2. *Semistrong 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.

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

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

and by the k-th speculator's demand strategy

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

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

The optimal trading strategy of each speculator depends on the information received about the asset payoff (v) and on the depth of the

[4] The assumption that the total amount of information available to speculators is fixed ($\sum_{k=1}^{M} S_{vk} = v$) 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.

market (λ^{-1}). If $M = 1$, Equations (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.

1.1.2 Testable implications. The intuition behind the parsimonious equilibrium of Equations (1) and (2) is similar to that in the multiperiod 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 —that is, 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 $x_k = \frac{\sigma_u}{\sigma_v\sqrt{M}}v$, which implies that the finite difference $\triangle M x_k = (M+1)\,x_k - M x_k = \frac{\sigma_u}{\sigma_v}\left(\sqrt{M+1} - \sqrt{M}\right) v > 0$. 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 monopolistic power on the private signal, because at least part of the information is exclusively known. Hence, as a group, they trade more cautiously—that is,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 $\sum_{k=1}^{M} x_k = \frac{\sigma_u}{\sigma_v} v < \frac{\sigma_u M}{\sigma_v\sqrt{M}} v$, that is, 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 "quasimonopolistic" 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.

[5] This 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).

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, and 4. 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

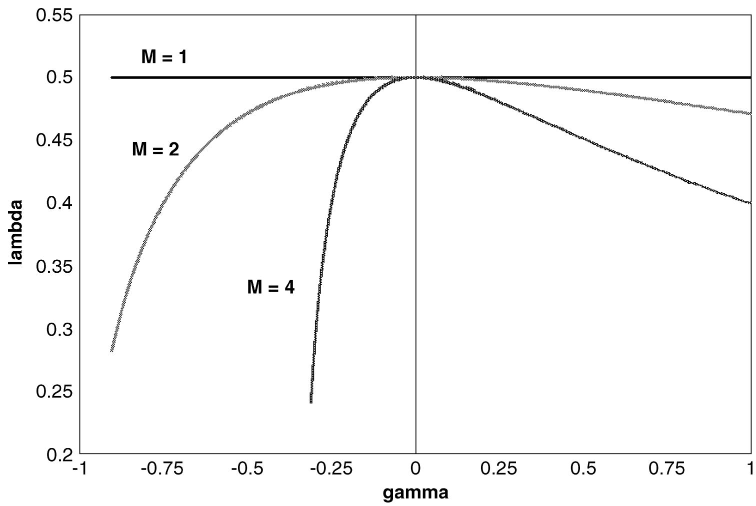

Figure 1
Equilibrium without a public signal

In this figure we plot 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, or 4 speculators, when $\sigma_v^2 = \sigma_u^2 = 1$. Since $\sigma_s^2 = \frac{\sigma_v^2 + M(M-1)\chi}{M^2}$, $\sigma_{ss} = \frac{\sigma_v^2 - M\chi}{M^2}$, and $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$, the range of correlations compatible with a positive definite Σ_s is obtained by varying the parameter $\chi = \sigma_s^2 - \sigma_{ss}$ within the interval [0, 10] when $M = 2$, and the interval [0, 5] when $M = 4$.

her own (pushing p_1 against her signal), hence trading on it to be more profitable.

1.2 Extension: a public signal

We now extend the basic model of Section 1.1 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, 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 zero and variance $\sigma_p^2 > \sigma_v^2$. We can think of S_p as any surprise public announcement (e.g. macroeconomic news) released simultaneously to all market participants. We further impose that $cov\left(S_p, v\right) = \sigma_v^2$, so that the parameter σ_p^2 controls for the quality of the public signal and $cov\left(S_p, S_{vk}\right) = \frac{\sigma_v^2}{M}$. The private information endowment of each speculator is then given by $\delta_k^* \equiv E\left(v|S_{vk}, S_p\right) - E\left(v|S_p\right) = \alpha S_{vk} + \beta S_p$, where $\alpha = \frac{M\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_p^2\left[\sigma_v^2+M(M-1)\chi\right]-\sigma_v^4} > 0$ and $\beta = -\frac{\sigma_v^4\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_p^2\{\left[\sigma_v^2+M(M-1)\chi\right]-\sigma_v^4\}} < 0$. Thus, $E\left(\delta_j^*|\delta_k^*\right) = E\left(\delta_j^*|S_{vk}, S_p\right) = \gamma_p\delta_k^*$, where $\gamma_p = \frac{M\alpha^2\sigma_{ss}+2\alpha\beta\sigma_v^2+M\beta^2\sigma_p^2}{M\alpha^2\sigma_s^2+2\alpha\beta\sigma_v^2+M\beta^2\sigma_p^2} \leq \gamma$.

1.2.1 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*

$$p_1 = \lambda_p\omega_1 + \lambda_s S_p \tag{3}$$

and by the k-th speculator's demand strategy

$$x_k = \frac{\lambda_p^{-1}}{2 + (M-1)\gamma_p}\delta_k^*, \tag{4}$$

[6] Admati 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 and Verrecchia (1991) argue that the disclosure of public information may reduce the volatility of the order flow, leading some MMs 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.

where $\lambda_p = \frac{\alpha^{\frac{1}{2}}\sigma_v\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]} > 0$ *and* $\lambda_s = \frac{\sigma_v^2}{\sigma_p^2}$.

The optimal trading strategy of each speculator in Equation (4) mirrors that of Proposition 1 [Equation (2)], yet it now depends only on δ_k^*, the truly private—hence less correlated ($\gamma_p \leq \gamma$)—component of speculator k's original private signal (S_{vk}) in the presence of a public signal of v. Hence, the MMs' belief update about v stemming from S_p makes speculators' private information less valuable. The resulting equilibrium price p_1 in Equation (3) can be rewritten as:

$$p_1 = \frac{\alpha}{2+(M-1)\gamma_p}v + \lambda_p u + \left[\lambda_s + \frac{M\beta}{2+(M-1)\gamma_p}\right]S_p. \tag{5}$$

According to Equation (5), the public signal impacts p_1 through two channels that [in the spirit of Evans and Lyons (2003)] we call *direct*, related to MMs' belief updating process ($\lambda_s > 0$), and *indirect*, via the speculators' trading activity ($\beta < 0$). Since $\lambda_s\left[2+(M-1)\gamma_p\right] > -M\beta > 0$, the former always dominates the latter. Therefore, public news always enter the equilibrium price with the "right" sign.

1.2.2 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 2

[7] Specifically, 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.

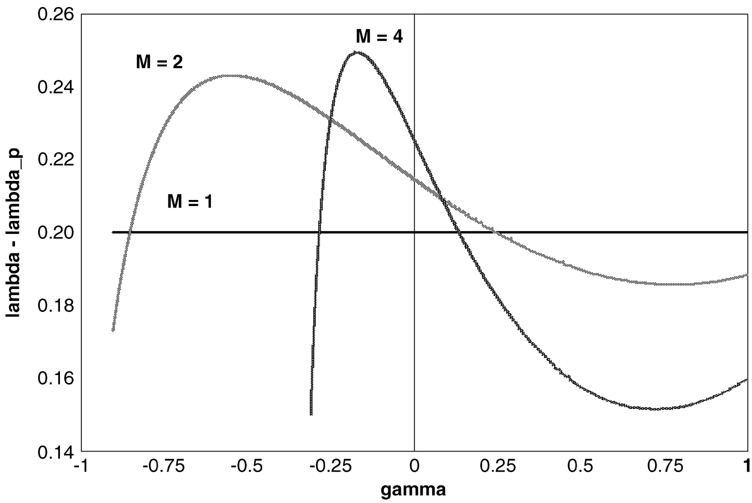

Figure 2
Equilibrium with a public signal
In this figure we plot the difference between the sensitivity of the equilibrium price to the order flow in the absence and in the presence of a public signal S_p, $\lambda - \lambda_p$, as a function of the degree of correlation of the speculators' signals, γ, in the presence of $M = 1$, 2, or 4 speculators, when $\sigma_v^2 = \sigma_u^2 = 1$. According to Proposition 1, $\lambda = \frac{\sigma_v^2}{\sigma_u \sigma_s \sqrt{M}[2+(M-1)\gamma]}$, while $\lambda_p = \frac{\alpha^{\frac{1}{2}} \sigma_v \left(\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}}{\sigma_u \sigma_p \left[2+(M-1)\gamma_p\right]}$ in Proposition 2, where $\gamma_p = \frac{\sigma_p^2\left(\sigma_v^2 - M\chi\right) - \sigma_v^4}{\sigma_p^2\left[\sigma_v^2 + M(M-1)\chi\right] - \sigma_v^4}$ and $\alpha = \frac{M\sigma_v^2\left(\sigma_p^2 - \sigma_v^2\right)}{\sigma_p^2\left[\sigma_v^2 + M(M-1)\chi\right] - \sigma_v^4}$. Since $\sigma_s^2 = \frac{\sigma_v^2 + M(M-1)\chi}{M^2}$, $\sigma_{ss} = \frac{\sigma_v^2 - M\chi}{M^2}$, and $\gamma = \frac{\sigma_v^2 - M\chi}{\sigma_v^2 + M(M-1)\chi}$, the range of correlations compatible with a positive definite Σ_s is obtained by varying the parameter $\chi = \sigma_s^2 - \sigma_{ss}$ within the interval [0, 10] when $M = 2$, and the interval [0, 5] when $M = 4$.

we plot the ensuing gain in liquidity, $\lambda - \lambda_p$, as a function of private signal correlations γ when the public signal's noise $\sigma_p = 1.25$, that is, 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.*

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 γ 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 Equation (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 Equation (1): $\lim_{\sigma_p \to \infty} \lambda_s = 0$ and $\lim_{\sigma_p \to \infty} \lambda_p = \lambda$.

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

2. Data Description

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

2.1 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 et al. (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 article, 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).[8] 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 (2003) appendix.

We report summary statistics for the daily raw yield and transaction data in Table 1. Bond yields are in percentage, that is, were multiplied by 100; bond yield changes are in basis points, that is, were multiplied by 10, 000. Not surprisingly, mean Treasury bond yields increase 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.

We also compare (but do not report here for economy of space) 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 nonannouncement days.[9]

[8] In our sample period (1992 to 2000), 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 article.

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

Table 1
GovPX Transaction data: summary statistics

	Mean	Stdev.	Max.	Min.	$\rho(1)$
			Two-year		
Daily yield × 100	5.49	0.89	7.73	3.70	0.998
Daily yield change × 10,000	0.05	6.10	35.10	−31.10	0.041
Number of buys	202.07	80.00	604	25	0.559
Number of sells	170.77	69.89	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	5.97	0.74	7.90	3.98	0.996
Daily yield Change × 10,000	−0.01	6.39	35.10	−29.30	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	6.26	0.74	8.03	4.16	0.997
Daily yield change × 10,000	−0.04	5.99	33.60	−23.00	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

In this table we report the mean, standard deviation, maximum, minimum, and first-order autocorrelation coefficient ($\rho(1)$) for the following variables: Two-year, five-year, and ten-year on-the-run 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 Equation (8). The data source is GovPX. Our sample period starts in January 2, 1992 and ends in December 29, 2000, for a total of 2 246 daily observations.

Bond yield changes are clearly more volatile on days when the Payroll numbers are announced, but yield changes during nonannouncement days are economically significant as well. These dynamics, together with the poor performance of public macroeconomic surprises in explaining fluctuations in bond yields on nonannouncement days, further motivate our study of the price discovery role of order flow when no public news arrives to the bond market.

2.2 Macroeconomic data

2.2.1 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. Fleming and Remolona (1997) and Andersen et al. (2003) discuss the main properties of MMS forecasts; Balduzzi et al. (2001) show that these forecasts are not stale and unbiased.

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

$$S_{jt} = \frac{A_{jt} - E_{jt}}{\widehat{\sigma}_j}, \tag{6}$$

Table 2
Macroeconomic news announcements and dispersion of beliefs

	Obs.	Source	Time	Mean	Stdev.	$\rho(Payroll)$	$\rho(1)$
			Quarterly announcements				
1- *GDP advance*	36	BEA	8:30	0.480	0.170	0.162*	−0.181
2- *GDP preliminary*	34	BEA	8:30	0.313	0.178	0.014	0.192
3- *GDP final*	35	BEA	8:30	0.128	0.051	0.083	0.250
			Monthly announcements				
Real Activity							
4- *Nonfarm payroll emp.*	108	BLS	8:30	41.814	14.212	1.000	0.424***
5- *Retail sales*	108	BC	8:30	0.302	0.158	0.109	0.047
6- *Industrial production*	107	FRB	9:15	0.183	0.135	0.236**	0.358***
7- Capacity utilization	107	FRB	9:15	n.a.	n.a.	n.a.	n.a.
8- Personal income	105	BEA	10:00/8:30	n.a.	n.a.	n.a.	n.a.
9- Consumer credit	108	FRB	15:00	n.a.	n.a.	n.a.	n.a.
Consumption							
10- *New home sales*	106	BC	10:00	19.270	10.235	0.151	0.099
11- Pers. cons. exp.	107	BEA	10:00/8:30	n.a.	n.a.	n.a.	n.a.
Investment							
12- *Durable goods orders*	106	BC	8:30/9:00/10:00	1.034	0.333	0.077	0.412***
13- *Factory orders*	105	BC	10:00	0.587	0.577	0.219**	0.015
14- *Construction spending*	105	BC	10:00	0.499	0.253	0.176*	0.192***
15- Business inventories	106	BC	10:00/8:30	n.a.	n.a.	n.a.	n.a.
Government purchases							
16- Government budget	107	FMO	14:00	n.a.	n.a.	n.a.	n.a.
Net exports							
17- *Trade balance*	107	BEA	8:30	0.790	0.851	0.122	0.018

Table 2
(Continued)

	Obs.	Source	Time	Mean	Stdev.	$\rho(Payroll)$	$\rho(1)$
Prices							
18- *Producer price index*	108	BLS	8:30	0.130	0.049	0.186*	0.287***
19- *Consumer price index*	107	BLS	8:30	0.086	0.051	0.146	0.221***
Forward-looking							
20- *Consumer conf. index*	106	CB	10:00	1.646	0.609	0.079	0.230***
21- *NAPM index*	107	NAPM	10:00	0.961	0.303	0.242**	0.382***
22- *Housing starts*	106	BC	8:30	0.045	0.038	0.160	0.246***
23- *Index of leading Ind.*	108	CB	8:30	0.202	0.137	0.134	0.480***
			Six-Week announcements				
24- Target fed funds rate	71	FRB	14:15	n.a.	n.a.	n.a.	n.a.
			Weekly announcements				
25- *Initial unemp. claims*	459	ETA	8:30	7.973	5.440	0.069	0.578***

In this table we report the number of observations, source, and release time for the 25 U.S. macroeconomic announcements in our sample. We also report summary statistics for the corresponding standard deviation across professional forecasts, our proxy for dispersion of beliefs among market participants (SD_{jt}), whenever available. Specifically, we report the mean, standard deviation, Spearman rank correlation with the Nonfarm Payroll Employment standard deviation [$\rho(Payroll)$], and the first-order autocorrelation coefficient [$\rho(1)$] for each series SD_{jt}. A " * ", " ** ", or " *** " indicate the latter two measures' significance at the 10%, 5%, or 1% level, respectively. The release time in the table, in Eastern Standard Time (EST, with Daylight savings time starting on the first Sunday of April and ending on the last Sunday of October), is constant throughout the sample except in the following circumstances: In 01/94, the personal income announcement time moved from 10:00 A.M. to 8:30 A.M.; beginning in 01/96, consumer credit was released regularly at 3:00 P.M. while prior to this date, its release times varied; in 12/93, the personal consumption expenditures announcement time moved from 10:00 A.M. to 8:30 A.M.; 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.; in 01/97, the business inventory announcement was moved from 10:00 A.M. to 8:30 A.M.; beginning in 3/28/94, the Fed funds rate was released regularly at 2:15 P.M., while prior to this date, the release times varied. The sources for the MMS data are: 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), and Employment and Training Administration (ETA). The standard deviation across professional forecasts of 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) is not available. The announcements for which SD_{jt} is available are italicized.

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 $\widehat{\sigma}_j$ is the sample standard deviation (SSD) of $A_{jt} - E_{jt}$. Equation (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 $\widehat{\sigma}_j$ is constant for any indicator j, the standardization affects neither the statistical significance of response estimates nor the fit of the regressions.

2.2.2 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 et al. (2002) and 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.

Overall, the dispersion of beliefs is large (e.g. roughly 22% on average of the mean absolute monthly Nonfarm Payroll Employment report), time-varying, and positively correlated across macroeconomic announcements. To conserve space, we do not show the correlation matrix of all the announcements, but only report (in Table 2) the pairwise correlation between each announcement and arguably the most important of them, the Nonfarm Payroll Employment report [e.g. Andersen and Bollerslev (1998), Andersen et al. (2004), and Brenner et al. (2005)]. This correlation is positive, albeit not statistically significant for most of the announcements. Thus, dispersion of beliefs in Nonfarm Payroll Employment 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 nonannouncement days: one based exclusively on the Payroll announcement, another based on 7 "influential" announcements (defined below), and the last one based on the 18 announcements for which the standard deviation of professional forecasts is available (i.e. those italicized in Table 2).

The use of the MMS database to calculate monthly measures of dispersion of beliefs raises two issues: (i) the announcements in Table 2 are released at different frequencies and (ii) the standard deviation of professional forecasts only measures heterogenous 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 [ρ (1) in Table 2] 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,

$$SSD_{Pt} = \sum\nolimits_{j=1}^{P} \frac{SD_{jt} - \widehat{\mu}(SD_{jt})}{\widehat{\sigma}(SD_{jt})}, \tag{7}$$

where SD_{jt} is the standard deviation of announcement j across professional forecasts and $\widehat{\mu}(SD_{jt})$ and $\widehat{\sigma}(SD_{jt})$ 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.[10] Lastly, P is equal to 18 when we use all the announcements for which the measure SSD_{Pt} is available in our sample (i.e. those italicized in Table 2). The standardization in Equation (7) is necessary because, as we mentioned earlier, units of measurement differ across economic variables.

We use the monthly dispersion estimates from these three methodologies to classify days in which the corresponding monthly variable SSD_{Pt} is above (below) the top (bottom) 70th (30th) percentile of its empirical distribution as days with high (low) information heterogeneity. The resulting time series of high (+1) and low (−1) dispersion days are positively correlated: Their correlations (not reported here) 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 3 the differences in the mean daily number of transactions (NT_t) 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 Griffiths et al. (2000) and Ranaldo (2004), among others (but also with the spirit of the model of Section 1), we interpret a big (small)

[10] In unreported analysis, we show that these announcements represent the most important information events in the U.S. Treasury market, that is, the only ones having a statistically significant impact on day-to-day bond yield changes, consistent with Fleming and Remolona (1997), among others.

Table 3
Dispersion of beliefs and traders aggressiveness

Announcement	b_h	b_m	b_l	$b_h - b_l$	R_a^2
			Two-Year		
Nonfarm payroll employment	366.687	362.978	374.983	−8.296	86.05%
s.e.	5.729	4.811	5.773	8.133	
Influential announcements	317.836	372.472	409.360	−91.524***	86.80%
s.e.	5.596	4.684	5.665	7.963	
All announcements	321.120	362.468	421.500	−100.38***	86.95%
s.e.	5.543	4.655	5.659	7.921	
			Five-Year		
Nonfarm payroll employment	603.503	570.535	648.080	−44.576***	85.73%
s.e.	9.475	7.958	9.541	13.447	
Influential announcements	562.774	626.650	599.127	−36.353***	85.54%
s.e.	9.617	8.044	9.721	13.675	
All announcements	534.212	607.237	657.696	−123.484***	85.91%
s.e.	9.459	7.937	9.642	13.507	
			Ten-Year		
Nonfarm payroll employment	530.563	505.908	570.922	−40.359***	85.56%
s.e.	8.353	7.015	8.411	11.854	
Influential announcements	496.024	554.288	527.157	−31.132***	85.55%
s.e.	8.490	7.096	8.576	12.068	
All announcements	452.617	546.248	584.260	−131.643***	86.20%
s.e.	8.266	6.931	8.420	11.799	

In this table we report 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 forecasts of the Nonfarm Payroll Employment report. Second, we aggregate the standard deviation of forecasts 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 available macroeconomic news announcements italicized in Table 2. R_a^2 is the adjusted R^2. All reported coefficient estimates for b_h, b_m, and b_l are statistically significant at the 1% level. A " * ", " ** ", or "*** " indicate significance of the difference $b_h - b_l$ at the 10%, 5%, or 1% level, respectively, using the Newey-West standard errors reported below each coefficient estimate (s.e.).

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. $b_h - b_l < 0$). Consistently, Spearman correlations between NT_t and either SSD_{1t}, SSD_{7t}, or SSD_{18t} (not reported here) are always negative for all maturities and mostly statistically significant. This evidence provides support for the basic intuition of our model and gives us further confidence in the heterogeneity proxies of Equation (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 1.1.1.

2.2.3 News or noise?. The U.S. government often revises previously released macroeconomic information. Aruoba (2004) identifies these data revisions as either "informative," that is, due to newly available information, or "uninformative," that is, due to definitional changes (such as changes in the base-year or changes in seasonal weights). In this article, we use the former revisions to measure public signal noise. Specifically, we use the Federal Reserve Bank of Philadelphia's "Real Time Data Set" (RTDS), which records not only real-time macroeconomic announcements but also their subsequent revisions.[11] Of the 18 announcements in Table 2 for which MMS forecasts are available, the RTDS contains monthly data on Capacity Utilization, Industrial Production, and the Nonfarm Payroll Employment report. The only variable undergoing "uninformative" changes over the sample period is Industrial Production, whose base-year was revised in February 1998. According to extant literature [e.g. Mork (1987), Aruoba (2004), and Faust et al. (2005)], (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).[12] 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 1.2), not its direction, we use the absolute value of this difference in our empirical analysis.

Consistent with Aruoba (2004), the resulting time series of simple and absolute macroeconomic data revisions—that is, the simple and absolute differences between the real-time announcement and the final revision for Capacity Utilization, Industrial Production, and Nonfarm Payroll Employment—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

[11] See Croushore and Stark (1999, 2001) for details of this database and examples of empirical applications. The database is available on the website of the Federal Reserve Bank of Philadelphia, at http://www.phil.frb.org/econ/forecast/reaindex.html.

[12] Much 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 et al. (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.

announcement, with correlations (not reported here) varying between a low of 0.18 (Industrial Production) and a high of 0.52 (Nonfarm Payroll Employment). 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.

3. Empirical Analysis

The model of Section 1 generates several implications that we now test in this section. In the database described in Section 2, we are able to directly observe price changes, $P_t - P_{t-1}$, as a proxy for p_1, public news surprises S_{jt}, as a proxy for S_p, 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 Equations (1) and (3).[13] 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 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),

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

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 Equation (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.[14] 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 Equation (8) within each day, $\Omega_t^* = \sum_{t_{in}=1}^{19} v(x)_{t-1+\frac{t_{in}}{19}}$, as a

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

[14] Our results are also robust to different specifications of Equation (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 (2006). 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 Equation (8) are lower than 4%.

proxy for ω_1. 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, the results are robust to either specification. We translate the equilibrium prices of Propositions 1 and 2 into the following estimable equations:

$$r_t = a + \lambda\Omega_t^* + \varepsilon_t \tag{9}$$

when no public signal is released [Equation (1)], and

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

when a public signal S_{jt} becomes available to all market participants on day t [Equation (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.

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 Equations (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 a negative and significant, or statistically insignificant, impact of lagged unanticipated net order flow on yield changes.

3.1 Non-announcement days

We start by estimating Equation (9) across nonannouncement 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 nonannouncement days consistently with our procedures to measure such heterogeneity (in Section 2.2.2). When $P = 1$, we define nonannouncement 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 nonannouncement days as all trading days when none of the corresponding announcements (either the influential ones or those italicized in Table 2) take place. We then test Corollary 1 by amending Equation (9) as follows:

$$r_t = a + \sum\nolimits_{i=0}^{N} \lambda_{hi}\Omega^*_{t-i}D_{ht} + \sum\nolimits_{i=0}^{N} \lambda_{li}\Omega^*_{t-i}D_{lt} + \sum\nolimits_{i=0}^{N} \lambda_{mi}\Omega^*_{t-i}(1 - D_{ht} - D_{lt}) + \sum\nolimits_{i=1}^{N} \beta_i r_{t-i} + \varepsilon_t, \qquad (11)$$

where D_{ht} (D_{lt}) is a dummy variable equal to one on nonannouncement days with high (low) heterogeneity of beliefs, as defined in Section 2.2.2, 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 Equation (11).[15] 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 nonannouncement 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

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

dispersion of beliefs about Nonfarm Payroll Employment announcements ($P = 1$).

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 Employment report 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 1.1: In the absence of a public signal, greater information heterogeneity among investors translates into greater adverse selection risk for the MMs, 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 SSD_{1t} (i.e. only with respect to the volatility of Nonfarm Payroll Employment forecasts), we find that a one standard deviation shock to unanticipated order flow in 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 ($R^2_{ha} = 41.38\%$) than during low dispersion days ($R^2_{la} = 9.65\%$).

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 Employment 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.

3.1.1 Omitted variable biases. In the model of Section 1, 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 Equation (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 Equation (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 the 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 Equation (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 Equation (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 nonsynchronous 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 Equation (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 Equation (11) additional variables capturing the interaction between (i.e. the product of): (i) order flow and daily realized volatility,[16] (ii) order flow and the number of transactions (NT_t), and (iii) order flow and a weight linearly increasing

[16] We estimate realized volatility applying the procedure of Andersen et al. (2003) to yield mid-quotes sampled at an "optimal" frequency determined according to Bandi and Russell (2006).

Table 4
Market liquidity on non−announcement days

Announcement	λ_{h0}	λ_{m0}	λ_{l0}	$\lambda_{h0}-\lambda_{l0}$	$\sum_{i=0}^{5}\lambda_{hi}$	$\sum_{i=0}^{5}\lambda_{mi}$	$\sum_{i=0}^{5}\lambda_{li}$	R^2_{ha}	R^2_{la}	R^2_a
					Two-year					
Nonfarm payroll	−0.213***	−0.182***	−0.121***	−0.092***	−0.161**	−0.182***	−0.072	28.54%	6.66%	21.69%
s.e.	0.033	0.025	0.034	0.048	0.067	0.050	0.056			
Influential	−0.140***	−0.108***	−0.080***	−0.060***	−0.106***	−0.096***	−0.049**	14.61%	10.65%	15.52%
s.e.	0.016	0.010	0.010	0.019	0.031	0.022	0.022			
All	−0.122***	−0.093***	−0.098***	−0.024	−0.152***	−0.086***	−0.086***	15.46%	16.92%	15.83%
s.e.	0.017	0.012	0.014	0.022	0.032	0.024	0.027			
					Five-year					
Nonfarm payroll	−0.210***	−0.153***	−0.085***	−0.125***	−0.285***	−0.136***	0.019	41.38%	9.65%	23.30%
s.e.	0.029	0.022	0.027	0.040	0.078	0.049	0.062			
Influential	−0.151***	−0.122***	−0.087***	−0.064***	−0.142***	−0.106***	−0.050**	19.14%	11.97%	20.31%
s.e.	0.014	0.010	0.010	0.018	0.036	0.022	0.025			
All	−0.155***	−0.097***	−0.102***	−0.053***	−0.167***	−0.079***	−0.083***	21.37%	18.76%	19.40%
s.e.	0.017	0.012	0.013	0.022	0.041	0.027	0.029			

	Ten-year									
Nonfarm payroll	−0.170***	−0.129***	−0.071	−0.099	−0.192**	−0.269***	−0.017	15.10%	1.02%	10.29%
s.e.	0.043	0.032	0.043	0.061	0.093	0.058	0.079			
Influential	−0.081***	−0.093***	−0.079***	−0.002	−0.075**	−0.109***	−0.053	2.83%	4.72%	6.05%
s.e.	0.018	0.013	0.013	0.025	0.035	0.027	0.042			
All	−0.075***	−0.086***	−0.071***	−0.004	−0.109**	−0.119***	−0.097**	3.82%	4.43%	6.16%
s.e.	0.023	0.017	0.019	0.029	0.053	0.033	0.038			

In this table we report estimates of the following regression model [Equation (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 3), D_{ht} (D_{lt}) is a dummy variable equal to one on nonannouncement days (defined in Section 3.1) 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 2.2.2). In the third, we aggregate the standard deviations of forecasts across all macroeconomic news announcements for which the standard deviation across professional forecasters is available (italicized in Table 2). R^2_{ha} (R^2_{la}) is the adjusted R^2 conditional on high (low) dispersion days, while R^2_a is the adjusted R^2 including all observations. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using the Newey-West standard errors reported below each coefficient estimate (s.e.).

as the announcement date approaches.[17] In our model, the degree of information heterogeneity affects both equilibrium price volatility and the aggressiveness of informed trading (proxied by NT_t, as in Section 2.2.2). Depending on the strength of these effects, the inclusion of those cross terms in Equation (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 NT_t 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.[18] This is not surprising, since we expect informed investors to be more 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 Equation (11).

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 Equation (11).[19] 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 Equation (11) may control for the 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.

[17] Presumably, 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 Employment announcements (i.e. SSD_{1t}), since then we only use the Fridays before the announcement dates to control for potential day-of-the-week effects.

[18] The resulting adjusted R^2 from the introduction of this cross term in Equation (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 Employment ($P = 1$), "influential" ($P = 7$), and all available macroeconomic news announcements ($P = 18$), respectively.

[19] The 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.

3.2 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 MMs. In our empirical analysis, this translates into observing a negative difference (since we work with yields) between λ [of Equation (1)] and λ_p [of Equation (3)] in the following regression:

$$\begin{aligned} r_t &= a + \sum\nolimits_{i=0}^{N} \lambda_i \Omega^*_{t-i}(1 - D_{Pt}) + \sum\nolimits_{i=0}^{N} \lambda_{pi} \Omega^*_{t-i} D_{Pt} \\ &\quad + \sum\nolimits_{i=1}^{N} \beta_i r_{t-i} + \varepsilon_t, \end{aligned} \tag{12}$$

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 italicized in Table 2 ($P = 18$) is released on day t and equal to zero otherwise. As in Equation (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 Equation (12) for each announcement type $P = 1$, 7, 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). 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 in Equation (3)] were noisy, since $\lim_{\sigma_p \to \infty} \lambda_p = \lambda$. Yet, our model (Corollary 3) also implies that noisy public signals should have little or no impact on price changes (i.e. $\lim_{\sigma_p \to \infty} \lambda_s = 0$ as well). This interpretation, although intriguing, is not exhaustive since in unreported analysis 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

Table 5
Market liquidity in announcement and nonannouncement days

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%
s.e.	0.021	0.027	0.034	0.041	0.064			
Influential	−0.103***	−0.112***	0.009	−0.075***	−0.059***	15.34%	12.29%	13.98%
s.e.	0.008	0.008	0.011	0.016	0.019			
All	−0.102***	−0.109***	0.007	−0.096***	−0.059***	16.00%	13.24%	13.99%
s.e.	0.011	0.006	0.013	0.023	0.015			
				Five-year				
Nonfarm payroll	−0.124***	−0.168***	0.044**	−0.121***	−0.242***	21.03%	19.61%	21.37%
s.e.	0.017	0.025	0.019	0.043	0.062			
Influential	−0.117***	−0.137***	0.020*	−0.095***	−0.137***	19.88%	20.88%	20.76%
s.e.	0.007	0.008	0.011	0.017	0.020			
All	−0.115***	−0.131***	0.016	−0.107***	−0.115***	20.29%	20.48%	20.70%
s.e.	0.011	0.006	0.012	0.024	0.016			
				Ten-year				
Nonfarm payroll	−0.087***	−0.053*	−0.034	−0.181***	−0.020	6.74%	3.59%	7.07%
s.e.	0.025	0.030	0.048	0.049	0.088			
Influential	−0.086***	−0.086***	0.000	−0.083***	−0.086***	6.73%	5.73%	6.52%
s.e.	0.010	0.011	0.015	0.021	0.026			
All	−0.077***	−0.090***	0.013	−0.103***	−0.076***	7.08%	5.99%	6.49%
s.e.	0.014	0.009	0.017	0.030	0.019			

In this table we report estimates of the following regression model [Equation (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 3), D_{Pt} is a dummy variable equal to one if either the Nonfarm Payroll Employment report ($P = 1$), any of the seven "influential" announcements listed in Section 2.2.2 ($P = 7$), or any of the announcements for which the standard deviation across professional forecasters is available ($P = 18$, italicized in Table 2) 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 Equation (12) over just nonannouncement (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 the Newey–West standard errors reported below each coefficient estimate (s.e.).

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 30-minute interval immediately after an announcement than during the thirty-minute interval immediately before the announcement or on nonannouncement days.

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 Equation (12) is always higher for nonannouncement 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 impact of unanticipated order flow in either the two-year or the ten-year Treasury notes on the corresponding yield changes is permanent during nonannouncement days (statistically significant $\sum_{i=0}^{5} \lambda_i$ in Table 5), but only transitory during Nonfarm Payroll Employment announcement days (statistically insignificant $\sum_{i=0}^{5} \lambda_{pi}$ in Table 5). This suggests that dealers rely more heavily on unanticipated order flow to set bond prices during nonannouncement days than on announcement days, consistent with our model and the findings in Brandt and Kavajecz (2004).

Overall, the evidence reported in Table 5 indicates (albeit not as strongly as in Section 3.1) that the release of public signals does not increase (and occasionally reduces) adverse selection costs and does not impair (and occasionally improves) market liquidity. Nonetheless, both the above discussion and the comparative statics of Figure 2 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.

3.2.1 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 Equation (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 a dummy equal to one on days with high (low) dispersion of beliefs (identified in Section 2.2.2) and $N = 5$, to account for multiple signals arriving on the same day. 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 Equation (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 MMs. 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 MMs and improving market liquidity [i.e. $\lambda_{ph0} - \lambda_{pl0} > 0$ in Equation (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 Employment 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 3.2 that public signal noise is "sufficiently" high in our sample. In Section 3.2.3, 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 1.2, a public signal can induce price (and yield) changes through two channels that, in the spirit of Evans and Lyons (2003), we call direct (through MMs' 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 Equation (13), that is, 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.

3.2.2 Public signal noise. Many of the results in Section 3.2.1 are generally weaker in correspondence with the aggregate proxies for information heterogeneity described in Equation (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 Equation (7) and the corresponding classification of announcement days implicitly assume that all U.S. macroeconomic news releases listed in Table 2 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.

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

Table 6
Public signals and market liquidity

Announcement	$\overline{\lambda_{sp}}$	λ_{ph0}	λ_{pm0}	λ_{pl0}	$\lambda_{ph0} - \lambda_{pl0}$	$\sum_{i=0}^{5} \lambda_{phi}$	$\sum_{i=0}^{5} \lambda_{pmi}$	$\sum_{i=0}^{5} \lambda_{pli}$	R^2_{fha}	R^2_{fla}	R^2_{fa}	R^2_a
						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%
s.e.	0.883	0.060	0.047	0.092	0.014	0.151	0.113	0.176				
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%
s.e.	0.322	0.019	0.012	0.016	0.024	0.047	0.031	0.036				
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%
s.e.	0.196	0.015	0.010	0.012	0.020	0.034	0.026	0.027				
						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%
s.e.	0.855	0.065	0.042	0.049	0.034	0.161	0.097	0.138				
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%
s.e.	0.318	0.017	0.012	0.015	0.023	0.048	0.030	0.038				
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%
s.e.	0.194	0.014	0.010	0.012	0.019	0.039	0.025	0.027				

(continued overleaf)

Table 6
(Continued)

Announcement	$\overline{\lambda_{sp}}$	λ_{ph0}	λ_{pm0}	λ_{pl0}	$\lambda_{ph0}-\lambda_{pl0}$	$\sum_{i=0}^{5}\lambda_{phi}$	$\sum_{i=0}^{5}\lambda_{pmi}$	$\sum_{i=0}^{5}\lambda_{pli}$	R^2_{fha}	R^2_{fla}	R^2_{fa}	R^2_a
						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%
s.e.	0.815	0.097	0.081	0.105	0.143	0.206	0.178	0.224				
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%
s.e.	0.329	0.024	0.018	0.023	0.033	0.062	0.039	0.057				
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%
s.e.	0.199	0.021	0.014	0.018	0.021	0.051	0.032	0.037				

In this table we report estimates of the following regression model [Equation (14)]:

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

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 3), 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 3.2). The coefficient $\overline{\lambda_{sp}}$ is the estimated price impact of the Nonfarm Payroll Employment report ($P = 1$) or the average estimated impact across either the "influential" ($P = 7$) or all ($P = 18$) macroeconomic announcements for which the standard deviation across professional forecasters is available (i.e. those italicized in Table 2). R^2_{fha} (R^2_{fla}) is the adjusted R^2 conditional on high (low) dispersion days and only using Ω^*_t, R^2_{fa} is the unconditional adjusted R^2 using only Ω^*_t, and R^2_a is the adjusted R^2 of the fully specified regression above. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using the Newey–West standard errors reported below each coefficient estimate (s.e.).

in which they occur are effectively nonannouncement days), or some announcements might be noisier than others. According to our 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 MMs rely more heavily on the order flow than on the public signal, thus requiring greater compensation for providing liquidity. The evidence in Table 7 supports this claim. There we report estimates of the following equation:

$$r_t = a + \lambda_{snh} S_{pt} D_{nht} + \lambda_{snl} S_{pt} D_{nlt} + \lambda_{snm} S_{pt} (1 - D_{nht} - D_{nlt}) + \sum_{i=0}^{N} \lambda_{pnhi} \Omega^*_{t-i} D_{nht} + \sum_{i=0}^{N} \lambda_{pnli} \Omega^*_{t-i} D_{nlt} + \sum_{i=0}^{N} \lambda_{pnmi} \Omega^*_{t-i} (1 - D_{nht} - D_{nlt}) + \sum_{i=1}^{N} \beta_i r_{t-i} + \varepsilon_t, \tag{14}$$

where D_{nht} (D_{nlt}) is a dummy variable equal to one on announcement days with high (low) public signal noise, defined in Section 2.2.3 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 Employment, 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 7 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 $\sum_{i=0}^{5} \lambda_{pnli}$ in Table 7), 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 ($D_{nlt} = 1$), that is, $R^2_{fnha} > R^2_{fnla}$; 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 1.2, albeit not importantly so.

Table 7
Public signal noise and market liquidity

Ann.	λ_{snh}	λ_{snm}	λ_{snl}	λ_{pnh0}	λ_{pnm0}	λ_{pnl0}	$\sum_{i=0}^{5}\lambda_{pnhi}$	$\sum_{i=0}^{5}\lambda_{pnmi}$	$\sum_{i=0}^{5}\lambda_{pnli}$	R^2_{sa}	R^2_{fnha}	R^2_{fnla}	R^2_{a}
							Two-year						
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%
s.e.	1.678	1.288	1.609	0.067	0.050	0.062	0.191	0.140	0.152				
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%
s.e.	0.916	1.035	1.337	0.043	0.034	0.058	0.092	0.090	0.116				
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%
s.e.	1.011	0.866	1.521	0.045	0.030	0.069	0.105	0.070	0.114				
							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%
s.e.	1.580	1.202	1.546	0.052	0.053	0.052	0.158	0.131	0.111				
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%
s.e.	0.963	1.125	1.597	0.043	0.034	0.067	0.113	0.094	0.138				
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%
s.e.	0.904	0.962	1.588	0.053	0.031	0.063	0.106	0.085	0.163				

						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%
s.e.	1.648	1.209	1.615	0.101	0.087	0.085	0.220	0.182	0.183				
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%
s.e.	0.991	1.084	1.538	0.077	0.073	0.078	0.142	0.11	0.143				
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%
s.e.	0.994	1.008	1.443	0.089	0.058	0.074	0.137	0.103	0.135				

In this table we report estimates of the following regression model [Equation (14)]:

$$r_t = a + \lambda_{snh} S_{pt} D_{nht} + \lambda_{snl} S_{pt} D_{nlt} + \lambda_{snm} S_{pt} (1 - D_{nht} - D_{nlt}) + \sum_{i=0}^{N} \lambda_{pnhi} \Omega^*_{t-i} D_{nht}$$
$$+ \sum_{i=0}^{N} \lambda_{pnli} \Omega^*_{t-i} D_{nlt} + \sum_{i=0}^{N} \lambda_{pnmi} \Omega^*_{t-i} (1 - D_{nht} - D_{nlt}) + \sum_{i=1}^{N} \beta_i r_{t-i} + \varepsilon_t ,$$

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 3), D_{nht} (D_{nlt}) is a dummy variable equal to one on days with high (low) public signal noise (defined in Section 2.2.3 using news revisions), and zero otherwise, and $N = 5$. We estimate Equation (14) just for Nonfarm Payroll Employment, Industrial Production, and Capacity Utilization, since no other revisions (from RTDS) are available. R^2_{sa} is the adjusted R^2 using public news as the only explanatory variable. R^2_{fnha} (R^2_{fnla}) is the adjusted R^2 of using contemporaneous order flow alone in high (low) public signal noise days. R^2_a is the adjusted R^2 of the fully specified model above. A " * ", " ** ", or " *** " indicate significance at the 10%, 5%, or 1% level, respectively, using the Newey–West standard errors reported below each coefficient estimate (s.e.).

Finally, we amend all the regression models specified above to account for the potential omitted variable biases described in Section 3.1.1. 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 2.2.3, 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 nonannouncement days.

4. Conclusions and Future Research

The main goal of this article 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 (2006) 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 the Nonfarm Payroll Employment report is the first news release for a given month [e.g. Fleming and Remolona (1997) and 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 report is the best predictor for future activity and inflation out of the 25 macroeconomic announcements in our sample.[20] 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 Employment 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.

Appendix A:

Proof of Proposition 1. As noted in Section 1.1.1, 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 $x_k = B_0 + B_1 S_{vk}$, respectively, where $A_1 > 0$. Those expressions and the definition of ω_1 imply that, for the k-th speculator,

$$E\left(p_1 | S_{vk}\right) = A_0 + A_1 x_k + A_1 B_0 \left(M - 1\right) + A_1 B_1 \left(M - 1\right) \gamma S_{vk}. \tag{A1}$$

[20] The NBER's Business Cycle Dating Committee mentions that no single macroeconomic variable is the most important predictor of recessions and expansions (e.g. see the discussion at 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 Employment announcements.

Using Equation (A-1), the first order condition of the maximization of the k-th speculator's expected profit $E(\pi_k|S_{vk})$ is given by:

$$\psi S_{vk} - A_0 - (M+1)\,A_1 B_0 - 2A_1 B_1 S_{vk} - (M-1)\,A_1 B_1 \gamma S_{vk} = 0, \tag{A2}$$

where $\psi = \frac{\sigma_v^2}{M\sigma_s^2}$. The second order condition is satisfied, since $2A_1 > 0$. For Equation (A-2) to be true, it must be that:

$$-A_0 = (M+1)\,A_1 B_0 \tag{A3}$$

$$2A_1 B_1 = \psi - (M-1)\,A_1 B_1 \gamma. \tag{A4}$$

The distributional assumptions of Section 1.1 imply that the order flow ω_1 is normally distributed with mean $E(\omega_1) = MB_0$ and variance $var(\omega_1) = \sigma_u^2 + B_1^2\sigma_v^2$. Since $cov(v, \omega_1) = B_1\sigma_v^2$, it ensues that:

$$E(v|\omega_1) = \frac{B_1\sigma_v^2}{\sigma_u^2 + B_1^2\sigma_v^2}(\omega_1 - MB_0). \tag{A5}$$

According to the definition of a Bayesian-Nash equilibrium in this economy (Section 1.1.1), $p_1 = E(v|\omega_1)$. Therefore, our conjecture for p_1 implies that:

$$A_0 = -A_1 M B_0 \tag{A6}$$

$$A_1 = \frac{B_1\sigma_v^2}{\sigma_u^2 + B_1^2\sigma_v^2}. \tag{A7}$$

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

$$A_1 = \frac{\psi}{B_1[2 + (M-1)\gamma]}. \tag{A8}$$

We then equate Equation (A-8) to Equation (A-7) to get $A_1^2 = \frac{\sigma_v^2\psi[2+(M-1)\gamma-\psi]}{\sigma_u^2[2+(M-1)\gamma]^2}$. This expression implies that $A_1 = \frac{\sigma_v\psi^{\frac{1}{2}}}{\sigma_u[2+(M-1)\gamma]}$, where $\psi^{\frac{1}{2}} = \frac{\sigma_v}{\sigma_s\sqrt{M}}$ is the unique square root of ψ, since $2 + (M-1)\gamma - \psi = 1$ and $\psi > 0$. Substituting the solution for A_1 into Equation (A-8) leads to $B_1 = \frac{\sigma_u\psi^{\frac{1}{2}}}{\sigma_v}$. Both λ and Equation (2) then ensue from the definitions of $\delta_k = \psi S_{vk}$ and ψ. 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 Equation (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, in correspondence with the same γ, the finite difference $\Delta\lambda = \lambda\,(\text{at } M+1) - \lambda\,(\text{at } M) =$

$\frac{\sigma_v^2\sqrt{M+1}\left[\sigma_v^2+(M+1)M\chi\right]^{\frac{1}{2}}}{\sigma_u\left[\sigma_v^2(M+2)+(M+1)M\chi\right]} - \frac{\sigma_v^2\sqrt{M}\left[\sigma_v^2+M(M-1)\chi\right]^{\frac{1}{2}}}{\sigma_u\left[\sigma_v^2(M+1)+M(M-1)\chi\right]} = 0$ only when speculators' information is heterogeneous (χ (at $M+1$) $= \frac{\sigma_v^2}{M+1}$ and χ (at M) $= \frac{\sigma_v^2}{M}$ such that $\gamma = 0$) and always negative otherwise. Moreover, $\lim_{M\to\infty} \lambda = 0$. Market liquidity is decreasing in the heterogeneity of speculators' S_{vk} since $\lambda = \frac{\sigma_v^2\sqrt{M}\left[\sigma_v^2+M(M-1)\chi\right]^{\frac{1}{2}}}{\sigma_u\left[\sigma_v^2(M+1)+M(M-1)\chi\right]}$ is a concave function of χ with its maximum at $\chi = \frac{\sigma_v^2}{M}$ (i.e. when $\sigma_{ss} = 0$). Indeed, $\frac{\partial\lambda}{\partial\chi} = -\frac{M^{\frac{3}{2}}(M-1)^2\sigma_v^2\left(M\chi-\sigma_v^2\right)}{2\sigma_u\left[\sigma_v^2+M(M-1)\chi\right]^{\frac{1}{2}}\left[\sigma_v^2(M+1)+M(M-1)\chi\right]^2}$, 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, 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 $x_k = B_0 + B_1S_{vk} + B_2S_p$, respectively, where $A_1 > 0$. Since the definition of δ_k^* implies that $E(v|S_{vk}, S_p) = \alpha S_{vk} + \left(\beta + \frac{\sigma_v^2}{\sigma_p^2}\right)S_p$ and $E(S_{vj}|S_{vk}, S_p) = \gamma_p S_{vk} + \left(\gamma_p - 1\right)\frac{\beta}{\alpha}S_p$, those expressions lead to the following first order condition of the maximization of $E(\pi_k|S_{vk}, S_p)$:

$$\alpha S_{vk} + \left(\beta + \frac{\sigma_v^2}{\sigma_p^2}\right)S_p - (M-1)A_1B_1\gamma_pS_{vk} - 2A_1B_1S_{vk} - (M+1)A_1B_0 \quad \text{(A9)}$$
$$-A_0 - (M+1)A_1B_2S_p - (M-1)A_1B_1\left(\gamma_p - 1\right)\frac{\beta}{\alpha}S_p - A_2S_p = 0.$$

The second order condition is satisfied, since $2A_1 > 0$. For Equation (A-9) to be true, it must be that:

$$-A_0 = (M+1)A_1B_0 \quad \text{(A10)}$$
$$2A_1B_1 = \alpha - (M-1)A_1B_1\gamma_p \quad \text{(A11)}$$
$$A_2 = -(M+1)A_1B_2 + \beta + \frac{\sigma_v^2}{\sigma_p^2} - (M-1)A_1B_1\left(\gamma_p - 1\right)\frac{\beta}{\alpha}. \quad \text{(A12)}$$

The distributional assumptions of Section 1.1 imply that:

$$E\left(v|\omega_1, S_p\right) = \frac{B_1\sigma_v^2\left(\sigma_p^2 - \sigma_v^2\right)}{\sigma_u^2\sigma_p^2 + B_1^2\sigma_v^2\left(\sigma_p^2 - \sigma_v^2\right)}(\omega_1 - MB_0) \quad \text{(A13)}$$
$$+\frac{\sigma_v^2\left[\sigma_u^2 - MB_1B_2\left(\sigma_p^2 - \sigma_v^2\right)\right]}{\sigma_u^2\sigma_p^2 + B_1^2\sigma_v^2\left(\sigma_p^2 - \sigma_v^2\right)}S_p.$$

Since $p_1 = E(v|\omega_1)$ in equilibrium, our conjecture for p_1 implies that

$$A_0 = -A_1 M B_0 \tag{A14}$$

$$A_1 = \frac{B_1\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_u^2\sigma_p^2 + B_1^2\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)} \tag{A15}$$

$$A_2 = \frac{\sigma_v^2\left[\sigma_u^2 - MB_1B_2\left(\sigma_p^2-\sigma_v^2\right)\right]}{\sigma_u^2\sigma_p^2 + B_1^2\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}. \tag{A16}$$

The expressions for A_0, A_1, A_2, B_0, B_1, and B_2in Proposition 2 must solve the system made of Equations (A-10), (A-11), (A-12), (A-14), (A-15), and (A-16) to represent a linear equilibrium. First, we solve Equation (A-11) for A_1 and equate the ensuing expression to Equation (A-15) to get $A_1^2 = \frac{\alpha\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_u^2\sigma_p^2\left[2+(M-1)\gamma_p\right]^2}$, since $2+(M-1)\gamma_p - \alpha = 1$. This implies that $A_1 = \frac{\alpha^{\frac{1}{2}}\sigma_v\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]} > 0$, where $\alpha^{\frac{1}{2}}$ and $\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}$ are the unique square roots of α and $\left(\sigma_p^2-\sigma_v^2\right)$, respectively, since $\alpha > 0$ and $\sigma_p^2 > \sigma_v^2$. Substituting this expression into Equation (A-11) implies that $B_1 = \alpha\sigma_u\sigma_p\left[\alpha\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)\right]^{-\frac{1}{2}}$. Substituting the solution for B_1 into Equation (A-16), plugging both the resulting expression for A_2 and the solution for A_1 into Equation (A-12), and solving for B_2 leads to $B_2 = B_1\frac{\beta}{\alpha}$. Replacing B_1 and B_2 in Equation (A-16) with their solutions above and α and β with their definitions in Section 1.2 gives $A_2 = \frac{\sigma_v^2}{\sigma_p^2}$. Finally, defining A_1B_0 from Equation (A-14) and plugging it into Equation (A-10) leads to $A_0 = 0$ and $B_0 = 0$. Equation (4) then ensues from the definition of $\delta_k^* = \alpha S_{vk} + \beta S_p$. ■

Proof of Corollary 2. To prove this statement, we compare λ and λ_p under all possible scenarios for M and γ. When $M = 1$, $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \frac{\sigma_v}{2\sigma_u\sigma_p}\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}$ since $\sigma_p^2 > \sigma_v^2$. Along the same lines, when $M > 1$ and $\chi = 0$ $(\gamma = 1)$, $\lambda = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u} > \lambda_p = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u\sigma_p}\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}$. When $M > 1$ and $\chi = \frac{\sigma_v^2}{M}$ $(\gamma = 0)$, $\lambda = \frac{\sigma_v}{2\sigma_u} > \lambda_p = \frac{\sqrt{M}\sigma_v}{\sigma_u\sigma_p}\left(\sigma_p^2-\sigma_v^2\right)\frac{\left(M\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}}{2M\sigma_p^2-(M+1)\sigma_v^2}$ since $\sigma_p^2 > \sigma_v^2$ implies that $3M\sigma_v^4\sigma_p^2(M+2) < \sigma_v^2\left(4M\sigma_v^4 + \sigma_v^2\sigma_p^2 + 4M^2\sigma_p^4\right)$. Finally, it can be shown that, when $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right)$ $(\gamma \in (0,1))$ or $\chi > \frac{\sigma_v^2}{M}$ $\left(\gamma \in \left(-\frac{1}{M-1}, 0\right)\right)$, $\lambda = \frac{\sigma_v^2\sqrt{M}\left[\sigma_v^2+M(M-1)\chi\right]^{\frac{1}{2}}}{\sigma_u\left[\sigma_v^2(M+1)+M(M-1)\chi\right]} > \lambda_p = \frac{\alpha^{\frac{1}{2}}\sigma_v\left(\sigma_p^2-\sigma_v^2\right)^{\frac{1}{2}}}{\sigma_u\sigma_p\left[2+(M-1)\gamma_p\right]}$, where $\gamma_p = \frac{\sigma_p^2\left(\sigma_v^2-M\chi\right)-\sigma_v^4}{\sigma_p^2\left[\sigma_v^2+M(M-1)\chi\right]-\sigma_v^4}$ and $\alpha = \frac{M\sigma_v^2\left(\sigma_p^2-\sigma_v^2\right)}{\sigma_p^2\left[\sigma_v^2+M(M-1)\chi\right]-\sigma_v^4}$. In addition, $\lim_{M\to\infty}\lambda - \lambda_p = 0$, since both variables converge to zero at the limit. ■

Proof of Remark 1. We prove this remark under all possible scenarios for M and γ. When $M = 1$, $\frac{\partial\lambda_p}{\partial\sigma_p} = \frac{\sigma_v^3}{2\sigma_p^2\sigma_u}\left(\sigma_p^2-\sigma_v^2\right)^{-\frac{1}{2}} > 0$ since $\sigma_p^2 > \sigma_v^2$. When $M > 1$ and $\chi = 0$ $(\gamma = 1)$, $\frac{\partial\lambda_p}{\partial\sigma_p} = \frac{\sqrt{M}\sigma_v^3}{(M+1)\sigma_p^2\sigma_u}\left(\sigma_p^2-\sigma_v^2\right)^{-\frac{1}{2}} > 0$. When $M > 1$ and $\chi = \frac{\sigma_v^2}{M}$ $(\gamma = 0)$, $\frac{\partial\lambda_p}{\partial\sigma_p} = \frac{\sqrt{M}\sigma_v^3\left[\sigma_v^4(M+1)+\sigma_p^2\left(\sigma_v^2+2M^2\sigma_p^2-5M\sigma_v^2\right)\right]}{\sigma_p^2\sigma_u\left[2\sigma_p^2-(M+1)\sigma_v^2\right]^2}\left(M\sigma_p^2-\sigma_v^2\right)^{-\frac{1}{2}}$ since $\sigma_v^4(M+1) + \sigma_p^2\left(\sigma_v^2+2M^2\sigma_p^2\right) > -5M\sigma_v^2$. When $M > 1$ and $\chi \in \left(0, \frac{\sigma_v^2}{M}\right)$ $(\gamma \in (0,1))$ or $\chi > \frac{\sigma_v^2}{M}$ $\left(\gamma \in \left(-\frac{1}{M-1}, 0\right)\right)$, it can be shown that $\frac{\partial\lambda_p}{\partial\sigma_p}$ yields a positive function of σ_p, σ_v, M, and

χ under the assumptions of Sections 1.1 and 1.2. Finally, in all of the above scenarios, $\lim_{\sigma_p \to \infty} \lambda_p = \lambda$. ∎

Proof of Remark 2. We prove this remark by first comparing the equilibrium λ_p when either $\gamma = 1$ ($\chi = 0$) or $\gamma = 0$ ($\chi = \frac{\sigma_v^2}{M}$). If speculators' signals are perfectly correlated, then $\lambda_p = \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u\sigma_p}\left(\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}$; if speculators' private signals are uncorrelated, then $\lambda_p = \frac{\sqrt{M}\sigma_v}{\sigma_u\sigma_p}\left(\sigma_p^2 - \sigma_v^2\right)\frac{\left(M\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}}{2M\sigma_p^2 - (M+1)\sigma_v^2}$. It then follows that it exists a unique $\sigma_p^{2*} > \sigma_v^2 > 0$ such that $\lambda_p > \frac{\sqrt{M}\sigma_v}{(M+1)\sigma_u\sigma_p}\left(\sigma_p^2 - \sigma_v^2\right)^{\frac{1}{2}}$ if $\sigma_p^2 > \sigma_p^{2*}$, given by $\sigma_p^{2*} = \frac{M+1}{M}\sigma_v^2$. More generally, it can be shown that it exists a unique $\chi^* = \left(1 - \frac{\sigma_v^2}{\sigma_p^2}\right)\frac{\sigma_v^2}{M} < \frac{\sigma_v^2}{M}$ (i.e. $\gamma^* = \frac{\sigma_v^2}{\sigma_p^2 M - (M-1)\sigma_v^2} > 0$) such that $\frac{\partial \lambda_p}{\partial \chi} \geq 0$ for $\chi \leq \chi^*$ (i.e. $\frac{\partial \lambda_p}{\partial \gamma} \leq 0$ for $\gamma \geq \gamma^*$) and negative (i.e. $\frac{\partial \lambda_p}{\partial \gamma} > 0$) otherwise. Hence, $\lambda_p$is negatively related to $\gamma \in [0, 1]$ for large σ_p^2 and positively related to $\gamma \in [0, 1]$ for small σ_p^2, since $\lim_{\sigma_p \to \infty} \gamma^* = 0$ and $\lim_{\sigma_p \to \sigma_v} \gamma^* = 1$, while λ_p is always positively related to $\gamma \in \left(-\frac{1}{M-1}, 0\right)$ for any σ_p^2. ∎

Proof of Corollary 3. The statement of the corollary follows from $\frac{\partial \lambda_s}{\partial \sigma_p} = -\frac{2\sigma_v^2}{\sigma_p^3} < 0$ for any M and γ. Furthermore, $\lim_{\sigma_p \to \infty} \lambda_s = 0$. ∎

References

Admati, A., and P. Pfleiderer. 1988. A Theory of Intraday Trading Patterns: Volume and Price Variability. *Review of Financial Studies* 1:3–40.

Andersen, T., and T. Bollerslev. 1998. Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies. *Journal of Finance* 53:219–65.

Andersen, T., T. Bollerslev, F. Diebold, and P. Labys. 2003. Modeling and Forecasting Realized Volatility. *Econometrica* 71:579–626.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega. 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review* 93:38–62.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega. 2004. Real-Time Price Discovery in Stock, Bond, and Foreign Exchange Markets. *Journal of International Economics* Forthcoming.

Aruoba, B. 2004. Empirical Properties of Macroeconomic Revisions. Working Paper, University of Pennsylvania.

Back, K., H. Cao, and G. Willard. 2000. Imperfect Competition Among Informed Traders. *Journal of Finance* 55:2117–55.

Balduzzi, P., E. Elton, and C. Green. 2001. Economic News and Bond Prices: Evidence From the U.S. Treasury Market. *Journal of Financial and Quantitative Analysis* 36:523–43.

Bandi, F., and J. Russell. 2006. Separating Microstructure Noise from Volatility *Journal of Financial Economics* 79:655–92.

Berry, T., and K. Howe. 1994. Public Information Arrival. *Journal of Finance* 49:1331–46.

Boyd, J., J. Hu, and R. Jagannathan. 2005. The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good For Stocks. *Journal of Finance* 60:649–72.

Brandt, M., and K. Kavajecz. 2004. Price Discovery in the U.S. Treasury Market: The Impact of Order Flow and Liquidity on the Yield Curve. *Journal of Finance* 59:2623–54.

Brenner, M., P. Pasquariello, and M. Subrahmanyam. 2005. Financial Markets and the Macro Economy. Working Paper, Ross School of Business, University of Michigan.

Chowdhry, B., and V. Nanda. 1991. Multimarket Trading and Market Liquidity. *Review of Financial Studies* 4:483–511.

Croushore, D., and T. Stark. 1999. A Real-Time Data Set of Macroeconomists: Does the Data Vintage Matter? Working Paper 99–21, Federal Reserve Bank of Philadelphia.

Croushore, D., and T. Stark. 2001. A Real-Time Data Set of Macroeconomists *Journal of Econometrics* 105:111–30.

Diamond, D., and R. Verrecchia. 1991. Disclosure, Liquidity, and the Cost of Capital. *Journal of Finance* 46:1325–59.

Diebold, F., and C. Li. 2006. Forecasting the Term Structure of Government Bond Yields. *Journal of Econometrics* 130:337–64.

Diether, K., C. Malloy, and A. Scherbina. 2002. Differences of Opinion and the Cross Section of Stock Returns. *Journal of Finance* 57:2113–41.

Duffee, G. 2002. Term Premia and Interest Rate Forecasts in Affine Models. *Journal of Finance* 57:405–43.

Easley, D., S. Hvidkjaer, and M. O'Hara. 2002. Is Information Risk a Determinant of Asset Returns? *Journal of Finance* 57:2185–221.

Estrella, A., and F. Mishkin. 1998. Predicting U.S. Recessions: Financial Variables as Leading Indicators. *Review of Economics and Statistics* 80:45–61.

Evans, M., and R. Lyons. 2002. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy* 110:170–80.

Evans, M., and R. Lyons. 2003. How is Macro News Transmitted to Exchange Rates. *Journal of Financial Economics* Forthcoming.

Evans, M., and R. Lyons. 2004. Exchange Rate Fundamentals and Order Flow. Working Paper, Haas School of Business, University of California, Berkeley.

Faust, J., J. Rogers, and J. Wright. 2005. News and Noise in G-7 GDP Announcements. *Journal of Money, Credit and Banking* 37:403–19.

Fleming, M. 1997. The Round-the-Clock Market of U.S. Treasury Securities. *Economic Policy Review*, Federal Reserve Bank of New York, 3:9–32.

Fleming, M. 2003. Measuring Treasury Market Liquidity. *Economic Policy Review*, Federal Reserve Bank of New York, 9:83–108.

Fleming, M., and E. Remolona. 1997. What Moves the Bond Market? *Economic Policy Review*, Federal Reserve Bank of New York, 3:31–50.

Fleming, M., and E. Remolona. 1999. Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information. *Journal of Finance* 54:1901–15.

Foster, F., and S. Viswanathan. 1990. A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets. *Review of Financial Studies* 3:593–624.

Foster, F., and S. Viswanathan. 1993. The Effect of Public Information and Competition on Trading Volume and Price Volatility. *Review of Financial Studies* 6:23–56.

Foster, F., and S. Viswanathan. 1996. Strategic Trading When Agents Forecast the Forecasts of Others. *Journal of Finance* 51:1437–78.

Garman, M. 1976. Market Microstructure. *Journal of Financial Economics* 3:257–75.

Goldreich, D., B. Hanke, and P. Nath. 2005. The Price of Future Liquidity: Time-Varying Liquidity in the U.S. Treasury Market. *Review of Finance* 9:1–32.

Goodhart, C., and M. O'Hara. 1997. High Frequency Data in Financial Markets: Issues and Applications. *Journal of Empirical Finance* 4:73–114.

Green, C. 2004. Economic News and the Impact of Trading on Bond Prices. *Journal of Finance* 59:1201–33.

Griffiths, M., B. Smith, D. Turnbull, and R. White. 2000. The Costs and the Determinants of Order Aggressiveness. *Journal of Financial Economics* 56:65–88.

Hasbrouck, J. 1991. Measuring the Information Content of Stock Trades. *Journal of Finance* 46:179–207.

Hasbrouck, J. 2004. Economic and Statistical Perspectives on the Dynamics of Trade in Securities Markets, Teaching notes, Stern School of Business, New York University.

Kallberg, J., and P. Pasquariello. 2004. Time-Series and Cross-Sectional Excess Comovement in Stock Indexes, Working Paper, Ross School of Business, University of Michigan.

Kavajecz, K., and S. Collins. 1995. Rationality of Preliminary Money Stock Estimates. *Review of Economics and Statistics* 77:32–41.

Kim, O., and R. Verrecchia. 1994. Market Liquidity and Volume around Earnings Announcements. *Journal of Accounting and Economics* 17:41–67.

Kim, O., and R. Verrecchia. 1997. Pre-Announcement and Event-Period Private Information. *Journal of Accounting and Economics* 24:395–419.

Kyle, A. 1985. Continuous Auctions and Insider Trading. *Econometrica* 53:1315–35.

Lee, C., and M. Ready. 1991. Inferring Trade Direction from Intraday Data. *Journal of Finance* 46:733–46.

Lucas, R. 1982. Interest Rates and Currency Prices in a Two-Country World. *Journal of Monetary Economics* 10:335–59.

Mankiw, N., D. Runkle, and M. Shapiro. 1984. Are Preliminary Announcements of the Money Stock Rational Forecasts? *Journal of Monetary Economics* 14:15–27.

McKelvey, R., and T. Page. 1990. Public and Private Information: An Experimental Study of Information Pooling. *Econometrica* 58:1321–39.

Moulton, P. 2004. Relative Repo Specialness in U.S. Treasuries. *Journal of Fixed Income* 14:40–7.

Mork, K. 1987. Ain't Behavin': Forecast Errors and Measurement Errors in Early GNP Estimates. *Journal of Business and Economic Statistics* 5:165–75.

Mork, K. 1990. Forecastable Money-Growth Revisions: A Closer Look at the Data. *Canadian Journal of Economics* 23:593–616.

Morris, S., and H. Shin. 2002. Social Value of Public Information. *American Economic Review* 92:1521–34.

Nelson, C., and A. Siegel. 1987. Parsimonious Modeling of Yield Curves. *Journal of Business* 60:473–89.

Novshek, W. 1984. Finding All n-Firm Cournot Equilibria. *International Economic Review* 25:61–70.

Ranaldo, A. 2004. Order Aggressiveness in Limit Order Book Markets. *Journal of Financial Markets* 7:53–74.