Demand for Information, Uncertainty, and the Response of U.S. Treasury Securities to News*

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Abstract

We propose to use information demand about a source of risk as a measure of investors' uncertainty. Consistent with this idea, we show, using novel data on financial news consumption, that there is a positive correlation between information demand about macroeconomic factors perceived as affecting the path of future interest rates and other measures of uncertainty about future interest rates. Moreover, an increase in information demand about these factors ahead of influential macroeconomic announcements predicts an increase in the reaction of U.S Treasury note yields to these announcements, consistent with our hypothesis that information demand is high when uncertainty is high.

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JEL Classifications: G12, G14, D83

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1 Introduction

Uncertainty plays a key role in financial economics.[1] For example, economic theory shows that uncertainty affects the price discovery process, asset prices, risk premia, and investment decisions (see, e.g., Grossman and Stiglitz, 1980; Pastor and Veronesi, 2012, 2013; Bernanke, 1983). However, analyzing the effects of uncertainty empirically is difficult because measuring uncertainty is challenging (see, e.g., Jurado et al., 2015).[2] We propose to use investors' demand for information about a particular source of risk (e.g., future changes in monetary policy) to measure uncertainty and we provide supporting evidence by exploiting novel data on news consumption.

Our proposal follows from economic theory. Suppose that the economy alternates between periods of high and low unconditional variance for the payoff of an asset.[3] Investors optimally search for more information when the variance of the asset payoff is high, because then the marginal benefit of more accurate signals for investment decisions is higher. The increased search intensity dampens the positive effect of a higher unconditional variance on uncertainty. However, we show – using a standard equilibrium model with endogenous information acquisition – that it does not fully offset the positive effect.[4] Hence, in equilibrium, an increase in the variance of the asset payoff leads to a positive correlation between uncertainty and information demand.

One implication of this theory is that information demand ahead of influential (e.g., macroeconomic or policy) announcements or information disclosure for an asset should be positively correlated with the reaction of its price to these announcements. Indeed, news plays a larger role in resolving uncertainty if uncertainty prior to the news arrival is higher (holding news accuracy constant). Thus, if information demand is a proxy for uncertainty, then an increases in information

[1] There are various definitions of uncertainty (see, Bloom, 2014). We define uncertainty about a variable as the variance of the forecasting error of this variable *conditional* on available information to investors. This definition is similar to the definition of uncertainty in, for instance, Jurado et al. (2015), Orlick and Veldkamp (2015) and Berger et al. (2019).

[2] Jurado et al. (2015) (p.1178) remark that "*a challenge in empirically examining the behavior of uncertainty, and its relation to macroeconomic activity, is that no objective measure of uncertainty exists.*"

[3] We define unconditional variance of a variable in a given period as the variance of the variable before conditioning on private signals collected in this period and the asset price in this period. The unconditional variance itself may be dependent on a publicly observable variable that varies over time as in Veldkamp (2006).

[4] The intuition is as follows. The marginal benefit of information acquisition increases with uncertainty, while the marginal cost of information increases with information demand. In equilibrium, an investor's information demand is such that the marginal benefit is equal to the marginal cost. Thus, if investors demand more information following a positive shock to uncertainty, their marginal cost increases and therefore the marginal benefit of information at the new equilibrium level must be higher. Thus, the new level of uncertainty after the shock must be higher than before the shock.

demand about a source of risk should be predictive of an increase in the strength of the price response to news for assets exposed to this risk.

We test this prediction by analyzing uncertainty about future interest rates, demand for information about macroeconomic variables perceived as affecting future interest rates, and the reaction of U.S. Treasury note yields to announcements about these variables. Our main analysis focuses on the nonfarm payroll announcement because the literature shows that it has, among all macroeconomic announcements, the biggest impact on U.S. Treasury yields. The reason is that it helps investors forecast the future path of monetary policy (see, Gilbert et al., 2017).[5] Since this announcement partially resolves uncertainty about future interest rates, search for information related to this announcement *ahead* of its release is likely to be related to this uncertainty.

We measure investors' demand for information using Bitly data on clicks by individuals on news articles. Bitly is a company that provides short-URL-links (SURLs) and a readership tracking system. SURLs are abridged versions of internet addresses (URLs). They are often created by journalists (or news agencies) to disseminate their articles and then used by journalists and other individuals to share these articles with others, e.g., on traders' Bloomberg terminal (via e-mail), micro-blogging platforms (e.g., Twitter), or social media (e.g., Facebook). Our data comprise 70 million SURLs created by Bitly from 2012 to 2018 and about 10 billion clicks on these SURLs. We measure information demand about a specific topic over a given time window by the number of clicks on SURLs that point to news related to this topic. We identify about $30,000$ SURLs related to the topic nonfarm payroll and about $650,000$ clicks on these SURLs. Of course, investors have many other ways to obtain information about future interest rates than by just clicking on SURLs related to the topic nonfarm payroll. Our premiss is that an increase in clicks on the SURLs related to this topic signals a more general increase in investors' effort to obtain information about future interest rates.

We first show that our measure of information demand about nonfarm payroll (computed at the monthly frequency) has a strong and positive correlation with other proxies of uncertainty about interest rates such as, for instance, a market-based measure of monetary policy uncertainty (based

[5] The nonfarm payroll announcement is often referred as the "king" of announcements by market participants, see, for example, Andersen and Bollerslev (1998). Gilbert et al. (2017) show that out of the 36 macroeconomic announcements they analyze, nonfarm payroll has the largest explanatory power for the variation in U.S. Treasury yields (see their Table 2).

on the implied volatility of options on one-year swap rates as in Carlston and Ochoa, 2017), the monthly realized volatility of two-year U.S. Treasury note returns, the level of disagreement among professional forecasters about forthcoming nonfarm payroll figures, or the frequency of news articles about policy (including monetary policy) uncertainty. This finding supports our hypothesis that there is a positive correlation between information demand about the future payoff of an asset and uncertainty about this payoff.

We then show that, in line with our prediction, the sensitivity of U.S. Treasury note yields (for various maturities) to the unexpected component of nonfarm payroll announcements (the "surprise" in these announcements) is significantly stronger when information demand about the topic nonfarm payroll is high in the two hours *preceding* the release of the official figures.[6] Specifically, a one standard deviation increase in the number of Bitly clicks in the two hours before an announcement raises the sensitivity of U.S. Treasury note yields by 4 to 6 bps (depending on maturity) during our sample period (2012-2018). This effect is economically significant since the unconditional sensitivity of U.S. Treasury note yields to nonfarm payroll announcements during our sample period varies between 3.5 bps (2-year maturity) to 7 bps (10-years maturity).

This strong positive relationship between information demand and the sensitivity of U.S. Treasury note yields to nonfarm payroll announcements persists even after controlling for a host of variables, including various proxies for uncertainty and the accuracy of nonfarm payroll announcements. In particular, it is not subsumed by variations in the number of news about nonfarm payroll employment (a news supply effect). Moreover, it cannot be explained by an increase in information demand due to an unexpected large surprise in the nonfarm payroll figure (or a large yield reaction to the news) because we measure information demand *before* the announcement. Importantly, we find that information demand is one of the few variables that is able to predict the sensitivity of U.S. Treasury yields to future news during our sample period.

In our model, the sign of the relationship between uncertainty and information demand depends on four factors: (i) the variance of the asset payoff (as we already explained), (ii) the volume of

[6]We consider the predictive role of information demand in the two hours before nonfarm payroll announcements for two reasons. First, a large fraction of the clicks on SURLs pointing to nonfarm payroll news in our sample happen on nonfarm payroll announcement days. Second, as we increase the time window over which we measure information demand, we increase the risk that our measure of information demand captures interest in topics unrelated to nonfarm payroll figures. This risk makes our measure noisier. Nevertheless, as shown in the internet appendix, our results are robust to using a daily or monthly window to measure information demand.

noise trading, (iii) the cost of information acquisition, and (iv) investors' risk aversion. When the cost of information (or risk aversion) increases, investors acquire less information and, through this channel, uncertainty increases. Thus, if time-variations in information costs or risk aversion were the primary sources of variations in information demand, high information demand ahead of news arrival should be *negatively* correlated with other measures of uncertainty and the impact of news on prices, and not *positively* as we find.

In contrast, variations in the volume of noise trading induces a positive correlation between uncertainty and information demand in our model, as variation in the variance of the asset payoff does, but for a different reason. When the volume of noise trading increases, the aggregate demand for the asset becomes a noisier signal about the value of the asset. This effect raises uncertainty because aggregate demand for the asset is also a (publicly available) source of information for investors. Investors react by buying more private information but, in equilibrium, this increase is insufficient to fully offset the increase in the noisiness of the aggregate demand for the asset. Thus, uncertainty increases and trades are less informative. In contrast, an increase in the variance of the asset payoff leads to more informative trades since investors demand more information, which makes aggregate demand more informative (holding the volume of noise trading constant). Hence, in each of these cases, the price impact of trades ahead of news arrival (a measure of order flow informativeness) is correlated with information demand. However, the sign of this correlation is negative if variations in information demand are due to shocks to noise trading, and positive if these variations stem from shocks to the variance of the asset payoff. In our sample, we find empirical support for the second scenario.

We also show that our measure of information is not associated with over- or under-reaction of U.S. Treasury yields to news. Thus, fluctuations in interest about the topic nonfarm payroll do not reflect fluctuations in the participation of less sophisticated investors in the U.S. Treasury market around nonfarm payroll announcements. This is another piece of evidence that our measure of investors' news consumption does not capture variations in noise traders' participation to the market around nonfarm payroll announcements.

In the last part of the paper, we consider information demand about topics related to other important macroeconomic announcements – announcements that significantly affect Treasury yields. Consistent with the results described above, we also find a strong positive association between information demand about these topics ahead of the release of these announcements and the reaction of U.S. Treasury yields to these announcements.

2 Literature Review and Contribution

Our paper contributes to the growing literature on uncertainty and its effects on asset prices. Bloom (2014) observes that "*there is no perfect measure of uncertainty but instead a broad range of proxies.*" The literature has used four types of proxies for uncertainty (see, Datta et al., 2017, for a review): (i) measures based on the realized volatility of asset returns, (ii) measures based on disagreement among forecasters or realized forecast errors, (iii) measures based on implied volatilities in option prices, and (iv) indexes based on the frequency of the word "uncertainty" in newspaper articles. To our knowledge, our paper is the first to use information demand as a measure of uncertainty and to show that higher information demand ahead of news predicts a stronger price reaction to news.

Our study is also related to the literature using search data to measure investors' attention and its effect on financial markets, in particular Ben-Rephael et al. (2017) and Fedyk (2018). Ben-Rephael et al. (2017) use an attention measure to a stock provided by Bloomberg, based on the number of times users of its terminals click on news or search news regarding a particular stock. They argue that this measure captures institutional investors' attention to a stock since institutional investors are the primary users of Bloomberg terminals. Ben-Rephael et al. (2017) show that institutional investors' attention to a stock reduces its post-earning (or post-analysts recommendation) price drift. Fedyk (2018) uses clicks by institutional investors on news articles and shows that a greater dispersion in the times at which investors access news lead to greater trading volume, in line with models of gradual information diffusion. These papers focus on the effect of investors' attention on the speed of adjustment to information or the intensity of trading *after* news announcements. In contrast, we focus on how investors' attention *before* news announcements is related to the size of jumps in prices at the announcement. We argue that elevated attention before announcements is symptomatic of greater uncertainty and therefore predicts a stronger reaction of prices to the announcement.[7]

We also contribute to the literature analyzing the sensitivity of U.S. Treasury yields to macroeconomic announcements.[8] Recent papers show that the sensitivity of U.S. Treasury yields to macroeconomic announcements varies over time (e.g., Swanson and Williams, 2014; Goldberg and Grisse, 2013) and across announcements (e.g., Gilbert et al., 2017). Our findings show that there is significant time-variations in investors' information demand ahead of yield-moving macroeconomic announcements and these variations explain variations in the strength of the response of U.S. Treasury yields to these announcements.

Lastly, there is some evidence of informed trading prior to influential macroeconomic announcements in U.S. Treasury markets (see, Kurov et al., 2016; Bernile et al., 2016). This evidence has raised concerns about possible leakages of information ahead of macroeconomic announcements.[9] As noted by Kurov et al. (2016), a more benign explanation might be that some market participants actively engage in collecting private information ahead of macroeconomic announcements. Our findings are consistent with this possibility.

3 Information Demand and Uncertainty

In this section, we present the model that motivates our empirical analysis. It is a standard rational expectations model of information acquisition (Grossman and Stiglitz, 1980; Kim and Verrecchia, 1991; Vives, 1995; Veldkamp, 2006, etc.). We use this model to show that shocks to the variance of cash-flows or the volume of noise trading induce a positive correlation between investors' uncertainty and information demand. This result justifies our claim that information demand is a proxy for uncertainty. The model further implies that greater information demand ahead of the news release is associated with a stronger reaction of asset prices to future news. We test these predictions in the next section.

[7]Kottimukkalur (2018) shows that investors pay more attention to stocks with higher earnings volatility around earnings releases, using Google search activity for stock tickers as a proxy for attention. This is consistent with our claim that an increase in the unconditional variance of an asset payoff leads investors to demand more information about this asset.

[8]For example, Fleming and Remolona (1997, 1999); Balduzzi et al. (2001); Goldberg and Leonard (2003); Gürkaynak et al. (2005); Beechey and Wright (2009); Swanson and Williams (2014).

[9]See, for instance, "Labor Department Panel Calls for Ending Lockup for Jobs Data", Wall Street Journal, Jan.2, 2014.

3.1 The Model

The model has four dates $t \in \{0,1,2,3\}$ (see Figure 1) and one risky asset whose payoff F is realized at date 3. The payoff of the asset has a zero mean normal distribution with variance $\text{Var}(F)$ (in the rest of the paper, $\text{Var}(x)$ denotes the variance of variable x). At date 2, a public signal (e.g., a macroeconomic announcement) A_e is released about F with:

$$A_e = F + \epsilon, \tag{1}$$

where ϵ is normally distributed with mean 0.

Insert Figure 1 About here

At date 0, a continuum of speculators with CARA utility functions (with risk aversion γ) privately collect information about the payoff of the asset. That is, each speculator $i \in [0,1]$ pays a cost $c(\tau_{\eta_i})$ to obtain a signal s_i about F such that:

$$s_i = F + \eta_i, \tag{2}$$

where η_i is normally distributed with mean zero, precision τ_{η_i}, and independent across speculators.[10] We assume that $c(\tau_{\eta_i})$ is increasing and strictly convex with $c(0) = 0$.

We interpret τ_{η_i} as the demand for information by speculator i prior to the announcement. Investors' aggregate demand for information is:[11]

$$\overline{\tau}_\eta = \int_i \tau_{\eta_i} di. \tag{3}$$

After receiving their signal, speculators can trade the risky asset at date 1. We model trading at date 1 as in Vives (1995). The price of the asset, p_1, is set by competitive risk neutral dealers.[12]

[10] As in Vives (1995), we assume that $\int_i \eta_i = 0$ almost surely so that the average speculators' signal is equal to F.

[11] In Grossman and Stiglitz (1980) or Veldkamp (2006), the decision to acquire information is binary: either an investor buys a signal of fixed precision or does not. Thus, in these models all informed investors have signals of the same precision and information demand is measured by the fraction of investors buying information. In our model, all investors can potentially be informed but with signals of varying precisions. This approach is more general (since acquiring no information at all is possible). In any case, we have checked that we obtain similar predictions with the first approach (defining information demand as the fraction of investors choosing to be informed).

[12] One does not need to literally interpret dealers as intermediaries. They can be viewed as well as risk neutral investors without private information. Results with this interpretation are identical.

Each informed investor submits a demand function $x_i(s_i, p_1)$. Moreover, a continuum of noise traders submit buy or sell market orders (i.e., orders inelastic to the price at date 1). Their aggregate demand, denoted by u, is normally distributed with mean zero. Dealers observe investors's aggregate demand for the asset, i.e.,

$$D(p_1) = \int_i x_i(s_i, p_1)di + u,$$

and, given this information, set the price for the asset such that their expected profit is zero. That is:

$$p_1 = \mathrm{E}(F\,|D(p_1)) \,. \tag{4}$$

At date 2, dealers observe the public signal A_e and update their quotes. Thus, the asset price becomes:

$$p_2 = \mathrm{E}(F\,|D(p_1), A_e) \,. \tag{5}$$

Finally, we assume that F, u, and error terms in traders' signals (η_i and ϵ) are independent.

Speculator i's equilibrium demand for the asset is (see Appendix A for derivations):

$$x_i(s_i, p_1) = a_i(s_i - p_1), \tag{6}$$

where $a_i = \frac{\tau_{\eta_i}}{\gamma}$. Thus, speculators' aggregate demand is:

$$D(p_1) = \frac{\overline{\tau}_\eta(F - p_1)}{\gamma} + u.$$

Observing this demand conveys a signal $z_1 = F + \chi_D$ about the asset payoff where $\chi_D = (\gamma\overline{\tau}_\eta^{-1}) \times u$ is the noise in this signal. Investors' aggregate demand for the asset is more informative (i.e., $\mathrm{Var}(\chi_D)$ is smaller) when (i) investors' aggregate information demand ($\overline{\tau}_\eta$) is higher or (ii) the variance of noise trading ($\mathrm{Var}(u)$) is smaller.

The equilibrium price at date 1 is:

$$p_1 = \mathrm{E}(F\,|D(p_1)) = \mathrm{E}(F\,|z_1) = \lambda z_1, \tag{7}$$

where $\lambda = \frac{Cov(F,z_1)}{Var(z_1)} = \frac{Var(F)}{Var(F)+Var(\chi_D)}$.

We measure uncertainty at date 1 by dealers' expected forecasting error conditional on public information at this date, i.e., $\mathrm{Var}(F \mid D(p_1))$. We obtain:

$$\mathrm{Var}(F \mid D(p_1)) = \mathrm{Var}(F \mid z_1) = \frac{\mathrm{Var}(\chi_D)\mathrm{Var}(F)}{\mathrm{Var}(F) + \mathrm{Var}(\chi_D)}. \tag{8}$$

Thus, uncertainty depends on the noisiness of investors' aggregate demand (it increases with $\mathrm{Var}(\chi_D)$). This is inversely related to speculators' aggregate information demand and therefore endogenous. Hence, ultimately, the effect of exogenous shocks (e.g., an increase in the variance of the asset) on uncertainty depends on how they affect information demand in equilibrium.

Now consider the equilibrium price at date 2. We have:

$$p_2 = \mathrm{E}(F\,|D(p_1), A_e) = \mathrm{E}(F\,|z_1, A_e) = p_1 + \beta \underbrace{(A_e - \mathrm{E}(A_e\,|z_1))}_{Announcement\quad Surprise}, \tag{9}$$

with

$$\beta = \frac{Cov(F, A_e\,|z_1)}{Var(A_e\,|z_1)} = \frac{Var(F\,|z_1)}{Var(A_e\,|z_1)} = \frac{Var(F\,|z_1)}{Var(F\,|z_1) + Var(\epsilon)}. \tag{10}$$

The sensitivity (β) of the asset price to the announcement surprise is stronger when (i) the announcement is more accurate ($\mathrm{Var}(\epsilon)$ is smaller) and (ii) when uncertainty, $\mathrm{Var}(F \mid z_1)$, is higher.

To close the model, it remains to derive speculator's demand for information in equilibrium. The certainty equivalent (denoted $\Pi(\tau_{\eta_i}, \overline{\tau}_\eta)$) of speculator i 's expected utility at date 0 when he acquires a signal of precision τ_{η_i} is (see Appendix A):

$$\Pi(\tau_{\eta_i}, \overline{\tau}_\eta) = \frac{1}{2\gamma}\ln\left(\frac{\mathrm{Var}(F\,|z_1)}{\mathrm{Var}(F\,|z_1, s_i)}\right) = \frac{1}{2\gamma}(\ln(1 + \tau_{\eta_i}\mathrm{Var}(F \mid z_1)) - c(\tau_{\eta_i}). \tag{11}$$

The marginal benefit of a more accurate signal is higher when uncertainty (measured by $\mathrm{Var}(F \mid z_1)$) is higher.[13] Now, as explained previously, uncertainty is inversely related to speculators' aggregate information demand, $\bar{\tau}_\eta$, (see eq.(8)). Thus, ultimately, a speculator's expected utility and the marginal benefit of a more accurate signal decreases as aggregate information demand

[13]The marginal benefit of a more accurate signal for an investor is given by the first derivative of the first term in eq.(11), which is equal to $\frac{\mathrm{Var}(F|z_1)}{2\gamma(1+\tau_{\eta_i}\mathrm{Var}(F|z_1))}$. It is therefore increasing in $\mathrm{Var}(F \mid z_1)$.

is higher ($\frac{\partial \Pi(\tau_{\eta_i},\overline{\tau}_\eta)}{\partial \overline{\tau}_\eta} < 0$ and $\frac{\partial^2 \Pi(\tau_{\eta_i},\overline{\tau}_\eta)}{\partial \tau_{\eta_i}\partial \overline{\tau}_\eta} < 0$). The reason is that a greater information demand makes aggregate demand more informative for dealers and therefore reduces the value of private information.

In sum, investors' demand for information depends on speculators' aggregate information demand and, in turn, aggregate information demand depends on each speculator's information acquisition choice. Thus, an equilibrium of the information acquisition stage at date 0 is a demand $\tau^*_{\eta_i}$ for each speculator and an aggregate demand $\overline{\tau}^*_\eta$ such that (i) $\tau^*_{\eta_i}$ maximizes $\Pi(\tau^*_{\eta_i},\overline{\tau}^*_\eta)$ (each speculator's demand is optimal given the equilibrium aggregate demand for information) and (ii) $\overline{\tau}^*_\eta = \int \tau^*_{\eta_i} di$ (the equilibrium aggregate demand for information is consistent with each speculator's information acquisition choice). As all speculators are identical, it is natural to consider symmetric equilibria in which all investors have the same demand for information: $\tau^*_{\eta_i} = \overline{\tau}^*_\eta$, $\forall i$. In this case, if there is an interior equilibrium (i.e., an equilibrium such that $\overline{\tau}^*_\eta > 0$), the first order condition of each speculator's information acquisition problem imposes $\frac{\partial \Pi(\overline{\tau}^*_\eta,\overline{\tau}^*_\eta)}{\partial \tau_{\eta_i}} = 0$. Thus, differentiating eq.(11) with respect to τ_{η_i}, we deduce that $\overline{\tau}^*_\eta$ solves:

$$1 - (2\gamma)c'(\overline{\tau}^*_\eta)(\mathrm{Var}(F)^{-1} + \gamma^{-2}\overline{\tau}^*_\eta \mathrm{Var}(u)^{-1} + \overline{\tau}^*_\eta) = 0. \tag{12}$$

Using this equilibrium condition, we obtain the following result (see Appendix A for a proof).

Proposition 1. *The equilibrium of the information acquisition stage is unique and such that $\overline{\tau}^*_\eta > 0$ (i.e., speculators demand information) if and only if $c'(0) < \frac{Var(F)}{2\gamma}$. Otherwise speculators demand no information ($\overline{\tau}^*_\eta = 0$). Moreover, an increase in (i) the variance of the asset payoff, $Var(F)$ or (ii) the variance of noise trading, $Var(u)$ raises (a) uncertainty ($Var(F \mid z_1)$), (b) the aggregate demand for information ($\overline{\tau}^*_\eta$), and (c) the sensitivity (β) of the asset price to news.*

Holding information acquisition constant, an increase in the variance of the asset payoff or noise trading increases uncertainty ($\mathrm{Var}(F \mid z_1)$). As explained previously, this effect increases the marginal value of information and therefore leads to an increase in information acquisition in equilibrium. This increase partially offsets the initial effect of an increase in the variance of the asset payoff (or noise trading) on uncertainty. However, Proposition 1 shows that it is never strong enough to overturn or neutralize it.[14] Thus, in equilibrium, an increase in the variance of the asset payoff or noise trading results in a joint increase in (a) uncertainty, (b) information demand, and (c) the impact of news on prices (since this impact is stronger when uncertainty is higher; (see eq.(10)).[15]

3.2 Prediction

It is difficult to empirically measure uncertainty (the variance of an asset payoff *conditional* on available information to investors) because investors' information set (e.g., z_1 in our model) cannot be directly observed. To overcome this problem, Proposition 1 suggests to use information demand as a proxy for uncertainty. Indeed, shocks to the variance of the asset payoff or the variance of noise trading induce a positive correlation between information demand and uncertainty. Moreover, if information demand and uncertainty are positively correlated, then an increase in information demand ahead of news arrival should predict a stronger price reaction to news. We test this implication in Section 5.

According to Proposition 1, either time-varying shocks to the variance of the asset payoff or the variance of noise trading can lead to a positive association between the price impact of news and information demand before the news release. One way to distinguish between these two scenarios empirically is to consider how information demand affects the informativeness of trades before the news arrival.

To see this, consider first an increase in the variance of the asset payoff. In equilibrium, this shock leads to an increase in information demand and, for this reason, it makes investors' aggregate demand less noisy.[16] Thus, in this scenario, one should observe that the price impact of trades

[14] To understand why, suppose to the contrary that the increase in information demand following an increase in the variance of the asset payoff is strong enough to reduce uncertainty. At the new equilibrium level for information demand, the marginal benefit of information is smaller than at the equilibrium level for information demand before the shock (since this marginal benefit increases with uncertainty). Yet the marginal cost is higher since information demand is higher and the information cost is increasing and strictly convex. Thus, the marginal benefit of information is strictly less than the marginal cost, which cannot be an equilibrium.

[15] Andrei and Hassler (2019) consider a dynamic portfolio model in which one investor controls the precision of signals that she receives about the drift of the return process for the risky asset. In their model, the uncertainty about the drift of the return process varies over time and is a state variable for investors' decisions at a given point in time. They show that the investor optimally raises the precision of her signal at a given date when uncertainty at this date is higher. However, in their model, the return process is exogenous. Thus, there is no feedback of the informativeness of the asset price on uncertainty (and therefore information demand) as happens in rational expectations models (e.g., in our model).

[16] Indeed, $\text{Var}(\chi_D)$ depends on $\text{Var}(F)$ only through speculator's aggregate information demand and decreases with this demand.

before news arrival is *stronger* (i.e., trades are more informative) when information demand is higher (see Section A in the Internet Appendix for a formal proof). Now consider an increase in the variance of noise trading. The direct effect of this increase is to make the aggregate demand for the asset noisier. This effect raises the profitability of trading on private information. Accordingly, investors' information demand increases. Yet, this indirect effect is never strong enough to offset the increase in the noise in investors' aggregate demand for the asset (which is the reason why uncertainty increases). Thus, in this scenario, one should observe that the price impact of trades before news arrival is *weaker* when information demand is higher (see Section A in the Internet Appendix for a formal proof). In our tests, consistent with the first scenario, we find that the price impact of trades is higher when information demand is higher (see Section 6.1).

The model suggests two additional sources of shocks that can explain variations in information demand and uncertainty: (i) shocks to investors' information acquisition cost or (ii) shocks to investors' risk aversion. Suppose that the marginal cost of acquiring information increases. The aggregate demand for information falls and, in this case, uncertainty increases in equilibrium. Thus, if shocks to information acquisition costs are the main driver of fluctuations in information demand then the model predicts a negative correlation between the sensitivity of prices to news and information demand ahead of news. This is also the case if variations in information demand refflect variations in risk aversion.[17] Thus, fluctuations in risk aversion or information acquisition costs cannot explain the positive association between information demand and the sensitivity of Treasury prices to news that we document in our tests (see Section 5.2).

3.3 Discussion

We have defined uncertainty from dealers' viewpoint (that is, traders who only observe public information). Alternatively, one could define uncertainty as the conditional variance of speculators' forecasting error, i.e., by $\mathrm{Var}(F \mid z_1, s_i)$. In Appendix A we show that in equilibrium:

$$\mathrm{Var}(F \mid z_1, s_i) = 2\gamma c'(\bar{\tau}_\eta^*). \tag{13}$$

[17]This point can be seen by multiplying the expression (eq. (11)) for the certainty equivalent of a speculator's expected utility by his risk aversion, γ. One then immediately sees that an increase in γ scales up the cost of information acquisition and therefore has the same effect as an increase in this cost. Intuitively, as risk aversion goes up, speculators trade less aggressively on their information, which reduces the incentive to buy private information in the first place.

Thus, Proposition 1 remains valid when uncertainty is measured by $\mathrm{Var}(F \mid z_1, s_i)$. Indeed, when the variance of the asset payoff or noise trading increases, the demand for information increases and therefore $c'(\bar{\tau}_\eta^*)$ increases (since $c(.)$ is strictly convex). It follows from eq. (13) that investors' uncertainty increases as well.

Our model is most closely related to Kim and Verrecchia (1991). However, there are three differences between our model and their model: (i) we allow for risk neutral uninformed investors ("dealers"), (ii) we do not allow speculators to retrade at date 2 (when the public signal is released), and (iii) the cost of information is strictly convex in speculators' information precision while it is linear in Kim and Verrechia (1991). It turns out that, for the purpose of our paper, the most important difference is the last one. Indeed, when the marginal cost of information is constant speculators' uncertainty ($\mathrm{Var}(F \mid z_1, s_i)$) does **not** depend on the variance of the asset payoff or the amount of noise trading in equilibrium. This holds true in our model and in Kim and Verrecchia (1991) (see their Proposition 3). The reason is simple. In equilibrium, the level of uncertainty must adjust (through variations in information demand) in such a way that the marginal benefit of information is equal to its marginal cost. Thus, when this cost is a constant, the marginal benefit of information must be insensitive to shocks to exogenous parameters (others than the information cost). This implies that, in equilibrium (i.e., after adjustments in information demand), uncertainty is independent of the variance of the asset payoff or the amount of noise trading.[18]

In Kim and Verrecchia (1991), the price reaction to the announcement is inversely related to speculators' uncertainty, $\mathrm{Var}(F \mid z_1, s_i)$. As the variance of the asset payoff or the amount of noise trading has no effect on uncertainty, these variables do not affect the strength of the price reaction to news in Kim and Verrecchia (1991). Thus, our implications regarding the effects of the variance of the asset payoff or noise trading on the strength of the price reaction to the announcement cannot be derived in Kim and Verrecchia (1991). For this reason, their model cannot predict the positive association between information demand and the price response to news that we find empirically while our model does. Kim and Verrecchia (1991)'s model with strictly convex cost of information is analytically intractable (this is the reason why they assume linear costs). However, we have checked numerically that the implications of our simpler model holds in Kim and Verrecchia (1991)

[18]For instance, in our model, $\mathrm{Var}(F \mid z_1, s_i) = 2\gamma c'(\bar{\tau}_\eta^*)$ in equilibrium (see eq. (13)). If $c'(\bar{\tau}_\eta^*)$ is constant, this implies that $\mathrm{Var}(F \mid z_1, s_i)$ is independent of $\mathrm{Var}(F)$ or $\mathrm{Var}(u)$ in equilibrium.

for a particular, non linear, specification of the cost function in their model. This shows that our main prediction is robust to variations in the modeling approach.

4 Data

Our main prediction is that investors' information demand about an asset ahead of news arrival is a leading indicator of the strength of the asset price response to news. We test it by analyzing the sensitivity of U.S. Treasury note yields to macroeconomic news announcements. We focus on U.S. Treasury notes, as opposed to equity or foreign exchange markets, because the link between U.S. Treasury yield movements and macroeconomic news is theoretically simpler and empirically stronger (see, e.g., Andersen et al., 2007; Fleming and Remolona, 1999; Balduzzi et al., 2001).

Among all macroeconomic announcements, we only consider those that significantly affect market participants' beliefs about future interest rates, as shown by their impact on U.S. Treasury notes yields. Out of 36 announcements, Gilbert et al. (2017) find that only three – namely nonfarm payroll, ISM Manufacturing PMI, and retail sales (listed in order of importance) – explain more than 10 percent of the variation in daily two-year U.S. Treasury yield changes.[19] According to Gilbert et al. (2017) investors are interested in these announcements, in part, because they contain information useful to forecast future monetary policy and therefore the future level of interest rates. We conjecture that searching and reading information related to these announcements is a way to improve forecasts of future interest rates. Our hypothesis is that greater information demand about topics related to these announcements is symptomatic of higher uncertainty about future interest rates.

Nonfarm payroll announcements take place at 8:30 a.m. on the first Friday of every month. Among all announcements, they have the biggest impact on Treasury yields. [20] For this reason, we first estimate the relationship between the sensitivity of Treasury yields to nonfarm payroll announcements and information demand about the topic nonfarm payroll employment. We then show that this relationship is similar for other influential macro-economic announcements in Section 6.3.

[19]ISM stands for Institute for Supply Management, formerly National Association of Purchasing Management (NAPM). PMI stands for Purchasing Manager Index.

[20]See Table 2 in Gilbert et al. (2017). For instance, for two-year U.S. Treasury notes, the R-squared of regressing yield changes on nonfarm payroll, ISM and retails sales surprises is 27.1%, 17.4%, and 12.5%, respectively.

In the rest of this section, we describe the data that we use to measure information demand about nonfarm payroll employment and we show that our measure of information demand is positively correlated with other measures of uncertainty.

4.1 Measuring Information Demand and Supply

To measure information demand before nonfarm payroll announcements, we use data provided to us by Bitly. Bitly provides short-URL-links (henceforth SURLs) and a readership tracking system since 2008.[21] SURLs are abridged versions of "Uniform Resource Locator" (URL) addresses. For example, consider the following URL: `https://blogs.wsj.com/economics/2016/01/07/why-december-private-payrolls-arent-a-great-predictor-of-the-jobs-report/`. The corresponding SURL created using Bitly is: `http://on.wsj.com/2oJQ2py`. Both links point to the same Wall Street Journal (WSJ) news article, "*Why December Private Payrolls Aren't a Great Predictor of the Jobs Report*," published prior to the release of the nonfarm payroll announcement of December 2015.

People create SURLs using Bitly for at least two reasons. First, SURLs are easier to share than original links, especially on micro-blogging sites, such as Twitter, or messaging technologies, or in the Bloomberg terminal. Second, Bitly sells readership tracking services to SURLs' creators (e.g., statistics on the number of clicks on a specific SURL, the geographical location of clickers etc.). Major news companies (e.g., Bloomberg or the Wall Street Journal) subscribe to these services and have purchased so called "*branded short domains*," i.e., customized SURLs. For example, the branded short domain of the WSJ is *http://on.wsj.com* and each SURL pointing to a WSJ article starts with this address instead of the regular *http://bit.ly/* link.

We have access to every single Bitly SURLs pointing to articles from 59 major online news providers (see the full list in Table IA.1 in the Internet Appendix) from January 2011 to July 2018. These include 9 traditional news providers (as in Chan, 2003) and 50 top online news providers according to the 2015 Pew Research Center ranking.[22]

[21] Bitly describes itself as the "*world's first and leading Link Management Platform*" and reports that it "has millions of customers, including close to three quarters of Fortune 500 firms." ("*Bitly Receives $63 million growth investment from Spectrum equity.*" Business Wire, July 12, 2017). Its website (`https://bitly.com/`) notes that Bitly's clients have created more than 38 billion links since 2008.

[22] The top online news entities according to Pew Research Center as of 2015 are listed here `http://www.journalism.org/media-indicators/digital-top-50-online-news-entities-2015/`.

For our analysis, we only consider SURLs created from 2012 to 2018 by the 38 news providers that already have branded domain names as of 2012.[23] This restriction avoids structural breaks in the time series of the number of clicks on SURLs pointing to articles of a given news provider.[24] We also exclude from our sample SURLs pointing to news from Marketwatch and CNBC because there are periods during which we cannot automate the reading of the URLs corresponding to SURLs pointing to news stories written by these two news providers.[25] This problem prevents us from identifying whether these news relate to nonfarm payroll employment or not (see below). Ultimately, our sample include SURLs pointing to articles from 36 different news providers from January 2012 to July 2018 (see Table IA.1 in the Internet Appendix).

For each SURL, we observe every single click on this SURL, the time at which a click occurs (with second precision), the location of the person clicking on the SURL and, when possible, how this person accessed the SURL (through a social media platform like Twitter or through an Internet browser). In addition, we observe the time at which the SURL was created, the login of its creator (which allows us to identify SURLs created by news providers), and the original URL of the SURL (henceforth "*seed URLs*"). Our dataset contains about 70 million unique SURLs generated by about 700,000 different user logins (there might be multiple individuals working for the same news provider who use the same login). Overall, we observe about 10 billion clicks on these SURLs.

Our measure of information demand about the topic nonfarm payroll employment over a given time interval is the number of clicks on Bitly SURLs directing to articles about nonfarm payroll employment during this interval. We automate the search for these articles using keyword searches (as in Baker et al., 2016; Husted et al., 2017) in seed URLs. Specifically, we collect all SURLs in our entire sample pointing to an URL containing the keywords "jobs report" or "payroll" or "jobless

[23]We start in 2012 because most news providers start paying for Bitly services (and therefore have branded domain names) in 2010 or 2011.

[24]Once a news agency has a branded domain, we observe that the number of SURL clicks increases dramatically.

[25]Our results are stronger when we include SURLs pointing to news from Marketwatch and CNBC. This is not surprising because, as we discuss in Section 5, interest in articles from the financial press is likely to better measure investors' information demand. However, we prefer to exclude these two sources because, in some years during our sample period, either the seed URL is encrypted or the data is missing, which prevents us from using keywords to identify articles from Marketwatch and CNBC relating to macroeconomic news.

rate" or "unemployment."[26] For instance, consider again the URL of the WSJ article mentioned in the first paragraph of this section. This URL contains two of our keywords ("payroll" and "jobs report"). Its SURL is therefore included in our sample. We refer to the resulting sample of SURLs as "*NFP SURLs*" and to the clicks on these SURLs as "*NFP clicks*." Overall, our sample contains $730,494$ NFP clicks.[27]

[Insert Figure 2 here]

Figure 2 shows the intra-day evolution of the average number of NFP clicks from 4:00 am to 5:00 pm ET during nonfarm payroll announcement days (there are 79 announcement days from January 2012 to July 2018). Figure 2 shows that the number of NFP clicks gradually increases before the announcement and experiences a sharp jump just after the announcement (at 8:30 am ET). Then it slowly decreases but remains elevated throughout the announcement day. Overall, there are 21,283 (148,971) NFP clicks in the 2 hours preceding (following) announcements in our sample.

[Insert Tables 1, 2 here]

Tables 1 and 2 provide a breakdown of nonfarm payroll clicks before (Panel A) and after (Panel B) nonfarm payroll announcements along two dimensions (i) the source of the news obtained with a click (Table 1), and (ii) the creator of the NFP SURL on which a click occurs (Table 2). Table 1 shows that the sources of nonfarm payroll news are concentrated among 5 providers (accounting for 91% to 72% of all news in the four hours around the announcement), with the WSJ and Bloomberg being the largest contributors, especially in the two hours prior to announcements. Thus, NFP clicks predominantly come from readers of the financial press, which supports our interpretation that they measure information demand of investors. Table 2 shows that Bitly links to popular news articles are often created by journalists from the main news providers.

[26] The choice of these keywords is based on the following analysis. We first collected all SURLs and the associated URLs accessed during a 17-minute window around nonfarm payroll annnouncements during our sample period. Then, using natural language processing (NLP) techniques, we removed common words –such as "a," or "the,"– from the original URL links and estimated the frequency of non-common words used in these links. We found that the relevant words with the highest frequency were "payroll," "unemployment", "jobless rate" and "jobs report" and, for a large set of URLs, we checked manually that URLs with these words do indeed point to articles about nonfarm payroll employment figures.

[27] As we move away from the nonfarm payroll announcement date, there are some very popular articles (with more than 10,000 clicks, when the median click on a payroll related article on announcement days is 200 clicks) that are not related to nonfarm payroll news. We remove these outliers that almost always occur outside announcement days by dropping articles with more than the top 99th percentile of clicks in the full sample. We also delete from our sample of NFP SURLs those pointing to news articles with headlines containing the word "sport" to avoid articles related to the payroll of sport stars.

Our measure of information demand over a given time interval is the number of NFP clicks during this interval, which we denote by "*Bitly Count*." In some tests, we also use an indicator variable (labeled "*High Bitly Count*") equal to one when *Bitly Count* is above its median value over the sample period (and zero otherwise).

Several studies use search data from Google Trends to measure investors' attention to particular events or assets (see, for instance, Da et al., 2011). To better isolate the predictive power of our measure of information demand, we control for the Google trend index for the topic "nonfarm payroll" in our tests.[28,29]

Variations in NFP clicks ahead of nonfarm payroll announcements might reflect variations in the supply of news stories about these announcements rather than variations in investors' consumption of news. To address this issue, in our empirical tests, we control for the number of available news stories written ahead of each announcement using data from Ravenpack's Story dataset. This dataset contains the headline of every news written by news providers covered by Ravenpack and a news release time stamp (up to the millisecond frequency).[30] We measure information supply over a given time interval as the number of Ravenpack news articles related to nonfarm payroll employment. We identify these news by searching in their headlines the same keywords as those used for identifying NFP SURLs.

4.2 Other Measures of Uncertainty

As explained previously, our contention is that information demand about an asset payoff can be used as a measure of uncertainty. To better highlight the incremental predictive power of our measure, in our tests, we also control for other measures of uncertainty about future interest rates (see Bloom, 2014; Datta et al., 2017, for a review of various measures of uncertainty).

[28] We obtain this index from Google trends website. The Google trend search index is constructed by first dividing the total number of searches over a given period (e.g., a week) using specific keywords by the total number of searches in Google over this period, and then dividing this ratio by the maximum of the ratio over a time period (15 years for monthly observations, 6 years for weekly observations, and one year for daily observations). The resulting figure is then multiplied by 100 to obtain the index for the chosen keyword (see Stephens-Davidowitz, 2013).

[29] One drawback of the Google trends search index for our purpose is that it is not available at high frequency over a long period of time. Hence, one cannot use it to measure separately information demand *shortly* before and after an announcement. This is problematic for our analysis since our model is about the relationship between information demand *before* announcements and the price reactions to announcements and not about the effect of these price reactions on subsequent information demand.

[30] News providers covered by Ravenpack include Dow Jones Newswires, the Wall Street Journal, Marketwatch, and Barron's, among others.

First, we use market-based and news-based measures of uncertainty about monetary policy. Our market-based measure is the implied volatility of options on one-year swap rates (swaptions) as in Carlston and Ochoa (2017).[31] Our news-based policy uncertainty indexes are those proposed by Baker et al. (2016) and Husted et al. (2017). Both indexes are based on a count of news stories that contain words related to uncertainty, government policies, and monetary policy. Husted et al. (2017)'s index specifically focuses on monetary policy uncertainty, while Baker et al. (2016) index measures economic policy uncertainty more broadly. The two measures are highly correlated during our sample period (correlation 0.52) and we obtain similar results with each measure. Thus, for brevity, we only report results using Husted et al. (2017)'s monetary policy uncertainty index.

We also use the absolute value of past forecasting errors by professional forecasters as a measure of uncertainty. Indeed, Scotti (2016) argues that the squared root of a weighted average – across macroeconomic announcements – of professional forecasters' squared forecast errors is a good measure of macroeconomic uncertainty. Thus, in every month, we compute the absolute value of the difference between the nonfarm payroll announcement and the median forecast of this figure (using real-time data from Bloomberg on professional forecasts) and use it as an alternative measure of uncertainty about future interest rates.

Increases in realized volatility may indicate an increase in future expected volatility because of GARCH effects (see Berger et al., 2019, for evidence). This corresponds to an increase in $\mathrm{Var}(F)$ before any information acquisition in our model and Proposition 1 implies that this should lead to an increase in uncertainty as well. Accordingly, we also use the realized monthly and daily volatility (an unconditional measure of volatility) in the two-, five-, and ten-year U.S. Treasury note futures returns as a measure of uncertainty about interest rates. Specifically, we sum the squared 1-minute returns, computed using midquotes, over the month or the day (during the New York trading hours from 7:00 am ET to 5:00 pm ET), respectively, and take the squared root and multiply by the squared root of 12 and 250, respectively, to annualize the monthly and daily volatility.[32]

[31]We thank Marcelo Ochoa for giving us the data. Carlston and Ochoa (2017) use swaption yields to estimate the implied volatility of one-year swap rate at different horizons. We use one-year horizon, but our results are qualitatively similar when we use horizons from 1 month to up to two years.

[32]The futures market is closed on certain U.S. holidays. Rather than keep track of holidays, we only keep days when there is at least one transaction every 30-minutes from 7:00 am to 5:00 pm ET. If quotes are not updated in a particular minute we copy down the previous quotes as long as the previous quote was updated in the last half-hour within the same day (the day starts at 7:00 am ET and ends at 5:00 pm ET).

Finally, we use the CBOE equity volatility index (VIX) because it is the most popular measure of equity market risk and uncertainty (see Bloom, 2014, 2009). The VIX is the implied option volatility of the S&P 500 index for option contracts with a one month maturity. Thus, it is a measure of the conditional variance of monthly returns on the S&P 500 index based on the "risk neutral" probability measure. For this reason, variations in the VIX can stem from time-variations in the actual (based on "physical" probabilities) conditional variance of the index (uncertainty), investors' risk aversion or both (see Bekaert and Hoerova, 2014). Another drawback of the VIX for our purpose is that it does not measure uncertainty on future interest rates per se.

4.3 Relationship between Information Demand and Measures of Uncertainty

In this section, we analyze the correlation between our measure of information demand ("*Bitly Count*") and the measures of uncertainty described in the previous section. Most of these measures are available at a daily or higher frequency, but the news-based monetary policy measure of Husted et al. (2017) is only available at a monthly frequency. We therefore compute the correlation of these measures at a monthly frequency.[33]

[Insert Table 3 about Here]

Table 3 shows that our proxy for monthly information demand is positively and significantly correlated with all the alternative monthly measures of uncertainty, especially with the market-based measure of monetary policy uncertainty (0.376) and realized interest rate volatility (0.358).[34] This is consistent with our claim that information demand is also a proxy for uncertainty.[35]

Table 3 also shows that our measure of information demand is positively correlated with information supply and the Google trend index for the topic nonfarm payroll. However, these two

[33]Aggregating to a monthly frequency avoids the problem of daily seasonality, e.g., some of the uncertainty measures are mechanically higher during nonfarm payroll announcement days than during non-announcement days, which induces a mechanical positive correlation across measures at a daily frequency.

[34]We obtain similar conclusions when our monthly measure of information demand uses the number of NFP clicks on nonfarm payroll days only because our monthly measure is mainly driven by clicks during nonfarm payroll announcement days.

[35]We have also analyzed the correlation between our information demand measure and Baker et al. (2016)' policy uncertainty index, Scotti (2016)'s macroeconomic uncertainty index, and Jurado et al. (2015)'s macroeconomic uncertainty index. At the monthly frequency, over our sample period, the correlation between Baker et al. (2016)' policy uncertainty index, Husted et al. (2017) monetary policy uncertainty index and Jurado et al. (2015) is high and positive (ranging from 0.2 to 0.53). The correlation between Scotti (2016)'s macroeconomic uncertainty index and the nonfarm payroll forecast error is 0.32. Consistent with the high positive correlation across measures, our measure of information demand is also positively correlated with these other measures.

measures are much less correlated with other measures of uncertainty than our measure of information demand. Information supply is positively correlated with the VIX index but its correlation with other measures of uncertainty is either non-significant or negative (in the case of realized volatility). The Google trend index is positively correlated with other measures of uncertainty but not always significantly (e.g., for the news-based measure of monetary uncertainty or for the realized volatility of two-year U.S. Treasuries).

[**Insert Figure 3 here**]

To explore this point in more detail, Figure 3 offers a visual representation of the relationships between our measure of information demand, the Google Trends search index, and interest rate realized volatility. Panel A of Figure 3 shows the monthly number of clicks on NFP SURLs (red line) and the Google Trends search index for the topic nonfarm payroll (blue line). Both series tend to increase when there are "global" uncertainty shocks, like the outcome of the Brexit referendum or the U.S. 2016 election. In Panel B of Figure 3, we show the time-series of Bitly information demand and interest rate volatility. We observe that during the Zero Lower Bound (ZLB) period (August 2011-December 2012), Bitly information demand was low and interest rate volatility was low. During this period, federal fund rates were close to zero and there was little uncertainty about the timing and pace of future changes in policy rates (see Swanson and Williams, 2014). One would therefore expect investors to demand less information about nonfarm payroll employment during this period and our measure of information demand shows that this is indeed the case. In contrast, the Google trend index remains high during the ZLB period, maybe because Google searches about nonfarm payroll regard unemployment in general rather than just information collection about future interest rates. Figure 3 also shows that interest rate realized volatility increases significantly after the ZLB period, maybe because of increased uncertainty about future monetary policy (see Husted et al., 2017).

5 Empirical Analysis

5.1 Benchmark

We first confirm that, as found in other studies, U.S. Treasury yields strongly respond to surprises in nonfarm payroll announcements. We also show that there is significant time variation in this response. This analysis serves as a benchmark to assess (in the next section) the economic size of the relationship between information demand and the sensitivity of U.S. treasury yields to nonfarm payroll announcements (see next section).

Following Balduzzi et al. (2001), we regress 30-minute U.S. Treasury yield changes on nonfarm payroll news.[36] Specifically, let t be a day with a nonfarm payroll announcement. We denote by y_t^m the yield of the futures on a U.S. Treasury note with maturity m (2-, 5-, and 10-years) on this day just after 8:59 am ET and by y_{t-1}^m the yield on this day just before 8:29 am ET.[37] We measure the yield reaction of U.S. Treasuries with maturity m to the nonfarm payroll announcement (at 8:30 am ET) on day t by estimating:

$$\Delta y_t = \alpha + \beta_S Surprise_t + \epsilon_t, \tag{14}$$

where $\Delta y_t = 100 \times (y_t^m - y_{t-1}^m)$ and $Surprise_t$ is defined as the difference between the actual release of the nonfarm payroll figure on day t and the median forecast about this figure submitted to Bloomberg by professional forecasters prior to the announcement.[38] This equation is the empirical analog of eq. (9) in the model and our predictions are about the effects of information demand on β_S. We estimate eq. (14) for two different samples period: (a) the long sample period (175 nonfarm payroll announcements): January 2004 to July 2018 for comparison with prior studies of the effect of nonfarm payroll announcements on Treasury yields and (b) the short sample period

[36] Our results are robust to using different frequencies of yield changes, 1-minute, 5-minute, daily, or even 5-day changes as shown in Section 6.2.

[37] We measure yields using intra-day data on bid and ask quotes of futures on U.S. Treasury notes from Thomson Reuters Tick History. There is a new U.S. Treasury note futures contract issued every three-months, in March, June, September, and December. The most recently issued ("front-month") contract, is the most heavily traded contract and is a close substitute for the underlying spot instrument. Thus, in our tests, we use the front-month futures contract, so that our results carry over to the spot rates, on the two-, five- and ten-year Treasury notes. When a new contract is issued there are a few days when the recently issued contract is slightly less liquid than the previously issued contract, we switch contracts when the trading volume of the recently issued contract is bigger than that of the previously issued contract. Once we switch contracts we do not switch back.

[38] Following Rogers et al. (2018, 2014), we approximate yield changes are approximated by dividing price changes by minus the modified duration of the cheapest-to-deliver security.

(79 nonfarm payroll announcements): January 2012 to July 2018 (during which our Bitly data is available). For ease of interpretation of the coefficient estimates, we standardize $Surprise_t$ by its standard deviation estimated using the long sample period in all of our tests.

[Insert Table 4 about here]

Table 4 reports estimates of eq. (14). The sensitivity (β_S) of Treasury yields to nonfarm payroll surprises for the long sample period (2004-2018) is similar to that in Balduzzi et al. (2001), who consider a different sample period (1991-1995). Specifically, the first column of Table 4 shows that a one-standard deviation increase in the nonfarm payroll surprise raises the two-year U.S. Treasury note yield by 4.95 basis point (which is 4.95 $\times$ 1.71 (average modified duration) = 5.79 basis point change in prices, compared to 6 basis point change in prices in Balduzzi et al., 2001). Column 2 shows that the impact of the nonfarm payroll surprise on the two-year U.S. Treasury note yield is much smaller, 3.2 bps, in the short sample period (2012-2018). This finding is consistent with Swanson and Williams (2014), who show that the impact of macroeconomic news announcements on two-year U.S. Treasury notes becomes smaller from August 2011 to December 2012, due to the federal fund rates being close to the zero lower bound.[39] Accordingly, we include in Column 3 an interaction term and a main effect for what we label the Swanson-Williams zero lower bound period ("SW ZLB period"), from August 2011 to December 2012, and confirm that the impact of nonfarm payroll announcement on two-year U.S. Treasury note futures is smaller during this period.[40]

5.2 Main Tests

We now study whether higher information demand ahead of nonfarm payroll announcements predicts a stronger reaction of treasury prices to these announcements. We restrict our analysis to the

[39]The federal funds target rate was essentially zero from December 2008 to December 2015. However Swanson and Williams (2014) find that two-year U.S. Treasury yields started being constrained in August 2011. The authors propose two reasons for this. First, until August 2011, market participants expected the zero lower bound to constrain monetary policy for only a few quarters, minimizing the zero bound's effects on medium and longer-term yields. In August 2011, the Federal Open Market Committee (FOMC) provided a specific date in the forward guidance, "*the Committee currently anticipates that economic conditions, including low rates of resource utilization and a subdued outlook for inflation over the medium run, are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013.*" Second, the Federal Reserve's large-scale purchases of long-term bonds and management of monetary policy expectations may have helped offset the effects of the zero bound on medium- and longer-term interest rates.

[40]We end the Swanson-Williams zero lower bound period on December 2012 for two reasons. First, on December 2012 the FOMC committee ends the "qualitative" and "calendar-based" forward guidance period and starts a data-dependent or "threshold based" forward guidance period based on particular unemployment and inflation thresholds (Femia et al., 2013). Second Swanson and Williams (2014)'s sample ends in December 2012.

short sample period (January 2012 - July 2018) since our measure of information demand starts in 2012. Moreover, in all our tests, we only measure information demand using the number of NFP clicks on NFP SURLs pointing to Bloomberg and Wall Street Journal news in the two hours preceding an announcement because (i) these are the predominant source of news in our sample (see Table 1); (ii) we want to capture investors' information demand, i.e., financial press readership; (iii) a large fraction (more than 46%) of NFP clicks are concentrated on the day of the announcement; and (iv) the key word search we use to identify news related to NFP announcements works better the closer we are to the announcement. Our findings are robust to these choices (see Sections C and D in the Internet Appendix).

We first estimate the following equation:

$$\Delta y_t = \alpha + \beta_S Surprise_t + \beta_{SI} Surprise_t \times \mathrm{IDem}_t^{before} + \beta_I \mathrm{IDem}_t^{before} + \epsilon_t, \tag{15}$$

where IDem_t^{before} measures information demand before the announcement on day t. It is either (i) the number of nonfarm payroll clicks in the two hours preceding the announcement on day t ("*Bitly Count*") divided by its standard deviation or (ii) an indicator variable ("*High Bitly Count*") equal to one if the number of nonfarm payroll clicks in the two hours preceding the announcement on day t is above its median value in the sample.

[Insert Table 5 about here]

Estimates of eq. (15) are reported in Table 5. As predicted, there is a strong positive and statistically significant association between the sensitivity (β_S) of Treasury yields to surprises in nonfarm payroll announcements and information demand prior to announcements. Namely, a one standard deviation increase in the number of Bitly clicks raises this sensitivity by 2.8 bps, 3.41 bps, and 2.6 bps for, respectively, the 2-, 5- and 10-year Treasury note futures (see Columns (1), (3), and (5)). These are large effects relative to the baseline effect of the surprise (which is two times smaller for the 5- and 10-year Treasury note futures and non-significant for the 2-year). We obtain similar conclusions when we measure information demand with "*High Bitly Count*" (see Columns (2), (4), and (6)).

To check wether the positive association between information demand and the response of Treasury yields to news is robust, we enrich our baseline specification (15) by adding various control variables. In particular, we control for the various measures of uncertainty described in Section 4.2. We estimate the following equation:

$$\begin{aligned}\Delta y_t = \alpha &+ \beta_S Surprise_t + \beta_{SI} Surprise_t \times \mathrm{IDem}_{t-1} \\ &+ \beta_I \mathrm{IDem}_{t-1} + \beta^{'}_{SX} Surprise_t \times X_t^{before} + \beta^{'}_X X_t^{before} + \epsilon_t,\end{aligned} \tag{16}$$

where X_t^{before} is a vector of control variables (discussed below) measured prior to the release of the announcement. They include our proxy for information supply, the measure of information demand based on the Google trends index, and additional variables that we group in four categories: (1) monetary policy, (2) risk, (3) information environment, and (4) trading environment:

1. **Monetary policy.** As previously discussed, U.S. Treasury yields are less responsive to macroeconomic news announcements during the ZLB period. Thus, in estimating eq. (16), we include a dummy variable ("SW ZLP") equal to 1 during the Swanson-Williams ZLB period. We also control for the level of the federal funds target rate (FFTR) because the Federal Open Market Committee (FOMC) might be less likely to raise interest rates in response to positive nonfarm payroll surprises when the FFTR is already high (see, Goldberg and Grisse, 2013). In addition, we control for the two measures of monetary policy uncertainty described in Section 4.2: the implied volatility of options on one-year swap rates (swaptions) and Husted et al. (2017)'s monetary policy uncertainty index.

2. **Risk.** We also include the CBOE equity volatility index (VIX) in our set of controls for two reasons.[41] First, this is a commonly used measure of uncertainty (see Section 4.2). Second, Goldberg and Grisse (2013) argue that U.S. Treasury yields could react less to macroeconomic news announcements in times of increased financial turmoil, due to its financial stability mandate

3. **Information Environment.** The sensitivity of Treasury notes yields to macroeconomic announcements should be stronger when these announcements are more accurate (see (eq. (10) in the model). An (inverse) measure of their accuracy is the extent to which they are subsequently revised (see, Hautsch and Hess, 2007; Gilbert, 2011, among others). Hence,

[41] In our regressions, we use the value of the VIX index at the close of the day preceding the nonfarm payroll announcement because options used to construct the index trade from 9:15 am to 4:15 pm ET.

in month t, we use the absolute value of the difference between the announced nonfarm payroll figure in the previous month minus the subsequent revision of this figure as an inverse measure of the accuracy of the nonfarm payroll announcement in month t (we call this variable "revision noise"). Imhoff and Lobo (1992) show that the dispersion of analysts' earnings forecasts is inversely related to the accuracy of earnings announcements. Thus, we also use the dispersion of professional forecasters' forecasts (normalized by the absolute value of the median forecast) prior to a given nonfarm payroll announcement as another proxy ("past forecast dispersion") for the variance of the noise in this announcement. Last, in month t, we control for the absolute value of the surprise in month $t-1$ ("past forecast errors') since, as explained in Section 4.2, professional forecasters' forecast errors are sometimes used as a proxy for uncertainty.

4. **Trading Environment.** We control for the realized daily volatility of the 2-, 5- and 10-year U.S. Treasury note futures return on the day before the announcement since this is an alternative measure of uncertainty. For each Treasury note futures contract, we also control for trading volume on the day before the announcement where trading volume is the number of contracts (in million) traded during the day (from 7:00 am ET to 5:00 pm ET).

[Insert Table 6 about here]

Table 6 shows estimates of eq. (16) for the 2-year Treasury note. In this table (and all subsequent tables), we just report the coefficients on interaction terms and the nonfarm payroll surprise for expositional clarity. In Columns (1) to (4), we consider each group of control variables separately (i.e., we include only control variables of one group in our estimation). We find that the sensitivity of U.S. Treasury yields to nonfarm payroll news (β_S) is significantly and negatively related to the Federal Funds Rate and the SW ZLB period indicator variable. Moreover, it is significantly and positively related to the market-based measure of monetary policy uncertainty and past realized volatility, consistent with the idea that news have a stronger impact on prices when prior uncertainty is higher. We also observe a negative and significant relationship between the dispersion of professional forecasters' forecasts and the response of U.S. Treasury yields to nonfarm payroll announcements (Column (3)), consistent with the prediction that news should move prices less when they are less accurate.

Column (5) shows that there is a positive and significant relationship between our proxy for information demand ("*BitlyCount*") and the reaction of U.S. Treasury yields to nonfarm payroll announcements, even after controlling for information supply and the Google trends index for google searches about nonfarm payroll.

In Column (6), we report estimates of eq. (16) with all control variables. Our proxy for information demand ("*BitlyCount*") is positively and significantly related to the sensitivity of U.S. Treasury notes yields to nonfarm payroll announcements. In fact this relationship is even stronger than that obtained in Table 5 since a one standard deviation increase in "*BitlyCount*" raises the sensitivity of the two-year U.S. Treasury note futures to surprises in nonfarm payroll news by 3.31 bps. None of the other control variables has a significant relationship with this sensitivity, except for the VIX variable which reduces it and the supply of information which increases it.

[Insert Tables 7 and 8 about here]

Tables 7 and 8 show estimates of eq. (16) for the five-year and ten-year U.S. Treasury notes, respectively. The results are similar to those for the two-year Treasury note. In particular, we again find a strong and statistically significant positive association between the sensitivity of U.S. Treasury note yields to nonfarm payroll announcements and our proxy for the demand of information about these announcements prior to their occurrence. In all cases, there is no significant relationship between this sensitivity and Google searches about nonfarm payroll unemployment, in line with the observation that the Google trend index is less correlated with uncertainty regarding future interest rates than our measure of information demand (see Table 3).

It is surprising that our measure of information demand is the only measure of uncertainty, among all those included as controls in our estimation of eq.(16), that is significantly related to the sensitivity of Treasury yields to news. One potential explanation is that none of the measures we consider are perfect. For example, the news-based monetary policy uncertainty measure is estimated over the previous entire month, and it therefore contains more stale information than the information demand measure, which is estimated right before the announcement. Another explanation is that there is not enough variability in other measures of uncertainty over our sample period to detect the effect of these measures.

Overall, our main finding in this section is that information demand ahead of nonfarm payroll announcements is positively related to the sensitivity of U.S. Treasury yields to these announcements, even after controlling for a host of other variables. It is worth stressing that this relationship is not causal. Rather, according to our model, it stems from time variations in investors' uncertainty about future interest rate that affect information demand and the sensitivity of US Treasury yields to nonfarm payroll announcements in the same direction. If one could control for investors' uncertainty directly and perfectly, the sign of the effect of information demand on the sensitivity of U.S. Treasury yields to news should be *negative*, not positive.

6 Additional Tests

6.1 Shocks to Noise Trading or to the Variance of Asset Payoffs?

According to Proposition 1, either shocks to the variance of asset payoffs (e.g., shocks to the variance of future interest rates for treasuries) or shocks to the volume of noise trading can generate an increase in both information demand and uncertainty before new announcements, and therefore explain our empirical findings in the previous section. However, as explained at the end of Section 3, these two shocks have different implications for the association between the price impact of trades before nonfarm payroll announcements and information demand ahead of these announcements. If fluctuations in uncertainty are mainly driven by shocks to the variance of asset payoffs, then this association should be positive. If instead they are mainly driven by shocks to noise trading, it should be negative. Thus, in this section, we study how the price impact of trades ahead of nonfarm payroll announcements and our proxy for information demand are related.

To this end, we define $OrderFlow_{\tau t}$ as the difference between buy and sell market orders (signed using the Lee and Ready (1991) algorithm) over interval $[\tau, \tau+1]$ on announcement day t, where each interval has a one minute duration and $\tau = 0$ is the time at which the announcement takes place. We then estimate the following equation:

$$
\begin{aligned}
\Delta OneMinYield_{\tau t} = \alpha &+ \beta_S Surprise_t + \beta_{SI} Surprise_t \times BitlyCount_t \\
&+ I_B(\lambda_B OrderFlow_{\tau t} + \kappa_B HighBitlyCount_t \times OrderFlow_t) \\
&+ I_A(\lambda_A OrderFlow_{\tau t} + \kappa_A HighBitlyCount_t \times OrderFlow_t) + \epsilon_t,
\end{aligned} \tag{17}
$$

where $\Delta OneMinYield_{\tau t}$ is the change in yields over the one minute interval $[\tau, \tau+1]$ on announcement day t, I_B is a dummy variable equal to one if $\tau < 0$ (before the announcement), and I_A is a dummy variable equal to one if $\tau \geq 0$ (after the announcement). We only use data two-hours before and two-hours after each announcement (i.e., from $\tau = -120$ to $\tau = 119$). Thus, λ_B (λ_A) measures the impact of trades on yields in the two-hours before (after) nonfarm payroll announcements. Coefficient κ_B (κ_A) measures the association between information demand (measured by the indicator variable "$HighBitlyCount_t$") and the impact of trades on yields two-hours before (after) nonfarm payroll releases, respectively. We report estimates of eq. (17) in Table 9.

[Insert Table 9]

As in Brandt and Kavajecz (2004) and Pasquariello and Vega (2007), we find that the impact of trades on Treasury notes yields is significant both before and after nonfarm payroll releases for all maturities, suggesting that trades contain information both before and after these releases.[42] However, trades are more informative after nonfarm payroll announcements than before. More importantly for our purpose, we find that the impact of trades is significantly stronger when the number of Bitly clicks is high, both after and before nonfarm payroll announcements (before the announcement the impact of trades is statistically significant only for the two-year U.S. Treasury note). Overall these findings suggest that (i) there is informed trading around nonfarm payroll announcements in Treasury markets, (ii) the number of Bitly clicks is a proxy for private information acquisition by investors, and that (iii) fluctuations in information demand by investors are driven by shocks to the variance of asset payoffs rather than shocks to the volume of noise trading (as theory predicts that in this case κ_B should be negative, not positive).

6.2 Information Demand by Rational Speculators or Noise Traders?

Automated searches about a specific stock by specific type of investors have been used as proxy for these investors' attention to this stock and therefore their trading activity. In particular, (see, Da et al., 2011) show that Google searches about a particular stock is a proxy for noise (retail) traders' participation in this stock while (see, Ben-Rephael et al., 2017) show that news searches

[42] When $\kappa_A = \kappa_B = 0$, our specification for measuring the yield impact of trades around nonfarm payroll announcements is very similar to that used in Brandt and Kavajecz (2004) and Pasquariello and Vega (2007).

on Bloomberg is a proxy for institutional investors' participation to the market. In the first case, an increase in investors' attention reduces price efficiency while in the second case it increases price efficiency (see (see, Da et al., 2011) and (see, Ben-Rephael et al., 2017)).

These findings suggest that time-variations in investors' attention might reflect time-variations in the population of investors trading around nonfarm payroll announcements. For instance, a surge in interest for news stories related to nonfarm payroll employment might simply stem from an increase in the number of noise traders around nonfarm payroll announcements. In anticipation of an announcement, these traders might read news about nonfarm payroll employment and overreact to announcements. Such a behavior would also lead to a positive association between information demand ahead of nonfarm payroll announcements and the sensitivity of Treasury prices to these announcements. However, in this case, part of the price jump in reaction to the announcement should be transient. Thus, in this scenario, an increase in information demand ahead of announcements should predict price reversals after the announcements.

[**Insert Figure 4 about Here**]

As a first look at this issue, Figure 4 shows cumulative yield changes on nonfarm payroll announcement days from two hours before the announcement up to five hours after the announcement, separately for days with (i) positive or negative surprises and (ii) a high number (higher than the median) or low number of NFP clicks. The figure confirms visually our main finding: nonfarm payroll announcements have a much larger impact on Treasury yields when the number of NFP clicks is high. Moreover, there is no sign of under or overreaction of Treasury yields to nonfarm payroll announcements *after* the announcement, whether the number of NFP clicks is high or low.

Next, to analyze this point more formally, we estimate the following equation at the daily frequency:

$$\Delta DailyYield_t = \alpha + \sum_{i=-30}^{30} \beta_{Si} Surprise_{t-i} + \sum_{i=-30}^{30} \beta_{BSi} Surprise_{t-i} \times BitlyCount_{t-i} + \epsilon_t, \quad (18)$$

This specification is similar to that of Lucca and Moench (2015) except that we interact leads and lags of the surprise variable with our proxy for information demand ($BitlyCount$). Estimates of eq. (18) are reported in Table 10.

[Insert Table 10]

We find no evidence of post announcement drift for nonfarm payroll announcements: the first lead coefficient on the surprise ($\beta_{S_{-1}}$) and the sum of the 30 lead coefficients are not statistically significant. This conclusion is unchanged for the coefficients on the interaction terms with the number of nonfarm payroll Bitly clicks.

We next consider whether the response to the nonfarm payroll announcement persists over the weekend after the release (which always takes place on Friday) and whether the persistence of the impact is related to Bitly counts. To this end, we estimate:

$$\Delta TwoDayYield_t = \alpha + \beta_S Surprise_t + \beta_{SB} Surprise_t \times BitlyCount_t + \epsilon_t, \tag{19}$$

where $\Delta TwoDayYield_t$ is estimated from the close of Thursday before the announcement to the close of the following Monday. The results are reported in Table 11. Again, we find that the coefficient on the interaction of the surprise in the announcement with Bitly is positive and statistically significant for all maturities. This finding shows, in another way, that a high number of Bitly nonfarm payroll clicks has a strong effect on the reaction of Treasury yields to nonfarm payroll announcements, so large that the yield reaction to the announcement can still be statistically detected on the Monday after the announcement.

Overall, the findings in Tables 10 and 11 suggest that a high number of Bitly clicks is not associated with over or underreaction of Treasury notes prices to nonfarm payroll announcements. Thus, the number of Bitly clicks is not a proxy for noise traders' participation to Treasury markets around nonfarm payroll announcements.

6.3 Other Macroeconomic Announcements

In this section, we study whether increased information demand about macroeconomic announcements, other than nonfarm payroll announcements, predicts a stronger reaction of U.S. Treasury yields to these announcements. For reasons explained in Section 4, we only consider the ISM manufacturing and retail sales announcements.

Our methodology to measure information demand about these variables is similar to that followed for nonfarm payroll news, but we use different keywords to build the relevant set of SURLs, namely “retail” or “sales” for measuring information demand ahead of retails sales announcements and “ism” or “manufacturing index” or “factory” or “factories” to measure information demand ahead of ISM manufacturing PMI. Similar to the nonfarm payroll announcements, we measure information demand ahead of these announcements by the number of clicks on relevant SURLs pointing to news released by Bloomberg and the WSJ.

[Insert Table 12]

As predicted, Table 12 shows that the impact of ISM manufacturing PMI and retail sales surprises on two year Treasury yields are significantly stronger when information demand related to these announcements is higher. A one standard deviation shock to information demand about retail sales increases the impact of retail sales surprises by 0.58 basis points, while a one standard deviation shock to information demand about ISM manufacturing increases the impact of ISM surprises by 0.36 basis points.

Nonfarm payroll announcements occur contemporaneously with the release of the unemployment rate (they are all part of the monthly employment report released by the Bureau of Labor Statistics). In Section E of the internet appendix, we estimate eq.(15) by adding the surprise in the employment rate figure as an additional control (and its interaction with our measure of information demand). We find that: (i) controlling for the unemployment rate surprise does not affect the significance and size of the relationship between the sensitivity of Treasury notes yields and information demand and (ii) the unemployment rate surprise (and its interaction with information demand) has no significant effect on Treasury notes yields.

Following the same methodology, we found that the interaction between information demand and macroeconomic surprise is not statistically significant for most of the other 36 announcements analyzed in Gilbert et al. (2017). As explained previously, these announcements have little impact on Treasury prices in the first place (i.e., have little informational content about future interest rates). We conclude that high information demand related to a particular announcement increases the sensitivity of yields to this announcement only if the announcement contains *relevant* information to begin with. This is consistent with the model in which the sensitivity of β to uncertainty (and therefore information demand) becomes small as the informativeness of the announcement (the inverse of $Var(\epsilon)$) becomes small. In other words, if the announcement does not contain relevant information, we find that information demand related to the announcement does not make the announcement relevant.

7 Conclusion

In this paper, we argue that shifts in information demand about a source of risk for an asset can be used as a proxy for investors' uncertainty about this source of risk. The reason is that shocks that exogenously increases investors' uncertainty also raise the marginal value of information. Investors respond by collecting more information, reducing thereby their uncertainty relative to its level after the initial shock. However, in equilibrium, it never fully offsets the effect of the initial shock, so that ultimately investors' demand for information is positively correlated with investors' uncertainty. One implication is that investors' demand for information ahead of influential news (e.g., economic policy changes) arrival is predictive of a stronger reaction of asset prices to news.

We test these implications by using novel data consisting of clicks on internet links pointing to news articles. Specifically, we use these data to measure information demand (consumption of news) about macro-economic variables (e.g., nonfarm payroll employment) that affect investors' beliefs about the path of future monetary policy. We first show that information demand about these variables is positively correlated with standard measures of uncertainty. Second, we show that an increase in information demand ahead of influential macroeconomic announcements predicts a stronger reaction of Treasury notes prices to the announcements, even after using standard measures of uncertainty as other predictors. Thus, information demand contains information about investors' uncertainty beyond and above the information provided by other proxies for uncertainty.

There is a growing interest by asset managers for obtaining data about individuals' consumption of information (e.g., search trends, web traffic data, or readership scores, such as those provided by Bloomberg).[43] Our findings suggest that these data are valuable because they can be used to forecast the size of price jumps when news arrives and therefore future volatility. Testing whether this is the case is an interesting venue for future research.

[43] See "Big data: Too popular for its own good", Institutional Investor, August 9, 2018.

References

Andersen, Torben, and Timothy Bollerslev, 1998, Deutsche mark-dollar volatility: intra-day activity patterns, macroeconomic announcements, and longer run dependencies, *Journal of Finance* 53, 219–265.

Andersen, Torben G, Tim Bollerslev, Francis X Diebold, and Clara Vega, 2007, Real-time price discovery in global stock, bond and foreign exchange markets, *Journal of International Economics* 73, 251–277.

Andrei, Daniel, and Michael Hassler, 2019, Dynamic attention behavior under return predictability, *Management Science, forthcoming* .

Baker, Scott, Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, *Quaterly Journal of Economics* 131, 1593–1636.

Balduzzi, Pierluigi, Edwin J. Elton, and T. Clifton Green, 2001, Economic news and bond prices: Evidence from the U.S. Treasury market, *Journal of Financial and Quantitative Analysis* 36, 523–543.

Beechey, Meredith J., and Jonathan H. Wright, 2009, The high-frequency impact of news on long-term yields and forward rates: Is it real?, *Journal of Monetary Economics* 56, 535–544.

Bekaert, Geert, and Marie Hoerova, 2014, The vix, the variance premium and stock market volatility', *Journal of Econometrics* 183, 181–192.

Ben-Rephael, Azi, Zhi Da, and Ryan D Israelsen, 2017, It depends on where you search: Institutional investor attention and underreaction to news, *Review of Financial Studies* 30, 3009–3047.

Berger, David, Ian Dew-Becker, and Stefano Giglio, 2019, Uncertainty shocks as second-moment news shocks, Technical report, Forthcoming Review of Economic Studies.

Bernanke, 1983, Irreversibility, uncertainty, and cyclical investment, *Quarterly Journal of Economics* 98, 85–106.

Bernile, Gennaro, Jianfeng Hu, and Yuehua Tang, 2016, Can information be locked up? informed trading ahead of macro-news announcements, *Journal of Financial Economics* .

Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623–668.

Bloom, Nicholas, 2014, Fluctuations in uncertainty, *Journal of Economic Perspectives* 28, 153–176.

Brandt, Michael, and Kenneth Kavajecz, 2004, Price discovery in the u.s. treasury market: The impact of orderflow and liquidity on the yield curve, *Journal of Finance* 59, 2623–2654.

Carlston, Ben, and Marcelo Ochoa, 2017, Macroeconomic announcements and investor beliefs at the zero lower bound, Technical report, Working Paper.

Chan, Wesley S., 2003, Stock price reaction to news and no-news: drit and reversal after headlines, *Journal of Financial Economics* 70, 223–260.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

Datta, Deepa, Juan M. Londono, Bo Sun, Daniel Beltran, Thiago Ferreira, Matteo Lacoviello, Mohammad R Jahan-Parvar, Calin Li, Marius Rodriguez, and John Rogers, 2017, Taxonomy of global risk, uncertainty, and volatility measures, Technical Report 1217, Working paper, Federal Board of Governors.

Fedyk, Anastassia, 2018, News-driven trading: who reads the news and when, Technical report, Working paper, Berkeley.

Femia, Katherine, Steven Friedman, and Brian Sack, 2013, The effects of policy guidance on perceptions of the fed's reaction function, Technical report, Federal Reserve Bank of New York, Staff Report No. 652.

Fleming, Michael J., and Eli M. Remolona, 1997, What moves the bond market?, *Economic Policy Review* 3, 31–50.

Fleming, Michael J., and Eli M. Remolona, 1999, Price formation and liquidity in the U.S. treasury market: The response to public information, *Journal of Finance* 54, 1901–1915.

Gilbert, Thomas, 2011, Information aggregation around macroeconomic announcements: Revisions matter, *Journal of Financial Economics* 101, 114–131.

Gilbert, Thomas, Chiara Scotti, Georg Strasser, and Clara Vega, 2017, Is the intrinsic value of a macroeconomic news announcement related to its asset price impact?, *Journal of Monetary Economics* 92, 78–95.

Goldberg, Linda, and Deborah Leonard, 2003, What moves sovereign bond markets? The effects of economic news on U.S. and German yields, *Current Issues in Economics and Finance* 9.

Goldberg, Linda S., and Christian Grisse, 2013, Time variation in asset price responses to macro announcements, Technical report, National Bureau of Economic Research.

Grossman, Sanford, and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson, 2005, The excess sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models, *American Economic Review* 95, 425–436.

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

Husted, Lucas, John Rogers, and Bo Sun, 2017, Monetary policy uncertainty, Technical report, International Finance Discussion Papers No. 1215.

Imhoff, Eugene A., and Gerald J. Lobo, 1992, The effect of ex ante earnings uncertainty on earnings response coefficients, *The Accounting Review* 67, 427–439.

Jurado, Kyle, Sydney Ludgvison, and Serena Ng, 2015, Measuring uncertainty, *American Economic Review* 105, 1177–1216.

Kim, Oliver, and Robert E. Verrecchia, 1991, Market reaction to anticipated announcements, *Journal of Financial Economics* 30, 273–309.

Kottimukkalur, Barinath, 2018, Earnings uncertainty and attention, Technical report, Working paper, George Washington University.

Kurov, Alexander, Alessio Sancetta, Georg Strasser, and Marketa H. Wolfe, 2016, Price drift before u.s. macroeconomic news: private information about public announcements?, Technical report, European Central Bank Working Paper Series No. 1901.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Lucca, David O., and Emanuel Moench, 2015, The pre-fomc announcement drift, *Journal of Finance* 70, 329–371.

Orlick, Anna, and Laura Veldkamp, 2015, Understanding uncertainty shocks and the role of black swans .

Pasquariello, Paolo, and Clara Vega, 2007, Informed and strategic order flow in the bond markets, *Review of Financial Studies* 20, 1975–2019.

Pastor, Lubos, and Pietro Veronesi, 2012, Uncertainty about goverment policy and stock prices, *Journal of Finance* 67, 1219–1263.

Pastor, Lubos, and Pietro Veronesi, 2013, Political uncertainty and risk premia, *Journal of Financial Economics* 110, 520–545.

Rogers, John H., Chiara Scotti, and Jonathan H. Wright, 2014, Evaluating asset-market effects of unconventional monetary policy: A cross-country comparison, Technical report, International Finance Discussion Papers No. 1101.

Rogers, John H., Chiara Scotti, and Jonathan H. Wright, 2018, Unconventional monetary policy and international risk premia, *Journal of Money, Credit and Banking* 50, 1827–1850.

Scotti, Chiara, 2016, Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises, *Journal of Monetary Economics* 82, 1–19.

Stephens-Davidowitz, Seth, 2013, The cost of racial animus on a black presidential candidate: Using google search data to find what surveys miss, Technical report, Harvard University.

Swanson, Eric T., and John C. Williams, 2014, Measuring the effect of the zero lower bound on medium-and longer-term interest rates, *American Economic Review* 104, 3154–3185.

Veldkamp, Laura L., 2006, Media frenzies in markets for financial information, *American Economic Review* 96, 577–601.

Vives, Xavier, 1995, Short-term investment and the informational efficiency of the market, *Review of Financial Studies* 8, 125–160.

Vives, Xavier, 2008, *Information and Learning in Markets* (Princeton University Press).

8 Appendix

Appendix A

Derivation of informed investors' demand

Using the fact that investors have a CARA utility function, we deduce that investor i's demand for the risky asset is:

$$x_i(s_i, p_1) = \frac{\mathrm{E}(F\,|s_i, p_1) - p_1}{\gamma \mathrm{Var}(F\,|s_i, p_1)} = \frac{(\mathrm{E}(F\,|s_i, z_1) - \mathrm{E}(F\,|z_1))}{\gamma \mathrm{Var}(F\,|s_i, z_1)}. \tag{20}$$

Moreover:

$$\mathrm{E}(F\,|s_i, z_1) = \mathrm{E}(F\,|z_1) + \tau_{\eta_i} \mathrm{Var}(F\,|s_i, z_1)\,(s_i - \mathrm{E}(F\,|z_1)), \tag{21}$$

Substituting eq. (21) in eq. (20) and using the fact that $p_1 = \mathrm{E}(F\,|z_1)$, we deduce that:

$$x_i(s_i, p_1) = \frac{\tau_{\eta_i}}{\gamma}(s_i - p_1). \tag{22}$$

Derivation of the certainty equivalent of investor i's expected utility at date 0.

Investors' final wealth at date 3 is:

$$W_{i3} = (F - p_1)x_i(s_i, p_1) - c(\tau_{\eta_i}). \tag{23}$$

Conditional on p_1 and s_i, W_{i3} has a normal distribution. Thus:

$$\mathrm{E}(-\exp(-\gamma W_{i3})\,|s_i, p_1) = -\exp(-\gamma(\mathrm{E}(W_{i3}\,|s_i, p_1) - \frac{\gamma}{2}\mathrm{Var}(W_{i3}\,|s_i, p_1))).$$

Using eq. (23), we obtain:

$$\mathrm{E}(-\exp(-\gamma W_{i3})\,|s_i, p_1) = -\exp(-0.5\gamma^2 x_i^2 \mathrm{Var}(F\,|s_i, p_1) + \gamma c(\tau_{\eta_i})).$$

Standard computations (see Vives (2008), Section 10.2.4)–using the expression for $x_i(s_i, p_1)$ in eq. (20) and the fact that $x_i(s_i, p_1)$ has a normal distribution–yield:

$$\begin{aligned}
\mathrm{E}(-\exp(-\gamma W_{i3})) &= \mathrm{E}(\mathrm{E}(-\exp(-\gamma W_{i3})\,|s_i, p_1)) \\
&= -\frac{\exp(\gamma c(\tau_{\eta_i}))}{(1+\gamma^2 \mathrm{Var}(F\,|s_i, p_1)\,\mathrm{Var}(x_i))^{\frac{1}{2}}}, \\
&= -\frac{\exp(\gamma c(\tau_{\eta_i}))}{(1+\frac{\mathrm{Var}(\mathrm{E}(F|s_i,p_1)-p_1)}{\mathrm{Var}(F|s_i,p_1)})^{\frac{1}{2}}}.
\end{aligned}$$

Thus, the certainty equivalent of investor i's expected utility is:

$$\Pi_i(\tau_{\eta_i}, \overline{\tau}_\eta) = \frac{1}{2\gamma}\ln(1+\frac{\mathrm{Var}(\mathrm{E}(F\,|s_i, p_1)-p_1)}{\mathrm{Var}(F\,|s_i, p_1)}) - c(\tau_{\eta_i}). \tag{24}$$

Now, using eq. (21) and the fact that $p_1 = \mathrm{E}(F \mid z_1)$:

$$\frac{\mathrm{Var}(\mathrm{E}(F\,|s_i, p_1)-p_1)}{\mathrm{Var}(F\,|s_i, p_1)} = \tau_{\eta_i}^2 \times \mathrm{Var}(F \mid z_1, s_i) \times \mathrm{Var}(s_i - E(F \mid z_1)). \tag{25}$$

As $\mathrm{Var}(s_i - E(F \mid z_1)) = \mathrm{Var}((F - E(F \mid z_1)) + \eta_i) = \mathrm{Var}(F \mid z_1) + \mathrm{Var}(\eta_i)$ and $\mathrm{Var}(F \mid z_1, s_i) = \frac{Var(\eta_i)Var(F|z_1)}{\mathrm{Var}(\eta_i)+\mathrm{Var}(F|z_1)}$, we deduce that (using the fact that by definition $\tau_{\eta_i} = Var(\eta_i)^{-1}$):

$$\frac{\mathrm{Var}(\mathrm{E}(F\,|s_i, p_1)-p_1)}{\mathrm{Var}(F\,|s_i, p_1)} = \tau_{\eta_i}\mathrm{Var}(F \mid z_1). \tag{26}$$

Replacing $\frac{\mathrm{Var}(\mathrm{E}(F|s_i,p_1)-p_1)}{\mathrm{Var}(F|s_i,p_1)}$ by its expression in eq. (26) in eq. (24), we obtain eq. (11) in the text.

Proof of Proposition 1.

Let $G(\overline{\tau}_\eta; \mathrm{Var}(F), \mathrm{Var}(u), \gamma)$ be such that:

$$G(\overline{\tau}_\eta; \mathrm{Var}(F), \mathrm{Var}(u), \gamma) \overset{def}{=} 1 - (2\gamma)c'(\overline{\tau}_\eta)(\mathrm{Var}(F)^{-1} + \gamma^{-2}\overline{\tau}_\eta \mathrm{Var}(u)^{-1} + \overline{\tau}_\eta) = 0. \tag{27}$$

As explained in the text, if there is an equilibrium in which $\overline{\tau}_\eta^* > 0$ then it solves:

$$G(\overline{\tau}_\eta^*; \mathrm{Var}(F), \mathrm{Var}(u), \gamma) = 0. \tag{28}$$

It is immediate that $G(.)$ decreases with $\overline{\tau}_\eta$ and that $G(0) > 0$ if and only if $c'(0) < 2\gamma^{-1}\text{Var}(F)$. Moreover, there is always a value of $\overline{\tau}_\eta$ large enough such that $G(\overline{\tau}_\eta; \text{Var}(F), \text{Var}(u), \gamma) < 0$. We deduce that if $c'(0) < 2\gamma^{-1}\text{Var}(F)$, Condition (28) has a unique root so that the equilibrium of the information acquisition stage is unique. Moreover, if $c'(0) > 2\gamma^{-1}\text{Var}(F)$ then $G(\overline{\tau}_\eta; \text{Var}(F), \text{Var}(u), \gamma) < 0$ for all $\overline{\tau}_\eta$ and therefore the unique equilibrium is $\overline{\tau}_\eta^* = 0$.

Now consider the case in which $\overline{\tau}_\eta^* > 0$. Using Condition (28) and the implicit function theorem, we obtain:

$$\frac{d\overline{\tau}_\eta^*}{d\text{Var}(F)} = \frac{\frac{\partial G}{\partial \text{Var}(F)}}{\frac{\partial G}{\partial \overline{\tau}_\eta}} > 0,$$

where the last inequality follows from the fact that $G(\overline{\tau}_\eta; \text{Var}(F), \text{Var}(u), \gamma)$ decreases with $\text{Var}(F)$ and $\overline{\tau}_\eta^*$. Thus, investors' aggregate demand for information increases with the variance of the asset payoff. The same reasoning shows that investors' aggregate demand for information increases with the variance of the noise trading. Moreover, observe that $G(\overline{\tau}_\eta^*; \text{Var}(F), \text{Var}(u), \gamma) = 0$ implies that in equilibrium:

$$\text{Var}(F \mid z_1) = \left(\frac{1}{2\gamma c'(\overline{\tau}_\eta^*)} - \overline{\tau}_\eta^*\right)^{-1}. \tag{29}$$

Thus, an increase in (i) the variance of the asset payoff, $\text{Var}(F)$ or (ii) the variance of noise trading, $\text{Var}(u)$ result in an increase in $\text{Var}(F \mid z_1)$ and therefore $|\beta|$ (by eq. (10)).

Speculators' expected forecasting errors in equilibrium.

Speculators observe their private signal and the asset price when they trade. Thus, speculators' expected forecasting error is:

$$E((F - E(F \mid s_i, p_1))^2) = Var(F \mid s_i, p_1) = \frac{\text{Var}(\eta_i)\text{Var}(F \mid z_1)}{\text{Var}(\eta_i) + Var(F \mid z_1)}. \tag{30}$$

In equilibrium:

$$\text{Var}(\eta_i) = (\bar{\tau}_\eta^*)^{-1}.$$

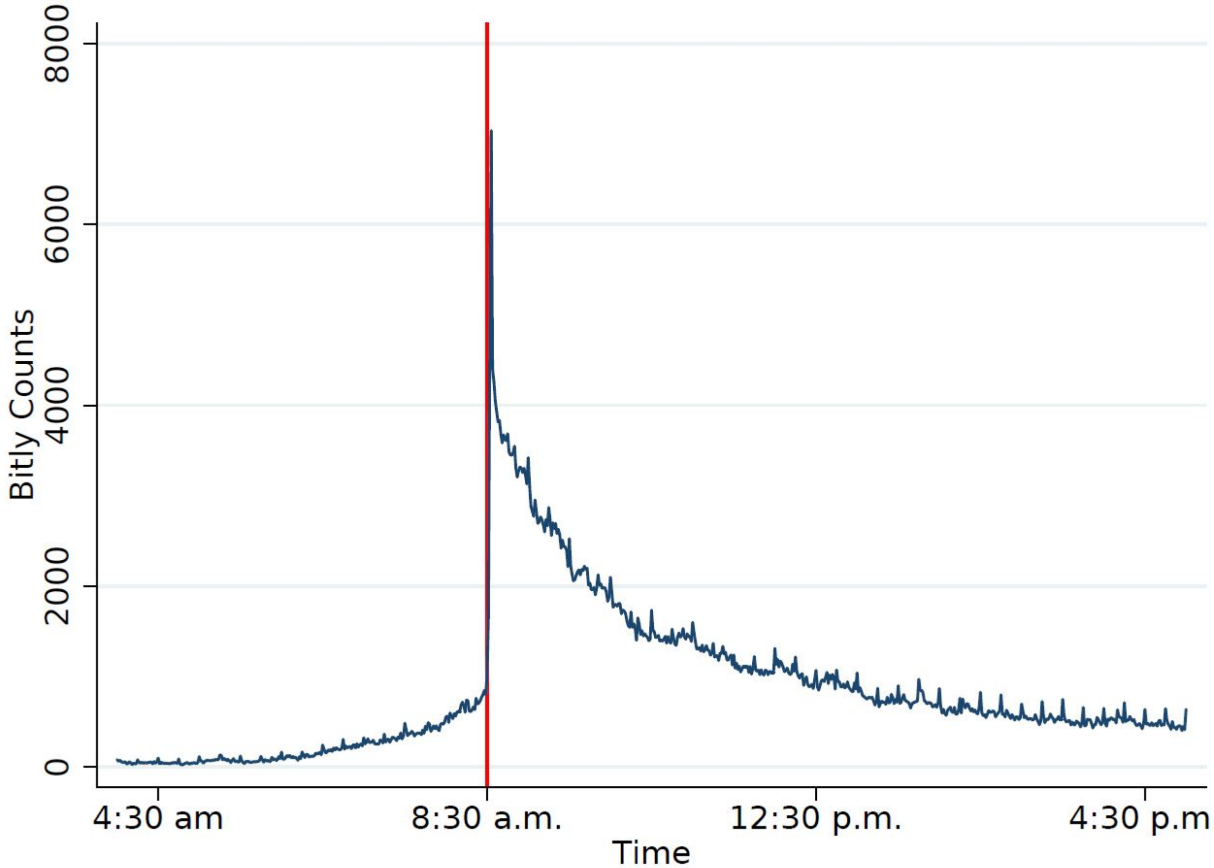
Thus, in equilibrium:

$$\text{Var}(F \mid s_i, p_1) = \frac{1}{\text{Var}(F \mid z_1)^{-1} + \bar{\tau}_\eta^*}. \tag{31}$$

Moreover, in equilibrium, $\text{Var}(F \mid z_1) = (\frac{1}{2\gamma c'(\overline{\tau}_\eta^*)} - \overline{\tau}_\eta^*)^{-1}$ (see eq. (29)). We deduce from eq. (32) that:

$$\text{Var}(F \mid s_i, p_1) = 2\gamma c'(\tau_\eta). \tag{32}$$

Figure 2: Intra Day Bitly Counts on Nonfarm Payroll Announcement Days



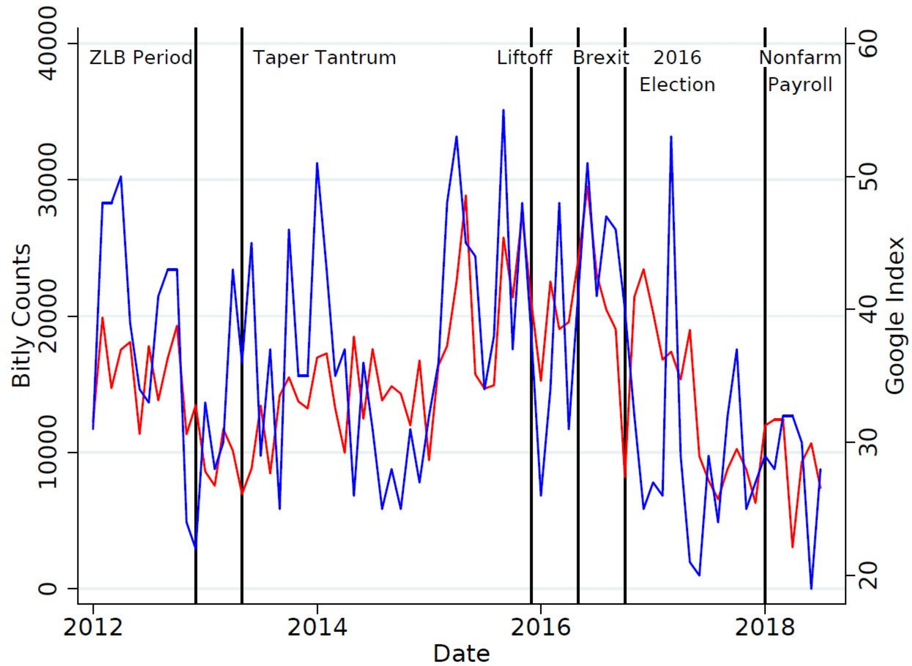
Notes: The figure shows the per minute number of nonfarm payroll Bitly clicks from 4:00 am ET to 5:00 pm ET, across all nonfarm payroll announcement days from January 2012 to July 2018 (91 days). The vertical red line identifies the release time of nonfarm payroll, 8:30 am ET.

Figure 1: **Timeline.**

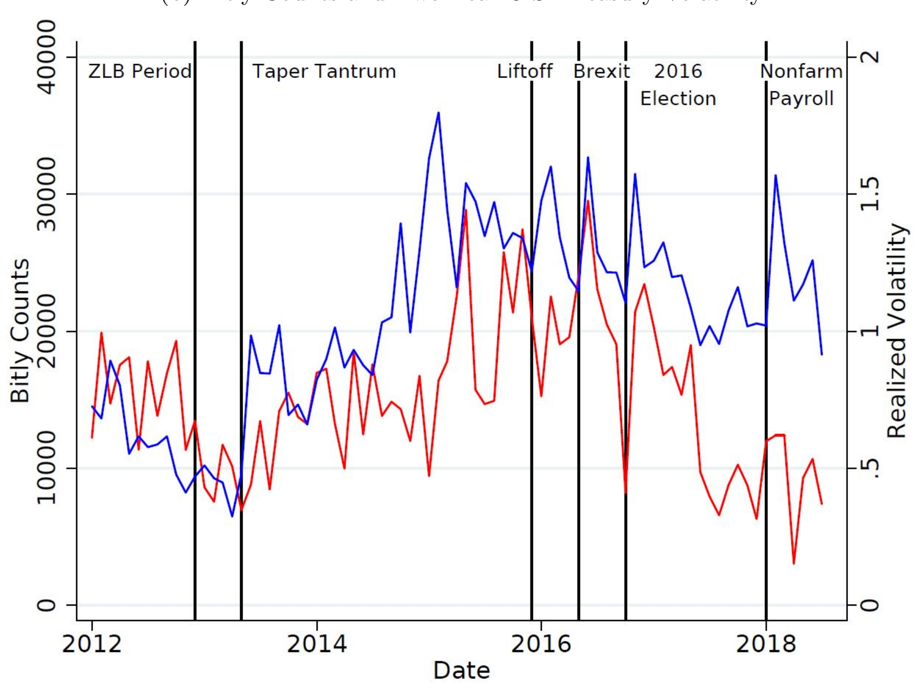
Date 0	Date 1	Date 2	Date 3
Information Acquisition	**Trading**	**News**	**Asset payoff is realized**
Each speculator chooses the precision, τ_i, of his signal about F.	Each speculator receives his signal $s_i = F + \eta_i$ and chooses his information demand $x_i(s_i, p_1)$.	News, A_e, arrives about the asset payoff with $A_e = F + \epsilon$.	
A signal of precision τ_i costs $c(\tau_i)$	Noise traders' demand, u is realized.	Dealers update the price of the asset based on news: $p_2 = E(F \mid A_e, D(p_1))$	
Aggregate information demand is $\bar{\tau} = \int_i \tau_i$	Dealers observe investors' aggregate demand $D(p_1)$ and choose a price equal to their expectation of the asset payoff: $p_1 = E(F \mid D(p_1))$.		

Figure 3: Comparing Different Measures of Information Demand and Two-Year U.S. Treasury Volatility

(a) Bitly Counts and Google Index

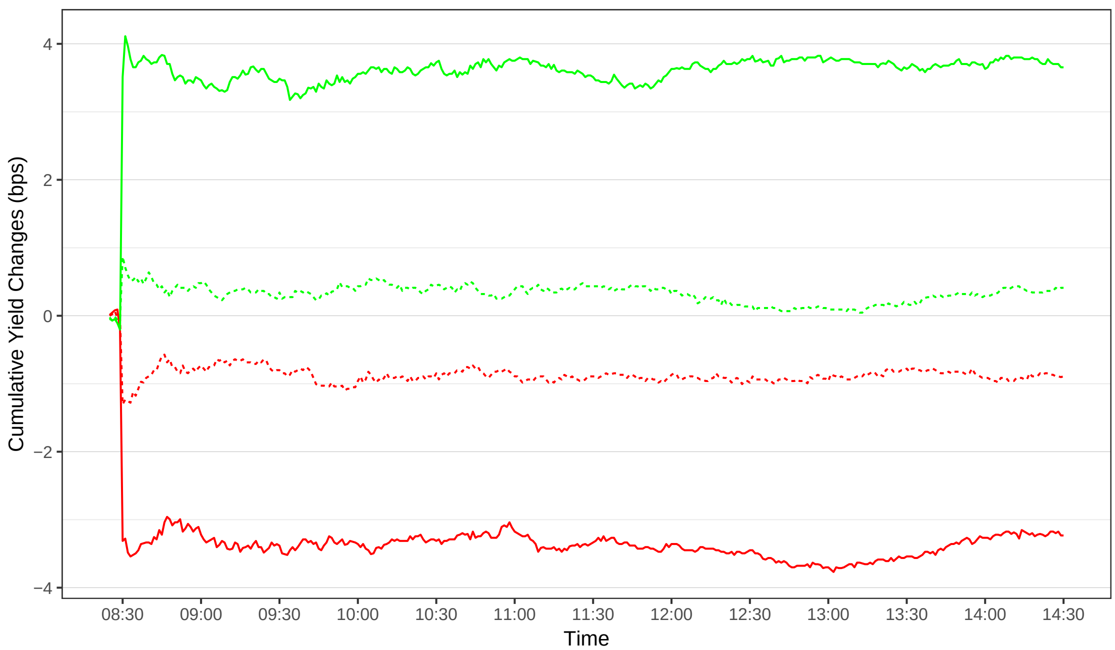


(b) Bitly Counts and Two-Year U.S. Treasury Volatility



Notes: Panel a shows monthly Bitly counts (red line) and Google Index (blue line) for the topic nonfarm payroll in our sample from January 2012 to July 2018. Panel b shows monthly Bitly counts (red line) and Two-Year U.S. Treasury Volatility (blue line).

Figure 4: Intra Day Two-Year U.S. Treasury Yield Reaction



Notes: The figure shows the aggregate intraday reaction of the Two-Year U.S. Treasury futures yields to nonfarm payroll surprises across 79 announcement days from January 2012 to July 2018. We perform a dependent sort. First we sort on positive (green lines) and negative (red lines) nonfarm payroll surprises, and then we sort on Bitly counts in the top 50% percentile (solid lines) and the bottom 50% percentile (dashed lines). The release time of nonfarm payroll is at 8:30 am ET.

Table 1: Popular News Sources of Articles Shared using Bitly

News Source	Number of Clicks	Percent of Total Number of Clicks	Cumulative Percent
Panel A: Prior to nonfarm payroll release, from 6:29 am ET to 8:29 am ET			
Wall Street Journal	7,137	34%	34%
Bloomberg	5,538	26%	60%
CNN	4,365	21%	80%
New York Times	1,219	6%	86%
USA Today	1,144	5%	91%
Panel B: During and after nonfarm payroll release, from 8:30 am ET to 10:30 am ET			
Wall Street Journal	26,200	18%	18%
CNN	24,291	16%	34%
Bloomberg	21,853	15%	49%
New York Times	21,092	14%	63%
USA Today	14,123	9%	72%

Notes: Our sample period is from January 2012 to July 2018, which includes a total of 79 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:29 am to 8:29 am ET. There are a total of 21,283 clicks during this period across the 79 announcements. In Panel B, we consider clicks during and after the announcement, from 8:30 am to 10:30 am ET. There are a total of 148,971 clicks during this period across the 79 announcements. The nonfarm payroll announcement is released by the Bureau of Labor Statistics at 8:30 am ET on the first Friday of the month.

Table 2: Who Shares Bitly Links

Bitly User Type	Number of Clicks	Percent of Total Number of Clicks	Cumulative Percent
Panel A: Prior to nonfarm payroll release, from 6:29 am ET to 8:29 am ET			
Official WSJ Users	4,755	22%	22%
Official Bloomberg Users	4,609	22%	44%
Official CNN Users	3,683	17%	61%
Three Individual Users	1,672	8%	69%
Anonymous	1,029	5%	74%
Official USA Today Users	965	5%	79%
Official NY Times Users	781	4%	82%
Panel B: During and after nonfarm payroll release, from 8:30 am ET to 10:30 am ET			
Official WSJ Users	18,747	13%	13%
Official NY Times Users	16,880	11%	24%
Official CNN Users	16,152	11%	35%
Official Bloomberg Users	15,295	10%	45%
Official USA Today Users	12,756	9%	54%
Three Individual Users	11,731	8%	61%
Anonymous	10,437	7%	68%

Notes: Our sample period is from January 2012 to July 2018, which includes a total of 79 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:29 am to 8:29 am ET. There are a total of 21,283 clicks during this period across the 79 announcements. In Panel B, we consider clicks during and after the announcement, from 8:30 am to 10:30 am ET. There are a total of 148,971 clicks during this period across the 79 announcements. The nonfarm payroll announcement is released by the Bureau of Labor Statistics at 8:30 am ET on the first Friday of the month. We aggregate clicks on links shared by three different individual users. News services often have more than one Bitly user account. In general, one Bitly user accounts for the majority of the clicks, but we aggregate across official users within a news services. The list of official usernames per news service was provided to us by Bitly.

Table 3: Contemporaneous Relation between Information Demand and Uncertainty Measures

	Information Demand	Market-based Policy Unc.	News-based Policy Unc.	VIX	Macro Uncertainty	Two-Year Volatility	Google Index	Information Supply
Information Demand	1							
Market-based Policy Uncertainty	0.376***	1						
News-based Policy Uncertainty	0.320**	0.553***	1					
VIX	0.217*	0.437***	0.280*	1				
Macro Uncertainty (Forecast Error)	0.245*	0.105	0.056	0.095	1			
Two-Year US Treasury Note Volatility	0.358**	0.645***	0.522***	0.147	-0.0001	1		
Google Index	0.459***	0.350**	0.145	0.224*	0.265*	0.057	1	
Information Supply	0.379***	-0.190	-0.148	0.309**	0.143	-0.459***	0.464***	1

Notes: We estimate the contemporaneous correlation between monthly information demand and monthly measures of uncertainty using data from January 2012 to July 2018. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: U.S. Treasury Futures Response to Nonfarm Payroll Surprises

	Jan. 2004 - Jul. 2018	Jan. 2012 - Jul. 2018	
	(1)	(2)	(3)
Panel A: Response of the Two-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	4.953***	3.188***	3.584***
	(0.606)	(0.701)	(0.819)
NFP Surprise × SW ZLB Period			-2.373**
			(0.920)
SW ZLB Period			-1.076
			(0.646)
Constant	0.632	0.0648	0.249
	(0.441)	(0.452)	(0.526)
Number of Observations	175	79	79
Adjusted R-squared	0.335	0.233	0.259
Panel B: Response of the Five-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	5.951***	6.437***	6.526***
	(0.735)	(0.992)	(1.151)
NFP Surprise × SW ZLB Period			-0.248
			(1.746)
SW ZLB Period			-2.656**
			(1.285)
Constant	0.371	-0.144	0.261
	(0.514)	(0.696)	(0.803)
Number of Observations	175	79	79
Adjusted R-squared	0.339	0.343	0.360
Panel C: Response of the Ten-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	5.881***	7.215***	6.790***
	(0.727)	(1.060)	(1.180)
NFP Surprise ×SW ZLB Period			3.038
			(2.137)
SW ZLB Period			-3.062*
			(1.617)
Constant	0.472	-0.180	0.259
	(0.506)	(0.730)	(0.820)
Number of Observations	175	79	79
Adjusted R-squared	0.342	0.374	0.399

Notes: We show estimates of equation 14 using two different samples. In column 1, the sample is from January 2004 to July 2018. In column 2, the sample is from January 2012 to July 2018, the sample for which we have Bitly data. The SW ZLB Period is an indicator variable equal to one during the Swanson-Williams period, when two-year U.S. Treasury note yields responded less to macroeconomic news announcements because of the Zero Lower Bound.

Table 5: Impact of Information Demand on the U.S. Treasury Futures Response to Nonfarm Payroll Surprises

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	0.362	1.082*	3.076**	4.019***	4.577***	5.344***
	(0.677)	(0.618)	(1.208)	(1.254)	(1.415)	(1.448)
Nonfarm Payroll Surprise × Bitly Count	2.873***		3.418***		2.660**	
	(0.819)		(1.125)		(1.191)	
Bitly Counts	1.010*		1.200		1.093	
	(0.574)		(0.775)		(0.746)	
NFP Surprise × High Bitly Count		4.013***		4.650**		3.564*
		(1.243)		(1.882)		(2.065)
High Bitly Count		0.0661		-0.0567		0.0629
		(0.870)		(1.347)		(1.418)
Constant	-1.004**	-0.274	-1.414*	-0.469	-1.309	-0.482
	(0.440)	(0.387)	(0.749)	(0.776)	(0.834)	(0.867)
Number of Observations	79	79	79	79	79	79
Adjusted R-squared	0.442	0.321	0.450	0.386	0.434	0.396

Notes: We estimate the response of U.S. Treasury futures on two-year, five-year, and ten-year notes to nonfarm payroll surprises using data from January 2012 to July 2018. The dependent variable is a 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The variables "Bitly Count" is the sum of clicks on news paper articles related to nonfarm payroll from two hours before the release of the announcement to one minute prior to the announcement. We divide Bitly counts by its standard deviation so that the magnitude of the coefficient can be interpreted more easily. The variable "High Bitly Count" is an indicator variable equal to one if the Bitly counts are above the median number of counts. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Response of the Two-Year US Treasury Futures to Nonfarm Payroll Surprises

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	-1.690	5.452*	6.254***	1.003	-2.320	-9.829
	(2.623)	(2.861)	(2.190)	(1.501)	(2.116)	(7.329)
Monetary Policy Variables						
NFP Surprise × FFR Level	-3.898***					5.004
	(0.888)					(4.266)
NFP Surprise × SW ZLB Period	-1.898**					1.944
	(0.835)					(1.818)
NFP Surprise × Market-based Uncertainty	2.701***					5.833**
	(0.959)					(2.496)
NFP Surprise × News-based Uncertainty	-0.013					-0.007
	(0.015)					(0.022)
Risk						
NFP Surprise × VIX Index		-0.150				-0.383**
		(0.175)				(0.144)
Information Environment						
NFP Surprise × Past Revision Noise			0.0193			0.0416
			(0.0626)			(0.0443)
NFP Surprise × Past Forecast Error			0.007			0.001
			(0.017)			(0.024)
NFP Surprise × Past Forecast Dispersion			-0.313***			-0.084
			(0.112)			(0.119)
Trading Volume and Volatility						
NFP Surprise × Past Trading Volume				-0.811		0.683
				(0.600)		(0.988)
NFP Surprise × Past Realized Volatility				5.598*		-13.73
				(3.301)		(8.753)
Information Demand and Supply						
NFP Surprise × Bitly Count					2.853***	3.319**
					(0.813)	(1.265)
NFP Surprise × Google Index					-0.701	-0.767
					(0.793)	(0.994)
NFP Surprise × Media Coverage Count					1.553***	2.559**
					(0.445)	(1.215)
Constant	-1.264	2.439	0.732	-2.151*	-0.933	0.845
	(2.097)	(2.015)	(1.335)	(1.231)	(1.566)	(4.825)
Number of observations	79	79	79	79	79	79
R-squared	0.420	0.250	0.309	0.299	0.485	0.622

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2012 to July 2018. The dependent variable is a 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. The variables Bitly count, Google index and media coverage count are divided by their standard deviation so that the magnitude of the coefficient can be interpreted more easily. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Response of the Five-Year US Treasury Futures to Nonfarm Payroll Surprises

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	7.104	8.466*	8.693***	0.0774	-2.724	5.301
	(5.081)	(4.516)	(2.955)	(4.835)	(3.019)	(12.07)
Monetary Policy Variables						
NFP Surprise × FFR Level	-8.078***					-2.830
	(1.772)					(5.353)
NFP Surprise × SW ZLB Period	-2.239					1.303
	(2.126)					(3.177)
NFP Surprise × Market-based Uncertainty	1.800					-0.949
	(1.450)					(2.721)
NFP Surprise × News-based Uncertainty	-0.0162					-0.0264
	(0.0219)					(0.0360)
Risk						
NFP Surprise × VIX Index		-0.134				-0.274
		(0.281)				(0.276)
Information Environment						
NFP Surprise × Past Revision Noise			0.0709			0.0288
			(0.0716)			(0.0959)
NFP Surprise × Past Forecast Error			-0.0166			-0.00898
			(0.0272)			(0.0416)
NFP Surprise × Past Forecast Dispersion			-0.258			-0.307
			(0.161)			(0.195)
Trading Volume and Volatility						
NFP Surprise × Past Trading Volume				-0.744**		0.471
				(0.327)		(0.770)
NFP Surprise × Past Realized Volatility				5.273**		0.511
				(2.266)		(4.349)
Information Demand and Supply						
NFP Surprise × Bitly Count					3.444***	4.171**
					(1.129)	(1.765)
NFP Surprise × Google Index					-1.744	-1.354
					(1.230)	(1.669)
NFP Surprise × Media Coverage Count					3.545***	3.036
					(0.732)	(2.097)
Constant	-0.402	3.610	0.787	-3.535	-1.566	-0.0805
	(3.661)	(3.076)	(1.988)	(3.140)	(2.502)	(9.190)
Number of observations	79	79	79	79	79	79
R-squared	0.485	0.356	0.379	0.410	0.528	0.619

Notes: We estimate the response of U.S. Treasury futures on five-year notes to nonfarm payroll surprises using data from January 2012 to July 2018. The dependent variable is a 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. The variables Bitly count, Google index and media coverage count are divided by their standard deviation so that the magnitude of the coefficient can be interpreted more easily. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Response of the Ten-Year US Treasury Futures to Nonfarm Payroll Surprises

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	11.11*	7.040	6.693**	0.786	-3.126	9.667
	(5.597)	(4.637)	(3.088)	(8.333)	(3.236)	(14.90)
Monetary Policy Variables						
NFP Surprise × FFR Level	-8.614***					-1.091
	(1.941)					(4.768)
NFP Surprise × SW ZLB Period	-0.0418					1.737
	(2.693)					(3.583)
NFP Surprise × Market-based Uncertainty	0.688					-1.109
	(1.519)					(2.236)
NFP Surprise x News-based Uncertainty	-0.0135					-0.0293
	(0.0234)					(0.0376)
Risk						
NFP Surprise × VIX Index		0.0130				-0.265
		(0.293)				(0.296)
Information Environment						
NFP Surprise × Past Revision Noise			0.131*			0.0760
			(0.0669)			(0.0962)
NFP Surprise × Past Forecast Error			-0.0361			-0.0183
			(0.0309)			(0.0451)
NFP Surprise × Past Forecast Dispersion			-0.0717			-0.332
			(0.182)			(0.243)
Trading Volume and Volatility						
NFP Surprise × Past Trading Volume				-0.537**		-0.134
				(0.248)		(0.454)
NFP Surprise × Past Realized Volatility				3.758**		1.359
				(1.660)		(2.578)
Information Demand and Supply						
NFP Surprise × Bitly Count					2.609**	3.736**
					(1.240)	(1.553)
NFP Surprise × Google Index					-1.576	-1.474
					(1.481)	(1.735)
NFP Surprise × Media Coverage Count					3.983***	3.023
					(0.858)	(2.048)
Constant	0.452	3.943	0.577	-3.537	-0.949	3.286
	(4.280)	(3.191)	(2.057)	(4.951)	(2.725)	(10.94)
Number of observations	79	79	79	79	79	79
R-squared	0.508	0.388	0.406	0.438	0.524	0.624

Notes: We estimate the response of U.S. Treasury futures on ten-year notes to nonfarm payroll surprises using data from January 2012 to July 2018. The dependent variable is a 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. The variables Bitly count, Google index and media coverage count are divided by their standard deviation so that the magnitude of the coefficient can be interpreted more easily. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: Order Flow Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	1.362***	1.401***	4.031***	4.082***	3.917***	4.232***
	(0.066)	(0.066)	(0.099)	(0.100)	(0.105)	(0.106)
NFP Surprise × Bitly Count	1.969***	1.920***	1.873***	1.806***	1.276***	0.871***
	(0.050)	(0.051)	(0.076)	(0.077)	(0.078)	(0.080)
Order Flow × Two Hours Before	0.636***	0.502***	1.257***	1.255***	1.210***	1.165***
	(0.054)	(0.063)	(0.098)	(0.138)	(0.064)	(0.086)
Order Flow × Two Hours Before × High Bitly Count		0.485***		0.00445		0.101
		(0.121)		(0.196)		(0.128)
Order Flow × Two Hours After	1.287***	1.042***	2.384***	2.171***	1.868***	1.525***
	(0.027)	(0.037)	(0.041)	(0.059)	(0.022)	(0.029)
Order Flow × Two Hours After × High Bitly Count		0.518***		0.418***		0.765***
		(0.0545)		(0.0825)		(0.0440)
Constant	0.0003	0.0003	-0.0018	-0.0017	-0.0023	-0.0026
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Number of Observations	18,960	18,960	18,960	18,960	18,960	18,960
Adjusted R-squared	0.325	0.329	0.404	0.405	0.484	0.492

Notes: We estimate the response of U.S. Treasury futures to nonfarm payroll announcements and order flow using data from January 2012 to July 2018. The dependent variable is one-minute U.S. Treasury futures yield change using the prevailing futures yield as of the end of the minute. Order flow is estimated using the Lee and Ready (1991) algorithm. We only use data two-hours before and two-hours after the nonfarm payroll announcement. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10: Pre- and Post-Announcement Reaction

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise(t-1)	-0.179	-0.182	-0.876	-1.218	-1.366	-1.556
	(0.498)	(0.689)	(1.944)	(2.721)	(3.344)	(4.695)
Sum of 30 Lagged NFP Surprise Coefficients	-4.035	-1.153	-16.527	-7.672	-26.149	-15.605
F-statistic	1.926	0.010	2.045	0.131	1.644	0.260
Nonfarm Payroll Surprise(t-1) × Bitly Count(t-1)		0.0224		0.311		0.242
		(0.516)		(2.039)		(3.518)
Sum of 30 Lagged NFP Surprise × Bitly Count Coefficients		-2.915		-9.031		-10.675
F-statistic		1.506		0.790		0.284
Nonfarm Payroll Surprise(t)	3.692***	1.308*	15.85***	10.08***	28.64***	22.52***
	(0.498)	(0.690)	(1.944)	(2.725)	(3.345)	(4.702)
Nonfarm Payroll Surprise(t) × Bitly Count		2.449***		6.156***		6.940*
		(0.520)		(2.053)		(3.541)
Nonfarm Payroll Surprise(t+1)	-0.419	-0.540	-1.243	-1.241	-1.563	-1.548
	(0.498)	(0.689)	(1.944)	(2.721)	(3.344)	(4.694)
Sum of 30 Lead NFP Surprise Coefficients	-0.825	-1.562	0.741	-7.587	9.147	-3.768
F-statistic	0.107	0.216	0.001	0.381	0.218	0.085
Nonfarm Payroll Surprise(t+1) × Bitly Count		0.126		-0.00198		0.0262
		(0.516)		(2.038)		(3.516)
Sum of 30 Lead NFP Surprise × Bitly Count Coefficients		0.664		7.997		12.354
F-statistic		0.091		0.740		0.685
Constant	0.0929	0.0933	0.102	0.0903	-0.0214	-0.0477
	(0.0623)	(0.0621)	(0.243)	(0.245)	(0.418)	(0.423)
Number of Observations	2,357	2,357	2,357	2,357	2,357	2,357
Adjusted R-squared	0.040	0.090	0.043	0.071	0.047	0.070

Notes: We estimate the response of U.S. Treasury futures prices to nonfarm payroll announcements using data from January 2012 to July 2018. The dependent variable is one-day U.S. Treasury futures yield changes using the prevailing futures yield as of 4:00 pm ET. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11: Weekend Response

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	3.584***	1.224	14.62***	7.761**	26.36***	17.81***
	(0.779)	(0.805)	(2.647)	(3.303)	(4.505)	(5.846)
Nonfarm Payroll Surprise × Bitly Count		2.521***		7.330**		9.136*
		(0.813)		(2.793)		(4.664)
Constant	-0.0151	-0.173	-0.347	-0.805	-1.197	-1.768
	(0.493)	(0.455)	(1.873)	(1.748)	(3.206)	(3.064)
Number of Observations	79	79	79	79	79	79
Adjusted R-squared	0.244	0.354	0.271	0.333	0.291	0.323

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2012 to July 2018. The dependent variable is the U.S. Treasury futures yield change using the prevailing futures yield as of 4:00 pm ET on Thursday, the day before the nonfarm payroll release, to 4:00 pm ET the Monday after the release. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 12: Other Important Macroeconomic News Announcements

	Retail Sales		ISM Manufacturing PMI	
Surprise	1.094***	0.725**	0.427**	0.371*
	(0.223)	(0.287)	(0.210)	(0.188)
Surprise x Bitly Count		0.581**		0.369***
		(0.284)		(0.132)
Bitly Counts		-0.194		0.0720
		(0.237)		(0.129)
Constant	-0.199	-0.102	0.206	0.104
	(0.231)	(0.287)	(0.187)	(0.178)
Number of Observations	79	79	79	79
Adjusted R-squared	0.238	0.278	0.301	0.334

Notes: We estimate the response of U.S. Treasury futures on two-year notes to ISM and Retail Sales surprises using data from January 2012 to July 2018. The dependent variable is a 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The variables Bitly count is the sum of clicks on news paper articles related to ISM or Retail Sales from two hours before the release of the announcement to one minute prior to the announcement. We divide Bitly counts by its standard deviation so that the magnitude of the coefficient can be interpreted more easily.Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.