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

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Abstract

We show that information demand about an asset is a proxy for uncertainty about its payoff. Indeed, investors have incentives to collect more information when shocks reduce their ability to forecast this payoff. Thus, in equilibrium, these shocks lead to a joint increase in information demand and uncertainty. One implication is that a greater information demand ahead of news arrival predicts a stronger sensitivity of prices to news. Consistent with these predictions, information demand about nonfarm payroll news is positively correlated with other measures of uncertainty and the sensitivity of U.S. Treasury notes yields to nonfarm payroll news more than doubles when information demand is high *before* the news.

Keywords: Uncertainty, Information Demand, Clicks data, Macroeconomic Announcements, U.S. Treasury futures.
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1 Introduction

Uncertainty is a central notion in financial economics. Intuitively, uncertainty about a variable (e.g., a firm's future earnings or a stock return) is higher when it is harder to forecast (see, Bloom, 2014).[1] Investors' forecasting errors are determined by shocks exogenous to investors' decisions, such as an increase in the dispersion of firms' cash-flows or stock returns, and investors' endogenous search for information, possibly in reaction to the former shocks. As investors' information sets are not directly observable, uncertainty is difficult to measure. In this paper, we propose to use investors' information demand as a proxy for uncertainty and we use data on news consumption to support our hypothesis that higher information demand is symptomatic of higher uncertainty.

This hypothesis follows from economic theory. Suppose that the economy alternates between periods of high and low unconditional variance for the payoff of an asset.[2] When the variance of the asset is high, the marginal benefit of more accurate signals for investment decisions is higher and, therefore, investors optimally search for more information in this case. This increased search intensity dampens the positive effect of a higher unconditional variance on uncertainty (the variance of the asset payoff conditional on all information, including private information and information in asset prices). However, we show–using a standard equilibrium model with endogenous information acquisition–that it does not fully offset it.[3] Hence, in equilibrium, variations in the asset variance induce a positive correlation between uncertainty about the asset payoff and information demand.

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

[2]Unconditional variance in a given period means 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).

[3]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.

One testable implication is that an increase in information demand *ahead* of news arrival about the payoff of an asset should be predictive of a stronger reaction of its price to news. Indeed, if the increase in information demand reflects higher perceived uncertainty by investors, then news plays a larger role in resolving uncertainty (holding news accuracy constant) and therefore news should move prices more.

We test this prediction by analyzing the reaction of U.S. Treasury note futures prices to nonfarm payroll announcements by the Bureau of Labor and Statistics. These announcements affect treasury prices because they are viewed by market participants as signals about future monetary policy and therefore the future level of interest rates. We focus on these announcements because they have the biggest impact on U.S. Treasury prices among all macro-economic announcements (see, for instance, Gilbert et al., 2017). Furthermore, nonfarm payroll announcements are known for having a strong impact on the prices other asset classes.[4] Thus, finding good predictors of this impact is of broad interest.

We measure investors' demand for information about nonfarm payroll figures using click data obtained from Bitly, 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 people to share these articles on social media (e.g., Facebook) or micro-blogging platforms (e.g., Twitter or Google+). Our data comprise 70 million SURLs created by Bitly from 2012 to 2018. We identify all SURLs (about $730,000$) pointing to news articles with the words "payroll" or "unemployment rate" or "jobs report" in their headlines and use the number of clicks on these SURLs over a given time interval (e.g., an hour or a month) as a measure of information demand about future interest rates. Of course, investors have many other ways to obtain such information. Our premiss is that an increase in clicks on the SURLs in our sample signals a more general increase in investors' effort to obtain information about future interest rates.

[4] For these reasons, the nonfarm payroll announcement is often referred as the "king" of announcements by market participants; see, e.g., Andersen and Bollerslev (1998) or Gilbert et al. (2017).

We first show that our measure of information demand 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 on the implied volatility of options on one-year swap rates as in Carlston and Ochoa (2017)), the monthly realized volatility of the 2-year U.S. Treasury note, the level of disagreement among professional forecasters about forthcoming nonfarm payroll figures, or the frequency of news articles about policy (including monetary) 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 analyze the sensitivity of U.S. Treasury notes yields (for various maturities) to the unexpected component on nonfarm payroll announcements (the "surprise" in these announcements). In line with our main prediction, this sensitivity is significantly stronger when investors demand more information related to nonfarm payroll employment in the two hours *before* the release of official figures.[5] 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 notes 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 notes yields to nonfarm payroll announcements during our sample period varies between 3.5bps (2-year maturity) to 7bps (10-years maturity).

This strong positive relationship between information demand and the sensitivity of U.S. Treasury notes 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 supply effect) because we control for this number in

[5]We only 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 (e.g., the general level of unemployment in the U.S.). This risk makes our measure noisier.

our tests. Moreover, it cannot be explained by an increase in information demand due to an unexpected large surprise in the nonfarm payroll figure (or large yield reaction) because we measure information demand *before* the announcement.

We do not claim that the previous finding is causal. Instead, our interpretation is that time-variations in some factors induce a positive time-series correlation between these two variables. In our model, there are four such factors: (i) the variance of the asset payoff, (ii) the volume of noise trading before announcements, (iii) the cost of information acquistion, and (iv) investors' risk aversion. However, these two last factors cannot explain our findings. Indeed, when the cost of information (or risk aversion) increases, investors acquire less in information and, through this channel, uncertainty increases. Thus, if variations in information costs or risk aversion were the primary sources of variations for 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. We find the opposite.

In contrast, both an increase in the variance of the asset payoff or the volume of noise trading result in an increase in uncertainty and information demand in equilibrium. We already gave the intuition why for the former case (see the 2^{nd} paragraph in this section). In the latter case (shocks to noise trading), information demand is high when the volume of noise trading is high because, in this case, trades are less informative and therefore informed trading is more profitable. However, as trades are less informative, the asset price before news arrival is less informative as well and therefore investors' uncertainty is high as well (because investors form their beliefs using their private signals *and* information in prices). In contrast, in the case of a variance shock, the increase in information demand raises the informativeness of trades but not sufficiently to offset the increase in uncertainty coming from the variance shock. Thus, these two types of shocks have opposite predictions for the effect of information demand on the price impact of trades before news announcements. Empirically, we find that the price impact of trades before nonfarm payroll announcements is stronger when our proxy for information demand is higher. This is consistent with the scenario in which time-variations in information demand and uncertainty are mainly due to variance shocks rather than shocks to noise trading.

Last, we find no evidence of overreaction or underreaction of U.S. Treasury notes prices to nonfarm payroll announcements and, more importantly, variations in our proxy for information demand has no effect on the speed at which Treasury prices adjust to these announcements. Thus, this proxy does not capture variations in the participation of investors with irrational beliefs about the effect of nonfarm payroll announcements on U.S. Treasury prices (as, for instance, Google searches about a specific stock does; see Da et al. (2011)).

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 (Datta et al. (2017) for a review): (i) measures based on the volatility of stock 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 newspapers about uncertainty. To our knowledge, our paper is first to use information demand as a measure of uncertainty.

Our study is also related to Ben-Rephael et al. (2017) and Fedyk (2018) who use clicks on news to measure investors' attention to earnings announcements. Ben-Rephael et al. (2017) use clicks on news articles available on Bloomberg terminals to measure the attention institutional investors pay to specific stocks. They show that the earnings price drift is reduced when institutional investors' attention is higher. In addition, Fedyk (2018) shows that trading volume after earnings announcements is stronger when the timing of investors' attention to news is more dispersed. Thus, these papers show that the speed at which prices adjust to news (earnings announcements) and the trading activity following news arrival depend on who read the news and when news is read. In contrast, we show that clicks *ahead* of scheduled news are predictive of the strength of the price response to the news because elevated demand for information before news arrival is a proxy for uncertainty.[6]

We also contribute to the literature analyzing the sensitivity of U.S. Treasury prices to macroeconomic announcements.[7] Recent papers show that the sensitivity of U.S. Treasury prices 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 investors' demand for information ahead of nonfarm payroll announcements can be used to forecast this sensitivity because it proxies for their uncertainty about the future level of interest rates.

Last, 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.[8] 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.

2 Information Demand and Uncertainty

In this section, we consider a model of price formation for a risky asset with endogenous information acquisition that motivates our empirical analysis. The model shows that, in equilibrium, investors' uncertainty and information demand jointly increase following shocks to the variance of the asset payoff or the volume of noise trading. As a result, greater

[6]Kottimukkalur (2018) show 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.

[7]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).

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

information demand ahead of news arrival predict a stronger reaction of asset prices to the news. We test this prediction in the next section.

2.1 The Model

The model has four dates $t \in \{0, 1, 2, 3\}$ and features one risky asset whose payoff F is realized at date 3. The payoff of the asset has a zero mean normal distribution with variance $Var(F)$ (in the rest of the paper, $Var(x)$ 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.

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.[9] 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:

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

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

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

neutral dealers.[10] 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 the aggregate demand $D(p_1) = \int_i x_i(s_i, p_1)di + u$ and, given this information, choose the price such that their expected profit is zero. Thus, the asset price at date 1 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.

Proceeding as in Vives (1995), we obtain (see Appendix A) that speculator i's equilibrium demand for the asset is:

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

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 $z_1 = F + \gamma\overline{\tau}_\eta^{-1}u$ about the asset payoff. We denote by $\chi_D = \gamma\overline{\tau}_\eta^{-1}u$, the noise in this signal and use $Var(\chi_D)^{-1} = (\gamma^2\overline{\tau}_\eta^{-2}Var(u))^{-1}$ as a measure of its informativeness. Investors' aggregate demand for the asset is more informative when (i) investors' aggregate information demand ($\overline{\tau}_\eta$) is higher or (ii) the variance of noise trading ($Var(u)$) is smaller.

[10] 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.

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 $\lambda = \frac{Cov(F,z_1)}{Var(z_1)} = \frac{Var(F)}{Var(F)+Var(\chi_D)}$. After trading, the variance of the asset payoff conditional on public information is:

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

This conditional variance measures the variance of dealers' forecasting error conditional on available public information (that is, the information contained in investors' aggregate demand). It is our measure of uncertainty. Uncertainty increases when (i) the variance of the asset payoff increases ($Var(F)$ increases) or (ii) the informativeness of investors' aggregate demand ($Var(\chi_D)^{-1}$) decreases. Thus, ultimately, the effect of exogenous shocks (e.g., an increase in the variance of the asset) on uncertainty depends on how it affects information demand in equilibrium (see below).

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

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

with

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

Thus, the sensitivity (β) of the asset price to the innovation in the announcement ($A_e - \mathrm{E}(A_e \mid z_1)$) is stronger when (i) the announcement is more accurate ($Var(\epsilon)$ is smaller) and (ii) when the uncertainty about the asset payoff prior to the announcement, $Var(F \mid z_1)$, is higher.

To close the model, we 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):

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

Each investor chooses his demand for information (τ_{η_i}) to maximize $\Pi(\tau_{\eta_i}, \overline{\tau}_\eta)$ *taking as given* other investors' information demands (i.e., $\overline{\tau}_\eta$).

The marginal benefit of collecting information is higher when uncertainty (measured by $Var(F \mid z_1)$) is higher.[11] Now, uncertainty depends on speculators' investment in information (see eq.(8)) because an increase in this investment raises the informativeness of their aggregate demand for forecasting the asset payoffs. As a result, the asset price at date 1 is closer to the asset's actual payoff, and the profitability of trading on private information is therefore smaller, when speculators expect other speculators to acquire more accurate signals ($\frac{\partial \Pi(\tau_{\eta_i}, \overline{\tau}_\eta)}{\partial \overline{\tau}_\eta} < 0$). Thus, uncertainty and investors' demand for information are jointly determined in equilibrium. An equilibrium at date 0 is a demand $\tau^*_{\eta_i}$ for each speculator such that $\tau^*_{\eta_i}$ maximizes $\Pi(\tau^*_{\eta_i}, \overline{\tau}^*_\eta)$ and $\overline{\tau}^*_\eta = \int \tau^*_{\eta_i} di$. 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, the first order condition of each speculator's information acquisition problem imposes $\frac{\partial \Pi(\tau^*_{\eta_i}, \overline{\tau}^*_\eta)}{\partial \tau_{\eta_i}} = 0$ for $\tau^*_i = \overline{\tau}^*_\eta$, which is equivalent to:

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

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

Proposition 1. *When (i) the variance of the asset payoff, $Var(F)$ or (ii) the variance of noise trading, $Var(u)$ increase then (i) uncertainty ($Var(F \mid z_1)$), (ii) the aggregate demand for information ($\overline{\tau}^*_\eta$) and (iii) the sensitivity (β) of the price to news at date 2 increase.*

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

The intuition is as follows. Holding information acquisition constant, an increase in the variance of the payoff of the asset or noise trading increases uncertainty ($Var(F \mid z_1)$). 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, it is never strong enough to overturn or neutralize it.[12] Thus, in equilibrium, an increase in the variance of the asset payoff or noise trading results in a joint increase in (i) uncertainty, (ii) information demand, and (iii) the impact of news on prices (since this impact is stronger when uncertainty is higher; (see eq.(10)).

2.2 Predictions

Measuring uncertainty directly is difficult since it is difficult to observe agents' information set (e.g., z_1 in our model). Proposition 1 suggests to use information demand as a proxy for uncertainty, provided that variations in information demand reflects shocks to the variance of asset payoff or the variance of noise trading. If this logic is correct, the model also implies that an increase in information demand ahead of news arrival should be predictive of a stronger price reaction to news. We test this prediction in Section 4.

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. One way to distinguish between these two scenarios empirically is to consider how information demand affects the informativeness of trades before news arrival.

[12] 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.

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 more informative[13] Thus, in this scenario, one should observe that the price impact of trades before news arrival is stronger (i.e., trades are more informative) when information demand is higher (see the online appendix for a formal proof). Now consider an increase in the variance of noise trading. The direct effect of this increase is to reduce the informativeness of the aggregate demand for the asset. 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 reduction in the the informativeness of the aggregate demand. Thus, in this scenario, one should observe a decrease in the price impact of trades when information demand is higher before news arrival (see the online appendix for a formal proof) . We analyze empirically the relationship between the price impact of trades and information demand in Section 5.1.

The model suggests two possible 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 association between the sensitivity of prices to news and information demand ahead of news. This is also the case for risk aversion.[14] Thus, fluctuations in risk aversion or information acquisition costs cannot explain the positive association between information demand and the sensitivity of Treasury prices to nonfarm payroll announcements that we find empirically.

[13]Indeed, $Var(\chi_D)^{-1}$ depends on $Var(F)$) only through speculator's aggregate information demand and increases with this demand.

[14]This is easily 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 riks aversion goes up, investors trade less aggressively on their information, which reduces the incentive to buy private information in the first place.

2.3 Discussion

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

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

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

The timing of our model is similar to Kim and Verrecchia (1991). However, there are three differences between our model and their model: (i) we allow for risk neutral uninformed investors, (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 ($Var(F \mid z_1, s_i)$) 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 the marginal cost. Thus, when this cost is constant, the marginal benefit of information must be the same for all parameter values other than the marginal 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 in equilibrium.[15]

In Kim and Verrecchia (1991), the price reaction to the announcement is inversely related to speculators' uncertainty, $Var(F \mid z_1, s_i)$. 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 with constant marginal costs cannot predict the position 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) for a particular, non linear, specification of the cost function in their model. This exercise shows that our main prediction is robust to variations in the modeling approach.

3 Data

Our key 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 the news. We test this prediction by analyzing the response of U.S. Treasury notes prices to nonfarm payroll employment announcements by the Bureau of Labor and Statistics. We focus on these announcements because they are known to have strong effects on prices for various asset classes (equity, forex, and fixed-income). We focus on U.S. Treasury notes, as opposed to equity or foreign exchange markets, because the link between U.S. Treasury yield movements

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

and macroeconomic news is theoretically simpler and empirically stronger (see Andersen et al. (2007), Fleming and Remolona (1999), and Balduzzi et al. (2001)).

Nonfarm payroll announcements take place at 8:30 a.m. on the first Friday of every month. They affect treasury prices because market participants expect monetary policy to account for variations in nonfarm payroll employment (e.g., to be more accommodating when nonfarm payroll employment is below expectations). Thus, nonfarm payroll announcements are public signals about the future level of interest rates. Searching information about nonfarm payroll figures is therefore a way to improve forecasts of future interest rates. Our hypothesis is that greater information demand about nonfarm payroll figures is symptomatic of higher uncertainty about future interest rates.

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.

3.1 Measuring Information Demand and Supply

To measure information demand before nonfarm payroll announcements, we use data provided to us by a company called "Bitly." Bitly provides short-URL-links (henceforth SURLs) and a readership tracking system since 2008.[16] 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/` and the corresponding SURL created using Bitly: `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.

[16] 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 (see "*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.

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. 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 bit.ly/ link.

We obtained every single Bitly SURLs pointing to articles from 59 major online news providers (see the on-line appendix for a full list) from January 2011 to July 2018. These include 9 traditional news providers (as in Chan (2003)) and 30 top online news providers according to the 2015 Pew Research Center ranking.[17]

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.[18] This restriction avoids structural breaks in the time series of the number of clicks on SURLs pointing to articles of a given news provider (this number increases dramatically after the acquisition of a branded domain name). 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 news providers. This problem prevents us from identifying whether these news relate to nonfarm payroll employment or not (see below).[19] Ultimately, our sample include SURLs pointing to articles from 36 different news providers from January 2012 to July 2018 (see the list in the on-line appendix).

[17]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/`.

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

[19]We checked that our results are stronger when we include SURLs pointing to news from Marketwatch and CNBC.

For each SURL in our sample, 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 multiple logins used by individuals working for the same news provider). Overall, we observe about 10 billion clicks on these SURLs.

We measure information demand about nonfarm payroll employment over a given time interval by 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) and Husted et al. (2017)) in seed URLs. Specifically, we collect all SURLs in our entire sample pointing to an URL containing the keywords "payroll" or "unemployment rate" or "jobs report."[20] 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.[21]

[Insert Figure 1 here]

[20]The choice of these keywords was based on the following analysis. We first collected all SURLs and the associated URLs accessed during a four hours time 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 words with the highest frequency were "payroll," "unemployment 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.

[21]We noticed that 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 the sample headlines that contain the word "sport" to avoid articles related to the payroll of sport stars.

Figure 1 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 1 shows that the number of NFP clicks gradually increases before the announcement and experiences a sharp jump just after an announcement. 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 in the two hours prior to announcements. This finding supports our interpretation that nonfarm payroll clicks ahead of nonfarm payroll announcements measure information demand by investors (readers of the financial press). Table 2 shows that Bitly links to popular news articles are often created by journalists from the main news providers.

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.[22],[23]

Variations in NFP clicks ahead of nonfarm payroll announcements might reflect variations in the number of news stories about these announcements (the supply of information) rather than variations in investors' incentive to collect information (i.e., read news) holding the number of news stories constant. To address this issue, in our 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).[24] 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.

3.2 Other Measures of Uncertainty

Uncertainty about future interest rates (the variance of future rates conditional on investors' information) is difficult to measure because it depends on investors' information set, which ultimately cannot be observed. 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

[22]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 τ (e.g., weekly) 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)).

[23]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 information demand about nonfarm payroll announcements shortly before the announcements. This is important since one expects announcements that have a strong effect on prices to cause search for information *after* the announcement. Our model is about the relationship between information demand *before* announcements and the price reactions to announcements.

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

of uncertainty about future interest rates (see Bloom (2014) and Datta et al. (2017) for a review of various measures of uncertainty).

First, we use market-based and news-based measures of uncertainty about monetary policy. Our market-based measure of uncertainty is the implied volatility of options on one-year swap rates (swaptions) as in Carlston and Ochoa (2017).[25] 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 focuses on monetary policy uncertainty, while Baker et al. (2016) index measures government policy uncertainty. 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 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 average value of professional forecasters' forecasts 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.

Increase in realized volatility may indicate an increase in future expected volatility (maybe because of GARCH effects; see Berger et al. (2019) for evidence). This corresponds to an increase in $Var(F)$ 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-

[25] We thank Marcelo Ochoa for giving us the data. Carlston and Ochoa (2017) use swaption yields to estimate the conditional 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.

, five- and ten-year U.S. Treasury notes futures 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 (from 3:00 am ET to 5:00 pm ET), respectively, and take the squared root and multiple by the squared root of 12 and 250, respectively, to annualize the monthly and daily volatility.[26]

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 month returns on the S&P 500 index based on the "risk neutral" probability measure, which is different the actual conditional variance (based on physical probabilities). Variations in the VIX should reflect both variations in the actual conditional variance of the index (uncertainty) and investors' risk aversion (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.

3.3 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.

[Insert Table 3 about Here]

[26]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 3:00 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 3:00 am ET and ends at 5:00 pm ET).

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 he market-based measure of monetary policy uncertainty (0.376) and realized interest rate volatility (0.358).[27] This is consistent with our claim that information demand is also a proxy for uncertainty.[28].

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 measures are much less correlated with other measures of uncertainty. 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 2 here]

To explore this point in more detail, Figure 2 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 2 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 Brexit referendum on June 2016. In Panel B of Figure 2, we show the time-series of Bitly information demand and interest rate volatility. We observe that during the Zero Lower

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

[28] 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.

Bound (ZLB) period, Bitly information demand was low and interest rate volatility was low.[29] This dynamic is consistent with investors not paying attention to nonfarm payroll news when monetary policy is less sensitive to this news (see Swanson and Williams (2014)). Yet, the Google trend index remains high during this period maybe because searches about the topic nonfarm payroll captures concerns about unemployment in general rather than just information collection about future interest rates. Overall, our measure of information demand based on Bitly might be more closely related to uncertainty on future interest rates than that based on the Google Trend index because NFP clicks show interest about news stories from the financial press (Bloomberg and the WSJ), i.e., interest from investors.

4 Empirical Analysis

4.1 Benchmark

As a benchmark for our main empirical findings, we first confirm that, as found in other studies, U.S. Treasury futures strongly respond to surprises in nonfarm payroll. 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 effects documented in the next section.

Following Balduzzi et al. (2001), we regress 30-minute U.S. Treasury yield changes on nonfarm payroll news.[30] 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, 10)

[29]The Zero Lower Bound period runs from August 2011 to December 2012. As explained in the next section, this is a period during which federal fund rates were close to zero and insensitive to nonfarm payroll news.

[30]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 5.2.

on this day just after 8:59 am ET and by y^m_{t-1} the yield on this day just before 8:29 am ET.[31] 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 the following equation:

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

where $\Delta y_t = 100 \times (y^m_t - y^m_{t-1})$ 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.[32] This equation is the empirical analog of eq.(9) in the model and our predictions are about the effects of information demand on β. We estimate eq.(14) for two different samples period: (a) the long sample period: 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: January 2012 to July 2018 (during which our Bitly data is available). There are 175 nonfarm payroll announcements in the long sample period and 79 in the short sample period. For ease of interpretation of the coefficient estimates, we standardize $Surprise_t$ by its standard deviation estimated using the long sample period in all 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

[31] 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.

[32] 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.

of Table 4 shows that a one-standard deviation increase in the nonfarm payroll surprise raises the two-year U.S. Treasury note futures 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 futures 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 federal fund rates being close to the zero lower bound.[33] 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 find that the impact of nonfarm payroll announcement on two-year U.S. Treasury note futures is smaller during this period.[34]

4.2 Information demand and the response of treasury yields to nonfarm payroll announcements

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 short period sample (January 2012-July 2018) since our measure of information

[33]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.

[34]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.

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 since (i) these are the predominant source of news in our sample (see Table 1) and (ii) a large fraction (more than 46%) of NFP clicks are concentrated on the day of the announcement. We have checked that our findings are robust to these choices (see the online appendix).

We first estimate the following equation:

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

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. In constructing these variables, we only use the number of nonfarm payroll clicks on NFP SURLs pointing to Bloomberg and Wall Street Journal news since these are the predominant source of news in our sample (see Table 1). Results are similar when we use all NFP SURLs (see the online appendix).

[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-years, 5-years and 10-years Treasury notes 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 years Treasury notes futures and non significant for the 2 years maturity).

In a next step, 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 3.2. Specifically, 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 that captures 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 3.2: 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.[35] First, this is a commonly used measure of uncertainty (see Section 3.2).

[35] 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.

Second, Goldberg and Grisse (2013) argue that U.S. Treasury note futures could react less to macroeconomic news announcements in times of increased financial turmoil because the Federal Reserve Board of Governors might be then less likely to increase the federal funds rate due to its financial stability mandate

3. **Information Environment.** The reaction of Treasury prices 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, in month t, we use the absolute value of the nonfarm payroll announcement in the previous month minus the revision of this announcement in this month 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) argue and provide evidence that the dispersion of analysts' earnings forecasts is a proxy for the noise in earnings announcements. Thus, we also use the dispersion of professional forecasters' forecasts (normalized by the absolute value of the median forecast to control for the level of forecasts) prior to a given nonfarm payroll announcement as another proxy (called "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 $t-1$ (which we call "past forecast errors') since, as explained in Section 3.2, professional forecasters' forecast errors are sometimes used as proxy for uncertainty.

4. **Trading Environment.** We control for the realized daily volatility of the 2, 5 and 10-year Treasury notes futures market on the day before the announcement since this is an alternative measure of uncertainty. For each Treasury notes 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 3:00 am ET to 5:00 pm ET).

[Insert Tables 6 and 7 about here]

Table 6 provides summary statistics for all control variables used in the estimation of eq.(16) and Table 7 shows estimates of this equation for the 2-year Treasury notes futures. In Table 7 (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 level of 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*") and the sensitivity of U.S. Treasury notes yields to nonfarm payroll announcements remains positively and significantly related. In fact this relationship is even stronger than that obtained in Table 5 (or Column (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 8 and 9 about here]

Tables 8 and 9 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 find a strong and statistically significant positive association between the sensitivity of U.S. Treasury notes 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 the Google trend index reflecting searches about nonfarm payroll news, in line with the observation that this index is less correlated with uncertainty (see Table 3).

Overall, our findings in this section show that information demand ahead of non farm payroll announcements is positively related to the strength of U.S. Treasury price reactions to these announcements. This is consistent with our hypothesis that information demand is a proxy for uncertainty and this proxy is distinct from other measures of uncertainty (since we control for other measures of uncertainty in our tests).

5 Additional tests

5.1 Shocks to noise trading or 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 both an increase in 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 2, 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 variance shocks 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 order flow imbalance, i.e., the difference between buy and sell market orders (signed using the Lee and Ready (1991) algorithm) over interval $[\tau, \tau+1]$ on 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 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 the 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 effect of information demand (measured by the indicator variable "$HighBitlyCount_t$") on the impact of trades on yields two-hours before (after) nonfarm payroll releases, respectively. We report estimates of eq.(17) in Table 10.

[Insert Table 10]

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.[36] However, trades are more informative after nonfarm payroll announcements

[36] 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).

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 variance shocks rather than shocks to the volume of noise trading (as theory predicts that in this case κ_B should be negative, not positive).

5.2 Investors' sentiment or information demand?

Search data on the internet have often been used as a proxy for investors' sentiment.[37] In line with this interpretation, researchers show that high search intensity for a given stock predict price reversals in this stock (see Da et al., 2011). In contrast to this literature, we use readership data, not search data, and we argue that these data are associated with rational information demand rather than investor sentiment. If our interpretation is correct, a high demand for nonfarm payroll information on the day of nonfarm payroll announcements should not predict subsequent yield reversals (i.e., be positively associated with overreaction to macroeconomic announcements).

[Insert Figure 3 about Here]

As a first look at this issue, Figure 3 shows cumulative returns 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 shows three things. First, it confirms visually our main finding: nonfarm payroll announcements have

[37] Investor sentiment, defined as in Baker and Wurgler (2007), is a belief about future cash flows and investment risks that is not justified by the facts at hand.

a much larger impact on Treasury yields when the number of NFP clicks is high. Second, there is no sign of under or overreaction of Treasury yields to nonfarm payroll announcements *after* the announcement, whether the number of nonfarm payroll clicks is high or low. Last, there is a small price drift before the announcement, in the direction of the price jump at the announcement, especially for positive surprises when nonfarm payroll clicks is high.[38] These two last observations are consistent with the idea that NFP clicks proxy for rational information demand rather than investors' sentiment.

We now examine the preliminary evidence provided by Figure 3 more formally. First, to estimate whether there is a post-announcement reversal 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 by our proxy for information demand ($BitlyCount$). Estimates of eq.(18) are reported in Table 11.

[Insert Table 11]

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. Similarly, we find no evidence of pre-announcement drift for nonfarm payroll announcements, at least at the daily frequency.[39].

We next consider whether the response to the nonfarm payroll announcement persists over the weekend after the release and whether the persistence of the impact is related to

[38] This finding is consistent with Kurov et al. (2016), who find evidence of pre announcement yield drift ahead of various macroeconomic announcements. They argue that this drift reflects trading on private information, which is consistent with our interpretation.

[39] Figure 3 suggests that one must zoom on minutes before the announcement to detect the drift

Bitly counts. To this end, we estimate the equation:

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

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 12. The coefficient on nonfarm payroll surprises is statistically significant for all maturities. However, when we include the interaction with Bitly the coefficient on surprise alone becomes insignificant and the interaction 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 11 and 12 do not suggest that there is systematic over- or under-reaction of Treasury yields to nonfarm payroll announcements or that over-reaction occurs when the number of Bitly nonfarm payroll clicks is high. Thus, the number of Bitly clicks is not a proxy for investors' sentiment.

6 Conclusion

In this paper, we argue that shifts in information demand about the future cash flows of an asset can be used as a proxy for investors' uncertainty about this cash-flow. Specifically, the marginal value of acquiring information increases when exogenous shocks increase investors' uncertainty about future cash flows. Investors respond by collecting more information but this response never fully offsets the effect of the initial shock, so that ultimately investors' demand for information and uncertainty are positively correlated. One implication is that investors' demand for information ahead of news arrival is predictive of a stronger reaction of asset prices to news.

We test this implication by considering the reaction of two-, five-, and ten-year U.S. Treasury notes to nonfarm payroll announcements using a novel dataset consisting of clicks on news articles to measure investors information demand. We find that, as predicted, when information demand is high *before* the release of nonfarm payroll announcements, the yield response of U.S. Treasury note futures to nonfarm payroll news surprises doubles. Overall the findings suggest that click data can be used to measure investors' demand for information and their uncertainty about asset payoffs.

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.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–157.

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.

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 price impact, *Journal of Monetary Economics* .

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.

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.

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, The speed of information revelation in a financial maket mechanism, *Journal of Economic Theory* 67, 178–204.

7 Appendix

Appendix A

Derivation of informed investors' demand

Using the fact that investors have a CARA utility function, we deduce that the demand of investor i 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 $p_1 =$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:

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

Using the expression for $x_i(s_i, p_1)$ in eq.(20), we deduce that:

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

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 $p_1 = E(F \mid z_1)$:

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

As $Var(s_i - E(F \mid z_1)) = Var((F - E(F \mid z_1)) + \eta_i) = Var(F \mid z_1) + Var(\eta_i)$ and $Var(F \mid z_1, s_i) = \frac{Var(\eta_i)Var(F|z_1)}{Var(\eta_i)+Var(F|z_1)}$, we deduce that:

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

using the fact that, by definition $\tau_{\eta_i} = Var(\eta_i)^{-1}$. 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 $G(\overline{\tau}_\eta; Var(F), Var(u), \gamma)$ be such that:

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

The equilibrium aggregate demand for information at date 0 solves:

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

Using the implicit function theorem, we obtain:

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

where the last inequality follows from the fact that $G(\overline{\tau}_{\eta}; Var(F), Var(u), \gamma)$ decreases with $Var(F)$ 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 $G(\overline{\tau}_{\eta}^{*}; Var(F), Var(u), \gamma) = 0$ implies that in equilibrium:

$$Var(F \mid z_1) = (\frac{1}{2\gamma c'(\overline{\tau}_{\eta}^{*})} - \overline{\tau}_{\eta}^{*})^{-1}. \tag{28}$$

Thus, an increase in (i) the variance of the asset payoff, $Var(F)$ or (ii) the variance of noise trading, $Var(u)$ result in an increase in $Var(F \mid z_1)$ 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:

$$E((F - E(F \mid s_i, p_1))^2) = Var(F \mid s_i, p_1) = \frac{Var(\eta_i)Var(F \mid z_1)}{Var(\eta_i) + Var(F \mid z_1)}. \tag{29}$$

In equilibrium:

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

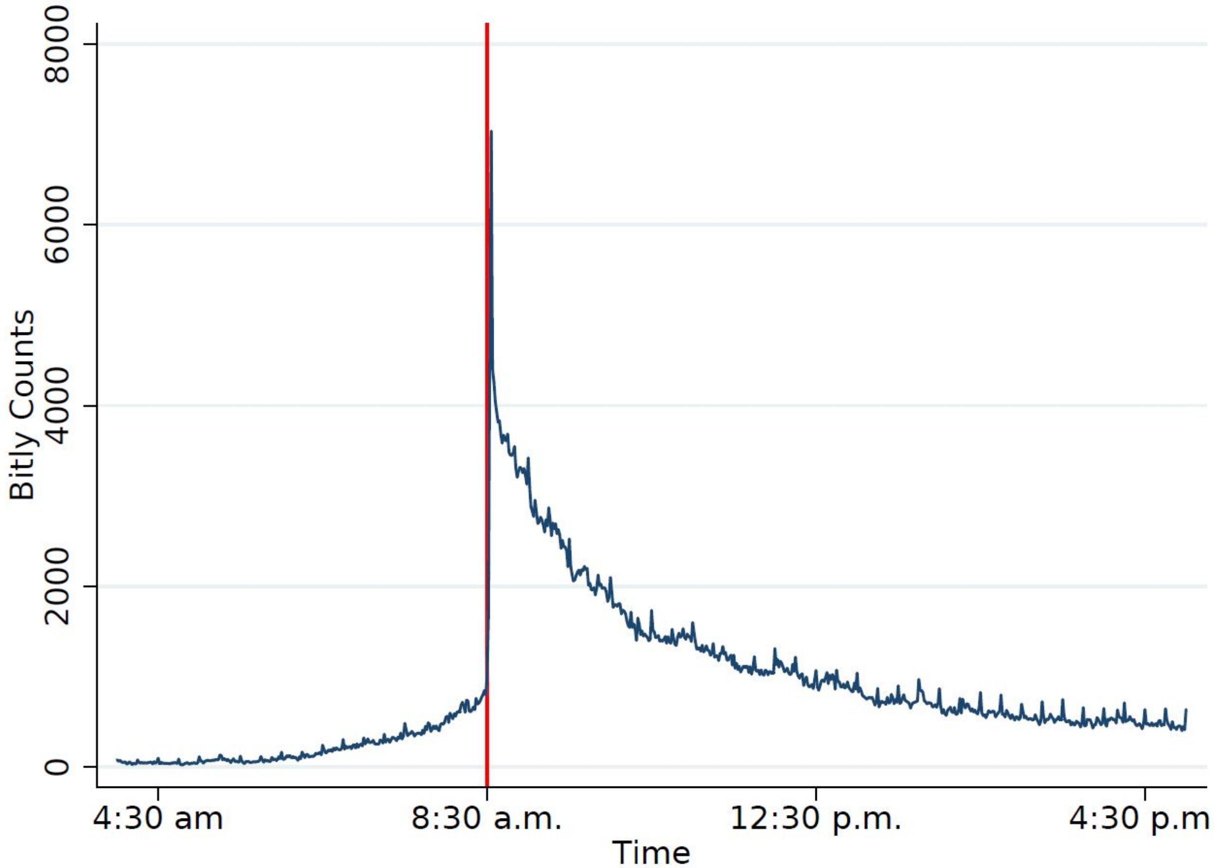
Thus, in equilibrium:

$$Var(F \mid s_i, p_1) = \frac{1}{Var(F \mid z_1)^{-1} + \overline{\tau}_\eta^*}. \tag{30}$$

Moreover, in equilibrium, $Var(F \mid z_1) = (\frac{1}{2\gamma c'(\overline{\tau}_\eta^*)} - \overline{\tau}_\eta^*)^{-1}$ (see eq.(28)). We deduce from eq.(31) that:

$$Var(F \mid s_i, p_1) = 2\gamma c'(\tau_\eta). \tag{31}$$

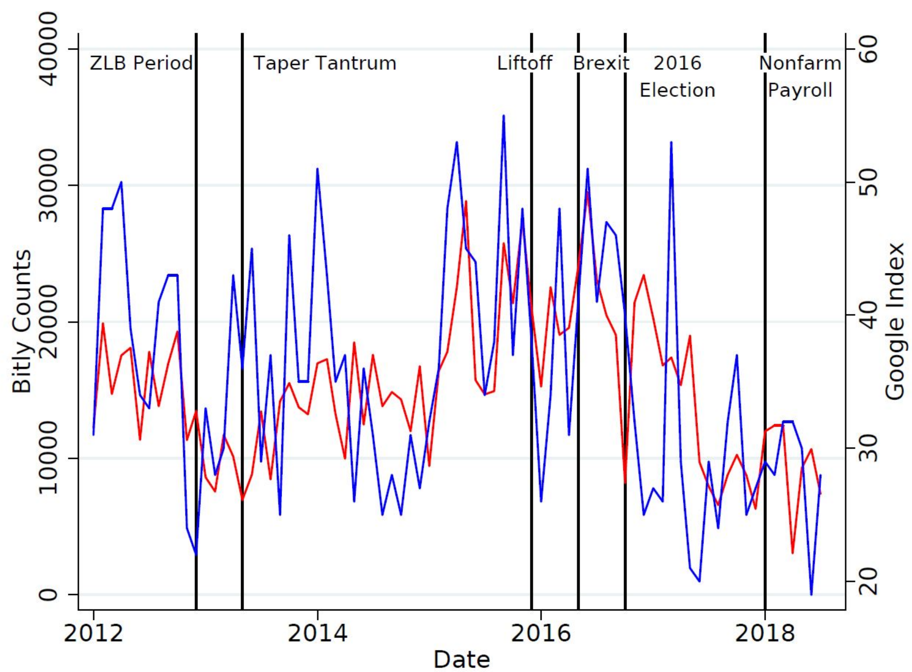
Figure 1: Intra Day Bitly Counts on Nonfarm Payroll Announcement Days



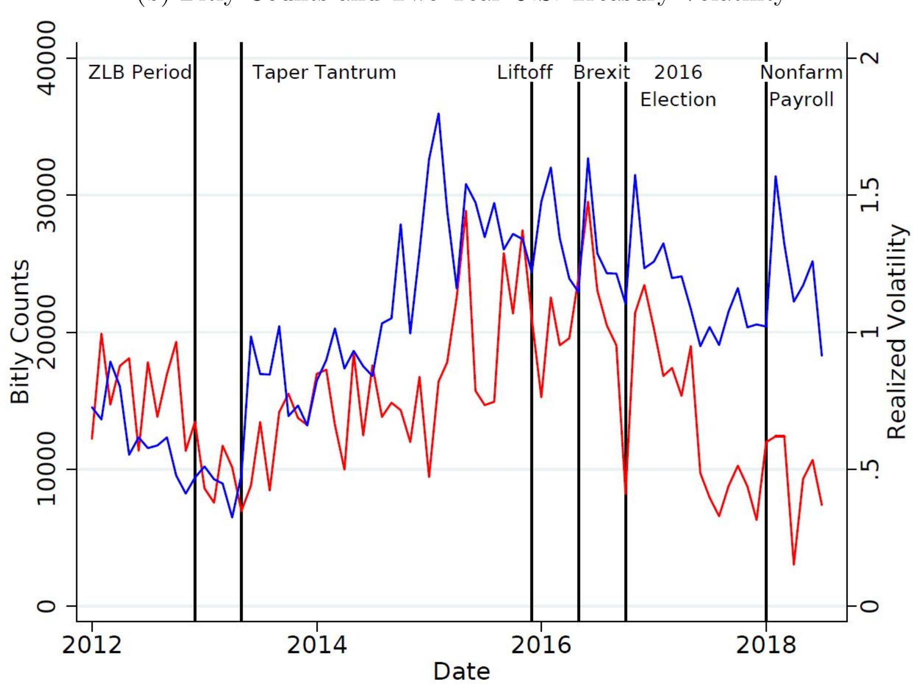
Notes: The figure shows the per minute number of nonfarm payroll Bitly clicks from 4:00 am ET to 5:00 pm ET, across all nonfarm payroll announcement days from January 2012 to July 2018 (91 days). The vertical red line identifies the release time of nonfarm payroll, 8:30 am ET.

Figure 2: Comparing Different Measures of Information Demand and Two-Year U.S. Treasury Volatility

(a) Bitly Counts and Google Index

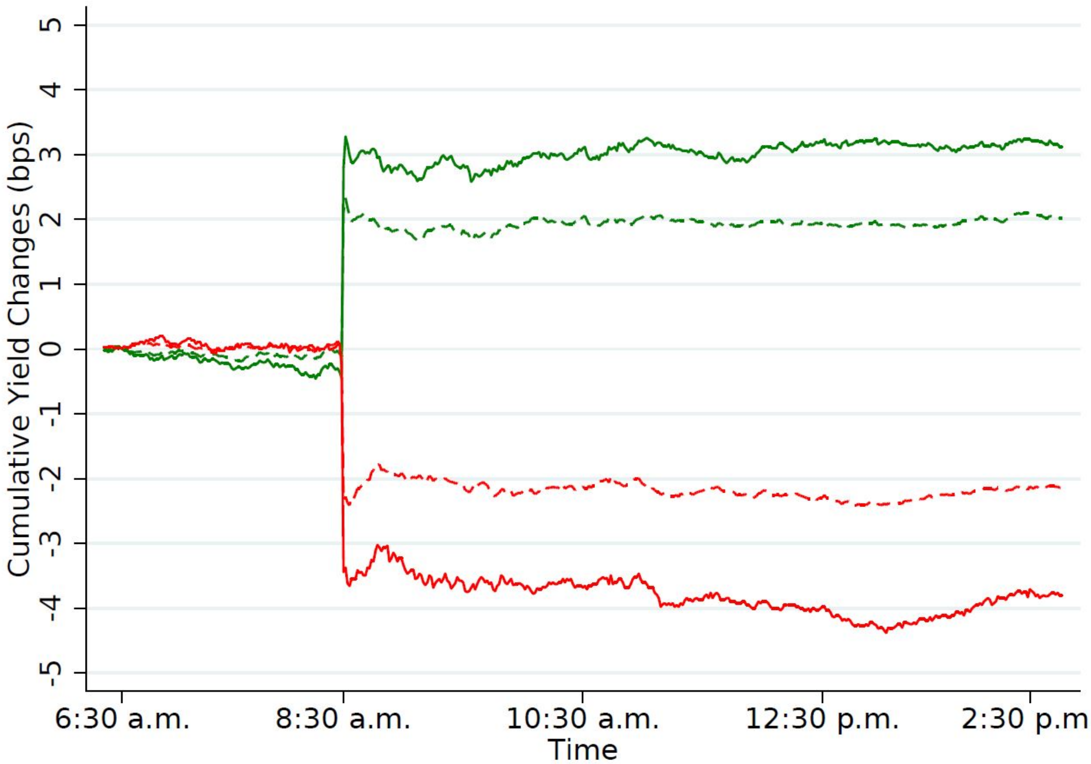


(b) Bitly Counts and Two-Year U.S. Treasury Volatility



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 3: 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 (dashed green line) and negative (dashed red line) nonfarm payroll surprises, and then we sort on Bitly counts in the top 50% percentile (solid green line) and the bottom 50% percentile (solid red line). 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	0.598	3.076**	3.027**	4.577***	4.406***
	(0.677)	(0.620)	(1.208)	(1.301)	(1.415)	(1.566)
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		4.446***		5.774***		4.657**
		(1.159)		(1.829)		(2.068)
High Bitly Count		0.194		0.538		0.788
		(0.820)		(1.273)		(1.358)
Constant	-1.004**	-0.382	-1.414*	-0.879	-1.309	-0.964
	(0.440)	(0.378)	(0.749)	(0.721)	(0.834)	(0.840)
Number of Observations	79	79	79	79	79	79
Adjusted R-squared	0.442	0.338	0.450	0.408	0.434	0.412

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 "High Bitly Count" variable 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: Summary Statistics

	Obs.	Mean	Std. Deviation	Min.	Max.
Sample: January 2012 to July 2018					
Monetary Policy Variables					
Federal Funds Rate	79	0.54	0.47	0.25	2
Swanson-Williams ZLB	79	0.15	0.36	0	1
Market-based Policy Uncertainty	79	1.83	0.55	0.84	3.06
News-based Policy Uncertainty	79	122	57	41	357
Risk					
VIX Index	79	15	3	10	24
Information Environment					
Nonfarm Payroll Surprise	79	1.01	56.86	-123	108
Absolute Value of Revision Noise	79	22.68	14.99	1	77
Absolute Value of Forecast Error	79	45.65	33.53	1	123
Analyst Forecast Dispersion	79	13.42	5.98	9.24	50
Trading Volume and Volatility					
Two-Year US Treasury Trading Volume	79	4.52	1.37	2.29	9.14
Two-Year US Treasury Realized Volatility	79	1.03	0.34	0.32	1.74
Information Demand and Supply					
Intraday Bitly Counts (Before Announcement)	79	160	188	0	775
Intraday Bitly Counts (During/After Announcement)	79	608	474	66	1,945
Google Trend Index (Monthly)	79	35	8	19	55
Ravenpack News Count (Before Announcement)	79	51	17	16	84

Notes: This table provides summary statistics for the variables used in our estimation of eq.(16). The units of trading volume are million of contracts.

Table 7: 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 8: 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 9: 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 10: 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 11: 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 12: 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.