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

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Abstract

We conjecture that an increase in investors' information demand about an asset signals that their perceived uncertainty about the value of this asset has increased. One implication is that an increase in investors' demand for information should be predictive of a stronger role of news (relative to trades) in price discovery. Consistent with this hypothesis, we find that the price response of U.S. Treasury note futures to non farm payroll announcements doubles when information demand (measured by clicks on news headlines related to non farm payrolls) is abnormally high before these announcements.

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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 cash-flows or a stock return) is higher when it is harder to forecast (see Bloom (2014)).[1] Investors' forecasting errors are determined by exogenous shocks (e.g., an increase in the dispersion of firms' cash-flows or stock returns) and investors' effort in collecting information. In this paper, we argue that an increase in investors' information demand about an asset signals that their perceived uncertainty about the value of this asset has increased. One implication is that an increase in investors' demand for information should be predictive of a stronger role of news (relative to trades) in price discovery. We exploit the increasing availability of large scale data on news consumption to provide evidence supporting this hypothesis.

Our predictions follow from economic theory. Suppose that the economy alternates between periods of high and low variance for the payoff of an asset (e.g., as in Veldkamp (2006)). When the variance of the asset is high, investors optimally search for more information because the marginal benefit of more accurate signals for investment decisions is higher. This increased search intensity dampens the positive effect of a higher unconditional variance on investors' expected forecasting errors. However, we show–using a standard equilibrium model of trading with endogenous information acquisition–that it does not fully offset it. Hence, in equilibrium, investors' expected forecasting errors and demand for information increase with the variance of the asset payoff. Thus, fluctuations in this variance over time induces a positive correlation between investors' demand for information and their (endogenous) uncertainty about the asset payoff.

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 the

[1] Uncertainty has various definitions (see Bloom (2014)). In this paper, we define uncertainty about a variable for an agent as the expected forecasting error of this variable conditional on the agent's information. This is similar to the definition of uncertainty in, for instance, Jurado, Ludgvison, and Ng (2015) or Orlick and Veldkamp (2015).

news. Indeed, if the increase in information demand reflects higher perceived uncertainty by investors then news play a larger residual role in resolving uncertainty (holding news accuracy constant) and therefore news arrival should move prices more.

We test this prediction by analyzing the reaction of treasury prices to non-farm payroll announcements because they have a strong impact on U.S. Treasury prices (see, for instance, Balduzzi, Elton, and Green, 2001; Andersen, Bollerslev, Diebold, and Vega, 2003; Hautsch and Hess, 2007; Swanson and Williams, 2014) and also affect other asset classes.[2] Thus, finding good predictors of this impact is of broad interest. Nonfarm payroll announcements affect treasury prices because investors' expect the level of employment to affect the future stance of monetary policy. Therefore, when uncertainty about the future level of interest rates rises, we expect investors to search for more information about nonfarm payroll figures.

We measure investors' demand for information about nonfarm payroll figures by the number of clicks on internet links referring to news headlines with the word "nonfarm payroll" in the hours preceding nonfarm payroll announcements. Our click data are provided by Bitly, a service that shortens long internet addresses and allows people (e.g., journalists) to track readership and share information on social medias (e.g., Facebook) or micro-blogging platforms (e.g., Twitter or Google+). Of course, investors have many other ways to collect information about nonfarm payroll figures than by clicking on links pointing to news about these figures. Our premiss is that an increase in clicks on these links is symptomatic of a more general increase in investors' effort to obtain information.

We measure the impact of nonfarm payroll announcements on treasury prices by regressing the change in the yields of U.S. treasury notes around announcements on the unexpected component of announcements and various control variables. Consistent with our prediction, we find that this impact is significantly stronger when investors demand more information related to nonfarm payroll *before* the release of official nonfarm payroll figures. Specifically, on days in which our proxy for information demand is abnormally high, the response of

[2]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, Scotti, Strasser, and Vega (2017).

U.S. treasury yields to nonfarm payroll announcements increases by 2.96 basis points (bps) for two-year Treasuries, 5.45 bps for five-year Treasuries, and 4.93 bps for ten-years Treasuries (after controlling for many known determinants of the reaction of Treasury prices to macroeconomic news). This effect is economically significant relative to the unconditional sensitivity of U.S. Treasury prices to surprises in nonfarm payroll announcements.[3] It cannot be explained by (i) an increase in the number of news about nonfarm payroll (a supply effect) because we control for this number in our tests or (ii) by an unexpected large surprise in the announcement itself or the price reaction to the announcement because we measure information demand *before* the announcement.

Interestingly, during our sample period (2011-2018), our proxy for information demand is one of the very few significant predictors of the strength of the response of U.S. Treasury prices to nonfarm payroll announcements. In particular, there is no significant association between this response and other measures of uncertainty considered in the literature (e.g., a measure of implied volatility of future interest rates, the realized volatility of treasuries returns, or the dispersion of experts' forecasts).

Our leading interpretation is that variations in information demand are driven by variations in the unconditional volatility of future interest rates. In support to this interpretation, we find that our measure of information demand is positively correlated with proxies for macroeconomic uncertainty. In particular, it is significantly higher when the implied volatility of options on one year swap rates (a measure of uncertainty on monetary policy; see Carlston and Ochoa, 2017; Husted, Rogers, and Sun, 2017) is higher.

However, theory suggests two possible alternative sources of variations for information demand. First, information demand could vary over time because of variations in the cost of acquiring information.[4]. However, in this case, high information demand ahead of news

[3]For instance, during our sample period, the sensitivity of two-year treasury prices to surprises in nonfarm payroll announcements is 6.61 bps, which is of the order of magnitude of the increase in this sensitivity on days in which the demand for information about nonfarm payroll is high.

[4]For instance, there might be periods during which investors have more time to collect information about nonfarm payrolls because other tasks require less attention

arrival should be negatively correlated with the impact of news on prices. We find the opposite for nonfarm payroll announcements. Second, information demand could vary over time because of variations in the volume of uninformed (noise) trading. In this scenario, 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. In this case, information demand is also high when uncertainty is high. However, the higher uncertainty stems from less informative trades rather than an increase in the variance of asset payoff. Thus, in this scenario, the price impact of trades before news arrival should be negatively associated with information demand while our leading interpretation (variations in information demand mainly stem from shocks to the variance of asset payoffs) predicts the opposite. Empirically, we find that the price impact of trades before nonfarm payroll announcements is stronger when our proxy for information demand is higher, in line with our interpretation.

Our findings contribute to the growing literature on measuring uncertainty (see Data, Londono, and Rogers (2017) for a review) and more specifically uncertainty of asset payoffs. Existing measures of risk uncertainty for various asset classes are based on measures of realized volatility or implied volatility obtained from option prices. However, the relationship between these measures and the accuracy of investors' forecasts about future returns is not clear. In contrast, there is a clear theoretical link between fluctuations in the accuracy of investors' forecasting errors about the payoff of an asset and their demand for information about this asset.

To measure investors' demand for information, we use clicks on news articles ("click data"), as in Ben-Rephael, Da, and Israelsen (2017) and Fedyk (2018). Ben-Rephael, Da, and Israelsen (2017) use clicks on news articles available on Bloomberg terminals to measure institutional investors' attention to specific stocks. They show that the earnings price drift is reduced when institutional investors' attention is higher.[5] In addition, Fedyk (2018) shows

[5]There is no average drift in treasury prices following nonfarm payroll announcements and, in the last part of our paper, we find that variations in the demand for information prior to nonfarm payroll announcements have no effect on the speed at which treasury prices adjust to these announcements.

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 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, consistent with our hypothesis that elevated demand for information before news arrival is a proxy for uncertainty.

We also contribute to the literature analyzing the sensitivity of U.S. Treasury prices to macroeconomic announcements.[6] Recent papers in this literature have highlighted that the response 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, Scotti, Strasser, and Vega, 2017). Our findings show that investors' demand for information ahead of nonfarm payroll announcements can be used to forecast the size of treasury price reactions to nonfarm payroll announcements because investors' demand for information rises when they are more uncertain about the future level of interest rates.

Last, there is some evidence of informed trading prior to influential macroeconomic announcements in treasury markets (see, Kurov, Sancetta, Strasser, and Wolfe, 2016; Bernile, Hu, and Tang, 2016). This evidence has raised concerns about possible leakages of information ahead of macroeconomic announcements.[7] As noted by Kurov, Sancetta, Strasser, and Wolfe (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.

[6] For example, Fleming and Remolona (1997, 1999); Balduzzi, Elton, and Green (2001); Goldberg and Leonard (2003); Gürkaynak, Sack, and Swanson (2005); Beechey and Wright (2009); Swanson and Williams (2014).

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

2 Information Demand and Uncertainty

In this section, we consider a model of price formation for a risky asset with endogenous information acquisition. The model has two key implications: (i) In equilibrium, shocks to the variance of the asset payoff or the volume of noise trading induces a positive correlation between information demand and investors' expected forecasting errors (the variance of the asset payoff conditional on information) and (ii) for this reason, these shocks induces a positive correlation between information demand ahead of news arrival and the strength of the price response to news. We test this prediction in the next section.

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 macro-economic 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. Specifically, at date 0, 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. 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 neutral dealers. 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 $D(p_1) = \int_i x_i(s_i, p_1) + u$ and, given this information, chooses the price such that their expected profit is zero. Thus:

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

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 (eta_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:

$$D(p_1) = \frac{\overline{\tau}_\eta}{\gamma}F - \gamma\overline{\tau}_\eta p_1 + u_1.$$

Observing this demand conveys a signal $z_1 = F + \gamma\overline{\tau}_\eta^{-1}$ 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.

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 dealers' expected 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 (measured by $Var(\chi_D)^{-1}$) decreases. Thus, 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

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

Thus, the sensitivity (β) of the price to the innovation in the announcement (i.e., $(A_e - \mathrm{E}(A_e \mid z_1))$ 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):

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

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 $Var(F \mid z_1)$ dealers' expected forecasting error conditional on information) is higher.[8] 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 the asset about its payoff. As a result, the asset price at date 1 is closer to the asset actual payoff, and the profitability of trading on private information is thefore 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

[8]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 $\frac{\tau_{\eta_i} Var(F|z_1)}{2\gamma(1+\tau_{\eta_i} Var(F|z_1))}$, which is increasing in $Var(F \mid z_1)$.

$\tau_i^* = \overline{\tau}_\eta^*$, which is equivalent to:

$$1 - (2\gamma)c'(\overline{\tau}_\eta^*)(Var(F)^{-1} + \gamma^{-2}\overline{\tau}_\eta^* Var(u_1)^{-1} + \overline{\tau}_\eta^*) = 0. \tag{12}$$

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 and (iii) the sensitivity (β) of the price to news at date 2 increase.*

The intuition is as follows. Holding investment in information acquisition constant, an increase in the variance of the payoff of the asset or noise trading increases dealers' 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 but not fully. 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)).

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 the next section.

Acccording 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 the informativeness of trades before news arrival.

To see this, consider first an increase in the variance of the asset payoff. In equilibrium, this shock leads to an increase in information demand and, for this reason, it makes investors' aggregate demand more informative ($Var(\chi_D)^{-1}$ depends on $Var(F)$) only through speculator's' aggregate information demand and increases with this demand). Thus, in this case, 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. 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 raises the profitability of trading on private information, which induces more investors to acquire information. However, precisely for this reason, the impact of trades on prices is smaller. Thus, in this case, one should observe that the price impact of trades before news arrival is smaller when information demand is higher. As shown in Section 4.2, our empirical findings are consistent with the first scenario, not the second.

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. 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.

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

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

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). Our model is simpler because (i) we do not allow speculators the possibility to retrade at date 2 (when the public signal arrives) and (ii) prices are set by risk neutral dealers.[9] Because of the second assumption, the price reaction to the announcement is determined by dealers' uncertainty ($Var(F \mid z_1)$). In contrast, in Kim and Verrecchia (1991) , the price reaction to the announcement is determined by speculators' uncertainty ($Var(F \mid z_1, s_i)$). For tractability, Kim and Verrecchia (1991) assume the cost of information acquisition is linear in speculators' information precision. In this special case case, speculators' uncertainty does **not** depend on the variance of the asset payoff or the amount of noise trading (Proposition 3 in Kim and Verrecchia (1991)). The reason is that an increase in this variance is exactly offset by an increase in speculators' information demand in equilibrium.[10] 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).[11] For this reason, this model cannot predict the position association between information demand and the price response to news that we find empirically while our model does.

[9] There are no risk neutral dealers in Kim and Verrecchia (1991). Prices at dates 2 and 1 are set such traders' net aggregate demand is equal to zero.

[10] This is also the case in our model when the cost of information acquisition is linear. Indeed, in this case, the R.H.S of eq.(13) is independent of $Var(F)$ or $Var(u)$. Thus, in equilibrium, $Var(F \mid z_1, s_i)$ does not depend on these parameters. However, this is not the case if the cost function is strictly convex, as assumed in our model.

[11] These implications may hold in Kim and Verrecchia (1991)'s framework when the cost of information acquisition is strictly convex. However, in this case, their model with endogenous information acquisition becomes analytically intractable, which precludes the type of analysis that leads to our Proposition 1.

3 Empirical Analysis

3.1 Measuring information demand

To measure the demand of information ahead of news, we use data from Bitly and we focus on nonfarm payroll announcements. Bitly (`https://bitly.com/`) provides short-URL-links (henceforth SURLs) and a readership tracking system since 2008. Short-URL links allow individuals (e.g., journalists) to shorten "Uniform Resource Locator" (URL) addresses to refer others to news articles and track the readership of these articles. For example, consider the following Wall Street Journal (WSJ) article entitled "*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. The original URL for this article is `https://blogs.wsj.com/economics/2016/01/07/why-december-private-payrolls-arent-a-great-predictor-of-the-jobs-report/` and the URL-shortened by Bitly is `http://on.wsj.com/2oJQ2py`. Both point to the original WSJ news article. In a July 12, 2017 press release, Bitly described itself as the "*world's first and leading Link Management Platform*."[12] and reported that it has millions of customers, including close to three quarters of Fortune 500 firms. Its website indicates that Bitly's clients have created more than 38 billion links since 2008.

People use Bitly for at least two reasons. First, Bitly provides statistics on the usage of the short-links to the creators of these links (e.g., the number of times individuals clicked on a specific link, geographical location of these individuals, the device they used to access the shortened link etc.). Thus, short-links' creators (e.g., journalists) can keep track of the readership of their articles. For this reason, several news companies (e.g., Bloomberg or the Wall Street Journal) buy URL-shortened custom links from Bitly (such as `http://on.wsj.com/2oJQ2py` in the previous example). Second, SURLs are easier to share than

[12] "Bitly Receives $63 million growth investment from Spectrum equity." Business Wire, July 12, 2017.

orignal links, especially on micro-blogging sites, such as Twitter, or messaging technologies, that often constrain the number of characters that users can post or send.

We obtained from Bitly 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 used by Chan (2003)), 30 (20) top online news providers according to the 2015 Pew Research Center ranking (Alexa's top business news rankings).[13]

The unit of observation in the data is a single click on a Bitly SURL, and each click comes with additional information such as the original URL link, the login of the creator of that link, a time stamp (with second precision time) for both the creation of the shortened-URL link and each new click on the Bitly SURL, the geographical origin of each click (based on the IP address of the click), and (whenever possible) whether the Bitly SURL was accessed, directly or through a social media platform. The final dataset contains about ten billion clicks distributed over more than 70 million unique Bitly links, generated by about 700,000 different user logins.

Our model implies that an increase in information demand about the payoff of a particular asset should predict a stronger reaction of its price to news about the asset payoff. To test, this prediction we must first select a specific set of news. We focus on nonfarm payroll employment announcements by the Bureau of Labor and Statistics because, among all macroeconomic announcements, they have the biggest impact on U.S. Treasury prices (see, for instance, Gilbert, Scotti, Strasser, and Vega, 2017). Moreover, as in the model, these announcements are anticipated by market participants since they take place at pre-set points in time (the first Friday of every month). Overall, there are 91 nonfarm payroll announcements during our sample period. We then identify in our sample of Bitly SURLs, all the SURLs pointing to an original URL link that contains the keyword "payroll" (NFP

[13]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/` and Alexa's top business news sources are listed here `https://www.alexa.com/topsites/category/Top/Business/News_and_Media/Newspapers`.

SURLs). Using this method, we identify 40,000 clicks on Bitly SURLs pointing to news articles related to nonfarm payroll announcements from January 2011 to July 2018.[14]. We refer to these 40,000 as "*nonfarm payroll clicks*".

Figure 1 shows the intra announcement day evolution of the number of nonfarm payroll clicks from 4:00 am to 5:00 pm ET. The figure shows that there is a sharp increase in the number of nonfarm payroll clicks just after the nonfarm payroll announcement and that this number remains elevated related to its value before the announcement for about thirty minutes.

[**Insert Figure 1 here**]

We measure information demand about future interest rate ahead of a specific nonfarm payroll announcement by the number of NFP clicks in our sample in the two hours preceding the announcement (from 6:25 am to 8:25 am ET). We observe 4,685 clicks in total in the two hours preceding all announcements in our sample (about 10% of all clicks related to nonfarm payroll in each announcement day and 52 per announcement day on average). In our tests, we use an indicator variable (called "*HighBitlyCount*")equal to one when our proxy for information demand is above its median value (and zero otherwise). Thus, we test whether "abnormally" high information demand is predictive of a stronger reaction of treasury prices to nonfarm payroll announcements. However, our results are very similar when use directly information demand as a predictor.

[**Insert Tables 1, 2, 3 here**]

Tables 1, 2, 3, provide a breakdown of nonfarm payroll clicks before (Panel A) and after (Panel B) nonfarm payroll announcements according to (i) the news provider associated with each NFP SURL (Table 1), (ii) the creator of each NFP SURL (Table 2), and (iii) clickers' geographical location (Table 3). Table 1 shows that news' sources are concentrated among

[14] We checked that using different keyword combinations (among "payroll", "nonfarm", or "employment") does not significantly change the set of NFP SURLs

6 providers (accounting for 95% of all news). Among these 6 news providers, Bloomberg is by far the most popular. Table 2 shows that Bitly links to popular news articles are often created by journalists from the main financial news providers and seven individuals (30% of clicks on Bitly links related to nonfarm payroll news). Table 3 provides information regarding the country where clickers' IP address is located. A majority of these addresses (48% to 53%) are located in the United States. However, a significant fraction of clickers are also located in Great Britain, Japan, and Canada.

[**Insert Figure 2 here**]

Figure 2 shows the daily number of clicks on news related to nonfarm payroll using news articles from Bloomberg (95% of all clicks in our sample). The vertical black lines are the days of nonfarm payroll announcements. As expected, the number of clicks on nonfarm payroll related news substantially increases on nonfarm payroll announcement days. However, the number of Bitly clicks on links referring to articles containing the word "payroll" can also be high on other days. However, as we move away from the date on the nonfarm payroll announcement, it is less clear that an increase in Bitly clicks captures search for information about future monetary policy. For instance, the red (dotted) vertical line on Figure 2 is the day on which President Obama announced a $447 billion jobs plan (September 8, 2011). On this day, there were 1,212 clicks on articles that contained the keyword "payroll" but the articles were not related to the past nonfarm payroll announcement on September 2, 2011, nor to the upcoming nonfarm payroll announcement on October 7, 2011. This is the reason why we measure information demand ahead of a particular announcements by Bitly clicks that happen shortly before the announcement. However, we checked that findings are similar if we measure information demand by the number of Bitly clicks over up to one day before the announcement (**TO DO**).

[**Insert Figure 3 here**]

Da, Engelberg, and Gao (2011) use search data from Google trend to measure investors' attention to a particular stock. Panel A of Figure 3 shows the weekly number of clicks on NFP SURLs (red line) and the Google Trends search index (which by construction varies from 0 to 100) for the topic nonfarm payroll (black dotted line), from Sunday to Saturday to match Google's aggregation procedure.[15] The two series have a positive correlation of 0.64. In Panel B of Figure 3, we only consider weeks with a nonfarm payroll announcement. The correlation between the Google trend index and Bitly counts drop significantly to 0.38. Overall, this suggests that our measure of information demand is distinct from one based on the Google trends index. In any case, in our tests we control for the value of the Google trends search index in the week of the announcement.[16]

Variations in NFP clicks ahead of nonfarm payroll announcements might reflect variations in the number of news stories about these announcements rather than variations in investors' incentive to collect information (e.g., read news) holding the number of news stories constant. To address this issue, we must control for the number of available news stories written ahead of each announcement in our tests. To this end, we use data from Ravenpack's Story dataset.[17]. This dataset contains the headline of every news written by news providers covered by Ravenpack and a news release time stamp (rounded to the nearest second).[18] We

[15]According to Stephens-Davidowitz (2013) the Google trend 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 (6 years for weekly windows of observation). The resulting figure is then multiplied by 100 to obtain the index for the chosen keyword. Hence by construction, the value 100 indicates which week in the 6 year period resulted in the largest number of searches of the topic nonfarm payroll. Kearney and Levine (2015) provide a detailed description of the google trends data and their drawbacks. In particular, Google's approach in constructing the index generates results that are strictly ordinal within a location/time period. One cannot concatenate index values to obtain a longer time-series than what is provided by Google.

[16]One drawback of the Google trends search index is that it is not available at high frequency. Hence, one cannot use it to measure information demand about nonfarm payroll announcements shortly before the announcements. This is important since high demand after announcements that have strong effect on prices is expected. Our model is about the relationship between information demand *before* announcements and the price reactions to announcements.

[17]Ravenpack is one of the major news analytics provider (alongside with Thomson Reuters and Bloomberg). It uses advanced text analytics techniques to classify news, relate them to particular securities (e.g., a stock) and, among other metrics, assign a score to each news indicating whether it is positive or negative for these securities.

[18]New providers for Ravenpack include Dow Jones Newswires, the Wall Street Journal, Marketwatch, and Barron's.

classify a news as providing information about nonfarm payroll employment if its headline contains the keyword "payroll" and refer to them as "NFP news."

[Insert Figure 4 about here]

Panel A of Figure 4 shows the *daily* number of NFP clicks and the daily number of NFP news. The two series are highly correlated, with a correlation of 0.67. Panel B of Figure 4 shows that this correlation drops to 0.13 if we restrict our attention to nonfarm payroll announcements days. Thus, variations in information demand are not completely driven by the supply of news about nonfarm payroll figures. In our tests, we use the number of NFP news in the two hours preceding an announcement as a proxy for the supply of information about nonfarm payroll figures and their effects on future monetary policy.

3.2 Benchmark: The response of U.S. Treasury note futures to nonfarm payroll announcements

In this section, 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 predictive power of our proxy for demand of information ahead of nonfarm payroll announcements, relative to other variables.

To estimate the response of U.S. Treasury yields to nonfarm payroll announcements, we use intra-day data on yields of futures on U.S. Treasury notes from 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, so our results should carry over to the spot rates.[19] Accordingly, we focus on the front-month futures contract on the two-year, five-year and ten-year Treasury notes.

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) on this day just after 8:30 am ET and by y_{t-1}^m the yield on this day just before 8:29 am ET.[20] We measure the yield reaction of U.S. Treasuries with maturity m to the nonfarm payroll announcement (at 8:30 am) on day t by regressing $\Delta y_t = 100 \times (y_t^m - y_{t-1}^m)$ on nonfarm payroll surprises:

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

where surprise is defined as the difference between the actual release of the nonfarm payroll figure on day t minus the median forecast about this figure submitted to Bloomberg by professional forecasters prior to the announcement (available from Bloomberg real-time data). For ease of interpretation of the coefficient estimates in the regression analysis, we standardize the surprise by its standard deviation estimated using our full sample period, from January 2004 to July 2018. 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 2011 to July 2018 (during which our Bitly data is available). Table 4 report estimates of β_S in eq.(14).

[Insert Table 4 about here]

[19]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.

[20]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 no transaction occurs in a particular second we copy down the previous yield as long as the previous yield was quoted in the last half-hour within the same day (the day starts at 3:00 am ET and ends at 5:00 pm ET).

The sensitivity of Treasury yields to nonfarm payroll surprises for the long sample period is similar to that in Balduzzi, Elton, and Green (2001), who consider a different sample period (1991 to 1995) and use 35-minutes returns (rather than 10 minutes returns as we do). Specifically, the first column of Table 4 shows that a one-standard deviation increase in the nonfarm payroll surprise increases the two-year U.S. Treasury note futures yield by 5.3 basis point (compared to 6 basis points in Balduzzi, Elton, and Green (2001)). Column 2 shows that the impact of the nonfarm payroll surprise on the two-year U.S. Treasury note futures is much smaller in the short sample period(3.3 bps). This finding is consistent with Swanson and Williams (2014), who show that the impact of macroeconomic news announcements on two-year U.S. Treasuries becomes smaller from August 2011 onward, due to federal fund rates being close to the zero lower bound.[21] Accordingly, we exclude in column 3 what we label the Swanson-Williams zero lower bound period ("Swanson-Williams 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 increases when we exclude this period.[22]

We next consider how the sensitivity of the yield reaction to the nonfarm payroll surprise depends on various variables already considered in the literature. To this end, we enrich our baseline specification as follows:

$$\Delta y_t = \alpha + \beta_S Surprise_t + \beta_{SX} Surprise_t \times X_t + \beta_X X_t + \epsilon_t \tag{15}$$

[21]The federal funds target rate was essentially zero starting in December 2008. 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.

[22]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, Friedman, and Sack, 2013). Second Swanson and Williams (2014)'s sample ends in December 2012.

where X_t are additional control variables (discussed below). We group them in four categories: (1) monetary policy, (2) risk, (3) information environment, and (4) trading environment:

1. **Monetary policy.** As previously discussed Swanson and Williams (2014) find that U.S. Treasury yields are less responsive to macroeconomic news announcements during the ZLB period. We thus include a dummy variable that captures the Swanson-Williams ZLB period. More generally, we also allow the response of U.S. Treasury yields to macroeconomic news announcements to depend on the level of the federal funds target rate (FFTR). Indeed, Goldberg and Grisse (2013) argue that the Federal Open Market Committee (FOMC) is less likely to raise interest rates in response to positive nonfarm payroll surprises when the FFTR is already high. Thus, in this situation, positive nonfarm payroll surprises should have a smaller impact on U.S. Treasury note futures. We also control for two measures of monetary policy uncertainty. First, as in Carlston and Ochoa (2017) and Husted, Rogers, and Sun (2017), we use the implied volatility of options on one-year swap rates (swaptions) as a market-based measure of uncertainty about future monetary policy.[23] Second, we use the monetary policy uncertainty index provided by Baker, Bloom, and Davis (2016). It is based on a count of news stories that contain words related to uncertainty and monetary policy[24] If these measures of uncertainty capture a change in investors' expected forecasting errors about future interest rates, we expect them to be positively associated with the impact of nonfarm payroll announcements on U.S. Treasury yields (as per eq.(10) in our model).

2. **Risk.** Goldberg and Grisse (2013) also argue that U.S. Treasury note futures should react less to macroeconomic news announcements in times of increased market volatil-

[23]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.

[24]Husted, Rogers, and Sun (2017) have also developed a news-based measure of monetary policy uncertainty. Our results are qualitatively similar when we use this measure.

ity, as measured by the CBOE equity volatility index (VIX).[25] First, during times of increased financial turmoil, the Federal Reserve Board of Governors is less likely to increase the federal funds rate, perhaps because of the financial stability mandate. Second, markets might place less weight on news announcements when the relationship between the news and the economic outlook is more uncertain.

3. **Information Environment.** The reaction of treasury prices to macro-economic announcements should be stronger when these announcements are more accurate (see (eq.(10) in the model)). An (inverse) measure of the accuracy of nonfarm payroll announcements is the extent to which these announcements are subsequently revised (see Hautsch and Hess (2007) and Gilbert (2011) among others). Hence, in month t, we use the absolute value of the nonfarm payroll announcement in month $(t-1)$ 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 experts' forecasts (normalized by the absolute value of a the median forecast) prior to a given nonfarm payroll announcement as another proxy (called "Past forecast dispersion") for the variance of the noise in this announcement.[26] We also control for the absolute value of the past NFP surprise ("past forecast errors") because Scotti (2016) argues that this is a proxy for uncertainty prior to given announcement.[27]

[25]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.

[26]We scale by the median forecasts to control for the level of forecasters' forecasts.

[27]This can be viewed as the absolute value of dealers' forecasting error in our model, i.e., $\mid A_e - E(A_e \mid z_1) \mid$. As A_e has a normal distribution, $E(\mid A_e - E(A_e \mid z_1) \mid z_1)$ is proportional to $(Var(A_e \mid z_1))^{\frac{1}{2}}$, which is equal to $(Var(A_r \mid z_1) + Var(\epsilon))^{\frac{1}{2}}$. Thus, $\mid A_e - E(A_e \mid z_1) \mid$ increases both in dealers' uncertainty prior to the announcement and the noise in the announcement. Thus it net effect on the sensitivity of treasury prices to onfarm payroll announcements is ambiguous according to our model. Note however, that the absolute value of the revision in the announcement should control for $Var(\epsilon)$ in our regression.

4. **Trading Environment.** Finally, we control for measures of trading activity, namely trading volume and asset yield volatility in the day before the announcement. We compute realized daily volatility in the two-year, five-year and ten-year Treasury notes futures market by summing the squared 1-minute returns over the day (from 3:00 am ET to 5:00 pm ET), taking the squared root and multiplying by the squared root of 250, to annualize the volatility. We also compute daily trading volume by summing the number of contracts traded during the day (from 3:00 am ET to 5:00 pm ET) divided by one million.

[**Insert Table 5 about here**]

Table 5 provides summary statistics for all the variables used in the rest of our analysis for the long sample period (Panel A) and the short sample period (Panel B). Comparing the standard deviation of the variables across samples, we note that the longer sample period is the period with the most variation in the variables. For example, the level of the federal funds target rate ranges from 5.25 percent to 25 basis points. Similarly, the VIX index ranges from about 10% to 60%. In contrast, for the shorter sample period, the standard deviation of these variables is relatively small. The level of the federal funds target rate ranges from 2 percent to 25 basis points, and the VIX index only ranges from 10% to 36%. The lack of variation in some of the variables in the shorter sample period makes it more difficult to identify their impact on the sensitivity of U.S. Treasury note futures to nonfarm payroll surprises.

[**Insert Table 6**]

Table 6 shows estimates of eq.(15) for the two-year U.S. Treasury note (we obtain similar results for other maturities and thus omit them for brevity). In this table (and all subsequent tables), we just report the coefficients on interaction terms and the surprise for expositional clarity. The results of Table 6 are largely consistent with the previous literature.

As previously discussed, the impact of nonfarm payroll surprises on Treasury yields is smaller during the Swanson-Williams ZLB period, from August 2011 to December 2012 (see Column (2)). Moreover, only the market-based measure of monetary policy uncertainty has a significant and positive relationships with the sensitivity of treasury price reactions to nonfarm payroll announcements. In contrast, the news based measure of uncertainty has a negative impact on this sensitivity (see Columns (3) and (6) in Table 6); this effect is significant only in Column (3)). Consistent with Goldberg and Grisse (2013), we also find that in times of increased financial turmoil, as measured by a high VIX index, U.S. Treasury notes react less to macroeconomic news announcements (see Columns (3) and (6)). There is no significant relationship between our measures of the noise in the nonfarm payroll announcement and the sensitivity of treasury prices to the announcement (see Columns (4) and (6)). In contrast, past forecast errors strengthen this impact, consistent with the notion that it measures uncertainty. Finally, there is a positive association between the reaction of treasury prices to nonfarm payroll announcements and realized volatility, maybe because an increase in realized volatility is positively correlated with an increase in uncertainty (see Columns (5) and (6)).

3.3 The role of the demand of information prior to nonfarm payroll announcements

We now show that, as implied by Proposition 1, there is a positive association between information demand ahead of nonfarm payroll announcements and the strength of the treasury price reaction to the announcement. To this end, we add our proxies for the demand and supply of information as control variables in eq.(15) (a dummy variable equal to one when NFP clicks or NFP news is larger than its median value in the sample). We also control for the Google trend index for forthcoming nonfarm payroll announcements. As our the Bitly data are available only from January 2011 to July 2018, we can estimate eq.(15) for the short sample period only.

[Insert Table 7]

Table 7 shows the findings for the two-year Treasury notes futures. The first four columns show that during the 2011-2018 period, among the previous variables considered in Table 6, only the level of the Federal Funds Rate has a statistically significant negative impact on the sensitivity of treasury prices to nonfarm payroll announcements, β_S. The lack of significance of the other variables might be due to the lack of variations in these variables during the short sample period (see Table 5).

In contrast, Columns (5) and (6) show that our proxy for information demand is significantly and positively related to the response of Treasury yields to surprises in nonfarm payroll announcements. The size of the effect is economically significant. Indeed, in days in which the demand for information just prior to nonfarm payroll announcements is abnormally high (Bitly clicks are above their median value), the sensitivity of the two-year Treasury notes futures yields to surprises in these announcements increases by about 3 bps (the unconditional sensitivity during the 2011-2018 period is 3 bps, which indicates that nonfarm payroll surprises only have an impact on U.S. Treasury yields when information demand is high; see Table 4).

Tables 8 and 9 show estimates of eq.(15) for the five-year and ten-year U.S. Treasury notes, respectively. The results in these two tables are similar to those for the two-year Treasury note. In particular, we find a strong and statistically significant positive association between the strength of the sensitivity of Treasury 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 relationships of this sensitivity with the supply of information prior to nonfarm payroll announcements or the Google trend index reflecting searches about nonfarm payroll news.

4 Additional tests

4.1 Is information demand positively correlated with uncertainty?

According to the model, the positive correlation between the strength of treasury yield reactions to surprises in nonfarm payroll announcements and information demand reflects the fact that information demand is high when uncertainty on future interest rates is high. If this interpretation is correct, we should also observe a positive correlation between our measure of information demand and conventional measures of uncertainty (to this extent that they do measure uncertainty on future interest rates). To study this point, we estimate following equation:

$$AbnormalInformationDemand_t = \alpha + \beta_X X_t + \epsilon_t, \tag{16}$$

where the dependent variable, $AbnormalInformationDemand_t$, is the ratio of the number of NFP clicks on day t to the average of the variable in the last 40-business days, so that the last nonfarm payroll announcement is included in the calculation. The vector of explanatory variables, X_t, include all variables used as explanatory variables in our yield reaction regressions with three differences. First, we do not control for nonfarm payroll surprises. Second, we include a dummy variable equal to 1 on nonfarm payroll announcement days. Last, we control for daily abnormal trading volume and realized volatility (defined as the ratio of each variable on day t divided by their average value of the 40 last days).

[Insert Table 10 about Here]

Table 10 reports estimates of eq.(16). First, in line with Figures 2 and 4, information demand is significantly higher on nonfarm payroll announcement days and is positively correlated with the number NFP news (our measure of information demand). More importantly for our purpose, our measure of information demand is positively and significantly correlated with the market-based measure of uncertainty (the implied volatility of swaptions).

Interestingly, it is also positively correlated with professional forecasters' forecasting error. As explained in Footnote 27, this error might be viewed as a proxy for $Var(F \mid z_1)$ and the model implies a positive correlation between $Var(F \mid z_1)$ and information demand (see Proposition 1)). Other measures of uncertainty (the news-based measure of uncertainty on monetary policy and the realized volatility of treasury notes returns are not significantly related to information demand.

4.2 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 and therefore explain the positive correlation between the impact of nonfarm payroll announcements on treasury yields and information demand ahead of these announcements. However, as explained at the end of Section 2, these two shocks have different predictions 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 the volume of 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 (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:

$$\Delta OneMinuteYield_{\tau t} = \alpha + \beta_S Surprise_t + I_B(\lambda_B OrderFlow_{\tau t} + \kappa_B HighBitlyCount_t \times OrderFlow_t) + \\ I_A(\lambda_A OrderFlow_{\tau t} + \kappa_A HighBitlyCount_t \times OrderFlow_t) + \epsilon_t, \quad (17)$$

where 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). Thus, λ_B and λ_A measure, respectively, the yield impact of trades before and after nonfarm payroll releases while κ_B and κ_A measures the effect of the number of Bitly clicks on the yield impact of trades before and after nonfarm payroll releases, respectively.We report estimates of eq.(17) in Table 13.

[Insert Table 13]

As in Brandt and Kavajecz (2004) and Pasquariello and Vega (2007), we find that the impact of trades is significant both before and after nonfarm payroll releases for all maturities, suggesting that trades contain information both before and after these releases.[28]. However, trades are more informative after nonfarm payroll announcements than before. More importantly for our purpose, we find that the impact of order flow is significantly stronger when the number of Bitly clicks is high, both after and before non farm payroll announcements (except for futures on the five year treasury for which the effect of HighBitly is not statistically significant before the announcement). Overall these findings are suggest that (i) there is informed trading around macroeconomic 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).

4.3 Investors' sentiment or rational information demand?

Researchers have often used search data on the internet as a proxy for investors' sentiment.[29] In line with this interpretation, researchers show that high search intensity for a given stock predict price reversals in this stock (see Da, Engelberg, and Gao, 2011). In contrast to this

[28]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)

[29]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.

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 5 about Here**]

As a first look at this issue, Figure 5 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 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.[30] 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 5 more formally. First, to estimate whether there is a post-announcement reversal we estimate the following equation at the daily frequency:

$$\Delta DailyYield_t = \alpha + \sum_{i=-30}^{30} \beta_{Si} Surprise_{t-i} + \sum_{i=-30}^{30} \beta_{BSi} Surprise_{t-i} \times HighBitlyCount_{t-i} + \epsilon_t, \tag{18}$$

[30] This finding is consistent with Kurov, Sancetta, Strasser, and Wolfe (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.

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 ($HighBitlyCount$). 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.[31].

We next consider whether the response to the nonfarm payroll announcement persists after one-week of the release and whether the persistence of the impact is related to high Bitly counts. We estimate the equation:

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

where $WeeklyReturn_t$ is estimated from the close of Thursday before the announcement to the following Thursday. 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 one week after the announcement.

[31]Figure 5 suggests that one must zoom on minutes before the announcement to detect the drift

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 overreaction occurs when the number of Bitly nonfarm payroll clicks. Overall, this suggests that this number is not a proxy for investors' sentiment.

5 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 when news arrives.

We test this implication by considering the reaction of treasury prices to nonfarm payroll announcements using a novel dataset consisting of clicks on news articles to measure demand for information. 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 agents' demand for information and their uncertainty about asset payoffs.

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6 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:

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

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

Investors' final wealth at date 3 is:

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

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:

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

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

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

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

$$\frac{\mathrm{Var}(\mathrm{E}(F\,|s_i, p_1)-p_1)}{\mathrm{Var}(F\,|s_i, p_1)} = \tau_{\eta_i}^2 \times Var(F \mid z_1, s_i) \times Var(s_i - E(F \mid z_1)). \tag{24}$$

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:

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

using the fact that, by definition $\tau_{\eta_i} = Var(\eta_i)$.

Proof of Proposition 1.

Let $G(\overline{\tau}_\eta; Var(F), Var(u_1), \gamma)$ be such that:

$$G(\overline{\tau}_\eta; Var(F), Var(u_1), \gamma) \overset{def}{=} 1 - (2\gamma)c'(\overline{\tau}_\eta(Var(F)^{-1} + \gamma^{-2}\overline{\tau}_\eta Var(u_1)^{-1} + \overline{\tau}_\eta^*) = 0. \tag{26}$$

The equilibrium aggregate demand for information at date 0 solves:

$$G(\overline{\tau}_\eta^*; Var(F), Var(u_1), \gamma) = 0.$$

Using the implicit function theorem, we obtain:

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

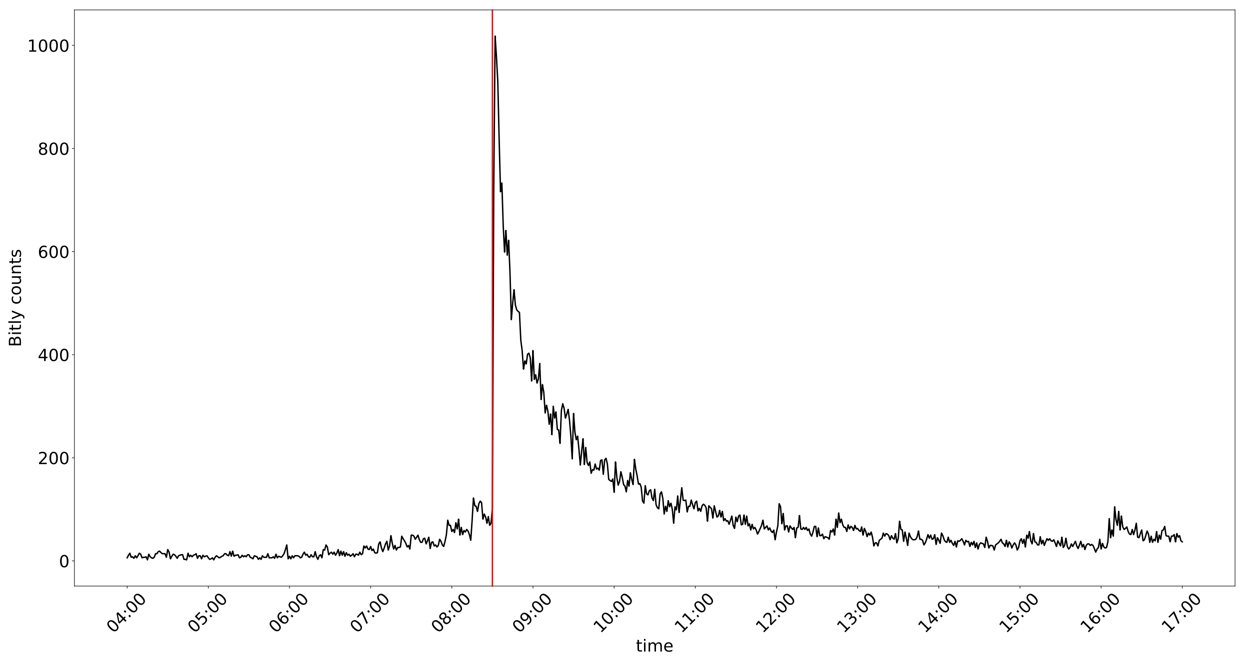
where the last inequality follows from the fact that $G(\overline{\tau}_\eta; Var(F), Var(u_1), \gamma)$ decreases with $Var(F)$ and $\overline{\tau}^*_\eta$. Thus, investors' aggregate demand for information increases with the variance of the asset payoff. The same reasoning shows that investors' aggregate demand for information increases with the variance of the noise trading. Moreover, observe that $G(\overline{\tau}^*_\eta; Var(F), Var(u_1), \gamma) = 0$ implies that in equilibrium:

$$Var(F \mid z_1) = (\frac{1}{2\gamma c'(\overline{\tau}^*_\eta)} - \overline{\tau}^*_\eta)^{-1}. \tag{27}$$

Thus, an increase in (i) the variance of the asset payoff, $Var(F)$ or (ii) the variance of noise trading, $Var(u_1)$ result in an increase in $Var(F \mid z_1)$ and therefore $|\beta|$ (by eq.(10)).

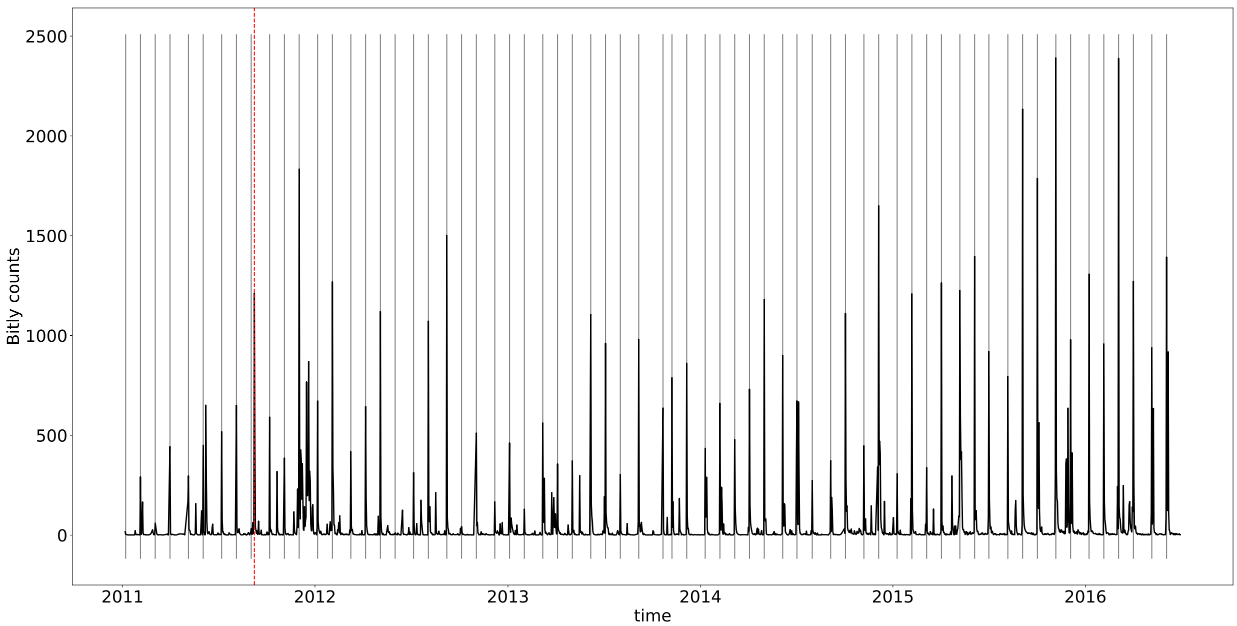
Appendix B: Figures and Tables

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 2011 to July 2018 (91 days). The vertical red line identifies the release time of nonfarm payroll, 8:30 am ET.

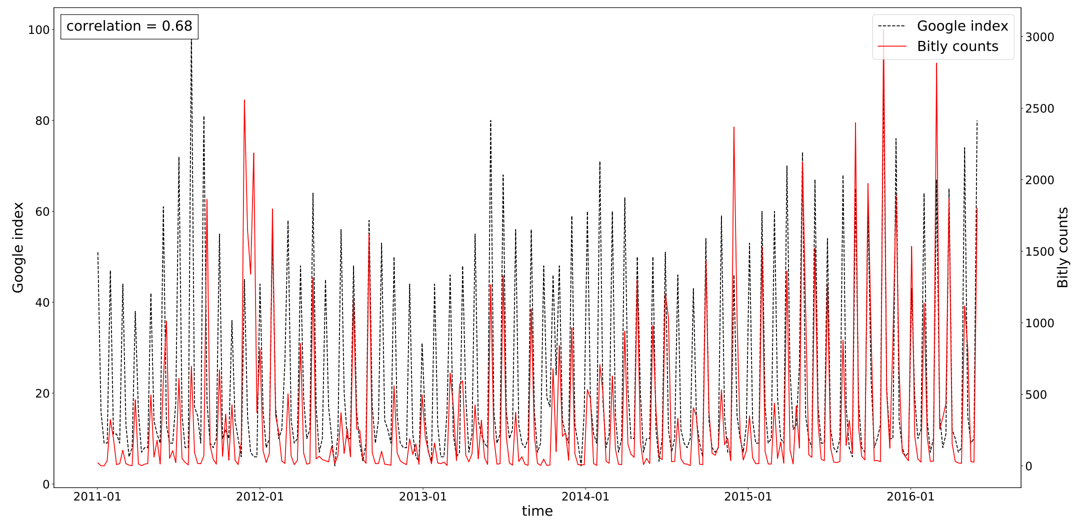
Figure 2: Bitly Daily Counts



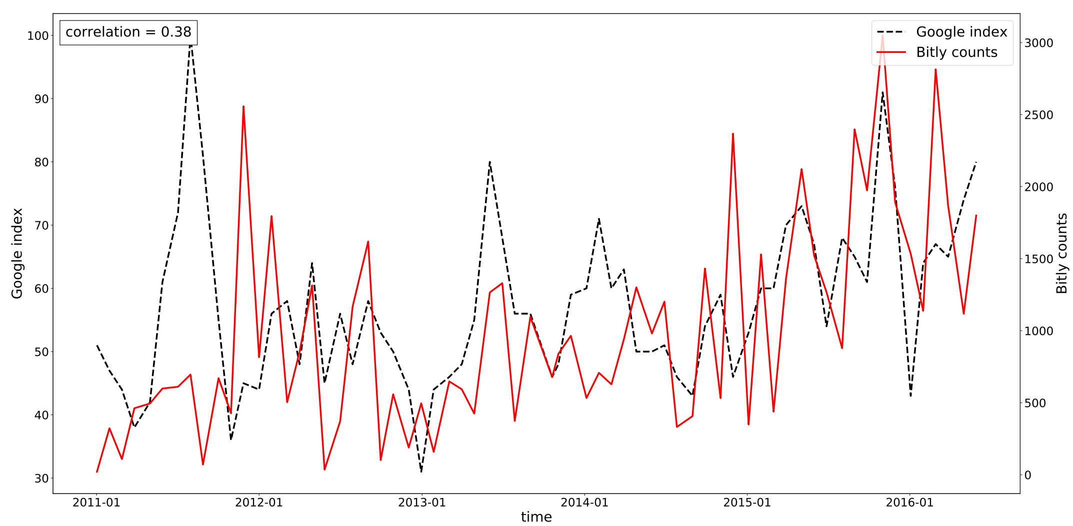
Notes: The figure shows the number of daily clicks in the Bitly dataset on headlines containing the word payroll for all days in our sample. The vertical black lines identify nonfarm payroll event days. the vertical red line identifies September 8, 2011, when President Obama announced a $447 billion jobs plan.

Figure 3: Comparing Different Measures of Information Demand: Bitly Counts and Google Trend Index

(a) Weekly Frequency



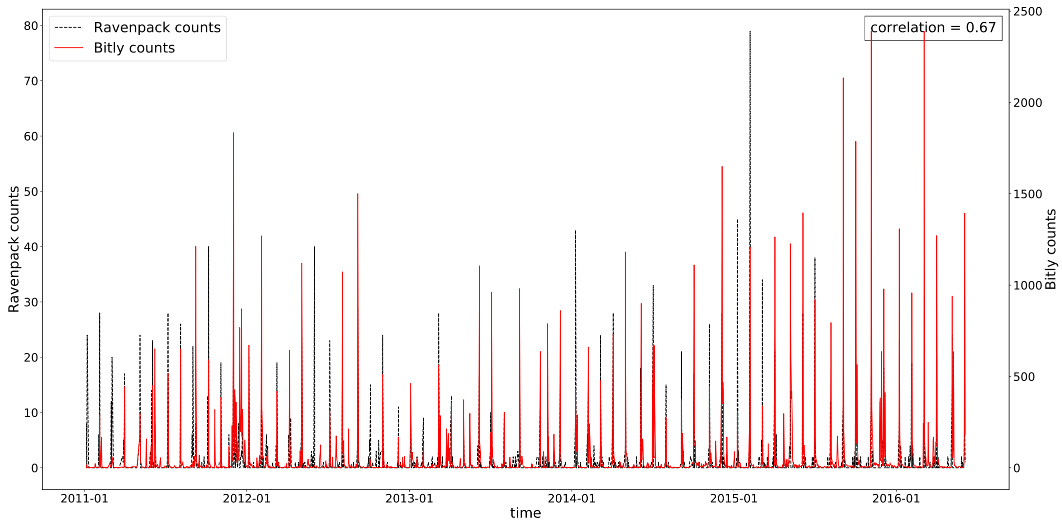
(b) Weeks with a Nonfarm Payroll Announcement Release



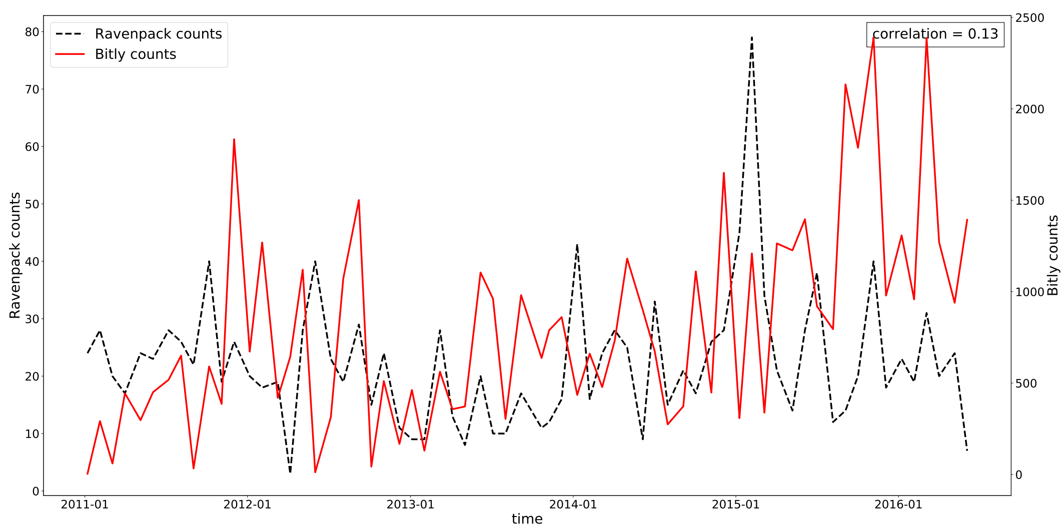
Notes: Panel a shows weekly Bitly counts and Google Trend Index for all the weeks in our sample from January 2011 to July 2018. Panel b shows weekly Bitly counts and Google Trend index for weeks when there was a nonfarm payroll release (a total of 91 weeks). The Bitly counts are based on headlines containing the word payroll, and the Google Trend Index is for the topic nonfarm payroll.

Figure 4: Information Demand and Supply: Bitly Counts and Ravenpack News Counts

(a) Daily Frequency



(b) Days with a Nonfarm Payroll Announcement Release



Notes: Panel a shows daily Bitly counts and Ravenpack news counts for all the days in our sample from January 2011 to July 2018. Panel b shows daily Bitly counts and Ravenpack news counts on days with a nonfarm payroll release (91 days). The Bitly counts and Ravenpack news counts are based on headlines containing the word payroll.

Figure 5: Intra Day Treasury Yield Reaction and Bitly Nonfarm Payroll Clicks

Notes: The figure shows the intraday reaction of the two-year U.S. Treasury futures yields to nonfarm payroll surprises from January 2011 to July 2018 (a total of 91 days). We perform a dependent sort on surprise and Bitly counts. Time 0 on the x-axis indicates the release time of nonfarm payroll, at 8:30 am ET.

Table 1: Popular News Sources of Articles Shared using Bitly

News Source	URL	Number of Clicks	Percent of Total Number of Clicks	Cumulative Percent
Panel A: Prior to nonfarm payroll release, from 6:29 am to 8:29 am				
Bloomberg	www.bloomberg.com	3,438	73	73
Marketwatch	www.marketwatch.com	340	7	80
Wall Street Journal	www.wsj.com	277	6	86
Financial Times	www.ft.com	221	5	91
USA Today	www.usatoday.com	173	4	95
CNBC	www.cnbc.com	153	3	98
Panel B: During and after nonfarm payroll release, from 8:30 am to 10:30 am				
Bloomberg	www.bloomberg.com	26,235	67	67
CNBC	www.cnbc.com	5,769	15	82
Reuters	www.reuters.com	1,860	5	87
Marketwatch	www.marketwatch.com	1,265	3	90
Wall Street Journal	www.wsj.com	1,173	3	93
USA Today	www.usatoday.com	772	2	95

Notes: Our sample period is from January 2011 to July 2018, which includes a total of 91 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 4,685 clicks during this period across the 91 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 38,963 clicks during this period across the 91 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	Cummulative Percent
Panel A: Prior to nonfarm payroll release, from 6:29 am to 8:29 am			
Official Bloomberg Users	2,508	54	54
Seven Individual Users	1,349	29	83
Official WSJ Users	201	4	87
Official USA Today Users	173	4	91
Official Marketwatch Users	148	3	94
Official CNBC Users	74	2	96
Official FT Users	57	1	97
Official Reuters Users	8	0.2	96.2
Panel B: During and after nonfarm payroll release, from 8:30 am to 10:30 am			
Official Bloomberg Users	18,228	47	47
Seven Individual Users	10,485	27	74
Official CNBC Users	3,914	10	84
Official Reuters Users	1,528	4	88
Official WSJ Users	1,031	3	94
Official USA Today Users	669	2	96
Official NPR Users	635	2	97
Official Marketwatch Users	257	1	98

Notes: Our sample period is from January 2011 to July 2018, which includes a total of 91 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 4,685 clicks during this period across the 91 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 38,963 clicks during this period across the 91 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 seven 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: Country of IP Address of the Reader of Bitly Links

Country of IP Address	Number of Clicks	Percent of Total Number of Clicks	Cummulative Percent
Panel A: Prior to nonfarm payroll release, from 6:29 am to 8:29 am			
United States	2,251	48	48
Unknown	532	11	59
Great Britain	271	6	65
Canada	155	3	68
Japan	131	3	71
Germany	91	2	73
India	88	2	75
Spain	81	2	77
Panel B: During and after nonfarm payroll release, from 8:30 am to 10:30 am			
United States	20,729	53	53
Unknown	2,676	7	60
Japan	2,668	7	73
Great Britain	1,190	3	63
Canada	1,033	3	66
Singapore	829	2	2
India	730	2	76
Germany	674	2	74

Notes: Our sample period is from January 2011 to July 2018, which includes a total of 91 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 4,685 clicks during this period across the 91 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 38,963 clicks during this period across the 91 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. The accuracy of the geolocation of IP addresses is fairly accurate, but not perfect.

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

	(1) Jan. 2004 - Jul. 2018	(2) Jan. 2011 - Jul. 2018	(3) Jan. 2011 - Jul. 2018 (exclud. SW ZLB period)
Response of the Two-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	5.376***	3.312***	3.673***
	(0.526)	(0.494)	(0.582)
Constant	0.563	0.0865	0.0998
	(0.435)	(0.343)	(0.411)
Number of Observations	175	91	74
Adjusted R-squared	0.377	0.335	0.356
Response of the Five-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	6.551***	6.380***	6.480***
	(0.577)	(0.806)	(0.954)
Constant	0.708	0.136	0.186
	(0.478)	(0.560)	(0.674)
Number of Observations	175	91	74
Adjusted R-squared	0.427	0.421	0.390
Response of the Ten-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	7.124***	6.491***	6.626***
	(0.851)	(0.560)	(0.989)
Constant	0.309	0.879*	0.269
	(0.591)	(0.463)	(0.698)
Number of Observations	175	91	74
Adjusted R-squared	0.437	0.441	0.384

Notes: We show estimates of equation 14 using three different samples. In column 1, the sample is from January 2004 to July 2018. In column 2, the sample is from January 2011 to July 2018, the sample for which we have Bitly data. In column 3, we use the shorter sample, from January 2011 to July 2018, and exclude 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: Summary Statistics

	Obs.	Mean	Std. Deviation	Min.	Max.
Panel A: January 2004 to June 2016					
Monetary Policy Variables					
Federal Funds Rate	175	1.44	1.69	0.25	5.25
Swanson-Williams ZLB	175	0.10	0.30	0	1
Market-based Policy Uncertainty	175	4.90	2.01	1.53	9.67
News-based Policy Uncertainty	175	119.99	45.99	44.78	283.67
Risk					
VIX Index	175	18.42	8.71	9.19	63.68
Information Environment					
Nonfarm Payroll Surprise	175	-8.65	67.84	-208.00	188.00
Revision Noise	175	26.47	21.63	0	125
Forecast Error	175	54.05	42.27	1.00	208.00
Analyst Forecast Dispersion	175	0.24	0.46	0	5.40
Trading Volume and Volatility					
Two-year US Treasury Trading Volume	175	0.19	0.10	0	0.57
Two-year US Treasury Realized Volatility	175	1.73	1.37	0.35	13.64
Panel B: January 2011 to June 2016					
Monetary Policy Variables					
Federal Funds Rate	91	0.50	0.45	0.25	2.00
Swanson-Williams ZLB	91	0.19	0.39	0	1
Market-based Policy Uncertainty	91	3.42	1.01	1.53	6.23
News-based Policy Uncertainty	91	136.32	43.09	63.88	283.67
Risk					
VIX Index	91	16.14	5.02	9.19	36.27
Information Environment					
Nonfarm Payroll Surprise	91	-2.27	57.54	-123.00	108.00
Revision Noise	91	23.18	15.23	1.00	77.00
Forecast Error	91	47.32	34.42	1.00	123.00
Analyst Forecast Dispersion	91	0.15	0.08	0.08	0.52
Trading Volume and Volatility					
Two-year US Treasury Trading Volume	91	0.22	0.09	0.02	0.57
Two-year US Treasury Realized Volatility	91	1.11	0.36	0.35	1.88
Information Demand and Supply					
Intraday Bitly Counts (before announcement)	91	51	85	0	426
Intraday Bitly Counts (during/after announcement)	91	612	587	3	2817
Weekly Google Trend Index	91	56	15	29	100
Ravenpack News Count	91	82	21	30	139

Notes: In Panel A our sample period is from January 2004 to July 2018 during non-farm payroll announcement days. In Panel A our sample period is from January 2011 to July 2018 during nonfarm payroll announcement days. The units of trading volume are million of contracts.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	5.640***	4.059	7.038***	3.366***	4.649***	3.015
	(0.741)	(2.515)	(1.126)	(1.133)	(1.182)	(3.135)
Monetary Policy Variables						
NFP Surprise x FFR Level	0.0163					-0.565
	(0.393)					(0.404)
NFP Surprise x SW ZLB Period	-4.225*					0.839
	(2.258)					(2.378)
NFP Surprise x Market-implied Uncertainty		0.834***				0.969**
		(0.260)				(0.449)
NFP Surprise x News-based Uncertainty		-0.0284**				-0.0139
		(0.0132)				(0.0174)
Risk						
NFP Surprise x VIX Index			-0.0823			-0.176**
			(0.0506)			(0.0855)
Information Environment						
NFP Surprise X Past Revision Noise				-0.0129		0.0116
				(0.0189)		(0.0255)
NFP Surprise x Past Forecast Error				0.0363***		0.0103
				(0.0114)		(0.0136)
NFP Surprise x Past Forecast Dispersion				1.914		2.841
				(1.858)		(1.901)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume					-10.27**	-1.692
					(4.766)	(5.503)
NFP Surprise x Past Realized Volatility					1.075***	0.752**
					(0.298)	(0.355)
Constant	0.390	-0.269	0.535	-0.935	0.786	-1.479
	(0.616)	(1.917)	(1.106)	(0.908)	(1.038)	(2.333)
Number of observations	175	175	175	175	175	175
R-squared	0.392	0.454	0.389	0.445	0.457	0.542

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2004 to July 2018. The dependent variable is a 1-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 59 seconds after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	4.944	3.957**	4.311***	3.584*	1.224	0.311
	(3.221)	(1.830)	(1.454)	(1.905)	(1.011)	(4.747)
Monetary Policy Variables						
NFP Surprise x FFR Level	-3.195**					-2.512
	(1.242)					(1.933)
NFP Surprise x SW ZLB Period	-2.593					0.382
	(1.638)					(2.499)
NFP Surprise x Market-implied Uncertainty	0.281					1.132
	(0.603)					(1.353)
NFP Surprise x News-based Uncertainty	-0.00431					0.0105
	(0.0121)					(0.0187)
Risk						
NFP Surprise x VIX Index		-0.0409				-0.113
		(0.112)				(0.182)
Information Environment						
NFP Surprise X Past Revision Noise			-0.0399			-0.0131
			(0.0367)			(0.0503)
NFP Surprise x Past Forecast Error			0.0196			0.0185
			(0.0161)			(0.0200)
NFP Surprise x Past Forecast Dispersion			-7.874			-8.164
			(8.163)			(12.02)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				-6.742		10.86
				(9.633)		(13.00)
NFP Surprise x Past Realized Volatility				1.068		-2.724
				(2.022)		(4.251)
Information Demand and Supply						
NFP Surprise x High Bitly Count					3.560***	2.964**
					(0.971)	(1.350)
NFP Surprise x High Media Coverage Count					0.773	1.031
					(1.005)	(1.538)
NFP Surprise x High Google Index					0.132	-0.0174
					(0.961)	(1.133)
Constant	-0.780	-0.320	0.0811	-1.378	0.124	0.458
	(2.088)	(1.175)	(0.959)	(1.166)	(0.584)	(2.877)
Number of observations	91	91	91	91	91	91
R-squared	0.426	0.337	0.365	0.354	0.446	0.529

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2011 to July 2018. The dependent variable is a 1-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 59 seconds after the announcement. The estimation also includes main effects, but we do not report these coefficients. 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	14.69***	5.479**	6.011***	4.770	2.300	3.990
	(4.648)	(2.600)	(2.109)	(3.314)	(1.497)	(7.583)
Monetary Policy Variables						
NFP Surprise x FFR Level	-7.346***					-5.686**
	(1.986)					(2.327)
NFP Surprise x SW ZLB Period	-3.457					2.412
	(2.532)					(4.016)
NFP Surprise x Market-implied Uncertainty	-1.311					-0.696
	(0.833)					(1.233)
NFP Surprise x News-based Uncertainty	0.00353					0.0302
	(0.0178)					(0.0246)
Risk						
NFP Surprise x VIX Index		0.0565				-0.167
		(0.153)				(0.255)
Information Environment						
NFP Surprise X Past Revision Noise			-0.0460			-0.0180
			(0.0549)			(0.0652)
NFP Surprise x Past Forecast Error			0.0232			0.0220
			(0.0241)			(0.0276)
NFP Surprise x Past Forecast Dispersion			1.014			-18.44
			(10.61)			(15.65)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				-2.456		6.072
				(6.334)		(8.863)
NFP Surprise x Past Realized Volatility				0.940		0.430
				(0.667)		(0.965)
Information Demand and Supply						
NFP Surprise x High Bitly Count					5.925***	5.451***
					(1.420)	(1.960)
NFP Surprise x High Media Coverage Count					2.198	1.805
					(1.486)	(2.010)
NFP Surprise x High Google Index					0.224	-0.894
					(1.410)	(1.666)
Constant	-2.183	-1.379	0.154	-0.394	-0.402	-0.530
	(3.044)	(1.629)	(1.408)	(1.983)	(0.860)	(4.192)
Number of observations	91	91	91	91	91	91
R-squared	0.501	0.429	0.445	0.435	0.538	0.619

Notes: We estimate the response of U.S. Treasury futures on five-year notes to nonfarm payroll surprises using data from January 2011 to July 2018. The dependent variable is a 1-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 59 seconds after the announcement. The estimation also includes main effects, but we do not report these coefficients. 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	16.69***	4.685	5.567**	5.063	3.764**	7.765
	(5.430)	(3.136)	(2.530)	(4.308)	(1.792)	(8.618)
Monetary Policy Variables						
NFP Surprise x FFR Level	-7.863***					-6.231**
	(2.094)					(2.665)
NFP Surprise x SW ZLB Period	-1.398					1.265
	(2.762)					(4.579)
NFP Surprise x Market-implied Uncertainty	-1.634					-0.831
	(1.017)					(1.447)
NFP Surprise x News-based Uncertainty	0.00146					0.0296
	(0.0204)					(0.0305)
Risk						
NFP Surprise x VIX Index		0.155				-0.0902
		(0.191)				(0.316)
Information Environment						
NFP Surprise X Past Revision Noise			0.0215			0.0283
			(0.0638)			(0.0800)
NFP Surprise x Past Forecast Error			-0.00119			0.00619
			(0.0280)			(0.0335)
NFP Surprise x Past Forecast Dispersion			7.869			-14.37
			(14.20)			(19.78)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				-1.241		1.060
				(4.093)		(5.400)
NFP Surprise x Past Realized Volatility				0.671		-0.0413
				(0.676)		(1.053)
Information Demand and Supply						
NFP Surprise x High Bitly Count					5.051***	4.931**
					(1.720)	(2.336)
NFP Surprise x High Media Coverage Count					1.484	1.379
					(1.780)	(2.315)
NFP Surprise x High Google Index					0.396	-0.425
					(1.703)	(1.937)
Constant	-1.381	-1.038	0.270	2.051	-0.355	0.813
	(3.521)	(2.014)	(1.668)	(2.652)	(1.035)	(4.892)
Number of observations	91	91	91	91	91	91
R-squared	0.537	0.447	0.454	0.457	0.506	0.607

Notes: We estimate the response of U.S. Treasury futures on ten-year notes to nonfarm payroll surprises using data from January 2011 to July 2018. The dependent variable is a 1-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 59 seconds after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively

Table 10: Contemporaneous Relation between Abnormal Information Demand, Monetary Policy Variables, Information Environment Variables, Trading Volume, Return Volatility and Information Supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NFP Announcement Day Dummy	25.22***	25.24***	16.03***	25.19***	20.49***	22.81***	13.38***
	(0.778)	(0.779)	(1.767)	(0.807)	(1.112)	(0.588)	(1.825)
Monetary Policy Variables							
FFR Level	-1.782						-1.071
	(2.285)						(2.280)
Swanson-Williams Period	0.0583						0.129
	(0.432)						(0.530)
Market-implied Policy Uncertainty	0.0302**						0.0308**
	(0.0118)						(0.0127)
News-based Policy Uncertainty	0.00166						0.00242
	(0.00227)						(0.00240)
Risk							
VIX Index		0.00264					-0.0470
		(0.0288)					(0.0432)
Information Environment							
Revision Noise			0.0682				0.0310
			(0.0458)				(0.0462)
Forecast Error			13.80***				12.93***
			(1.856)				(1.849)
Forecast Dispersion			2.001				3.708
			(1.910)				(2.544)
Trading Volume and Volatility							
Abnormal Trading Volume				0.424			0.448
				(0.341)			(0.334)
Abnormal Realized Volatility				-0.347			-1.349
				(1.206)			(1.185)
Information Demand and Supply							
Media Coverage Count					0.243***		0.211***
					(0.0411)		(0.0413)
Weekly Google Index						0.146	
						(0.119)	
Constant	-1.134	0.457	0.185	0.419	0.377**	0.310*	-0.509
	(1.109)	(0.527)	(0.345)	(1.096)	(0.167)	(0.169)	(1.493)
Number of Observations	2,417	2,417	2,017	2,017	2,017	2,081	2,017
R-squared	0.429	0.426	0.448	0.427	0.440	0.555	0.463

Notes: We estimate the contemporaneous relation between abnormal information demand, monetary policy variables, information environment variables, trading volume, return volatility and information supply using data from January 2011 to July 2018. 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)	0.916	27	-0.725	-8.891	-1.030	150
	(2.833)	(25.09)	(4.675)	(7.098)	(19.01)	(168.5)
Sum of 30 Lagged NFP Surprise Coefficients	-8.791	79.109	-2.520	-18.944	-29.438	349.942
F-statistic	1.843	2.002	0.048	1.277	0.472	0.860
Nonfarm Payroll Surprise(t-1) x High Bitly Count(t-1)		-26.56		13.70		-154.70
		(25.26)		(9.426)		(169.6)
Sum of 30 Lagged NFP Surprise x High Bitly Count Coefficients		-89.027		27.221		-382.182
F-statistic		2.500		1.294		1.010
Nonfarm Payroll Surprise(t)	3.634***	2.464***	16.20***	12.33***	28.68***	23.67***
	(0.458)	(0.631)	(1.863)	(2.619)	(3.075)	(4.239)
Nonfarm Payroll Surprise(t) x High Bitly Count		2.343**		8.964**		9.527
		(0.921)		(3.761)		(6.185)
Nonfarm Payroll Surprise(t+1)	-0.853	-1.156	-2.627	-5.059	-4.752	-7.668
	(0.459)	(0.634)	(1.770)	(2.462)	(3.081)	(4.259)
Sum of 30 Lead NFP Surprise Coefficients	4.139	-12.201	-9.908	-21.500	13.422	28.857
F-statistic	0.344	0.069	1.258	2.772	0.131	0.007
Nonfarm Payroll Surprise(t+1) x High Bitly Count		0.632		4.793		5.554
		(0.917)		(3.567)		(6.160)
Sum of 30 Lead NFP Surprise x High Bitly Count Coefficients		14.381		24.090		-14.733
F-statistic		0.099		1.811		0.001
Constant	0.094	0.098	-0.021	-0.072	0.011	0.006
	(0.0624)	(0.0626)	(0.241)	(0.242)	(0.419)	(0.420)
Number of Observations	2,384	2,384	2,692	2,692	2,385	2,385
Adjusted R-squared	0.044	0.084	0.049	0.076	0.050	0.089

Notes: We estimate the response of U.S. Treasury futures prices to nonfarm payroll announcements using data from January 2011 to July 2018. The dependent variable is one-day U.S. Treasury futures yield changes using the prevailing futures yield as of 5:00 pm ET. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 12: Weekly Response

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise(t)	3.620***	2.479***	15.67***	11.27***	28.28***	23.39***
	(0.609)	(0.834)	(2.200)	(3.003)	(3.736)	(5.172)
Nonfarm Payroll Surprise(t) x High Bitly Count		2.370*		9.145**		10.17*
		(1.205)		(4.336)		(6.467)
Constant	0.0252	-0.0516	-0.161	-0.458	-0.542	-0.871
	(0.419)	(0.415)	(1.514)	(1.493)	(2.571)	(2.570)
Number of Observations	91	91	91	91	91	91
Adjusted R-squared	0.277	0.307	0.356	0.386	0.384	0.396

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2011 to July 2018. The dependent variable is one-week U.S. Treasury futures yield changes using the prevailing futures yield as of 5:00 pm ET on Thursday. We only use weeks when there is a nonfarm payroll announcement. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 13: Order Flow Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	3.025***	3.022***	5.623***	5.600***	4.875***	4.840***
	(0.0503)	(0.0503)	(0.0697)	(0.0697)	(0.0728)	(0.0727)
Order Flow x Two Hours Before	0.700***	0.525***	1.372***	1.462***	1.277***	1.160***
	(0.0601)	(0.0682)	(0.0994)	(0.146)	(0.0636)	(0.0871)
Order Flow x Two Hours Before x High Bitly Count		0.777***		-0.166		0.248*
		(0.144)		(0.199)		(0.127)
Order Flow x Two Hours After	1.382***	1.307***	2.564***	2.252***	1.946***	1.722***
	(0.0302)	(0.0432)	(0.0422)	(0.0614)	(0.0223)	(0.0315)
Order Flow x Two Hours After x High Bitly Count		0.145**		0.582***		0.419***
		(0.0599)		(0.0830)		(0.0418)
Constant	0.000352	0.000277	-0.00139	-0.00106	-0.000831	-0.000484
	(0.00245)	(0.00245)	(0.00310)	(0.00310)	(0.00307)	(0.00306)
Number of Observations	21,724	21,724	21,724	21,724	21,724	21,724
Adjusted R-squared	0.267	0.269	0.377	0.378	0.465	0.468

Notes: We estimate the response of U.S. Treasury futures to nonfarm payroll announcements and order flow using data from January 2011 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. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.