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

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February 19, 2019

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 in price discovery. Consistent with this hypothesis, we find that the impact of nonfarm payroll news on U.S. Treasury note futures more than doubles when information demand (measured by the number of people reading related news) is high *before* the release of the announcement.

Keywords: Uncertainty, Information Demand, Clicks data, Macroeconomic Announcements, U.S. Treasury futures.
JEL Classifications: G12, G14, D83

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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, such as an increase in the dispersion of firms' cash-flows or stock returns, and endogenous decisions, such as 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 impact of news on prices. 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 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 U.S. Treasury note futures prices to nonfarm payroll announcements because this announcement is known for having a strong impact on U.S. Treasury note prices (see, for instance, Balduzzi, Elton, and Green, 2001; Andersen, Bollerslev, Diebold, and Vega, 2003; Hautsch and Hess, 2007; Swanson and Williams, 2014) and other asset classes.[2] Thus, finding good predictors of this impact is of broad interest. Nonfarm payroll announcements affect U.S. Treasury note prices because investors' expect the level of employment to affect the future stance of monetary policy, among other things. 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 "payroll" or "unemployment rate" or "jobs report" 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 media (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 U.S. Treasury notes by regressing the change in yields for two-, five-, and ten-year Treasury futures around an-

[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).

nouncements on the unexpected component of announcements and various control variables.[3] 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 above the median, the response of U.S. Treasury yields to nonfarm payroll announcements increases by 4.44 basis points (bps) for two-year U.S. Treasury notes, 5.77 bps for five-year Treasury notes, and 4.65 bps for ten-year Treasury notes and this impact is economically and statistically significant after controlling for many known determinants of the reaction of Treasury note securities to macroeconomic news. In particular, this effect is economically significant relative to the unconditional sensitivity of U.S. Treasury yields to surprises in nonfarm payroll announcements.[4] 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 (2012-2018), our proxy for information demand is one of the very few significant predictors of the strength of the response of U.S. Treasury notes to nonfarm payroll announcements. In particular, there is no significant association between this response and most other measures of uncertainty considered in the literature (e.g., the realized volatility of U.S. Treasury returns prior to the announcement, past forecast errors, or the dispersion of experts' forecasts).

Our leading interpretation is that variations in information demand are driven by variations in uncertainty regarding future interest rates. In support of this interpretation, we find that our measure of information demand is positively correlated with proxies for macroeconomic, monetary policy and interest rate uncertainty. In particular, it is highly significantly

[3]Following the methodology in Rogers, Scotti, and Wright (2018) and Rogers, Scotti, and Wright (2014), for all government bond futures, yield changes are approximated by dividing price changes by minus the modified duration of the cheapest-to-deliver security.

[4]For instance, during our sample period, the sensitivity of two-year treasury yields to surprises in nonfarm payroll announcements is 3.18 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.

correlated with the implied volatility of options on one year swap rates (a measure of uncertainty on monetary policy; see Carlston and Ochoa, 2017).

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.[5] However, in this case, high information demand ahead of news 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. Thus, information demand is also high when uncertainty is high. However, in this case, the higher uncertainty stems from less informative trades, not an increase in the variance of asset payoff. Consequently, 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, although not always statistically significantly so, 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, Sun, Beltran, Ferreira, Lacoviello, Jahan-Parvar, Li, Rodriguez, 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, it is not clear in theory how these variables should be related to the accuracy of investors' forecasts about future returns. In contrast, our models shows that there is a clear theoretical link between fluctuations in the accuracy

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

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.[6] In addition, Fedyk (2018) shows that trading volume after earnings announcements is stronger when the timing of investors' attention to news is more dispersed. Thus, these papers show that the speed at which prices adjust to news 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.[7] 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 the reaction of U.S. Treasury yields to nonfarm payroll news because investors' demand for information rises when they are more uncertain about the future level of interest rates. In fact, our proxy for information demand is one of the few variables that forecast the reaction of treasury prices to nonfarm payroll news during our sample period. This highlights

[6]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.

[7]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).

the difficulty of measuring uncertainty and the importance of using proxies for information demand to do so.

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.[8] 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.

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 induce 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 macroeconomic announcement) A_e is released about F with:

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

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

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.[9] We assume that $c(\tau_{\eta_i})$ is increasing and strictly convex with $c(0) = 0$.

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

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

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

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

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

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

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

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

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

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

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

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

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

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):

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

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

The marginal benefit of collecting information is higher when uncertainty (measured by $Var(F \mid z_1)$ dealers' expected forecasting error conditional on information) is higher.[10] 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

[10] 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 $Var(F \mid z_1)$.

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

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

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

Proposition 1. *When (i) the variance of the asset payoff, $Var(F)$ or (ii) the variance of noise trading, $Var(u)$ increase then (i) uncertainty ($Var(F \mid z_1)$), (ii) the aggregate demand for information 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 (see the online appendix for a formal proof). Now consider an increase in the variance of noise trading. The direct effect of this increase is to reduce the informativeness of the aggregate demand for the asset. This 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 (see the online appendix for a formal proof). 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 4.1, 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.[11] 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

[11] 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.

by an increase in speculators' information demand in equilibrium.[12] 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).[13] 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.

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. In a July 12, 2017 press release, Bitly described itself as the "*world's first and leading Link Management Platform.*"[14] 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.

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-`

[12]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.

[13]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.

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

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.

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, most news companies (e.g., Bloomberg or the Wall Street Journal) are paid customers of Bitly which allows them to have URL-shortened custom links (called '*'branded short domain*"). For example, *Wall Street Journal* pays for the shortened links to start with http://on.wsj.com (instead of the regular bit.ly/ link). Second, SURLs are easier to share than original 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).[15] All these providers pay to obtain a branded domain name from Bitly and its reader tracking service. We start our sample in 2012 to avoid structural changes in the coverage of Bitly. Once a company pays for Bitly services, clicks on shortened links that include its branded domain increase substantially. For this reason, in our analysis we just consider clicks on articles from online news providers that started paying for Bitly services before 2012.

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

[15] 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.

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.

3.1.1 Nonfarm Payroll Clicks

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 take place at pre-set points in time, on the first Friday of every month, and market participants are ready to trade based on the information released. There are 79 nonfarm payroll announcements from January 2012 to July 2018.

As in Baker, Bloom, and Davis (2016) and Husted, Rogers, and Sun (2017), we use keyword searches to identify Bitly SURLs directing to news articles about nonfarm payroll. We search for keywords in the original URL, which, as explained above, contains the title of the news article. For example, the original URL for the article entitled "*Why December Private Payrolls Aren't a Great Predictor of the Jobs Report*," is `https://blogs.wsj.com/economics/2016/01/07/why-december-private-payrolls-arent-a-great-predictor-of-the-jobs-report/`. To identify relevant keywords, we first collect SURLs and the original URL clicked on during the four hours time window around nonfarm payroll announcements, when media coverage related to nonfarm payroll is very high. Using natural language processing (NLP) techniques, we remove common words, such as "a," "the," from the original URL and estimate the frequency of non-common words used in the original URL link.

We find the following non-common words to be the most frequently used in the original URL: "payroll," "unemployment rate" and "jobs report." We assume (and manually verify the assumption for a large set of articles) that the presence of these words in a URL link during the four hour period surrounding the announcement indicates that this link is likely to direct to news about nonfarm payroll. Accordingly, we identify in our entire sample of Bitly SURLs, all the SURLs pointing to an original URL link that contains the keyword "payroll" or "unemployment rate" or "jobs report". Using this method, we identify $730,494$ clicks on Bitly SURLs pointing to news articles related to nonfarm payroll announcements from January 2012 to July 2018.[16] We refer to these clicks as "*nonfarm payroll clicks*". A significant fraction (46%) of the news articles accessed by these clicks are written on the days of nonfarm payroll announcements.

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 throughout the day.

[Insert Figure 1 here]

We measure information demand about future interest rates ahead of a specific nonfarm payroll announcement by the number of NFP clicks in our sample in the two hours preceding the announcement (from 6:29 am to 8:29 am ET). Over our entire sample, we observe about $21,000$ clicks in the two hours that precede nonfarm payroll announcements (about 6% of all nonfarm payroll clicks occurring on announcement days). In our tests, we measure information demand ahead of a particular announcement in two ways: (i) the total number

[16] We noticed that as we move away from the nonfarm payroll announcement date, there are some very popular articles (with more than 10,000 clicks, when the median click on a payroll related article on announcement days is 200 clicks) that are not related to nonfarm payroll news. We remove these outliers that almost always occur outside announcement days by dropping articles with more than the top 99th percentile of clicks in the full sample.

of nonfarm payroll clicks in the two hours preceding this announcement divided by the standard deviation of this variable (called "*Bitly Count*") or (ii) an indicator variable (called "*High Bitly Count*") equal to one when *Bitly Count* is above its median value (and zero otherwise).

3.1.2 News Sources

[Insert Tables 1, 2 here]

Tables 1, 2, 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), and (ii) the creator of each NFP SURL (Table 2). Table 1 shows that news' sources are concentrated among 5 providers (accounting for 91% to 72% of all news in the four hours around the announcement). Among these 5 news providers, the Wall Street Journal and Bloomberg are the most popular during the two hours prior to the announcement. The results we present are robust to estimating information demand using all sources or only these two sources. The former finding is consistent with our interpretation that nonfarm payroll clicks ahead of nonfarm payroll announcements measure investors' information demand.[17] Table 2 shows that Bitly links to popular news articles are often created by journalists from the main news providers, accounting for 54% to 70% of the clicks during the four hour period surrounding the announcement.

3.1.3 Relationship between Information Demand and Measures of Uncertainty

Proposition 1 in our model shows that time-variations in the variance of noise trading or the asset payoff induces a positive correlation between information demand and investors'

[17]There are two important financial news sources, namely Market Watch and CNBC, that we did not include in our sample . We dropped these sources because we are either missing data for these sources or the original URL is scribbled and does not embed the article headline in it (thus precluding us from searching the URL for the keywords that identify nonfarm payroll news). Our results are stronger when we include these two sources, but these gaps in coverage introduce structural breaks in our measure of information demand, so we decided to drop them.

uncertainty about the asset payoff. It is therefore interesting to analyze the correlation between our measure of information demand ("*BitlyCount*") and measures of uncertainty about future interest rates used in the prior literature.

We consider six alternative measures of uncertainty, all of which are available at a monthly frequency: (i) the market-based monetary policy uncertainty implied by the volatility of options on one-year swap rates (swaptions) as in Carlston and Ochoa (2017), (ii) the news-based monetary policy uncertainty index provided by Husted, Rogers, and Sun (2017), (iii) the CBOE equity volatility index (VIX), (iv) the realized daily volatility of the two-year Treasury note (v) the daily trading volume of the two year treasury note and (vi) the forecasting error, i.e., the absolute value of the difference between the actual release of the nonfarm payroll figure on a given day and the median forecast of this figure submitted to Bloomberg by professional forecasters prior to the announcement (available from Bloomberg real-time data).[18] We provide more information on the construction of these variables in Section 3.3. We use all of them as controls when we test the prediction that an increase in information demand predicts a stronger reaction of treasury prices to nonfarm payroll announcements.

[Insert Table 3 about Here]

Even though our study focuses on the two hours prior to the announcement, to compare our information demand to monthly uncertainty measures (the highest frequency some of the variables described above are available at) we aggregate Bitly counts over a month. In Table 3 we show that our proxy for monthly information demand is positively and significantly

[18] This variable 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.

correlated with all the monthly measures of uncertainty mentioned above, except for Trading Volume.[19]

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 (i.e., read news) holding the number of news stories constant. To address this issue, in our tests, we control for the number of available news stories written ahead of each announcement measured using data from Ravenpack's Story dataset. This dataset contains the headline of every news written by news providers covered by Ravenpack and a news release time stamp (up to the millisecond frequency).[20] To identify Ravenpack news articles related to nonfarm payroll news we use the same keywords we used to identify Bitly articles, specifically we search for the keywords "payroll" or "unemployment rate" or "jobs report" in the headline. We refer to these news as "information supply."

Table 3 shows that, as expected, information supply and information demand are positively correlated. Interestingly, in contrast to information demand, there is no significant or a negative correlation between the supply of news related to nonfarm payroll and other measures of uncertainty about future interest rates.

Several studies use search data from Google Trend to measure investors' attention to particular events or assets (see, for instance, Da, Engelberg, and Gao (2011)). Thus, in our tests, we also control for the Google trend index for the topic nonfarm payroll.[21] Table 3

[19]We also correlate our monthly information demand measure with Baker, Bloom, and Davis (2016)' policy uncertainty index, Scotti (2016)'s macroeconomic uncertainty index and Jurado, Ludgvison, and Ng (2015)'s macroeconomic uncertainty index. Over our sample period, the correlation between Baker, Bloom, and Davis (2016)' policy uncertainty index, Husted, Rogers, and Sun (2017) monetary policy uncertainty index and Jurado, Ludgvison, and Ng (2015) is high and positive (ranging from 0.2 to 0.53). The correlation between Scotti (2016)'s macroeconomic uncertainty index and the nonfarm payroll forecast error is 0.32. Accordingly, our measure of information demand is also positively correlated with these other measures. We also note that the correlation matrix above is qualitatively similar when our monthly measure of information demand only uses nonfarm payroll days rather than everyday in the month.

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

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

shows that the Google Trend index is positively correlated with our measure of information demand. This index is also positively correlated with other measures of uncertainty but not always significantly (e.g., for the news-based measure of monetary uncertainty or for the realized volatility of two-year U.S. Treasuries). We conjecture that our measure of information demand is more closely related to uncertainty on future interest rates than the Google Trend index because Bitly information demand is driven by financial news sources, which are more likely to be read by investors.

[**Insert Figure 2 here**]

Figure 2 offers another perspective of the relationships between our measure of information demand, a measure of information demand based on the Google Trend search index and interest rate volatility. Panel A of this figure shows the monthly number of clicks on NFP SURLs (red line) and the Google Trends search index for the topic nonfarm payroll (blue line).[22] The two series have a positive correlation of 0.46 as shown in Table 3. Both series tend to increase when there are "global" uncertainty shocks, like the Brexit referendum on June 2016. However, Table 3 shows that Bitly information demand and interest rate volatility are positively correlated, while the Google Trend index and interest rate volatility are very weakly correlated. In Panel B of Figure 2, we show the time-series of Bitly information demand and interest rate volatility. We observe that during the Zero Lower Bound (ZLB) period, Bitly information demand was low, interest rate volatility was low, but Google Trend index was high.[23] This dynamic is consistent with investors not paying attention to nonfarm

[22]According to Stephens-Davidowitz (2013) the Google trend search index is constructed by first dividing the total number of searches over a given period τ (e.g., weekly) using specific keywords by the total number of searches in Google over this period, and then dividing this ratio by the maximum of the ratio over a time period (15 years for monthly windows of observation, 6 years for weekly data, and one year for daily data). 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 15 year period resulted in the largest number of searches of the topic nonfarm payroll. We download the index from 2004 to the present. 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.

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

payroll news when monetary policy is less sensitive to this news (see Swanson and Williams (2014)). In contrast, concerns about unemployment might have been high during this period and this is what the Google Trend index captures.

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 carry over to the spot rates.[24] Accordingly, we focus on the front-month futures contract on the two-year, five-year and ten-year Treasury notes.

Following Balduzzi, Elton, and Green (2001), we regress 30-minute U.S. Treasury yield changes on news.[25] Specifically, let t be a day with a nonfarm payroll announcement. We denote by y_t^m the yield of the futures on a U.S. Treasury note with maturity m (2, 5, 10) on this day just after 8:59 am ET and by y_{t-1}^m the yield on this day just before 8:29 am ET. Following Rogers, Scotti, and Wright (2018) and Rogers, Scotti, and Wright (2014),

[24]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.

[25]Our results are robust to using different frequencies of yield changes, 1-minute, 5-minute, daily, and even 5-day changes as shown in Section 4.2.

for all government bond futures, yield changes are approximated by dividing price changes by minus the modified duration of the cheapest-to-deliver security.[26] We measure the yield reaction of U.S. Treasuries with maturity m to the nonfarm payroll announcement (at 8:30 am ET) on day t by 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 $Surprise_t$ is defined as the difference between the actual release of the nonfarm payroll figure on day t and the median forecast about this figure submitted to Bloomberg by professional forecasters prior to the announcement (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 2012 to July 2018 (during which our Bitly data is available). We report in Table 4 the estimates of β_S in eq.(14).

[Insert Table 4 about here]

The sensitivity of Treasury yields to nonfarm payroll surprises for the long sample period (2004-2018) is similar to that in Balduzzi, Elton, and Green (2001), who consider a different sample period (1991 to 1995). 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 4.95 basis point (which is 4.95 $\times$ 1.71 (average modified duration) = 5.79 basis point change in prices, compared to 6 basis point change in prices in

[26]The average modified duration for the two-, five- and ten-year notes over our sample period is 1.71, 3.91 and 5.87, respectively.

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, 3.2 bps, in the short sample period (2012-2018). This finding is consistent with Swanson and Williams (2014), who show that the impact of macroeconomic news announcements on two-year U.S. Treasuries becomes smaller from August 2011 to December 2012, due to federal fund rates being close to the zero lower bound.[27] Accordingly, we include in column 3 an interaction term and a main effect for what we label the Swanson-Williams zero lower bound period ("SW ZLB period"), from August 2011 to December 2012, and find that the impact of nonfarm payroll announcement on two-year U.S. Treasury note futures is lower during this period.[28]

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

We next consider how the sensitivity of the yield reaction to the nonfarm payroll surprise depends on information demand measured using Bitly data. First we consider this variable alone, and then we make it compete with other measures of uncertainty. We measure information demand using Bloomberg and Wall Street Journal news only. In untabulated results we observe that our findings are qualitatively similar when we use all news sources to measure information demand because our information demand measure is predominantly driven by these two financial news sources. In Table 5, we show the estimation of the following

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

[28]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.

equation:

$$\Delta y_t = \alpha + \beta_S Surprise_t + \beta_{SI} Surprise_t \times \mathrm{IDem}_{t-1} + \beta_I \mathrm{IDem}_{t-1} + \epsilon_t, \tag{15}$$

where IDem_{t-1} measures information demand ahead of the announcement on day t. It is either the number of nonfarm payroll clicks in the two hours preceding the announcement on day t divided by its standard deviation ("*Bitly Count*") or an indicator variable ("*High Bitly Count*") equal to one if the number of nonfarm payroll clicks in the two hours preceding the announcement on day t is above its median value in the sample. Table 5 Columns (1) and (2) show that the response of two-year U.S. Treasury yields to nonfarm payroll surprises is only statistically significant when information demand is high. For the five- and ten-year U.S. Treasury yields the response to nonfarm payroll surprises doubles during high information demand days.

We next study how the sensitivity of the yield reaction to the nonfarm payroll surprise depends on information demand controlling for various variables already considered in the literature. To this end, we enrich specification (15) as follows:

$$\Delta y_t = \alpha + \beta_S Surprise_t + \beta_{SI} Surprise_t \times \mathrm{IDem}_{t-1} + \beta_I \mathrm{IDem}_{t-1} + \beta_{SX} Surprise_t \times X_{t-1} + \beta_X X_{t-1} + \epsilon_t, \tag{16}$$

where X_{t-1} are additional control variables (discussed below) measured prior to the release of the announcement. 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), we use the implied volatility of options on one-year swap rates (swaptions) as a market-based measure of uncertainty about future monetary policy.[29] Second, we use two news-based policy uncertainty indexes, Baker, Bloom, and Davis (2016)'s and Husted, Rogers, and Sun (2017)'s. Both of them are based on a count of news stories that contain words related to uncertainty and monetary policy. We tabulate results with the Husted, Rogers, and Sun (2017)'s index, but the results are qualitatively similar when we use Baker, Bloom, and Davis (2016)'s index. Over our sample period, the correlation between the two indexes is 0.53. 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 volatility, as measured by the CBOE equity volatility index (VIX).[30] 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.

[29]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.

[30]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.

3. **Information Environment.** The reaction of treasury prices to macroeconomic announcements should be stronger when these announcements are more accurate (see (eq.(10) in the model). An (inverse) measure of the accuracy of nonfarm payroll announcements is the extent to which these announcements are subsequently revised (see, Hautsch and Hess, 2007; Gilbert, 2011, ,among others). Hence, in month t, we use the absolute value of the nonfarm payroll announcement in 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"). Eugene A. 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.[31] 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.[32]

4. **Trading Environment.** Finally, we control for measures of trading activity, namely trading volume and U.S. Treasury price 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

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

[32] Our results are robust to controlling for Jurado, Ludgvison, and Ng (2015)'s macroeconomic uncertainty index. The index combines financial variables with macroeconomic data releases, while the nonfarm payroll forecast error and Scotti's index only use macroeconomic data.

the number of contracts traded during the day (from 3:00 am ET to 5:00 pm ET) divided by one million.[33]

[**Insert Table 6 about here**]

Table 6 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 24%. 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 7**]

As a baseline, Table 7 shows estimates of eq.(16) for the two-year U.S. Treasury note and the long sample period (we obtain similar results for other maturities and thus omit them for brevity). Thus, in this table, we do not control for information demand since we do not observe it over the long sample period. In Table 7 (and all subsequent tables), we just report the coefficients on interaction terms and the surprise for expositional clarity. The results of Table 7 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 the beginning of our sample to December 2012 (see Column (2)). Moreover, only the market-based measure of monetary policy

[33] 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).

uncertainty has a significant and positive relationships with the sensitivity of treasury price reactions to nonfarm payroll announcements. 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)), although the coefficient is only statistically significant in column (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, although the coefficient is only significant in column (4). Finally, there is a positive association between the reaction of treasury prices to nonfarm payroll announcements and realized volatility, albeit not significant, maybe because an increase in realized volatility is positively correlated with an increase in uncertainty (see Columns (5) and (6)).

Next, we estimate eq.(16) for the short sample period, adding our proxies for the demand and supply of information as control variables in eq.(16). We also control for the Google trend index that uses the nonfarm payroll topic and information supply using Ravenpack data.

[Insert Table 8]

Table 8 shows the findings for the two-year Treasury notes futures. The first four columns show that during the 2012-2018 period, among the previous variables considered in Table 7, the level of the Federal Funds Rate, the SW ZLB period indicator variable, the market-based monetary policy uncertainty, and realized volatility in the two-year U.S. Treasury prices have a statistically significant 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 6).

Consistent with our main prediction, 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. One standard deviation shock to information demand just prior to nonfarm payroll announcements increases the sensitivity of the two-year Treasury notes futures yields to surprises by about 3 bps (the unconditional sensitivity during the 2012-2018 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 9 and 10 show estimates of eq.(16) 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 Google trend index reflecting searches about nonfarm payroll news, perhaps because our measure of information demand is driven by clicks on *financial press* articles.

4 Additional tests

4.1 Shocks to noise trading or the variance of asset payoffs?

According to Proposition 1, either shocks to the variance of asset payoffs (e.g., shocks to the variance of future interest rates for treasuries) or shocks to the volume of noise trading can generate both an increase in information demand and uncertainty 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, i.e., the difference between buy and sell market orders (signed using the Lee and Ready (1991) algorithm) over interval $[\tau, \tau+1]$ on day t, where each interval has a one minute duration and $\tau = 0$ is the time at which the announcement takes place. We then estimate the following equation:

$$\begin{aligned} \Delta OneMinYield_{\tau t} &= \alpha + \beta_S Surprise_t + \beta_{SI} Surprise_t \times \text{Idem}_{t-1} \\ &+ I_B(\lambda_B OrderFlow_{\tau t} + \kappa_B HighBitlyCount_t \times OrderFlow_t) \\ &+ I_A(\lambda_A OrderFlow_{\tau t} + \kappa_A HighBitlyCount_t \times OrderFlow_t) + \epsilon_t, \end{aligned} \tag{17}$$

where I_B is a dummy variable equal to one if $\tau < 0$ (before the announcement) and I_A is a dummy variable equal to one if $\tau \geq 0$ (after the announcement). We only use data two-hours before and two-hours after the announcement. Thus, λ_B and λ_A measure, respectively, the yield impact of trades two-hours before and two-hours 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 two-hours before and two-hours after nonfarm payroll releases, respectively. We report estimates of eq.(17) in Table 11.

[Insert Table 11]

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.[34]. 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 nonfarm payroll announcements

[34]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)

(although, before the announcement the impact of order flow is only statistically significant for the two-year U.S. Treasury note). Overall these findings 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).

4.2 Investors' sentiment or rational information demand?

Researchers have often used search data on the internet as a proxy for investors' sentiment.[35] 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 literature, we use readership data, not search data, and we argue that these data are associated with rational information demand rather than investor sentiment. If our interpretation is correct, a high demand for nonfarm payroll information on the day of nonfarm payroll announcements should not predict subsequent yield reversals (i.e., be positively associated with overreaction to macroeconomic announcements).

[Insert Figure 3 about Here]

As a first look at this issue, Figure 3 shows cumulative returns on nonfarm payroll announcement days from two hours before the announcement up to five hours after the announcement, separately for days with (i) positive or negative surprises and (ii) a high number (higher than the median) or low number of NFP clicks. The figure shows three things. First, it confirms visually our main finding: nonfarm payroll announcements have 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

[35] 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.

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.[36] These two last observations are consistent with the idea that NFP clicks proxy for rational information demand rather than investors' sentiment.

We now examine the preliminary evidence provided by Figure 3 more formally. First, to estimate whether there is a post-announcement reversal we estimate the following equation at the daily frequency:

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

This specification is similar to that of Lucca and Moench (2015) except that we interact leads and lags of the surprise variable by our proxy for information demand ($BitlyCount$). Estimates of eq.(18) are reported in Table 12.

[Insert Table 12]

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.[37].

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

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

[36]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.

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

where $\Delta TwoDayYield_t$ is estimated from the close of Thursday before the announcement to the close of the following Monday. The results are reported in Table 13. The coefficient on nonfarm payroll surprises is statistically significant for all maturities. However, when we include the interaction with Bitly the coefficient on surprise alone becomes insignificant and the interaction with Bitly is positive and statistically significant for all maturities. This finding shows, in another way, that a high number of Bitly nonfarm payroll clicks has a strong effect on the reaction of treasury yields to nonfarm payroll announcements, so large that the yield reaction to the announcement can still be statistically detected on the Monday after the announcement.

Overall, the findings in Tables 12 and 13 do not suggest that there is systematic over- or under-reaction of treasury yields to nonfarm payroll announcements or that over-reaction occurs when the number of Bitly nonfarm payroll clicks is high. Our findings suggest that the number of Bitly clicks 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 to news.

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

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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:

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

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

Investors' final wealth at date 3 is:

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

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:

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

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

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

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

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

using the fact that, by definition $\tau_{\eta_i} = Var(\eta_i)^{-1}$. Replacing $\frac{\mathrm{Var}(\mathrm{E}(F|s_i,p_1)-p_1)}{\mathrm{Var}(F|s_i,p_1)}$ by its expression in eq.(26) in eq.(24), we obtain eq.(11) in the text.

Proof of Proposition 1.

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

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

The equilibrium aggregate demand for information at date 0 solves:

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

Using the implicit function theorem, we obtain:

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

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

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

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

Speculators' expected forecasting errors in equilibrium.

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

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

In equilibrium:

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

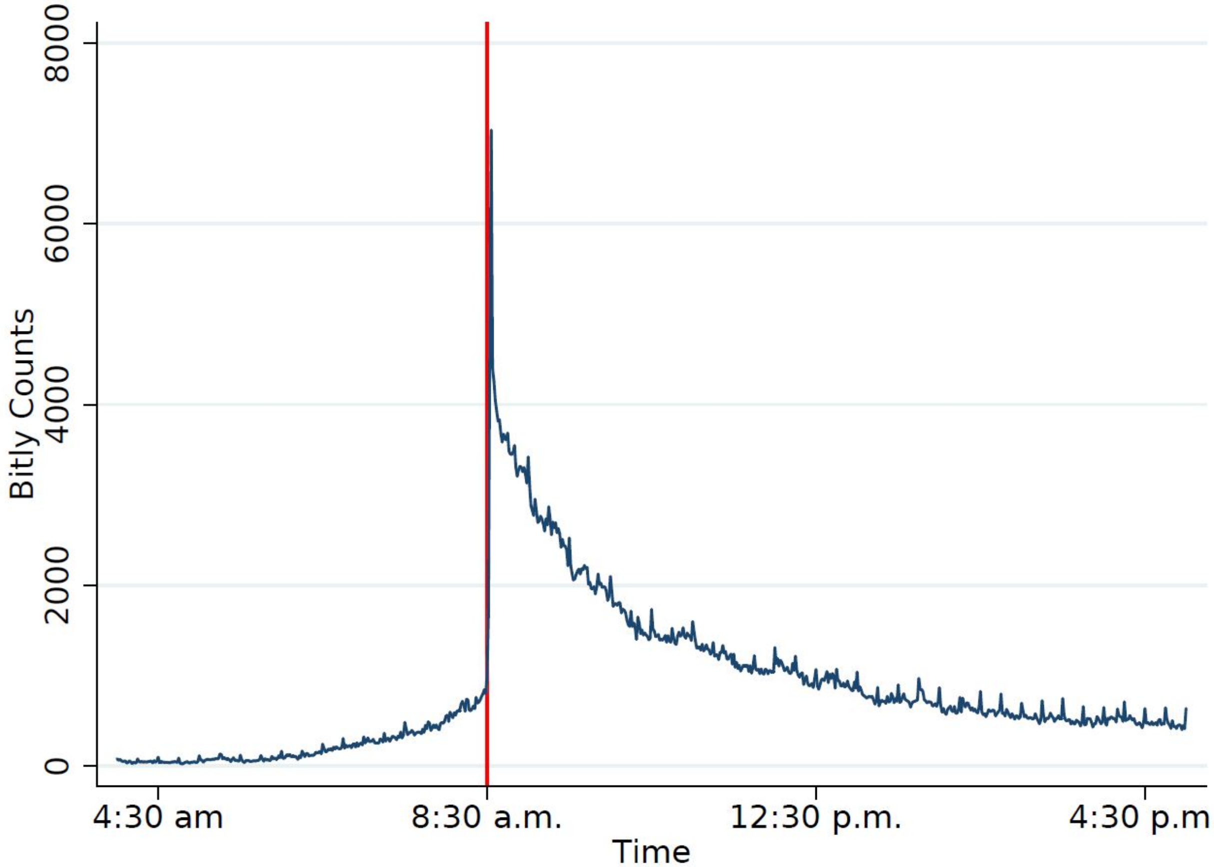
Thus, in equilibrium:

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

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

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

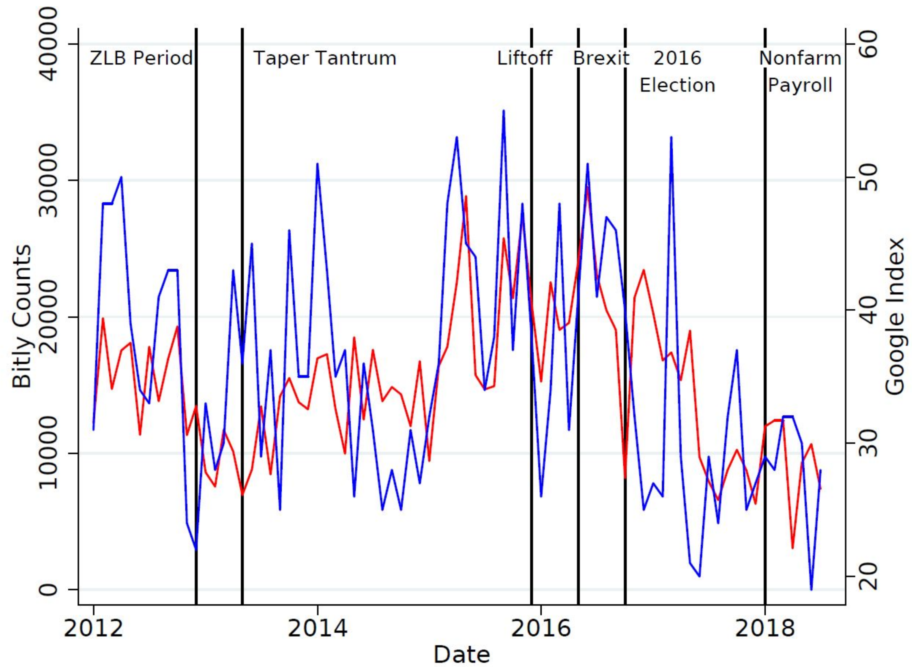
Figure 1: Intra Day Bitly Counts on Nonfarm Payroll Announcement Days



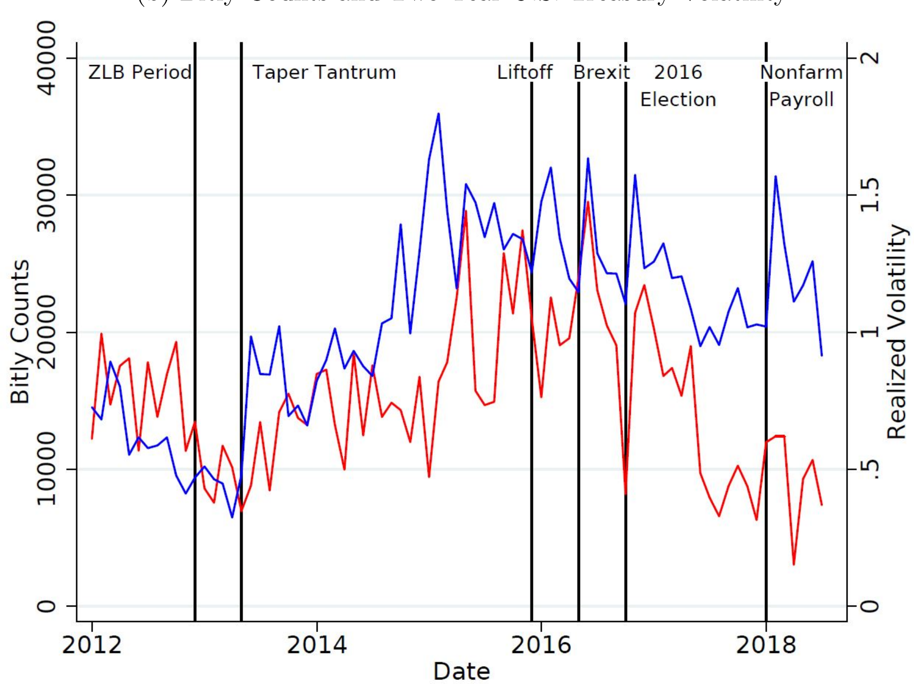
Notes: The figure shows the per minute number of nonfarm payroll Bitly clicks from 4:00 am ET to 5:00 pm ET, across all nonfarm payroll announcement days from January 2012 to July 2018 (91 days). The vertical red line identifies the release time of nonfarm payroll, 8:30 am ET.

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

(a) Bitly Counts and Google Index

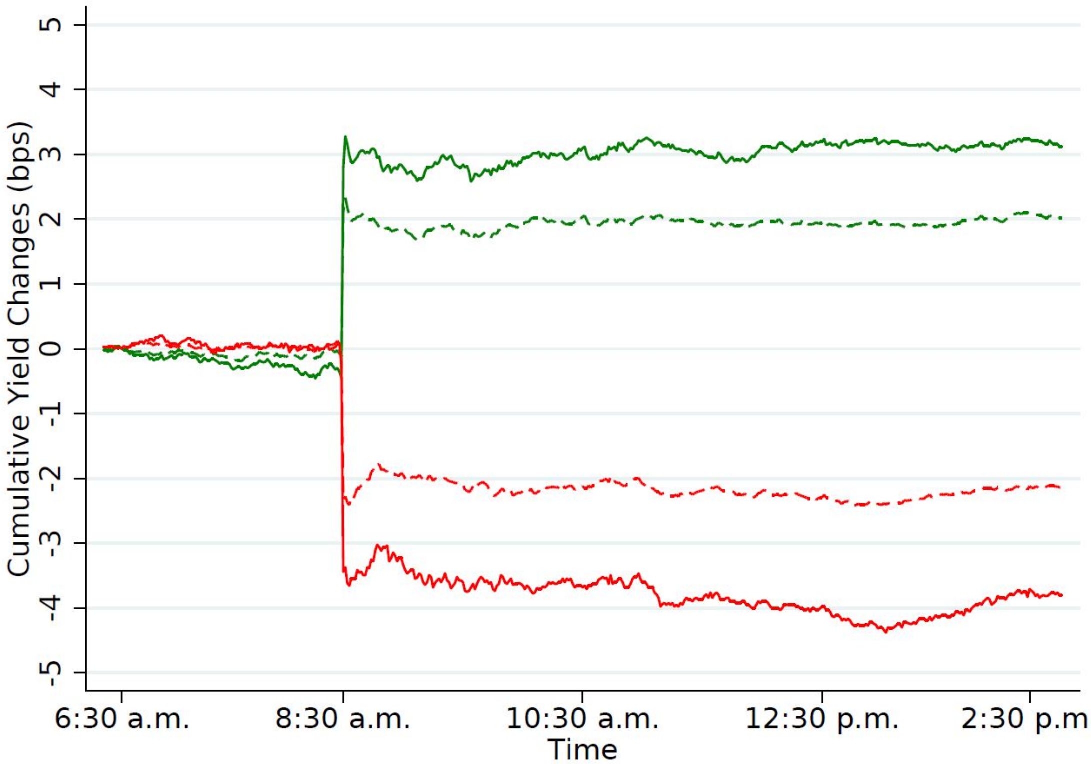


(b) Bitly Counts and Two-Year U.S. Treasury Volatility



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

Figure 3: Intra Day Two-Year U.S. Treasury Yield Reaction



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

Table 1: Popular News Sources of Articles Shared using Bitly

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

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

Table 2: Who Shares Bitly Links

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

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

Table 3: Contemporaneous Relation between Information Demand and Uncertainty Measures

	Information Demand	Market-based Policy Unc.	News-based Policy Unc.	VIX	Macro Uncertainty	Two-Year Volatility	Two-Year Volume	Google Index	Information Supply
Bitly Count (Inf. Demand)	1								
Market-based Policy Unc.	0.376***	1							
News-based Policy Unc.	0.320**	0.553***	1						
VIX	0.217*	0.437***	0.280*	1					
Macro Unc. (Forecast Error)	0.245*	0.105	0.0583	0.0948	1				
Two-Year US Treasury Volatility	0.358**	0.645***	0.522***	0.147	-0.0001	1			
Two-Year US Treasury Volume	0.0826	0.321**	0.202	0.000893	-0.0655	0.699***	1		
Google Index	0.459***	0.350**	0.145	0.224*	0.265*	0.057	-0.150	1	
Information Supply	0.379***	-0.19	-0.148	0.309**	0.143	-0.459***	-0.629***	0.464***	1

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

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

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	0.362	0.598	3.076**	3.027**	4.577***	4.406***
	(0.677)	(0.620)	(1.208)	(1.301)	(1.415)	(1.566)
Nonfarm Payroll Surprise × Bitly Count	2.873***		3.418***		2.660**	
	(0.819)		(1.125)		(1.191)	
Bitly Counts	1.010*		1.200		1.093	
	(0.574)		(0.775)		(0.746)	
NFP Surprise × High Bitly Count		4.446***		5.774***		4.657**
		(1.159)		(1.829)		(2.068)
High Bitly Count		0.194		0.538		0.788
		(0.820)		(1.273)		(1.358)
Constant	-1.004**	-0.382	-1.414*	-0.879	-1.309	-0.964
	(0.440)	(0.378)	(0.749)	(0.721)	(0.834)	(0.840)
Number of Observations	79	79	79	79	79	79
Adjusted R-squared	0.442	0.338	0.450	0.408	0.434	0.412

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

Table 6: Summary Statistics

	Obs.	Mean	Std. Deviation	Min.	Max.
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	0.1	0.3	0	1
Market-based Policy Uncertainty	175	3.39	2.18	0.84	13.16
News-based Policy Uncertainty	175	105	50	25	357
Risk					
VIX Index	175	18	8	10	62
Information Environment					
Nonfarm Payroll Surprise	175	-8.65	67.84	-208	188
Absolute Value of Revision Noise	175	26.53	21.59	0	125
Absolute Value of Forecast Error	175	53.62	42.26	1	208
Analyst Forecast Dispersion	175	22.22	24.34	9.24	165
Trading Volume and Volatility					
Two-Year US Treasury Trading Volume	175	3.7	1.77	0.15	9.14
Two-Year US Treasury Realized Volatility	175	1.53	0.77	0.32	4.98
Panel B: January 2012 to June 2016					
Monetary Policy Variables					
Federal Funds Rate	79	0.54	0.47	0.25	2
Swanson-Williams ZLB	79	0.15	0.36	0	1
Market-based Policy Uncertainty	79	1.83	0.55	0.84	3.06
News-based Policy Uncertainty	79	122	57	41	357
Risk					
VIX Index	79	15	3	10	24
Information Environment					
Nonfarm Payroll Surprise	79	1.01	56.86	-123	108
Absolute Value of Revision Noise	79	22.68	14.99	1	77
Absolute Value of Forecast Error	79	45.65	33.53	1	123
Analyst Forecast Dispersion	79	13.42	5.98	9.24	50
Trading Volume and Volatility					
Two-Year US Treasury Trading Volume	79	4.52	1.37	2.29	9.14
Two-Year US Treasury Realized Volatility	79	1.03	0.34	0.32	1.74
Information Demand and Supply					
Intraday Bitly Counts (Before Announcement)	79	160	188	0	775
Intraday Bitly Counts (During/After Announcement)	79	608	474	66	1,945
Google Trend Index (Monthly)	79	35	8	19	55
Ravenpack News Count (Before Announcement)	79	51	17	16	84

Notes: 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 2012 to July 2018 during nonfarm payroll announcement days. The units of trading volume are million of contracts.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	5.496***	-0.169	6.164***	1.077	3.620*	-0.765
	(0.873)	(1.651)	(1.056)	(1.292)	(1.936)	(3.026)
Monetary Policy Variables						
NFP Surprise × FFR Level	-0.175					-1.123**
	(0.444)					(0.553)
NFP Surprise × SW ZLB Period	-4.243***					1.664
	(0.939)					(1.336)
NFP Surprise × Past Market-based Unc.		0.865***				0.979*
		(0.312)				(0.513)
NFP Surprise × Past News-based Unc.		0.00374				-0.00842
		(0.00997)				(0.0109)
Risk						
NFP Surprise × VIX Index			-0.0589			-0.307***
			(0.0477)			(0.0915)
Information Environment						
NFP Surprise × Past Revision Noise				-0.00203		0.0161
				(0.0168)		(0.0262)
NFP Surprise × Past Forecast Error				0.0314***		0.00739
				(0.0113)		(0.0107)
NFP Surprise × Past Forecast Disp.				0.111		0.0869
				(0.0746)		(0.0573)
Trading Volume and Volatility						
NFP Surprise × Past Trading Volume					-0.295	0.295
					(0.271)	(0.348)
NFP Surprise × Past Realized Volatility					1.447	3.234
					(1.118)	(1.978)
Constant	0.140	-0.124	0.215	-0.407	-0.730	1.960
	(0.607)	(1.366)	(1.161)	(0.926)	(1.381)	(2.492)
Number of observations	175	175	175	175	175	175
R-squared	0.361	0.386	0.344	0.402	0.373	0.513

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 30-minute U.S. Treasury futures yield change using the prevailing futures price as of one second before the announcement to 30 minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

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

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

Table 9: Response of the Five-Year US Treasury Futures to Nonfarm Payroll Surprises

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

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

Table 10: Response of the Ten-Year US Treasury Futures to Nonfarm Payroll Surprises

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

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

Table 11: Order Flow Impact

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

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

Table 12: Pre- and Post-Announcement Reaction

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

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

Table 13: Weekend Response

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

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