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

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Abstract

We measure demand for information prior to nonfarm payroll announcements using a novel dataset consisting of clicks on news articles. We find that when information demand is high shortly before the release of the nonfarm payroll announcement, the price response of U.S. Treasury note futures to nonfarm payroll news surprises doubles. We argue that this relationship stems from the fact that market participants have more incentive to collect information when uncertainty about asset payoffs is higher, as implied by Bayesian learning models. Thus, high information demand about macroeconomic news is a proxy for high macroeconomic uncertainty.

Keywords: Public information, Macroeconomic News, Uncertainty, U.S. Treasury futures, Investors' Attention, Information Demand, Bitly, Media Coverage.
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1 Introduction

Understanding how news affect asset prices is important for various areas of financial economics (see, for instance, Tetlock, 2014, for a survey). Such understanding requires studying how investors behave around news arrival. For instance, limited attention to news can lead to delayed price adjustment to new information (see, e.g., Hirshleifer, Lim, and Teoh, 2008; Dellavigna and Pollet, 2009). In this paper, we provide evidence that investors demand more information ahead of scheduled macroeconomic announcements when the effect of these announcements on treasury prices is more uncertain, consistent with rational models of demand for information (e.g., Grossman and Stiglitz, 1980; Veldkamp, 2006). Thus, a high demand for information ahead of a macroeconomic announcement predicts a stronger reaction of treasury prices to the announcement because both information demand and price reaction are positively related to macroeconomic uncertainty.

We measure investors' demand for information about forthcoming macroeconomic announcements by the number of clicks on internet links referring to news articles about these announcements. Our data are provided by Bitly, a service that shortens long internet addresses, and allows people (e.g., journalists in news agencies such as Bloomberg) to track readership and share information on social medias (e.g., Facebook) or micro-blogging platforms (e.g.,Twitter or Google+). We focus on clicks on links referring to news about nonfarm payrolls because they have the highest impact on U.S. Treasury yields.[1] Specifically, we consider all nonfarm payroll releases from 2011 to 2016 (66 overall) and we use the number of clicks on links pointing to news containing the word "payroll" in their headlines in the two hours *preceding* nonfarm payroll releases as a measure of investors' demand for information related to nonfarm payroll figures.[2]

[1]The nonfarm payroll is among the most significant of the announcements for all of the markets, and it is often referred to as the "king" of announcements by market participants; see, e.g., Andersen and Bollerslev (1998) or Gilbert, Scotti, Strasser, and Vega (2017).

[2]Of course, investors have many other ways to collect information about nonfarm payroll figures than by clicking on links pointing to news about nonfarm payroll. Our premiss is that an increase in clicks on these links is symptomatic of a more general increase in investors' effort in information collection.

There is a large literature documenting a strong reaction of U.S. Treasury prices to nonfarm payroll announcements (see, for instance, Balduzzi, Elton, and Green, 2001; Andersen, Bollerslev, Diebold, and Vega, 2003; Hautsch and Hess, 2007; Swanson and Williams, 2014). Positive surprises in these announcements (higher nonfarm payrolls than expected) lead to a significant drop in U.S. Treasury prices as market participants expect monetary policy to become less accommodating (interest rates to rise). We show that this impact is substantially amplified when investors demand more information related to nonfarm payroll shortly before the release of official nonfarm payroll figures. Specifically, on days in which this demand for information is abnormally high, the response of treasury prices to nonfarm payroll announcements increases by 6 basis points (bps) for two-year U.S. Treasuries, 20 bps for five-year U.S. Treasuries, and 26 bps for ten-years U.S. Treasuries (after controlling for many known determinants of the reaction of Treasury prices to macroeconomic news). This amplification is strong given the unconditional sensitivity of U.S. Treasury prices to surprises in nonfarm payroll announcements.[3] Moreover, during our sample period, our proxy for the demand of information ahead of macroeconomic announcements is one the very few significant predictors of the strength of the response of U.S. Treasury prices to nonfarm payroll announcements and its effect does not vanish when we control for media coverage about forthcoming nonfarm payroll announcements.

The richness of our data allows us to measure demand for information shortly before nonfarm payroll announcements. Thus, our main finding cannot be explained by reverse causality, i.e., a strong investor interest in news about nonfarm payrolls after abnormally large price reactions to nonfarm payroll announcements. However, this does not mean that one can give a causal interpretation to our findings. In fact, Bayesian learning models implies that reaction to news about an asset should be *weaker* if investors have collected more information about this payoff *before* news arrivals. We find exactly the opposite. We

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

argue that the reason is that demand for information is *endogenous*: investors have more incentive to acquire information about asset payoffs when these payoffs are more uncertain in the first place. The net effect is that both the demand for information ahead of news and the price reaction to news are high when uncertainty is high. Thus, the demand for information ahead of news appears positively correlated with price reaction to news (as we find in the data), even though the true causal effect of the demand for information ahead of news on price reaction is negative. We illustrate this point using a simple rational expectations model of trading ahead of public news arrival with endogenous information acquisition based on Vives (1995).

We further validate our interpretation in two ways. First, we show that our measure of the demand for information is positively correlated with proxies for macroeconomic uncertainty. In particular, it is significantly higher when the implied volatility of options on one year swap rates (a measure of uncertainty on monetary policy; see Carlston and Ochoa, 2017; Husted, Rogers, and Sun, 2017)) is higher. Second, we show that trades are more informative (move treasury prices more) on announcement days in which our proxy for information demand is abnormally high, both before and after the release of nonfarm payroll figures.

Our findings contribute to three distinct strands of literature. First, we contribute to the literature on the effect of investor's attention to asset prices since information demand about an asset (or news affecting the value of this asset) is a form of attention. Da, Engelberg, and Gao (2011) find that greater attention to a stock, proxied by google search data, is associated with retail buying pressure and predicts short run price increases and long run price reversals for this stock. Other papers suggest that lack of attention lead to underreaction to news, such as earnings announcements (e.g., Hirshleifer, Lim, and Teoh, 2008; Dellavigna and Pollet, 2009). Using data on news reading activity by institutional investors, Ben-Rephael, Da, and

Israelsen (2017) show that greater attention by institutional investors accelerate the speed at which information get impounded into prices (reduces the post earnings drift).[4]

Our analysis differs in several ways. First, we consider a macroeconomic announcement that attracts a lot of attention from sophisticated investors in the first place (i.e., does not compete for attention with other contemporaneous news events or activities). Second, we do not focus on whether a high or a low demand of information about a news affects the speed at which prices react to the news after they arrived. In fact, in treasury markets, there is no under or overreaction to macroeconomic announcements and prices adjust extremely fast to these announcements. We show that this is the case in our data whether our proxy for demand of information is high or low. Instead, we analyze how the *size* of the immediate price reaction to news depends on *prior* information demand related to the news itself.[5] This approach gives us the possibility to test whether the correlation observed between prior information demand ("attention") and the price reaction is consistent or not with rational models of information demand. We find it is if information demand is endogenous. Overall, our findings illustrate the importance of accounting for the endogeneity of attention for interpreting relationships between attention, news and prices.

Second, we contribute to the literature analyzing the sensitivity of U.S. Treasury prices to macroeconomic announcements and in particular to nonfarm payroll announcements.[6] Recent papers in this literature have highlighted that the response of U.S. Treasury prices to macroeconomic announcements varies over time (e.g., Swanson and Williams, 2014; Goldberg and Grisse, 2013) and across announcements (e.g., Gilbert, Scotti, Strasser, and Vega, 2017). It is well understood in this literature that time-variations in uncertainty about macroeconomic fundamentals might trigger variations in the strength of U.S. Treasury price reactions

[4]Engelberg and Parsons (2011) and Peress (2014) show that media coverage affect stock prices and trading volume, possibly because they bring stock specific news to investors' attention. Peress and Schmidt (2018) show that market liquidity goes down when retail investors are distracted.

[5]We are not aware of other papers doing so.

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

to macroeconomic announcements (see, in particular, Goldberg and Grisse, 2013). However, finding a good proxy for uncertainty about the fundamentals underlying macroeconomic announcements has proved difficult. Our findings suggest that the extent to which investors consume news about forthcoming announcements shortly before they occur is informative about macroeconomic uncertainty because the former drives the later. Interestingly, the positive relationship between our measure of demand for information prior to nonfarm payroll announcements and price reactions persists even after controlling for various news-based measures of macroeconomic and monetary policy uncertainty and media coverage. This suggests that data on news consumption contain information distinct from that in news supply about macroeconomic uncertainty.

Last, there is some evidence of informed trading prior to influential macroeconomic announcements in treasury markets (see, Kurov, Sancetta, Strasser, and Wolfe, 2016; Bernile, Hu, and Tang, 2016). This evidence has raised concerns about possible leakages of information ahead of macroeconomic announcements.[7] As noted by Kurov, Sancetta, Strasser, and Wolfe (2016), a more benign explanation might be that some market participants actively engage in collecting private information ahead of macroeconomic announcements. Our findings that demand for information increases with macroeconomic uncertainty is consistent with this possibility.

We proceed as follows. In Section 2, we describe our measure of information demand and compare it to measures based on google trend search data and news supply. In Section 3, as a benchmark, we measure the response of U.S. Treasury prices to nonfarm payroll surprises during our sample period and we study how this response varies with various known determinants of treasury price reactions to macroeconomic announcements. Then, in Section 4, we show that prior demand for information about nonfarm payrolls is a strong predictor of this response, even after controlling for variables considered in Section 3. In

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

Section 5, we show that this finding is consistent with rational demand for information and we perform additional tests supporting this interpretation. Section 6 concludes.

2 Measuring information demand

This section describes the data used in our paper to measure investors' demand for information ahead of scheduled macroeconomic announcements.

2.1 Bitly

Bitly (`https://bitly.com/`) provides short-URL-links (henceforth SURLs) and a readership tracking system since 2008. Short-URL links allow individuals (e.g., journalists) to shorten "Uniform Resource Locator" (URL) addresses to refer others to news articles (that they wrote or find of interest) and track the readership of the 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 in December 2015 prior to the release of the nonfarm payroll announcement in this month. The original URL for this article is `https://blogs.wsj.com/economics/2016/01/07/why-december-private-payrolls-arent-a-great-predictor-of-the-jobs-report/` and the URL-shortened by Bitly is `http://on.wsj.com/2oJQ2py`. These two URL addresses point to the original WSJ news article. However, the URL-shortened link has several advantages for users. First, Bitly provides statistics (e.g., number of clicks, geographical location, devices used to access the shortened link etc.) about short-link clickers (henceforth "clickers"). This feature allows short-links' creators (e.g., journalists) to keep track of the popularity of the articles that they share. In fact, several news companies such as Bloomberg, Wall Street Journal, buy URL-shortened custom links from Bitly (such as `http://on.wsj.com/2oJQ2py` in the previous example) to track readership more easily. Second, SURLs help users to disseminate information through micro-blogging sites, such as Twitter, or messaging technologies, as these medias often constrain the number of characters that users can post or send.[8] Third, SURLs are often much easier to manipulate and share than the original URL address.

As for now, Bitly is the most popular provider of SURLs.[9] In a July 12, 2017 press release, Bitly described itself as the "*world's first and leading Link Management Platform.*"[10] In the same press release, Bitly reported that they have 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.

2.2 Measuring information demand with Bitly data

We use data provided by Bitly from January 2011 to June 2016. Specifically, we asked Bitly to provide us with every single Bitly SURLs pointing to articles from 59 major online news providers. Out of these 59 news providers, 9 are traditional news providers (as used by Chan (2003)), 30 belong to the top online news providers according to the 2015 Pew Research Center ranking, and 20 belong to Alexa's top business news rankings.[11] The complete list of news sources we use is available in the online Appendix.

The unit of observation in the data is a single click on a Bitly SURL, and each click comes with a rich array of additional information such as the original URL link, the login of the creator of that link, a time stamp (with second precision time) for both the creation of the shortened-URL link and each new click on the Bitly SURL, the geographical origin of each click (based on the IP address of the click), and (whenever possible) whether the Bitly SURL was accessed, directly or through a social media platform. The final dataset contains

[8] The incentive to post shortened links in Twitter weakened in September 2015, when Twitter announced that all URL-links will count as 22 or 23 characters long regardless of the actual length of the URL.

[9] One of its early competitor was TinyURL. However, in May 2009, Twitter changed its default link shortener from TinyURL to Bitly giving a marked advantage to Bitly (see "Bit.ly Eclipses TineyURL on Twitter." The New York Times, May 7, 2009.). Given the popularity of Bitly, many companies (e.g., Facebook and Tweeter) started their own URL-shortening services. Nevertheless, Bitly remains the most popular URL-shortening providers because it provides users with summary statistics on clickers.

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

[11] 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`.

about ten billion clicks distributed over more than 70 million unique Bitly links, generated by about 700,000 different user logins.

Among these clicks, we focus on those pointing to articles related to nonfarm payroll employment announcements. The main reason is due to data processing constraints: the large size of our dataset (ten billion clicks, about 10 Terabytes) makes it computationally difficult to implement the algorithm that we use to identify news related to a particular macroeconomic announcement (see below) for all these announcements (e.g., Gilbert, Scotti, Strasser, and Vega (2017) identifies 30 macroeconomic announcements that are released monthly). Hence, we must necessarily restrict attention to only a few macroeconomic announcements. Among these announcements, nonfarm payroll employment is a natural candidate since the literature has shown that, among all macroeconomic announcements, these announcements have the biggest impact on U.S. Treasury prices (see, for instance, Gilbert, Scotti, Strasser, and Vega, 2017). This finding suggests that market participants pay close attention to nonfarm payroll announcements. Thus, considering nonfarm payroll announcements seem to be a good starting point to analyze whether investors' demand for information ahead of macroeconomic announcements reflect macroeconomic uncertainty. Our sample period features 66 nonfarm payroll announcements (one per month).

To identify Bitly SURLs that point to news articles related to nonfarm payroll announcements, we proceed as follows. We first select all Bitly SURLs that refer to an original URL link that contains the keyword "payroll". Using this method, we identify $40,000$ clicks on Bitly SURLs pointing to news articles related to nonfarm payroll announcements from January 2011 to June 2016. We checked that using different keyword combinations (among "payroll", "nonfarm", or "employment") does not significantly change the set of news identified with our method. We refer to these $40,000$ as "*nonfarm payroll clicks*".

Using this method, 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 right after the nonfarm payroll announcement and this number remains elevated related to its value before the announcement for about thirty minutes.

[Insert Figure 1 here]

In our analysis, we focus on information demand shortly *before* the release of the nonfarm payroll numbers. To this end, on each announcement day, we measure the number of nonfarm payroll clicks from 6:25 am to 8:25 am ET on this day. Then, we use this number as a proxy for prior information demand about the nonfarm payroll figure released on this day or, alternatively, an indicator variable (called "*High Bitly Count*") equal to one when the number of nonfarm payroll clicks from 6:25 am to 8:25 am ET is above its median value in the sample and zero otherwise. As our findings are very similar with both measures, we just report those obtained with High Bitly Count as a proxy for the demand for information about forthcoming nonfarm payroll announcements. Overall, we observe 4,685 clicks in total in the two hours preceding all announcements in our sample (about 10% of all clicks related to nonfarm payroll in each announcement day and 52 per announcement day on average).

[Insert Table 1, 2, 3 here]

Tables 1, 2, 3, provide a breakdown of nonfarm payroll clicks before (Panel A) and after (Panel B) nonfarm payroll announcements according to (i) the news providers, (ii) the creator of the nonfarm payroll Bitly link, and (iii) the geographical location of users. Table 1 shows that news' sources are concentrated among 6 providers (accounting for 95% of all news). Among these 6 news providers, Bloomberg is by far the most popular. Table 2 shows that Bitly links to popular news articles are often created by journalists from the main financial news providers and seven influential individuals (30% of clicks on Bitly links related to nonfarm payroll news). Table 3 provides information regarding the country where clickers' IP address is located. A majority of these addresses (48% to 53%) are located in the United States. However, a significant fraction of clickers are also located in Great Britain, Japan, and Canada.

Finally, in Table 4, we show through which media (Twitter, SMS, e.mails, Facebook, Google etc.) clickers access the Bitly links. About 50% of the clicks come from Twitter and 41% of the clicks are direct clicks (SMS, e.mail, newspaper alerts). The rest are clicks on Facebook pages and to a lesser extent they come from a Google search. Untabulated statistics show that almost all the Bitly links accessed through Facebook are links shared by individuals. Journalists are equally likely to share links directly or through Twitter. Specifically, 54 (41) percent of the articles shared by Bloomberg journalists prior to (during and after) nonfarm payroll announcements are accessed through Twitter compared to 40 (46) percent that are accessed directly.

2.3 Advantages of Bitly data for measuring information demand

The literature has considered various ways to measure information demand for stocks around informational events (e.g., earnings announcements), namely historical search data about a stock ticker from Google trends (see, Da, Engelberg, and Gao, 2011; Vlastakis and Markellos, 2012) and historical readership data from Bloomberg collected via a Bloomberg terminal, as in Ben-Rephael, Da, and Israelsen (2017). However, so far, existing data of this type have been available to researchers only at low frequency (daily, weekly etc.).[12] Thus, researchers have not been able to accurately separate the demand for information about a stock occurring prior to the event of interest from that occurring after this event. As observed by Ben-Rephael, Da, and Israelsen (2017), this problem prevents researchers from studying whether information demand is driven by price reactions to the event itself or vice versa.[13] One way to circumvent this problem is to measure information on days preceding the event day. However, this raises an "attribution problem," in the sense that information demand far ahead of the event of interest might be due to other preceding events.

[12] Hourly frequency is available for Google trends, but only over the last 24 hours.

[13] The large number of clicks on Bitly links *after* nonfarm payroll announcements in our data shows that this is a serious problem. Demand for information is definitely higher after nonfarm payroll announcements than before. Our goal however is to analyze the role of demand for information prior to the event.

[Insert Figure 2 here]

To illustrate the importance of the attribution problem, Figure 2 shows the daily number of clicks on news related to nonfarm payroll using news articles from Bloomberg (95% of all clicks in our sample). The vertical black lines are the days of nonfarm payroll announcements. As expected, the number of clicks on nonfarm payroll related news substantially increases on nonfarm payroll announcement days. However, the number of Bitly clicks on links referring to articles containing the word "payroll" can also be high on other days. These articles are less likely to be about the next nonfarm payroll announcements. For instance, the red (dotted) vertical line on Figure 2 is the day on which President Obama announced a $447 billion jobs plan (September 8, 2011). On this day, there were 1,212 clicks on articles that contained the keyword "payroll" but the articles were not related to the past nonfarm payroll announcement on September 2, 2011, nor to the upcoming nonfarm payroll announcement on October 7, 2011. In sum, low frequency measures of demand for information about the next nonfarm payroll announcement (e.g., the weekly number of nonfarm payroll Bitly clicks ahead of the next announcement) are more prone to type I errors (false positives) than our high frequency measure (the number of nonfarm payroll Bitly clicks in the two hours preceding the announcement itself).

2.4 Relationship between Bitly data and Google trend data

Da, Engelberg, and Gao (2011)) use search data from Google trend to measure investors' attention to a particular stock. It is therefore interesting to study how our measure of information demand relates to a measure of attention to nonfarm payroll announcements built using Google trend, as in Da, Engelberg, and Gao (2011)). To this end, Panel A of Figure 3 shows the weekly number of clicks on Bitly links referring to articles containing the word "payroll" (red line) and the Google Trends search index for the topic nonfarm payroll (black dotted line), from Sunday to Saturday to match Google's aggregation procedure. We do not specify a location, so our google index captures global searches. By construction, the Google trend index takes values from 0 to 100.[14]

[Insert Figure 3 here]

As can be seen from 3, the Google trend index and Bitly counts are correlated with a correlation of 0.64. In Panel B of Figure 3, we only consider weeks with a nonfarm payroll announcements. The correlation between the Google trend index and Bitly counts drop significantly to 0.38. Overall, our measure of information demand about forthcoming nonfarm payroll announcements based on Bitly counts is distinct from a measure based on Google trends.

2.5 Information demand vs. information supply

Our goal is to measure demand for information (actual consumption of news about forthcoming nonfarm payroll announcements) rather than information supply (volume of news available about forthcoming nonfarm payroll announcements). Intuitively, a high supply of information does not mean that demand is high as investors might choose not to read the news. Yet, news supply and news demand should be correlated. To control for information supply, we use data from Ravenpack's Story dataset. Ravenpack is one of the major news analytics provider (alongside with Thomson Reuters and Bloomberg). It uses advanced text analytics techniques to classify news from Dow Jones Newswire and, among other metrics, assign a score to each news indicating whether it is positive or negative. The Ravenpack's

[14] According to Stephens-Davidowitz (2013) the Google trend index is constructed by first dividing the total number of searches over a given period τ (e.g., weekly), including keywords for a topic, by the total number of searches in Google over this period, and then dividing this ratio by the maximum of the ratio over a time period (6 years for weekly windows of observation). This ratio is multiplied by one 100. Hence by construction, the value 100 indicates which week in the 6 year period resulted in the largest number of searches of the topic nonfarm payroll. Kearney and Levine (2015) provide a detailed description of the google trends data and their drawbacks. In particular, Google's approach in constructing the index generates results that are strictly ordinal within a location/time period. One cannot concatenate index values to obtain a longer time-series than what Google provides you with, unless the partially overlapping time-series shares the same maximum value. In our case, we extend the time series with 22 additional observations by downloading Google Trends data from January 2011 to January 2016, and from July 2011 to July 2016. During these two time-series the maximum value of the data occurred on July 31, 2011.

Story dataset contains the headline of every news covered by Ravenpack and a news release time stamp (rounded to the nearest second).[15] We identify news related to nonfarm payroll in the Ravenpack data set the same way we identify them in the Bitly data set, namely we search for the keyword "payroll" in the headline of the news. In Panel A of Figure 4, we plot the *daily* number of nonfarm payroll Bitly clicks along with the daily number of headlines that contain the keyword payroll in the Ravenpack's Story dataset (our measure of information supply). The two series are highly correlated, with a correlation of 0.67. Panel B of Figure 4 shows that this correlation drops to only 0.13 if we restrict our attention to nonfarm payroll announcements days. Thus, high demand for information on days of nonfarm payroll announcements is distinct from high supply on these days. For our tests, we use the number of Ravenpack nonfarm payroll news in the two hours preceding a nonfarm payroll announcement as a proxy for the supply of information about these announcements shortly before their occurrence.

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

As explained in the Introduction, an extensive literature has studied the response of U.S. Treasury prices to macroeconomic news 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 explanatory power of our proxy for demand of information ahead of nonfarm payroll announcements, relative to other variables that have been considered to explain variation in the price response of U.S. Treasury note prices to macroeconomic announcements.

[15]Sources for Ravenpack include Dow Jones Newswires, the Wall Street Journal, Marketwatch, Barron's, and other traditional news sources. Hence, this data is well suited to capture the supply of information.

To estimate the response of U.S. Treasury prices to nonfarm payroll announcements, we use intra-day data on prices of futures on U.S. Treasury notes from Reuters Tick History. There is a new U.S. Treasury note futures contract issued every three-months, in March, June, September, and December. The most recently issued ("front-month") contract, is the most heavily traded contract and is a close substitute for the underlying spot instrument, so our results should carry over to the spot rates.[16] Accordingly, we focus on the front-month futures contract on the two-year, five-year and ten-year Treasury notes.

Let t be a day with a nonfarm payroll announcement. We denote by p_t^m the price of the futures on a U.S. Treasury note with maturity m (2, 5, 10) on this day just before 8:35 am ET and by p_{t-1}^m the price on this day just before 8:25 am ET.[17] We measure the price reaction of U.S. Treasuries with maturity m to the nonfarm payroll announcement (at 8:30 am) on day t by regressing $TenMinuteReturn_t = 10000 \times (ln(p_t^m) - ln(p_{t-1}^m))$ on nonfarm payroll surprises:

$$TenMinuteReturn_t = \alpha + \beta_S Surprise_t + \epsilon_t, \tag{1}$$

where surprise is defined as the difference between the actual release of the nonfarm payroll figure on day t minus the median forecast about this figure submitted to Bloomberg by professional forecasters prior to the announcement (available from Bloomberg real-time data). Our main focus is on the sensitivity, β_S, of Treasury prices to the surprise in nonfarm payroll announcements. 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 June 2016. We estimate eq.(1) for two different samples period: (a) January 2004 to June 2016 (similar to that used in prior studies) and

[16] 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.

[17] 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 price as long as the previous price 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).

(b) January 2011 to June 2016 (during which our Bitly data is available). Table 6 report estimates of β_S in eq.(1).

[Insert Table 6 about here]

The sensitivity of Treasury prices to nonfarm payroll surprises for the longer sample period, from January 2004 to June 2016, is similar to that in Balduzzi, Elton, and Green (2001), who consider a different sample period (1991 to 1995) and use 35-minutes returns (rather than 10 minutes returns as we do). Specifically, the first column of Table 6 shows that a one-standard deviation increase in the nonfarm payroll surprise decreases the two-year U.S. Treasury note futures price by 11 basis point and the ten-year U.S. Treasury note futures price by 41 basis point (compared to 16 basis points and 41 basis points in Balduzzi, Elton, and Green (2001)). Column 2 shows that the impact of the nonfarm payroll surprise on the two-year U.S. Treasury note futures is much smaller in the 2011-2016 sample (6 bps vs. 11 bps). This finding is consistent with Swanson and Williams (2014), who show that the impact of macroeconomic news announcements on two-year U.S. Treasuries becomes smaller from August 2011 onward, due to federal fund rates being close to the zero lower bound.[18] Accordingly, we exclude in column 3 what we label the Swanson-Williams zero lower bound period ("Swanson-Williams ZLB period"), from August 2011 to December 2012, and find that the impact of nonfarm payroll announcement on two-year U.S. Treasury note futures increases when we exclude this period.[19]

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

[19]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.

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

$$TenMinuteReturn_t = \alpha + \beta_S Surprise_t + \beta_{SX} Surprise_t \times X_t + \beta_X X_t + \epsilon_t \quad (2)$$

where X_t are additional control variables (discussed below) that may affect the response of U.S. Treasury note futures to surprises in macroeconomic announcements. We first describe these variables before reporting estimates of eq.(2). We group them in four categories: (1) monetary policy, (2) risk, (3) information environment, and (4) trading environment:

1. As previously discussed Swanson and Williams (2014) find that U.S. Treasury prices 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 prices 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 consider two monetary policy uncertainty measures. The first measure is the implied volatility of options on one-year swap rates (swaptions).[20] This measure is used by Carlston and Ochoa (2017) and Husted, Rogers, and Sun (2017) as a market-based measure of monetary policy uncertainty. The second measure is a news-based monetary policy uncertainty measure. Baker, Bloom, and Davis (2016) and Husted, Rogers, and Sun (2017) have developed two news-based monetary policy uncertainty

[20] We thank Marcelo Ochoa for giving us the data. Carlston and Ochoa (2017) use swaption prices 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.

measures that are highly correlated (0.62 correlation). For brevity we only report results with the Baker, Bloom, and Davis (2016) major news paper monetary policy uncertainty index, but our results are qualitatively similar when we use the Husted, Rogers, and Sun (2017) monetary policy uncertainty index. The model we sketch in section 5 and Bayesian learning models in general predict that high uncertainty about the value of the assets (high monetary policy uncertainty) is associated with a higher impact of macroeconomic news surprises on U.S. Treasury prices.

2. 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).[21] 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, consistent with the predictions of a standard Bayesian learning models (see Section 5).

3. The model we sketch in Section 5 and Bayesian learning models in general predict that the information environment should affect the response of asset prices to macroeconomic news. Specifically, according to these models the response of asset prices to macroeconomic news surprises should increase in the ratio of the precision of the signals conveyed by macroeconomic news to investors to the precision of signals available to investors prior to the announcement. One proxy for the noise in macroeconomic announcements (the inverse of their precision) is the extent to which these announcements are subsequently revised (see Hautsch and Hess (2007) and Gilbert (2011) among others). Hence, in month t, we use the absolute value of the nonfarm payroll announcement in month $(t-1)$ minus the revision of this announcement in this month as a proxy for

[21] 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.

the noise in nonfarm payroll announcement in month t (we call this variable "revision noise"). Eugene A. Imhoff and Lobo (1992), among others, show that higher dispersion in analysts' earnings forecasts are associated with a smaller response of stock market prices to earnings announcements. This suggests that the dispersion of professional forecasters' forecasts prior to nonfarm payroll announcement is another possible proxy for the noise in this announcement. We measure this dispersion by the ratio of the standard deviation across professional forecasters to the absolute value of the median forecast (times 100).[22] To proxy for investors' uncertainty prior to the announcement, we follow Scotti (2016) and use past forecast errors (defined as the absolute value of past NFP surprise) as a proxy for investor's uncertainty prior to the announcement.

4. Finally, we control for measures of trading activity, namely trading volume and asset 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 the number of contracts traded during the day (from 3:00 am ET to 5:00 pm ET) divided by one million.

[**Insert Table 5 about here**]

Table 5 provides summary statistics for all the variables used in the rest of our analysis. In Panel A, we show summary statistics for the January 2004 to June 2016 sample period and in Panel B, we show summary statistics for the January 2011 to June 2016 sample period. Comparing the standard deviation of the variables across samples, we note that the longer sample period, Panel A, 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 10% to 60%. In contrast, for the shorter sample period

[22] We scale by the median forecasts to control for the magnitude of the forecast.

(Panel B), the standard deviation of these variables is relatively small. The level of the federal funds target rate ranges from 25 basis points to 50 basis points, and the VIX index only ranges from 10% to 36%. The lack of variation in some of these variables in the shorter sample period, Panel B, makes it more difficult to identify their impact on the sensitivity of U.S. Treasury note futures to nonfarm payroll surprises.

[Insert Table 7]

Table 7 shows estimates of eq.(2) for the two-year U.S. Treasury note (we obtain similar results for other maturities and thus omit them for brevity). In this table (and all subsequent tables), we just report the coefficients on interaction terms and the surprise for expositional clarity, we do not report (but include in the regression) main effects (the coefficient estimates of β_X). The results of Table 7 are largely consistent with the previous literature. As previously discussed, the impact of nonfarm payroll surprises on Treasury prices is smaller during the Swanson-Williams ZLB period, from August 2011 to December 2012.

Moreover, in line with Bayesian learning models (and the model in Section 5), high uncertainty about the value of the assets, as measured by high market-based uncertainty about short-term interest rates (Carlston and Ochoa, 2017) and/or past forecast errors (Scotti, 2016), is associated with a higher impact of nonfarm payroll surprises on U.S. Treasury prices. However, the news-based policy uncertainty measure does not have a statistically significant impact on the response to nonfarm payroll surprises. Husted, Rogers, and Sun (2017) point out the market-based and news-based monetary policy uncertainty measures are not highly correlated during our sample period, which contains the zero lower bound period because, by construction, the market-based uncertainty measures was low during the zero lower bound period, when interest rate volatility was extremely low, while the news-based monetary policy uncertainty measure was high because it captured other dimensions of monetary policy uncertainty, not only interest rate volatility, but uncertainty regarding the timing and pace of policy rate normalization. Our results suggest that the impact of nonfarm payroll news is more closely related to short-term interest rate volatility than to news-based monetary policy uncertainty.

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. Consistent with Hautsch and Hess (2007) and Gilbert (2011), among others, and the model we sketch in section 5, we find that the announcement noise, measured by past revision noise, in nonfarm payroll announcements dampens the response of U.S. Treasury prices to these announcements. However, the effect is not statistically significant. Finally, past trading volume is associated with a smaller response of U.S. Treasury prices to nonfarm payroll announcements. To the extent that past trading volume is associated with informed trading the day before, these results are consistent with the model sketched in 5. In Column 6 of Table 7, we observe that market-based uncertainty about short-term interest rates and the VIX index have the strongest impact on the response of U.S. Treasury note futures to surprises in macroeconomic announcements.

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

We now present our main and novel empirical finding, namely the strong positive association between the strength of the response of Treasury prices to nonfarm payroll announcements and the demand for information about nonfarm payroll prior to these announcement. To this end, we add our proxies for the demand and supply of information as control variables in eq.(2).[23] We also control for Google trend searches for forthcoming nonfarm payroll announcements. As our the Bitly data are available only from January 2011 to June 2016, we can estimate eq.(2) for this period only.

[23] As explained previously, these proxies are dummy variables equal to one when the number of nonfarm payroll clicks (demand) or the number of Ravenpack news containing the word payroll in the two hours preceding a nonfarm payroll announcement are higher than their median value over the sample period.

[Insert Table 8]

Table 8 shows the findings for the two-year Treasury notes futures. The first four columns show that during the 2011-2016 period, among the previous variables considered in Table 7, only the Swanson-Williams indicator variable has a statistically significant impact on the response coefficient, β_S. As explained previously, this variable significantly dampens the response of Treasury prices to nonfarm payroll announcements. The lack of significance of the VIX index, market-based uncertainty about short-term interest rates, and the information environment variables in Table 8 might be due to the lack of variations in these variables during the 2011-2016 period as shown in Table 5.

In contrast, columns (5) and (6) show that our proxy for information demand is significantly and positively related to the absolute value of the response of Treasury prices to surprises in nonfarm payroll announcements. The size of the effect is economically significant. Indeed, in days in which the demand for information just prior to nonfarm payroll announcements is abnormally high (Bitly clicks are above their median value), the sensitivity of the two-year Treasury notes futures prices to surprises in these announcements increases by about 5 bps (the unconditional sensitivity during the 2011-2016 period is 6.6bps in absolute value; see Table 6).

In Tables 9 and 10 we show estimates of eq.(2) for the five-year and ten-year U.S. Treasury notes, respectively. The results in these two tables are consistent with 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 prices to nonfarm payroll announcements and our proxy for the demand of information about these announcements prior to their occurrence.

5 Interpretation and additional tests

In the previous section, we have shown that there is a strong positive association between nonfarm payroll Bitly clicks and the sensitivity of Treasury prices to surprises in nonfarm payroll announcements. In this section, we show that this association is consistent with a model in which investors react to greater uncertainty about macroeconomic variables such as nonfarm payroll announcements and their effect on asset prices by demanding more information. We then test additional predictions of the model.

5.1 Equilibrium Demand for Information and macroeconomic Uncertainty

The model has four dates $t \in \{0, 1, 2, 3\}$ and features one risky asset whose payoff F is realized at date 4. We assume that:

$$F = \mu + \alpha A_r, \tag{3}$$

where A_r has a normal distribution with mean 0 and precision (inverse of the variance) τ_{A_r}. The lower is τ_{A_r}, the *higher* is the uncertainty about the value of the asset. We interpret A_r as the realization of a macroeconomic variable (e.g., nonfarm payroll) that influences the payoff of the risky asset. Parameter α measures the sensitivity of the asset value to this variable. For instance, in reality, investors expect the FED to raise interest rates following an increase in nonfarm payroll figures, which decreases the value of Treasury notes. Thus, in this case $\alpha < 0$ and $|\alpha|$ can be interpreted as the sensitivity (or perceived sensitivity) of monetary policy to the macroeconomic variable, A_r. As pointed out by Goldberg and Grisse (2013), this sensitivity might vary over time (e.g., it might be low during our sample for reasons discussed in Swanson and Williams (2014)).

At date 2, a public signal A_e is released about A_r. This signal is:

$$A_e = A_r + \epsilon, \tag{4}$$

where ϵ is normally distributed with mean 0 and precision τ_ϵ. We interpret this public signal as the macroeconomic announcement (nonfarm payroll) considered in our data. In reality, macroeconomic announcements are preliminary estimates of actual figures and are subsequently revised by statistical agencies providing these figures, sometimes very significantly (see Gilbert (2011)). Thus, ϵ represents the size of the revision and τ_ϵ the accuracy of the initial announcement.

At date 0, a continuum of investors privately collect information about A_r.[24] Specifically, at date 0, each investor $i \in [0, 1]$ pays a cost $c(\tau_{\eta_i})$ to obtain a signal s_i about A_r such that:

$$s_i = A_r + \eta_i, \tag{5}$$

where η_i is normally distributed with mean zero and precision τ_{η_i}. Thus, $\tau_{\eta_i}$is the precision of the signal received by investor i about the "underlying" of the forthcoming announcement. We assume that $c(\tau_{\eta_i})$ is increasing and convex with $c(0) = 0$. Thus, not collecting information is equivalent to $\eta_i = 0$. Moreover, η_{is} are independent across agents.

Investors receive their signal between dates 0 and 1 and can use it to trade the risky asset before the announcement at date 1. We interpret τ_{η_i} as the demand for information by investor i prior to the announcement. The signals obtained by investors are positively correlated (since $cov(s_i, s_j) = (\tau_{A_r})^{-1} > 0$). However, investors possibly differ in the intensity in which they search for information (τ_{η_i} might not be the same for all investors) and in their interpretation of the information they receive (the η_{is} are independent across agents). We define investors' aggregate demand for information before the announcement at date 2 as

[24] As shown by Gilbert (2011), investors care about the final revised value of a macroeconomic series, not preliminary announcements about this value per se. They just use these announcements as an additional source of information to refine their estimates of the final revised value.

the average precision of all investors' private signals:

$$\overline{\tau}_\eta = \int \tau_{\eta_i} di. \tag{6}$$

We interpret the number of nonfarm payroll Bitly clicks as a proxy for investors' aggregate demand for information, $\overline{\tau}_\eta$.

Investors have a CARA utility function with a risk aversion coefficient γ and trade *only* at date 1 to simplify (i.e., they hold their initial position until date 3). We denote by p_t the price of the risky asset at date t. This price is set by risk neutral market makers conditional on the information available to them at date t (see below). We model trading at date 1 as in Vives (1995). Namely, each investor submits a demand function $d(s_i, p_1)$. Moreover, a continuum of noise traders submit buy or sell market orders (i.e., orders inelastic to the price at date 1). Noise traders' aggregate demand at date 1 is denoted u_1. It is normally distributed with mean zero and precision τ_{u_1}. Market makers in the risky asset observe the aggregate demand $D(p_1) = \int_i d_i(s_i, p_2) + u_1$ and set a price p_1 at which they absorb this demand. Competition between market makers and their risk neutrality implies that p_1 is equal to their expectation of F conditional on $D(p_1)$:

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

At date 2, dealers update their quotes based on the announcement A_e and the asset price becomes:

$$p_2 = \mathrm{E}(F \,| D(p_1), A_e) \,. \tag{8}$$

Proceeding as in Vives (1995), it is easily shown (see the appendix) that investors' equilibrium demands at date 1 is:

$$d_i(s_i, p_1) = a_i(\mu + \alpha s_i - p_1), \tag{9}$$

where $a_i = (\gamma\alpha)^{-2}\tau_{\eta_i}$. Thus, in equilibrium, investors aggregate demand conveys a signal $z_1 = A_r + (\gamma\alpha)\overline{\tau}_\eta^{-1}u_1$ about the asset payoff.[25] It follows that the equilibrium price at date 1 is:

$$p_1 = \mathrm{E}(F\,|D(p_1)) = \mathrm{E}(F\,|z_1) = \mu + \alpha\lambda z_1, \tag{10}$$

where $\lambda = \frac{Cov(A_r,z_1)}{Var(z_1)} = \frac{(\gamma\alpha)^{-2}\overline{\tau}_\eta\tau_{u_1}}{\tau_{A_r}+\,(\gamma\alpha)^{-2}\overline{\tau}_\eta\tau_{u_1}}$.

After observing the aggregate demand at date 1, all market participants face less uncertainty about the actual realization of A_r. Specifically, their uncertainty on A_r drops from $Var(A_r)$ to $Var(A_r\,|z_1)$ or, equivalently the precision of their forecast of A_r increases from $\tau_{A_r} = Var(A_r)^{-1}$ to $\tau_1 = Var(A_r\,|z_1)^{-1}$. Using the definition of z_1, we obtain:

$$\tau_1 = \tau_{A_r} + \ (\gamma\alpha)^{-2}\overline{\tau}_\eta\tau_{u_1}. \tag{11}$$

Thus, the aggregate demand at date 1 is more informative ($\tau_1 - \tau_{A_r}$ is high) when (i) the variance of noise traders' demand is low (τ_{u_1} is high), (ii) investors' are less risk averse (γ is low) or (iii) the average precision of investors' private signals ($\overline{\tau}_\eta$) is high. Thus, the stronger is information demand before the announcement date, the more informative is the price of the asset before this date (and the better informed are all participants about A_r prior to the announcement).

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

$$p_2 = \mathrm{E}(F\,|D(p_1), A_e) = \mathrm{E}(F\,|z_1, A_e) = p_1 + \beta(A_e - \mathrm{E}(A_e\,|z_1))\,, \tag{12}$$

with $\beta = \alpha\frac{E(A_rA_e|z_1)}{Var(A_e|z_1)} = \alpha\frac{Var(A_r|z_1)}{Var(A_e|z_1)}$. The last term in eq.(12) is the unexpected component of the announcement at date 2. It corresponds to the "surprise" in nonfarm payroll announce-

[25] Indeed, $D(p_1) = (\gamma\alpha)^{-2}\overline{\tau}_\eta(\mu - p_1) + (\gamma)^{-2}(\alpha)^{-1}\overline{\tau}_\eta A_r + u_1$. Thus, observing $D(p_1)$ is observationally equivalent to observe z_1.

ments in our empirical analysis.[26] Thus, the response of the price to the surprise in the announcement at date 2 is measured by β. Its sign is the same as that of α. Using eq.(4), we can rewrite $|\beta|$ as:

$$|\beta| = |\alpha| \frac{Var(A_r\,|z_1)}{Var(A_e\,|z_1)} = |\alpha| \frac{Var(A_r\,|z_1)}{Var(A_r\,|z_1) + Var(\epsilon\,|z_1)} = \frac{|\alpha|\,\tau_\epsilon}{\tau_\epsilon + \tau_1}. \tag{13}$$

Thus, in absolute value, the sensitivity of the price to the surprise in the announcement ($|\beta|$) is stronger when (i) the announcement A_e about A_r is more accurate (τ_ϵ is higher) and (ii) market participants are more uncertain about A_r prior to the announcement (τ_1 is smaller). These are standard implications of rational bayesian learning model like ours (see, for instance, Kim and Verrecchia (1991b) or Hautsch and Hess (2007)).

Other things equal, the causal effect of an increase in the aggregate demand for information about A_r prior to public news arrival about A_r is to *reduce* the sensitivity of the asset price to the news ($(\frac{\partial|\beta|}{\partial\overline{\tau}_\eta} < 0$) because it reduces uncertainty about A_r prior to the news ($\frac{\partial\tau_1}{\partial\overline{\tau}_\eta} = (\gamma\alpha)^{-1}\overline{\tau}_\eta\tau_{u_1} > 0$). Empirically, we find a positive association between our proxy for information demand and the sensitivity of treasury prices to the news. We believe that the reason is that information demand is endogenous: it is higher in equilibrium when macroeconomic uncertainty is high (τ_{A_r} is high). As controlling properly for macroeconomic uncertainty is difficult, we find empirically a positive association between demand for information ahead of nonfarm payroll announcements and treasury price reactions to these announcements.

To show this point formally, we endogenize the aggregate demand for information by solving for each investor's demand for information at date 0. Standard calculations (see the appendix) show that the certainty equivalent of investor i 's expected utility at date 0 when

[26] In our empirical analysis, we proxy for this surprise by the difference between the actual announcement and the median forecast of professional forecasters about this announcement. This approach should yield an unbiased estimate of β provided that the median forecast is itself an unbiased estimate of $\mathrm{E}(A_e\,|z_1)$.

acquires a signal of precision τ_{η_i} at date 0 is:

$$\Pi(\tau_{\eta_i}, \overline{\tau}_\eta) = \frac{1}{2\gamma} \ln(\frac{Var(A_r \,|z_1)}{Var(A_r \,|z_1, s_i)}) = \frac{1}{2\gamma}(\ln(1 + \alpha^2 \frac{\tau_{\eta_i}}{\tau_1}) - c(\tau_{\eta_i}). \tag{14}$$

Other things equal, the benefit of collecting information is smaller for a given investor when the average demand of information of all other investors is high ($\frac{\partial \Pi(\tau_{\eta_i}, \overline{\tau}_\eta)}{\partial \overline{\tau}_\eta} < 0$). The reason is that investors' aggregate demand and therefore the equilibrium price is then more informative. This effect reduces the ability of each individual investor to profit from his own private information.

In equilibrium, 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., $\overline{\tau}_\eta$). An equilibrium at date 0 is a demand $\tau^*_{\eta_i}$ for each investor such that $\tau^*_{\eta_i}$ maximizes $\Pi(\tau^*_{\eta_i}, \overline{\tau}^*_\eta)$ with $\overline{\tau}^*_\eta = \int \tau^*_{\eta_i} di$. As all investors are identical, it is natural to consider symmetric equilibria in which all investors choose the same precision: $\tau^*_{\eta_i} = \overline{\tau}^*_\eta$, $\forall i$. In this case, the first order condition of each investor's information acquisition problem imposes $\frac{\partial \Pi(\tau_{\eta^*_i}, \overline{\tau}^*_\eta)}{\partial \tau_{\eta_i}} = 0$ for $\tau^*_i = \overline{\tau}^*_\eta$. From this condition, we deduce that the equilibrium demand for information, $\overline{\tau}^*_\eta$, solves:

$$G(\overline{\tau}^*_\eta, \gamma, \tau_u, \tau_{A_r}, \alpha) \stackrel{def}{=} \alpha^2 - (2\gamma) c'(\overline{\tau}^*_\eta)(\tau_{A_r} + (\gamma\alpha)^{-2} \overline{\tau}^*_\eta \tau_{u_1} + \overline{\tau}^*_\eta) = 0. \tag{15}$$

Thus, we obtain the following implication.

Proposition 1. *When uncertainty about the macroeconomic variable A_r increases (i.e., τ_{A_r} decreases) then (i) the aggregate demand for information increases ($\overline{\tau}^*_\eta$ decreases with τ_{A_r}) and (ii) the sensitivity of the price to the macroeconomic announcement A_e is higher in absolute value ($|\beta|$ decreases with τ_{A_r}).*

Proof: Part (i) of the proposition directly follows from the fact that $G(\overline{\tau}^*_\eta, \gamma, \tau_u, \tau_{A_r}, \alpha)$ decreases both in τ_{A_r} and $\overline{\tau}^*_\eta$ (see eq.(15)). For Part (ii), observe that $G(\overline{\tau}^*_\eta, \gamma, \tau_u, \tau_{A_r}, \alpha) = 0$

implies:

$$\tau_1^* = (\tau_{A_r} + (\gamma\alpha)^{-2}\overline{\tau}_\eta^*(\tau_{A_r})\tau_{u_1}) = \frac{\alpha^2}{2\gamma c'(\overline{\tau}_\eta^*(\tau_{A_r}))} - \alpha^2\overline{\tau}_\eta^*(\tau_{A_r}). \tag{16}$$

It follows from the second equality and the fact that $\overline{\tau}_\eta^*(\tau_{A_r})$ decreases with τ_{A_r} that τ_1^* increases with τ_{A_r}. Thus, as $|\beta| = \frac{|\alpha|\tau_\epsilon}{\tau_\epsilon+\tau_1^*}$ (see eq.(13)), we deduce that $|\beta|$ decreases with τ_{A_r} as well.$\square$

In sum, when market participants are more uncertain about the actual value of the macroeconomic variable A_r, both the demand for information and the sensitivity of prices to macroeconomic announcements about A_r increases. The true effect of the increase in information demand is to dampen the effect of uncertainty on the sensitivity of the price response to macroeconomic announcements. However, in equilibrium, this effect does not fully offset the direct positive effect of an increase in uncertainty about A_r on $|\beta|$. As a result, empirically, $|\beta|$ and the aggregate demand for information before macroeconomic announcements appear positively correlated, as we find in the data. This positive correlation would disappear (and become negative) if one could control for investors' prior uncertainty about A_r. However, this is notoriously difficult. In fact, our results suggest that investors' demand for information ahead of macroeconomic announcements, as proxied by clicks on links to news referring to these announcements, can serve as a proxy for this uncertainty.

Kim and Verrecchia (1991a) develop a model of trading ahead of public news arrivals in which investors' information acquisition is endogenous. However, they do analyze the effect of an increase in prior uncertainty about the asset payoff on the price reaction to public news arrival. It can be checked that their model predicts no effect of such an increase because of the particular specification of the cost of acquiring information in their model. Our model is very similar to theirs but simpler and predicts that when uncertainty increases, both information demand and the reaction of prices to public news arrival should increase.

5.2 Does demand for information increase with macroeconomic uncertainty?

According to the model, the positive correlation between the strength of treasury price reactions to surprises in nonfarm payroll announcements and information demand reflects the fact that information demand is high when macroeconomic uncertainty is high. Thus, if our interpretation is correct, we should observe a positive correlation between measures of macroeconomic uncertainty and our proxy for information demand ahead of nonfarm payroll announcements. To study this point, we estimate following equation:

$$AbnormalInformationDemand_t = \alpha + \beta_X X_t + \epsilon_t, \tag{17}$$

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

[Insert Table 11 about Here]

Table 11 reports estimates of eq.(17). We find that information demand about nonfarm payroll is significantly positively correlated with our market-based measure of macroeconomic uncertainty. It is also positively correlated with the news-based measure but the correlation is not significantly different from zero. Other variables are in general not significant, except the supply of news related to nonfarm payroll. Not surprisingly, the supply and demand of information about nonfarm payroll figures are positively related. Prior literature has shown that investor attention is related to information supply, trading volume and asset price volatility, but we are the first to show that it is also correlated with macroeconomic uncertainty.

5.3 Investors' sentiment or rational information demand?

Researchers have often used search data on the internet as a proxy for investors' sentiment rather than a proxy for information demand.[27] 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 price reversals (i.e., be positively associated with overreaction to macroeconomic announcements).

[Insert Figure 5 about Here]

To give a first look at this issue, we plot in Figure 5, cumulative returns on nonfarm payroll announcement days from two hours before the announcement up to 5 hours after the announcement, separately for days with (i) positive or negative surprises) and (ii) a high number of nonfarm payroll clicks (higher than the median) or a low number of nonfarm payroll clicks. The figure shows three things. First, it confirms visually our main finding: nonfarm payroll announcements have a much larger impact on treasury prices when the number of nonfarm payroll clicks is high than on days in which this number is low. Second, there is no sign of under or overreaction of treasury prices to nonfarm payroll announcements *after* the announcement, whether the number of nonfarm payroll clicks is high or low. Last, there is small price drift before the announcement, in the direction of the price jump at

[27] 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.

the announcement, especially for positive surprises when nonfarm payroll clicks is high.[28] These two last observations are consistent with the view that these clicks proxy for rational information demand rather than investors' sentiment.

We now examine the preliminary evidence provided by Figure 5 more formally. First, to estimate whether there is a post-announcement reversal we estimate the following equation:

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

This specification is similar to that of Lucca and Moench (2015) except that we interact leads and lags of the surprise variable by our proxy for information demand ($HighBitlyCount$). results 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. However, (Figure 5 suggests that one must zoom on minutes before the announcement to detect the drift).

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

$$WeeklyReturn_t = \alpha + \beta_S Surprise_t + \beta_S BSurprise_t \times HighBitlyCount_t + \epsilon_t, \tag{19}$$

[28] This finding is consistent with Kurov, Sancetta, Strasser, and Wolfe (2016), who find evidence of pre announcement price drift ahead of various macroeconomic announcements. They argue that this drift reflects trading on private information, which is consistent with our interpretation.

where $WeeklyReturn_t$ is estimated from the close of Thursday before the announcement to the following Thursday. We drop 3 announcements out of the 66 because they were not released on a Friday. The results are reported in Table 13. The coefficient on nonfarm payroll surprises is statistically not significant for all maturities. Intuitively, over one week, the flow of news affecting treasury prices is so intense that the effect of macroeconomic announcements on price changes cannot be detected at this frequency. This highlights the importance of estimating the effect of macro news on treasury prices using very narrow time intervals around the arrival of news (see Andersen, Bollerslev, Diebold, and Vega (2003) and Andersen, Bollerslev, Diebold, and Vega (2007)). However, the coefficient on the interaction with Bitly is negative 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 prices to nonfarm payroll announcements, so large that the price reaction to the announcement can still be statistically detected one week after the announcement.

Overall, the findings in Tables 12 and 13 do not suggest that there is systematic over or under reaction of treasury prices to nonfarm payroll announcements or that overreaction occurs when the number of Bitly nonfarm payroll clicks. Overall, this suggests that this number is not a proxy for investors' sentiment.

Next, we investigate more formally our conjecture that the number of Bitly nonfarm payroll clicks is a proxy for the acquisition of private information about the effect of nonfarm payroll figures on treasury prices. If this is the case then the model implies that the price impact of trades before nonfarm payroll announcements should be higher on days in which the number of Bitly nonfarm payroll clicks is high. Indeed, in the model, this impact is measured by $\alpha\lambda$. From the expression for *lambda*, we deduce that the price impact of the order flow at date 1 (i.e., $D(p_1*)$) increases with (i) macroeconomic uncertainty ($\tau_{A_r}^{-1}$) and (ii) information demand ($\bar{\tau}_\eta$), other things equal. As an increase in macro-uncertainty itself foster information demand, the combination of these two effects implies that the price impact of trades before nonfarm payroll announcements should be higher on days in which the number of Bitly nonfarm payroll clicks is high.

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

$$OneMinuteReturn_{\tau t} = \alpha + \beta_S Surprise_t + I_B(\lambda_B OrderFlow_{\tau t} + \kappa_B HighBitlyCount_t \times OrderFlow_t) + I_A(\lambda_A OrderFlow_{\tau t} + \kappa_A HighBitlyCount_t \times OrderFlow_t) + \epsilon_t, \quad (20)$$

where I_B is a dummy variable equal to one if $\tau < 0$ (before the announcement) and I_A is a dummy variable equal to one if $\tau \geq 0$ (after the announcement). Thus, λ_B and λ_A measure, respectively, the price impact of trades before and after nonfarm payroll releases while κ_B and κ_A measures the effect of the number of Bitly clicks on the price impact of trades before and after nonfarm payroll releases, respectively. Our specification for measuring the price impact of trades around nonfarm payroll announcements is similar to that used in Brandt and Kavajecz (2004) and Pasquariello and Vega (2007). We report estimates of eq.(20) in Table 14.

[Insert Table 14]

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. However, trades are more informative after nonfarm payroll announcements than before. Overall these findings are consistent with Brandt and Kavajecz (2004) and Pasquariello and Vega (2007), who find evidence of informed trading in treasury markets on macroeconomic announcement days. More importantly for our purpose, we find that the impact of order flow is significantly stronger when the number of Bitly clicks is high. This effect is always statistically significant after nonfarm payroll announcements. It is statistically significant before nonfarm payroll announcements only for two year and ten year treasuries. Overall these findings are consistent with the view that (i) there is informed trading around macroeconomic announcements in treasury markets and (ii) the number of Bitly clicks is a proxy for private information acquisition by investors.

6 Conclusion

We measure demand for information prior to nonfarm payroll announcements using a novel dataset consisting of clicks on news articles. We find that when information demand is high shortly before the release of nonfarm payroll announcements, the price response of U.S. Treasury note futures to nonfarm payroll news surprises doubles. We show that this relationship is consistent with Bayesian learning models of information acquisition. Namely, market participants collect more information about macroeconomic variables affecting treasury prices when uncertainty about these variables is higher. As treasury prices respond more strongly to news when macroeconomic uncertainty is high, this behavior leads to a positive correlation between measures of information demand and treasuries price responses to nonfarm payroll announcements.

Overall, this finding suggest that greater investor attention (demand for information) can affect not only price discovery *after* news arrival (as found in the literature) but also *before* news arrival. Moreover, shifts in this attention prior to macroeconomic news release might be used to measure shifts in market participants perception of economic uncertainty. One possible venue for future research is to check the external validity of our findings (i.e., that they are valid for other types of scheduled news).

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7 Appendix

Appendix A

In this appendix, we complete the derivations of the results obtained in Section 5.

Derivation of informed investors' demand

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

$$d_i(s_i, p_1) = \frac{\mathrm{E}(F\,|s_i, p_1) - p_1}{\gamma \mathrm{Var}(F\,|s_i, p_1)} = \frac{(\mathrm{E}(A_r\,|s_i, z_1) - \mathrm{E}(A_r\,|z_1))}{\gamma\alpha \mathrm{Var}(A_r\,|s_i, p_1)}, \tag{21}$$

where the second equality follows from the fact that (i) $p_1 = \mu + \alpha \mathrm{E}(A_r\,|s_i, z_1)$ and (ii) z_1 is a sufficient statistics for p_1. Moreover:

$$\mathrm{E}(A_r\,|s_i, z_1) = \mathrm{E}(A_r\,|z_1) + \frac{\tau_{\eta_i}}{\tau_{\eta_i} + \tau_1}(s_i - \mathrm{E}(A_r\,|z_1)), \tag{22}$$

and

$$\mathrm{Var}(A_r\,|s_i, z_1) = \frac{1}{\tau_{\eta_i} + \tau_1}, \tag{23}$$

where τ_1 is defined in eq.(11). Substituting eq.(22) and eq.(23) in eq.(21) and using the fact that $\mathrm{E}(A_r\,|s_i, z_1) = \alpha^{-1}(p_1 - \mu)$, we deduce that:

$$d_i(s_i, p_1) = a_i(\alpha s_i + \mu - p_1),$$

where a_i is defined as in the text.

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

Investors' final wealth at date 3 is:

$$W_{i3} = (F - p_1)d_i(s_i, p_1) - c(\tau_{\eta_i}). \tag{24}$$

Conditional on p_1 and s_i, W_{i3} has anormal 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.(24), we obtain:

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

Using the expression for $d_i(s_i,p_1)$ in eq.(21), we deduce that:

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

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

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

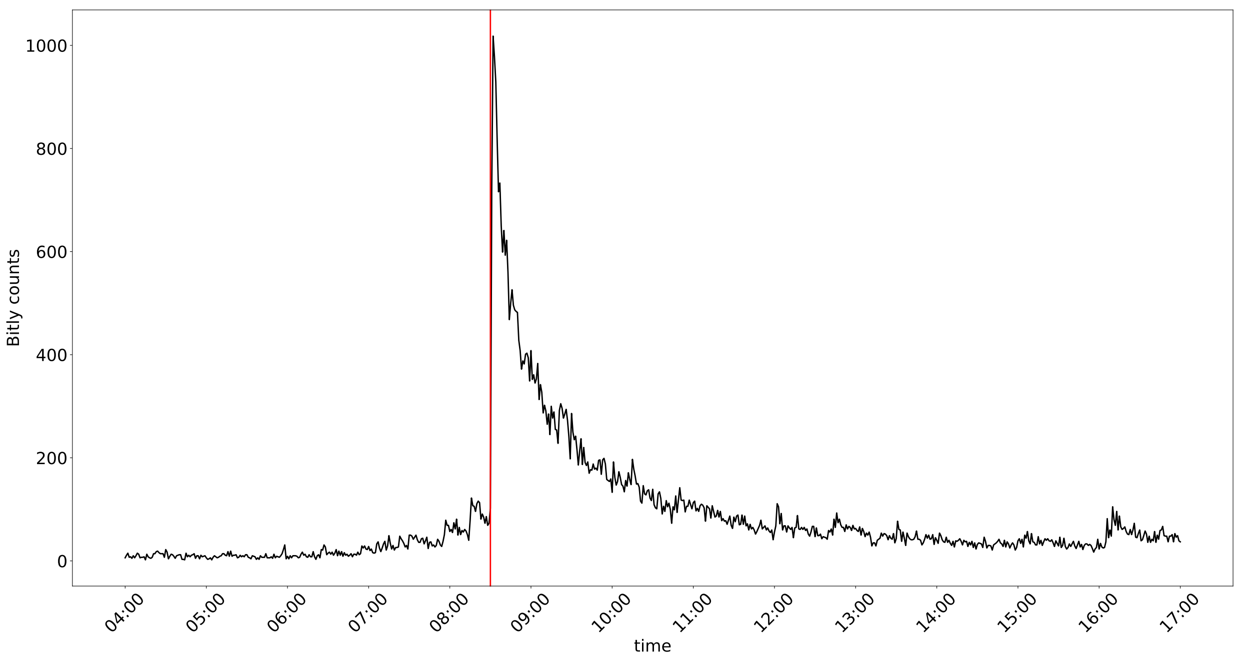
Now,

$$\begin{aligned}
\frac{\mathrm{Var}(\mathrm{E}(F\,|s_i,p_1)-p_1)}{\mathrm{Var}(F\,|s_i,p_1)} &= \frac{\alpha^2\tau_{\eta_i}^2}{(\tau_{\eta_i}+\tau_1)^2}\frac{\mathrm{Var}(s_i-\mathrm{E}(A_r\,|p_1))}{(\tau_{\eta_i}+\tau_1)^{-1}} \\
&= \frac{\alpha^2\tau_{\eta_i}^2}{(\tau_{\eta_i}+\tau_1)}\mathrm{Var}(A_r-\mathrm{E}(A_r\,|p_1)+\eta_i) \\
&= \frac{\alpha^2\tau_{\eta_i}^2}{(\tau_{\eta_i}+\tau_1)}(\tau_{\eta_i}^{-1}+\tau_1^{-1}) \\
&= \frac{\alpha^2\tau_{\eta_i}}{\tau_1}.
\end{aligned}$$

where the penultimate equality folllows from the fact that (i) $\mathrm{Var}(A_r - \mathrm{E}(A_r\,|p_1)) = \mathrm{Var}(A_r\,|p_1) = \tau_1^{-1}$ and (ii) $A_r - \mathrm{E}(A_r\,|p_1)$ is independent from η_i.

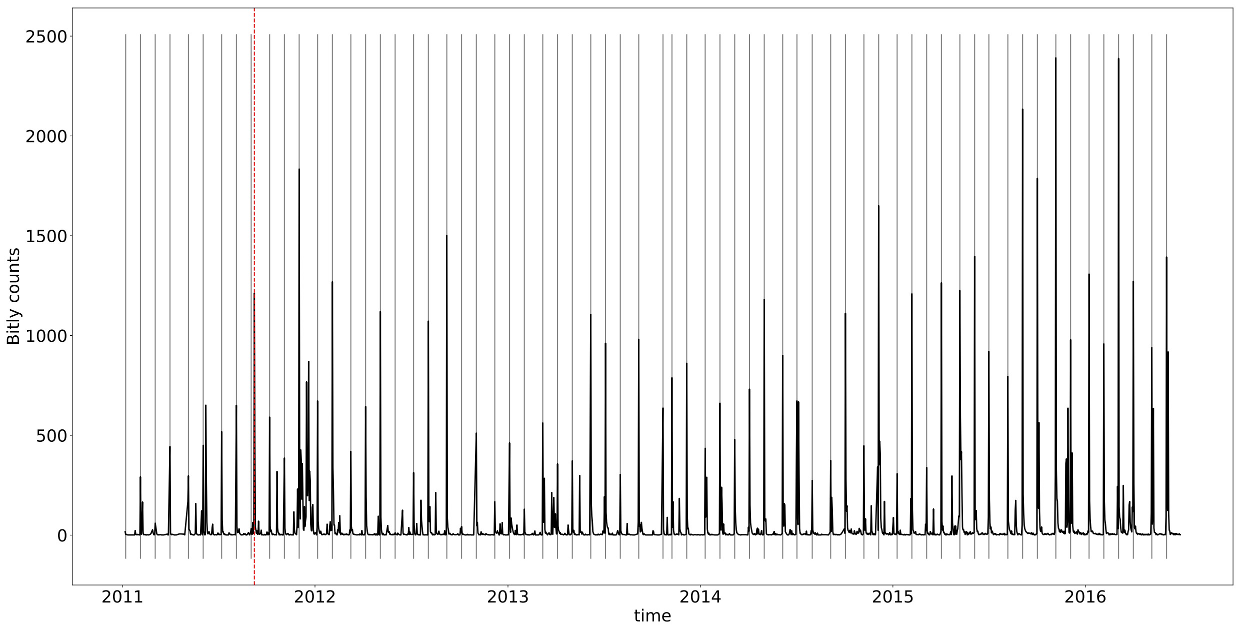
Appendix B: Figures and Tables

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



Notes: The figure shows the per minute number of nonfarm payroll Bitly clicks from 4:00 am ET to 5:00 pm ET, across all nonfarm payroll announcement days from January 2011 to June 2016 (66 days). The vertical red line identifies the release time of nonfarm payroll, 8:30 am ET.

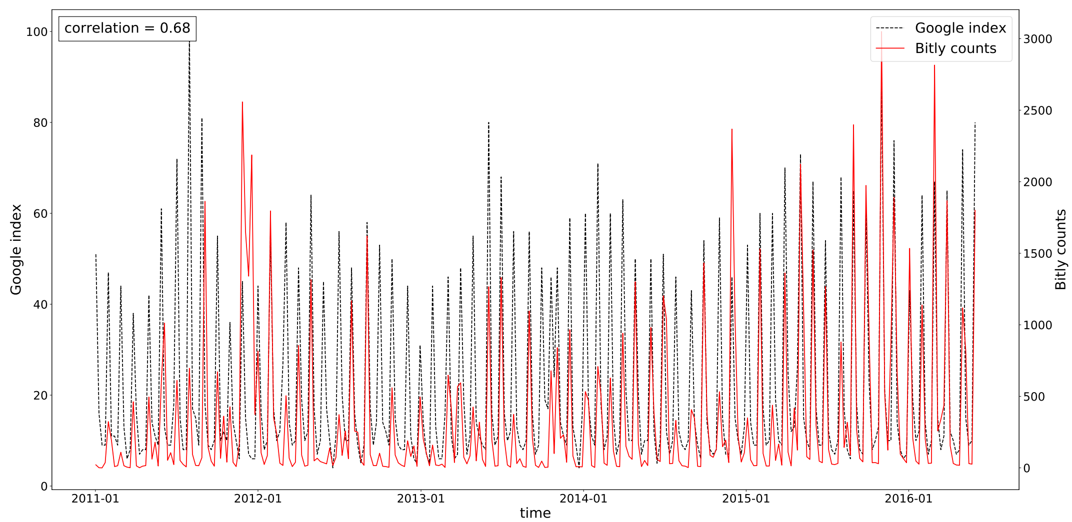
Figure 2: Bitly Daily Counts



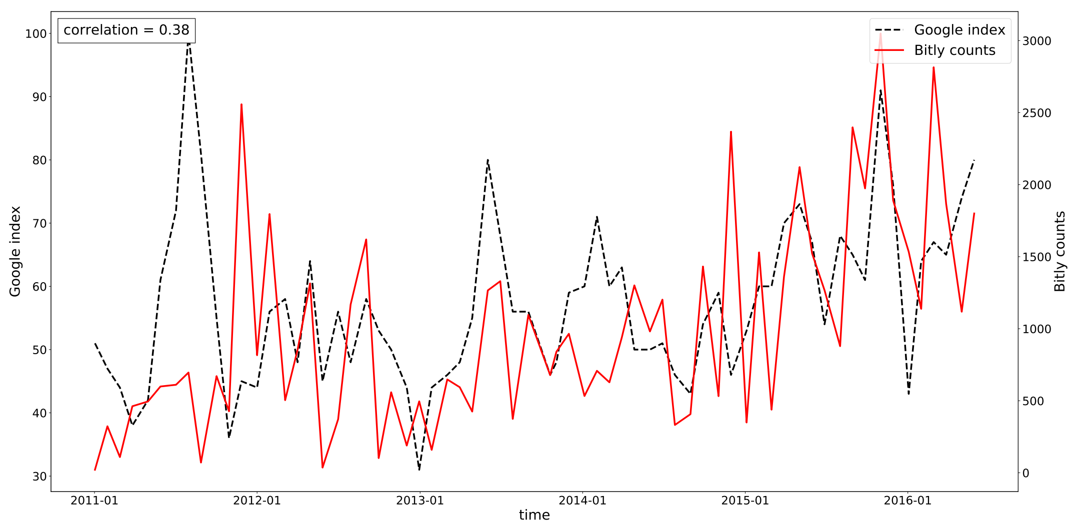
Notes: The figure shows the number of daily clicks in the Bitly dataset on headlines containing the word payroll for all days in our sample. The vertical black lines identify nonfarm payroll event days. the vertical red line identifies September 8, 2011, when President Obama announced a $447 billion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

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

(a) Weekly Frequency



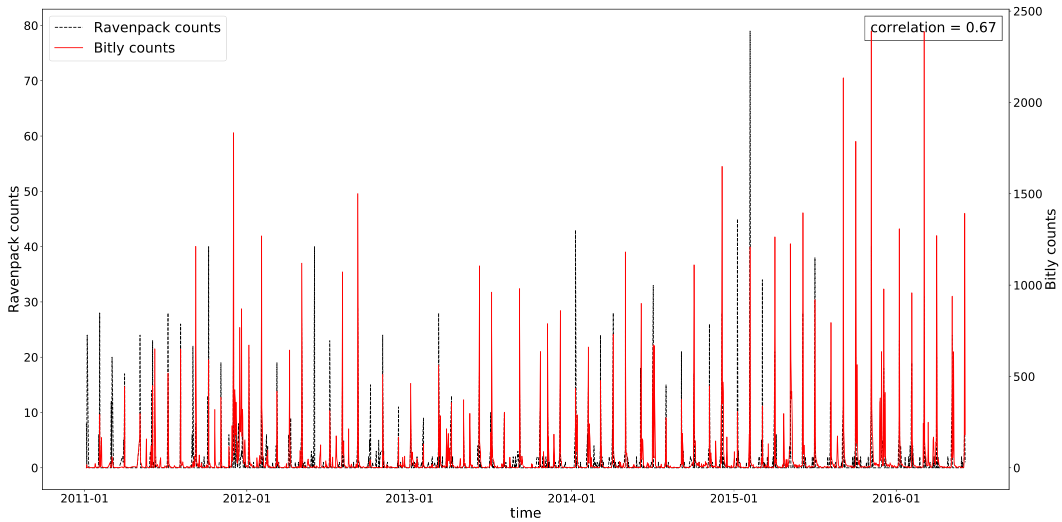
(b) Weeks with a Nonfarm Payroll Announcement Release



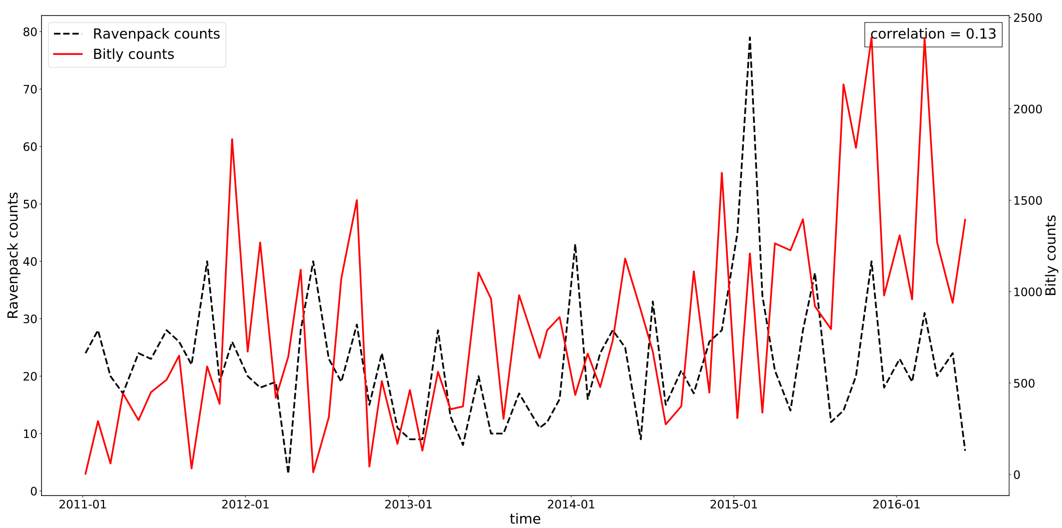
Notes: Panel a shows weekly Bitly counts and Google Trend Index for all the weeks in our sample from January 2011 to June 2016. Panel b shows weekly Bitly counts and Google Trend index for weeks when there was a nonfarm payroll release (a total of 66 weeks). The Bitly counts are based on headlines containing the word payroll, and the Google Trend Index is for the topic nonfarm payroll.

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

(a) Daily Frequency



(b) Days with a Nonfarm Payroll Announcement Release



Notes: Panel a shows daily Bitly counts and Ravenpack news counts for all the days in our sample from January 2011 to June 2016. Panel b shows daily Bitly counts and Ravenpack news counts on days with a nonfarm payroll release (66 days). The Bitly counts and Ravenpack news counts are based on headlines containing the word payroll.

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

Notes: The figure shows the intraday reaction of the two-year U.S. Treasury futures prices to nonfarm payroll surprises from January 2011 to June 2016 (a total of 66 days). We perform a dependent sort on surprise and Bitly counts. Time 0 on the x-axis indicates the release time of nonfarm payroll, at 8:30 am ET.

Table 1: Popular News Sources of Articles Shared using Bitly

News Source	URL	Number of Clicks	Percent of Total Number of Clicks	Cumulative Percent
Panel A: Prior to nonfarm payroll release, from 6:25 am to 8:25 am				
Bloomberg	www.bloomberg.com	3,438	73	73
Marketwatch	www.marketwatch.com	340	7	80
Wall Street Journal	www.wsj.com	277	6	86
Financial Times	www.ft.com	221	5	91
USA Today	www.usatoday.com	173	4	95
CNBC	www.cnbc.com	153	3	98
Panel B: During and after nonfarm payroll release, from 8:26 am to 10:26 am				
Bloomberg	www.bloomberg.com	26,235	67	67
CNBC	www.cnbc.com	5,769	15	82
Reuters	www.reuters.com	1,860	5	87
Marketwatch	www.marketwatch.com	1,265	3	90
Wall Street Journal	www.wsj.com	1,173	3	93
USA Today	www.usatoday.com	772	2	95

Notes: Our sample period is from January 2011 to June 2016, which includes a total of 66 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:25 am to 8:25 am ET. There are a total of 4,685 clicks during this period across the 66 announcements. In Panel B, we consider clicks during and after the announcement, from 8:26 am to 10:26 am ET. There are a total of 38,963 clicks during this period across the 66 announcements. The nonfarm payroll announcement is released by the Bureau of Labor Statistics at 8:30 am ET on the first Friday of the month.

Table 2: Who Shares Bitly Links

Bitly User Type	Number of Clicks	Percent of Total Number of Clicks	Cummulative Percent
Panel A: Prior to nonfarm payroll release, from 6:25 am to 8:25 am			
Official Bloomberg Users	2,508	54	54
Seven Individual Users	1,349	29	83
Official WSJ Users	201	4	87
Official USA Today Users	173	4	91
Official Marketwatch Users	148	3	94
Official CNBC Users	74	2	96
Official FT Users	57	1	97
Official Reuters Users	8	0.2	96.2
Panel B: During and after nonfarm payroll release, from 8:26 am to 10:26 am			
Official Bloomberg Users	18,228	47	47
Seven Individual Users	10,485	27	74
Official CNBC Users	3,914	10	84
Official Reuters Users	1,528	4	88
Official WSJ Users	1,031	3	94
Official USA Today Users	669	2	96
Official NPR Users	635	2	97
Official Marketwatch Users	257	1	98

Notes: Our sample period is from January 2011 to June 2016, which includes a total of 66 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:25 am to 8:25 am ET. There are a total of 4,685 clicks during this period across the 66 announcements. In Panel B, we consider clicks during and after the announcement, from 8:26 am to 10:26 am ET. There are a total of 38,963 clicks during this period across the 66 announcements. The nonfarm payroll announcement is released by the Bureau of Labor Statistics at 8:30 am ET on the first Friday of the month. We aggregate clicks on links shared by seven different individual users. News services often have more than one Bitly user account. In general, one Bitly user accounts for the majority of the clicks, but we aggregate across official users within a news services. The list of official usernames per news service was provided to us by Bitly.

Table 3: Country of IP Address of the Reader of Bitly Links

Country of IP Address	Number of Clicks	Percent of Total Number of Clicks	Cummulative Percent
Panel A: Prior to nonfarm payroll release, from 6:25 am to 8:25 am			
United States	2,251	48	48
Unknown	532	11	59
Great Britain	271	6	65
Canada	155	3	68
Japan	131	3	71
Germany	91	2	73
India	88	2	75
Spain	81	2	77
Panel B: During and after nonfarm payroll release, from 8:26 am to 10:26 am			
United States	20,729	53	53
Unknown	2,676	7	60
Japan	2,668	7	73
Great Britain	1,190	3	63
Canada	1,033	3	66
Singapore	829	2	2
India	730	2	76
Germany	674	2	74

Notes: Our sample period is from January 2011 to June 2016, which includes a total of 66 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:25 am to 8:25 am ET. There are a total of 4,685 clicks during this period across the 66 announcements. In Panel B, we consider clicks during and after the announcement, from 8:26 am to 10:26 am ET. There are a total of 38,963 clicks during this period across the 66 announcements. The nonfarm payroll announcement is released by the Bureau of Labor Statistics at 8:30 am ET on the first Friday of the month. The accuracy of the geolocation of IP addresses is fairly accurate, but not perfect.

Table 4: How are Bitly Links Accessed

How are links accessed	Number of Clicks	Percent of Total Number of Clicks	Cummulative Percent
Panel A: Prior to nonfarm payroll release, from 6:25 am to 8:25 am			
Twitter	2,338	50	50
Directly	1,928	41	91
Facebook	261	6	97
Google	29	1	98
Financial Times	16	0.3	98.3
Stock Twits	16	0.3	98.6
Market Early Bird	11	0.2	98.8
Panel B: During and after nonfarm payroll release, from 8:26 am to 10:26 am			
Twitter	17,690	45	45
Directly	16,046	41	86
Facebook	3,819	10	96
Google	508	1	97
Daily FX	88	0.2	97.2
Hoot Suite	56	0.1	97.3
Market Early Bird	42	0.1	97.4

Notes: Our sample period is from January 2011 to June 2016, which includes a total of 66 nonfarm payroll announcements. In Panel A, we consider clicks two hours prior to the release of the nonfarm payroll announcement, from 6:25 am to 8:25 am ET. There are a total of 4,685 clicks during this period across the 66 announcements. In Panel B, we consider clicks during and after the announcement, from 8:26 am to 10:26 am ET. There are a total of 38,963 clicks during this period across the 66 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. Links that are accessed directly are links that are copied and pasted by the individual into the browser. They could have received the link via SMS text, e-mail or saw the link on Twitter, but rather than click on it using Twitter, copied and pasted the link into a browser.

Table 5: Summary Statistics

	Obs.	Mean	Std. Deviation	Min.	Max.
Panel A: January 2004 to June 2016					
Monetary Policy Variables					
Federal Funds Rate	150	1.49	1.81	0.25	5.25
Swanso-Williams ZLB	150	0.11	0.32	0	1
Market-based Policy Uncertainty	150	85.67	30.53	32.05	158.97
News-based Policy Uncertainty	150	139.73	71.02	30.8	377.41
Risk					
VIX Index	150	19.08	8.91	10.08	59.93
Information Environment					
Nonfarm Payroll Surprise	150	-10.22	69.71	-208	188
Revision Noise	150	27.61	22.68	0	125
Forecast Error	150	55.10	43.68	1	208
Analyst Forecast Dispersion	150	0.26	0.49	0.07	5.33
Trading Volume and Volatility					
Two-Year US Treasury Trading Volume	150	0.21	0.12	0.01	0.50
Two-Year US Treasury Realized Volatility	150	2.39	1.53	0.39	10.02
Panel B: January 2011 to June 2016					
Monetary Policy Variables					
Federal Funds Rate	66	0.27	0.07	0.25	0.5
Swanso-Williams ZLB	66	0.26	0.44	0	1
Market-based Policy Uncertainty	66	60.85	16.70	32.05	105.74
News-based Policy Uncertainty	66	169.31	74.58	57.45	377.41
Risk					
VIX Index	66	17.04	5.59	10.32	36.2
Information Environment					
Nonfarm Payroll Surprise	66	-3.48	58.65	-123	103
Revision Noise	66	24.35	16.27	1	77
Forecast Error	66	46.91	34.90	1	123
Analyst Forecast Dispersion	66	0.16	0.08	0.09	0.51
Trading Volume and Volatility					
Two-Year US Treasury Trading Volume	66	0.25	0.10	0.08	0.50
Two-Year US Treasury Realized Volatility	66	1.50	0.78	0.39	3.82
Information Demand and Supply					
Intraday Bitly Counts (Before Announcement)	66	52	85	0	413
Intraday Bitly Counts (During Announcement)	66	398	311	1	1385
Weekly Google Trend Index	66	57	13	31	100
Ravenpack News Count	66	22	11	3	79

Notes: In Panel A our sample period is from January 2004 to June 2016 during non-farm payroll announcement days. In Panel A our sample period is from January 2011 to June 2016 during nonfarm payroll announcement days. The units of trading volume are million of contracts.

Table 6: U.S. Treasury Futures Response to Nonfarm Payroll Surprises

	(1)	(2)	(3)
	Jan. 2004 - Jun. 2016	Jan. 2011 - Jun. 2016	Jan. 2011 - Jun. 2016 (exclud. SW ZLB period)
Response of the Two-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	-11.00***	-6.613***	-8.020***
	(0.904)	(0.964)	(1.183)
Constant	-0.786	0.255	0.0705
	(0.745)	(0.660)	(0.833)
Number of Observations	150	66	49
Adjusted R-squared	0.500	0.424	0.494
Response of the Five-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	-29.81***	-28.17***	-30.92***
	(2.135)	(3.220)	(4.013)
Constant	-1.651	0.759	0.216
	(1.759)	(2.203)	(2.826)
Number of Observations	150	66	49
Adjusted R-squared	0.568	0.545	0.558
Response of the Ten-Year U.S. Treasury Note Futures			
Nonfarm Payroll Surprise	-41.58***	-43.93***	-44.93***
	(2.938)	(4.728)	(5.854)
Constant	-3.629	-0.449	-0.990
	(2.421)	(3.234)	(4.123)
Number of Observations	150	66	49
Adjusted R-squared	0.575	0.574	0.556

Notes: We show estimates of equation 1 using three different samples. In column 1, the sample is from January 2004 to June 2016. In column 2, the sample is from January 2011 to June 2016, the sample for which we have Bitly data. In column 3, we use the shorter sample, from January 2011 to June 2016, and exclude the Swanson-Williams period when two-year U.S. Treasury note yields responded less to macroeconomic news announcements because of the Zero Lower Bound.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	-10.73***	-1.646	-16.03***	-7.711***	-14.34***	-1.345
	(1.230)	(4.293)	(1.760)	(1.907)	(2.926)	(4.607)
Monetary Policy Variables						
NFP Surprise x FFR Level	-0.798					-0.0496
	(0.631)					(0.631)
NFP Surprise x Swanson-Williams Period	9.419**					0.624
	(3.621)					(3.752)
NFP Surprise x Market-implied Uncertainty		-0.112***				-0.179***
		(0.0302)				(0.0477)
NFP Surprise x News-based Uncertainty		0.0129				-0.0116
		(0.0161)				(0.0172)
Risk						
NFP Surprise x VIX Index			0.241***			0.403***
			(0.0730)			(0.139)
Information Environment						
NFP Surprise x Past Revision Noise				0.0432		-0.0330
				(0.0306)		(0.0411)
NFP Surprise x Past Forecast Errors				-6.695***		-1.357
				(1.618)		(1.928)
NFP Surprise x Past Forecast Dispersion				-0.679		-1.891
				(3.035)		(3.047)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume					32.36***	5.006
					(10.18)	(13.71)
NFP Surprise x Past Realized Volatility					-0.614	1.273
					(1.692)	(2.714)
Constant	-0.217	-0.803	-0.658	0.835	-1.375	-1.412
	(1.029)	(2.957)	(0.722)	(1.518)	(2.521)	(3.352)
Number of observations	150	150	150	150	150	150
R-squared	0.537	0.568	0.534	0.583	0.546	0.676

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll surprises using data from January 2004 to June 2016. The dependent variable is a 10-minute U.S. Treasury futures return using the prevailing futures price as of five minutes before the announcement to five minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	-3.401	-8.281**	-9.970***	-9.985	-0.956	-2.817
	(6.328)	(3.814)	(2.763)	(9.312)	(1.955)	(13.40)
Monetary Policy Variables						
NFP Surprise x FFR Level	-0.362					-9.528
	(15.61)					(20.49)
NFP Surprise x Swanson-Williams Period	5.727*					4.052
	(2.941)					(4.822)
NFP Surprise x Market-implied Uncertainty	-0.0387					-0.0812
	(0.0694)					(0.114)
NFP Surprise x News-based Uncertainty	-0.0115					-0.000145
	(0.0177)					(0.0233)
Risk						
NFP Surprise x VIX Index		0.0997				-0.383
		(0.220)				(0.373)
Information Environment						
NFP Surprise x Past Revision Noise			0.0704			0.00710
			(0.0616)			(0.0826)
NFP Surprise x Past Forecast Errors			-2.370			-3.105
			(3.040)			(4.003)
NFP Surprise x Past Forecast Dispersion			23.53			15.17
			(15.64)			(26.77)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				4.749		8.833
				(6.702)		(10.23)
NFP Surprise x Past Realized Volatility				-23.64		-6.211
				(20.07)		(26.08)
Information Demand and Supply						
NFP Surprise x High Bitly Count					-5.335***	-4.125*
					(1.872)	(2.433)
NFP Surprise x High Media Coverage Count					-3.508*	-2.765
					(1.969)	(3.008)
NFP Surprise x High Google Index					-1.196	-2.102
					(1.894)	(2.543)
Constant	-0.0656	0.271	-0.0266	-4.800	1.170	0.516
	(4.480)	(0.665)	(1.815)	(6.193)	(1.327)	(8.998)
Number of observations	66	66	66	66	66	66
R-squared	0.511	0.426	0.506	0.445	0.576	0.659

Notes: We estimate the response of U.S. Treasury futures on two-year notes to nonfarm payroll announcements using data from January 2011 to June 2016. The dependent variable is a 10-minute U.S. Treasury futures returns using the prevailing futures price as of five minutes before the announcement to five minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	-50.17**	-30.15**	-28.84***	-14.80	-13.15*	-47.32
	(22.05)	(12.76)	(9.674)	(16.66)	(6.862)	(36.17)
Monetary Policy Variables						
NFP Surprise x FFR Level	62.45					90.94
	(54.40)					(59.44)
NFP Surprise x Swanson-Williams Period	17.25*					28.61
	(10.25)					(18.05)
NFP Surprise x Market-implied Uncertainty	0.102					0.643
	(0.242)					(0.449)
NFP Surprise x News-based Uncertainty	-0.0315					-0.000489
	(0.0616)					(0.0808)
Risk						
NFP Surprise x VIX Index		0.118				-1.390
		(0.737)				(1.234)
Information Environment						
NFP Surprise x Past Revision Noise			0.0516			0.114
			(0.216)			(0.274)
NFP Surprise x Past Forecast Errors			-9.149			-15.22
			(10.64)			(13.70)
NFP Surprise x Past Forecast Dispersion			34.42			104.8
			(54.76)			(106.4)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				-0.865		-16.68
				(5.089)		(10.95)
NFP Surprise x Past Realized Volatility				-18.77		59.25
				(29.93)		(43.72)
Information Demand and Supply						
NFP Surprise x High Bitly Count					-16.56**	-16.64**
					(6.570)	(7.892)
NFP Surprise x High Media Coverage Count					-4.589	-6.992
					(6.910)	(9.888)
NFP Surprise x High Google Index					-6.918	-7.926
					(6.648)	(8.938)
Constant	1.322	0.779	2.240	-8.376	3.236	1.477
	(15.61)	(2.223)	(6.356)	(9.916)	(4.657)	(22.42)
Number of observations	66	66	66	66	66	66
R-squared	0.579	0.545	0.571	0.567	0.630	0.735

Notes: We estimate the response of U.S. Treasury futures on five-year notes to nonfarm payroll announcements using data from January 2011 to June 2016. The dependent variable is a 10-minute U.S. Treasury futures returns using the prevailing futures price as of five minutes before the announcement to five minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
NFP Surprise	-65.95***	-35.73*	-40.33**	-57.93*	-27.41**	-34.69
	(17.62)	(18.70)	(19.38)	(29.22)	(10.31)	(48.96)
Monetary Policy Variables						
NFP Surprise x FFR Level	72.54					90.76
	(57.74)					(60.48)
NFP Surprise x Swanson-Williams Period	7.304					15.15
	(11.82)					(15.20)
Risk						
NFP Surprise x VIX Index		-0.490				-1.625
		(1.080)				(1.633)
Information Environment						
NFP Surprise x Past Revision Noise			-0.182			-0.262
			(0.318)			(0.364)
NFP Surprise x Past Forecast Errors			-2.297			-9.910
			(17.12)			(23.60)
NFP Surprise x Past Forecast Dispersion			16.15			26.84
			(77.25)			(135.0)
Trading Volume and Volatility						
NFP Surprise x Past Trading Volume				1.268		-1.545
				(5.570)		(8.300)
NFP Surprise x Past Realized Volatility				5.525		26.62
				(24.79)		(29.87)
Information Demand and Supply						
NFP Surprise x High Bitly Count					-17.96*	-20.37*
					(9.578)	(10.47)
NFP Surprise x High Media Coverage Count					-2.922	-4.017
					(10.18)	(12.48)
NFP Surprise x High Google Index					-10.05	-13.26
					(9.599)	(10.56)
Constant	-0.513	-0.531	-0.286	-0.282	-0.0654	-0.0367
	(3.249)	(3.260)	(3.337)	(3.297)	(3.182)	(3.364)
Number of observations	66	66	66	66	66	66
R-squared	0.586	0.576	0.577	0.576	0.614	0.649

Notes: We estimate the response of U.S. Treasury futures on ten-year notes to nonfarm payroll announcements using data from January 2011 to June 2016. The dependent variable is a 10-minute U.S. Treasury futures returns using the prevailing futures price as of five minutes before the announcement to five minutes after the announcement. The estimation also includes main effects, but we do not report these coefficients. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11: Contemporaneous Relation between Abnormal Information Demand, Monetary Policy Variables, Information Environment Variables, Trading Volume, Return Volatility and Information Supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NFP Announcement Day Dummy	25.22***	25.24***	16.03***	25.19***	20.49***	22.81***	13.38***
	(0.778)	(0.779)	(1.767)	(0.807)	(1.112)	(0.588)	(1.825)
Monetary Policy Variables							
FFR Level	-1.782						-1.071
	(2.285)						(2.280)
Swanson-Williams Period	0.0583						0.129
	(0.432)						(0.530)
Market-implied Policy Uncertainty	0.0302**						0.0308**
	(0.0118)						(0.0127)
News-based Policy Uncertainty	0.00166						0.00242
	(0.00227)						(0.00240)
Risk							
VIX Index		0.00264					-0.0470
		(0.0288)					(0.0432)
Information Environment							
Revision Noise			0.0682				0.0310
			(0.0458)				(0.0462)
Forecast Error			13.80***				12.93***
			(1.856)				(1.849)
Forecast Dispersion			2.001				3.708
			(1.910)				(2.544)
Trading Volume and Volatility							
Abnormal Trading Volume				0.424			0.448
				(0.341)			(0.334)
Abnormal Realized Volatility				-0.347			-1.349
				(1.206)			(1.185)
Information Demand and Supply							
Media Coverage Count					0.243***		0.211***
					(0.0411)		(0.0413)
Weekly Google Index						0.146	
						(0.119)	
Constant	-1.134	0.457	0.185	0.419	0.377**	0.310*	-0.509
	(1.109)	(0.527)	(0.345)	(1.096)	(0.167)	(0.169)	(1.493)
Number of Observations	1,417	1,417	1,417	1,417	1,417	1,381	1,417
R-squared	0.429	0.426	0.448	0.427	0.440	0.555	0.463

Notes: We estimate the contemporaneous relation between abnormal information demand, monetary policy variables, information environment variables, trading volume, return volatility and information supply using data from January 2011 to June 2016. 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)	1.747*	1.271	4.700	3.178	7.192	4.525
	(1.016)	(1.497)	(3.796)	(5.587)	(6.295)	(9.314)
Sum of 30 Lagged NFP Surprise Coefficients	-4.82	-1.90	-19.91	7.06	-37.10	-3.19
F-statistic	0.75	0.05	0.91	0.05	1.15	0
Nonfarm Payroll Surprise(t-1) x High Bitly Count(t-1)		1.140		4.143		6.802
		(2.051)		(7.658)		(12.77)
Sum of 30 Lagged NFP Surprise x High Bitly Count Coefficients		-4.37		-43.08		-50.10
F-statistic		0.17		1.15		0.56
Nonfarm Payroll Surprise(t)	-6.627***	-4.808***	-28.30***	-21.86***	-48.21***	-42.40***
	(1.016)	(1.497)	(3.796)	(5.587)	(6.295)	(9.314)
Nonfarm Payroll Surprise(t) x High Bitly Count		-3.904*		-12.86*		-11.79
		(2.051)		(7.658)		(12.77)
Nonfarm Payroll Surprise(t+1)	0.534	0.621	1.948	4.597	2.709	8.695
	(1.016)	(1.497)	(3.796)	(5.587)	(6.295)	(9.314)
Sum of 30 Lead NFP Surprise Coefficients	1.60	1.86	1.76	5.66	5.18	26.56
F-statistic	0.08	0.06	0.01	0.04	0.02	0.29
Nonfarm Payroll Surprise(t+1) x High Bitly Count		0.0301		-5.214		-11.85
		(2.051)		(7.658)		(12.77)
Sum of 30 Lead NFP Surprise x High Bitly Count Coefficients		-0.23		-11.30		-48.63
F-statistic		0		0.08		0.53
Constant		0.00246	0.236	0.266	0.643	0.729
		(0.142)	(0.532)	(0.532)	(0.882)	(0.886)
Number of Observations	1,359	1,359	1,359	1,359	1,359	1,359
Adjusted R-squared	0.077	0.125	0.086	0.136	0.085	0.126

Notes: We estimate the response of U.S. Treasury futures prices to nonfarm payroll announcements using data from January 2011 to June 2016. The dependent variable is one-day U.S. Treasury futures returns using the prevailing futures price as of 5:00 pm ET. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 13: Weekly Response

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise(t)	-4.169**	0.532	-15.87*	1.226	-26.64*	-3.147
	(2.023)	(2.792)	(8.085)	(11.25)	(13.48)	(18.97)
Nonfarm Payroll Surprise(t) x High Bitly Count		-9.175**		-33.36**		-45.84*
		(3.896)		(15.69)		(26.48)
Constant	3.456**	3.544**	11.12*	11.44**	16.98*	17.42*
	(1.396)	(1.347)	(5.579)	(5.427)	(9.301)	(9.156)
Number of Observations	63	63	63	63	63	63
Adjusted R-squared	0.065	0.144	0.059	0.125	0.060	0.105

Notes: We estimate the response of US Treasury futures prices to nonfarm payroll announcements using data from January 2011 to June 2016. The dependent variable is one-week U.S. Treasury futures returns using the prevailing futures price as of 5:00 pm ET on Thursday. We only use weeks when there is a nonfarm payroll announcement. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 14: Order Flow Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Two-Year		Five-Year		Ten-Year	
Nonfarm Payroll Surprise	-5.715***	-5.708***	-22.82***	-22.76***	-27.56***	-27.47***
	(0.103)	(0.103)	(0.299)	(0.298)	(0.466)	(0.465)
Order Flow x Two Hours Before	0.104***	0.0797***	0.515***	0.573***	0.698***	0.630***
	(0.0124)	(0.0139)	(0.0421)	(0.0639)	(0.0407)	(0.0565)
Order Flow x Two Hours Before x High Bitly Count		0.122***		-0.104		0.141*
		(0.0308)		(0.0849)		(0.0812)
Order Flow x Two Hours After	0.203***	0.185***	0.999***	0.888***	1.071***	0.942***
	(0.00605)	(0.00851)	(0.0186)	(0.0269)	(0.0144)	(0.0198)
Order Flow x Two Hours After x High Bitly Count		0.0362***		0.206***		0.247***
		(0.0120)		(0.0362)		(0.0262)
Constant	0.00225	0.00236	0.00342	0.00292	0.000976	0.000715
	(0.00449)	(0.00449)	(0.0128)	(0.0128)	(0.0187)	(0.0187)
Number of Observations	15,840	15,840	15,840	15,840	15,840	15,840
Adjusted R-squared	0.237	0.238	0.424	0.425	0.496	0.499

Notes: We estimate the response of U.S. Treasury futures to nonfarm payroll announcements and order flow using data from January 2011 to June 2016. The dependent variable is one-minute U.S. Treasury futures returns using the prevailing futures price as of the end of the minute. Order flow is estimated using the Lee and Ready (1991) algorithm. We only use data two-hours before and two-hours after the nonfarm payroll announcement. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.