Missing Events in Event Studies: Identifying the Effects of Partially-Measured News Surprises*

Refet S. Gürkaynak[†], Burçin Kısacıkoğlu,[‡] and Jonathan H. Wright[§]

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Abstract

Macroeconomic news announcements are elaborate and multi-dimensional. We consider a framework in which jumps in asset prices around macroeconomic news and monetary policy announcements reflect both the response to observed surprises in headline numbers and latent factors, reflecting other details of the release. The details of the non-headline news, for which there are no expectations surveys, are unobservable to the econometrician, but nonetheless elicit a market response. We estimate the model by the Kalman filter, which essentially combines OLS- and heteroskedasticity-based event study estimators in one step, showing that those methods are better thought of as complements rather than substitutes. The inclusion of a single latent factor greatly improves our ability to explain asset price movements around announcements.

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[†]Department of Economics, Bilkent University, CEPR, CESIfo, and CFS. E-mail: refet@bilkent.edu.tr

[‡]Department of Economics, Bilkent University. E-mail: bkisacikoglu@bilkent.edu

[§]Department of Economics, Johns Hopkins University, and NBER. E-mail: wrightj@jhu.edu

1 Introduction

It is notoriously difficult to establish causality among movements in macroeconomic variables and asset prices due to simultaneity and endogeneity. High frequency macroeconomic event studies have proved to be a fruitful strategy to address the issue. The event study literature studies the reaction of asset prices to news releases, such as the employment report, GDP, or FOMC policy announcements. It exploits the lumpy manner in which news are released to the public as a powerful source of identification since within short windows (daily or higher frequency) around news releases, it is clear that asset price changes do not cause news (Faust et al., 2007; Gürkaynak and Wright, 2013; Kuttner, 2001). One can then interpret the results to make inference on macroeconomic fundamentals and beliefs of market participants about the structure of the economy. Still, it is troubling that even in tight intraday windows of 20 minutes around news announcements, event study regressions explain only a small to moderate fraction of asset price changes. Looking at the glass as half full, it is helpful to be able to link asset prices to news about macroeconomic fundamentals. Looking at the glass as half empty, it is a puzzle that we cannot explain the majority of asset price changes even around news announcements. A further puzzle is that the two ways of carrying out event studies, OLS regressions and heteroskedasticity-based identification, produce strikingly different results.

This paper contributes to the theory and implementation of event studies. Our perspective is that macroeconomic news announcements are complex and multi-dimensional. The event study literature focuses on headline numbers and survey expectations for these numbers. We argue that these are only a part of news releases, and so the surprise is only partially measured. For example, the US employment report that is generally released on the first Friday of each month includes aggregate employment in nonfarm payrolls, the civilian unemployment rate, and average hourly earnings. The event-study literature focuses on the effects of surprises in these numbers. But the employment report also includes around 40 pages of other data. Alas, there are no survey expectations for these other elements, which also elicit a market response to the extent that some of those numbers contain updates to market participants' information sets. In this paper, we nonetheless offer a way of capturing the non-headline surprises in data releases, in addition to the headline surprises for which we have survey expectations. Our approach, described in detail later, can be thought of as combining OLS estimation of the event-study regression with identification through heteroskedasticity. Our method can explain the puzzle of why event study regressions explain a limited share of asset price changes.

The basic idea of the method we develop comes from the heteroskedasticity-based identification literature that was proposed by Rigobon (2003) and applied very elegantly by Rigobon and Sack (2004, 2005, 2006). This approach measures the effect of an unobservable surprise simply by knowing that there are certain days on which the variance of that surprise is unusually large. However, in considering the effects of news announcements, we also have survey expectations of headline numbers that have desirable properties as expectations proxies. They pass standard rationality tests and outperform simple benchmarks (Balduzzi et al., 2001; McQueen and Roley, 1993; Pearce and Roley, 1985) . We provide further evidence on this, showing that survey-based expectations fare similarly to market-based expectations. Thus we argue that it is appropriate to treat the headline surprise as observed. But announcements contain information beyond the headline number. We measure the effects of other dimensions of news announcements on asset prices using identification through heteroskedasticity. The identifying assumption is simple: there is more macroeconomic news around the times of announcements than at other times.

Our approach treats OLS and heteroskedasticity-based identification as complements that capture different aspects of the market reaction to news, rather than as substitutes. We propose a way of setting up the model that gives us explicit estimates of the non-headline components of macroeconomic news surprises and estimate the model, that now includes an unobservable component, via the Kalman filter. The results show that the headline surprise combined with a single latent news factor that captures macroeconomic and monetary policy news, can explain a great majority of the yield curve movements around news announcements.

We relate the latent news factor to FOMC statements around monetary policy releases and to non-surveyed parts of news around other macroeconomic data releases. The significant increase in explanatory power remains when we allow for release-specific latent factors rather than a common one and when we allow for an ever-present background noise factor. The factor that we identify is indeed related to news and is not picking up a level factor that is always in the data.

Our contribution is therefore in two dimensions. The methodological contribution is showing that OLS and heteroskedasticity-based identification are complements rather than substitutes and developing an efficient method to combine these to measure the yield curve reaction to both observed and unobserved surprises in macroeconomic data releases. The second contribution is to show that, using this method, we understand almost all of the yield curve movements in event windows and are able to get a handle on what moves yields, at least at times of macroeconomic releases.

The plan for the remainder of this paper is as follows. In section 2, we discuss the event study methodology, showing how it can be implemented via OLS or via heteroskedasticity-based identification, and reporting results using both methods. In section 3 we discuss why these methods are complements rather than substitutes and show how they can be simultaneously employed. Section 4 presents a discussion of the interpretation of the heteroskedasticity-identified latent release factors and goes back to the properties of the survey expectations, showing that the standard reasons to doubt survey-based expectations are very unlikely to be problems in the data used in macroeconomic event studies. This section also provides a demonstration of why it is correct to interpret the heteroskedasticity-based estimator as measuring something conceptually different from the OLS-based event study. Section 5 presents robustness checks and extensions. Section 6 concludes.

2 Event-Study Methodology

Macro-finance event studies relate releases of macroeconomic data and changes in asset prices to each other. For example, we may be interested in learning how, say, the five-year yield reacts to the non-farm payrolls release. We will denote the news, or unexpected, component of the macro series or monetary policy decisions being released as s_t. With forward-looking investors the log return of the asset or change in yield, y_t, depends on the change in the information set, and hence on s_t. This is why expectations surveys are important for macroeconomic news releases—they allow us to construct the unexpected component of the data release, which should drive changes in asset prices.

The general modeling setup is a system of an asset price return in a window around an event being related to a surprise that may be measured with error (Rigobon and Sack, 2006):[1]

$$y_t = \alpha s_t^* + \varepsilon_t \tag{2.1}$$

$$s_t = s_t^* + \eta_t \tag{2.2}$$

where s_t^* is the true surprise (unobservable to the econometrician), s_t is the observed surprise, and ε_t and η_t are uncorrelated error terms. The parameter of interest is α, but it is not identified due to s_t^* being unobservable. There are two ways of identifying α, via OLS and via heteroskedasticity-based identification.

2.1 OLS Identification in Event Studies

If we think that measurement error is negligible, $s_t = s_t^*$, then the surprise is observable and equation (2.1) can simply be estimated by an OLS regression of y_t on s_t over announcement windows:

$$y_t = \alpha s_t + \varepsilon_t \tag{2.3}$$

Equation (2.3) is the standard simple implementation of the event-study methodology that only requires basic OLS and the interpretation of the result is straightforward. The equation fit should be perfect if s_t is the only source of variation in this window. This

[1]Including simultaneity and endogeneity into this system is easy and does not change our results. We do not do so both because it leads to cluttered notation and more importantly because it is very hard to envision how these may be issues in high-frequency event studies of the type that we are looking at.

method requires data on expectations of upcoming announcements, but these are available from surveys, notably the long-running survey by Action Economics, which is the successor to Money Market Services (MMS), or alternatively from the Bloomberg Survey.

Table 1 shows the results of such OLS-based event studies for non-farm payrolls, GDP, unemployment, durable goods orders, CPI, core CPI, PPI, core PPI, retail sales, retail sales excluding autos, average hourly earnings, the employment cost index, initial claims and FOMC policy announcements concerning the target funds rate. The asset returns are changes in yields on the first and fourth Eurodollar futures contracts, and on two-, five-, ten- and thirty-year Treasury futures. The windows that we are using are from 5 minutes before the data release and FOMC policy announcement times, to 15 minutes afterwards. Expectations are measured using MMS/Action Economics survey results, except that the FOMC policy surprise is calculated using price changes in short-dated federal funds futures contracts, as proposed by Kuttner (2001). A detailed explanation of the data sources and construction is provided in Appendix A.

Our sample period is from January 1992 to December 2017 (except for FOMC surprises, which end in 2007). This includes the period from December 2008 to December 2015 when the U.S. was stuck at the zero lower bound (ZLB) for short-term nominal interest rates. We could drop this period, but that would greatly reduce the sample size. Swanson and Williams (2014), in their careful study of the effects of ZLB on the sensitivity of asset prices to news, show that while very short-term interest rates were clearly constrained by the ZLB, one- and two-year interest rates were affected for only part of the period, and the sensitivity of longer-term interest rates was essentially unchanged throughout the sample. Hence we use the full sample but in section 5 we show results from a sample ending in 2007 as a robustness check.

The results shown in Table 1 are in line with the literature (Andersen et al., 2003). In terms of asset price responses, non-farm payrolls is by far the most important macroeconomic release. A one standard deviation non-farm payrolls surprise increases bond yields by 2 to 6 basis points. However, asset price responses to other macroeconomic announcements are also both economically and statistically significant. This pattern is consistent with Gilbert et al. (2017), who show that news with higher intrinsic value–in terms of timeliness and relation to fundamentals–elicit larger asset price responses. We see that yields at all maturities move in the same direction, but we also see a hump-shaped response of yields to macroeconomic announcements, meaning that the medium term maturities are affected by the macro releases the most. The fact that while magnitudes are different, the shape of the yield curve response is common to all data surprises will be important when jointly analyzing observed and unobserved surprises below.

For monetary policy surprises, the first Eurodollar futures (ED1) response is larger than for other maturities. This is intuitive because monetary policy decisions affect shorter term maturities the most. The findings reported in this table are also consistent with the literature going back to Kuttner (2001).

Nonetheless, even with the very high frequency data that we have, the headline surprises explain less than 40% of the variance of yields around news announcements. This means that there are other factors that affect yields in this window and/or that there is measurement error in the surprises. These are often thought of as the main limitations of the OLS method. Heteroskedasticity-based identification takes these concerns seriously and suggests an alternative way of identifying α that allows for classical measurement error in the surprise.

2.2 Heteroskedasticity-Based Identification in Event Studies

The system of equations (2.1)-(2.2) contains four parameters, α, σ_η^2, σ_ε^2 and σ_*^2, where σ_η^2, σ_ε^2 and σ_*^2 are the variances of η_t, ε_t and s_t^*. The variance-covariance matrix of $(y_t, s_t)'$ in the event window we are looking at is:

$$\Omega^E = \begin{pmatrix} \alpha^2\sigma_*^2 + \sigma_\varepsilon^2 & \alpha\sigma_*^2 \\ \cdot & \sigma_*^2 + \sigma_\eta^2 \end{pmatrix} \tag{2.4}$$

which only has three entries, less than the number of parameters. This confirms that α is not identified without further assumptions, which we made in the OLS case by asserting that the only relevant source of variation in the event window for the measured surprise is the true surprise ($\sigma^2_\eta = 0$). Heteroskedasticity-based identification offers another way of measuring α without making those assumptions.

The key insight here, going back to Rigobon (2003) and Rigobon and Sack (2004), is that one can also look at windows where there is no event but that are otherwise comparable. Think of these windows as a period covering the same length of time, but on a day with no news announcement. In these windows the structure of (2.1)-(2.2) is the same, but there is no surprise. The variance-covariance matrix of $(y_t, s_t)'$ for the non-event window is:

$$\Omega^{NE} = \begin{pmatrix} \sigma^2_\varepsilon & 0 \\ 0 & 0 \end{pmatrix} \tag{2.5}$$

In the event window, we observe y_t and s_t, and so can estimate Ω^E. Call this $\hat{\Omega}^E$. In the non-event window, s_t is zero by assumption, and we observe y_t. We can estimate Ω^{NE}, all elements of which are 0, except for the 1,1 element, which is informative about the variance of noise. Subtracting (2.4) from (2.5) gives

$$\Omega^E - \Omega^{NE} = \begin{pmatrix} \alpha^2\sigma^2_* & \alpha\sigma^2_* \\ \cdot & \sigma^2_* + \sigma^2_\eta \end{pmatrix} \tag{2.6}$$

from which one can identify the parameter of interest, α. Concretely, one can simply estimate α as $\frac{[\hat{\Omega}^E]_{1,1} - [\hat{\Omega}^{NE}]_{1,1}}{[\hat{\Omega}^E]_{1,2}}$, as proposed by Rigobon and Sack (2004, 2006).

Table 2 shows the same exercise that was carried out in Table 1, this time using heteroskedasticity-based identification. It is striking that all coefficients are much larger when identification via heteroskedasticity is employed, compared to OLS, which would be the natural effect of correcting for attenuation bias in the measurement error model. Therefore, a possible interpretation of this finding is that headline news is indeed measured with substantial error, leading to attenuation bias, and that heteroskedasticity-based identification is robust to these problems. This is the interpretation offered by Rigobon and Sack

(2006). But σ_η^2 would have to be large for this to be true.

In this paper, we offer a different interpretation, more in line with the evidence showing the broad efficiency of survey expectations of data releases. We argue that survey expectations are measuring headline surprises correctly but instead there are surprise components in news announcements that are not directly observed by the econometrician, which have important effects on asset prices. Our reasons for thinking along these lines, and the proposed methodology to accommodate this feature of the data are presented in the next section.

3 Partially-Measured News and Heteroskedasticity-Based Identification

We recognize that data releases are elaborate and multi-dimensional. The "news" that is captured in OLS-based event studies is only headline news—the deviation of the headline number from its survey expectation. The survey expectations are well measured and usually pass standard forecast rationality tests. Gürkaynak and Wolfers (2006) find that survey-based forecasts are roughly comparable in efficiency to market-based ones, and we expand on this argument in Section 4 below.

However, it remains the case that the headline news are only part of news releases. Releases also contain other information such as revisions to past data and information on sub-components. For example, the GDP release reports the contributions of different expenditure items, and markets may react differently to increases in GDP driven by gross capital formation versus inventory increases. Some releases contain a discussion of current conditions and even forecasts. The FOMC release is the obvious example, where the statement has for some time garnered more attention than the immediate policy setting. Yet in terms of "news", only the headline is observable as there are surveys for these numbers alone. The balance of the news in the release is unobservable to the econometrician, but elicits a market response as well. We argue that this is why the R^2s of OLS-based event studies are not very high. The regression only captures the contribution of the headline news to the variance of asset prices and effects of all other news in the same release show up in the residual.

Notice that under this interpretation, the OLS-based event study answers a narrowly defined question correctly: it determines the relationship between the headline news (but not the whole news release) and the asset price in question. The heteroskedasticity-based estimator instead allows the news to be unobservable and conditions only on the time of the data release. To the extent that news are multidimensional, the increase in variance at the time of the release is due to more than the headline surprise. The heteroskedasticity-based estimator captures the asset price response to the news release as a whole, not only to the headline number. This, rather than sizable measurement error in survey expectations, is why the heteroskedasticity-based estimator always finds larger asset price response coefficients. In the next section, we show this analytically, and bring direct evidence to verify that heteroskedasticity-based estimator, along with the headline surprise effects, captures the effects of non-headline component of the release.

We therefore posit that a complete understanding of yield changes in news release event windows is possible, using OLS to partial out the effects of the observable news on the asset prices, and then using heteroskedasticity-based identification to find out the effect of non-headline, unobservable news in the data release. This could be done in two steps, with heteroskedasticity-based identification applied to residuals from the OLS regression[2] but we instead introduce an efficient, one-step estimator via the Kalman filter. This has the useful by-product of giving an estimate of the unobserved news component in any given data release, which is not directly available from identification through heteroskedasticity.

We let y_t denote the 6x1 vector of yield changes (of maturities studied in Tables 1 and 2) from 8:25am to 8:45am. Some days have macroeconomic announcements at 8:30am, while others do not, but all the macroeconomic announcements that we consider come out at 8:30am. In the implementation for FOMC policy surprises, we let y_t denote the 6x1

[2]We report the results from doing this in Appendix B.

vector of yield changes from 2:10pm to 2:30pm (incorporating some minor deviations of timing to accommodate FOMC announcements times early in the sample). Data from these intradaily windows are included regardless of whether they contain an announcement or not.

The model that we specify is then:

$$y_t = \beta' s_t + \gamma' d_t f_t + \varepsilon_t \tag{3.1}$$

where s_t is the vector of surprises in macroeconomic or monetary policy announcements,[3] d_t is a dummy that is 1 if there is an announcement in that window and 0 otherwise, f_t is an iid $N(0,1)$ latent variable and ε_t is iid normal with mean zero and diagonal variance-covariance matrix. The sample period and the data used to measure surprises remain the same. Note that in this implementation f_t is a latent factor common to all data releases.

Equation (3.1) would essentially collapse to the standard OLS event study regression if the f_t term were dropped, and to a heteroskedasticity-based estimator if the s_t term were dropped. As it stands, this equation can be estimated by maximum likelihood via the Kalman filter.[4]

Table 3 reports the results, along with R^2 values from the regressions of y_t on s_t alone, and from regressions augmented with the Kalman-smoothed estimate of f_t in equation (3.1), around announcement times. The headline surprise alone explains less than 40% of announcement-window variation in each of the yields considered here, as in Table 1. Augmenting the regression with one latent factor brings the explained share up to over 90%. We can explain about all of the movements in the term structure of interest rates around news announcements with the headline surprise and one latent factor. Inclusion of the latent factor makes little difference to the estimated coefficients on the headline surprises, although it does reduce the error variance and hence the standard errors.

The specification in equation (3.1) implies that the latent factor has the same loadings

[3] s_t is set to 0 for any announcement that does not take place in that window.

[4] Maximum likelihood estimates are obtained via the EM algorithm. Our code can handle any number of releases, asset price changes and latent factors and is made available for others to use.

for all announcement types and it is worth noting that the R^2s are so high despite this constraint. The releases are clearly heteroskedastic, with the employment report creating the largest variance, and so the model is literally misspecified: the draws of f_t on employment report days have sample variance greater than 1. That does not prevent the model from fitting well, which means that different announcements have similar *relative* effects at different points on the yield curve. Nonetheless, we can extend the model to incorporate release-specific factors, specifying instead that:

$$y_t = \beta' s_t + \Sigma_{i=1}^{I} d_{it} \gamma_i f_{it} + \varepsilon_t \tag{3.2}$$

where d_{it} is a dummy that is 1 if an announcement of the ith type comes out in window t and zero otherwise and I is the number of latent factors. Because they always come out concurrently, non-farm payroll/unemployment/average hourly earnings, retail sales/retail sales ex autos, core PPI/PPI and core CPI/CPI surprises each share a single latent factor, and so there are $I = 8$ latent macroeconomic announcement factors, even though there are 13 8:30am macroeconomic announcements. Including the monetary policy factor, in total we have $I = 9$ release related factors to be estimated. The factors $\{f_{it}\}_{i=1}^{I}$ are all standard normal and are independent over time and independent of each other. This extended model can also be estimated by maximum likelihood via the Kalman filter. The results are reported in Table 4. The coefficient estimates on the headline surprises are similar to those in Tables 1 and 3.[5]

Table 4 also includes the R^2 values from regressions of elements of y_t on s_t alone, and from regressions augmented with the Kalman smoothed estimates of the latent factors associated with macro announcements. Incorporating the macro factors again increases the R^2 values from below 40% to above 90% for most maturities. The R^2s are similar to

[5]We constructed counterparts of Tables 3 and 4 using daily data, with changes in Treasury yields as independent variables rather than Treasury futures rates. The results, not reported, show that for all surprises, the estimated coefficients are similar to their intraday counterparts. However, these coefficients have higher standard errors and the regressions have smaller R^2s. This result is intuitive: There are other financial market developments happening on a given day along with macroeconomic announcements. This introduces additional noise to the event study regression. Nonetheless, when the latent factor is introduced, the fraction of yield changes explained once again dramatically increase.

the single factor case, even though the single factor model is nested in equation (3.2).

4 Discussion: Understanding the latent factor

In this section we study the relationship between measurement error, latent factors, OLS, and heteroskedasticity-based estimators. To do so, we analytically explore the implications of different modeling assumptions about the data generating process on OLS and heteroskedasticity-based estimates and turn to empirical evidence to see which of these are consistent with the data. We then study the properties of the latent factor and show that it is indeed related to non-headline news and discuss how these results help improve our understanding of yield curve movements.

4.1 A General Model

The heteroskedasticity-based parameter estimates are larger in absolute value than their OLS counterparts but this is consistent with either attenuation bias from measurement error in the headline surprises or the presence of an unobservable latent factor. To show this formally, we consider a general model which incorporates both measurement error and an unobservable latent factor, nesting both cases. The model is:

$$
\begin{aligned}
y_t &= \beta' s_t^* + \gamma' d_t f_t + \varepsilon_t \\
s_t &= s_t^* + \eta_t
\end{aligned}
$$

where y_t is a log return or yield change (a scalar, without loss of generality), s_t is the observed surprise, s_t^* is the true headline surprise, d_t is a dummy that is 1 on an announcement day and 0 otherwise, f_t is an iid $N(0,1)$ latent variable, and ε_t and η_t are processes measuring noise in yields and measurement error of the headline surprise. We assume that s_t^*, ε_t and η_t are iid, mutually uncorrelated, have mean zero, and variances σ_*^2, σ_ε^2 and σ_η^2, respectively. To estimate β, the parameter of interest in event studies, using OLS and identification through heteroskedasticity, we need the variance-covariance matrices for event (Ω^E) and non-event (Ω^{NE}) windows:

$$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_*^2 + \sigma_\eta^2 \end{pmatrix}, \ \Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

In this general model, the OLS estimate for β is:

$$\hat{\beta}^{OLS} = \frac{[\hat{\Omega}^E]_{1,2}}{[\hat{\Omega}^E]_{2,2}}$$

and the identification through heteroskedasticity estimate of β is:

$$\hat{\beta}^{HET} = \frac{[\hat{\Omega}^E]_{1,1} - [\hat{\Omega}^{NE}]_{1,1}}{[\hat{\Omega}^E]_{1,2}}$$

This general model collapses to a model with no latent factor if $\gamma = 0$ and it collapses to the no measurement error case (the case presented in this paper) when $\sigma_\eta^2 = 0$. In the general model, as shown in Appendix C, the probability limits of the two estimators are:

$$\hat{\beta}^{OLS} \to \beta \left(1 - \frac{\sigma_\eta^2}{\sigma_*^2 + \sigma_\eta^2}\right)$$

and

$$\hat{\beta}^{HET} \to \beta \left(1 + \frac{\gamma^2}{\beta^2\sigma_*^2}\right)$$

If there is neither a latent factor ($\gamma = 0$) nor measurement error in the surprise ($\sigma_\eta^2 = 0$), the OLS and heteroskedasticity based estimators both uncover the true β and should coincide. However, as Tables 1 and 2 show, these are significantly different from each other, implying that this is not the relevant case.

With a latent factor, the heteroskedasticity-based estimator is biased *away from* zero. Note that the term $\frac{\gamma^2}{\beta^2\sigma_*^2}$ is proportional to the variance share of the latent factor in the event window changes of yields. As the relative variance share of the latent factor increases (non-headline news carry more information affecting yields), the bias of the heteroskedasticity-based estimator for the headline effect increases.[6]

With measurement error, the OLS estimate will be biased *towards* zero because of classical attenuation bias. This bias is proportional to the share of measurement error in total variance of the observed surprise, $\frac{\sigma_\eta^2}{\sigma_*^2+\sigma_\eta^2}$.

Except for the case where the is no latent factor and no measurement error in the surprise, the probability limit of the heteroskedasticity-based estimator will always be larger than the OLS estimate in absolute value, as we find in the data. However, this could be because of a latent factor ($\gamma \neq 0$), or measurement error ($\sigma_\eta^2 \neq 0$), or both. It is this observational equivalence that makes it impossible to judge whether OLS is consistent or not by only looking at the difference between the OLS and heteroskedasticity-based estimates. One has to take a stance on the extent of measurement error. Given the observed difference between the two estimators, that stance is consequently also on the presence of unobserved surprises and the consistency of the heteroskedasticity-based estimator.

We argue that measurement error in survey-based surprises is negligible, and so $\sigma_\eta^2 \approx 0$, and therefore $\hat{\beta}^{OLS}$ is consistent, whereas $\hat{\beta}^{HET}$ is not. We shall do this in subsection 4.2, by bringing in data from economic derivatives to show that measurement error in the survey-based surprises is likely to be negligible for event studies. As further corroborating evidence, the bias term for heteroskedasticity-based identification when there is a latent factor, discussed above, shows that the difference between $\hat{\beta}^{HET}$ and $\hat{\beta}^{OLS}$ should be larger when $|\gamma|$ is bigger, that is when events have larger non-headline components. To examine this, in subsection 4.3, we shall compare monetary policy announcements with and without accompanying statements. We will show that heteroskedasticity-based estimates are closer to the OLS counterparts on days without monetary policy statements compared to the days with statements.

[6] As the variance of the latent factor σ_f^2 is normalized to unity, γ^2 itself is the measure of variance due to the latent factor.

4.2 Quality of survey expectations

The surveys used in event studies are those of news releases that are to take place very soon, no longer than a week after the time of the survey. And the "event" is the release of information on something that has already taken place. Hence, these expectations are not necessarily subject to the anomalies often reported in analysis of long-term expectations (Fuhrer, 2017).[7]

Nonetheless, three areas of concern remain: (i) the survey expectation may be stale, i.e. there may be incoming news between a respondent's reporting of her expectation and the releases which change her expectations, (ii) respondents may not have sufficient skin in the game, and (iii) respondents may have an incentive to be right in the extreme case, not on average, therefore reporting numbers closer to the tails rather than their true expectations, especially if their predictions are not anonymous. We argue that while these concerns sound relevant, in practice survey expectations work remarkably well and are not subject to large measurement errors.

To do so, we compare the survey-based expectations to timely market-based expectations. The latter data come from Gürkaynak and Wolfers (2006) who analyze the market for Economic Derivatives. This was a market, now defunct, where Deutsche Bank and Goldman Sachs allowed trades of binary options on news releases about half an hour before the release itself.[8] Market-based expectations of data releases are not subject to any of the potential measurement error problems that survey-based ones might be. The market operates minutes before the data release, hence there is no scope for staleness; the traders do have skin in the game as they bet on their expectations; and since the market returns are anonymous they have no special incentive to get low probability events right.

We construct market- and survey-based expectations and news surprises based on these and directly test whether there is measurement error in survey-based expectations by com-

[7]Notwithstanding these anomalies, Ang et al. (2007) show that survey expectations remain the best forecasts among many alternatives, even at longer horizons.

[8]These call options paid off if the release came in at or above the buyer's strike price. Gürkaynak and Wolfers (2006) describe the market and these options, as well as the methodology to use them to construct risk neutral probability density functions of market perceived data release outcomes.

paring the market responses to the two surprise measures. If there is sizable measurement error in survey-based surprises, event study coefficients based on these should be significantly smaller than coefficients based on Economic Derivatives-based surprises, which are not subject to measurement error.

We run SUR regressions for the four releases covered by Economic Derivatives (Nonfarm payrolls, NAPM, Retail Sales ex-Autos, and Initial Claims) of the form:

$$y_t = \sum_{i=1}^{4} \theta_i^s S_{it}^{\text{SURVEY}} + \varepsilon_t \tag{4.1}$$

$$y_t = \sum_{i=1}^{4} \theta_i^m S_{it}^{\text{ECON-DERIV}} + \varepsilon_t \tag{4.2}$$

where S_{it}^{SURVEY} and $S_{it}^{\text{ECON-DERIV}}$ are surprises where expectations are measured using surveys and Economic Derivatives, respectively. Measurement error in survey expectations will lead to smaller θ^s compared to θ^m. Table 5 reports the results as well as the joint test of the hypothesis that $\theta_i^s = \theta_i^m$ for all i. It is striking that while all estimated θ_i^ss are somewhat smaller than corresponding θ_i^ms (consistent with minor classical measurement error) the differences in point estimates are small and in no cases individually or jointly statistically significant.[9] Thus we conclude that survey expectations capture market expectations extremely well. Even if one attributes all of the difference between point estimates to measurement error, the differences are on the order of 5 to 15 percent, an order of magnitude smaller than the gap between OLS and heteroskedasticity-based estimates shown in Tables 1 and 2. These substantial differences cannot be predominantly due to measurement error in surveys and resulting attenuation bias in the coefficients.

4.3 Comparison of OLS and Heteroskedasticity-Based Estimates

A well-studied and well-understood case of multi-dimensional data release is that of FOMC announcements, which contain both the interest rate decision and an accompanying state-

[9]In his discussion of Gürkaynak and Wolfers (2006), Carroll (2006) notes how the survey- and market-based expectations are remarkably similar to each other in terms of first moments. This is consistent with what we find here.

ment providing information on the future course of interest rates. This is a case we will return to in more detail but here we will exploit the fact that FOMC releases did not always contain statements. Until 1994, the FOMC did not issue statements and until 1999 statements were only issued when the policy rate was changed.

Under the measurement error model, the difference between OLS and heteroskedasticity-based estimators should not depend on the presence of an accompanying statement. If on the other hand, as we suggest, heteroskedasticity-based identification provides the asset price response to the whole "event" rather than just the headline, the difference between the two measures should be larger when the non-headline component is more important, i.e. γ is larger. Increasing the importance of non-headline news is exactly what the FOMC did when it began to issue statements. So, if our conjecture is correct, the coefficient estimates of the impact of FOMC announcements on yields measured by OLS- and heteroskedasticity-based estimators should be closer for a sample of events consisting of policy actions only, than for a sample consisting of announcements that also have statements providing information on the policy path.

For monetary policy surprises, as before, we follow the standard procedure and use federal funds futures-based surprises as suggested by Kuttner (2001). Table 6 shows that when statements do not accompany the policy rate decision, the OLS- and heteroskedasticity-based estimates of the asset price reactions are quite similar—though the OLS estimates are smaller due to market participants' inference of information even in the absence of formal statements. But for the sample that includes statements the heteroskedasticity-based estimator yields a reaction coefficient that is two to 400 times larger than the OLS estimator.

What is striking here is not that OLS coefficients are a little smaller and statistically less significant in the latter sample. This is due to the dearth of policy action surprises in the 21st century, when policy actions were usually signaled ahead of the FOMC meeting date. What is noteworthy is the increase in the spread between OLS- and heteroskedasticity-based estimators, and the fact that the spread becomes significantly more pronounced as maturity increases. This is exactly what one would expect to find based on our conjecture: the presence of a statement will increase the distance between OLS- and heteroskedasticity-based estimates for all maturities but as the statement is more informative for longer maturities[10] the heteroskedasticity-based estimator will find even larger coefficients for those maturities.

Thus, by studying the FOMC announcement dates, we conclude that the heteroskedasticity-based estimator provides a convolution of the asset price responses to the headline and non-headline components of news, whereas our partial observability-based Kalman filtering methodology provides asset price responses to headline news and the latent non-headline news component separately. An additional benefit is that this method estimates the latent component directly, and allows it to be given an economic interpretation.

It can be shown, as we do in Appendix C, that the heteroskedasticity-based estimator is essentially the sum of the OLS response to the observables and the response to the latent variable that can be extracted from the residuals. The method we developed does this efficiently, in one step.

4.4 Interpreting the Latent Factor

So far we have focused on the relationship between the heteroskedasticity-based, OLS- and Kalman filter-based estimators and showed that the discrepancy between the two is better understood as arising from the presence of unobserved surprises in releases rather than measurement error in observed surprises. We also showed that a single factor estimated using the Kalman filter along with observable headline surprises is sufficient to explain the variation in asset prices around macroeconomic news events. In this subsection, we closely examine the economic interpretation of that latent factor.

To begin with, Table 7 lists the five largest readings of the latent factor on FOMC announcement windows and shows that based on the comments in the financial press,

[10] The literature, described in the next section, finds that quantifying the statement can explain the movement in longer maturities, whereas short maturities are more responsive to the immediate policy action.

these are indeed days of well-known "statement surprises." Monetary policy statement surprises are well understood and it is reassuring that the latent factor we extract behaves as expected. Non-headline surprises in other macroeconomic data releases are much less well understood, not only in the academic literature but also in the financial press. Thus, the financial press reports of non-headline items are always boilerplate, listing the numbers without much commentary, so doing the same exercise for macroeconomic data releases is not possible. We therefore do the next best thing and create psuedo-unobservable surprises.

To verify that our method indeed picks up un-surveyed news in data releases we take the observable surprises in the employment report–nonfarm payrolls, unemployment rate, and hourly earnings–and drop the nonfarm payrolls surprise from the data, treating it as if this component of the employment report is not surveyed and hence its surprise is unobservable to the econometrician.[11] We then look at the correlation between the latent factor we extract on employment report release days and the surprise we have excluded from the data. Figure 1 shows the results of the exercise. The correlation between the nonfarm payrolls surprise and the latent factor extracted from the factor model is striking. The estimated latent factor indeed tracks the surprise–as measured by the survey–market participants have perceived. The correlation is not perfect because the true unobserved surprises are also being picked up by the factor but as the nonfarm payrolls surprise has a large variance share, this is closely tracked by the estimated latent factor.

4.4.1 Why is a Single Factor Sufficient?

One of the most interesting findings of this paper is that a single latent factor is sufficient to capture almost all of the non-headline variation in yields around news releases. This would have been surprising if a single factor per release were sufficient—all the non-surveyed/unobservable information in the employment report being captured by a single latent factor—but it is very surprising that a single factor *across* releases is sufficient. The model with a single latent factor is literally misspecified in that it ignores differences in

[11]Doing this for the other two observed surprises produces similar results but since nonfarm payrolls surprises elicit the largest yield curve responses, visually this case is easier to present.

variance across releases, as evidenced by the fact that the latent variable spikes most often on employment report days (not shown for brevity). However this does not prevent the single factor from capturing almost all non-headline variation in yields around announcements. This is because individual latent factors are simply different scalings of the common factor. In Figure 2 we show the correlation of the common factor with the individual latent factors and show that there is almost perfect correlation in most cases.[12]

Not only is it the case that all individual *latent* factors elicit the same response from the yield curve, *observable* surprises also elicit this response. The latent factor has a hump shaped effect on the yield curve, which is very similar to the hump-shaped effect of observed macroeconomic news surprises on the yield curve documented in Table 1.[13] Both latent and observed news surprises have peak effects at a maturity around one to two years. They also both have a sizeable effect on long-term yields. In this paper we remain silent on why long-term yields are sensitive to incoming macroeconomic news.[14] We do not get into that question in this paper. But it is important to have shown that this reaction can be tied almost fully to macroeconomic news releases.

Given that all news, observed or unobserved, have the same hump-shaped effect on the yield curve, one might suppose that we could have treated the headline news as unobservable as well and only extracted a single latent factor, without compromising the fit. Table 8 shows the result of this exercise, and the fit is indeed about the same. Note that mechanically these are the heteroskedasticity-based estimator effects but our methodology allows measuring R^2, and shows that the fit remains about the same when all news are treated as unobservable. This is closely related to another approach considered by Rigobon and Sack

[12]While some panels, such as the employment report, show an almost exact match, others, such as initial claims, depict two sets of points, one along the 45-degree line and one not. The latter are less important releases that do not dominate the change in the variance when there are multiple releases in the same window. When they are the only release in that window the common factor and the individual factor line up exactly but days with other releases in the same window produce the diffuse set of points.

[13]The "hump-shape" language is well known in the macro VAR literature. That is a hump over time, whereas here we find a hump over maturities. The two are related but working out the exact nature of that relationship is a separate study.

[14]One author of this paper has work arguing that the sensitivity of long rates is due to updating of steady state inflation beliefs (Gürkaynak et al., 2005b), another has argued that it is due to changes in expected real rates (Beechey and Wright, 2009) and the third has argued that neither explains the yield curve behavior in a model consistent way (Kısacıkoğlu, 2016).

(2006), which is simply to measure the news surprise by the first principal component of y_t in announcement windows alone.

This finding reinforces our argument that news releases are multidimensional and unobserved/unsurveyed surprises also elicit asset price responses. In all likelihood, every release has *many* unobserved surprises but since all of them elicit the same response in terms of the shape of the yield curve reaction, one latent factor per release is sufficient, as is one latent factor across releases. The hump shaped factor that we find is closely related to the level and slope components of the yield curve, with the bulk of it being level.[15] Thus, our procedure, as a by product of this application, finally lets us have a handle on what moves the yield curve, as captured predominantly by level, in event windows. It is driven by news, but we do not how much of the effect represents expectations of future short rates versus term premia.

It is important to emphasize the two separate findings here. The first is that observed and latent news both elicit hump-shaped responses from the yield curve, as shown by the regression coefficients. The second is that yield curve movements in the event window are almost completely explained by those observed and latent factors, as shown by the R^2s.

5 Extensions and robustness

There are several extensions and robustness checks that are in order. These are (i) limiting the sample to the period before the financial crisis, so that estimates will not be affected by the short end being stuck at the ZLB, (ii) verifying that the latent factor is not just capturing a factor that is always driving yield curve movements and is unrelated to economic news, (iii) verifying that the Kalman filter, which uses all yields in extracting the latent factor, is not mechanically explaining long yields with themselves, (iv) comparing the FOMC release factor to a well-studied statement factor derived using a different, two

[15] In unreported results, we extracted a level factor from yields in event windows and showed that we are able to explain about all of the variation in level in these windows with our method. The hump-shaped factor itself is close to level but the hump is critically important as this is what turns out to differentiate the latent factor we extract, from ever-present background noise.

step procedure, and (v) allowing for an unrestricted variance-covariance matrix for ε_t in equation (3.1). In this section we tackle these issues.

5.1 Pre-crisis sample and ever-present level factor

We take on the first two issues simultaneously. We limit the sample to the pre-crisis period and introduce a new latent factor that is ever-present. This is in the spirit of Altavilla et al. (2017), who argue for the presence of a yield curve factor that is present on announcement and non-annuncement days alike and is not driven by news. The ever-present factor is identified using the yield change covariances in non-announcement days. The extended model that we estimate is:

$$y_t = \beta' s_t + \Sigma_{i=1}^{I} d_{it}\gamma_i f_{it} + \gamma_0 f_{0t} + \varepsilon_t \tag{5.1}$$

and applies on all days, as before. The new factor f_{0t} affects yields on all days, whether they have announcements or not and captures the "background" common movement in asset prices that would be present even without any announcement. This latent factor turns out to be a level factor and we refer to it as the "ever-present" level factor. It does not have the hump shape that we saw for the effects of news announcements on yields and indeed this is how the unobserved event and ever-present factors are separately identified.

Maximum-likelihood estimates are reported in Table 9. This shows that our results hold even more strongly in the pre-crisis period. Thus our results are not driven by the somewhat unusual behavior of the yield curve in the zero lower bound period. More importantly, the results also show that introducing an ever-present level factor does not detract from the importance of non-headline statement factors. That is, the effect introduced by the non-headline news factor is distinct from the background factor that is always present. This exercise also reports marginal R^2 measures for headline surprises, non-headline latent factors, and the ever-present level factor.[16] We observe that R^2s are below 40% when only

[16] These regressors have negligible covariance with each other, so that changes in R^2 can be interpreted as marginal R^2 measures.

the headline surprises are included, increase substantially to about 90% when the latent non-announcement factors are included, and increase further when the common background factor is also included. When the ever-present level factor is not separately included in the analysis, latent factors proxy for this as well, which inflates their R^2 contributions, as in section 2, but this effect turns out to be minor.

5.2 Short-end factor

The methodology that we propose efficiently extracts the latent factor and the coefficients relating the headline surprises and the latent factor to yields at various maturities in one step. While the efficiency is desirable, information from long-term yields is used to estimate the factor, which in turn helps fit the changes in these yields. One worry therefore is whether we are mechanically explaining long-term yields with themselves.

To be sure that we are not, we sacrifice efficiency for a moment and use only information from the short-end of the yield curve, covering maturities up to one year. We then use this latent factor to help explain the changes in longer term yields in the event window. This exercise can only be done with the pre-crisis sample as during the ZLB episode yields up to one year were stuck at their lower bounds and were not responsive to incoming data, as was persuasively shown by Swanson and Williams (2014).

Coefficient estimates and R^2s from the two-step procedure are shown in Table 10. It is clear that the results are about the same, showing that the latent factor we extract from the short-end of the yield curve in the first step can explain the changes in the long-end as well.

5.3 The monetary policy path surprise

This exercise segues nicely into our last robustness check. Extracting latent factors from the short-end of the yield curve and rotating these to admit policy action and policy path surprise definitions was done by Gürkaynak et al. (2005a) for FOMC announcement windows. Their policy action surprise mechanically coincides with our observed headline news. We now check whether their principal components and factor rotation-based two step procedure and our Kalman filtering-based method produce similar path (latent non-headline) factors. The Gürkaynak et al. (2005a) path factor has been extensively used in academic and policy work during the past decade to study the effects of forward guidance. Verifying that the series we produce for FOMC non-headline news is close to that series would instill confidence that our macroeconomic data release latent factors, for which there is no comparison series, is also capturing non-headline news that are in the release.

Figure 3 shows the paths of the Gürkaynak et al. (2005a) path factor and our latent FOMC factor based on the pre-crisis sample. The close correspondence between the two series is impressive—the two series have a correlation of more than 90%. Hence, the methodology we propose in this paper does in one step what was done in two steps by Gürkaynak et al. (2005a), but finds the same latent path factor. This makes it easier to be assured that the latent factors extracted for other macroeconomic data releases are also measures of non-headline news as perceived by market participants.

5.4 Generalized Variance-Covariance Matrix

As a final robustness check, instead of having a diagonal variance-covariance matrix for ε_t in equations (3.1) and (3.2), we allow for an unrestricted variance-covariance matrix for the background noise. Thus the variance-covariance matrix now incorporates any ever-present factor (like the one considered in equation (5.1)), which is not separately identified any more.

This model can also be estimated by maximum likelihood, and the results are reported in Table 11, for the case with a single factor and Table 12, with release-specific factors. Having unrestricted noise makes no difference for our results. As in the case in the benchmark model where ε_t has a diagonal variance-covariance matrix, the OLS coefficients are essentially unchanged from those reported in Table 1. And it remains the case that the measured surprise plus one latent factor are sufficient to explain the vast majority of yield curve movements around announcements.

6 Conclusions

In this paper we have proposed a new way of thinking about the impacts of macroeconomic news announcements on asset prices. The effects are assumed to come both from a measured surprise component of the announcement and from latent factors that we think of as representing details of the news announcement. The inclusion of a single latent factor greatly increases the fraction of asset price movements bracketing news announcements that we can explain.

A narrow reading of this paper is that this is a contribution to econometrics of event studies. We showed that OLS- and heteroskedasticity-based event studies are complements rather than substitutes. We also showed how to implement these two methods simultaneously, in a one-step procedure. We expect this to be a standard procedure when the aim is to explain as much of the asset price response as possible, without sacrificing interpretability.

A broader reading would also focus on the applications we presented. It appears that a single latent factor drives the non-headline component of the news releases in every case. This latent factor has a "hump-shaped" effect on the yield curve. Importantly, we show that when studied using our method, news can explain the vast majority of yield curve movements in the event window. Thus, we understand more–in fact most–of yield curve movements in windows involving macroeconomic data and policy releases, a goal that had hitherto been elusive.

Although we show that news, which may not be observable to the econometrician, explain the yield curve movements in the event window, more work is needed to understand why the response has the hump shape and how exactly that shape relates to the usual level, slope, and curvature decomposition of the yield curve. We leave these interesting questions to future research, in the hope that it will benefit from the methodology that we have developed and insights that it has provided.

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Tables and Figures

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
Non-Farm	2.89***	5.69***	4.55***	5.31***	3.99***	2.42***
	(0.32)	(0.51)	(0.42)	(0.45)	(0.34)	(0.22)
Initial Claims	−0.33***	−0.73***	−0.61***	−0.69***	−0.55***	−0.33***
	(0.05)	(0.08)	(0.06)	(0.07)	(0.06)	(0.04)
Durable	0.40***	0.75***	0.74***	0.86***	0.61***	0.39***
	(0.12)	(0.22)	(0.18)	(0.20)	(0.16)	(0.10)
Emp Cost	0.70***	1.59***	1.05***	1.51***	1.17***	0.77***
	(0.21)	(0.46)	(0.36)	(0.44)	(0.34)	(0.23)
Retail	0.32*	0.68***	0.46**	0.55**	0.39*	0.15
	(0.18)	(0.22)	(0.19)	(0.23)	(0.20)	(0.15)
Retail Ex. Auto	0.41***	0.87***	0.97***	1.22***	0.97***	0.74***
	(0.15)	(0.23)	(0.21)	(0.23)	(0.19)	(0.13)
GDP	0.68***	1.65***	1.25***	1.62***	1.23***	0.72***
	(0.14)	(0.34)	(0.24)	(0.31)	(0.25)	(0.17)
CPI	0.00	−0.10	−0.08	0.07	0.12	0.17
	(0.10)	(0.23)	(0.15)	(0.20)	(0.16)	(0.12)
Core CPI	0.74***	1.48***	1.16***	1.55***	1.27***	0.80***
	(0.12)	(0.22)	(0.17)	(0.21)	(0.17)	(0.12)
PPI	0.11	0.21	0.16	0.18	0.23*	0.16*
	(0.10)	(0.17)	(0.15)	(0.16)	(0.13)	(0.09)
Core PPI	0.62***	0.98***	0.83***	1.05***	0.91***	0.69***
	(0.13)	(0.21)	(0.16)	(0.17)	(0.14)	(0.10)
Hourly Earnings	0.88***	1.81***	1.48***	2.02***	1.61***	0.97***
	(0.25)	(0.35)	(0.28)	(0.34)	(0.27)	(0.18)
Unemp	−1.21***	−2.00***	−1.61***	−1.65***	-1.14***	−0.65***
	(0.22)	(0.37)	(0.28)	(0.31)	(0.24)	(0.16)
FOMC	0.64***	0.55***	0.23**	0.15	0.05	−0.01
	(0.09)	(0.12)	(0.11)	(0.09)	(0.06)	(0.03)
R^2	0.41	0.36	0.35	0.35	0.34	0.29

Table 1: OLS estimates of equation (2.3). White standard errors in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$). Macroeconomic surprises are normalized by their respective standard deviations. Monetary policy surprises are in basis points. Responses of ED1, ED4, two-year, five-year, ten-year, and thirty-year yields are in basis points. Regressions are only run on announcement days. The sample is 1992-2017 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

	ED1	ED4	2-year	5-year	10-year	30-year
Non-Farm	7.98***	13.23***	10.25***	12.23***	9.45***	6.32***
	(0.70)	(1.00)	(0.70)	(0.86)	(0.69)	(0.49)
Initial Claims	−1.69***	−2.66***	−1.81***	−2.36***	−1.99***	−1.47***
	(0.48)	(0.62)	(0.28)	(0.29)	(0.25)	(0.21)
Durable	1.02	3.43**	3.32***	3.46***	2.86***	1.80***
	(1.51)	(1.39)	(0.76)	(0.75)	(0.66)	(0.49)
Emp Cost	2.74**	3.39**	2.40	3.14**	2.38**	1.55*
	(1.17)	(1.69)	(1.56)	(1.25)	(1.03)	(0.84)
Retail Ex. Auto	5.19*	7.33**	3.96***	3.96***	3.00***	1.81***
	2.99	2.98	1.25	1.12	0.88	0.55
GDP (advance)	7.59	8.08**	5.76*	6.77**	5.46*	2.91*
	(5.91)	(3.82)	(2.95)	(3.37)	(2.94)	(1.75)
Core CPI	2.79***	5.75***	4.02***	5.22***	4.12***	2.90***
	(1.02)	(1.12)	(1.16)	(0.8)	(0.60)	(0.44)
Core PPI	4.22***	5.33***	4.41***	5.59***	4.70***	3.20***
	(1.30)	(1.36)	(1.16)	(1.40)	(1.15)	(0.70)
FOMC	0.94***	2.70***	2.57**	3.95*	6.25	−7.46
	(0.12)	(1.01)	(1.05)	(2.17)	(7.43)	(17.79)

Table 2: Heteroskedasticity-based estimates following Rigobon (2003) and Rigobon and Sack (2004, 2005, 2006). Asymptotic standard errrors are in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$). Macroeconomic surprises are normalized by their respective standard deviations. Monetary policy surprises are in basis points. esponses of ED1, ED4, two-year, five-year, ten-year, and thirty-year yields are in basis points. Regressions are only run on announcement days. The sample is 1992-2017 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

	ED1	ED4	2-Year	5-Year	10-Year	30-year
Non-Farm	2.89***	5.71***	4.55***	5.31***	3.99***	2.42***
	(0.16)	(0.25)	(0.21)	(0.22)	(0.17)	(0.11)
Initial Claims	−0.32***	−0.74***	−0.58***	−0.68***	−0.55***	−0.33***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Durable	0.39***	0.88***	0.71***	0.86***	0.60***	0.39***
	(0.06)	(0.11)	(0.09)	(0.10)	(0.08)	(0.05)
Emp Cost	0.69***	1.51***	1.17***	1.51***	1.17***	0.77***
	(0.10)	(0.23)	(0.18)	(0.22)	(0.17)	(0.12)
Retail	0.32***	0.76***	0.53***	0.56***	0.39***	0.15***
	(0.09)	(0.12)	(0.10)	(0.12)	(0.10)	(0.07)
Retail Ex. Auto	0.41***	0.95***	0.94***	1.21***	0.97***	0.74***
	(0.07)	(0.12)	(0.10)	(0.12)	(0.10)	(0.07)
GDP	0.67***	1.64***	1.24***	1.62***	1.23***	0.72***
	(0.07)	(0.17)	(0.12)	(0.15)	(0.13)	(0.09)
CPI	0.01	-0.09	0.00	0.07	0.12	0.17***
	(0.05)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
Core CPI	0.72***	1.66***	1.21***	1.55***	1.27***	0.80***
	(0.06)	(0.11)	(0.09)	(0.11)	(0.08)	(0.06)
PPI	0.10**	0.25***	0.20***	0.18**	0.23***	0.16***
	(0.05)	(0.09)	(0.07)	(0.08)	(0.06)	(0.05)
Core PPI	0.63***	1.08***	0.78***	1.05***	0.91***	0.69***
	(0.07)	(0.10)	(0.08)	(0.09)	(0.07)	(0.05)
Hourly Earnings	0.88***	1.83***	1.45***	2.02***	1.61***	0.97***
	(0.12)	(0.17)	(0.14)	(0.17)	(0.14)	(0.09)
Unemp	−1.21***	−2.01***	−1.64***	−1.65***	−1.14***	−0.65***
	(0.11)	(0.18)	(0.14)	(0.15)	(0.12)	(0.08)
FOMC	0.64***	0.53***	0.32***	0.25***	0.12***	0.04*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.02)
Factor	1.46***	3.25***	2.52***	3.04***	2.35***	1.50***
	(0.04)	(0.06)	(0.04)	(0.05)	(0.03)	(0.02)
R^2 no factor	0.41	0.36	0.35	0.35	0.34	0.29
R^2 with factor	0.74	0.92	0.94	0.98	0.96	0.88

Table 3: Estimates of equation (3.1). Standard errors in parentheses ($^*p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$). Macroeconomic surprises are normalized by their respective standard deviations. Monetary policy surprises are in basis points. Responses of ED1, ED4, two-year, five-year, ten-year, and thirty-year yields are in basis points. The sample is 1992-2017 for macroeconomic announcements, 1992-2007 for monetary policy surprises. Factor is estimated via Kalman Filter using changes in asset prices around macroeconomic and FOMC releases. The R^2 values are those of announcement day yields using (i) just headline surprises, (ii) headline surprises and the latent factor.

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
Non-Farm	2.89***	5.71***	4.55***	5.31***	3.99***	2.42***
	(0.16)	(0.25)	(0.21)	(0.22)	(0.17)	(0.11)
Initial Claims	−0.33***	−0.75***	−0.60***	−0.70***	−0.56***	−0.34***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Durable	0.42***	0.92***	0.74***	0.89***	0.63***	0.40***
	(0.06)	(0.11)	(0.09)	(0.10)	(0.08)	(0.05)
Emp Cost	0.70***	1.51***	1.17***	1.51***	1.17***	0.77***
	(0.11)	(0.23)	(0.18)	(0.22)	(0.16)	(0.11)
Retail	0.26***	0.63***	0.42***	0.42***	0.28***	0.07
	(0.08)	(0.10)	(0.09)	(0.10)	(0.08)	(0.06)
Retail Ex. Auto	0.45***	1.03***	1.00***	1.29***	1.03	0.78***
	(0.07)	(0.12)	(0.10)	(0.11)	(0.09)	(0.06)
GDP	0.67***	1.65***	1.25***	1.63***	1.24***	0.72***
	(0.07)	(0.16)	(0.11)	(0.14)	(0.12)	(0.08)
CPI	0.01	−0.08	0.00	0.08	0.13	0.18***
	(0.05)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
Core CPI	0.69***	1.59***	1.15***	1.49***	1.22***	0.77***
	(0.06)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
PPI	0.11**	0.27***	0.22***	0.21**	0.25***	0.17***
	(0.05)	(0.09)	(0.07)	(0.08)	(0.06)	(0.05)
Core PPI	0.65***	1.10***	0.81***	1.08***	0.93***	0.71***
	(0.07)	(0.10)	(0.08)	(0.09)	(0.07)	(0.05)
Hourly Earnings	0.88***	1.83***	1.45***	2.02***	1.61***	0.98***
	(0.12)	(0.17)	(0.14)	(0.17)	(0.14)	(0.09)
Unemp	−1.21***	−2.01***	−1.64***	−1.66***	−1.14***	−0.65***
	(0.11)	(0.18)	(0.14)	(0.15)	(0.12)	(0.08)
FOMC	0.64***	0.53***	0.34***	0.25***	0.12***	0.03
	0.05	0.05	0.05	0.05	0.03	0.02
$f_{CPI,t}$	1.13***	2.64***	2.08***	2.63***	2.10***	1.47***
	(0.06)	(0.09)	(0.07)	(0.08)	(0.06)	(0.05)
$f_{Durable,t}$	0.77***	1.97***	1.50***	1.86***	1.50***	1.00***
	(0.06)	(0.10)	(0.06)	(0.06)	(0.05)	(0.03)
$f_{EmpCost,t}$	0.84***	2.54***	2.10***	2.68***	2.07***	1.42***
	(0.14)	(0.25)	(0.20)	(0.30)	(0.26)	(0.19)
$f_{GDP,t}$	1.45***	3.16***	2.30***	2.87***	2.31***	1.45***
	(0.32)	(0.24)	(0.19)	(0.18)	(0.14)	(0.10)
$f_{Claims,t}$	0.87***	1.81***	1.30***	1.58***	1.27***	0.82***
	(0.11)	(0.13)	(0.07)	(0.06)	(0.04)	(0.02)
$f_{NonFarm,t}$	2.63***	5.78***	4.56***	5.64***	4.34***	2.75***
	(0.11)	(0.18)	(0.14)	(0.13)	(0.11)	(0.08)
$f_{PPI,t}$	1.30***	2.45***	1.98***	2.40***	1.98***	1.37***
	(0.09)	(0.10)	(0.07)	(0.09)	(0.08)	(0.05)
$f_{Retail,t}$	1.45***	2.90***	2.30***	2.54***	1.96***	1.21***
	(0.15)	(0.18)	(0.11)	(0.10)	(0.07)	(0.05)
$f_{FOMC,t}$	2.42***	6.21***	4.91***	5.31***	3.72***	2.10***
	(0.20)	(0.33)	(0.24)	(0.32)	(0.22)	(0.15)
R^2 No Factor	0.41	0.36	0.35	0.35	0.34	0.29
R^s Release Factors	0.74	0.93	0.94	0.98	0.96	0.88

Table 4: Estimates of equation (3.2). Standard errors in parentheses ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$). Macroeconomic surprises are normalized by their respective standard deviations. Monetary policy surprises are in basis points. The R^2 values reported are those for announcement day yields using (i) just headline surprises, (ii) headline surprises and latent factors. The sample is 1992-2017 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

		Non-Farm	Initial Claims	NAPM	Retail	Obs.	R^2	p-value (χ^2)
ED1	Auction	1.4***	-0.12	0.05	0.19	152	0.31	0.82
		(0.19)	(0.13)	(0.12)	(0.19)			
	Survey	1.33***	-0.11	0.04	0.17	152	0.28	
		(0.20)	(0.13)	(0.12)	(0.19)			
ED4	Auction	6.99***	-0.53	0.43	0.40	153	0.48	0.87
		(0.63)	(0.44)	(0.43)	(0.65)			
	Survey	6.75***	-0.51	0.37	0.38	153	0.45	
		(0.66)	(0.46)	(0.45)	(0.68)			
Two-Year	Auction	4.72***	-0.38	0.36	0.35	153	0.42	0.87
		(0.49)	(0.34)	(0.32)	(0.50)			
	Survey	4.54***	-0.36	0.30	0.33	153	0.38	
		(0.52)	(0.36)	(0.34)	(0.53)			
Five-Year	Auction	5.62***	-0.47	0.54	0.49	153	0.45	0.78
		(0.54)	(0.37)	(0.37)	(0.56)			
	Survey	5.39***	-0.44	0.45	0.45	153	0.41	
		(0.57)	(0.40)	(0.39)	(0.39)			
Ten-Year	Auction	4.37***	-0.37	0.42	0.41	153	0.43	0.88
		(0.45)	(0.31)	(0.30)	(0.46)			
	Survey	4.22***	-0.35	0.36	0.38	153	0.4	
		(0.47)	(0.33)	(0.32)	(0.48)			

Table 5: Seemingly unrelated regression (SUR) results for ED1, ED4, and on-the-run two-, five-, ten-, and thirty-year yields. "Auction" are the coefficients for the auction based surprises and "Survey" are MMS/Action Economics survey based surprise coefficients. Standard errors in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$). P-value is the joint test statistic of equality between auction and survey estimates. The sample is from October 2002 to July 2005.

	ED1	ED4	2-year	5-year	10-year	30-year
No FOMC Statement						
OLS	0.53^{***}	0.65^{**}	0.28^{*}	0.18^{*}	0.08	0.02
	(0.15)	(0.29)	(0.17)	(0.11)	(0.06)	(0.04)
ID HET	0.82^{***}	1.22^{***}	0.80^{***}	0.76^{***}	0.66	0.55
	(0.13)	(0.24)	(0.16)	(0.27)	(0.43)	(0.63)
FOMC Statement						
	ED1	ED4	2-year	5-year	10-year	30-year
OLS	0.54^{***}	0.39^{***}	0.21	0.13	0.03	-0.03
	(0.10)	(0.14)	(0.13)	(0.12)	(0.08)	(0.04)
ID HET	0.99^{***}	3.20^{**}	3.35^{**}	5.76	12.21	-4.38
	(0.17)	(1.40)	(1.64)	(4.29)	(27.41)	(6.08)

Table 6: OLS and Heteroskedasticity-based estimates of the effects of target federal funds rate surprises using FOMC days with and without monetary policy statements. Standard errors in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Date	Factor	Commentary
January 28, 2004	4.62	Statement drops commitment to keep policy unchanged for "considerable period", bringing forward expectations of future tightenings.
August 13, 2002	-2.85	Statement announces balance of risks has shifted from neutral to economic weakness
January 3, 2001	2.77	Large surprise intermeeting ease reportedly causes financial markets to mark down probability of a recession; Fed is perceived as being "ahead of the curve" and as needing to ease less down the road as a result.
May 17, 1994	-2.50	Fed's move is perceived as a "combative response to markets that for weeks have been demanding convincing evidence…that it was doing enough to rein in economic growth and dampen inflation expectations." (The New York Times, May 18, 1994).
October 15, 1998	-2.48	First intermeeting move since 1994 and statement pointing to "unsettled conditions in financial markets... restraining aggregate demand" increases expectations of further easings.

Table 7: FOMC commentary. Table shows the 5 largest (absolute) values of the latent factor monetary policy announcements with associated dates and the summary of the statements. January 28, 2004, August 13, 2002, October 15, 1998 and January 3, 2001 commentary are from Gürkaynak et al. (2005).

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
Factor	2.08***	4.14***	3.26***	3.88***	2.98***	1.87***
	(0.08)	(0.09)	(0.07)	(0.07)	(0.06)	(0.04)
R^2	0.65	0.92	0.93	0.98	0.96	0.86

Table 8: Estimates of equation (3.1) when headline and FOMC surprises are unobservable. Standard errors in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$). Responses of ED1, ED4, two-year, five-year, ten-year, and thirty-year yields are in basis points.

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
Non-Farm	3.70***	6.84***	5.41***	5.92***	4.35***	2.52***
	(0.22)	(0.37)	(0.29)	(0.32)	(0.24)	(0.16)
Initial Claims	−0.48***	−0.90***	−0.69***	−0.74***	−0.56***	−0.32***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.03)	(0.02)
Durable	0.70***	1.36***	1.05***	1.20***	0.81***	0.51***
	(0.08)	(0.15)	(0.12)	(0.12)	(0.10)	(0.06)
Emp Cost	0.84***	1.83***	1.41***	1.72***	1.35***	0.92***
	(0.16)	(0.33)	(0.26)	(0.30)	(0.23)	(0.17)
Retail	0.32***	0.83***	0.54***	0.55***	0.36***	0.10
	(0.12)	(0.17)	(0.13)	(0.13)	(0.11)	(0.08)
Retail Ex. Auto	0.81***	1.42***	1.23***	1.26***	0.99***	0.72***
	(0.10)	(0.18)	(0.14)	(0.15)	(0.12)	(0.08)
GDP	0.93***	2.32***	1.68***	2.05***	1.49***	0.83***
	(0.10)	(0.21)	(0.14)	(0.18)	(0.15)	(0.10)
CPI	-0.02	−0.37**	-0.11	-0.13	-0.03	0.09
	(0.08)	(0.16)	(0.12)	(0.15)	(0.12)	(0.09)
Core CPI	1.10***	2.42***	1.69***	2.15***	1.72***	1.09***
	(0.08)	(0.16)	(0.13)	(0.15)	(0.12)	(0.09)
PPI	0.16**	0.30**	0.30***	0.34***	0.36***	0.25***
	(0.07)	(0.13)	(0.11)	(0.11)	(0.09)	(0.07)
Core PPI	0.96***	1.67***	1.12***	1.39***	1.19***	0.90***
	(0.10)	(0.15)	(0.12)	(0.12)	(0.10)	(0.07)
Hourly Earnings	1.23***	2.22***	1.76***	2.16***	1.76***	1.15***
	(0.18)	(0.24)	(0.19)	(0.23)	(0.18)	(0.12)
Unemp	−1.75***	−2.49***	−2.02***	−1.95***	−1.28***	−0.68***
	(0.15)	(0.27)	(0.20)	(0.22)	(0.17)	(0.12)
FOMC	0.64***	0.52***	0.33***	0.24***	0.10***	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.02)
$f_{CPI,t}$	1.15***	2.65***	2.15***	2.32***	1.64***	1.10***
	(0.09)	(0.15)	(0.13)	(0.17)	(0.15)	(0.12)
$f_{Durable,t}$	0.79***	1.78***	1.44***	1.46***	1.08***	0.61***
	(0.08)	(0.17)	(0.11)	(0.13)	(0.11)	(0.08)
$f_{EmpCost,t}$	1.23***	3.32***	2.66***	3.21***	2.43***	1.80***
	(0.19)	(0.36)	(0.28)	(0.44)	(0.38)	(0.21)
$f_{GDP,t}$	1.95***	3.34***	2.36***	2.73***	2.08***	1.10***
	(0.39)	(0.39)	(0.36)	(0.46)	(0.38)	(0.22)
$f_{Claims,t}$	0.95***	1.75***	1.12***	1.04***	0.62***	0.30***
	(0.18)	(0.23)	(0.14)	(0.16)	(0.13)	(0.08)
$f_{NonFarm,t}$	3.45***	6.18***	4.98***	5.35***	3.77***	2.28***
	(0.17)	(0.30)	(0.20)	(0.27)	(0.24)	(0.18)
$f_{PPI,t}$	1.54***	2.87***	2.29***	2.53***	1.97***	1.40***
	(0.12)	(0.18)	(0.11)	(0.14)	(0.12)	(0.09)
$f_{Retail,t}$	1.83***	3.22***	2.26***	2.21***	1.52***	0.80***
	(0.15)	(0.25)	(0.15)	(0.18)	(0.14)	(0.09)
$f_{FOMC,t}$	2.67***	5.96***	4.50***	4.35***	2.75***	1.28***
	(0.21)	(0.37)	(0.29)	(0.38)	(0.28)	(0.19)
$f_{0,t}$	0.62***	1.60***	1.20***	1.69***	1.47***	1.00***
	(0.06)	(0.08)	(0.06)	(0.06)	(0.04)	(0.03)
R^2 No Factor	0.48	0.39	0.38	0.36	0.34	0.30
R^2 Release Factors	0.85	0.89	0.90	0.82	0.74	0.65
R^2 All Factors	0.86	0.96	0.97	0.99	1.00	0.97

Table 9: Estimates of equation (5.1). Standard errors in parentheses ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$). See Table 3 for data description. The sample is 1992-2007 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

	ED1	ED4	2-Year	5-Year	10-Year	30-year
Non-Farm	3.70***	6.85***	5.41***	5.92***	4.35***	2.52***
	(0.17)	(0.22)	(0.19)	(0.21)	(0.21)	(0.15)
Initial Claims	−0.46***	−0.86***	−0.65***	−0.69***	−0.53***	−0.30***
	(0.02)	(0.03)	(0.05)	(0.05)	(0.04)	(0.03)
Durable	0.64***	1.26***	0.98***	1.12***	0.77***	0.48***
	(0.04)	(0.06)	(0.10)	(0.09)	(0.08)	(0.06)
Emp Cost	0.85***	1.92***	1.36***	1.79***	1.40***	0.95***
	(0.09)	(0.11)	(0.23)	(0.27)	(0.20)	(0.17)
Retail	0.36***	1.00***	0.63***	0.66***	0.44***	0.16**
	(0.06)	(0.07)	(0.12)	(0.12)	(0.09)	(0.07)
Retail Ex. Auto	0.82***	1.44***	1.26***	1.27***	1.00***	0.72***
	(0.06)	(0.09)	(0.15)	(0.16)	(0.12)	(0.10)
GDP	0.86***	2.22***	1.63***	2.02***	1.48***	0.84***
	(0.11)	(0.12)	(0.18)	(0.24)	(0.22)	(0.17)
CPI	-0.04	−0.32***	−0.18*	-0.14	-0.03	0.09
	(0.06)	(0.08)	(0.10)	(0.13)	(0.12)	(0.11)
Core CPI	1.13***	2.57***	1.71***	2.19***	1.75***	1.11***
	(0.06)	(0.08)	(0.12)	(0.13)	(0.13)	(0.11)
PPI	0.13***	0.25***	0.24***	0.30***	0.33***	0.23***
	(0.04)	(0.05)	(0.09)	(0.10)	(0.08)	(0.07)
Core PPI	0.87***	1.77***	1.03***	1.29***	1.13***	0.87***
	(0.06)	(0.08)	(0.11)	(0.13)	(0.11)	(0.08)
Hourly Earnings	1.23***	2.22***	1.78***	2.15***	1.76***	1.15***
	(0.14)	(0.18)	(0.19)	(0.20)	(0.18)	(0.15)
Unemp	−1.74***	−2.50***	−2.00***	−1.94***	−1.27***	−0.68***
	(0.10)	(0.13)	(0.17)	(0.20)	(0.17)	(0.12)
FOMC	0.64***	0.47***	0.32***	0.26***	0.13***	0.04
	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)	(0.03)
Factor	2.32***	4.38***	3.01***	3.38***	2.52***	1.56***
	(0.06)	(0.09)	(0.08)	(0.09)	(0.08)	(0.06)
R^2 no factor	0.48	0.39	0.38	0.36	0.34	0.30
R^2 with factor	0.93	0.96	0.86	0.86	0.82	0.74

Table 10: As for Table 3, except that in estimating the latent factor, only ED1 and ED4 are used. Other yield changes are regressed on the estimated latent factor. The sample is 1992-2007.

	ED1	ED4	2-Year	5-Year	10-Year	30-year
Non-Farm	2.89***	5.72***	4.54***	5.31***	3.99***	2.42***
	(0.16)	(0.25)	(0.21)	(0.22)	(0.17)	(0.11)
Initial Claims	−0.32***	−0.76***	−0.58***	−0.69***	−0.55***	−0.33***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Durable	0.39***	0.90***	0.70***	0.86***	0.60***	0.39***
	(0.06)	(0.11)	(0.09)	(0.10)	(0.08)	(0.05)
Emp Cost	0.69***	1.50***	1.17***	1.51***	1.17***	0.77***
	(0.10)	(0.23)	(0.18)	(0.22)	(0.17)	(0.12)
Retail	0.32***	0.79***	0.52***	0.56***	0.39***	0.15**
	(0.09)	(0.13)	(0.10)	(0.12)	(0.10)	(0.07)
Retail Ex. Auto	0.41***	0.99***	0.94***	1.21***	0.97***	0.74***
	(0.07)	(0.13)	(0.10)	(0.12)	(0.10)	(0.07)
GDP	0.67	1.64***	1.23***	1.62***	1.23***	0.72***
	(0.07)	(0.17)	(0.12)	(0.15)	(0.13)	(0.09)
CPI	0.01	-0.07	0.00	0.07	0.12	0.17***
	(0.05)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
Core CPI	0.73***	1.69***	1.22***	1.55***	1.27***	0.80***
	(0.06)	(0.11)	(0.09)	(0.11)	(0.08)	(0.06)
PPI	0.11**	0.25***	0.20***	0.18**	0.23***	0.16***
	(0.05)	(0.09)	(0.07)	(0.08)	(0.06)	(0.05)
Core PPI	0.61***	1.12***	0.77***	1.05***	0.91***	0.69***
	(0.07)	(0.10)	(0.08)	(0.09)	(0.07)	(0.05)
Hourly Earnings	0.88***	1.84***	1.45***	2.02***	1.61***	0.97***
	(0.12)	(0.17)	(0.14)	(0.17)	(0.14)	(0.09)
Unemp	−1.21***	−2.02***	−1.63***	−1.65***	−1.14***	−0.65***
	(0.11)	(0.18)	(0.14)	(0.15)	(0.12)	(0.08)
FOMC	0.64***	0.52***	0.31***	0.23***	0.10***	0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.02)
Factor	1.26***	3.11***	2.40***	2.77***	2.07***	1.26***
	(0.11)	(0.08)	(0.05)	(0.06)	(0.05)	(0.04)
R^2 no Factor	0.41	0.36	0.35	0.35	0.34	0.29
R^2 with Factor	0.69	0.94	0.96	0.96	0.90	0.77

Table 11: As for Table 3, except with an unrestricted variance-covariance matrix for the background noise.

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
Non-Farm	2.89***	5.71***	4.54***	5.30***	3.99***	2.42***
	(0.16)	(0.25)	(0.21)	(0.22)	(0.17)	(0.11)
Initial Claims	−0.33***	−0.77***	−0.59***	−0.69***	−0.56***	−0.34***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Durable	0.41***	0.93***	0.72***	0.88***	0.62***	0.40***
	(0.06)	(0.11)	(0.09)	(0.10)	(0.08)	(0.05)
Emp Cost	0.74***	1.60***	1.24***	1.60***	1.25***	0.81***
	(0.11)	(0.23)	(0.18)	(0.22)	(0.17)	(0.11)
Retail	0.27***	0.68***	0.42***	0.44***	0.30***	0.08
	(0.08)	(0.12)	(0.09)	(0.10)	(0.09)	(0.06)
Retail Ex. Auto	0.43***	1.05***	0.99***	1.26***	1.00***	0.76***
	(0.07)	(0.13)	(0.10)	(0.11)	(0.09)	(0.06)
GDP	0.70***	1.73***	1.31***	1.71***	1.30***	0.76***
	(0.07)	(0.15)	(0.10)	(0.14)	(0.11)	(0.08)
CPI	0.01	-0.05	0.01	0.08	0.13	0.18***
	(0.05)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
Core CPI	0.70***	1.62***	1.17***	1.50***	1.23***	0.78***
	(0.06)	(0.11)	(0.08)	(0.10)	(0.08)	(0.06)
PPI	0.11**	0.25***	0.20***	0.18**	0.23***	0.16***
	(0.05)	(0.09)	(0.07)	(0.08)	(0.07)	(0.05)
Core PPI	0.64***	1.17***	0.81***	1.09***	0.94***	0.71***
	(0.07)	(0.10)	(0.08)	(0.09)	(0.07)	(0.05)
Hourly Earnings	0.88***	1.84***	1.45***	2.02***	1.61***	0.97***
	(0.12)	(0.17)	(0.14)	(0.17)	(0.14)	(0.09)
Unemp	−1.21***	−2.02***	−1.63***	−1.65***	−1.14***	−0.65***
	(0.11)	(0.18)	(0.14)	(0.15)	(0.12)	(0.08)
FOMC	0.64***	0.52***	0.31***	0.22***	0.09***	0.01***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.02)
$f_{CPI,t}$	0.97***	2.47***	1.99***	2.39***	1.84***	1.29***
	(0.08)	(0.11)	(0.08)	(0.09)	(0.07)	(0.06)
$f_{Durable,t}$	0.40**	1.69***	1.30***	1.45***	1.14***	0.72***
	(0.19)	(0.12)	(0.07)	(0.11)	(0.10)	(0.07)
$f_{EmpCost,t}$	0.66***	2.21***	1.95***	2.37***	1.75***	1.21***
	(0.18)	(0.31)	(0.19)	(0.25)	(0.21)	(0.16)
$f_{GDP,t}$	1.21***	2.99***	2.15***	2.72***	2.22***	1.34***
	(0.35)	(0.23)	(0.19)	(0.22)	(0.18)	(0.12)
$f_{Claims,t}$	0.57***	1.34***	0.93***	1.10***	0.82***	0.48***
	(0.15)	(0.17)	(0.10)	(0.10)	(0.07)	(0.04)
$f_{NonFarm,t}$	2.42***	5.68***	4.53***	5.49***	4.08***	2.45***
	(0.25)	(0.22)	(0.19)	(0.15)	(0.17)	(0.15)
$f_{PPI,t}$	1.22***	2.26***	1.83***	2.13***	1.76***	1.23***
	(0.14)	(0.13)	(0.08)	(0.11)	(0.09)	(0.06)
$f_{Retail,t}$	1.20***	2.91***	2.13***	2.29***	1.73***	1.00***
	(0.18)	(0.20)	(0.11)	(0.11)	(0.09)	(0.07)
$f_{FOMC,t}$	1.90***	6.17***	4.79***	4.99***	3.40***	1.84***
	(0.42)	(0.36)	(0.23)	(0.33)	(0.24)	(0.17)
R^2 No Factor	0.41	0.36	0.35	0.35	0.34	0.29
R^2 Release Factors	0.69	0.94	0.95	0.96	0.90	0.79

Table 12: As for Table 4, except with an unrestricted variance-covariance matrix for the background noise.

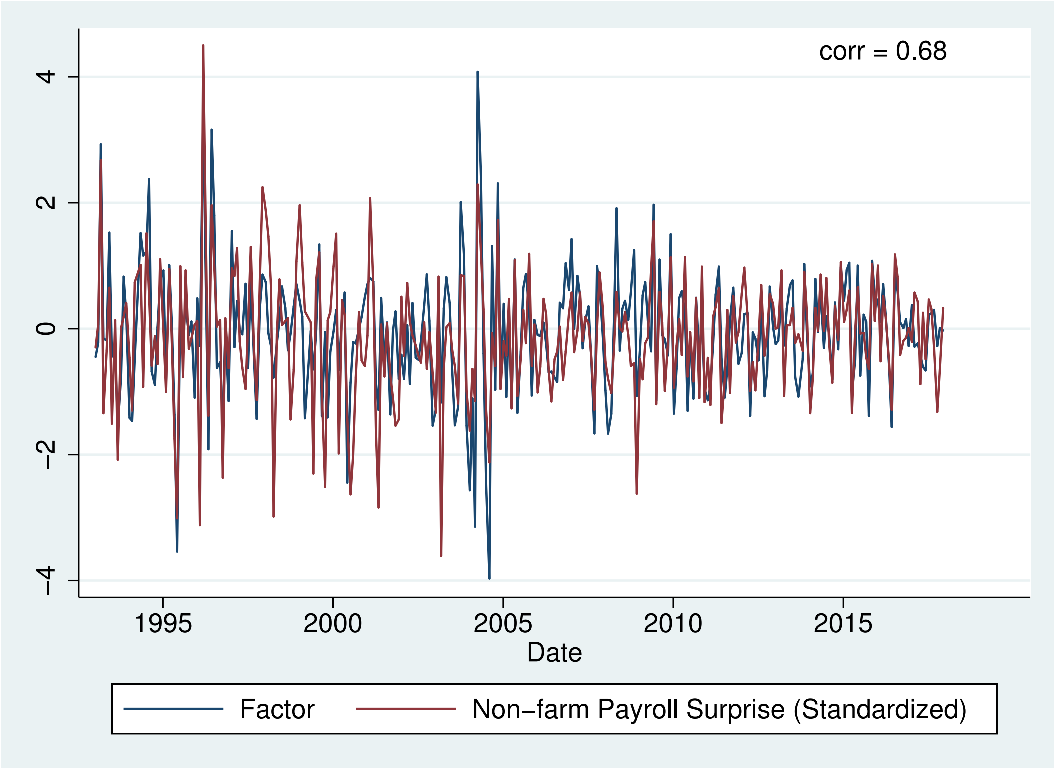

Figure 1: Shows the time series of nonfarm payrolls surprise and the latent factor estimated around employment report days treating nonfarm payrolls surprise as unobservable.

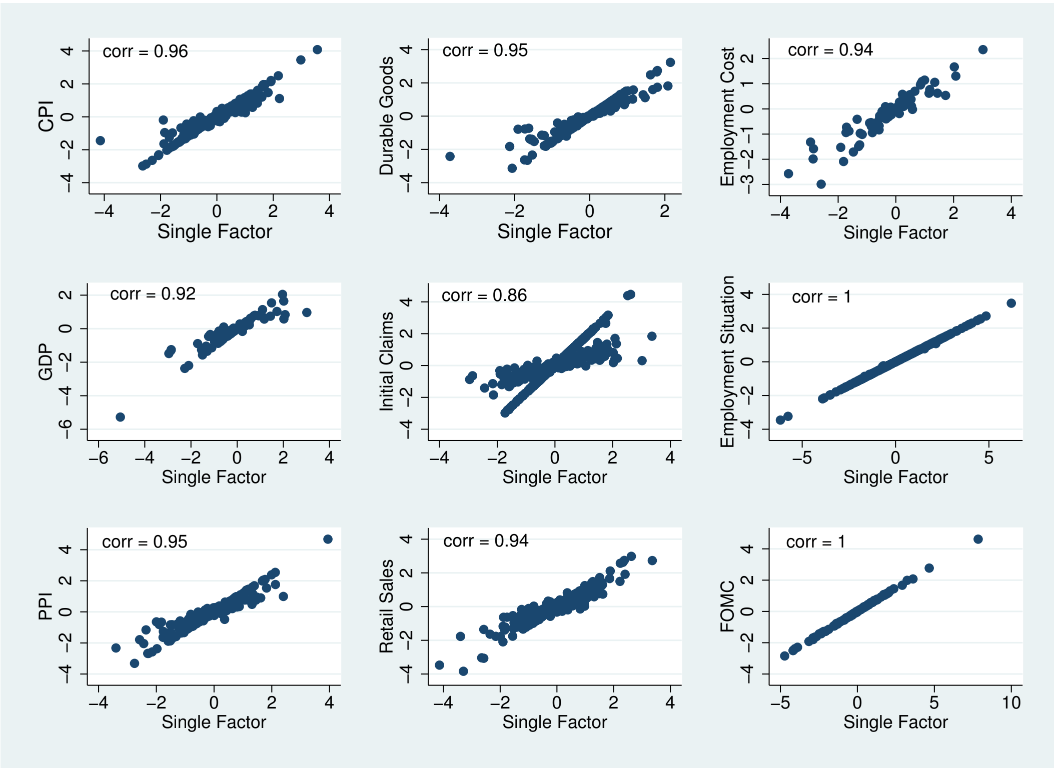

Figure 2: Scatter plot of the single factor and individual release factors around relevant event windows.

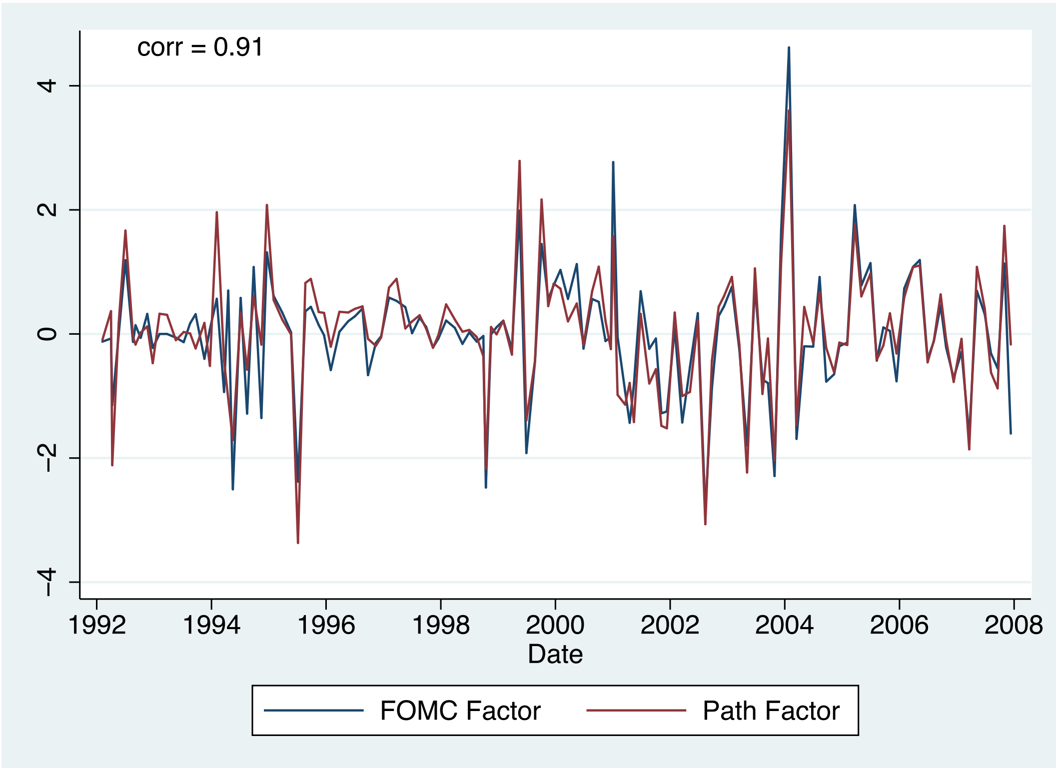

Figure 3: Comparison of Gürkaynak et al. (2005) path factor and the estimated latent factor. Path factor is standardized to have unit variance. Latent factor estimated from monetary policy surprises and the asset price responses around monetary policy announcements. The sample is 1992-2007.

Appendices

A. Data Sources and Construction

Our data sources and basic information on the releases are presented in the table below.

Data Release	Source	Frequency	Release time	Surprise St. Dev.	Units
Non-farm	BLS	Monthly	8:30	90.81	Thousands
Init. Claims	ETA	Weekly	8:30	17.82	Thousands
Durable	Census	Monthly	8:30	2.74	Percentage change mom
Emp. Cost	BLS	Monthly	8:30	0.19	Percentage change mom
Retail	Census	Monthly	8:30	0.55	Percentage change mom
Retail Ex. Auto	Census	Monthly	8:30	0.42	Percentage change mom
GDP (advance)	BEA	Quarterly	8:30	0.75	Percentage change qoq, ar
CPI	BLS	Monthly	8:30	0.12	Percentage change mom
Core CPI	BLS	Monthly	8:30	0.09	Percentage change mom
PPI	BLS	Monthly	8:30	0.40	Percentage change mom
Core PPI	BLS	Monthly	8:30	0.25	Percentage change mom
Hourly Earn.	BLS	Monthly	8:30	0.15	Dollars per hour
Unemp.	BLS	Monthly	8:30	0.14	Percent
FOMC	Fed	8 per year	14:15*	8.1	Basis points

(*) We incorporate some minor deviations of timing to accommodate FOMC announcement times in the early sample. However, in the majority of our sample the announcements are made around 14:15.

Notes: Acronyms for the sources are as follows: BEA (Bureau of Economic Analysis), BLS (Bureau of Labor Statistics), Census (Bureau of the Census), ETA (Employment and Training Administration), Fed (Federal Reserve Board of Governors). Acronyms of the unite are: mom (month-on-month), qoq (quarter-on-quarter) and ar (annualized rate). Standard deviations are for the sample 1992-2017. For the FOMC, the sample is 1992-2007.

To calculate the macroeconomic data release surprises used in the study we proceed as follows. Let $R_{j,t}$ be the released value of a variable j at time t. Let $E_{j,t}$ be the expectation (or the survey) of this release. Then the surprise is defined as:

$$S_{j,t} = R_{j,t} - E_{j,t}$$

Then we standardize the surprises to so that units are comparable across different types of announcements, and transmission coefficients capture per standard deviation effects:

$$s_{j,t} = \frac{S_{j,t}}{\sigma_{S_j}}$$

where σ_{S_j} is the standard deviation of the surprise for the announcement type j. For expectations, we use the median prediction from the survey conducted by MMS/Action Economics on the previous Friday of a release.

Monetary policy surprises are measured using intraday changes of Fed Funds Futures implied yield changes around FOMC announcements, following the methodology of Kuttner (2001).

For the yields, our high frequency data consists of 5-minute quotes of first Eurodollar (ED1), fourth Eurodollar (ED4), on the run 2-year, 5-year, 10-year and 30-year Treasury futures from Chicago Mercantile Exchange (CME). Eurodollar futures prices are converted to interest rates by subtracting the price of ED1 and ED4 from 100. We calculate 20-minute changes in future prices around macroeconomic and FOMC releases:

$$\Delta P_{j,d} = P_{j,d,t-5min} - P_{j,d,t+15min}$$

where $P_{j,d}$ is the futures price of an asset $j \in$\{2-year, 5-year, 10-year, 30-year\} on the day d of a specific announcement and t is the time of that announcement (e.g. 8:30am). For Eurodollar futures, we use implied interest rates to calculate announcement window changes. For the Treasury futures, we divide the price changes by the approximate duration of the bonds and flip the sign to convert them to yield changes.

B. Heteroskedasticity-Based Estimation Applied to the OLS Residuals

An event study regression with a latent factor and no measurement error has the form:

$$y_t = \beta s_t + \gamma d_t f_t + \varepsilon_t$$

where $s_t = s_t^*$. In the usual event study setup, β can be separately identified by OLS run on data from event days. The residual of this regression is:

$${\phi_t}^E = \gamma f_t + \varepsilon_t$$

The counterpart for non-event days is:

$${\phi_t}^{NE} = \varepsilon_t$$

We then have the following event and non-event variance-covariance matrices for ϕ_t:

$$\Omega^{\phi_E} = \begin{pmatrix} \gamma^2 + \sigma_\varepsilon^2 & 0 \\ . & \sigma_s^2 \end{pmatrix}$$

$$\Omega^{\phi_{NE}} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

Thus, the heteroskedasticity-based estimator for γ is given by $\sqrt{\hat{\Omega}_{1,1}^{\phi_E} - \hat{\Omega}_{1,1}^{\phi_{NE}}}$. Below we show that this two-step estimation procedure produces similar coefficients to the one step estimation we employed.

We demonstrate this point by considering FOMC announcements. To make sure that our results are not influenced by the different number of observations, we drop the days with at least one missing yield change. Then, we estimate equation (3.2) around FOMC announcement days and compare the estimates of γ from the one step estimation with that of the two step estimates.

	ED1	ED4	2-year	5-year	10-year	30-year
Kalman Filter	2.10	6.96	5.62	6.00	4.24	2.44
Two-step	2.84	6.64	5.05	5.20	3.89	2.54

Notice that the estimated coefficients are very close, implying that Kalman filter and the (two step) heteroskedasticity-based estimates are very similar. But the estimates are not exactly equal. The Kalman filter takes into account the covariance between yield changes around announcements, since the filter uses all assets at once. However, the two step estimation is done asset by asset. Due to this information loss, coefficients are slightly different.

C. OLS and Heteroskedasticity-based Estimators

We consider a general model which incorporates both measurement error and an unobservable latent factor, nesting both cases. The model is:

$$y_t = \beta s_t^* + \gamma d_t f_t + \varepsilon_t$$
$$s_t = s_t^* + \eta_t$$

where y_t is a log return or yield change (a scalar, without loss of generality), s_t is the observed surprise, s_t^* is the true headline surprise, d_t is a dummy that is 1 on an announcement day and 0 otherwise, f_t is an iid $N(0,1)$ latent variable, and ε_t and η_t are processes measuring noise in yields and measurement error of the headline surprise. We assume that s_t, ε_t and η_t are iid, mutually uncorrelated, have mean zero, and variances σ_*^2, σ_ε^2 and σ_η^2, respectively. To estimate β, the parameter of interest in event studies, using OLS and identification through heteroskedasticity, we need the variance-covariance matrices for event (Ω^E) and non-event (Ω^{NE}) windows:

$$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_*^2 + \sigma_\eta^2 \end{pmatrix}, \ \Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

In this general model, the OLS estimate for β is:

$$\hat{\beta}^{OLS} = \frac{[\hat{\Omega}^E]_{1,2}}{[\hat{\Omega}^E]_{2,2}}$$

and the identification through heteroskedasticity estimate of β is:

$$\hat{\beta}^{HET} = \frac{[\hat{\Omega}^E]_{1,1} - [\hat{\Omega}^{NE}]_{1,1}}{[\hat{\Omega}^E]_{1,2}}$$

Below we derive the OLS and heteroskedasticity-based estimates in four possible cases:

1. $\gamma = 0$, $\sigma_\eta^2 = 0$ This is the case where there is neither measurement error nor a latent factor.

   Since $s_t = s_t^*$, the model simplifies to:

   $$y_t = \beta s_t^* + \varepsilon_t$$

   The variance-covariance matrices around event and non-event windows are as follows:

   $$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_*^2 \end{pmatrix}$$
   $$\Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

The OLS coefficient is given by:

$$\frac{\beta\sigma_*^2}{\sigma_*^2} = \beta$$

Heteroskedasticity-based estimate is given by:

$$\frac{\beta^2\sigma_*^2 + \sigma_\varepsilon^2 - \sigma_\varepsilon^2}{\sigma_*^2} = \beta$$

In this case both estimates are consistent and should produce the same result.

2. $\gamma = 0$, $\sigma_\eta^2 \neq 0$

   This case is the classical errors in variables problem for survey-based surprises that Rigobon and Sack (2006) consider. Now the model takes the following form:

$$\begin{aligned} y_t &= \beta s_t^* + \varepsilon_t \\ s_t &= s_t^* + \eta_t \end{aligned}$$

   Variance-covariance matrices around event and non-event windows are given as follows:

$$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_s^2 \end{pmatrix}$$

$$\Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

   The OLS coefficient is given by:

$$\frac{\beta\sigma_*^2}{\sigma_s^2} = \frac{\beta\sigma_*^2}{\sigma_*^2 + \sigma_\eta^2} = \beta\left(1 - \frac{\sigma_\eta^2}{\sigma_*^2 + \sigma_\eta^2}\right)$$

   Heteroskedasticity-based estimator is given by:

$$\frac{\beta^2\sigma_*^2 + \sigma_\varepsilon^2 - \sigma_\varepsilon^2}{\beta\sigma_*^2} = \beta$$

   In this case OLS has attenuation bias but heteroskedasticity-based estimate is consistent.

3. $\gamma \neq 0$, $\sigma_\eta^2 = 0$

   In this case, since $s_t = s_t^*$ the model takes the following form:

$$y_t = \beta s_t^* + \gamma d_t f_t + \varepsilon_t$$

   Model implied variance-covariance matrices around event and non-event windows are given by:

$$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_*^2 \end{pmatrix}$$
$$\Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

The OLS coefficient is given by:

$$\frac{\beta\sigma_*^2}{\sigma_*^2} = \beta$$

Using the variance-covariance matrices we can derive the heteroskedasticity-based estimator:

$$\frac{\beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 - \sigma_\varepsilon^2}{\beta\sigma_*^2} = \beta + \frac{\gamma^2}{\beta\sigma_*^2} = \beta\left(1 + \frac{\gamma^2}{\beta^2\sigma_*^2}\right)$$

This time OLS is consistent and heteroskedasticty-based estimate is increased in absolute value due to the variance of the latent factor. The paper shows that this is the relevant case.

4. $\gamma \neq 0$, $\sigma_\eta^2 \neq 0$

Now we are back to the general model:

$$y_t = \beta s_t^* + \gamma d_t f_t + \varepsilon_t$$
$$s_t = s_t^* + \eta_t$$

Event and non-event window variance-covariance matrices are given as follows:

$$\Omega^E = \begin{pmatrix} \beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 & \beta\sigma_*^2 \\ . & \sigma_s^2 \end{pmatrix}$$
$$\Omega^{NE} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix}$$

Using the event window variance covariance matrix, we derive the OLS coefficient:

$$\frac{\beta\sigma_*^2}{\sigma_s^2} = \frac{\beta\sigma_*^2}{\sigma_*^2 + \sigma_\eta^2} = \beta\left(1 - \frac{\sigma_\eta^2}{\sigma_*^2 + \sigma_\eta^2}\right)$$

The heteroskedasticity-based estimate is given as follows:

$$\frac{\beta^2\sigma_*^2 + \gamma^2 + \sigma_\varepsilon^2 - \sigma_\varepsilon^2}{\beta\sigma_*^2} = \beta + \frac{\gamma^2}{\beta\sigma_*^2} = \beta\left(1 + \frac{\gamma^2}{\beta^2\sigma_*^2}\right)$$

The table below summarizes the four cases and their implications for the coefficients:

Case	$\hat{\beta}^{OLS} \rightarrow$	$\hat{\beta}^{HET} \rightarrow$
1. $\gamma = 0, \sigma_\eta^2 = 0$	β	β
2. $\gamma = 0, \sigma_\eta^2 \neq 0$	$\beta(1 - \frac{\sigma_\eta^2}{\sigma_*^2+\sigma_\eta^2})$	β
3. $\gamma \neq 0, \sigma_\eta^2 = 0$	β	$\beta(1 + \frac{\gamma^2}{\beta^2\sigma_*^2})$
4. $\gamma \neq 0, \sigma_\eta^2 \neq 0$	$\beta(1 - \frac{\sigma_\eta^2}{\sigma_*^2+\sigma_\eta^2})$	$\beta(1 + \frac{\gamma^2}{\beta^2\sigma_*^2})$

In the paper, we rule out cases 1, 2 and 4. Furthermore, if the interpretation offered by case 3 is correct, the heteroskedasticity-based estimator should provide an estimate approximately equal to the sum of the OLS event study estimate, and the variation caused due to the unobservable component of the news. We check this in the table below. Here γ^2 is identified following the methodology in Appendix B. The OLS estimates for the announcements differ from Table 1 because days with multiple releases are dropped. It is striking that the sum in all cases is about equal to the heteroskedasticity-based estimator. The difference (for some coefficients) is caused by small sample issues (verified by a Monte Carlo exercise) and they are economically insignificant. This validates that the extra term in the heteroskedasticity-based estimator is indeed the unobserved news effect and that this estimator finds the combined effect of the headline surprise and the latent factor.

(a) β^{HET}

IDHET

	ED1	ED4	TU	FV	TY	US
Non-Farm	7.98	13.23	10.25	12.23	9.45	6.32
Initial Claims	-1.69	-2.66	-1.81	-2.36	-1.99	-1.47
Durable	1.02	3.43	3.32	3.46	2.86	1.80
Emp Cost	2.74	3.39	2.40	3.14	2.38	1.55
Retail Ex. Auto	5.19	7.33	3.96	3.96	3.00	1.81
GDP (advance)	7.59	8.08	5.76	6.77	5.46	2.91
Core CPI	2.79	5.75	4.02	5.22	4.12	2.90
Core PPI	4.22	5.33	4.41	5.59	4.70	3.20
FOMC	0.94	2.70	2.57	3.95	6.25	-7.46

(b) β^{OLS}

OLS

	ED1	ED4	TU	FV	TY	US
	3.27	5.99	4.81	5.49	4.10	2.48
	-0.36	-0.77	-0.62	-0.72	-0.57	-0.35
	0.52	1.03	0.84	1.08	0.79	0.50
	0.45	1.25	0.82	1.21	0.93	0.54
	0.36	1.04	0.92	1.23	0.95	0.67
	0.98	2.22	1.75	1.99	1.42	0.78
	0.76	1.73	1.06	1.77	1.51	1.06
	0.95	1.40	1.17	1.49	1.27	0.96
	0.53	0.43	0.21	0.15	0.05	-0.01

(c) γ^2

	ED1	ED4	2-year	5-year	10-year	30-year
Non-Farm	15.47	43.43	26.33	36.98	21.99	9.53
Initial Claims	0.49	1.52	0.76	1.18	0.81	0.39
Durable	0.26	2.72	2.10	2.58	1.64	0.65
Emp Cost	1.07	2.77	1.29	2.34	1.35	0.55
Retail Ex. Auto	1.73	6.79	2.78	3.39	1.96	0.77
GDP (advance)	6.49	13.01	7.07	9.51	5.73	1.66
Core CPI	1.53	7.23	3.11	6.15	3.96	1.95
Core PPI	3.15	5.22	3.99	6.11	4.35	2.14
FOMC	10.95	48.99	26.33	26.64	13.53	4.80

(d) $\beta^{OLS} + \frac{\gamma^2}{\beta\sigma_s^2}$

Sum

	ED1	ED4	TU	FV	TY	US
	8.00	13.24	10.29	12.23	9.46	6.32
	-1.70	-2.75	-1.85	-2.36	-1.99	-1.47
	1.03	3.68	3.34	3.46	2.87	1.80
	2.81	3.46	2.40	3.14	2.38	1.55
	5.22	7.57	3.94	3.98	3.02	1.82
	7.59	8.08	5.79	6.77	5.46	2.91
	2.78	5.91	3.99	5.24	4.14	2.90
	4.26	5.13	4.59	5.59	4.70	3.20
	0.94	2.70	2.57	3.95	6.25	-7.47

Table A1: a) Heteroskedasticity-based Event Study Estimates b) OLS-based Event Study Estimates c) Effect of the latent factor (identified following Appendix B) d) Reconstructing the heteroksedasticity-based estimates from the OLS-based estimates and the latent factor effects