Online Appendix for "Missing Events in Event Studies: Identifying the Effects of Partially-Measured News Surprises" by Refet S. Gürkaynak, Burçin Kısacıkoğlu and Jonathan H. Wright.

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	91.52	Thousands
Init. Claims	ETA	Weekly	8:30	17.60	Thousands
Durable	Census	Monthly	8:30	2.71	Percentage change mom
Emp. Cost	BLS	Monthly	8:30	0.19	Percentage change mom
Retail	Census	Monthly	8:30	0.54	Percentage change mom
Retail Ex. Auto	Census	Monthly	8:30	0.41	Percentage change mom
GDP (advance)	BEA	Quarterly	8:30	0.73	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
Unemployment	BLS	Monthly	8:30	0.14	Percent
FOMC	Fed	8 per year	14:15*	8.42	Basis points

(*) We incorporate some minor deviations of timing to accommodate FOMC announcement times.

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 units are: mom (month-on-month), qoq (quarter-on-quarter) and ar (annualized rate). Standard deviations are for the sample 1992-2018. 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 so that units are comparable across different types of announcements and 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 Friday before the 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 yields, our high-frequency data consist of 5-minute quotes of first Eurodollar (ED1), fourth Eurodollar (ED4), 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 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 population 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 variance-covariance matrix for $(\phi_t^E, s_t)'$ on event days:

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

The counterpart for non-event days is:

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

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 (8) 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	6.07	4.50	5.17	3.62	2.04
Two-step	3.22	6.84	4.80	5.06	3.61	2.15

Notice that the estimated coefficients are close, implying that Kalman filter and the (two step) heteroskedasticity-based estimates are 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. The two estimators would be numerically identical if we used just one asset.

The exercise above clearly shows that there is a need for a latent factor to explain yield changes around announcements. However, one could directly compare the OLS residual variances on announcement and non announcement days to see if the variance of residuals around announcement days are larger than the non-announcement days. Table below shows the results of this exercise:

	$\text{var}(\phi_t^E)$	$\text{var}(\phi_t^{NE})$	$\text{var}(\phi_t^E) - \text{var}(\phi_t^{NE})$	F-test stat
ED1	3.41	0.80	2.61	4.26***
ED4	11.61	1.96	9.65	5.93***
2-year	6.76	1.11	5.65	6.09***
5-year	9.49	1.58	7.91	5.97***
10-year	5.97	1.14	4.83	5.24***
30-year	2.84	0.66	2.18	4.29***

The second and third columns of the table show the variance of OLS residuals on *all* announcement and non-announcement days, respectively. The fourth column is the difference between variances and the last column is the F-test statistic (the ratio between announcement and non-announcement day variances of OLS residuals) testing for equal variances. The table shows that the announcement day residual variance is larger (statistically significant at 1% level) than the non-announcement day residual variance, which allows our methodology to identify the latent factor. To make this more concrete, we calculate the difference between announcement and non announcement day residual variance covariance matrices and show that the estimated γ coefficients given in Table 3 can closely match the difference in the variance covariance matrices.

Difference in Variance Covariance Matrices:						
	ED1	ED4	2-year	5-year	10-year	30-year
ED1	2.61					
ED4	3.95	9.65				
2-year	2.95	7.02	5.65			
5-year	3.12	8.08	6.28	7.91		
10-year	2.25	6.00	4.65	6.06	4.83	
30-year	1.31	3.69	2.84	3.79	3.12	2.18
One factor representation as $\gamma\gamma'$:						
	ED1	ED4	2-year	5-year	10-year	30-year
ED1	1.88					
ED4	4.30	9.86				
2-year	3.32	7.60	5.86			
5-year	4.03	9.23	7.11	8.64		
10-year	3.12	7.16	5.52	6.70	5.20	
30-year	2.00	4.58	3.53	4.29	3.33	2.13

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:

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

The 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:

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

   The 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:

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

   The 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}

	ED1	ED4	TU	FV	TY	US
Non-farm	7.47	12.92	9.97	12.03	9.33	6.22
Initial Claims	-1.51	-2.52	-1.72	-2.23	-1.87	-1.35
Durable	0.93	3.28	3.39	3.52	2.94	1.98
Emp Cost	3.05	3.39	2.54	3.08	2.34	1.51
Retail ex auto	1.98	4.26	2.78	2.56	1.88	1.23
GDP	7.40	7.86	5.82	6.63	5.46	3.04
Core CPI	2.67	5.61	3.90	4.98	3.89	2.79
Core PPI	4.08	5.31	4.33	5.46	4.58	3.10
FOMC	0.85	1.93	1.46	3.11	6.69	-4.09

(b) β^{OLS}

ED1	ED4	TU	FV	TY	US
2.94	5.70	4.59	5.34	4.02	2.45
-0.34	-0.73	-0.59	-0.69	-0.54	-0.33
0.49	0.97	0.80	0.99	0.72	0.45
0.34	1.06	0.71	1.21	0.92	0.52
0.32	0.97	0.86	1.21	0.94	0.67
0.94	2.13	1.62	1.92	1.37	0.76
0.71	1.67	1.06	1.73	1.46	1.03
0.91	1.27	1.11	1.40	1.20	0.91
0.57	0.43	0.27	0.14	0.03	-0.02

(c) γ^2

	ED1	ED4	TU	FV	TY	US
Non-farm	13.38	41.16	24.76	35.71	21.37	9.24
Initial Claims	0.40	1.36	0.69	1.06	0.72	0.34
Durable	0.22	2.44	2.07	2.50	1.60	0.69
Emp Cost	0.94	2.55	1.30	2.26	1.31	0.51
Retail ex auto	0.53	3.29	1.64	1.65	0.89	0.38
GDP	6.06	12.21	6.85	9.04	5.59	1.73
Core CPI	1.38	6.76	2.98	5.65	3.57	1.81
Core PPI	2.92	4.72	3.73	5.68	4.07	2.00
FOMC	10.39	46.73	23.07	25.58	13.02	4.64

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

ED1	ED4	TU	FV	TY	US
7.49	12.92	9.98	12.03	9.34	6.22
-1.52	-2.60	-1.76	-2.23	-1.88	-1.35
0.93	3.49	3.40	3.52	2.94	1.98
3.13	3.46	2.54	3.08	2.34	1.51
1.99	4.35	2.76	2.57	1.88	1.24
7.38	7.86	5.84	6.63	5.46	3.04
2.66	5.72	3.87	5.00	3.90	2.79
4.12	4.99	4.48	5.46	4.58	3.10
0.85	1.93	1.46	3.11	6.69	-4.09

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

D. Identification and the Kalman Filter

In this section we consider a model with a single latent factor and show how the model is identified. Consider the model given in equation (7):

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

where y_t is an $n \times 1$ vector of returns or yield changes, s_t is a $K \times 1$ vector of surprises in macroeconomic or monetary policy announcements, which are observed without error, d_t is a dummy that is 1 if there is an announcement in that window or 0 otherwise, f_t is an iid $N(0, \sigma_f^2)$ latent variable that is common to all releases, β is a $K \times n$ matrix of loadings on the observable surprises, γ is an $n \times 1$ vector of loadings on the latent factor, and ε_t is iid with mean zero and diagonal variance-covariance matrix of Σ_ε.

As discussed in the text, we uncover f_t using Kalman filter, which is estimated via maximum likelihood. The log-likelihood function for this model can be written as:

$$\begin{aligned} l(\theta) = -\frac{1}{2}\Sigma_{t=1}^{T}\mathbf{1}(d_t = 1)\{(y_t - \beta' s_t)'(\Sigma_\varepsilon + \gamma\gamma')^{-1}(y_t - \beta' s_t) + \log(|\Sigma_\varepsilon + \gamma\gamma'|)\} \\ + \mathbf{1}(d_t = 0)\{y_t'\Sigma_\varepsilon^{-1} y_t + \log(|\Sigma_\varepsilon|)\} \end{aligned}$$

where $\mathbf{1}(.)$ is an indicator function and θ is the vector of parameters to be estimated. Note that, given the number of assets n, the log-likelihood function implies a system of n equations. With these n equations, one needs to identify the coefficients in β and γ, the variances in Σ_ε, and σ_f^2. However, without further restrictions, we can clearly only identify γ up to scale. Hence to be able to identify γ we impose the identifying restriction that σ_f^2 is unity. We also normalize one element of γ to be positive (say the first, without loss of generality). We explain this below.

To show identification, the expected log-likelihood has a unique maximum satisfying the following equations:

1. For β:

$$\begin{aligned} E[\mathbf{1}(d_t = 1) s_t \otimes (\Sigma_\varepsilon + \gamma\gamma')^{-1}(y_t - \beta' s_t)] = 0 \\ \therefore vec\left((\Sigma_\varepsilon + \gamma\gamma')^{-1} E[\mathbf{1}(d_t = 1)(y_t - \beta' s_t) s_t']\right) = 0 \\ \therefore E[\mathbf{1}(d_t = 1)(y_t - \beta' s_t) s_t'] = 0 \\ \therefore \beta = E(\mathbf{1}(d_t = 1) s_t s_t')^{-1} E(\mathbf{1}(d_t = 1) s_t y_t') \end{aligned}$$

   where the second line uses $vec(ABC) = (C' \otimes A)vec(B)$. Last condition implies that the maximum likelihood estimate of β should be the same as OLS estimates that are estimated from announcement days only.

2. For Σ_ε:

$$\Sigma_\varepsilon = E(y_t' y_t \mathbf{1}(d_t = 0))$$

3. For γ:

$$\gamma\gamma' = E((y_t - \beta' s_t)'(y_t - \beta' s_t)\mathbf{1}(d_t = 1)) - \Sigma_\varepsilon$$

   Here the parameters are identified as long as one can recover γ from $\gamma\gamma'$, which requires the sign of one element of γ is normalized to be positive.

Note that this identification scheme is valid even if y_t is a scalar. In this case, the condition for γ reduces to:

$$\gamma^2 = E((y_t - \beta' s_t)^2 \mathbf{1}(d_t = 1)) - \sigma_\varepsilon^2$$

where σ_ε^2 is the variance of the noise. For a non-degenerate distribution of d_t, one can recover γ using the Kalman filter as long as the latent factor is heteroskedastic and the noise is homoskedastic. Importantly, yield covariances are not needed to identify γ.

The Kalman filter gives a recipe for computing the log-likelihood and obtaining an estimate of the latent factor. It is a non-standard application of the Kalman filter because equation (7) is the measurement equation, but the transition equation is degenerate as the latent factor is simply iid.

The updating equations of the Kalman filter specify that the estimate of the factor as of time t is:

$$f_{t|t} = \gamma' F_t^{-1} v_t d_t$$

with variance:

$$P_{t|t} = 1 - \gamma' F_t^{-1} \gamma d_t$$

where $F_t = (\gamma\gamma' d_t + \Sigma_\varepsilon)^{-1}$ and $v_t = y_t - \beta' s_t$. The prediction equations are degenerate as the density of the factor at time $t+1$ conditional on data at time t is simply normal with mean zero and variance 1. The log-likelihood is then given by:

$$l(\theta) = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\Sigma_{t=1}^T \log|F_t| - \frac{1}{2}\Sigma_{t=1}^T v_t' F_t^{-1} v_t.$$

E. Response of 10 Industry Sorted Portfolio Returns to Non-farm Payroll Surprises and the Latent Factor

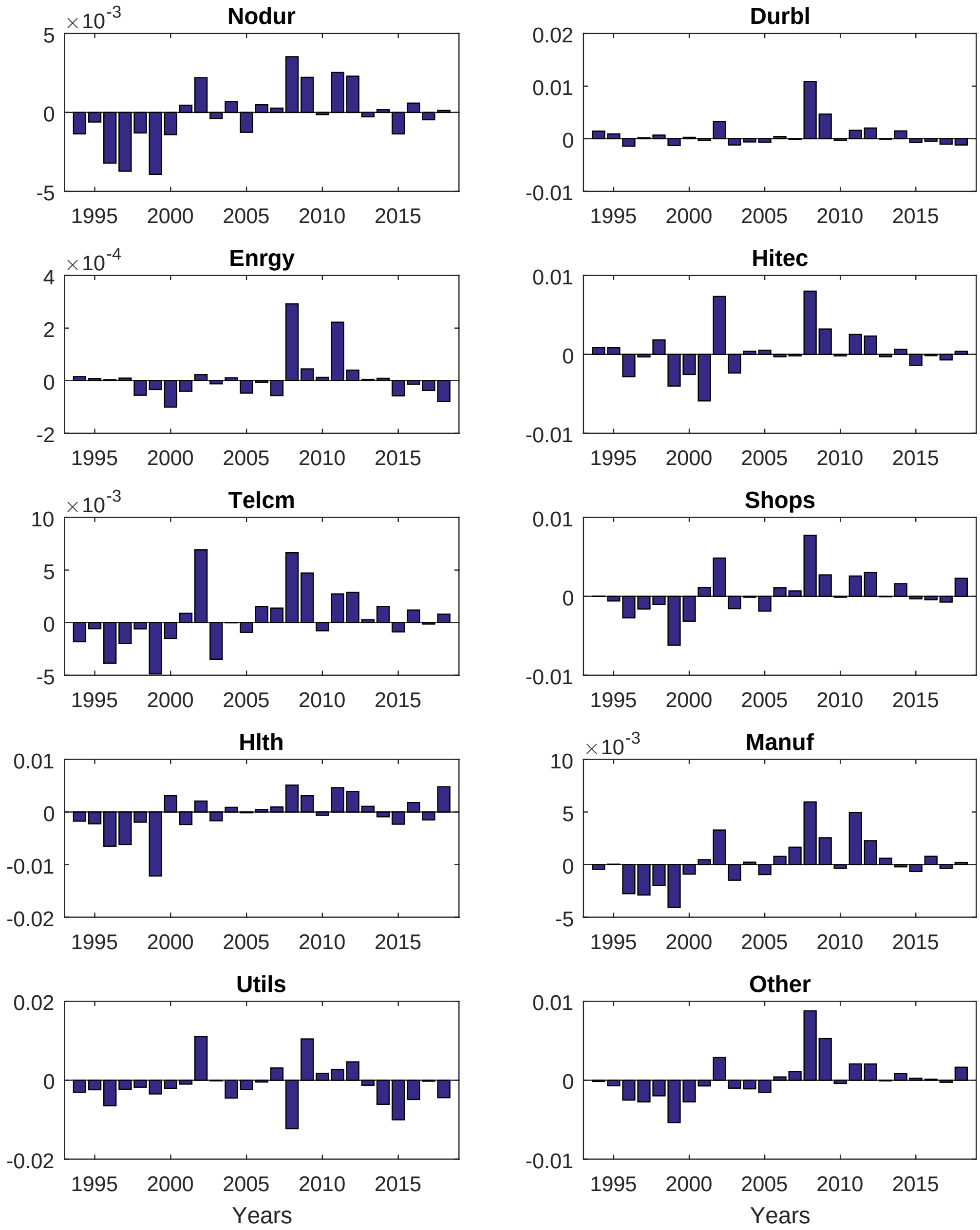


Figure A1: Time-varying response of 10 industry sorted portfolio returns to non-farm payroll surprise obtained from estimating equation (11). Sample is from 1994 to 2018. Return data are from Kenneth French's Data Library.

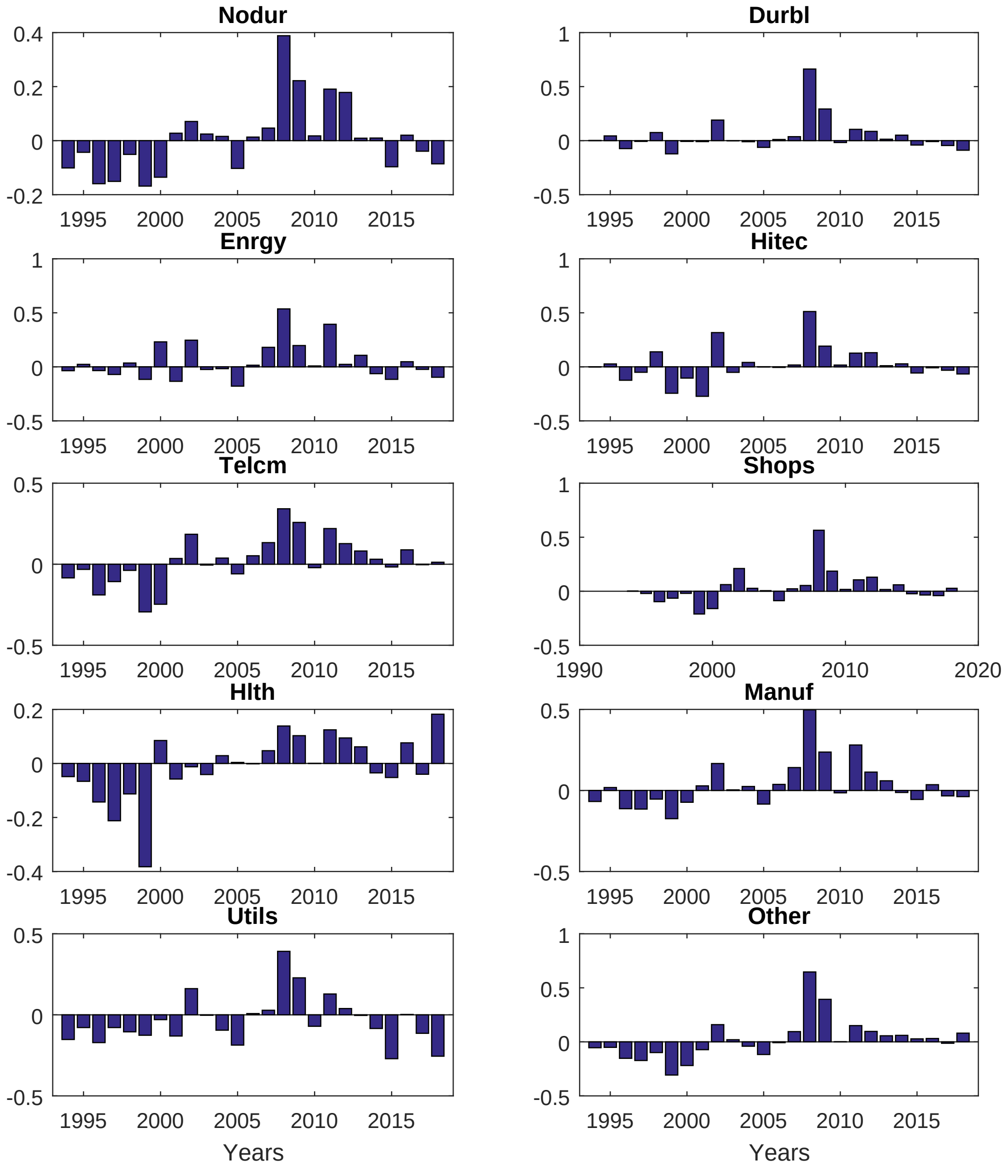


Figure A2: Time-varying response of 10 industry sorted portfolio returns to the latent factor obtained from estimating equation (12). Sample is from 1994 to 2018. Return data are from Kenneth French's Data Library.

F. Nonlinear Responses

	ED1	ED4	2-year	5-year	10-year	30-year
Core CPI×(Core CPI>0)	0.94***	2.02***	1.47***	1.92***	1.62***	1.04***
	(0.16)	(0.37)	(0.28)	(0.31)	(0.25)	(0.19)
Durable× (Durable>0)	0.31*	0.54*	0.47**	0.51**	0.34*	0.20
	(0.16)	(0.29)	(0.24)	(0.24)	(0.20)	(0.12)
Emp Cost× (Emp Cost>0)	0.25	1.02***	0.78**	1.05***	0.83***	0.46**
	(0.18)	(0.41)	(0.39)	(0.45)	(0.36)	(0.22)
GDP×(GDP>0)	0.76***	1.56***	1.25***	1.59***	1.18***	0.62***
	(0.20)	(0.45)	(0.24)	(0.44)	(0.36)	(0.25)
Claims×(Claims>0)	−0.27***	−0.59***	−0.50***	−0.56***	−0.46***	−0.29***
	(0.07)	(0.10)	(0.08)	(0.09)	(0.08)	(0.05)
Non-farm×(Non-farm>0)	3.38***	6.57***	5.43***	6.30***	4.66***	2.96***
	(0.47)	(0.87)	(0.65)	(0.71)	(0.60)	(0.41)
Core PPI×(Core PPI>0)	0.33	0.42	0.40	0.69**	0.68***	0.49***
	(0.21)	(0.32)	(0.29)	(0.33)	(0.25)	(0.19)
Retail×(Retail>0)	0.13	0.56***	0.45***	0.43**	0.29	0.07
	(0.10)	(0.19)	(0.17)	(0.20)	(0.18)	(0.13)
Unemp×(Unemp>0)	−1.27***	-2.49***	−1.74***	−1.84***	−1.33***	−0.71**
	(0.49)	(0.65)	(0.52)	(0.60)	(0.48)	(0.28)
Hourly Earn.×(Hourly Earn.>0)	0.47	1.81***	1.71***	1.98***	1.71***	1.04***
	(0.38)	(0.68)	(0.53)	(0.64)	(0.51)	(0.35)
PPI×(PPI>0)	0.21	0.49*	0.35	0.36	0.33	0.31**
	(0.16)	(0.29)	(0.26)	(0.30)	(0.22)	(0.16)
Ret ex. Auto×(Ret ex. Auto>0)	0.46***	1.05***	0.90***	1.03***	0.83***	0.63***
	(0.12)	(0.31)	(0.28)	(0.29)	(0.24)	(0.17)
CPI×(CPI>0)	-0.22	-0.42	-0.31	-0.07	-0.03	0.10
	(0.16)	(0.38)	(0.26)	(0.36)	(0.28)	(0.21)
FOMC×(FOMC>0)	0.53***	0.37	0.22	0.17	0.04	-0.03
	(0.10)	(0.26)	(0.16)	(0.15)	(0.11)	(0.06)
Core CPI×(Core CPI<0)	0.53***	1.04***	0.94***	1.25***	0.96***	0.61***
	(0.21)	(0.30)	(0.24)	(0.31)	(0.24)	(0.17)
Durable×(Durable<0)	0.48***	0.97***	0.96***	1.21***	0.88***	0.58***
	(0.14)	(0.26)	(0.20)	(0.22)	(0.17)	(0.12)
Emp Cost×(Emp Cost<0)	1.03***	2.00***	1.23***	1.85***	1.42***	0.98***
	(0.28)	(0.69)	(0.54)	(0.64)	(0.48)	(0.34)
GDP×(GDP<0)	0.51***	1.68***	1.10***	1.57***	1.24***	0.82***
	(0.16)	(0.47)	(0.29)	(0.35)	(0.28)	(0.18)
Claims×(Claims<0)	−0.35***	−0.82***	−0.67***	−0.76***	−0.61***	−0.36***
	(0.06)	(0.12)	(0.08)	(0.09)	(0.07)	(0.05)
Non-farm×(Non-farm<0)	2.46***	4.98***	3.84***	4.56***	3.50***	2.04***
	(0.48)	(0.74)	(0.60)	(0.68)	(0.50)	(0.32)
Core PPI×(Core PPI<0)	0.80***	1.38***	1.11***	1.25***	1.03***	0.82***
	(0.20)	(0.34)	(0.20)	(0.23)	(0.18)	(0.14)
Retail×(Retail<0)	0.90**	1.04*	0.88*	0.94*	0.69	0.39
	(0.39)	(0.62)	(0.49)	(0.54)	(0.42)	(0.29)
Unemp×(Unemp<0)	−1.19***	−1.60***	−1.29***	−1.41***	−0.94***	−0.53**
	(0.37)	(0.57)	(0.42)	(0.46)	(0.34)	(0.24)

Hourly Earn.×(Hourly Earn.<0)	1.21***	1.81***	1.31***	2.07***	1.54***	0.93***
	(0.43)	(0.62)	(0.47)	(0.57)	(0.46)	(0.32)
PPI×(PPI<0)	0.05	-0.05	-0.05	0.06	0.16	0.04
	(0.18)	(0.27)	(0.22)	(0.24)	(0.20)	(0.14)
Ret ex. Auto×(Ret ex. Auto<0)	0.05	0.46	0.65*	1.05***	0.82***	0.64***
	(0.27)	(0.44)	(0.38)	(0.42)	(0.34)	(0.23)
CPI×(CPI<0)	0.20	0.24	0.13	0.27	0.32	0.29**
	(0.16)	(0.31)	(0.22)	(0.25)	(0.21)	(0.15)
FOMC×(FOMC<0)	0.58***	0.45***	0.29***	0.14*	0.03	-0.02
	(0.09)	(0.11)	(0.10)	(0.08)	(0.05)	(0.02)
R^2	0.41	0.37	0.37	0.36	0.35	0.31

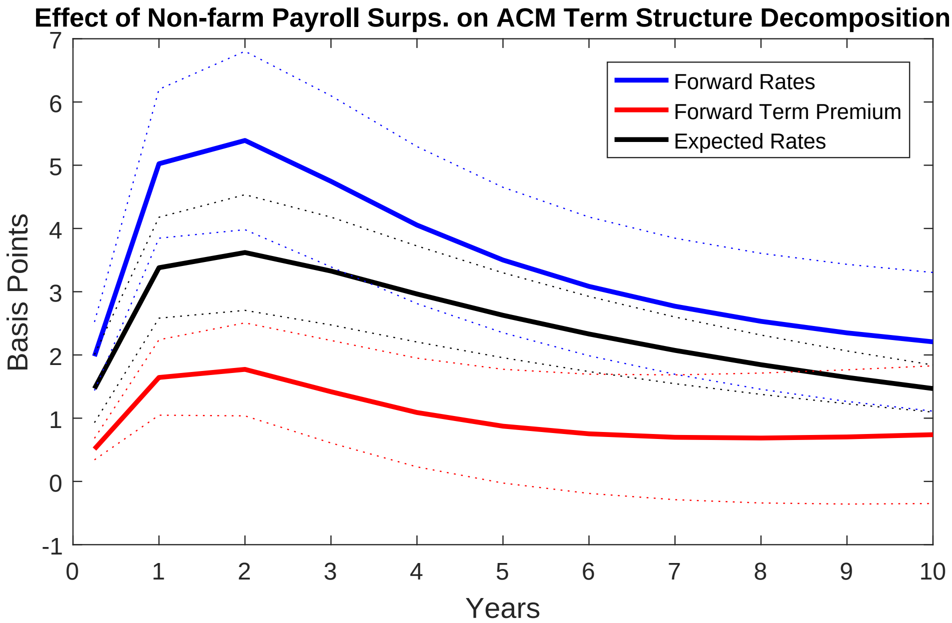
Table A2: Coefficient estimates from OLS regressions of yield changes onto positive headline surprises and negative headline surprises. Standard errors in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$). Macroeconomic surprises are normalized by their respective standard deviations. Monetary policy surprises are in basis points. The sample is 1992-2018 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

	ED1	ED4	2-year	5-year	10-year	30-year
Core CPI	0.73***	1.51***	1.19***	1.58***	1.29***	0.82***
	(0.11)	(0.22)	(0.17)	(0.21)	(0.16)	(0.12)
Durable	0.43***	0.81***	0.79***	0.94***	0.67***	0.43***
	(0.10)	(0.19)	(0.15)	(0.16)	(0.13)	(0.09)
Emp Cost	0.70***	1.58***	1.04***	1.51***	1.17***	0.76***
	(0.18)	(0.43)	(0.35)	(0.41)	(0.31)	(0.22)
GDP	0.60***	1.57***	1.15***	1.55***	1.19***	0.70***
	(0.12)	(0.33)	(0.22)	(0.29)	(0.23)	(0.16)
Claims	−0.30***	−0.70***	−0.59***	−0.66***	−0.53***	−0.32***
	(0.04)	(0.08)	(0.06)	(0.06)	(0.05)	(0.04)
Non-farm	2.90***	5.77***	4.62***	5.40***	4.06***	2.49***
	(0.27)	(0.47)	(0.36)	(0.42)	(0.34)	(0.22)
Core PPI	0.52***	0.89***	0.71***	0.95***	0.85***	0.65***
	(0.11)	(0.20)	(0.16)	(0.18)	(0.14)	(0.11)
Retail	0.65***	0.96***	0.78***	0.86***	0.67***	0.37***
	(0.21)	(0.37)	(0.29)	(0.31)	(0.24)	(0.16)
Unemp	−1.27***	−2.05***	−1.51***	−1.61***	−1.10***	−0.60***
	(0.23)	(0.37)	(0.28)	(0.33)	(0.27)	(0.17)
Hourly Earn.	0.83***	1.80***	1.49***	2.02***	1.62***	0.98***
	(0.24)	(0.34)	(0.27)	(0.34)	(0.27)	(0.18)
PPI	0.13	0.21	0.15	0.20	0.24*	0.16*
	(0.10)	(0.17)	(0.14)	(0.16)	(0.13)	(0.09)
Ret. Ex Auto	0.19	0.66**	0.72***	0.95***	0.74***	0.57***
	(0.14)	(0.27)	(0.22)	(0.24)	(0.19)	(0.13)
CPI	0.01	-0.08	-0.08	0.10	0.14	0.19
	(0.10)	(0.22)	(0.15)	(0.19)	(0.15)	(0.11)
FOMC	0.58***	0.54***	0.32***	0.23**	0.09	0.00
	(0.07)	(0.15)	(0.10)	(0.09)	(0.07)	(0.04)

$(\text{Core CPI})^2$	0.11	0.22^{*}	0.10	0.18	0.18	0.11
	(0.08)	(0.13)	(0.12)	(0.14)	(0.11)	(0.08)
$(\text{Durable})^2$	-0.06^{*}	-0.09^{*}	-0.11^{**}	-0.14^{***}	-0.11^{***}	-0.07^{***}
	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)	(0.02)
$(\text{Emp Cost})^2$	-0.18^{***}	-0.23	-0.08	-0.20	-0.15	-0.13
	(0.07)	(0.17)	(0.16)	(0.17)	(0.13)	(0.09)
$(\text{GDP})^2$	0.13^{*}	0.07	0.10	0.07	0.03	-0.02
	(0.07)	(0.19)	(0.13)	(0.16)	(0.12)	(0.08)
$(\text{Claims})^2$	0.01	0.03	0.02	0.02	0.02	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)
$(\text{Non-farm})^2$	0.23^{*}	0.40^{**}	0.38^{**}	0.37^{*}	0.23	0.18
	(0.13)	(0.20)	(0.17)	(0.21)	(0.18)	(0.11)
$(\text{Core PPI})^2$	-0.11^{*}	-0.14	-0.14^{**}	-0.09	-0.05	-0.05
	(0.06)	(0.09)	(0.05)	(0.06)	(0.05)	(0.04)
$(\text{Retail})^2$	-0.07^{***}	-0.06	-0.04	-0.07^{**}	-0.06^{**}	-0.05^{***}
	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
$(\text{Unemp})^2$	-0.04	-0.15	-0.01	0.02	0.02	0.02
	(0.16)	(0.21)	(0.16)	(0.17)	(0.13)	(0.08)
$(\text{Hourly Earn.})^2$	-0.21	-0.04	0.05	-0.06	0.03	0.04
	(0.18)	(0.25)	(0.20)	(0.24)	(0.19)	(0.14)
$(\text{PPI})^2$	0.06	0.10	0.10	0.08	0.03	0.04
	(0.04)	(0.08)	(0.07)	(0.08)	(0.06)	(0.04)
$(\text{CPI})^2$	0.05	0.11	0.05	0.01	0.02	0.02
	(0.06)	(0.10)	(0.09)	(0.09)	(0.07)	(0.04)
$(\text{Ret Ex Auto})^2$	-0.06	-0.07	-0.07	-0.03	-0.05	-0.01
	(0.05)	(0.11)	(0.07)	(0.11)	(0.08)	(0.06)
$(\text{FOMC})^2$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.41	0.37	0.38	0.37	0.35	0.31

Table A3: Coefficient estimates from OLS regressions of yield changes onto headline surprises and squared headline surprises. 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 sample is 1992-2018 for macroeconomic announcements, 1992-2007 for monetary policy surprises.

G. Forward Rate Decomposition



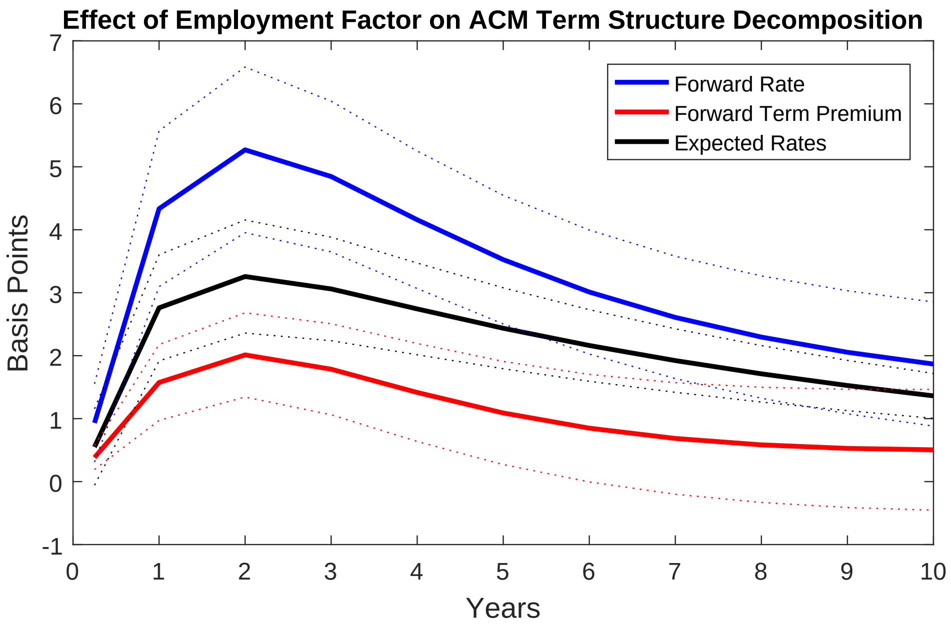


Figure A3: Response of the instantaneous forward rates and their components to the non-farm payroll headline surprise and the latent employment factor. The sample is 1992-2018. These are obtained by regression of changes in forward rates and their components onto the headline surprise (top panel) and latent employment factor (bottom panel). Dashed lines represent 95% confidence intervals. This represents the same Figure as Figure 5 of the paper, except for the inclusion of confidence intervals.