ONLINE APPENDICES

A Assumptions and technical derivations

Assumptions of the underlying model

In this appendix, we are more precise about the underlying semimartingale model which directly translates from Bibinger et al. (2019). The assumptions impose the maximal degree of generality that still allow the estimation of pre-averaged yields (3) and returns (4) in the context of Proposition 2.1. We consider (1) on some filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t), \mathbb{P})$. The jumps J_t in (1) are split into compensated (small) jumps and finitely many large jumps:

$$J_t = \int_0^t \int_{\mathbb{R}^2} \delta(s,z) \mathbb{1}_{\{|\delta(s,z)| \le 1\}} (\mu - \nu)(ds, dz) + \int_0^t \int_{\mathbb{R}^2} \delta(s,z) \mathbb{1}_{\{|\delta(s,z)| > 1\}} \mu(ds, dz), \quad \text{(A.1)}$$

with the jump size function δ, defined on $\Omega \times \mathbb{R}_+ \times \mathbb{R}^2$, and the Poisson random measure μ, which is compensated by $\nu(ds, dz) = \lambda(dz) \otimes ds$ with a σ-finite measure λ. The smoothness of the elements of the drift $b_t^{(i)}$ and $\sigma_t^{(i,j)}$, $i, j = a, b$ of spot squared volatility $\Sigma_t = \sigma_t \sigma_t'$ is defined by the following assumption:

Assumption 1 *In (1), for assets $i, j = a, b$, the drift $(b_t^{(i)})_{t \ge 0}$ is a locally bounded process. The volatilities never vanish, $\inf_{t \in [0,1]} \sigma_t^{(i,i)} > 0$ almost surely. For all $0 \le t + s \le 1$, $t \ge 0$, some constants $C_n, \tilde{C}_n > 0$, some $\beta > 1/2$ and for a sequence of stopping times T_n increasing to ∞, we have that*

$$\left| \mathbb{E}\big[\sigma^{(i,j)}_{(t+s)\wedge T_n} - \sigma^{(i,j)}_{t \wedge T_n} \,|\mathcal{F}_t\big] \right| \le C_n \, s^{\beta} \,, \quad \text{(A.2)}$$

$$\mathbb{E}\Big[\sup_{\mathrm{t} \in [0,s]} |\sigma^{(i,j)}_{(\mathrm{t}+t)\wedge T_n} - \sigma^{(i,j)}_{t \wedge T_n}|^2 \Big] \le \tilde{C}_n \, s \,. \quad \text{(A.3)}$$

We impose the following regularity conditions on the (co)jumps

Assumption 2 *Assume for the predictable function δ in* (A.1) *that* $\sup_{\omega,x} |\delta(t,x)|/\gamma(x)$ *is locally bounded with a non-negative deterministic function γ that satisfies*

$$\int_{\mathbb{R}^2} (\gamma^r(x) \wedge 1)\lambda(dx) < \infty\,, \tag{A.4}$$

with jump activity index r, $0 \leq r < 4/3$.

The index r in (A.4) measures the (co)jump activity of the bond yields in (1). Smaller values of r make (A.2) more restrictive. $r = 0$ results in finite-activity jumps and $r = 1$ implies jumps that are summable. The upper bound on r is proved by Bibinger et al. (2019) to make the univariate version of Proposition 2.1 hold.

Proof of Proposition 2.1

We fill the missing part of the proof of Proposition 3.1 of Bibinger et al. (2019) for the bivariate model. We state here only the crucial extensions of the covariance of the Brownian component and the noise. The higher order n of the drift part allows us to neglect the drifts. Properties of the pre-averaged estimator (drift, Brownian and jump parts) for the individual bonds $i = a, b$, including the mixed normality is shown in Bibinger et al. (2019), and carry over to the bivariate setting. Hence the missing part which proves Proposition 2.1 is the covariance between the Brownian components C_t and noise ϵ of the two assets at some known stopping time τ, respectively.

We rewrite the vector of pre-averaged returns of the observed yields in terms of increments $\Delta\tilde{y}_j = \tilde{y}_j - \tilde{y}_{j-1}$, and study the independent Brownian and noise component separately,

$$\begin{aligned} M_n^{-1}\left(\sum_{k=0}^{M_n-1} \tilde{y}_{\lceil \tau n\rceil+k} - \sum_{k=-M_n}^{-1} \tilde{y}_{\lceil \tau n\rceil+k}\right) &= M_n^{-1}\sum_{k=0}^{M_n-1}\left(\tilde{y}_{\lceil \tau n\rceil+k} - \tilde{y}_{\lceil \tau n\rceil+k-M_n}\right) \\ &= M_n^{-1}\left(\sum_{k=1}^{M_n-1} \Delta\tilde{y}_{\lceil \tau n\rceil+k}(M_n-k) + \sum_{k=0}^{M_n-1} \Delta\tilde{y}_{\lceil \tau n\rceil-k}(M_n-k)\right). \end{aligned} \tag{A.5}$$

The strategy of the proof in Bibinger et al. (2019) is then to exploit the above equation with respect to the individual signal parts of the process $y_t^{(i)}$, $i = a, b$ in (2) and (1). For the covariance of the increments of the Brownian components this gives:

$$\begin{aligned}
\mathrm{Cov}\Bigg[&\sum_{k=1}^{M_n-1} \Delta C^{(a)}_{(\lceil \tau n\rceil+k)/n}\frac{M_n-k}{M_n}+\sum_{k=0}^{M_n-1} \Delta C^{(a)}_{(\lceil \tau n\rceil-k)/n}\frac{M_n-k}{M_n},\\
&\sum_{k=1}^{M_n-1} \Delta C^{(b)}_{(\lceil \tau n\rceil+k)/n}\frac{M_n-k}{M_n}+\sum_{k=0}^{M_n-1} \Delta C^{(b)}_{(\lceil \tau n\rceil-k)/n}\frac{M_n-k}{M_n}\Bigg]\\
&=\sum_{k=1}^{M_n-1}\mathrm{E}\left[\Delta C^{(a)}_{(\lceil \tau n\rceil+k)/n}\Delta C^{(b)}_{(\lceil \tau n\rceil+k)/n}\right]\left(1-\frac{k}{M_n}\right)^2\\
&\quad+\sum_{k=0}^{M_n-1}\mathrm{E}\left[\Delta C^{(a)}_{(\lceil \tau n\rceil-k)/n}\Delta C^{(b)}_{(\lceil \tau n\rceil-k)/n}\right]\left(1-\frac{k}{M_n}\right)^2,
\end{aligned}$$

with uncorrelated increments on disjoint intervals in case of stochastic volatility. Itô isometry,

$$\mathrm{E}\left[\int_0^t \sigma_s^{(a,a)}dW_s^{(a)}\int_0^t \sigma_s^{(b,b)}dW_s^{(b)}\right]=\int_0^t \mathrm{E}[\sigma_s^{(a,a)}\sigma_s^{(b,b)}]\rho_s^{(a,b)}ds,$$

and the smoothness of the volatility and correlation imply that

$$\begin{aligned}
\mathrm{E}\left[\Delta C^{(a)}_{(\lceil \tau n\rceil+k)/n}\Delta C^{(b)}_{(\lceil \tau n\rceil+k)/n}|\mathcal{F}_\tau\right]&=\mathrm{E}\left[\int_{(\lceil \tau n\rceil+k-1)/n}^{(\lceil \tau n\rceil+k)/n}\sigma_s^{(a,b)}ds|\mathcal{F}_\tau\right]+\mathcal{O}_P(n^{-2})\\
&=\frac{\rho_\tau^{(a,b)}\sigma_\tau^{(a,a)}\sigma_\tau^{(b,b)}}{n}+\mathcal{O}_P\left(\sqrt{\frac{M_n}{n}}n^{-1}\right),
\end{aligned}$$

for $k = 1, ..., M_n - 1$. Similarly, we obtain to the left of τ

$$\begin{aligned}
\mathrm{E}\left[\Delta C^{(a)}_{(\lceil \tau n\rceil-k)/n}\Delta C^{(b)}_{(\lceil \tau n\rceil-k)/n}|\mathcal{F}_\tau\right]&=\mathrm{E}\left[\int_{(\lceil \tau n\rceil-k-1)/n)}^{(\lceil \tau n\rceil-k)/n}\sigma_s^{(a,b)}ds|\mathcal{F}_\tau\right]+\mathcal{O}_P(n^{-2})\\
&=\frac{\rho_{\tau-}^{(a,b)}\sigma_{\tau-}^{(a,a)}\sigma_{\tau-}^{(b,b)}}{n}+\mathcal{O}_P\left(\sqrt{\frac{M_n}{n}}n^{-1}\right).
\end{aligned}$$

The increments in *iid* noise contribute

$$\mathrm{E}\left[\Delta\epsilon^{(a)}_{\lceil \tau n\rceil-k}\Delta\epsilon^{(b)}_{\lceil \tau n\rceil-k}|\mathcal{F}_\tau\right]=\mathrm{E}\left[(\epsilon^{(a)}_{\lceil \tau n\rceil-k}-\epsilon^{(a)}_{\lceil \tau n\rceil-k-1})(\epsilon^{(b)}_{\lceil \tau n\rceil-k}-\epsilon^{(b)}_{\lceil \tau n\rceil-k-1})\right]=2\eta^{(a,b)}.$$

Finally, in conjunction with the identities

$$\sum_{k=1}^{M_n-1}\left(1-\frac{k}{M_n}\right)^2=\frac{1}{3}M_n-\frac{1}{2}+\frac{1}{6}M_n^{-1},\quad\text{and}\quad\sum_{k=0}^{M_n-1}\left(1-\frac{k}{M_n}\right)^2=\frac{1}{3}M_n+\frac{1}{2}+\frac{1}{6}M_n^{-1},$$

we obtain the asymptotic covariance of event returns of asset a and b:

$$\sqrt{M_n}\mathrm{E}\left[\Delta\hat{y}_{\tau n}^{(a)}\Delta\hat{y}_{\tau n}^{(b)}\right] \to \left(\frac{\rho_\tau^{(a,b)}\sigma_\tau^{(a,a)}\sigma_\tau^{(b,b)}}{3} + \frac{\rho_{\tau-}^{(a,b)}\sigma_{\tau-}^{(a,a)}\sigma_{\tau-}^{(b,b)}}{3}\right)c^2 + 2\eta^{(a,b)}. \tag{A.6}$$

The positivity of Γ_τ is a direct consequence of the additive structure in (6) and the positivity of the noise covariance matrix η. ■

Proof of Corollary 2.3

We provide a general analytic expression for the dotted region in Figure 1 that relates to the area in the event-return space where incoherent test results occur. To simplify notation, we consider random variables $x = n^{1/4}\Delta y_\tau^{(a)}$, $y = n^{1/4}\Delta y_\tau^{(b)}$. Symmetry allows us to focus on the upper rejection area. Integration boundaries in the x and y dimension are determined by the Bonferroni test (7) and the Lee-Mykland test (9). The integration bounds of x are

$$\begin{aligned} &\text{lower:} \quad x_1(\alpha, \Gamma_\tau^{(a,a)}) = (\Gamma_\tau^{(a,a)})^{1/2} q_\alpha(N), \\ &\text{upper:} \quad x_2(\alpha, \Gamma_\tau) = (\Gamma_\tau^{(b,b)})^{1/2} q_{1-\alpha/2}(N) - (\Gamma_\tau^{(a,a)} + \Gamma_\tau^{(b,b)} - 2\Gamma_\tau^{(a,b)})^{1/2} q_{1-\alpha}(N). \end{aligned}$$

These are the x coordinates, where the upper border of the diagonal corridor crosses the square. The corresponding coordinates of y determine the integration bounds for y:

$$\begin{aligned} &\text{lower:} \quad y_1(x, \alpha, \Gamma_\tau) = x + (\Gamma_\tau^{(a,a)} + \Gamma_\tau^{(b,b)} - 2\Gamma_\tau^{(a,b)})^{1/2} q_{1-\alpha}(N), \\ &\text{upper:} \quad y_2(\alpha, \Gamma_\tau^{(b,b)}) = (\Gamma_\tau^{(b,b)})^{1/2} q_{1-\alpha/2}(N). \end{aligned}$$

Equipped with those bounds and the bivariate normality result from Proposition 2.1, we can express the joint probability of conflicting test results

$$P\left(\varphi_\alpha^{\mathrm{S}}(\mathrm{LM}) = 1, \varphi_\alpha^{\mathrm{B}}(\mathrm{Bonf}) = 0\right) = 2\int_{x_1(\alpha,\Gamma_\tau^{(a,a)})}^{x_2(\alpha,\Gamma_\tau)} \int_{y_1(x,\alpha,\Gamma_\tau)}^{y_2(\alpha,\Gamma_\tau^{(b,b)})} \phi(x, y, \Gamma_\tau)\, dy\, dx,$$

where $\phi(\cdot)$ refers to the bivariate normal distribution function. The probability is positive as soon as upper integration bounds are larger than the lower integration bounds, which is always true, given the α level of both tests. ■

B Additional simulation results

This section contains the simulation results of the the spread jump tests. We report frequencies of jump detection of the univariate Lee-Mykland jump test applied to the spread (9), as well as the IUT in Proposition 2.4.

We use the same bivariate stochastic volatility model with price and volatility jumps as introduced in Section 3. The (co)volatility is estimated using the pre-averaging method of Christensen et al. (2010) with a window size of $\lceil \sqrt{n} \rceil$. We apply the universal threshold with the median absolute deviation of pre-averaged returns to truncate jumps in the estimation of (co)volatilities (see Koike, 2016, immediately after Theorem 5.1). The market microstructure noise is estimated based on equation (12) of Christensen et al. (2010). We use the 'yuima' package in R for our computations.

The pre-average estimator of the event return at $t = \tau$ uses a block size of $M_n = \lceil \sqrt{n}/18 \rceil$. The constant $c = 1/18$ is chosen according to Table 5 of Lee and Mykland (2012). The simulation results do not change much by slightly increasing M_n. We simulate jumps at the event time $t = \tau$ whose sizes are multiples of the pre-average estimation noise γ, defined as

$$\gamma = n^{-1/4} (\Gamma_\tau^{(i,i)})^{1/2}, \quad i = a, b, \tag{B.1}$$

with $\Gamma_\tau^{(i,i)}$ as in (6). Since the estimation noise γ directly relates to the asymptotic distribution of the pre-average return estimator, it determines the detection properties of the jump tests. The detection of a jump in yields becomes more difficult if: (i) the noise level q is higher; (ii) the volatility of the Brownian component is larger; and (iii) the sample size n is smaller. However, as we define jump sizes as multiples of γ, the simulated jump sizes increase in γ. This allows studying how estimation precision of the pre-average estimators and the noise level affect the test decisions. Notice that the simulation setup provides both bonds ($i = a, b$) with the same integrated volatility and noise level, and hence γ does not depend on the specific bond.

Table B.1 shows the rejection frequencies of the three spread jump tests at level $\alpha = 1\%$. The three different spread jump tests are the univariate Lee-Mykland test applied to the spread alone, and the IUT with either the Bonferroni approach or the χ^2 bivariate jump test in the first step. We consider two different sampling frequencies, 30-second ($n = 360$) and 5-second ($n = 2160$). The top panel of Table B.1 reports the simulation results when the noise variance is low ($q^2 = 0.0001$), and the bottom panel for high noise variance ($q^2 = 0.01$). Each simulation is repeated 3,000 times. The jump sizes reported in columns three and four belong to the null hypothesis of no spread jump, while all other columns correspond to the alternative of a jump in the spread.

Under the null of no spread jump, all three tests exhibit reasonable size properties, with actual sizes below the nominal level of 1%. We conduct two experiments: (i) Neither of the two underlying bond yields has a jump at time τ (column three of Table B.1); (ii) Both bond yields have a jump of the same size (column four of Table B.1). In the latter case, the IUT detects jumps in the bond yields with high probability in the first step, and its test outcome is almost fully determined by the test for equal returns in the second step. As a result, rejection rates of all three tests are almost identical across different noise levels and sample sizes. In particular, there is little difference between the Bonferroni and χ^2-based IUT tests under the null hypothesis.

The Power advantage of the χ^2-based IUT over the Bonferroni approach becomes apparent when the spread jump is induced by a jump in only one of the two bond yields. These results are shown in columns five to seven of Table B.1. The Bonferroni-based IUT always has lower power than the χ^2 approach, because it does not make use of the information on the covariance between the two bond yields. When the jump size is small (2γ) and noise level is high ($q = 0.1$), the power loss of using the Bonferroni-based IUT compared to the univaraite Lee-Mykland test on the spread is well above 50%. These results are consistent

Table B.1: Rejection frequencies of spread jump tests.

Jump size	Bond a / Bond b	0 / 0	4γ / 4γ	2γ / 0	3γ / 0	4γ / 0	4γ / 2γ	5γ / 2γ
Noise level: $q = 0.01$								
30-sec (n=360)	LM	0.009	0.009	0.309	0.679	0.926	0.302	0.670
	IUT(Bonf)	0.000	0.008	0.044	0.168	0.415	0.168	0.486
	IUT(χ^2)	0.003	0.009	0.227	0.596	0.896	0.275	0.649
5-sec (n=2,160)	LM	0.015	0.011	0.591	0.938	0.998	0.605	0.938
	IUT(Bonf)	0.001	0.011	0.136	0.479	0.773	0.506	0.887
	IUT(χ^2)	0.009	0.011	0.506	0.914	0.996	0.596	0.937
Noise level: $q = 0.1$								
30-sec (n=360)	LM	0.000	0.000	0.776	0.999	1.000	0.782	1.000
	IUT(Bonf)	0.000	0.000	0.085	0.560	0.960	0.757	0.999
	IUT(χ^2)	0.000	0.000	0.650	0.999	1.000	0.781	1.000
5-sec (n=2,160)	LM	0.001	0.001	0.776	0.998	1.000	0.762	0.998
	IUT(Bonf)	0.000	0.001	0.141	0.594	0.941	0.726	0.995
	IUT(χ^2)	0.000	0.001	0.670	0.995	1.000	0.760	0.998

Note: Jump sizes in the first two rows are given as a multiple of the estimation noise γ, which is defined in equation (B.1). Each cell shows the frequency of rejections at significance level $\alpha = 0.01$ across 3,000 repetitions. LM indicates the Lee-Mykland test applied to the spread (9). IUT(Bonf) is the Bonferroni-adjusted IUT (7) that uses the Bonferroni-adjusted Lee-Mykland test to test for jumps in the two bond yields in the first step. IUT(χ^2) implements the χ^2 bivariate jump test (8) in the first step.

with findings in Section 3 under the alternative of a spread jump. In contrast, the χ^2-based IUT does not suffer from such large power loss over the univariate Lee-Mykland test. The difference in the rejection frequencies between these two tests are below 10%, and approaches 0 as the jump size becomes larger.

The last two columns of Table B.1 show jump detection rates when the jump in the spread is induced by jumps of different sizes in the two bond yields. Compared to situations when the jump in the spread is induced by a jump in only one of the two bond yields, the test power of the univariate Lee-Mykland test is not much affected. This is because it does not take into account the properties of the underlying bond yields. In contrast, the two IUT procedures have higher detection rate. This increase in test power is driven the bivariate jump test in the first step of the IUT, where jumps in the two bond yields are more easily detected than a jump in only one of them. For the same reason, the difference between the Bonferroni and χ^2-based IUT procedures also become smaller.

Under the alternative hypothesis, it is not surprising that larger sample size n almost always leads to higher detection rate. Its effect is more evident when the noise level is low ($q = 0.01$). Comparing the top and bottom panels of Table B.1, we see that the power of all tests increases when the noise level is higher, keeping other parameters fixed. This is because the simulated jump sizes are multiples of the estimation noise γ defined in (B.1), which increases with the variance of the microstructure noise. As a result, the simulated jumps has larger magnitudes in the bottom panel for higher noise level.

C Data

This section provides information on the U.S. macroeconomic news announcements and Treasury bonds data used in the empirical analyses. Table C.1 presents the list of macroeconomic news announcements we use to investigate jumps in bond yields and yield spreads. These announcements are classified into four broad categories: price, output, employment, and consumption.

Table C.1: Macroeconomic news releases examined in the empirical analyses.

Subject	Category	Frequency	Release time
Consumer price index	Price	Monthly	8:30 am
Producer price index	Price	Monthly	8:30 am
Employment cost index	Price	Quarterly	8:30 am
Gross domestic product	Output	Quarterly	8:30 am
Durable goods orders	Output	Monthly	8:30 am
ISM manufacturing	Output	Monthly	10:00 am
Chicago PMI	Output	Monthly	9:45 am
Empire state manufacturing	Output	Monthly	8:30 am
Business inventories	Output	Monthly	10:00 am
Production and utilization	Output	Monthly	9:15 am
Employment report	Employment	Monthly	8:30 am
ADP employment change	Employment	Monthly	8:15 am
Initial jobless claims	Employment	Weekly	8:30 am
Personal spending	Consumption	Monthly	8:30 am
Advance retail sales	Consumption	Monthly	8:30 am
Consumer confidence	Consumption	Monthly	10:00 am

The high-frequency data on U.S. Treasury bond yields are obtained from Refinitiv DataScope Select provided by Thomson Reuters Tick History. Tables C.2 provides information on the individual nominal (left column) and inflation-indexed bonds (right column). We use maturities that are closest to 2, 5, 10, and 20 years at the time of each news release. When there are several bonds available, we select the bond that has the highest number of non-zero 30-second returns on the day of the announcement, which is considered to be the

Table C.2: The list of U.S. Treasury bonds and TIPS used in the empirical analyses.

Treasury bonds			TIPS		
CUSIP	Coupon	Maturity	CUSIP	Coupon	Maturity
912810ED6	8.125	15/08/2019	912828JX9	2.125	15/01/2019
912810EM6	7.250	15/08/2022	912828TE0	0.125	15/07/2022
912810EY0	6.500	15/11/2026	912828S50	0.125	15/07/2026
912810PU6	5.000	15/05/2037	912810QP6	2.125	15/02/2041
912810EZ7	6.625	15/02/2027	912810QF8	2.125	15/02/2040
912810PT9	4.750	15/02/2037	912828JE1	1.375	15/07/2018
912810FT0	4.500	15/02/2036	912828SA9	0.125	15/01/2022
912810FA1	6.375	15/08/2027	912828QV5	0.625	15/07/2021
912810EK0	8.125	15/08/2021	912828LA6	1.875	15/07/2019
912810EN4	7.725	15/11/2022	912810PS1	2.375	15/01/2027
912810PW2	4.375	15/02/2038	912828X39	0.125	15/04/2022
912810EC8	8.875	15/02/2019	912828V49	0.375	15/01/2027
912810EE4	8.500	15/02/2020	912828C99	0.125	15/04/2019
912810EL8	8.000	15/11/2021	912828UH1	0.125	15/01/2023
912810FB9	6.125	15/11/2027	912828MF4	1.375	15/01/2020
912810EP9	7.125	15/02/2023	912810PV4	1.750	15/01/2028
912810FE3	5.500	15/08/2028	9128282L3	0.375	15/07/2027
912810PX0	4.500	15/05/2038	912810FQ6	3.375	15/04/2032
912810EF1	8.750	15/05/2020	912828VM9	0.375	15/07/2023
912810EQ7	6.250	15/08/2023	912810FD5	3.625	15/04/2028
912810EG9	8.750	15/08/2020	912828K33	1.375	15/04/2020
912810QA9	3.500	15/02/2039	912828NM8	1.250	15/07/2020
912810FF0	5.250	15/11/2028	912810PZ5	2.500	15/01/2029
912810ES3	7.500	15/11/2024	9128283R9	0.500	15/01/2028
912810EH7	7.875	15/02/2021	9128284H0	0.625	15/04/2023
912810QB7	4.250	15/05/2039	912828B25	0.625	15/01/2024
912810FG8	5.250	15/02/2029	912828PP9	1.125	15/01/2021
912810EJ3	8.125	15/05/2021	912828Y38	0.750	15/07/2028
912810FJ2	6.125	15/08/2029	912828WU0	0.125	15/07/2024
912810ET1	7.625	15/02/2025	912810FH6	3.875	15/04/2029
912810QC5	4.500	15/08/2039	912828Q60	0.125	15/04/2021
912810QD3	4.375	15/11/2039	9128286N5	0.500	15/04/2024
912810FM5	6.250	15/05/2030	912810FR4	2.375	15/01/2025
912810QE1	4.625	15/02/2040	912828YL8	0.125	15/10/2024
912810FP8	5.375	15/02/2031	912828XL9	0.375	15/07/2025

most liquid bond at a given maturity.

Table C.3 presents some statistics of the nominal and inflation-indexed bond yields used in the empirical analyses. These statistics are calculated using 30-second bond yields data on 430 unique announcement dates from 7am to 5pm. Panel A summarizes some simple descriptive statistics of the 30-second returns. The first row reports that the average number of non-zero returns ranges from 230 to 450 for different bond types and maturities. In general, long-dated bonds tend to have more movements in the yields, which partly reflect the liquidity level of the bond. The average yield change is always very close to zero. We also present the mean of the yield changes after taking the absolute value of the change to show the typical size of a 30-second return. It varies between 0.03 to 0.05 basis points for different types of bonds and maturities on these announcement days. Lastly, the standard deviation of the yield changes ranges between 0.09 to 0.18 basis points, which is much larger than the average size of the return.

Table C.3: Descriptive statistics of government bond yields and yield spreads.

Maturity	Nominal bonds				Indexed bonds		
	2Y	5Y	10Y	20Y	5Y	10Y	20Y
Panel A: observed 30-second returns							
# $\Delta\tilde{y}_i \neq 0$	269	252	300	387	233	270	442
Mean $\Delta\tilde{y}_i$	-0.0001	-0.0004	-0.0001	-0.0001	-0.0002	-0.0002	-0.0001
Mean $\lvert\Delta\tilde{y}_i\rvert$	0.0387	0.0366	0.0384	0.0431	0.0455	0.0471	0.0493
St.dev. $\Delta\tilde{y}_i$	0.1114	0.1809	0.0972	0.0976	0.1537	0.1263	0.1107
Panel B: microstructure noise							
p-value	0.027	0.149	0.204	0.142	0.091	0.116	0.194
rejection rate	93.7%	64.2%	52.1%	61.2%	77.9%	71.9%	53.7%
noise level	0.105	0.103	0.092	0.094	0.131	0.123	0.105

Note: The bond data are 30-second observations from 7am to 5pm on 430 macroeconomic news release dates from 2017 to 2019. The reported sizes of the return are in basis points. The p-value refers to the autocorrelation based test for microstructure noise proposed by Aït-Sahalia and Xiu (2019). The fraction of rejecting the null of no noise using the same test at 5% significance level is reported in row labeled rejection rate. The average noise level is estimated using Proposition 1 of Lee and Mykland (2012).

Panel B of Table C.3 provides evidence on the prevalence of market microstructure noise in the bond data. We report the median p-value and the percentage of rejections at a 5% level for the autocorrelation based noise test proposed by Aït-Sahalia and Xiu (2019). The small p-values and high rejection rates of no noise, particularly for shorter-term bond yields and yield spreads, support the importance of our noise-robust method proposed in Section 2. The noise level in the last row of Table C.3 reports the average value of the estimated η, obtained using the noise estimator of Lee and Mykland (2012). The noise level has similar magnitudes to the high noise level used in the simulation in Section 3 across different bonds and spreads, and is comparable to the standard deviation of the 30-second returns.