Online Appendixes to "Credit Risk, Liquidity, and Lies"

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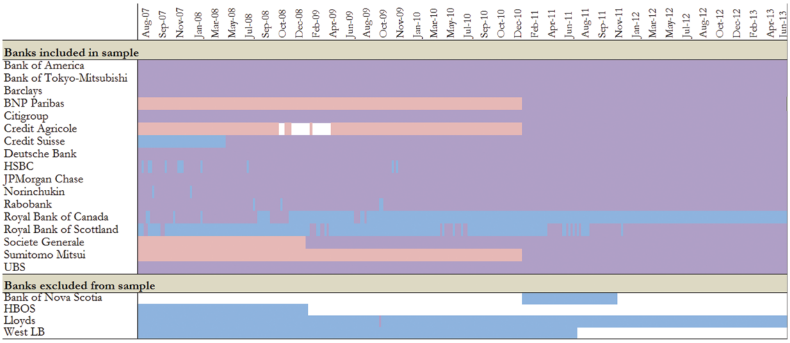
Appendix A. Data and CDS Curves

Figure A.1 shows the week-by-week breakdown of the data used in the model in the weeks for which each bank was a member of the USD LIBOR panel (in blue) and therefore has LIBOR-submission data available; the weeks for which short-maturity CDS data are available for each bank (in red); and the weeks for which both the CDS and LIBOR data are available (in purple). Blank cells indicate that a bank was neither in the LIBOR panel nor had CDS data available that week.

We obtain daily bank-level LIBOR submissions from Bloomberg for every USD LIBOR panel bank at maturities of one week, one month, three months, six months, and one year. These submissions are available on all weekdays, excluding U.K. holidays. As noted in the text, we subtract maturity-matched USD OIS rates, also obtained from Bloomberg, from each LIBOR submission on each day. We then take weekly averages of each bank's LOIS spread at each maturity. Figure A.1 shows the composition of the LIBOR panel during the sample period used in the estimation: July 30, 2007 through June 28, 2013. (Figure 1 in the text shows some of the daily data dating back to when they first become available.) The blue and purple regions indicate the weeks during which each bank was in the panel.

We obtain daily bank-level CDS quotes from Markit for each of the LIBOR panel banks at maturities of six months and 1, 2, 3, 4, 5, 7, 10, 15, 20, and 30 years, when those quotes are available. Markit surveys over 30 dealers for end-of-day indicative quotes and

Figure A.1. Data Summary



Notes: The weeks for which each bank was a member of the USD LIBOR panel are colored blue and therefore have LIBOR-submission data available. The weeks for which short-maturity CDS data are available for each bank are colored red, and the weeks for which both the CDS and LIBOR data are available are shown as purple. Blank cells indicate that a bank was neither in the LIBOR panel nor had CDS data available that week.

reports an aggregate of each underlying CDS name at each maturity. They exclude contributor quotes that they judge to be stale or that are outliers in the cross-section, and they do not report a composite CDS spread for a given maturity on a given day if they do not have at least two underlying quotes that meet these standards. The data are available on all weekdays, including U.S. and U.K. holidays (although there tends to be very little movement on days such as Christmas). We drop all bank-day observations for which Markit does not report both 6- and 12-month spreads and all bank-day observations for which it does not report spreads for at least five different maturities in total. The red and purple regions in figure A.1 indicate the weeks during which we have CDS observations for each bank after applying these filters. (Figure 2 in the text shows some of the daily data dating back to when they first become available, although the summary statistics shown there are based on fewer banks as they go further back in time.)

We have at least some CDS quotes for 17 of the 21 banks that were ever in the LIBOR panel during our period, but the four remaining banks never show up in our CDS data. (One of these banks, Lloyds, does have CDS quotes on a single day, which we drop

Table A.1. Average Nelson-Siegel CDS Fitting Errors

	6-Month	**12-Month**
Average Absolute Fitting Error	1.8 bp	2.9 bp
As Percentage of Average Level	2.7%	3.9%

as an anomaly.) While our Kalman-filtering procedure can handle missing data, as described below, it does not add information to the estimation to include banks for which the independent variables are always missing. We therefore exclude these four banks altogether. Because three of them were only in the LIBOR panel for part of the sample period, the associated data amounts to only 12 percent of all bank-week LOIS observations.

For each bank in our CDS data, we fit a curve of the Nelson and Siegel (1987) form to the cross-section of CDS quotes on each day. Specifically, we estimate

$$C_{imt} = b_{0it} + b_{1,it}\frac{1 - e^{-m/\tau}}{m/\tau} + b_{2it}\left(\frac{1 - e^{-m/\tau}}{m/\tau} - e^{-m/\tau}\right), \quad \text{(A.1)}$$

where C_{imt} is bank i's CDS quote at maturity m on day t, and b_{0it}, b_{1it}, b_{2it}, and τ_{it} are bank-day-specific parameters. We fit the curve to the full term structure of CDS quotes in our data, minimizing the weighted sum of the squared errors across maturities, where the weights are proportional to $1/m$. We use fitted values from these curves (on the days that we can estimate them) to match the maturities of our LOIS data for each bank.

Table A.1 displays the average absolute fitting errors from this procedure, both in absolute terms and as a fraction of the level of the raw CDS spreads. The curves generally fit quite well at the short end. Nonetheless, one potential concern is that, especially given the exponential terms in the Nelson-Siegel specification, our procedure could generate explosive behavior out of sample and thus introduce substantial measurement error for very short maturities. While we of course have no way of verifying the accuracy of our extrapolation, we can check that it does not generate values that appear implausible, in the sense of being too far out of line with the observed data at the short end. To do this, we use the raw 6-month, 12-month,

Table A.2. Differences between CDS Term Structure Features in Extrapolated and Raw Data

	Percentile						
	1	**5**	**25**	**50**	**75**	**95**	**99**
Level	−23.4	−8.3	0.1	6.4	13.6	26.3	34.7
Slope	−17.3	−9.8	−3.1	0.5	4.4	11.8	24.6
Curvature	−80.9	−30.1	−8.1	−1.8	4.7	19.9	56.4

Notes: The table shows percentiles of the distributions of the differences between the Nelson-Siegel-imputed CDS curves at very short maturities and the raw CDS curves at slightly longer maturities. Specifically, the "Level" row compares the raw 6-month quote with the imputed 1-week quote; the "Slope" row compares the difference between the 6-month and the 12-month quotes in the raw data with the difference between the 1-week and 6-month imputed quotes; the "Curvature" row compares the 6-month/12-month/2-year second difference in the raw data (adjusted for the different period lengths) with the 1-week/6-month/12-month second difference in the imputed quotes.

and two-year CDS data to compute measures of the level, slope, and curvature of the short-maturity CDS curve. We then compare these with the level, slope, and curvature computed using our extrapolated Nelson-Siegel data. Specifically, for level, we compare C_{6mn} in the raw data with C_{1wk} in the fitted values; for slope, we compare $(C_{1yr} - C_{6mn})$ in the raw data with $(C_{6mn} - C_{1wk})$ in the fitted values; for curvature, we compare $((C_{2yr} - C_{1yr})/2) - (C_{1yr} - C_{6mn})$ in the raw data with $((C_{1yr} - C_{6mn}) - (C_{6mn} - C_{1wk}))$ in the fitted values.

Table A.2 shows the distributions of the differences between the extrapolated curve features and those at the short end of the raw data. The first row shows that the imputed one-week spread differs from the raw six-month spread by less than 27 basis points for more than 90 percent of the observations. (For context, the middle 90 percent of the raw six-month CDS spreads is 9 to 201 basis points.) The second row shows that the imputed 1-week/6-month slope differs from the raw 6-month/12-month slope by less than 12 basis points for more than 90 percent of the observations. The final row shows that the imputed 1-week/6-month/12-month curvature differs from the raw 6-month/12-month/2-year curvature (adjusted for the difference in period lengths) by less than 31 basis points for more than 90 percent of the observations. These statistics are not suggestive of wild swings in the extrapolated data. As an additional measure to guard against noise potentially introduced by our curve fitting, in the estimation we drop all observations for which the percentage fitting error at either the 6- or 12-month maturity is greater than 25 percent.

Appendix B. Measures of CDS Liquidity

To further investigate concerns about the potential for CDS illiquidity to contaminate our results, we constructed two measures of CDS liquidity. These measure are used in the validation exercises in subsection 5.3.2 of the paper. Here, we briefly describe the data.

First, we exploit the errors in our Nelson-Siegel CDS curves. As discussed above, we calculate the absolute value of the percentage deviation of each raw 6- and 12-month CDS quote from the fitted curves on each day. This measure can be computed for each bank in our sample on each day when CDS spreads are reported. To construct a time-series index, we take the median across banks, on each day at each of the two maturities. Fitting errors from similar curves are often taken to be proxies for market functioning and liquidity, since we would generally expect arbitrage to result in relatively smooth term structures (e.g., Hu, Pan, and Wang 2013; Musto, Nini, and Schwarz 2018).

The second measure of illiquidity we use is the bid/ask spread on CDS contracts. Markit constructs average bid/ask spreads, for each CDS name at each maturity on each day that they receive sufficient quotes. Unfortunately, Markit only began collecting these data in 2010, and only for the dominant currency for each CDS name. In practice, the latter condition means that we only have observations for the three U.S. banks in the LIBOR panel. Nonetheless, one might expect CDS liquidity to be highly cross-sectionally correlated across banks. Therefore, we construct indexes of bank-CDS liquidity at the 6- and 12-month horizons by averaging the three bid/ask spreads that we observe at each of those maturities on each day. Summary statistics for the two short-term CDS liquidity measures are presented in table B.1 below.

Table B.1. Summary Statistics for CDS Liquidity Measures

		Mean	Std. Dev.	Min.	Max.
Median Abs. % Fitting Error from NS Curve	6M	3.50%	4.20%	0.00%	28.90%
	12M	4.10%	2.20%	0.10%	11.20%
Avg. Bid/Ask Spread across Three Banks (Starts 2010)	6M	0.25%	0.10%	0.13%	0.59%
	12M	0.14%	0.06%	0.07%	0.34%

Appendix C. Estimation Procedure

Our estimation applies the Kalman filter to the linear state-space system described by the measurement and state transition equations equation (8) and equation (9). The fixed parameters are estimated via Gibbs sampling, following Kim and Nelson (1999).

The specific structure of the estimated model can be written as follows. Stacking the data across firms and maturities at each point in time, the measurement equations of the state-space representation equation (8) can be written compactly as

$$\widehat{\mathbf{L}}_t = \mathbf{X}_t \boldsymbol{\theta}_t + \boldsymbol{\varepsilon}_t, \tag{C.1}$$

where $\widehat{\mathbf{L}}_t$ is the 85×1 vector of LOIS across banks and maturities (recall that we are using data from five different maturities for each of 17 firms), $\mathbf{X}_t$ is the matrix of independent variables, and $\boldsymbol{\theta}_t$ is the vector of time-varying coefficients. $\mathbf{X}_t$ is 85×24 and has the structure

$$\mathbf{X}_t = \left(\mathbf{I}_5 \otimes 1_{17} \qquad \Sigma_t^C \qquad \mathbf{C}_t \qquad \left[\mathbf{C}_t - \overline{\mathbf{C}}_t \right] \right), \tag{C.2}$$

where $\mathbf{I}_k$ is the k-dimensional identity matrix, 1_{17} is a vector of ones of length 17, Σ_t^C is an 85×17 matrix that consists of five stacked copies of the 17×17 diagonal matrix with the cross-sectional standard deviations of CDS spreads for maturity m at time t (σ_{mt}^C) along the diagonal, $\mathbf{C}_t$ is the 85×1 vector containing the C_{imt}'s, and $\overline{\mathbf{C}}_t$ is a 85×1 vector containing the $\overline{C}_{mt}$'s stacked on top of each other (each $\overline{C}_{mt}$ is a 17×1 vector repeating the average CDS for the given maturity at the given date).

To deal with missing data, we follow the procedure of Aruoba, Diebold, and Scotti (2009). This process starts with the initial data that have missing values and use a matrix, noted W_t in that paper, to eliminate missing observations, creating a situation where the left- and right-hand variables in the observation equation within the filter are of a different size in each period. W_t is created by beginning with a identity matrix of size 85×85, and then keeping only the rows from that matrix which correspond to the observed elements within the data for date t. Thus, we then use the Kalman filter and Gibbs procedure on $\widehat{\mathbf{L}}_t^W = W_t \widehat{\mathbf{L}}_t$ and $\mathbf{X}_t^W = W_t \mathbf{X}_t$, and note also that $\varepsilon_t^W = W_t \varepsilon_t$. More details are available in Aruoba, Diebold, and Scotti (2009) and included references.

We treat the coefficient vector as a hidden state vector that evolves according to equation (9), where $\mathbf{Q}$ is the 24×24 covariance matrix of innovations in the state transition equation. We assume that the measurement errors $\boldsymbol{\varepsilon_t}$ are identically and independently distributed normal random variables with mean zero and covariance matrix $\mathbf{R}$, and, in order to reduce the dimensionality of the estimation, we follow standard practice by assuming that $\boldsymbol{\varepsilon_t}$ and $\boldsymbol{\nu}_t$ are uncorrelated. Further, we assume that the covariance matrices $\mathbf{R}$ and $\mathbf{Q}$ themselves are also diagonal. Note that, since $\mathbf{R}$ is diagonal by assumption, the measurement-error RMSE mentioned in section 5.4 is equal to $\sqrt{tr[\mathbf{R}]/\mathbf{k}}$.

We assume that the hyperparameters $\mathbf{R}$ and $\mathbf{Q}$ and the initial state $\boldsymbol{\theta}_0$ are independent from each other, that the initial state is a normal random variable with mean $\bar{\boldsymbol{\theta}}_0$ and covariance matrix $\bar{\mathbf{P}}_0$. We set the initial mean $\bar{\boldsymbol{\theta}}_0$ to line up with a world in which the true LOIS spread is derived from the individual-firm CDS with identical recovery rates between bondholders and interbank lenders. That is, we set the mean of ϕ_0 equal to 1. In light of results by Youle (2014) and others, we set the mean of β_{1i0} equal to –1, implying a small amount of misreporting on average. However, we make these initial distributions quite flat, with a covariance of matrix of $\bar{\mathbf{P}}_0$ that has values of 10 along the diagonal and zero along the off-diagonals. (Reasonable variants on these choices do not change the qualitative results.) The prior parameterization of the hyperparameters $\mathbf{R}$ and $\mathbf{Q}$ are also set to diffuse values; each element of the diagonal is an inverse gamma with a single degree of freedom and shape parameters of 10^{-4}. By making these priors very flat, we allow the data to drive the shape and position of the posterior distributions. We use a two-step Gibbs algorithm: (i) states given hyperparameters and (ii) hyperparameters given states. See Kim and Nelson (1999) for details concerning the construction of the posterior distributions.

All estimates reported in the text are based on posterior draws of the smoothed state vector (i.e., the distributions of the state conditional on the full-sample information). We take 250,000 Gibbs draws, of which we discard the first 5,000 as a "burn-in" sample. We checked convergence by increasing and decreasing the number of draws, by changing the starting values, and by examining the time series of the individual variables.

In the results presented in the main paper, we estimate the model on weekly averages of the daily data. If our specification were the true data-generating process, the frequency of the data used should make no systematic difference for our estimates. However, if the model is misspecified—say, because the true state variables do not follow pure random walks—different choices for the time aggregation can matter. Our choice of weekly data as the baseline is driven by several considerations. First, the daily data are not reported at a constant frequency because of weekends and holidays. This creates difficulties for the Kalman filter, which assumes that observations are equally spaced over time. Second, particular observations in the daily data may be driven by idiosyncratic events, such as quarter-end or reserve-maintenance reporting dates, that our model does not capture. Finally, the timing of the data (for example, when a day's CDS quotes are reported, relative to when LIBOR is posted) and the information flows among market participants at the intraday horizon is somewhat unclear. In our model, we have assumed that banks have knowledge of the distribution of other banks' quotes when choosing their own, but at a daily frequency this might be unrealistic. By averaging across days, the weekly data smoothes out this microstructure variation, as well as other potential sources of high-frequency noise, while still allowing the parameters to move rapidly enough to realistically capture abrupt changes in market conditions.

C.1 Extra Step for Estimating Fixed-ϕ Model

Subsection 5.5 of the paper discusses an alternative model in which credit risk sensitivity is fixed rather than time varying. This model is estimated by adding another step to the Gibbs algorithm. That is, we extracted ϕ from the θ_t vector, creating θ_t^* (and Q^*), which continues to evolve according to equation (9) in the main paper, and then a fixed ϕ parameter was drawn in a separate step. The algorithm (once initial draws are obtained from the prior distributions) is as follows:

(i) Draw path of $\theta_t^{*(i)}$ for all t, conditional on the data, $R^{(i-1)}$, $Q^{*(i-1)}$, $\phi^{(i-1)}$.

(ii) Draw $\phi^{(i)}$ conditional on the data, $R^{(i-1)}$, $Q^{*(i-1)}$ and the path of $\theta_t^{*(i)}$ for all t.

(iii) Draw $R^{(i)}$ conditional on the data, $Q^{*(i-1)}$, $\phi^{(i)}$ and the path of $\theta_t^{*(i)}$ for all t.

(iv) Draw $Q^{(i)}$ conditional on the data, $R^{*(i)}$, $\phi^{(i)}$ and the path of $\theta_t^{*(i)}$ for all t.

This algorithm adds step (ii) to the original process and allows us to find the posterior distribution for the fixed ϕ parameter, shown in the main text as figure 6.

Appendix D. Additional Results and Robustness Checks

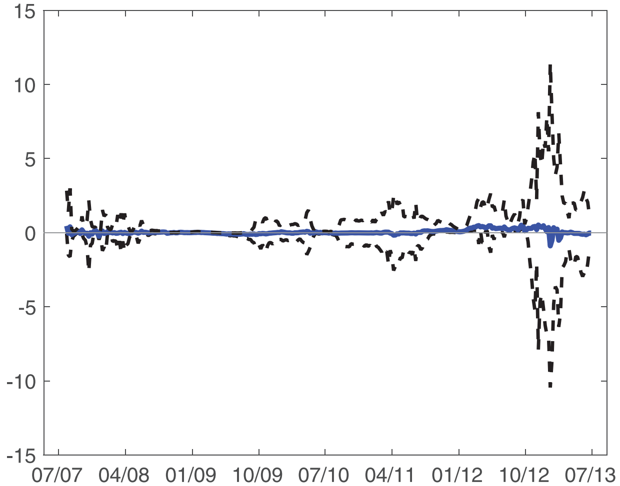
D.1 Ratio of Misreporting Costs in Baseline Model

Subsection 5.1 one the paper reported on the fact that the perceived cost of differing from other banks was always much greater than the perceived cost of lying per se. All else equal, a value of γ_{2t}/γ_{3t} close to zero would imply that banks do not vary their reported LIBOR quotes commensurately with their credit risk, but that they would all want to report similar values. (Because only the ratio can be identified, all we can say from this is that $\gamma_{2t} \ll \gamma_{3t}$.). Figure D.1 shows the time-series estimate of the γ_{2t}/γ_{3t} ratio.

D.2 Liquidity Spread Validation Regressions

Subsection 5.3.1 of the paper contains regressions of our model's liquidity premium estimates on external measures of funding market

Figure D.1. Estimated Path of the Ratio of Misreporting Costs (γ_{2t}/γ_{3t}), with 5th and 95th Percentiles



liquidity. Because of the high serial correlation of the errors, in the text we report the report the results using Cochrane-Orcutt estimation. For completeness, in table D.1 we report the same regressions using OLS with Newey-West standard errors. (Note that the R^2 in these regressions is biased upward.)

Table 3 of the paper, and table D.1 include joint estimation of the affect of T-bill spreads and TAF total capacity. Given that they are both being used as measures of external validation of our liquidity proxy, concerns about multicolinearity are diminished by examining the regressions in two steps. The first two columns for each maturity show regressions where the T-bill spread and the TAF capacity are performed independently, with the final column showing the joint regressions. The results are generally similar.

D.3 Sensitivity to CDS Liquidity Metrics

Subsection 5.3.2 of the paper contains regressions of our model estimates on external measures of CDS liquidity. Because of the high serial correlation of the errors, in the text we report the results using Cochrane-Orcutt estimation. For completeness, in table D.2,

Table D.1. External Validation of λ, Using OLS with Newey-West

	1 Week			1 Month			3 Months			6 Months			12 Months[b]		
Intercept	0.02	0.13***	0.08***	0.03	0.18***	0.06***	0.12***	0.28***	0.11***	0.34***	0.41***	0.27***	0.72***	0.63***	0.65***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)
T-Bill Spread[a]	0.19***		0.22***	0.43***		0.45***	0.92***		0.89***	1.61***		1.48***	−0.38		−0.47*
	(0.06)		(0.06)	(0.05)		(0.05)	(0.05)		(0.06)	(0.17)		(0.15)	(0.44)		(0.25)
TAF Total Capacity		−0.52***	−0.55***		−0.35***	−0.41***		0.31*	0.19*		0.74***	0.70***		0.64***	0.64***
		(0.09)	(0.08)		(0.09)	(0.07)		(0.17)	(0.10)		(0.06)	(0.05)		(0.03)	(0.03)
Adj. R^2	0.05	0.15	0.21	0.28	0.08	0.39	0.62	0.06	0.64	0.32	0.39	0.66	0	0.84	0.85
Durbin-Watson	0.2	0.24	0.23	0.14	0.09	0.17	0.24	0.03	0.24	0.11	0.02	0.2	0.01	0.08	0.09
N. Obs.	308	308	308	308	308	308	308	308	308	308	308	308	264	264	264

Notes: Regression performed using standard OLS with the Newey-West procedure to account for serial correlation in the errors. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

[a]In the regression for the one-week horizon, we use the one-month Treasury note-bill spread, which is the shortest maturity available; all other maturities are matched exactly.

[b]Twelve-month data only available since 2008.

Table D.2. Checking for Contamination from CDS Illiquidity

	λ^{6M}		λ^{12M}		ϕ	
	Full Sample	**Since 2010**	**Full Sample**	**Since 2010**	**Full Sample**	**Since 2010**
A. Procedure: OLS with Newey-West						
Intercept	0.55**	0.27***	0.80***	0.65***	0.20	0.14
	(0.27)	(0.03)	(0.11)	(0.06)	(0.15)	(0.18)
6-Month Fit Err.	−1.33	0.05			−1.38	0.81***
	(1.58)	(0.11)			(3.64)	(0.24)
6-Month B/A		28.70***				−6.84
		(11.00)				(58.00)
12-Month Fit Err.			−2.72*	−1.18*	1.46	−2.95*
			(1.42)	(0.66)	(9.83)	(1.69)
12-Month B/A				−16.90		54.50
				(20.50)		(142.10)
Adj. R^2	0.05	0.27	0.15	0.39	0.01	0.40
Durbin-Watson	0.02	0.08	0.06	0.07	0.11	0.16
N. Obs.	309	168	309	168	309	168
B. Procedure: Cochrane and Orcutt (1949)						
Intercept	0.01***	0.01***	0.02***	0.01***	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
6-Month Fit Err.	−0.01	0.02			0.39	0.23*
	(0.12)	(0.03)			(0.48)	(0.14)
6-Month B/A		−0.15				−0.15
		(1.31)				(0.28)
12-Month Fit Err.			−0.08	−0.11*	−0.52	−0.76
			(0.13)	(0.06)	(0.65)	(15.50)
12-Month B/A				1.41		3.18
				(2.62)		(27.90)
Error AR(1)	0.99	0.99	0.97	0.99	0.95	0.96
Adj. R^{2a}	0.00	0.01	0.00	0.17	0.01	0.12
N. Obs.	308	167	308	167	308	167

Notes: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.
[a]Adjusted R^2 for Cochrane-Orcutt procedure excludes contribution of lagged error term.

Table D.3. Model Results Using Only Five-Year CDS: Relative Contributions of Model Components

	1 Week	1 Month	3 Months	6 Months	12 Months
A. Average Value					
Liquidity	0.054	0.122	0.304	0.497	0.702
Credit Risk	0.384	0.384	0.384	0.384	0.384
Misreporting	−0.248	−0.248	−0.248	−0.248	−0.248
B. Average Fraction of "True" LOIS Spread					
Liquidity	28%	39%	58%	69%	74%
Credit Risk	72%	61%	42%	31%	26%
Misreporting	−64%	−58%	−44%	−31%	−22%

Notes: Panel A shows the average level of each of the indicated components of the average LOIS spread at each maturity, reported in percentage points. Panel B shows the unweighted average value of each component when normalized by the contemporaneous value of the bias-corrected LOIS spread. The contributions are calculated using the medians of the posterior distributions of the estimates.

panel A, we report the same regressions using OLS with Newey-West standard errors. (Note that the R^2 in these regressions is biased upward.)

D.4 Estimation Using Only Five-Year CDS Spreads

Tables D.3 and D.4 present a version of the results shown in tables 1 and 2 for the specification where the full term structure of CDS was replaced with just five-year CDS.

D.5 Raw vs. Smoothed CDS Quotes

We do not find large fitting errors for the 6- and 12-month CDS spreads, even on the days of the greatest dislocation in our sample. For horizons less than six months, we use the curves to extrapolate, and there is no direct way to validate the accuracy of this procedure since CDS quotes shorter than six months do not exist. However, the good in-sample fit of the curves gives us some comfort, and the slope and curvature of our fitted curves at the short end do not behave in erratic ways.

Table D.4. Model Results Using Only Five-Year CDS: Variance Decomposition

	1 Week	1 Month	3 Months	6 Months	12 Months
Liquidity	0.097	0.067	0.031	0.017	0.012
Credit Risk	0.219	0.219	0.219	0.219	0.219
ϕ Only	0.185	0.185	0.185	0.185	0.185
$\bar{C}$ Only	0.02	0.02	0.02	0.02	0.02
Liq./Credit Risk Cov.	−0.186	−0.116	0.016	0.063	0.027

Notes: The table shows the approximate contribution of each of the indicated components to the overall time-series variance of the average LOIS spread at each maturity. Units are percentage points squared. Contributions are calculated using the medians of the posterior distributions of the estimates.

To test whether our results were being driven by the smoothing procedure, we input the raw 6- and 12-month CDS quotes into our estimated model, in place of the smoothed quotes at those maturities. If the model were very sensitive to the Nelson-Seigel approach, applying the model to the raw quotes instead of the Nelson-Seigelized quotes would give significantly different predicted values for the corresponding maturities of LOIS. Figure D.2 shows that this is not the case by showing the *very small* differences in implied credit risk under raw versus Nelson-Siegel curve CDS results. At most, the estimates of the credit risk and misreporting components differ briefly by a few basis points. Figure D.3 shows that the effect of exchanging raw for Nelson-Siegel curve CDS is similarly minuscule for the measure of misreporting as well.

D.6 Fixed-ϕ Estimation

Tables D.5 and D.6 present a version of the results shown in tables 1 and 2 for the model with fixed credit risk sensitivity.

Figure D.2. Credit Risk Measure when Replacing Nelson-Siegel CDS Spreads with Raw CDS Spreads

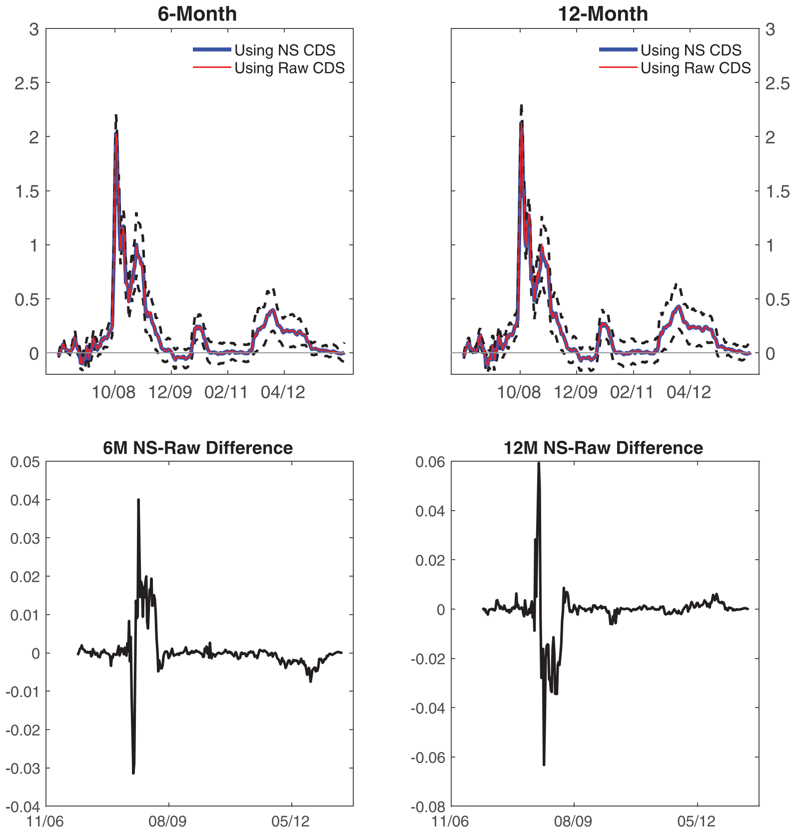


Figure D.3. Misreporting Measure when Replacing Nelson-Siegel CDS Spreads with Raw CDS Spreads

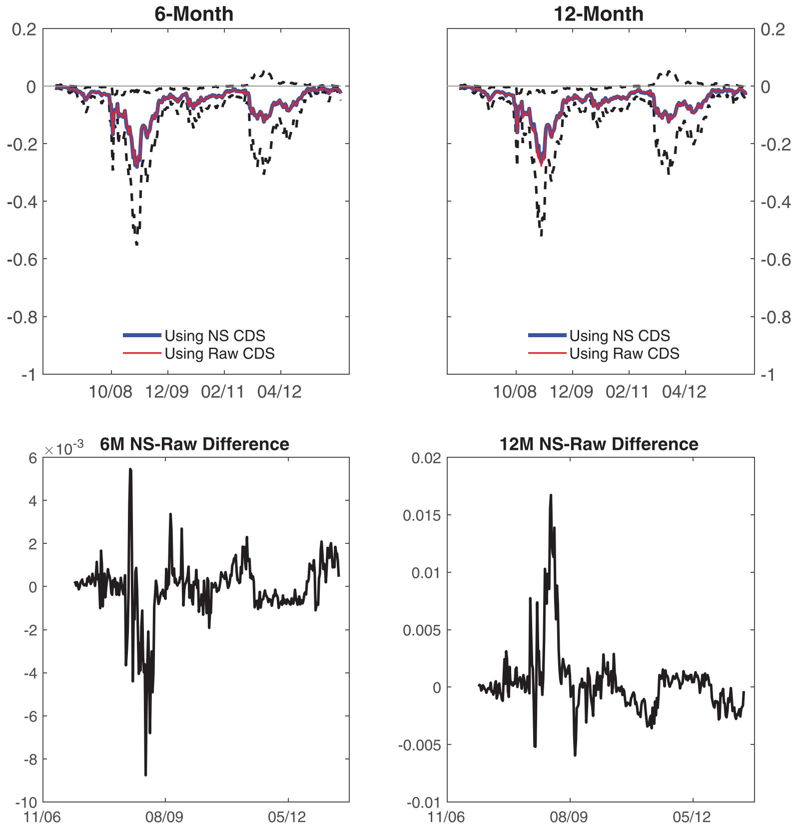


Table D.5. Model Results with Fixed ϕ: Relative Contributions of Model Components

	1 Week	1 Month	3 Months	6 Months	12 Months
A. Average Value					
Liquidity	0.098	0.164	0.342	0.528	0.718
Credit Risk	0.145	0.146	0.151	0.16	0.178
Misreporting	−0.067	−0.068	−0.068	−0.069	−0.072
B. Average Fraction of "True" LOIS Spread					
Liquidity	19%	36%	59%	74%	80%
Credit Risk	75%	61%	39%	25%	19%
Misreporting	−36%	−29%	−18%	−11%	−8%

Notes: Panel A shows the average level of each of the indicated components of the average LOIS spread at each maturity, reported in percentage points. Panel B shows the unweighted average value of each component when normalized by the contemporaneous value of the bias-corrected LOIS spread. The contributions are calculated using the medians of the posterior distributions of the estimates.

Table D.6. Model Results with Fixed ϕ: Variance Decomposition

	1 Week	1 Month	3 Months	6 Months	12 Months
Liquidity	0.11	0.14	0.18	0.173	0.11
Credit Risk	0.015	0.015	0.015	0.015	0.015
ϕ Only	0	0	0	0	0
$\bar{C}$ Only	0.015	0.015	0.015	0.015	0.015
Liq./Credit Risk Cov.	−0.012	−0.002	0.038	0.061	0.068

Notes: The table shows the approximate contribution of each of the indicated components to the overall time-series variance of the average LOIS spread at each maturity. Units are percentage points squared. Contributions are calculated using the medians of the posterior distributions of the estimates.

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