Internet Appendix for
"Liquidity Supply by Broker-Dealers and Real Activity"

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Internet Appendix 1. List of primary dealers

Below is the list of firms designated as primary dealers by the Federal Reserve Bank of New York, as of September 2016.

Bank of Nova Scotia, New York Agency
BMO Capital Markets Corp.
BNP Paribas Securities Corp.
Barclays Capital Inc.
Cantor Fitzgerald & Co.
Citigroup Global Markets Inc.
Credit Suisse Securities (USA) LLC
Daiwa Capital Markets America Inc.
Deutsche Bank Securities Inc.
Goldman, Sachs & Co.
HSBC Securities (USA) Inc.
Jefferies LLC J.P.
J. P. Morgan Securities LLC
Merrill Lynch, Pierce, Fenner & Smith Incorporated
Mizuho Securities USA Inc.
Morgan Stanley & Co. LLC
Nomura Securities International, Inc.
RBC Capital Markets, LLC
RBS Securities Inc.
Societe Generale, New York Branch
TD Securities (USA) LLC
UBS Securities LLC
Wells Fargo Securities, LLC

The current list, together with historical lists of primary dealers, can be found at https://www.newyorkfed.org/markets/primarydealers.html. The aggregate daily primary dealer transaction volume in nominal Treasury securities averaged $500 billion in 2016.

Internet Appendix 2. Detailed variable definitions

Noise and dealer gross positions in nominal Treasury securities

- *Noise* is an estimate of the deviations of individual yields from a fitted Svensson (1994) yield curve. For each day d, noise is the root mean square error between the model-implied yield and the market yield. To obtain a monthly measure, noise is averaged across trading days with available data.

- *Dealer gross positions in nominal Treasury bonds* are the sum of gross long and gross short positions of primary dealers in nominal Treasury coupon securities from the Federal Reserve Weekly Report of Dealer Positions (FR 2004 A), deflated using the Consumer Price Index (all items less food and energy).

Real activity, asset prices, and standard illiquidity measures

- The *unemployment rate* is the civilian unemployment rate from the Bureau of Labor Statistics (BLS) household survey.

- *Payroll employment* is total non-farm payroll employment from the BLS establishment survey.

- *Industrial production* and the *capacity utilization rate* are from the Federal Reserve G.17 release.

- The *job posting ratio* is total private job openings as a share of the civilian labor force 16 years and over, from JOLTS beginning December 2000 and from Hall (2017) and Petrosky-Nadeau, Zhang, and Kuehn (2018) before December 2000.

- *Construction spending* is construction put in place from the Census Bureau.

- *VIX* is the Chicago Board of Exchange (CBOE) Volatility Index.

- The *corporate bond spread* is the Moody's Seasoned Baa Corporate Bond Yield less the 10-year Treasury constant maturity yield.

- *Corporate bond Amihud* is the median Amihud (2002) price impact proxy for the corporate bond market calculated from Trade Reporting and Compliance Engine (TRACE) data.

- *Equity market Amihud* is the mean Amihud (2002) price impact proxy calculated from Center for Research in Security Prices (CRSP) data.

- The mortgage-backed security OAS is the option-adjusted spread over swap yields from JP Morgan, averaging LIBOR and Treasury swap yields.

Aggregate financing and investment (source: Financial Accounts of the United States)

- Flow variables are *net debt issuance* (FA104104005), *net equity issuance* (FA103164103), and *capital expenditures* (FA105050005) for non-financial corporate businesses (table F.103) and *net mortgage issuance* (FA893065005, table F.217).

- *Aggregate credit of the non-financial sector* is the sum of *household debt* (FL154104015, table L.101) and *non-financial business debt* (FL144104005, table L.102).

Corporate finance panel data (source: Compustat)

- Firm-level *net equity issuance* is SSTK-PRSTKC. Firm-level *net debt issuance* is DLTIS-DLTR. Firm-level issuance variables are normalized by beginning-of-period assets. Firm-level *capital expenditure* is CAPX and is normalized by beginning-of-period fixed assets. Firm-level *employees* is EMP. Issuance and capital expenditure data is quarterly; employment data is annual. For items from the quarterly statement of cashflows that are reported in year-to-date terms, I use the original amount for the first fiscal quarter and compute quarterly values for the remaining quarters in the fiscal year by differencing the year-to-date data. Outliers are winsorized at the 1 and 99 percentiles. I exclude financial firms (SIC from 6000 to 6999).

References not included in main text

Petrosky-Nadeau, N., Zhang, L. and Kuehn, L.A., 2018. Endogenous disasters. *American Economic Review*, forthcoming.

Internet Appendix 3. Comparison with quantitative structural models

This appendix compares the responses of outcome variables to a liquidity supply shift as estimated in this paper with the responses to liquidity shocks from two leading quantitative structural models. I find that the signs and the magnitudes of the responses estimated in this paper to a one-standard-deviation liquidity supply shift are similar to the responses obtained in the structural models, suggesting that liquidity supply can indeed drive the responses of liquidity, issuance, investment, and employment obtained in this paper.

The two structural models I use are Jermann and Quadrini (2012) and Ajello (2016) (hereafter, JQ and Ajello). For the purposes of this appendix, these models feature three important advantages that facilitate a comparison with the outcomes studied in this paper. First, JQ and Ajello feature endogenous issuance, investment, and employment; these are key outcome variables in this paper. Second, JQ and Ajello are dynamic stochastic models, allowing a comparison of the dynamic responses to a liquidity shock. Third, JQ and Ajello are general equilibrium models; the dynamic responses captured in this paper are inclusive of any general equilibrium effects, which Ajello argues are quantitatively important.

I summarize the response of each outcome variable as the average response over the quarter in which the liquidity shock occurs and the subsequent four quarters. That is, for JQ and Ajello, I denote the impulse response of outcome y at horizon h to a liquidity shock by β_s^h, where h is measured in quarters. To obtain the average response, I calculate $\frac{1}{5}\sum_{h=0}^{4}\beta_s^h$. Studying the average response is helpful because JQ and Ajello do not focus on the adjustment costs that typically generate hump-shaped responses for variables such as issuance and investment; thus, in their models, issuance and investment respond immediately to a shock, whereas in this paper, the estimated responses feature a lag or hump shape for some issuance and investment measures, likely reflecting a variety of costs of adjusting issuance and investment (e.g., Strebulaev, 2007).

Table IA.3.1 compares the average responses estimated using the local projection in Eq. (11) with the responses from the structural models of JQ and Ajello. The results in Table

IA.3.1 compare responses to one standard deviation shocks in each model with a one standard deviation liquidity supply shift from this paper.

Note that JQ and Ajello do not define their issuance and investment variables exactly as in this paper. Hence, to facilitate a comparison, I use Eq. (11) to estimate responses using outcome variables adjusted to make comparisons with JQ and Ajello. In particular, Table IA.3.1 compares the responses of net debt issuance and net equity issuance from Eq. (11) to the responses in JQ; for this appendix, following JQ, I re-normalize the net issuance variables in Section 3.3 by gross corporate value-added rather than corporate assets. For Ajello, I estimate Eq. (11) directly on the issuance variable studied in Ajello: the financing gap share, a measure of the extent to which capital expenditures exceed net financing raised, constructed using Compustat data. See Ajello for details; I am grateful to Andrea Ajello for providing data on the financing gap share and for discussing how to map the results in this paper to those in Ajello (2016). In addition, to measure labor, both JQ and Ajello use hours worked rather than payroll employment or the unemployment rate, so I estimate Eq. (11) for hours worked and report the results in Table IA.3.1. These re-normalizations explain why the local-projection estimates in Table IA.3.1 are not the same as reported in the main text of this paper.

Table IA.3.1: Comparison with structural models

Average response over a one-year horizon to a one standard deviation liquidity or liquidity supply shock			
	JQ (2012)	Ajello (2016)	Local Projection (Eq. 11)
Net Debt Issuance (scaled by value-added)	-1.69	-	-1.77
Net Equity Issuance (scaled by value-added)	0.84	-	0.96
Financing Gap Share (percentage points)	-	-9.11	-3.06
Investment (percent)	-2.37	-2.03	-3.00
Hours Worked (percent)	-0.85	-0.65	-0.87
Corporate debt transaction cost (percent)	-	7.85	10.27

This table compares the responses of outcome variables to a one standard deviation liquidity shock (Jermann and Quadrini (2012) and Ajello (2016)) and a one standard deviation liquidity supply shift (Local Projection (Eq. 11)). The response of each outcome variable is summarized as the average response over the quarter in which the liquidity shock occurs and the subsequent four quarters. That is, for JQ and Ajello, denote the impulse response of outcome y at horizon h to a liquidity shock by β_s^h, where h is measured in quarters. To obtain the average response, I calculate $\frac{1}{5}\sum_{h=0}^{4}\beta_s^h$. The responses shown in this table can be found in Fig. 6 of JQ and Fig. 4 of Ajello and are obtained from the replication files for those papers. Debt issuance is the negative of debt repurchases. For outcome variables that are not reported in JQ and Ajello, the response in this table is marked with a hyphen to denote that it is not available. See text for details.

As shown in Table IA.3.1, the results from JQ and Ajello are roughly similar to the results based on the local projection.

At this point, a discussion of the shocks and mechanisms in JQ and Ajello is helpful. The financial shocks in JQ and Ajello capture fluctuations in liquidity, as explained in their papers. For JQ, the shock affects the resaleability of collateral and thus affects debt issuance by firms, thereby limiting access to the working capital needed to hire workers. A negative shock to resaleability leads firms to decrease debt, raise equity, and cut hiring. Ajello is built on the theoretical model of liquidity of Kiyotaki and Moore (2012). In Ajello, a bid-ask spread or transaction cost for financial assets is hit by a shock. A negative liquidity shock reduces a firm's ability to finance capital expenditure by selling the existing financial assets held on its balance sheet and by issuing new claims on its own future cash flows. A key feature of these shocks in Ajello and JQ is that they are estimated to be persistent. Thus, the key outcome variables capturing the mechanisms in JQ and Ajello are aligned with those studied in this paper.

Overall, the responses estimated in this paper are similar to those obtained from the structural models of JQ and Ajello, providing evidence that liquidity supply shocks can indeed drive the responses of illiquidity, issuance, investment, and real activity studied in this paper.

Internet Appendix 4. Supply and demand shift proxies

Table IA.4.1 reports the pairwise correlations of the supply and demand shift proxies with the variables shown in Table 1 as well as alternative estimates of supply and demand shifts. In particular, to assess the robustness of the liquidity supply and demand shift estimates described in Section 2, this appendix considers two alternative methods of estimating supply and demand shifts that use the same sign restrictions as in the Bayesian method described in Appendix B but in different ways.

Time-varying parameter VAR

Consider the time-varying parameter VAR (TVP-VAR) of Primiceri (2005):

$$Y_t = \mu_t + \sum_{i=1}^{l} B_{i,t} Y_{t-i} + C_t^{-1} S_t \delta_{t,tvp},$$

where $Y_t = [noise_t \ positions_t]'$ is a 2 x 1 vector, μ_t is a time-varying 2 x 1 intercept vector, $B_{i,t}$ is a time-varying 2 x 2 matrix of coefficients, C_t is a lower-triangular 2 x 2 matrix with ones on the diagonal, S_t is a 2 x 2 diagonal matrix of time-varying standard deviations, and $\delta_{t,tvp}$ is a 2 x 1 vector of disturbances with variance equal to the identity matrix. The evolution of the time-varying parameters is as described in Primiceri (2005); all time-varying coefficients follow random walks except for S_t, which follows a geometric random walk. Let the reduced-form covariance matrix be Ω_t, with $C_t \Omega_t C_t' = S_t S_t'$. The prior distributions are identical to Primiceri (2005) except that fewer degrees of freedom are assigned to the priors for the variances of shocks to the $B_{i,t}$ (coefficient matrices) and S_t (standard deviations), to favor the possibility that the coefficients and standard deviations have significant time variation. Specifically, I use 20 degrees of freedom for the inverse-Wishart prior for the variance of the shocks to $B_{i,t}$ and 3 degrees of freedom for the inverse-Wishart prior for the variance of shocks to S_t; the results are also robust to using 40 and 4 degrees of freedom, respectively, as in Primiceri (2005). The initial subsample used the calibrate the priors is the first 48 months (September 1990 to August 1994). TVP-VARs similar to this have been successful in tracking smooth structural change as well as highly non-linear dynamics including regime shifts (Baumeister and Peersman, 2013).

Following Benati (2008), among others, let $\Omega_t = P_t D_t P_t'$ be the eigenvalue-eigenvector decomposition of the reduced-form covariance matrix. I estimate the model using a Gibbs sampling procedure. For each draw of Ω_t, I define $A_t = P_t D_t^{\frac{1}{2}} Q$, where Q is an orthonormal matrix drawn uniformly from the unit circle. I keep the draw if A_t satisfies the sign restrictions. I perform 10,000 iterations of the Gibbs sampler, automatically discarding the first nine out of every ten draws after an initial burn period of 10,000 iterations.

Coarse estimation procedure

This method infers shifts in liquidity supply and demand using the "paired" one-step-ahead prediction errors for noise and dealer gross positions. In particular, building on Cohen, Diether, and Malloy (2007), I estimate Eq. (3) via OLS and divide the estimates of paired residuals $(\xi_{noise,t}, \xi_{positions,t})$ into quadrants. For example, if there is an unexpected rise in noise and an unexpected decline in dealer gross positions ($\xi_{noise,t} > 0$ and $\xi_{positions,t} < 0$), this change is counted as an inward shift in liquidity supply. Of course, a supply shift is not necessarily the only change that has occurred—a demand shift might have taken place as well; however, at least a positive supply shift must have occurred. The other quadrants are labeled accordingly. I denote the alternative proxy by $\delta_{t,alt} = [\delta^s_{t,alt}\ \delta^d_{t,alt}]'$, where

$$\delta^s_{t,alt} = \begin{cases} 1 & \text{if } \xi_{noise,t} > 0 \text{ and } \xi_{positions,t} < 0 \\ -1 & \text{if } \xi_{noise,t} < 0 \text{ and } \xi_{positions,t} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\delta^d_{t,alt} = \begin{cases} 1 & \text{if } \xi_{noise,t} > 0 \text{ and } \xi_{positions,t} > 0 \\ -1 & \text{if } \xi_{noise,t} < 0 \text{ and } \xi_{positions,t} < 0 \\ 0 & \text{otherwise.} \end{cases}$$

Properties of the supply and demand shift estimates from the TVP-VAR and coarse estimation

The supply shift proxy in the paper, δ_t^s, has a correlation of 0.98 with the TVP-based proxy $\delta_{t,tvp}^s$ and a correlation of 0.75 with the coarse proxy $\delta_{t,alt}^s$. The demand shift proxy in the paper, δ_t^d, has a correlation of 0.99 with the TVP-based proxy $\delta_{t,tvp}^d$ and a correlation of 0.77 with the coarse proxy $\delta_{t,alt}^d$.

Table IA.4.1: Pairwise correlations

Pairwise correlations, in percentage points

		2	3	4	5	6	7	8	9	10
1	Δ Noise	-16	65	47	45	50	66	41	38	33
2	Δ Positions		-60	40	10	-11	-56	33	-47	31
3	δ_t^s supply shift proxy			0	17	30	98	5	75	1
4	δ_t^d demand shift proxy				23	20	17	99	-5	77
5	Δ VIX					52	19	22	7	15
6	Δ Baa spread						34	18	9	13
7	$\delta_{t,tvp}^s$							20	76	14
8	$\delta_{t,tvp}^d$								2	79
9	$\delta_{t,alt}^s$									0
10	$\delta_{t,alt}^d$									

This table shows the pairwise correlations of the supply and demand shift proxies with other financial variables. The frequency is monthly. Noise reflects the deviations of individual bond yields from a fitted Svensson (1994) yield curve. Dealer gross positions is the sum of gross long and gross short positions held by primary dealers. The construction of the liquidity supply and demand shift proxies is detailed in Section 2.3. $\delta_{t,tvp}^s$ and $\delta_{t,tvp}^d$ are supply and demand shift proxies based on a time-varying parameter VAR, as described in this Internet Appendix. $\delta_{t,alt}^s$ and $\delta_{t,alt}^d$ are coarse supply and demand shift proxies based on using the "paired" one-step-ahead prediction errors for noise and dealer gross positions, also described in this Internet Appendix. Sample period: 1990m9 to 2017m5.

References not included in main text

Baumeister, C. and Peersman, G., 2013. Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics* 5(4), 1-28.

Benati, L., 2008. Investigating inflation persistence across monetary regimes. *The Quarterly Journal of Economics* 123(3), 1005-1060.

Primiceri, G.E., 2005. Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies* 72(3), 821-852.

Internet Appendix 5. Responses of additional outcome variables

This appendix studies the responses to a liquidity supply shift for additional outcome variables not shown in the main text. The first type of outcome studied is corporate bond and equity liquidity for investment-grade and junk-rated firms. The second type of outcome studied is net debt issuance in securities markets and net bank borrowing. Responses are obtained by estimating Eq. (11), as described in Section 3.1.

Changes in liquidity for firms of different credit quality

Fig. IA.5.1 displays the responses of equity liquidity and corporate bond liquidity to a liquidity supply shift for high-yield and investment-grade firms.

Changes in net issuance of debt securities and net bank borrowing

Fig. IA.5.2 displays the responses of the net issuance of debt securities and net bank borrowing using Financial Accounts of the United States data.

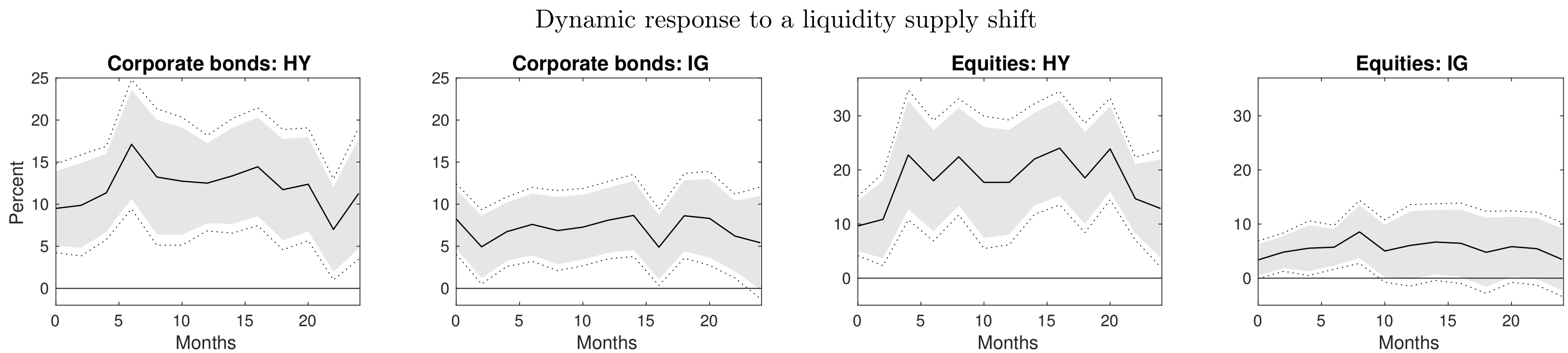

Fig. IA.5.1. Dynamic response of corporate bond and equity liquidity, by credit quality of firm. The figure plots the expected change in illiquidity following a liquidity supply shift for corporate bonds and equities, for high-yield (HY) and investment-grade (IG) firms. Expected changes in illiquidity are calculated using the local projection method of Jordà (2005), varying the horizon h in Equation 11. Illiquidity is measured using the Amihud price impact proxy; the change in liquidity is defined as the log-difference. 90-percent (shaded area) and 95-percent (dotted lines) confidence intervals calculated using the Newey-West covariance matrix are shown.

Dynamic response to a liquidity supply shift

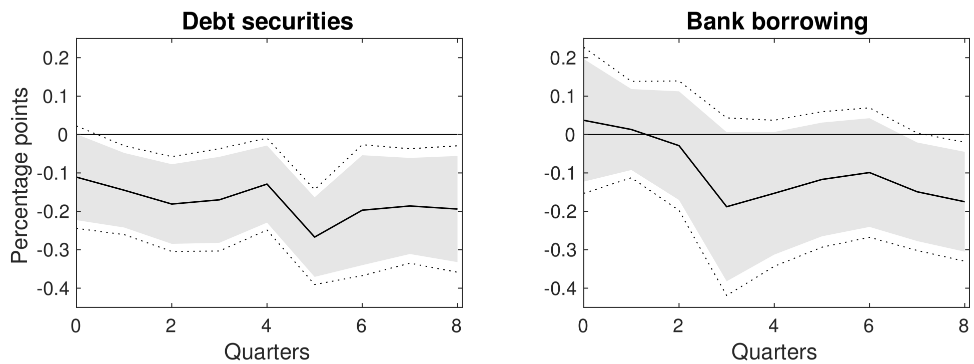

Fig. IA.5.2. Issuance of debt securities and bank borrowing. The figure plots the expected change in net issuance of debt securities and net bank borrowing following a liquidity supply shift. Data are from the Financial Accounts of the United States. *Net issuance of debt securities* is the sum of the net issuance of corporate bonds, industrial revenue bonds (i.e., municipal bonds issued by corporate firms), and commercial paper (FA104122005); the net issuance of institutional leveraged loans to non-bank investors (FA103169803); and net mortgage issuance (FA893065005) less net mortgage borrowing from banks (FA703065005). *Net bank borrowing* is net borrowing through commercial and industrial loans and business leases (FA103168005) and net mortgage borrowing from banks (FA703065005). Issuance and borrowing are normalized by lagged value-added. Estimates are reported for Equation 11, controlling for innovations to bank loan supply from Bassett, Chosak, Driscoll, and Zakrajšek (2014). 90-percent (shaded area) and 95-percent (dotted lines) confidence intervals calculated using the Newey-West covariance matrix are shown.

Internet Appendix 6. Additional vulnerability measures

Table IA.6.1: Household and Business Credit Growth as Vulnerability Measures

Dependent variable: 12-month change in real activity				
Panel A. Using credit growth of households				
	UN	EMP	CAP	RAI
δ_t^s supply shift	-0.11*	0.13*	0.05	0.17*
	(0.06)	(0.08)	(0.16)	(0.10)
δ_t^d demand shift	-0.03	0.14*	0.21	0.12
	(0.05)	(0.08)	(0.15)	(0.09)
δ_t^s supply shift x Lagged credit growth	1.19***	-1.41***	-2.17**	-2.02***
	(0.41)	(0.45)	(0.99)	(0.63)
δ_t^s demand shift x Lagged credit growth	0.62**	-1.14**	-1.15	-1.30
	(0.31)	(0.54)	(1.04)	(0.83)
Lagged credit growth	4.57***	-5.71***	-19.22***	-8.02***
	(1.20)	(1.91)	(4.57)	(3.06)
N	321	321	321	321
ΔR^2	23.43	12.08	35.71	17.49
R^2	63.16	75.16	61.19	56.82

This table presents an analysis of lagged credit growth as a measure of vulnerability to liquidity supply shifts. Estimates are reported for Equation 11. The dependent variable is the change in real activity over a 12-month horizon, $\Delta^{12}y_{t+12}$. In Panel A, additional controls include growth in aggregate credit of households over a three-year horizon prior to month t and its interactions with the liquidity supply shift proxy and the liquidity demand shift proxy. In Panel B, additional controls include credit growth of non-financial businesses and its interactions with the liquidity supply shift proxy and the liquidity demand shift proxy. Each specification also controls for lags of $\triangle y_t$ (not reported), with the lag length determined by the Akaike information criterion. UN is the unemployment rate, EMP is employment, CAP is capacity utilization, and RAI is the real activity index. OLS coefficient estimates and Newey-West standard errors are shown. For detailed variable definitions, see Internet Appendix 2. The frequency is monthly; N is the number of months. OLS coefficient estimates and Newey-West standard errors are shown. *, **, and *** mean significance at the 10%, 5%, and 1% level, respectively.

(continued)

Continued

Dependent variable: 12-month change in real activity				
Panel B. Using credit growth of non-financial businesses				
	UN	EMP	CAP	RAI
δ_t^s supply shift	0.04	-0.06	-0.16	-0.01
	(0.05)	(0.06)	(0.16)	(0.10)
δ_t^d demand shift	-0.00	0.03	0.36*	0.08
	(0.05)	(0.08)	(0.18)	(0.11)
δ_t^s supply shift $\times$ Lagged credit growth	0.83***	-0.88*	-2.57**	-1.82**
	(0.31)	(0.47)	(1.26)	(0.85)
δ_t^s demand shift $\times$ Lagged credit growth	0.22	-0.32	-1.41	-0.69
	(0.21)	(0.41)	(1.05)	(0.63)
Lagged credit growth	1.94***	-1.61**	-3.32	-2.09*
	(0.55)	(0.68)	(2.50)	(1.17)
N	321	321	321	321
ΔR^2	10.35	3.33	7.16	5.26
R^2	50.08	66.41	32.64	44.59

Internet Appendix 7. Out-of-sample predictive power of liquidity supply shifts

This appendix studies the predictive power of liquidity supply in securities markets using an out-of-sample analysis. The analysis compares the performance of forecasts from a model including the liquidity supply shift as an explanatory variable with forecasts from a model that excludes liquidity supply.

As before, $\triangle^h y_{t+h}$ denotes the change in an outcome between months $t-1$ and $t+h$. Denote by $\triangle^h \hat{y}_{t+h}$ the h-step-ahead forecast of $\triangle^h y_{t+h}$ from the predictive regression in Eq. (11) estimated using only data available through time $t-1$; the forecasting error is $u_{t+h} = \triangle^h y_{t+h} - \triangle^h \hat{y}_{t+h}$. A sequence of such forecasts is obtained and the mean square forecast error is denoted by

$$MSFE = \frac{1}{N_{oos}} \sum_{t=\tau+1}^{T} u_{t+h}^2,$$

where T is the total number of months in the sample, τ is the number of months used in making the initial forecast, and $N_{oos} = T - \tau$ is the number of months in the out-of-sample period. The out-of-sample period used is January 1998 to May 2017. Following the literature on forecast evaluation, the gain in out-of-sample forecasting accuracy is summarized by

$$\triangle R^2_{OOS} = 1 - \frac{MSFE}{MSFE_{no\_liq}},$$

where $MSFE_{no\_liq}$ is the mean square forecast error when excluding liquidity supply from Eq. (11).

As shown in Table IA.7.1, including liquidity supply as an explanatory variable results in improved out-of-sample forecast accuracy. For inference, I use the Clark and West (2007) test, as in Chen et al. (2018). The test statistic is

$$CW = \frac{MSFE - MSFE_{no\_liq} + ADJ}{\sqrt{N_{oos}} S_d},$$

where ADJ represents an adjustment for sampling error and S_d is the long-run (asymptotic) variance of the adjusted loss differential using an estimator allowing serial correlation of order h. The Clark-West test is a one-sided test. Table IA.7.1 shows that including liquidity supply as an explanatory variable results in improved out-of-sample forecast accuracy for liquidity for all four asset classes studied (corporate bonds, equities, MBS, and Treasury bonds), two of three net issuance measures (corporate debt and equities), each of the three investment measures (capital expenditure, job posting, and construction spending), and all four measures of real activity studied in Section 3. In addition, using the Clark-West test, the null hypothesis of equal predictive accuracy is rejected for most of these outcomes.

Table IA.7.1: Out-of-sample forecasting

Improvement in out-of-sample predictability								
Panel A. Liquidity in multiple asset classes (Δy_t, contemporaneous change)								
	Corporate Bonds	Equities	Mortgage	Treasury				
ΔR^2_{OOS}	24.20	6.80	1.98	95.71				
$Pr > CW$	0.006	0.001	0.028	0.000				
Panel B. Issuance and investment ($\Delta^h y_{t+h}$, $h = 4$ quarters)								
	Issuance					Investment		
	Corporate Debt	Equity	Mortgage			Capex	Job Posting	Construction
ΔR^2_{OOS}	15.82	9.35	-3.52			15.36	15.25	2.83
$Pr > CW$	0.031	0.021	0.891			0.032	0.018	0.151
Panel C. Real activity ($\Delta^h y_{t+h}$, $h = 12$ months)								
	UN	EMP	CAP	RAI				
ΔR^2_{OOS}	5.01	3.31	5.04	3.03				
$Pr > CW$	0.050	0.035	0.028	0.039				

This table reports the results from out-of-sample forecasting exercises. The forecasting target is $\Delta^h y_{t+h}$, the h-month change in an outcome variable y, where h varies by outcome variable. The forecasting model is given by Eq. 11. ΔR^2_{OOS} is the change in out-of-sample R^2 from including the liquidity supply shift proxy in the forecasting model relative to a model that excludes the liquidity supply proxy but is otherwise equivalent. $Pr > CW$ is the p-value for the one-sided Clark-West test of equal predictive ability using a HAC estimate of the long-run (asymptotic) variance. Forecasts are based on a recursive estimation procedure with an out-of-sample period of January 1998 to May 2017; for two of the time series used as outcome variables (liquidity for corporate bonds and MBS), data are not available for the entire sample period and the out-of-sample period begins four years after the first observation of the time series. UN is the unemployment rate, EMP is employment, CAP is capacity utilization, and RAI is the real activity index. The frequency is monthly in Panels A and C and quarterly in Panel B.