Central Banks and Dynamics of Bond Market Liquidity[1]

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Abstract

This study investigates market illiquidity and flow-price dynamics, with particular attention to central banks, using a comprehensive dataset for Indian government bonds. While, theoretically, liquidity provision by central banks should promote market depth and stability, some argue that overly active interventions may actually have the opposite effect. We find that bond market liquidity improves with greater funding liquidity provision by the central bank. The small magnitude of this effect challenges theories implying a tight link between funding liquidity and market liquidity but alleviates concerns that large interventions in either direction - like quantitative easing or its reversal - may be destabilizing.

KEYWORDS: GOVERNMENT BONDS, MARKET LIQUIDITY, FUNDING LIQUIDITY.

JEL CLASSIFICATIONS: E51, G12, G18.

1 Introduction

Bond market liquidity has recently become the focus of growing concern for global investors, regulators, and banks. While regulatory pressures since the financial crisis have drastically reduced the capacity and willingness of banks to facilitate trade in corporate debt markets, trade in government debt – which is substantially less subject to regulatory constraints[2] – had been thought to be less vulnerable. Yet in Spring 2015 a series of sharp market moves in German, US, and Japanese government bonds demonstrated that liquidity deterioration had reached the strongest and most active segments of the fixed-income universe. This has lead many to speculate about channels beyond bank capital regulation driving liquidity.

Theoretical arguments predict that funding liquidity (in the balance sheet sense) affects market liquidity (in the market depth sense) positively.[3] However, some commentators have paradoxically suggested that central banks' own actions to supply funding liquidity may actually be playing a role in driving down market liquidity. With the central banks themselves becoming dominant participants in bond markets via "quantitative easing" programs, it is natural to ask how their policies affect the incentives of others to provide intermediation services. A May 2015 research report from Citibank[4] assessing the liquidity drought in government bond markets states the case this way:

"We think the most likely candidate [driving illiquidity] is central banks increasing hold over markets. ... We argue that central banks' distortion of markets has reduced the

[2]For example, the U.S. "Volcker Rule" regulations specifically exempts government bond trading.
[3]For example, see Brunnermeier and Pedersen (2009) and Johnson (2009).
[4]Cited in `http://ftalphaville.ft.com/2015/05/11/2128946/`.

heterogeneity of the investor base, forcing them to be 'the same way round' to a greater extent than ever previously... This creates markets which ... are then prone to sudden corrections... It also leaves investors more focused on central banks than ever before - and is liable to make it impossible for central banks to make a smooth exit."

The informal notion here seems closely related to the mechanism in the corporate governance literature (Holmström and Tirole 1993) whereby the liquidity of a stock is adversely affected as ownership concentration increases – not so much because of the potential for adverse selection as because of the crowding out of ordinary participants ("noise traders") who make liquidity provision worthwhile. We will refer to the idea that central bank intervention may hurt market liquidity as the "crowding out hypothesis".

With this background, the present study investigates the interaction between funding liquidity and market liquidity in the Indian government bond market. India is one of the only major economies in which government bond trade is largely centralized in a single, transparent electronic limit order book system.[5] Our dataset consists of all orders and trades in this system, known as NDS-OM. This offers unique opportunities for high-frequency identification of microstructural effects. Of particular interest will be the potential effects on the system dynamic of the policy actions of the Reserve Bank of India (RBI). Here, again, India offers experience worth studying as the *variation* in RBI policy has been greater than that in most developed economies in recent years. Our sample encompasses periods of both substantial tightening and substantial easing. (See Figure 1.) The last decade has seen the central bank make, on average, 7-8 changes per year to

[5] Electronic trade in U.S. Treasury bonds can take place on one of several private interdealer platforms. There is no consolidated record of all trades.

the key policy rates or reserve requirements.[6]

Panel A: Net liquidity injection by RBI   Panel B: RBI Policy Rate

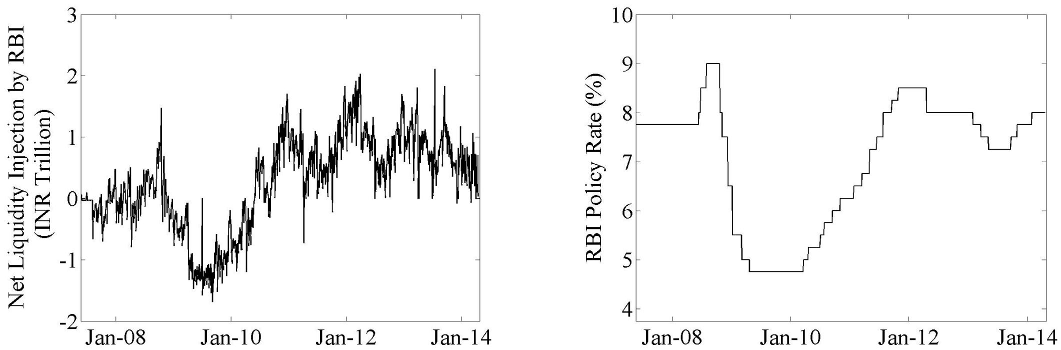

Figure 1: RBI Policy Variables
Panel A plots daily net liquidity injection by the RBI via net repurchase agreements (repos), marginal standing facility and changes in the cash reserves required to be held by the banks. Panel B shows daily RBI repo rate.

Moreover, while not engaging in the explicit "quantitative easing" seen in the U.S., Europe, and Japan, the RBI is a large and active participant in Indian fixed-income markets. The RBI manages the funding liquidity in the financial system via direct intervention in the government bond market, as well as via repo and foreign exchange markets. The size of these interventions is quite large compared to the size of the bond markets. In our sample, the average absolute weekly liquidity injection by RBI is INR 2.84 trillion, more than 300% the average weekly volume traded in the government bond market.[7] For comparison, the U.S. Federal Reserve purchased on average USD 0.05 trillion bonds per month between December 2008 to December 2013 via its Large Scale Asset Repurchase program.[8] This was mere 0.5% of the monthly volume in the U.S. Treasury markets

[6]Source: Monetary Policy Report by the RBI, April 2015 and data from `www.rbi.org.in`.

[7]One US dollar (USD) was equal to around 60 Indian rupees (INR) at the end of our sample in May 2014. We use this exchange rate throughout the paper.

[8]Based on data from `http://www.federalreserve.gov/monetarypolicy/bst_openmarketops.htm`.

during the same period.[9]

Further, as in the U.S. and Europe, considerations about economic growth and inflation inform the Indian central bank's monetary policy interventions.[10] Thus the questions about linkages between central bank actions and bond market activity in the Indian context are very relevant for drawing conclusions about these issues globally.

Our primary tool in examining this market is an estimation technique (developed in Deuskar and Johnson (2011)) that econometrically identifies transaction demand as exogenous shocks to order flow. The methodology provides high-frequency estimates of price impact (illiquidity), as well as a unique quantification of *how much illiquidity matters* at each point in time, via the amount of market volatility that is due to transaction demand moving prices. Both illiquidity and the component of volatility that it induces are time-varying. We examine that variation and model the dynamics of its components, allowing for conditioning on RBI policy and other potential covariates.

We focus on the most active benchmark 10-year government bond. As a first contribution, we document the baseline properties of illiquidity supply and demand in this market. During times of normal limit order book depth, a one-standard-deviation shock to flow moves prices by nearly 0.7 basis points or by about 0.47 standard deviations. Moreover, the price impact is effectively permanent at the time-scales we measure. The uncondi-

[9]Data from Securities Industry and Financial Markets Association (SIFMA).

[10]For example, a statement on September 13, 2012 by the U.S. Federal Open Market Committee states "Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee is concerned that, without further policy accommodation, economic growth might not be strong enough to generate sustained improvement in labor market conditions. The Committee also anticipates that inflation over the medium term likely would run at or below its 2 percent objective." Similarly, the RBI's 2013-14 annual report, while describing the rationale for its interventions, says "In 2013-14 concerns about the slowdown in growth significantly weighed on monetary policy [Later in the year] unrelenting inflationary pressures driven by persisting food inflation necessitated a tightening of the policy stance."

tional fraction of bond market volatility caused by price impact is nearly 50%. Thus policy actions that substantially increase or decrease market liquidity have the potential to have first-order effects on the riskiness of Indian government bonds.

When we examine the impact of RBI policy on system dynamics, we find a number of statistically significant, but economically modest effects. We proxy for RBI policy using net liquidity injection and the interest rate charged by the RBI to provide financing via repurchase agreements (the repo rate). We find that funding liquidity provision has a direct positive effect on market liquidity (a negative effect on the price impact of flows). On the other hand, we find that liquidity injection by the central bank increases order flow volatility which may be viewed as increasing liquidity demand. However, we find that higher flow volatility improves order book depth, reinforcing the direct effect of policy on price impact. Further, liquidity injection dampens return volatility, which in turn, also makes the bond markets more liquid. Finally, we explore the effect of other proxies for funding liquidity (including foreign investor flows and U.S. policy variables) and find similar effects - positive but small - on market liquidity.

Thus, we do not find support for the hypothesis that central bank actions may have adverse impact on bond market resilience and stability. However, given the small economic magnitudes of the effects we find, our results also do not support the concern that a reversal of recent easing policies in other countries may significantly disrupt government bond markets.

Our study contributes to the relatively recent but growing literature on the role of order flow in setting interest rates. Recent studies about the US Treasury market have shown that order flow plays an important role in price discovery.[11] Other studies have documented temporary as well as persistent effects of supply shocks on bond prices.[12] Many of these find that market liquidity plays an important role in the flow-return relationship.

Perhaps surprisingly, given the widespread perception that central bank provision of funding liquidity plays an important role in determining market liquidity, there is not an extensive body of empirical evidence on the topic.[13] This paper is among the first to directly test for such an effect in government bond markets.

In addition to improving our understanding about the flow-return dynamics with changing market and funding liquidity conditions, this paper also aims to provide insights about the bond markets in India, the third largest economy in the world.[14] Over the last decade or so, the RBI has been making changes - such as introduction of a new trading system, establishment of the Clearing Corporation of India Limited (CCIL), allowing short selling, among others - to improve market liquidity and promote price discovery in the secondary market for Indian government securities. Further, the Expert Committee to Revise and Strengthen the Monetary Policy Framework in India has recommended that the RBI increase use of trading on the NDS-OM platform to conduct open market operations. However, as yet, there is no study examining the extent to which trading affects prices in Indian government bond market and how this changes over time. This paper aims to fill this gap. Understanding the nature of return-flow dynamics in this market is also important for use of instruments of monetary policy by the RBI and the

[11] For example, see Brandt and Kavajecz (2004), Green (2004), Pasquariello and Vega (2007), and Menkveld, Sarkar, and Wel (2012) among others.

[12] For example see, Greenwood and Vayanos (2010, 2014), and D'Amico and King (2013) among others.

[13] See Chordia, Sarkar, and Subrahmanyam (2005) and Goyenko and Ukhov (2009).

[14] Based on purchasing power parity (PPP) valuation of GDP for 2014 from IMF World Economic Outlook Database, April 2015.

effectiveness of the monetary transmission mechanism.

A well-functioning secondary market for government bonds is important for the development of the yield curve. A well-developed yield curve is essential for pricing of riskier assets, particularly corporate debt. The concerns for development of market-determined yield curve, deepening of the corporate bond markets, and effective transmission of monetary policy via bond markets are shared by many emerging market economies.[15] Thus, the findings of this study may be useful for emerging market economies other than India.

The rest of the paper is structured as follows. The next section explains our identification methodology. Section 3 describes the market for Government of India bonds, our data and our measure of market illiquidity. Section 4 presents our baseline results on the flow-return relationship. Section 5 investigates the impact of central bank policies on the dynamics of this relationship. The final section summarizes our findings and concludes.

2. Econometric strategy

Our empirical work seeks to address two topics. First, using high-frequency bond market variables, we attempt to measure the *degree of illiquidity* of the market and quantify how much illiquidity matters in terms of induced price variation. Second, we try to measure the effect of policy actions on the various components that affect the liquidity calculations. This section describes the specifications we employ.

[15] See discussion in Mehrotra, Miyajima, and Villar (2012) and Mohanty (2012).

2.1. Identifying the effect of order flow

The first goal of empirical analysis in this paper is to measure the degree of liquidity in the bond market, as well as the exogenous demand for liquidity. Together, these permit us to quantify the fraction of variance of bond price movements explained by transaction demand. The approach here follows that in Deuskar and Johnson (2011).

The initial goal is simply to estimate an equation of the form:

$$return_t = b_r \ flow_t + \ \epsilon_{r,t} \tag{1}$$

where $return_t$ is return or price changes for the bond over the time interval t, and $flow_t$ is contemporaneous order flow i.e. quantity of buy orders net of quantity of sell orders. b_r is the price impact coefficient. However, it would be incorrect to run this regression without accounting for reverse causality i.e. flow being driven by price movements. This can happen because market participants may trade in response to price movements to rebalance their portfolio or otherwise have price contingent trading strategies. This could also happen due to purely mechanical reasons such as trade resulting from existence of stale orders. To overcome this problem of reverse causality, D'Amico and King (2013) use individual security's characteristics as instruments for the quantity bought. Menkveld et al. (2012) try to control for the endogeneity by including macro-economic surprise in the regression of yield changes on order flow.

To address the reverse causality, this paper explicitly models dependence of flow on returns

$$flow_t = b_f \ return_t + \ \epsilon_{f,t} \tag{2}$$

where $\mathrm{E}[\epsilon_f \ \epsilon_r] = 0$. Equations (1) and (2) are estimated as a simultaneous system, as discussed below, to obtain b_r and b_f. Then $return_t$ can decomposed as[16]

$$return_t = \frac{1}{[1 - b_r b_f]} \ \epsilon_{r,t} + \frac{b_r}{[1 - b_r b_f]} \ \epsilon_{f,t}. \tag{3}$$

The second term in this decomposition captures the effect of exogenous shocks to flow on prices. It is important to note that this component exists only if b_r, the price impact coefficient is non-zero. The first term in the decomposition captures movements in prices due to exogenous reasons (i.e. exogenous to trading). This can be viewed as the effect of public information.

From (3), variance of $return_t$ can be written

$$\frac{1}{[1 - b_r b_f]^2} \ \sigma^2_{r,t} + \frac{b_r^2}{[1 - b_r b_f]^2} \ \sigma^2_{f,t} \tag{4}$$

where $\sigma^2_{r,t}$ is the conditional variance of $\epsilon_{r,t}$, and $\sigma^2_{f,t}$ is that of $\epsilon_{f,t}$. The second term in (4) captures the variance of price changes that can explained by trading. The magnitude of this term again crucially depends on the key coefficient b_r. We call the fraction of total variance due to price impact of flows as flow-driven variation (FDV), which is given by

$$FDV = \frac{b_r^2 \ \sigma^2_{f,t}}{\sigma^2_{r,t} + b_r^2 \ \sigma^2_{f,t}}. \tag{5}$$

[16]The decomposition follows from matrix algebra. See Deuskar and Johnson (2011) for details.

Thus, for calculating FDV, getting coefficient estimates for Equations (1) and (2) are essential. We employ a method-of-moments procedure called identification through heteroskedasticity (ITH) from Rigobon (2003) to estimate the two equations simultaneously. The method imposes the key orthogonality condition, $\mathrm{E}[\epsilon_r \epsilon_f] = 0$. Writing $\mathrm{E}[\epsilon_r \epsilon_f]$ as $\mathrm{E}[(r - b_r f)(f - b_f r)]$ and setting it to zero requires

$$(1 + b_r b_f)\ \mathrm{Cov}(r_t, f_t) = b_r\,\mathrm{Var}(f_t) + b_f\,\mathrm{Var}(r_t). \tag{6}$$

To estimate b_r and b_f we need at least two distinct periods - two regimes - in the sample when the ratio of the two variances changes.[17] In effect, (6) regresses the covariance on the two variances. As Rigobon (2003) explains, the periods in which flow is relatively more volatile, there is greater likelihood of exogenous shocks to flow and vice-versa. Thus, the two volatilities act as probabilistic instruments to identify the simultaneous system. This allows us to allocate causality, and estimate the response coefficients and exogenous shocks to each variable.[18]

We next generalize the ITH estimation strategy to include conditional variation in the response coefficients. In particular, our interest is in *changes* in the price impact coefficient, b_r, as market conditions change.[19] We therefore model b_r as a function of

[17] A bit more accurately, as explained in Deuskar and Johnson (2011), in the two-regime case the variance-covariance matrix of the series $(r - b_r f)$ and $(f - b_f r)$ differs across regimes and its elements define a system of six equations in the six parameters $b_r, b_f, \sigma_{r,1}, \sigma_{f,1}, \sigma_{r,2}, \sigma_{f,2}$.

[18] One caveat must be kept in mind that the estimation must assign causality to either return or flow. If there were some third, omitted variable driving order flow while also moving prices, then, the estimation would attribute the influence to whichever included variable is a less noisy proxy for the omitted one.

[19] There is no reason why b_f should not also change over time. However, unlike b_r, we do not have strong *a priori* hypotheses about its variation. Also notice that b_f drops out of the formula for FDV.

conditioning variables:

$$b_{r,t} = b_0 + b' X_t. \tag{7}$$

Here, in principle, X_t can include anything strictly exogenous to time-t returns and flows. In practice, we will employ only variables observed prior to t. Most importantly, we will be able to use directly observable information on market depth from the limit order book, as described in Section 3.

2.2. Policy effects

Including conditional coefficient specifications in the simultaneous-equations framework, as just described, immediately offers one way to assess the impact of central bank actions on market liquidity and flow-driven risk in government bonds. We can include measures of policy directly in the specification of the price impact coefficient in (7).

In addition, we can ask whether such policies affect the other variables in our system. For example, central bank actions could increase or decrease return volatility, or market depth. These questions are interesting in their own right, and have not been extensively studied.

To investigate, we will estimate an auxiliary vector autoregression (VAR). This will allow us to examine dynamic responses of price impact to policy shocks through the volatility channels. The VAR can also shed light on the dynamic interdependence of the non-policy variables, such as the sensitivities of volatility to market depth and vice versa.

Note that the VAR system will not be primarily concerned with very high-frequency effects. (Our fastest moving policy variables are daily, for example.) We can also, in principle, improve the identification of policy innovations through the inclusion of other macroeconomic variables to which policy itself may respond.

3. Data

This section describes the data used for estimation in this paper and the construction of the primary variables.

3.1 Government securities market

The government bond market is a large and important part of the Indian financial system. For 2013-14, the volume of government securities traded was 88 trillion INR (about 1.5 trillion USD) compared to volume in the equity markets of about 33 trillion INR.[20] The government securities market in India is dominated by institutions. Table 1 provides some background information about this market. As can be seen from Panel A of the table, banks are the dominant players in this market accounting for about 70% of the volume during 2007-2014 period. Primary dealers are the next largest group with a share under 20% and mutual funds, insurance companies and other financial institutions with a share of about 10%.

The Negotiated Dealing System (NDS) is the primary venue where trading as well as reporting of the over-the-counter (OTC) trades in Indian Government securities happens. In 2005 the RBI added to the NDS an anonymous order driven electronic module called NDS-OM. Nath (2013) reports that around 80% of the traded volume in Indian

[20] Volume in equity market is the sum of volume on the National Stock Exchange and the Bombay Stock Exchange. See `http://www.moneycontrol.com/stocks/marketstats/turnover/`.

Government securities happens via NDS-OM. This study uses trade and order book data from NDS-OM. These data are maintained by the RBI and are made available to us by The Centre for Advanced Financial Research and Learning (CAFRAL) at the RBI. Our sample period goes from May 21, 2007 to April 20, 2014.

Our data contain all order entries on NDS-OM during the sample period. An entry is made every time an order is placed, updated, cancelled or traded. Each order is tracked using a unique order identification number. All orders come with a price and quantity. An order can display full or partial quantity, can expire at the end of the day or at a specified time before the end of the day. It can be of the type all-or-nothing or immediately-or-cancel. Panels B and C of Table 1 show the distribution of different order types. A large majority of the orders come without any quantity restrictions and expire at the end of the day. The trade data report all trades that happen on the NDS-OM. Each trade record has order numbers for the buy order and sell order that it matches, indicator as to whether the buy or the sell order triggered the trade, trade quantity and price. All entries come with a time stamp. Panel D shows the distribution of order quantity and trade quantity, measured in INR billions of bond face value. The fifth percentile as well as the median for both is at 50 million INR, the minimum order size for institutional investors.

Trading in the state government bonds as well as Government of India securities (treasury bills as well as bonds) happens on NDS-OM. However, activity is dominated by Government of India bonds, which account for around 95% of the trading volume on NDS-OM. Even, among Government of India (GOI) bonds, not all bonds are actively traded. Figure 2 plots average daily volume traded during our sample for the GOI bonds by maturity bucket. We can see a large spike around maturity of 9 to 10 years. During the sample period for this study, GOI bonds with remaining maturity of between 9 to 10 years account for around 40% of the total volume of all GOI bonds. We focus on bonds with 9 to 10 years of remaining maturity. This makes the interpretation of the price changes consistent throughout.

Even within this maturity bucket, the trading is concentrated in a single bond at a time that the market considers as benchmark. For the purpose of this study, from the maturity bucket of 9 to 10 years, we choose the bond with highest trading volume each day as the benchmark bond. Trading in the benchmark bond accounts for around 95% of volume in this maturity bucket during the sample period. Figure 3 shows the prices, yield and volume for the benchmark bond over our sample period.

3.2 Limit order book and order flow

We combine the order and trade data to construct limit order book at every minute. A limit order book at a point in time is collection of all open orders at that point in time. Using the limit order snapshots for each minute, we take the midpoint of the best bid and the best ask quotes as the price at that minute. Per-minute returns are calculated as the simple difference between midpoint prices for the current minute and the previous minute. We do not include overnight returns in our analysis. We have also conducted all our analysis using yield changes as returns. All the results are practically identical.[21]

The data allow us to identify whether each trade was triggered by a buy order or sell order. For every minute, we define net order flow as the difference between total quantity

[21]These are not included but are available from the authors on request.

for buyer initiated trades and total quantity of seller initiated trades, measured in INR billions of bond face value.

The limit order book data also allow us to continuously gauge not just the depth or quantity of orders, but also the sensitivity of that depth to price. We summarize the information in the limit order book in a single proxy of expected price impact following Deuskar and Johnson (2011).

To do so, for each limit order book snapshot, we construct a slope measure by fitting a line through cumulative quantities against limit order prices. Specifically, the *inverse limit order book slope* (ILOBS) is calculated as follows:

$$ILOBS = \frac{\sum_{s=Bid,Ask} \sum_{i=1}^{K} Mdist_{s,i} \cdot Mdist_{s,i}}{\sum_{s=Bid,Ask} \sum_{i=1}^{K} Mdist_{s,i} \cdot CQ_{s,i}}. \tag{8}$$

K is the number of limit order prices on each side. s is a side of the limit order book, which can be bid or ask. $Mdist_{s,i}$ is the difference between the ith limit order price on side s and the midprice. $CQ_{s,i}$ is the cumulative quantity in billions of INR of bond face value of all limit orders between the midprice and the ith limit order price on side s. Midprice is the midpoint of the best bid and best ask quotes for this limit order book. We treat bid side quantities as negative values, in line with the convention used for order flow calculation. Figure 4 graphically depicts the construction of ILOBS.

ILOBS is designed to capture the expected effect of market orders on prices and hence is a measure of price impact of potential trades – i.e., an *ex ante* measure of market illiquidity. Its units quantify the expected effect of an order of one billion INR of the bond face value on the price of the bond, holding the limit orders fixed.[22] Figure 5 plots the daily median of ILOBS in our sample. As can be seen, ILOBS shows substantial variation in this period.

Table 2 presents descriptive statistics for returns, order flow, bid-ask spreads and ILOBS. During our sample period, price changes are very symmetric around 0. Bid-ask spreads are fairly tight with mean of 4 basis points. Both 1-minute returns and order flow show substantial variation over the sample period. A relevant question is whether the activity in the benchmark 10-year bond is frequent enough to justify the analysis over one-minute intervals. It turns out that it is: 73% of one-minute intervals in our sample have some activity in the limit order book - new orders, order updates, order cancellations or trades. This provides sufficient variability for efficient estimation. However, we also conduct analysis for five-minute intervals as well as at daily frequency as part of our robustness checks.

In the next section, we estimate and discuss the conditional and unconditional relationship between returns and flow.

4. Order flow and flow-driven variation

This section presents baseline estimation results – not conditioning on RBI policy – that establish the degree to which bond market dynamics are affected by the price impact of order flow.

For the benchmark 10-year Government of India bond, the correlation between order

[22] This construction of ILOBS assumes linearity in the order book, treating orders close to and far from the best quotes equivalently. Later we investigate robustness of our results to different versions of ILOBS.

flow during a minute and the concurrent price change is 0.36 in our sample. This suggests that order flow and prices tend to move in the same direction. However, this is simple correlation and we cannot say whether flow is moving prices or vice-versa. Disentangling the two effects is the first step in our analysis.

4.1. Price impact of flow

We estimate a simultaneous system of returns and flow using identification through heteroskedasticity (ITH) as described in Section 2.1. The system is identified using distinct periods - regimes - over which the ratio of volatilities of the two dependent variables changes. The first two panels of Figure 6 show time series of daily volatility of 1-minute price changes and of 1-minute flow. Both show a great deal of variation over time. Most importantly for our purposes, the ratio of the two volatilities – which enables identification – also changes over time, as seen from Panel C.

ITH requires that we specify the regime length. The longer the length of each regime, the more efficient is the estimate of variance within each one. But there is an efficiency tradeoff because with longer regimes, there are fewer number of them across which to estimate the simultaneous coefficients. Fortunately, Rigobon (2003) shows that even if the regimes are misspecified, the method provides consistent estimates of the coefficients. We present the results for regimes of varying lengths from 5 days (1 week) to 66 days (3 months) to gauge robustness of our results. In the return as well as flow equations, we control for 10 lags of the dependent variables, since high frequency data can show considerable time series correlations.[23] Observations where the lags happen on the previous

[23]The lag coefficients are not estimated via ITH but by OLS within each minimization step. This is

day are excluded from the estimation.

Panel A of Table 3 presents the results for a relationship between price changes and flow, where the price impact of flow – coefficient b_r – does not change over time. The first row of the panel shows the results of OLS regression of returns on flow. Coefficient b_r is 0.020. Thus, a flow of one billion INR moves the bond price by 2 basis points. If flow is higher by one standard deviation – which is 0.27 billion INR from Table 2 – , the bond price moves up by 0.54 basis points, 35% of standard deviation of price changes. This effect is substantial. However, as we argued in Section 2.1, the OLS coefficient is biased if there is reverse causality. It turns out that, in our setting, OLS overestimates the effect of flow on prices.

The remaining rows in Panel A of Table 3 show the results of simultaneous system of returns and flow using ITH for different regime lengths with t-statistics based on asymptotic standard errors in parentheses.[24] There are three takeaways from these results. First, the ITH coefficient b_r of 1.1 basis points per billion INR is only about half of the OLS coefficient. There is considerable reverse causality from flow to returns as captured by highly statistically significant coefficient b_f. Second, based on the return decomposition in Section 2.1 (Equations (3)-(5)), we can calculate flow-driven variation (FDV) of returns. FDV turns out to be small. Only about 3% to 5% of variance of returns is accounted for by flows, once we account for reverse causality and control for lags. However, this finding will turn out not to be robust to more general specifications. Third, the magnitude and

equivalent to a two-stage GMM procedure. The standard errors that we report account for the joint dependence of the two stages.

[24]Asymptotic standard errors are computed from the general covariance matrix for extremum estimators. See Appendix B in Deuskar and Johnson (2011) for details.

the statistical significance of the coefficients as well as magnitude of FDV are not sensitive to choice of regime length.

The results so far assume that price impact of flow is constant over the entire sample. We now relax that assumption using additional information on order book depth.

4.2. Time-varying impact of flow

As discussed in Section 3.2, we summarize the state of the limit order book at any point in time using ILOBS, a measure of ex ante price impact of flow. It captures the effect on price of flow of one billion INR holding the limit order book constant. We use ILOBS as a conditioning variable in our ITH specification to allow for time-varying effect of flow on prices. To be specific, coefficient b_r in Equation (1), that models effects of flow on prices, depends on ILOBS as follows:

$$b_{r,t} = b_0 + b_i \; ILOBS_t, \tag{9}$$

where returns and flow are measures over the minute t and $ILOBS_t$ summarizes the limit order book at the beginning of minute t. Thus, ILOBS is exogenous to time t returns and flows and hence a legitimate conditioning variable. There is no assumption that ILOBS is exogenous to returns and flows prior to t. Panel B of Table 3 presents the results for this specification. Again, we see a significant reverse casuality from flow to prices as captured by the coefficient b_f. Thus, the OLS estimates of b_0 and b_i are biased upward.

ITH estimates of b_i, for the interaction of ILOBS and flow are all positive and statistically significant. So ILOBS is doing a useful job as a conditioning variable for impact of flow on prices. Looking at the ITH specification with 10-day regimes in Panel B, b_0 is 0.007 and b_i is 0.08. At the median level of ILOBS of 0.14, this translates into about 1.8 basis points of price change for one billion INR of flow - an effect 50% larger than that based on the unconditional estimates from Panel A. In standardized terms, a one-standard-deviation flow leads to price change of about 0.30 standard deviations at median ILOBS. Of course, the price impact coefficient b_r changes a great deal as ILOBS changes. Flow of one billion INR causes the prices to move by only 0.9 basis points when ILOBS is at its 5th percentile, as opposed to 7 basis points when ILOBS is at 95th percentile.

In absolute terms, the market for the 10-year Indian benchmark bond is on average about three times more illiquid than its U.S. counterpart. Recent estimates in that market[25] indicate an unconditional price impact of approximately 3.2 basis points for flow of USD 100 million for on-the-run 10 year bonds. (At the end of our sample USD 100 million is equivalent to 6 billion INR. Thus $6 * 1.8/3.2 = 3.4$.) However, the standardized magnitude documented by Brandt and Kavajecz (2004), who find that one standard deviation excess daily flow is associated with approximately half standard deviation movement in daily yields for U.S. Treasury bonds, is comparable to the standardized impact of flow of 0.30 standard deviations for Indian bond market.

Allowing b_r to vary over time also has an impact on FDV, the fraction of return variance that is explained by flow shocks. From 3%-5% in Panel A of Table 3, FDV goes up to about 50% in Panel B. Since ILOBS as a conditioning variable has quite a significant

[25] See `http://libertystreeteconomics.newyorkfed.org/2015/08/has-us-treasury-market-liquidity-deteriorated.html`.

effect, we use the specification conditional on ILOBS as our baseline specification in the rest of the paper.

We have already seen that the results are not sensitive to varying length of a regime for the ITH estimation. Now we investigate the robustness of the results by varying the number of lags of the dependent variables, the time interval over which returns and flow are measured, and the ways in which the limit order book is summarized. Table 4 shows these results for ITH estimation with 10-day regimes for the conditional specification. Specifications in Panel A have returns and flow over either 1-minute or 5-minute intervals and include different number of lags. The results are very similar to the baseline conditional specification in Panel B in Table 3.

The version of ILOBS we have used to this point, assumes that the order flow of any size will have the same per unit impact on prices. Also, we give the same weight to orders close to and far from the mid-price. In Panel B of Table 4, we relax these assumptions. The first row repeats the results for the main version of ILOBS for 10-day regimes from Panel B of Table 3. The rest of the rows present results for different versions of ILOBS. ILOBS-Narrow is based only on the best bid and the best ask quotes and associated quantities. Thus, the orders beyond the best bid and the best ask are given zero weight. ILOBS-Asymmetric is ILOBS for ask side for positive net flow and ILOBS for bid side for negative net flow. ILOBS-wt1 and ILOBS-w2 are inverse of the weighted slope of the limit order book. Weights are, respectively, inverse of the absolute distance from the midprice and inverse of the squared distance from the midprice. In these two versions, the orders beyond the best bid and the best ask are considered but given lower weight than the best quotes. In the last row of the table, we present results using bid-ask spread instead of ILOBS. All the results with different versions of ILOBS are very similar. Thus, in the rest of the paper, we continue to use the main version of ILOBS.

So far we have established the degree to which flow moves prices of the benchmark bond, but we have not investigated the persistence of this price impact. The persistence is important for the economic interpretation of market illiquidity. Transient "price pressure" is important to active traders, but does not represent an increase in real risk. Permanent effects do imply increases in market volatility, and thus affect the risk-reward tradeoffs faced even by buy-and-hold investors.

4.3 Persistence of price impact

The longer-term impact of flows on prices (including the contribution of lagged effects) can be judged from the system impulse responses. In Table 5, we report conditional impulse responses, following the approach in Deuskar and Johnson (2011), using coefficients for the conditional ITH specification in Panel B of Table 3 based on 10-day regimes.

The table reports $I_{f,r,0}$, the immediate impact and $I_{f,r,\infty}$, the cumulative infinite horizon impact on return of one-standard-deviation exogenous flow shock for 5th, 50th and 95th percentile values of ILOBS. Since $I_{f,r,\infty}$ is always larger than $I_{f,r,0}$, there is no reversal of instantaneous effect of flow on prices. The reason for this is that flow is positively autocorrelated. There is very little estimated autocorrelation in returns, and not much estimated cross-correlation between returns and lags of flow or vice-versa. An initial shock to flow results in a direct positive impact on return only instantaneously. However, it has a positive impact on future flow which then affects future returns positively.

Thus, the effect of flow on prices seems permanent and not due to temporary price pressure. The implication of this is that flow-driven variation is a type of liquidity risk that is borne even by long-term, buy-and-hold investors who do not need to trade. Since the price impact of trades does not revert, everyone assumes the extra uncertainty that comes from the liquidity demand of other participants. Given the FDV numbers for the conditional specification in Table 3, this risk is large - nearly 50% of risk in the benchmark 10-year Government of India bond is due to order flow.

One caveat is that the 50% fraction is of intra-day return variation. We do not include overnight returns since there is no trading overnight. So flow-driven variation will be a smaller fraction of return variation that includes overnight returns.

The impulse responses in Table 5 are based on 10 lags. We reach similar conclusions if we measure returns and flow over 1-minute or 5-minute intervals and vary the number of lags, covering prior 5 minutes to prior 50 minutes. Still, none of these specifications account for longer term lags. So we also estimate a simultaneous system of daily returns and flow using previous day's median ILOBS as a conditioning variable for the price impact coefficient, b_r. We control for 5 lags of daily variables. The coefficients of the simultaneous system are very similar to those reported in Panel B of Table 3 and FDV stays around 50%. For this specification, we find that at median ILOBS, $I_{f,r,\infty}$, the cumulative infinite horizon impact on return of one-standard-deviation exogenous flow shock is about 80% of $I_{f,r,0}$, the immediate impact. Thus, large fraction of price impact of flow is permanent even after controlling for autocorrelation at daily frequency.

Having established that the flow-driven variation in government bonds in substantial and permanent, we now investigate how central bank policies affect the return-flow dynamics.

5. Effect of central bank policies

As discussed in the introduction, conventional wisdom as well as theoretical models (Brunnermeier and Pedersen (2009) and Johnson (2009)) predict that greater funding liquidity leads to better market liquidity. However, recent experience has led some to suggest an alternative hypothesis: that too much central bank funding liquidity (in the form of quantitative easing) may actually increase market fragility. We call this the "crowding out hypothesis" – drawing an analogy with models (such as by Holmström and Tirole (1993)) that suggest an inverse relation between a stock's liquidity and ownership concentration. Surprisingly little evidence is available on these conjectures. We now address them in the context of our sample.

Our estimation methodology allows us to study variation both in price impact (measured by b_r) and in the components of market volatility, σ_f and σ_r. Together these determine the degree of flow-driven risk in the market. We examine the effect of central bank provision of funding liquidity on each of these quantities.

5.1 Policy variables

We consider two variables as proxies for funding liquidity provision by the RBI - net liquidity injections and the primary policy rate, both measured at daily frequency. Net liquidity injection by RBI is the sum of net repurchase agreements (repos), liquidity provided through marginal standing facility and net changes in cash reserves required to be held by the banks.[26, 27] The RBI's policy rate is the repo rate. This is equivalent of the discount window rate in the U.S. Table 6 provides some descriptive statistics for the policy variables. As noted in the introduction, both measures show substantial variation during our sample.

The two measures are plotted in Figure 1. The figure raises an important issue for interpretation. One would think that monetary tightness would be associated with less liquidity provision. Yet, counterintuitively, the two series consistently track each other positively. The reason for this is the passive nature of funding provision through the RBI's liquidity adjustment facility (LAF). Borrowing through this facility is the largest component of our liquidity injection series. Given the policy rate, LAF funds are supplied elastically. Thus such activity relects liquidity *demand*. Unconditionally, positive LAF provision is indicative of *tight* funding conditions among banks. Controlling for the level of tightness (as proxied by the policy rate) removes the passive component however. Thus we would argue that, conditionally, variation in the liquidity provision series regains its natural interpretation: positive injections are indicative of greater funding liquidity.

[26]Net liquidity injection at daily frequency does not include net open market purchases due to lack of daily data for those over the entire sample. However, for the period over which these data are available, liquidity injection including these items has a correlation of 0.97 with liquidity injection excluding them.

[27]Government of India maintains an account with the RBI. The balance in this account changes with revenue collection and expenditure by the government. Some component of liquidity injection by RBI is to counter the changes in the government's account. One may argue that this component should not be part of the liquidity injection series for our analysis. However, changes in the government's balance have a standard deviation of only 6% of the standard deviation of the liquidity injection. The liquidity injection series after subtracting the changes in the government's balance has a correlation of 0.998 with the series without this adjustment.

5.2 Policy effect on market liquidity

We now examine the effect of central bank policies on market liquidity in two ways: first, by directly incorporating policy variables (denoted $Policy$) in the b_r specification in our primary system, and second, in a reduced form, by examining the effect on order book depth (ILOBS), which itself is a determinant of b_r. In addition, we consider the effect of policy on the components of volatility, which determine the degree to which illiquidity drives market volatility (and which may also affect market depth).

Panel A of Table 7 presents the results of our ITH estimation where b_r, the response coefficient of returns to order-flow, is a function of the policy variables as $b_r = b_0 + b_i ILOBS + b_p Policy$. The first row include both policy variables, measured daily. The coefficients on both are significant, and the signs are consistent with the natural interpretation: lower rate and funding injections both imply less price impact, i.e., more market liquidity. These results lend support to the funding liquidity hypothesis, and not for the crowding out hypothesis.

Turning to economic magnitudes, the effect of the policy variables on bond market liquidity is small. Using the coefficients in the first row, a one-standard-deviation lower liquidity injection or higher policy rate, is associated with a 16% to 22% increase in price impact (b_r) from the baseline median (using the point estimate with 10-day regimes in Panel B of Table 3). This is equivalent to a change of 5% - 7% of one standard deviation of b_r. In terms of returns, such a decrease in liquidity would mean that the additional price impact of a one-standard-deviation order flow (0.27 billion INR) during a minute would be 0.07 to 0.11 basis points or 5% to 7% of the standard deviation of 1-minute bond returns.[28]

These small magnitudes pose a challenge to theoretical models (and conventional wisdom) that posit a first-order role for funding conditions in the determination of market illiquidity. They also suggest that policy-makers' concerns in the U.S. about the impact on market stability of a reversal of recent easing policies may be overdone.

Interestingly, despite the unconditional correlation of the policy variables, when each is used alone in the estimation, the coefficient signs remain the same as in the joint estimation. This is shown on the second and third rows of the Panel A. These univariate policy specifications yield somewhat smaller (though still significant) effects. For interpretation purposes, the results imply that the conditional variation in the liquidity injection series (which we argued was unambiguously associated with positive funding conditions) is the dominant component of this series in affecting market liquidity. Thus, most of the remainder of our specifications will employ this single policy variable, and we will interpret it as (positively) measuring funding liquidity.

Because of the particular concern with changes in policy that withdraw funding liquidity from the market, we investigate a possible asymmetric response of bond market liquidity to funding liquidity injections and withdrawals. These results are in Panel B of Table 7. Interestingly, we find that when net liquidity injection is positive, it reduces the price impact coefficient b_r, but negative net liquidity injection - i.e., liquidity withdrawal - has no significant effect. In other words, bond market liquidity improves with funding liquidity injection by the RBI but does not appreciably deteriorate with liquidity withdrawal. A possible reason for this is because funding liquidity withdrawals come at a time

[28]The magnitudes are similar using the weekly version of the liquidity injection series.

when market has access to other sources of funding liquidity. We specifically look at such other sources in Section 5.3.

Panel C of Table 7 presents the result for two subsamples. The first row repeats the result for the whole sample. Rows 2 and 3 show the results for two roughly equal subsamples - May 2007-Oct 2010 and Nov 2010-Apr 2014. For both the subsamples, the coefficients - mostly statistically significant - for liquidity injection and policy rate go in the same direction as the whole sample. Smaller magnitude and lower significance in the second subsample is perhaps driven by less variation in policy variables during that period.

Since the policy variables are measured at daily frequency, we also aggregate the returns and flows to one-day intervals and use previous day's median ILOBS in our return-flow-policy analysis. Panel D of Table 7 presents these results. Again coefficients for both the policy variables are significant and support the the funding liquidity hypothesis, reinforcing the conclusions based on high-frequency returns, flow and ILOBS.

Our inferences so far are incomplete in the sense that they do not account for potential effects of $Policy$ on market depth (ILOBS), which is also a determinant of price impact. Moreover, the overall effect of illiquidity on bond market stability is also a function of the components of volatility σ_f and σ_r, which could themselves be affected by (or affect) $Policy$.

To address these questions, we estimate a vector autoregression at daily frequency with four variables - liquidity injection, the standard deviations of the exogenous shocks to returns and flow, ($log(\sigma_r)$ and $log(\sigma_f)$ respectively (as computed from our ITH estimation that conditions on RBI liquidity injections), and the daily median of ILOBS.[29]

The results are presented in Table 8. Two interesting findings emerge: the effect of liquidity injection on volatilities and the effect of volatilities on ILOBS. Figure 7 shows the four impulse responses in standardized units corresponding to these patterns. A one-standard-deviation shock to liquidity injection results in a marginally significant decrease in volatility of the return shocks - the magnitude at its highest is about 0.04 standard deviations. The direction of the effect is consistent with the interpretation that higher liquidity injection by the RBI is associated with lower uncertainty and hence lower volatility of return shocks. But the magnitude of the effect is quite small.

On the other hand, a one-standard-deviation shock to liquidity injection results in a statistically significant increase in volatility of order flow shocks of up to 0.08 standard deviation units. But again the magnitude of the effect is economically small.

Next, if we look at response of ILOBS to innovations in the volatilities, we see that a one-standard deviation positive shock to flow volatility reduces ILOBS, while a similar shock to return volatility increases ILOBS - both effects go as high as about 0.20 in standard deviation units. One way to interpret the effect is using a model by Kyle (1985), where price impact of order flow increases in the volatility of the fundamental asset value and decreases in the volatility of the noise trader activity. We can interpret exogenous shocks to flows as due to noise trader activity, whose volatility decreases the price impact. Exogenous shocks to returns can be taken as fundamental changes in the asset value, whose volatility increases the price impact. Then the positive effect of liquidity injection

[29]The results below are robust to inclusion of other variables in the VAR such as changes in the bond yields, changes in the INR/USD exchange rate and net money flow by foreign institutional investors in Indian debt and equity markets. They are also similar in VARs estimated at weekly frequency.

on σ_f seems to imply that greater funding liquidity provision by the central bank, in fact, encourages greater noise trader activity, not less. This is further evidence against the "crowding out hypothesis".

Overall, then, the initial direct positive effect of *Policy* on market liquidity is augmented by an additional small – but also positive – effect that comes through an increase in σ_f and a reduction in σ_r both of which, in turn, improve market depth. We do not find a significant direct effect of *Policy* on market depth, however. Finally, the positive effect of liquidity injection on σ_f implies a destabilizing effect in that order-flow driven variation in bond prices rises. This effect too is economically minor.

Thus, the VAR results support the earlier assertion that central bank policy changes are unlikely to be disruptive for the bond markets. While our sample does not literally capture an event comparable to the ending of quantitative easing in the developed economies, India did experience a substantial and extended tightening from 2010 through 2011 as can be seen from Figure 1. By visual comparison (see Figures 5 and 6), this episode did not lead to an erosion of market depth or a substantial increase in volatilities.

5.3 Other sources of funding liquidity

We also investigate whether other sources of funding liquidity affect bond market liquidity. We model the price impact coefficient b_r as $b_0 + b_i ILOBS + b_p Policy + b_{fnlq} FundLiq$. FundLiq captures an additional source of funding liquidity different from the RBI policy. We consider three variables - 1. net inflows by foreign portfolio investors (FPI) in Indian debt and equity markets, 2. U.S. Fed funds rate, and 3. changes in log value of securities held by the US Federal Reserve.

Foreign portfolio investors are foreign participants in the Indian financial markets, and include both institutional or non-institutional investors.[30] Data on their net daily inflows in Indian markets are obtained from the National Securities Depository Limited's website. Collectively, these are large players in Indian markets. FPI volume as fraction of total volume in the Indian equity markets is around 10% to 20% in our sample.[31] For debt markets, the fraction for our sample is around 8%. We are looking at FPI net inflows both into debt and equity, because both of these would increase funding liquidity available in the Indian markets.

We also look at U.S. monetary policy variables because of the dominant position the U.S. commands in the global economy. The U.S. Fed funds rate is the target rate established by US Federal Open Market Committee for overnight lending to each other by depository institutions. Since it captures a component of bank funding costs, a higher Fed funds rate may be indicative of lower funding liquidity globally. We also include a measure of "unconventional" monetary policy. Increases in the value of the securities held by the U.S. Fed capture active liquidity provision during the various Quantitative Easing programs, as argued by (Bhattarai, Chatterjee, and Park 2015). Again, this could have implications for the behavior of financial institutions worldwide.

Table 9 presents our estimation using these variables. We find support for the idea that funding liquidity provided by foreign investors as well as by looser U.S. policy improves Indian bond market liquidity: a negative coefficient b_{fnlq} for the net FPI flows and changes

[30] Definition as per regulations by Securities and Exchange Board of India.

[31] See `http://www.nseindia.com/content/us/ismr2014ch7.pdf`.

in log value of securities held by the Fed, and positive for the Fed funds rate. The economic magnitude of the effect of other funding liquidity variables is small and similar in magnitude to that of the effect of RBI policy. Inclusion of these additional variables does not change the magnitude or statistical significance of the effect of RBI policy.

Thus, the positive effect of these other funding liquidity variables on bond market liquidity provides further support to the funding liquidity hypothesis, without changing the conclusion that the effects are small.

6. Conclusion

Recent turbulence in the global government bond markets has led some observers to hypothesize about possible unforeseen linkages between funding liquidity provided by central banks and bond market stability. In this study, we employ a unique data set from India to examine the linkages between central bank policy and microstructure effects in the government bond market.

We first document that the dynamics of liquidity provision are responsible for a major component of government bond price dynamics. Using a high-frequency identification methodology, we isolate exogenous shocks to order flow. Flow-driven risk – the component of bond price variance due to the effect of liquidity demand – comprises as much as 50 percent of total variance. Impulse response functions reveal that effect of flow on prices is not temporary. Thus flow-driven variation represents a real risk borne by long-term market participants which may affect the government's cost of capital.

We investigate the effect of central bank policies on market liquidity and volatility.

We find that funding liquidity injection by central bank is associated with a modest improvement in bond market liquidity. Other funding liquidity variables capturing the U.S. monetary policy and foreign investor activity in Indian markets also have a similar - positive but small - effect on market liquidity of Indian bonds but they do not diminish the effect of Reserve Bank of India's policies.

Results based on a vector autoregression suggest that liquidity injection by the central bank is associated with a small increase volatility of flow shocks and a small decrease in volatility of return shocks. Both higher flow volatility and lower return volatility, in turn, improve market liquidity. Thus, overall, we do not find support for the concern that central bank liquidity injection may have adverse impact on bond markets. The modest nature of all the effects is somewhat surprising, and poses a challenge for theories that suggest a tight linkage (e.g., via collateral constraints) between funding liquidity and market liquidity. A consequence of this finding is that concerns over disruptive effects ("market tantrums") resulting from future changes in central bank policies may be overdone.

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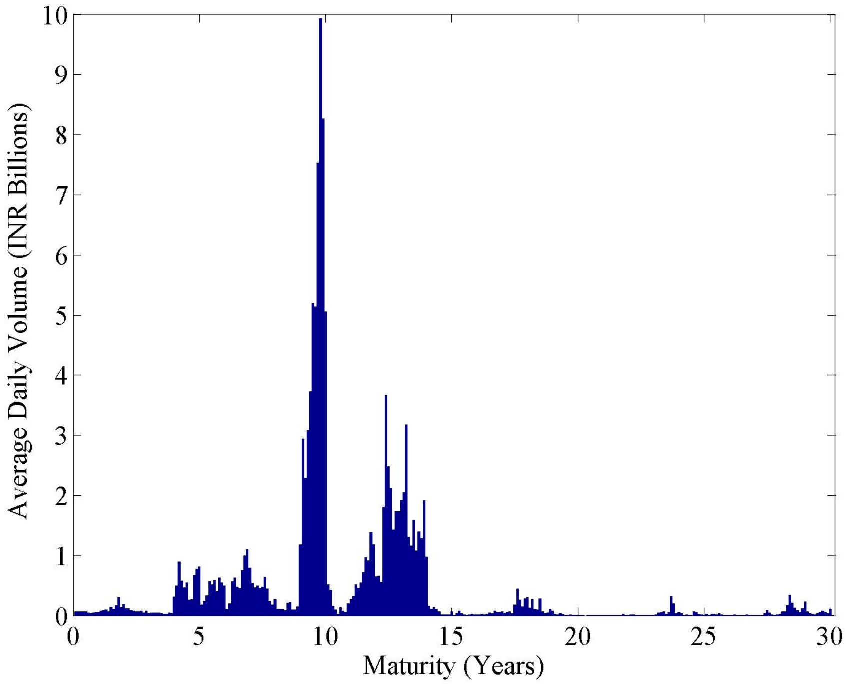
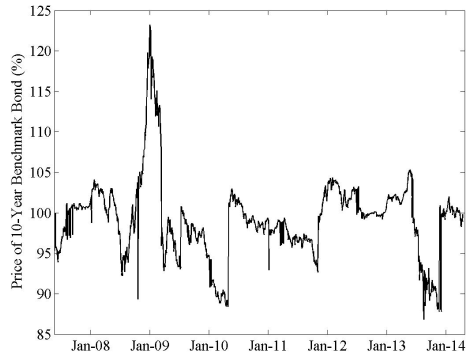
Figure 2
Daily trading volume by maturity



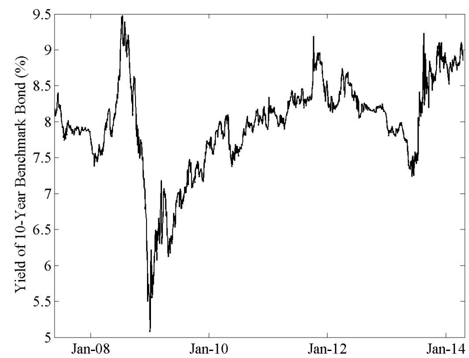
The figure plots average daily trading volume of the Government of India bonds, by maturity buckets, during the sample period of May 2007 to April 2014.

Figure 3
Time series of bond prices and volume

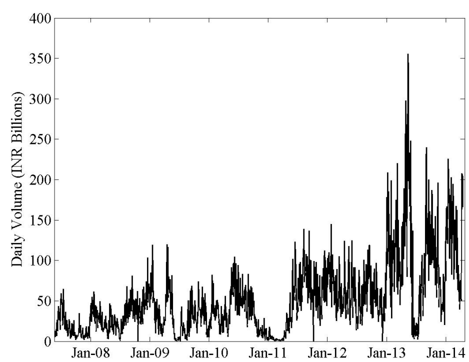
Panel A: Bond Prices



Panel B: Bond Yields



Panel C: Daily Trading Volume

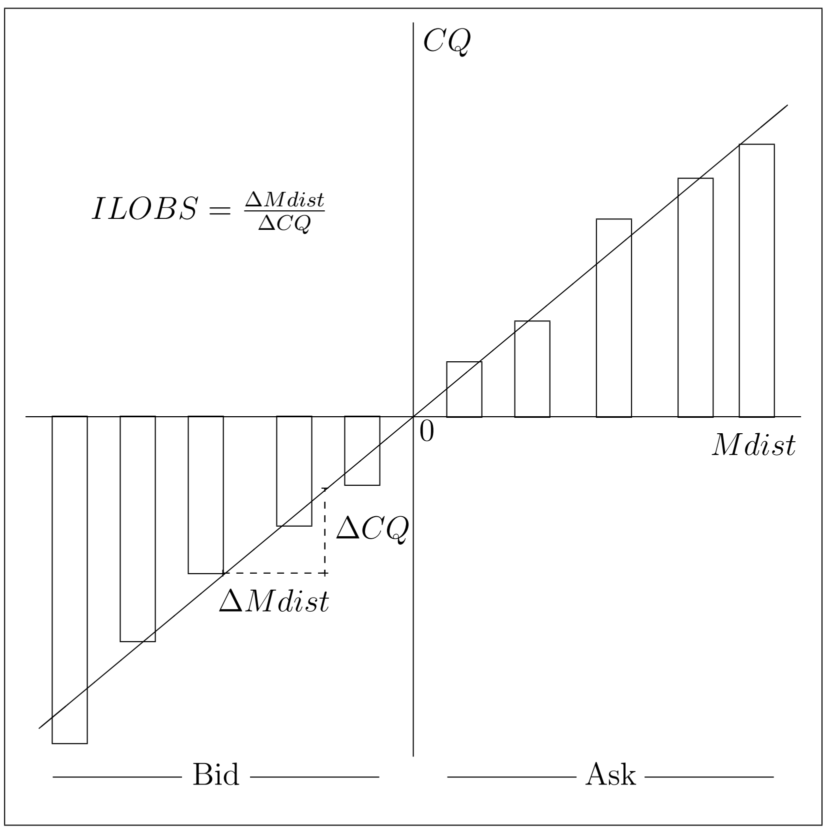


The figure shows prices, yields and trading volume for the benchmark 10-year maturity Government of India bond for the sample period May 21, 2007, to April 20, 2014. Panel A shows the time series of daily closing prices. Panel B shows the time series of daily closing yields. Panel C shows the time series of daily trading volume in billions of INR of bond face value.

Figure 4
Construction of the inverse slope of the limit order book (ILOBS)

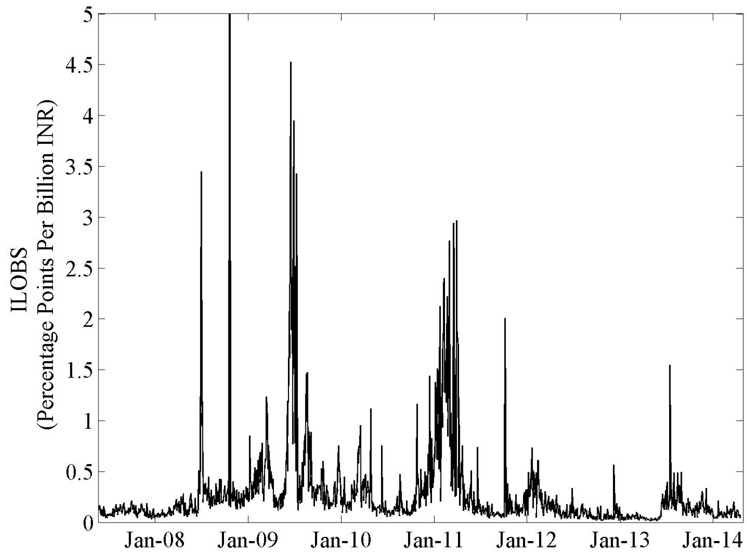
Panel A: Limit Order Book

Panel B: Construction of ILOBS



Panel A depicts the limit order book at a point in time. The horizontal axis shows price, and the vertical axis shows quantity. Each bar represents the total limit order quantity at a particular price. Panel B shows construction of ILOBS associated with the limit order book in Panel A. The horizontal axis shows $Mdist$, the difference between a limit order price and the midprice. The vertical axis shows CQ, the cumulative quantity for all limit orders between the midprice and a given limit order price. Bid-side quantities are treated as negative values. Change, along the fitted line, in CQ is termed as ΔCQ and in $Mdist$ is termed as $\Delta Mdist$.

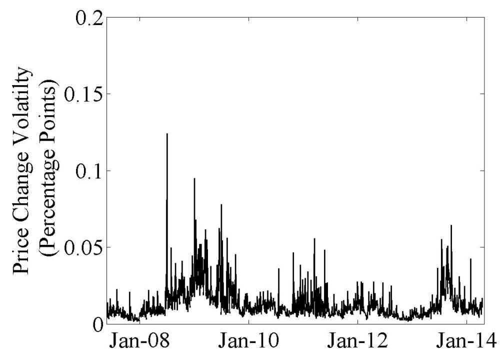
Figure 5
Time series of market illiquidity



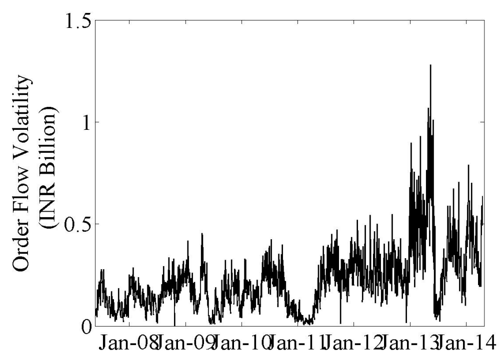
Market illiquidity is given by the inverse slope of the limit order book (ILOBS) for the benchmark 10-year maturity Government of India bond and is measured in percentage points per billion INR of bond face value. Section 3.2 and Figure 4 give details of the construction of ILOBS. Data are sampled at one-minute intervals over the period May 21, 2007, to April 20, 2014. The figure shows the time series of daily median ILOBS.

Figure 6
Time series of volatility

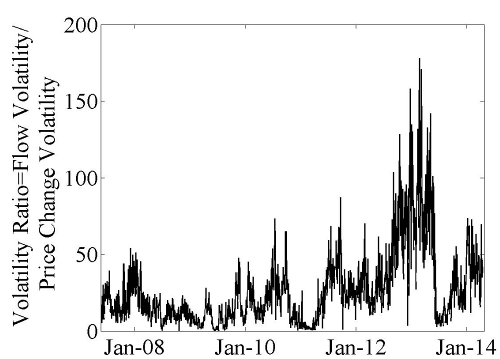
Panel A: Daily volatility of price changes



Panel B: Daily volatility of order flow

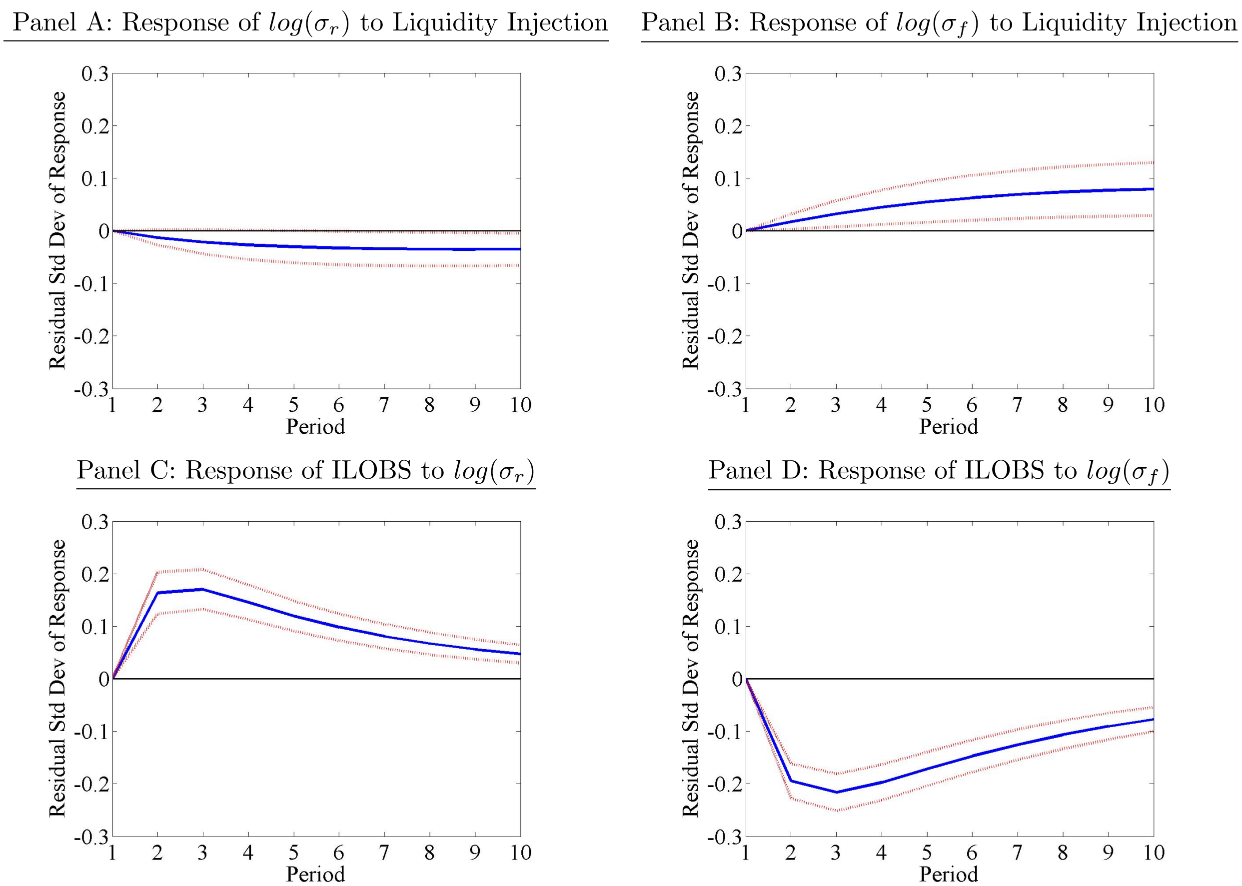


Panel C: Ratio of daily volatilities



Data are sampled at one-minute intervals over the period May 21, 2007, to April 20, 2015. Panel A shows the time series of daily volatility of one-minute price changes. Panel B shows the time series of daily volatility of one-minute order flow. Panel C shows the time series of ratio of volatility of order flow to volatility of price changes.

Figure 7
Impulse Responses from Vector Autoregression



This figure shows the impulse response functions based on vector autoregression at daily frequency of net liquidity injection by the RBI, volatilities of the return and order flow shocks, and daily median ILOBS. Section 3.2 and Figure 4 give the details of the construction of ILOBS. Returns, order flow, and median ILOBS for the benchmark 10-year maturity Government of India bond are calculated at daily frequency for the period May 21, 2007, to April 20, 2014. Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. ILOBS, a proxy of market illiquidity, is measured in percentage points per billion INR of bond face value. Net liquidity injection at the daily frequency is sum of net repurchase agreements (repos), liquidity provided through marginal standing facility and effect of net change in cash reserves required to be held by the bank, measured in INR trillions. σ_r and σ_f are standard deviations of exogenous shocks returns and flow respectively, estimated using a simultaneous system of 1-minute returns and 1-minute flow, identified through heteroskedasticity (ITH). Table 8 shows the results for the VAR. Each panel shows the response in units of residual standard deviation of the dependent variable to one-standard-deviation innovation in the independent variable along with 95% confidence bounds.

Table 1
Trading in the Government Bond Market

This table provides some descriptive statistics about the government bond market in India. Panel A provides share of volume for different categories of participants from April to March from April 2003 to March 2014. Panels B to D provide descriptive statistics for orders and trades on the NDS-OM trading platform. Panels B and C show of fractions of different types of orders and Panel D gives descriptive statistics of about the order size and trade size measured in billions of INR of bond face value.

Panel A: Share of annual volume over 2007-08 to 2013-14

	Primary Dealers	Banks	FIs, Insurance Companys, Mutual Funds	Others
Mean	18.90%	70.35%	9.62%	1.13%
Minimum	15.84%	66.10%	6.74%	0.47%
Maximum	26.35%	74.25%	13.24%	2.00%

Panel B: Distribution of orders by quantity restrictions

Type of restriction	Fraction of Order Entries
No restriction	73.76%
Displayed quantity smaller than order quantity	18.98%
All-or-nothing	7.26%

Panel C: Distribution of orders by expiry

Expiry	Fraction of Order Entries
Expiring at the end of the day	87.16%
Expiring at specific time during the day	0.47%
Immediate-or-cancel	12.37%

Panel D: Distribution of quantity

	Mean	Std Dev	Median	5th Percentile	95th Percentile
Order quantity	0.16	0.24	0.05	0.05	0.50
Trade quantity	0.09	0.10	0.05	0.05	0.25

Table 2
Descriptive statistics

This table presents descriptive statistics of price changes, order flow, bid-ask spreads and the inverse slope of the limit order book (ILOBS) for the benchmark 10-year maturity Government of India bond. Price changes and bid-ask spread are in percentage points per 100 INR of bond face value. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. ILOBS, a proxy of market illiquidity, is measured in percentage points per billion INR of bond face value. Section 3.2 and Figure 4 give the details of the construction of ILOBS. Data are sampled at one-minute intervals over the period May 21, 2007, to April 20, 2014.

Sample	Obs	Mean	Std Dev	Median	5th Percentile	95th Percentile
Price Changes	794890	-0.0000	0.0154	0.0000	-0.0150	0.0138
Order Flow	855740	0.02	0.27	0.00	-0.20	0.30
Bid-Ask Spread	797283	0.04	0.07	0.03	0.01	0.13
ILOBS	797790	0.28	0.69	0.14	0.03	0.92

Table 3
Effect of flow on prices

This table provides results for price impact of order flow for the benchmark 10-year maturity Government of India bond. Returns and order flow are measured over one-minute intervals over the period May 21, 2007, to April 20, 2014. Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades, in billions of INR of bond face value. b_r (effect of order flow on return) and b_f (effect of return on order flow) are the structural coefficients from simultaneous estimation using identification through heteroskedasticity (ITH). t-statistics based on asymptotic standard errors are given in parentheses. FDV is the ratio of variance of the flow-driven component of returns to total variance, as defined in Equation (5) in Section 2.1. Each row gives results for ITH estimation using different length of a regime in days. *Obs* gives the total number of observations and the last column gives the number of heteroskedasticity regimes used in the estimation. The first row provides OLS estimates. The estimation controls for 10 lags of the dependent and independent variables. Panel A models b_r as constant. Panel B models b_r as $b_0+b_i ILOBS$. ILOBS, a proxy of market illiquidity, is measured in percentage points per billion INR of bond face value. Section 3.2 and Figure 4 give the details of the construction of ILOBS.

Panel A: Unconditional Effect of Flow

Estimation	b_r	b_f	FDV	Obs	Regimes
OLS	0.020	-	0.15	761840	-
	(369.210)				
ITH 5 day	0.012	5.34	0.05	761840	506
	(36.908)	(30.54)			
ITH 10 days	0.011	5.56	0.04	761840	253
	(25.718)	(22.46)			
ITH 22 days	0.010	6.36	0.04	761840	116
	(16.639)	(19.27)			
ITH 66 days	0.009	6.81	0.03	761840	40
	(8.223)	(12.51)			

Panel B: Conditional Effect of Flow

Estimation	b_0	b_i	b_f	FDV	Obs	Regimes
OLS	0.015	0.05	-	0.18	761840	-
	(226.360)	(169.05)				
ITH 5 day	0.007	0.07	2.49	0.50	761840	506
	(16.647)	(16.38)	(15.20)			
ITH 10 days	0.007	0.08	2.79	0.50	761840	253
	(11.848)	(12.72)	(13.58)			
ITH 22 days	0.007	0.06	4.03	0.54	761840	116
	(9.577)	(8.58)	(11.66)			
ITH 66 days	0.006	0.06	4.65	0.50	761840	40
	(5.262)	(5.94)	(7.62)			

Table 4
Conditional effect of flow on prices: Different specifications

This table presents price impact of order flow conditional on the inverse slope of the limit order book (ILOBS) estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Price changes are in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. The table presents a linear specification where $return = (b_0 + b_i ILOBS)Flow$ and $Flow = b_f return$. Section 3.2 and Figure 4 give the details of the construction of ILOBS, a proxy of market illiquidity, measured in percentage points per billion INR of bond face value. Returns, order flow, and ILOBS for the benchmark 10-year maturity Government of India bond are calculated over one-minute or five-minute intervals over the period May 21, 2007, to April 20, 2014. t-statistics based on asymptotic standard errors are in parentheses. FDV is the ratio of variance of the flow-driven component of returns to total variance, as defined in Equation (5) in Section 2.1. ITH estimation is done using 10-day regimes. Panel A presents results for one-minute and five-minute intervals controlling for different number of lags of the dependent and independent variables. Panel B shows results conditioning on different versions of ILOBS or bid-ask spread using returns and flow over one-minute intervals controlling for 10 lags of the dependent and independent variables. ILOBS-Narrow is based on the best bid and the best ask quotes. ILOBS-Asymmetric is ILOBS for ask side for positive net flow and ILOBS for bid side for negative net flow. ILOBS-wt1 and ILOBS-wt2 are inverse of the weighted slope of the limit order book. Weights are, respectively, inverse of the absolute distance from the midprice and inverse of the squared distance from the midprice. Bid-ask spread is the difference, in percentage points, between best ask and best bid quotes.

Panel A: Different Intervals, Different Lags

Estimation	b_0	b_1	b_f	FDV
1-Minute Interval, 5 lags	0.007	0.07	2.85	0.56
	(11.749)	(12.73)	(13.83)	
1-Minute Interval, 10 lags	0.007	0.08	2.79	0.50
	(11.848)	(12.72)	(13.58)	
1-Minute Interval, 15 lags	0.007	0.08	2.73	0.51
	(11.893)	(12.70)	(13.32)	
5-Minute Interval, 1 lag	0.007	0.08	5.68	0.49
	(13.285)	(13.71)	(17.04)	
5-Minute Interval, 3 lags	0.007	0.08	5.41	0.46
	(13.030)	(14.70)	(16.95)	
5-Minute Interval, 5 lags	0.006	0.09	5.17	0.50
	(12.682)	(14.87)	(16.71)	

Panel B: Conditioning on Different Versions of ILOBS

Estimation	b_0	b_1	b_f	FDV
ILOBS	0.007	0.08	2.79	0.50
	(11.848)	(12.72)	(13.58)	
ILOBS-Narrow	0.0010	0.17	0.36	0.49
	(2.4139)	(43.11)	(4.86)	
ILOBS-Asymmetric	0.0119	0.04	4.29	0.51
	(26.7810)	(6.84)	(16.03)	
ILOBS-wt1	0.012	0.08	3.95	0.47
	(26.652)	(9.02)	(15.25)	
ILOBS-wt2	0.0121	0.13	3.85	0.49
	(26.5770)	(10.36)	(15.16)	
Bid-Ask Spread	-0.0036	0.88	0.67	0.44
	(-5.7659)	(35.07)	(6.44)	

Table 5
Impulse response

This table provides estimates of instantaneous and long-run impact of one-standard-deviation shock to the innovations in order flow and returns for the benchmark 10-year maturity Government of India bond using identification through heteroskedasticity (ITH) corresponding to the results presented in Table 3, Panel B for 10-day volatility regimes. "Shock to Flow" columns present impact of a shock to the innovations in order flow. "Shock to Returns" columns present impact of a shock to the innovations in returns. $I_{i,j,0}$ and $I_{i,j,\infty}$, respectively, capture instantaneous and long-run responses of variable j to a shock to variable i. i and j can be r for returns or f for order flow. Returns and order flow are measured over one-minute intervals over the period May 21, 2007, to April 20, 2014. Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. ILOBS, a proxy of market illiquidity, is measured in percentage points per billion INR of bond face value. Different rows in each panel report the responses conditional on ILOBS being at its 5th, 50th, and 95th percentiles.

	Shock to Flow				Shock to Returns			
ILOBS	$I_{f,r,0}$	$I_{f,r,\infty}$	$I_{f,f,0}$	$I_{f,f,\infty}$	$I_{r,r,0}$	$I_{r,r,\infty}$	$I_{r,f,0}$	$I_{r,f,\infty}$
5th %ile	0.19	0.24	1.03	1.78	1.03	1.01	0.14	0.30
50th %ile	0.37	0.52	1.05	1.82	1.05	1.05	0.15	0.31
95th %ile	1.93	2.82	1.27	2.13	1.27	1.45	0.18	0.37

Table 6
Descriptive statistics: Macro variables

This table presents descriptive statistics of various central bank policy variables and other macro variables. Net liquidity injection is the sum of net repurchase agreements (repos), liquidity provided through marginal standing facility and net changes in cash reserves required to be held by the banks, measured over the previous day in trillion INR. RBI policy rate is the rate charged by the RBI for financing via repos, measured as a fraction. Net FPI flows are net inflows of capital by foreign portfolio investors in Indian debt and equity markets. Fed Funds Rate is the target rate established by US Federal Open Market Committee for overnight lending to each other by depository institutions, measured as a fraction. Securities held by US Fed is total value of securities held outright by the US Federal Reserve Board. Change in this variable is our proxy of the open market operations by the US Fed.

Sample	Obs	Mean	Std Dev	Median	5th Percentile	95th Percentile
Net Liquidity Injection - Daily - INR Trillion	1667	0.239	0.740	0.307	-1.192	1.309
RBI Policy Rate - Daily	1667	0.070	0.013	0.077	0.048	0.085
Net FPI Flows - Daily - INR Trillion	1654	0.004	0.014	0.003	-0.016	0.026
Fed Funds Rate - Daily	1607	0.008	0.015	0.002	0.001	0.049
Securities Held by US Fed - Weekly - USD Billion	361	1991.133	1021.413	2067.676	488.312	3732.212

Table 7
Conditioning on central bank policies

This table presents price impact of order flow conditional on the inverse slope of the limit order book (ILOBS) and central bank policy, estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. Section 3.2 and Figure 4 give the details of the construction of ILOBS, a proxy of market illiquidity, measured in percentage points per billion INR of bond face value. Returns, order flow, and ILOBS for the benchmark 10-year maturity Government of India bond are calculated over the period May 21, 2007, to April 20, 2014. Panels A, C and D present specifications where $Flow = b_f return$ and $return = b_r Flow$. Panel A has $b_r = b_0 + b_i ILOBS + b_{p-lq} Policy - Lq + b_{p-rt} Policy - Rate$. $Policy - Lq$ is daily net liquidity injection by RBI. $Policy - Rate$ is the RBI policy rate. Panel B has $b_r = b_0 + b_i ILOBS + b_{p-lqin} Policy - Injection + b_{p-lqwd} Policy - Withdrawal$. $Policy - Injection$ is equal to daily net liquidity injection when the net injection is positive and zero otherwise. $Policy - Withdrawal$ is equal the daily net liquidity injection when the net injection is negative and zero otherwise. Net liquidity injection is the sum, over the previous day, of net repurchase agreements (repos), liquidity provided through marginal standing facility and changes to cash reserves required to be held by banks and is measured in trillion INR. RBI policy rate is the repo rate lagged by one day and is measured as a fraction. t-statistics based on asymptotic standard errors are in parentheses. FDV is the ratio of variance of the flow-driven component of returns to total variance, as defined in Equation (5) in Section 2.1. In Panels A, B and C, the estimation uses returns and flow over one-minute intervals, controls for 10 lags of the dependent and independent variables and uses ITH 10-day regimes. In Panel D, the estimation uses returns and flow over one-day intervals, controls for 5 lags of the dependent and independent variables and uses ITH 10-day regimes.

Panel A: Conditioning on Policy Variables

Policy Variable	b_0	b_i	b_{p-lq}	b_{p-rt}	b_f	FDV
Net Liquidity Injection and RBI Policy Rate	-0.006	0.07	-0.0054	0.22	2.72	0.52
	(-1.850)	(10.82)	(-7.4238)	(5.15)	(14.20)	
Net Liquidity Injection	0.010	0.06	-0.0039		2.77	0.49
	(14.135)	(10.15)	(-6.3288)		(13.97)	
RBI Policy Rate	-0.000	0.08		0.09	2.77	0.50
	(-0.107)	(12.95)		(2.42)	(13.57)	

Panel B: Conditioning on Daily Liquidity Injection and Withdrawal

Policy Variables	b_0	b_i	b_{p-lqin}	b_{p-lqwd}	b_f	FDV
Liquidity Injection and Withdrawal	0.011	0.07	-0.0053	0.0008	2.75	0.50
	(14.269)	(10.47)	(-6.7313)	(0.4727)	(13.98)	

Panel C: Subsample Analysis

Sample Period	b_0	b_i	b_{p-lq}	b_{p-rt}	b_f	FDV
May '07-Apr '14	-0.006	0.07	-0.0054	0.22	2.72	0.52
	(-1.850)	(10.82)	(-7.4238)	(5.15)	(14.20)	
May '07-Oct '10	-0.012	0.06	-0.0050	0.38	2.29	0.50
	(-3.457)	(6.30)	(-3.6222)	(8.15)	(11.65)	
Nov '10-Apr '14	-0.003	0.07	-0.0026	0.14	2.40	0.32
	(-0.341)	(9.20)	(-2.9084)	(1.21)	(7.06)	

Panel D: Daily Returns and Flow

Policy Variable	b_0	b_i	b_{p-lq}	b_{p-rt}	b_f	FDV
Net Liquidity Injection and RBI Policy Rate	0.004	0.03	-0.0053	0.07	7.75	0.50
	(1.953)	(10.59)	(-10.6130)	(2.09)	(17.22)	
Net Liquidity Injection	0.008	0.04	-0.0045		7.95	0.48
	(20.859)	(13.79)	(-12.9180)		(18.28)	
RBI Policy Rate	-0.000	0.08		0.09	2.77	0.50
	(-0.107)	(12.95)		(2.42)	(13.57)	

Table 8
Vector Autoregression

This table presents results of vector autoregression at daily frequency of net liquidity injection by the RBI, volatilities of the return and order flow shocks, and daily median ILOBS. Net liquidity injection is the sum of net repurchase agreements (repos), liquidity provided through marginal standing facility and net change in cash reserves required to be held by the banks, measured in trillion INR. σ_r and σ_f are daily standard deviations of exogenous shocks to one-minute returns and one-minute flow respectively, estimated using a simultaneous system of return and flow, identified through heteroskedasticity (ITH). Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. Section 3.2 and Figure 4 give the details of the construction of ILOBS, a proxy of illiquidity, measured in percentage points per billion INR of bond face value. Returns, order flow, and median ILOBS are for the benchmark 10-year maturity Government of India bond for the period May 21, 2007, to April 20, 2014. The variables in the VAR are scaled by their own standard deviation. Panel A presents coefficients and t-stats in parentheses. Panel B shows the correlations of the residuals from the VAR.

Panel A: Coefficient Estimates

	Liquidity Injection	$log(\sigma_r)$	$log(\sigma_f)$	ILOBS
Liquidity Injection (-1)	0.955	-0.035	0.035	0.018
	(132.259)	(-1.825)	(2.380)	(0.816)
$log(\sigma_r(-1))$	-0.015	0.659	-0.078	0.190
	(-2.036)	(33.669)	(-5.248)	(8.341)
$log(\sigma_f(-1))$	0.009	-0.033	0.831	-0.299
	(1.169)	(-1.538)	(51.454)	(-12.039)
ILOBS(-1)	-0.009	0.037	0.018	0.260
	(-1.157)	(1.786)	(1.127)	(10.686)
Adj. R-squared	0.923	0.452	0.686	0.260

Panel B: Residual Correlations

	Liquidity Injection	$log(\sigma_r)$	$log(\sigma_f)$	ILOBS
Liquidity Injection	1.000	0.063	0.054	0.005
$log(\sigma_r(-1))$	0.063	1.000	0.370	0.113
$log(\sigma_f(-1))$	0.054	0.370	1.000	-0.160
ILOBS	0.005	0.113	-0.160	1.000

Table 9
Conditioning on funding liquidity

This table presents price impact of order flow conditional on the inverse slope of the limit order book (ILOBS) estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Returns are measured as price changes in percentage points. Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades and is in billions of INR of bond face value. Section 3.2 and Figure 4 give the details of the construction of ILOBS, a proxy of market illiquidity, measured in percentage points per billion INR of bond face value. Returns, order flow, and ILOBS for the benchmark 10-year maturity Government of India bond are calculated over one-minute intervals over the period May 21, 2007, to April 20, 2014. The table presents a linear specification where $return = (b_0 + b_i ILOBS + b_p Policy + b_{fnlq} FundLiq)Flow$ and $Flow = b_f return$. *Policy* is lagged daily net liquidity injection by RBI, measured as the sum of net repurchase agreements (repos), liquidity provided through marginal standing facility and changes to cash reserves required to be held by banks, in trillion INR. *FundLiq* are other variables capturing funding liquidity in the market - such as Net FPI Flows, Fed Funds Rate, or Δ(Log Fed Assets). Net FPI Flows are lagged net inflows by foreign portfolio investors in Indian debt and equity markets in trillion INR. Fed Funds Rate is the target rate established by US Federal Open Market Committee for overnight lending to each other by depository institutions. It is lagged by a day and expressed as a fraction. Δ(Log Fed Securities) is lagged weekly change in log total securities held by the US Federal Reserve Board and it our proxy of the net open market purchases by the US Fed. *FDV* is the ratio of variance of the flow-driven component of returns to total variance, as defined in Equation (5) in Section 2.1. The estimation controls for 10 lags of the dependent and independent variables and uses ITH 10-day regimes.

FundLiq	b_0	b_i	b_p	b_{fnlq}	b_f	FDV
Net FPI Flows	0.011	0.06	-0.0037	-0.11	2.74	0.48
	(15.018)	(9.72)	(-6.1380)	(-4.27)	(14.28)	
Fed Funds Rate	0.008	0.07	-0.0027	0.16	2.45	0.49
	(10.816)	(11.29)	(-3.9817)	(6.36)	(13.38)	
Δ(Log Fed Securities)	0.010	0.06	-0.0034	-0.12	2.77	0.48
	(14.275)	(10.45)	(-5.2553)	(-3.67)	(14.12)	