Funding Liquidity and Market Liquidity in Government Bonds*

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Abstract

This study investigates the effects of funding liquidity conditions on price impact and order-book depth using a comprehensive dataset of orders and trades in the Indian government bond market. We measure funding liquidity along both price and quantity dimensions in the repo market, as well as the interaction of the two. Our price-impact tests provide modest support for the hypothesis that a lower repo rate promotes market liquidity. But, contrary to expectations, the marginal effect of increased funding demand is to lower price impact, improving market liquidity. We show that two channels partially contribute to this result: uninformed trading increases when funding conditions are tight; and funding demand is cyclically related to positive economic conditions that promote intermediation. Time-series regressions show that order-book depth also responds mildly positively to greater funding liquidity. This is again tempered by the indirect positive effect of tighter funding conditions on order-book depth via greater uninformed bond trading. Overall, the results suggest that there is limited scope for liquidity policy to affect bond market depth or resilience.

Keywords: government bonds, market liquidity, funding liquidity.

JEL CLASSIFICATIONS: E51, G12, G18.

1 Introduction

How important are funding conditions in money markets for the resilience and stability of markets for other risky assets? To put it another way, does funding liquidity – the financing environment facing banks and intermediaries – promote market liquidity – the depth of stock and bond markets? The hypothesis that it does (which we will call FLH: the funding liquidity hypothesis) is widely held by regulators, practitioners, and market commentators. Perhaps surprisingly, however, there is scant empirical evidence on the topic.[1] This paper present detailed new measurement on the strength and channels of funding liquidity effects in government bond markets.

The FLH matters because avoiding market disruptions or fire-sale conditions in asset markets is a key goal of regulators in preventing contagion effects from amplifying negative economic shocks, and provision of funding liquidity is regarded as an important tool for achieving this objective. The mechanism they have in mind is a straightforward (if informal) inventory channel, described by one regulator (Geithner (2007)) as follows "Although the two concepts [of liquidity] are distinct, they are closely related and often mutually reinforcing. Fundamentally this is so because when funding liquidity is abundant traders have the resources with which to finance trading positions that smooth price shocks and make markets liquid". Note that the logic here posits a direct causal channel from levels of funding provision to asset market conditions.[2] Unconventional policy measures,

[1]There is some support in Chordia, Sarkar, and Subrahmanyam (2005) and Goyenko and Ukhov (2009). Recently, Jylha (2015) has provided evidence that lower margin requirements for index options resulted in significant improvements in liquidity for those option.

[2]In the academic literature, financially constrained intermediaries are also the crucial ingredient in the limits-to-arbitrage literature stemming from Shleifer and Vishny (1997). Gromb and Vayanos (2002) formally model the liquidity provision decision of arbitrageurs subject to exogenous financing constraints. Allen and Gale (2004) link the funding liquidity of intermediaries facing incomplete markets to asset

such as permanent open market operations, may also affect market stability through changing risk bearing capacity.[3] However, the FLH mechanism is viewed as operating via ordinary monetary policy channels[4]

Government bond markets, which rely very heavily on the ability of participants to finance positions in repo markets, would seem likely to offer a clear illustration of this mechanism. Moreover, maintaining stability and depth in the markets for their own debt, particularly in times of stress, is clearly a high priority for governments.[5] Globally, governments have exempted their own debt markets from recent increases in regulatory constraints and explicit capital requirements that apply to other debt markets.[6] In part, this leniency is designed to promote the liquidity of government bond markets. It is thus important to ask quantitatively, how much does secondary market liquidity in government bonds respond to changes in funding conditions.

We address this topic in the context of the market for the benchmark 10-year bonds of the Government of India. India offers an advantageous setting for several reasons. First, recent experience encompasses periods of both substantial tightening and substantial easing of liquidity conditions. (Our sample covers the period from May 2007 to April 2014.) The last decade has seen the Reserve Bank of India (RBI) make, on average, 7-8 changes per year to the key policy rates or reserve requirements. (Figure 1 shows the time series

volatility. In Brunnermeier and Pedersen (2009) funding constraints both induce market illiquidity and, in turn, are tightened by it.

[3]See Johnson (2009) and Silva (2016).

[4]We thank Lubomir Petrasek for pointing out this distinction.

[5]Aside from the U.S. and Germany, few governments benefit from flight-to-quality effects in their bond markets.

[6]For example, the U.S. "Volcker Rule" regulations specifically exempts government bond trading. Even during the recent European sovereign debt crisis, all debt of euro-area governments was permitted zero weighting in bank capital requirements.

of daily liquidity demanded by market participants and of the benchmark policy rate.) A second advantage, however, is that the *mechanisms* of policy have not changed *too much*, and thus our sample period can be regarded as relatively stationary in terms of monetary regime. (By contrast, most western cental banks have engaged in policy experimentation of historical magnitude since 2008.) In our time period, bank liquidity conditions have been governed by a minimum cash-reserve requirement (CRR) and a policy rate (the repo rate) both set by RBI. Given these two parameters, reserves have been provided elastically in exchange for government bond collateral at the repo rate.[7]

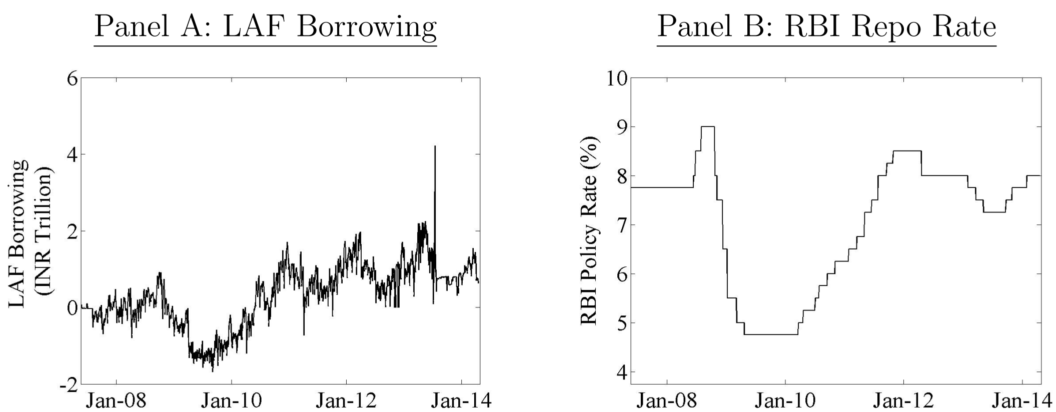

Figure 1: RBI Policy Variables
Panel A plots daily outstanding net repurchase agreements (repos) provided to banks via the RBI's Liquidity Adjustment Facility. Panel B shows the daily RBI repo rate which is the benchmark policy rate.

A third key advantage of the Indian setting is the availability of comprehensive electronic records for activity in the government bond market. Unlike, for example, the U.S. Treasury bond market where trade takes place simultaneously in several distinct venues[8]

[7]Other policy interventions by RBI include temporary open market operations in bond and currency markets. Also some specifics of policy implementation have changed over time. We discuss institutional details further in Section 2.

[8]Electronic trade in U.S. Treasury bonds can take place on one of several private interdealer platforms. Dealer-to-customer trade still takes place mostly via bilateral OTC exchanges.

none of which report their activity publicly, India is one of the only major economies in which a substantial majority of government bond trade – around 85% – is centralized in a single, transparent electronic limit order book system. Our dataset consists of all orders and trades in this system, known as NDS-OM. This gives us a consolidated view of the market, and offers unique opportunities for identification of market liquidity.

India has been actively fostering the depth and liquidity of the secondary market for government securities.[9] The RBI has expressed the explicit goal of promoting price discovery for government bonds, to provide stability for government funding needs, and also for the effective transmission of monetary policy. A first contribution of our work is to provide quantitative evidence on the degree of liquidity in this market. There is no existing study examining the extent to which trading affects prices and how this changes over time.

Another policy goal in India has been to provide a stable government yield curve as a step towards building depth in the market for corporate bonds.[10] Notably, the RBI has also expressed its belief in the FLH in furthering this goal. In August 2016 it announced that its primary funding liquidity vehicle, known as the Liquidity Adjustment Facility (LAF), would accept high grade corporate bonds as collateral, and it explicitly cited the goal of promoting secondary market depth in doing so.[11] The central empirical question of our study aims to quantify precisely how much effect such moves should be expected to have.

[9] In addition to the creation of NDS-OM, recent measures include the introduction of central clearing via the Clearing Corporation of India Limited (CCIL), allowing short selling, and the establishment of a private repo market.

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

[11] `https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=37875`

In examining this market, we have two primary tools. First, we gauge market liquidity directly by measuring the effect of order flow on prices. Because of the simultaneous determination of these variables, we employ an estimation technique (developed in Deuskar and Johnson (2011)) that econometrically identifies transaction demand as exogenous shocks to order flow. We use this approach to initially measure the level of price impact of order flow, and to gauge the total contribution of this trading-induced variation to bond market risk. We then go on to employ conditional versions of the technique to allow us to identify the contribution to price impact of measures of funding liquidity conditions.

Second, our data permits us to construct explicit measures of the depth of the limit order book, which itself is an important contributor to the price impact function. We can then assess the effect of funding liquidity variables on the evolution of market depth in time-series regressions. These allow us to examine lower-frequency (daily or longer) liquidity responses, and to examine indirect channels of funding liquidity transmission e.g., through effects of funding liquidity on volatility and trading volume.

We thus study effects of funding liquidity both directly on bond market transactions and indirectly on the depth of orders. Our primary independent variables measure the price of funding liquidity (e.g., via the policy repo rate) and the quantity demanded by banks (e.g., by the amount of borrowed reserves). Both market liquidity and funding liquidity are endogenous properties of the economy. Conceptually, however, it is worthwhile to note that the FLH is not an assertion about exogenous variation (or shocks) in funding conditions. Rather, it postulates that levels of these conditions directly affect the willingness of others to intermediate transaction demand in asset markets.

Our primary results are as follows.

First, flow does move prices in the market for the benchmark 10-year government bond. 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 of price changes. Moreover, the price impact is effectively permanent at the time-scales we measure. The unconditional 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.[12]

When we examine the effect of funding variables on price impact we find a positive, statistically significant effect of the level of the benchmark policy rate. This effect is economically modest: a one standard deviation increase in the interest rate increases price impact by 10-12 percent from its unconditional mean. This effect rises to 15-20 percent when the funding conditions are tight (meaning when repo demand is one standard deviation above its mean) due to a significant positive interaction effect.

Surprisingly, the marginal effect of funding demand itself on illiquidity is significantly negative: markets appear to absorb trading demand better when banks face higher cash needs. We identify two channels that could explain this finding. However, our tests leave a substantial component of the effect unaccounted for.

Turning to our analysis of limit order book depth, we again document modest support for FLH in daily time-series regressions in the form of an interaction effect between price

[12]Recent studies in the US Treasury market have shown that order flow plays an important role in price discovery. For example, see Brandt and Kavajecz (2004), Green (2004), Pasquariello and Vega (2007), and Menkveld, Sarkar, and Wel (2012). Other studies have documented temporary as well as persistent effects of supply shocks on bond prices. For example see, Greenwood and Vayanos (2010, 2014), and D'Amico and King (2013).

and quantity of funding liquidity. In these tests, the marginal contribution of funding demand has the expected sign, but the funding rate is no longer significant. We also document that funding liquidity variables have positive effects on bond market order-flow volatility i.e., there is more transaction demand when funding conditions are tighter. This effect goes against FLH, because higher order-flow volatility induces better order book depth i.e. more liquidity provision. This indirect effect is novel and, though not economically large, is statistically strong.

Summarizing, our study provides a quantitative evaluation of the funding liquidity hypothesis in a market setting where the hypothesized effects of funding on intermediary's asset positions should be tangible and immediate. The Indian government bond market also offers some noteworthy measurement advantages of both bond market trading and banks' liquidity demand. The empirical evidence tells us that funding liquidity effects, while detectable, are quantitatively small and may be mitigated by indirect channels. The results suggest that there is only limited scope for policy to affect market stability and resilience via the funding of intermediaries.

The rest of the paper is structured as follows. Section 2 describes the market for Government of India bonds, our data, and the construction our empirical measures. The next section explains our econometric methodology. Section 4 gives baseline results on the flow-return relationship. Section 5 presents our findings on the direct effect of funding liquidity on price impact. Section 6 documents the effect of funding liquidity on market depth. The final section summarizes our results and concludes.

2. Background and Data

This section provides background on the institutional setting for the paper, and describes the data used for estimation and the construction of the primary variables.

2.1 Indian 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.[13] 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 Government of India 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 Government of India 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

[13] 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/`.

sample period goes from May 21, 2007 to April 20, 2014. In this period, we see the share of NDS-OM in the volume of Government of India bonds rose from around 77% in 2007-08 around 89% in 2013-14, with average of around 85%. See Fleming, Saggar, and Sareen (2016) for a thorough, descriptive study of the Indian government bond market.

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. Similar to the observation in Fleming et al. (2016), we 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. In this study, 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. This approach is similar to the one taken by The Fixed Income Money Market and Derivatives Association of India while declaring benchmark bonds (see Fleming et al. (2016)). 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.

2.2 Limit order book and order flow

We combine the order and trade data to construct the complete 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 time. Per-minute returns are calculated as the simple difference between midpoint prices at the end of 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.[14]

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

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

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

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

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.[15] 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, one-minute 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 as well as one-day intervals as part of our robustness checks.

2.3 Funding liquidity

As in the U.S. Treasury bond market, participants in the Indian government securities markets can fund their bond positions (long and short) through repurchase and reverse repurchase agreements, collectively referred to as the repo market. The central bank (RBI) directly affects dealer financing through its conduct of monetary policy. As described in

[15] 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.

the introduction, RBI fixes bank cash reserve ratios as a fraction of deposits (the CRR) and then provides funding elastically via the LAF at its benchmark policy rate (the repo rate or the reverse repo rate when demand is negative, i.e., when banks have excess reserves). We employ funding liquidity measures that capture the price and quantity dimension of bank cash demand separately.

On the price dimension, the government repo rate is the obvious variable as it directly affects the funding cost of dealers in the government bond markets. For robustness tests, we consider two alternatives. First, there is also a market for direct (uncollateralized) lending of overnight reserves between banks – the analogue of the U.S. Fed Funds market – which carries its own market interest rate, known as the call money rate. We also present results using the secondary market repo rate, which fluctuates between RBI's reverse repo and repo rates.

On the quantity dimension, we attempt to measure financing demand as it relates to government bonds. Banks that act as dealers in the government bond market may or may not need to fund their positions in the repo market, the alternative being to finance their positions using their balance sheet, in effect, using cash raised from deposits. The aggregate net amount of repo financing that the banking system employs is approximately equal to the amount provided by the RBI.[16] Thus the total cash (reserves) provided by the LAF is a natural measure of funding demand specifically for government bond positions.[17] This is our primary quantity variable.

We also examine some related quantity measures for robustness checks. The FLH

[16]Non-bank participation in the repo market is relatively minor.

[17]It is worthwhile to clarify that interpretation of this variable depends crucially on the fact that the LAF supplies funds passively. We discuss this further in Section 5.2.

suggest that overall demand for cash liquidity may affect bond market stability. The total demand for cash of the banking system is driven by the CRR. Banks have no motivation to hold reserves in excess of this floor as long as alternative liquid instruments earn positive interest. We thus measure total required reserves in excess of non-borrowed reserves for all banks as an alternative measure of liquidity demand. This gap is equivalent to total borrowed reserves plus the difference between required and actual reserves.[18]

Table 3 presents descriptive statistics for our funding liquidity proxies and pairwise correlations between them. Time series plots of the primary measures are shown in Figure 1 in the introduction. It is clear from the plots that the price and quantity variables are positively correlated with each other. This is a consequence of RBI policy: when the central bank wants tighter conditions, the repo rate and CRR are increased until high funding demand is observed in the banking system. At the same time, there is considerable orthogonal variation along the two dimensions, reflecting external influences on the supply of credit. Our different versions of price and quantity proxies are, however, very highly correlated with one another.

3. 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

[18]To compute required reserves, we follow Fecht, Nyborg, and Rocholl (2011) in defining both forward and backward looking measures within a maintenance cycle. Indian banks are required to maintain the required percentage of deposits (CRR) on an average basis within fortnightly cycles. *Liquidity deficit* is defined as LAF borrowing + (cumulative required reserves − cumulative actual reserves) / days past in the cycle. *Liquidity need* is defined as LAF borrowing + (total required reserves for the cycle − cumulative actual reserves) / days remaining in the cycle - current actual reserves. Cumulative reserves are the sum of daily reserves (required or actual) from the beginning of the cycle to the observation date.

much illiquidity matters in terms of induced price variation. Second, we try to measure the effect of funding liquidity on the quantities affecting market liquidity. This section describes the specifications we employ.

3.1. Identifying the price impact of order flow

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

$$return_t = b_r \ flow_t + \ \epsilon_{r,t} \tag{2}$$

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. The approach here follows that in Deuskar and Johnson (2011).

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

$$flow_t = b_f \ return_t + \ \epsilon_{f,t} \tag{3}$$

where $\mathrm{E}[\epsilon_f \ \epsilon_r] = 0$. Equations (2) and (3) are estimated as a simultaneous system, as discussed below, to obtain b_r and b_f. Then $return_t$ can decomposed as[19]

$$return_t = \frac{1}{[1 - b_r b_f]} \ \epsilon_{r,t} + \frac{b_r}{[1 - b_r b_f]} \ \epsilon_{f,t}. \tag{4}$$

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 (4), variance of $return_t$ can be written

$$\frac{1}{[1 - b_r b_f]^2} \ \sigma^2_{r,t} + \frac{b_r^2}{[1 - b_r b_f]^2} \ \sigma^2_{f,t} \tag{5}$$

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 (5) 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

$$FDV = \frac{b_r^2 \ \sigma^2_{f,t}}{\sigma^2_{r,t} + b_r^2 \ \sigma^2_{f,t}}. \tag{6}$$

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

Thus, for calculating FDV, getting coefficient estimates for Equations (2) and (3) 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

$$(1 + b_r b_f)\ \mathrm{Cov}(r_t, f_t) = b_r \mathrm{Var}(f_t) + b_f \mathrm{Var}(r_t). \tag{7}$$

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.[20] In effect, (7) 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.[21]

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.[22] We therefore model b_r as a function of

[20]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 $b_r, b_f, \sigma_{r,1}, \sigma_{f,1}, \sigma_{r,2}, \sigma_{f,2}$.

[21] 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.

[22]There is no reason why b_f should not also change over time. However, notice that b_f drops out of the formula for FDV.

conditioning variables:

$$b_{r,t} = b_0 + b' X_t. \tag{8}$$

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 2.

3.2. Funding liquidity effects

Including conditional coefficient specifications in the simultaneous-equations framework, as just described, immediately offers one way to assess the impact of funding liquidity conditions on market liquidity in government bonds. We can include our interest rate and funding need measures directly in the specification of the price impact coefficient in (8) to measure their direct effect on price stability.

As described in the introduction, we also examine the effects of funding liquidity conditions on order book depth, as measured by ILOBS. We will show that ILOBS is a key conditioning variable in determining price impact. We explore its sources of variation in lower frequency time-series regressions. We also examine whether funding liquidity variables affect the other market quantities in our system. In particular, our high-frequency estimation gives us estimates of time-varying volatilities of both order flow and the fundamental (non-flow driven) component of interest rate volatility. By including them in the analysis, we can assess dynamic responses of ILOBS to funding liquidity through indirect volatility channels.

In both price-impact estimation as well as ILOBS regressions we condition on both the price and quantity dimensions of funding liquidity, as described in Section 2.3. In addition, following Fecht et al. (2011), we consider the interaction of these two variables. The logic of the FLH implies that bond market intermediaries should be most sensitive to the price of funding when their need for borrowed funds is highest, implying a positive interaction effect of the two components on measures of market illiquidity.

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 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 3.1. 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 day are excluded from the estimation.

Panel A of Table 4 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. The estimated 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 3.1, the OLS coefficient is biased if there is reverse causality. It turns out that, in our setting, OLS

[23]The lag coefficients are not estimated via ITH but by OLS within each minimization step. This is equivalent to a two-stage GMM procedure. The standard errors that we report account for the joint dependence of the two stages.

overestimates the effect of flow on prices.

The remaining rows in Panel A of Table 4 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 3.1 (Equations (4)-(6)), 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 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 2.2, 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

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

prices. To be specific, coefficient b_r in Equation (2), 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 measured over 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 4 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.

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 the 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 4, FDV goes up to about 50% in Panel B. We return to the significance of this finding below.

We have already seen that the results are not sensitive to varying length of a regime for the ITH estimation. We also investigated 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. All these different specifications yield results very similar to Panel B of Table 4.[26] 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

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

[26]We measured returns and flow over either 1-minute or 5-minute intervals and included different number of lags. 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 robustness tests we relax these assumptions by constructing ILOBS that is based i) only on the best bid and the best ask quotes and associated quantities ii) only on ask side for positive net flow and only on bid side for negative net flow or iii) on weighing orders by inverse of the absolute distance from the midprice and inverse of the squared distance from the midprice. In version iii), the orders beyond the best bid and the best ask are considered but given lower weight than the best quotes. We do not report these results to conserve space but they are available upon request.

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 4 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 4, this risk is large - nearly 50% of risk in the benchmark 10-year Government of India bond is due to order flow.[27]

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 4 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, a 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 funding liquidity affects the return-flow dynamics.

[27]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

5. Funding Liquidity and Price Impact

We now come to our first tests of the funding liquidity hypothesis (FLH). Using the econometric design introduced in the previous section, we re-estimate price impact using our high-frequency data while conditioning on proxies for the price and quantity of intermediary funding.

5.1 Test of FLH

Panel A of Table 6 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 $b_r = b_0 + b_q\ Quantity + b_r t\ Rate$ where $Quantity$ and $Rate$ denote our proxies for funding liquidity quantity demanded and interest rate, respectively. These variables are measured daily and are expressed in standardized form. Also, following Fecht et al. (2011), we estimate with an interaction term $b_r = b_0 + b_q\ Quantity + b_{rt}\ Rate + b_{qrt}\ Quantity * Rate$ in Panel B. The implication of FLH is that all three coefficients should have positive signs. High demand for funds, high cost of funds, and high costs when demand is also high, are all expected to increase the price impact function.

Consistent with FLH, we find that b_{rt} and b_{qrt} are positive. Price impact is increasing in the cost of repo financing, and this effect is stronger when funding liquidity demand is particularly high. Based on the specification with 10-day regimes in Panel A, one-standard-deviation higher rate is associated with price impact higher by about 8% of the unconditional impact (as measured by b_0). In Panel B, the effect of a one-standard-deviation rate change is about 12% of the unconditional effect when the funding liquidity demand is average. The effect rises to about 20% of b_0 when the funding demand is one standard-deviation higher than average.

On the other hand, contrary to FLH, we find that the marginal effect of b_q on price impact is negative. This negative quantity effect is actually larger than the marginal interest rate effect, and, in most specifications, it remains so when taking into account the positive interaction term when the interest rate is one standard-deviation above its average. This result is sufficiently unusual that we examine possible mechanisms for it in Section 5.2 below.

To assess the robustness of our results, we next employ the alternative proxies for funding liquidity described in Section 2.3. Results based on ITH specification with 10-day regimes are in Table 7. The coefficient estimates are very similar to those in Table 6. We also conduct subsample analyses. The first two rows in each panel in Table 8 present the results for the two subsamples - May 2007-Oct 2010 and Nov 2010-Apr 2014. We generally find that b_{rt} and b_{qrt} are positive and b_q negative, but some coefficients lose statistical significance.

We do most of our analysis using high frequency return and order flow data. But since funding liquidity variables are measured at daily frequency, we also estimate an ITH system with returns and order flow aggregated up to daily level. We use 10-day ITH regimes and control for 5 daily lags of the dependent variables. These results are presented in the last row of each panel in Table 8. Again, b_{rt}, b_{qrt} are positive and b_q negative, all with statistical significance of at least 10%. At daily frequency, the positive coefficients (supporting FLH) become economically negligible, however the negative b_q

coefficient becomes economically more important: a positive one-standard deviation shock to liquidity demand now moves the baseline price impact 0.0120 down by 0.0046, or 38 percent. We now consider some possible explanation for this puzzling finding.

5.2 The Quantity Effect Puzzle

The previous subsection reports positive support for the notion that the increases in the rate at which the central bank provides funds to banks and bond market intermediaries affects the degree to which they are willing to provide intermediation services in the bond market. However, in seeming contradiction to the FLH, we also report that the quantity of bank funding requirements varies oppositely with bond market liquidity. Our results imply that when dealers have to rely more on repo funding, the bond market is more liquid in the sense that transaction demand moves prices less. While not very large economically, the result appears statistically solid. This subsection considers interpretation and potential explanations of this finding.

An important initial issue to address is whether our quantity measure is measuring the supply of, rather than demand for, funding liquidity. Recall that RBI practice through out our period was to provide repo financing elastically at the policy rate. This underpins our interpretation that we are measuring demand. Confirming this, in its quarterly discussion of monetary conditions, RBI regularly assesses whether or not funding conditions are tight based upon the quantity of borrowing from the repo facility (LAF). Occasionally, RBI actively supplies reserves via open market operations in government bonds and foreign currency. These actions, increase total bank reserves, but they do not directly affect borrowing from LAF, which is what we are measuring.

Next, we consider two possible omitted variable issues that could be confounding the negative supply effect. The first is technical, the second is cyclical.

The technical issue is that funding requirements may covary with uninformed bond market volume. As per standard microstructural logic, anything that increases uninformed volume will make intermediation more profitable and thus increase liquidity (for example, see Kyle (1985)). Bond trading for balance sheet management would qualify as uninformed trading in the sense that it conveys no private information, i.e., about economic fundamentals. If more balance sheet management occurs among banks when funding liquidity is tight, bond market liquidity could improve.[28] For example, if RBI increases the cash-reserve ratio (CRR) funding liquidity tightens automatically, and interbank bond trade may reflect the marginal need of some banks for cash. To assess this possibility, we can control for interbank heterogeneity in cash position via the volume of direct interbank lending of reserves in the call-money market.

The cyclical issue affecting liquidity demand is that the economy's overall need for cash may be positively correlated with investors' outlook for investment opportunities, which could also affect banks' willingness to intermediate. In "good times" cash needs could be high as firms economic activity pick up, while at the same time risk perceptions may be low, making banks more comfortable with trading-desk positions in risky assets. The channel could also run through RBI policy: in times of turbulence (for example in the financial crisis) when intermediation is risky, the central bank made sure ample

[28]In effect, this argument hypothesizes that when conditions are loose in aggregate, *all* banks have surplus funds. Whereas when they are tight, banks' reserve positions differ: *some* need funds and others still have surpluses.

funding liquidity was available precisely *because* of the risk in asset markets. Whereas, as the economy recovered and risk declined, traditional inflation concerns caused them to tighten reserves. This line of argument suggests controlling for macroeconomic conditions like risk measures and proxies for growth rate and inflation expectations.

Table 9 reports results of conditional ITH estimation of price impact using additional controls motivated by the above stories. We use volume in the call money market as a proxy of uninformed trading. Two stock market-based measures serve as proxies for cyclicality - price to earnings (P/E) ratio of the Nifty 50 index and the standard deviation of daily returns on the Nifty index calculated over the trailing 22-trading-day period. Higher Nifty P/E ratios would indicate better macro-economic times. Higher Nifty standard deviation would indicate turbulent times.

In fact, the stories themselves do find support: each of our additional proxies is estimated to have a statistically significant effect on price impact that goes in the hypothesized direction. Higher call money volume and higher Nifty P/E each reduce the price impact while higher Nifty standard deviation increases it. The economic magnitude of effect of the standardized variables is between 7%-13% of the unconditional price impact for the first two variables and around 20%-25% for the Nifty standard deviation.

However, despite the significance of these variables, the negative quantity effect persists through out the estimation and is little diminished. It remains possible that the economic logic of the stories is the true explanation for this, and that we simply fail to have sufficiently precise proxies.[29]

Last, we investigate whether our findings are affected by other potential omitted vari-

[29] We do find some support for this notion in Section 6.

ables capturing the price or quantity of funding liquidity.

On the quantity side, we include a measure of net money inflows by foreign portfolio investors (FPI) to Indian capital markets. It is possible that government bond market intermediaries are sensitive to this source of funding for their overall balance sheet requirements. Foreign portfolio investors, as defined by the Securities and Exchange Board of India, are collectively, large players in Indian markets.[30] Data on daily net FPI inflows are obtained from the National Securities Depository Limited's website. Note that, unlike our measure of repo quantities, FPI flows constitute shocks to funding supply rather than demand. Thus the FLH would predict a negative effect on price impact.

On the price dimension, we include the U.S. Fed funds rate. Because of the dominant position the U.S. commands in the global economy, the Fed funds rate captures a global component of the funding cost of major banks. Conceivably this component is important in affecting bond market intermediation, even after controlling for the cost of domestic funds.

Table 10 presents our estimation using these proxies as additional conditioning variables for the price impact coefficient b_r. 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 for the net FPI flows and a positive one for the Fed funds rate. The economic magnitude of the effect of these standardized funding liquidity variables is around 4%-10% of the unconditional price imapct.

Even with inclusion of these additional variables, b_q, – the effect of funding liquidity

[30]FPI volume as fraction of total volume in the Indian equity markets is around 10% to 20% during our sample period.See `http://www.nseindia.com/content/us/ismr2014ch7.pdf`. For debt markets, the fraction for our sample is around 8%.

demanded – remains negative and b_{rt} and b_{qrt} remain positive, with magnitude and significance broadly similar to that in Table 6. Thus, while the positive effect of these other funding liquidity variables on bond market liquidity provides further support to FLH, it does not explain the negative effect of quantity of funding liquidity demanded.

6. Order Book Dynamics

As described in Section 2, our data allow us to directly construct the full order book for the 10-year bond at each point in time. In Section 3, we showed that the inverse slope of limit-order depth (ILOBS) captures a highly significant component of the time variation of price impact, and thus constitutes a distinct and direct way of measuring market illiquidity. To complement our high-frequency analysis of funding liquidity effects on price impact, we now examine the effects upon ILOBS in time-series regressions.

Our measures of funding liquidity are the same as in Section 5: the total outstanding borrowing from the repo facility (LAF), which we refer to as *Quantity*, and the RBI repo rate, referred to as *Rate*. We also include in the analysis the two components of bond volatility estimated in our high-frequency analysis, σ_f and σ_r, which themselves are expected to affect market depth, and which could also be affected by funding liquidity, presenting an indirect channel by which FLH could operate.[31]

Table 11 presents estimation results for a joint specification of these variables at the daily frequency. (ILOBS is the daily median of the values constructed every one minute

[31]Here σ_r and σ_f are daily standard deviations of the exogenous shocks to one-minute returns and flows respectively. The shocks – ϵ_r and ϵ_f – are estimated using the ITH specification conditioning on ILOBS using 10-day regimes. The results of this ITH specification are reported in Panel B of Table 4.

from the limit order book.) We run a vector autoregression of ILOBS, $log(\sigma_f)$ and $log(\sigma_r)$ with the lagged funding liquidity measures as additional explanatory variables, meaning that we are regarding prior-day funding liquidity as exogenous with respect to current-day bond market limit orders. All variables in the regressions are in standardized units for ease of interpretation. The specification includes the nonlinear interaction of *Quantity* and *Rate*, as in Section 5, because the economic logic of FLH makes makes a clear prediction that the interaction should have a positive effect on market illiquidity.

As the first column in the table shows, this prediction finds support in our data. The interaction coefficient of 0.091 means that when both *Quantity* and *Rate* are one standard deviation above their means the order book is thinner by nine percent of its unconditional standard deviation.

Interestingly, the anomalous negative marginal effect of *Quantity* on price-impact documented in the previous section is reversed here, where the marginal effect is a significantly positive ten percent (0.102). However, the positive effect of *Rate* on price-impact is absent (insignificantly negative) in the daily ILOBS specification.

Combining marginal and interaction coefficients, when *Quantity* and *Rate* are both one standard deviation above their means, ILOBS is above its mean by 15 percent of the unconditional standard deviation. Moreover, while ILOBS itself is not very persistent, both of the funding liquidity variables are highly persistent, meaning that these effects are long-lived.

The first column also documents the strong effects of the volatility components on order book depth. These are in accordance with prior expectation: higher return volatility raises inventory risk and discourages intermediation; higher flow volatility, on the other hand, is indicative of greater liquidity demand (uninformed trading) and thus elicits intermediation.[32] Both these effects are found very strongly in our data.

The interpretation of σ_f as proxying for uninformed volume may help explain why the sign of the *Quantity* effect is reversed here, relative to our price-impact results. Recall that we hypothesized that the negative contribution to price impact was due to a positive association between uninformed trade and tight monetary conditions (which could be due to increased cash management by underfunded banks). The current specification controls cleanly for this effect. Indeed, we find that dropping σ_f from the regression causes the coefficients on both *Quantity* and *Rate* to become substantially more negative.(These results are omitted for brevity.)

The sensitivity of ILOBS to the two volatility components raises the issue of whether funding liquidity affects σ_f or σ_r. The second column presents evidence that, indeed, there is a positive and significant effect of the interaction $Quantity{*}Rate$ on σ_r. Each of the marginal effects is insignificant. But the interaction coefficient of 0.065 coupled with the σ_r coefficient in the ILOBS equation implies a modest one percent additional effect (in standardized units) on the order book $(+0.173 * (0.039 - 0.042 + 0.065))$ when *Quantity* and *Rate* are both one standard deviation above their means.

The third column confirms the assertion above that the effects of funding liquidity on order flow volatility (and hence trading volume) are also positive and significant, both marginally and in the interaction term. And, as in Section 5.2, this effect works against the FLH. Multiplying the strong negative σ_f coefficient by the sum of the funding liquidity

[32] Recall that σ_f is the volatility of the component of order flow that is *not* related to return news.

effects on σ_f, the effect of *Quantity* and *Rate* both being one standard deviation above their means is a six percent $(-0.325 * (0.061 + 0.048 + 0.072))$ reduction in ILOBS, i.e., an increase in order-book depth and bond market liquidity.

Overall, the ILOBS regressions provide statistically solid support for FLH, at least in its interaction formulation. The 15 percent positive response to tight funding conditions in the first equation is tempered by the net negative five percent indirect effect via the volatility channels. These estimates can provide quantitative guidance to policy makers in judging the likely effects of changes in funding conditions on bond market fragility.

Our primary findings are also robust to several variations in the estimated specification. In unreported results, we have included controls for stock market volatility and valuation levels to control for growth rate expectations. We have also expanded the time-scale to five- and ten-day intervals. We have also substituted our alternate liquidity demand and interest rate proxies (described in Section 2.3) for the primary *Quantity* and *Rate* variables. In each variation, there is modest support for FLH coming through the *Quantity* and interaction terms. The mitigating effect through the σ_f channel also remains present. However, the economic magnitudes of the effects in these alternative specifications are not larger than those in Table 11.

7. Conclusion

The belief that intermediary funding conditions affect market resilience – what we have termed the funding liquidity hypothesis or FLH – is widely held by both policy makers and market participants. Yet measures of the actual strength of this linkage are largely lacking in the empirical literature. In this study, we have examined the hypothesis using a unique and advantageous data set from the Indian government bond market. Due to their reliance on repo markets, government bond market participants are highly sensitive to funding liquidity, suggesting that the mechanism thought to drive the FLH should be especially salient.

We first document the level and dynamics of price-impact, or market illiquidity, for the benchmark 10-year government bond. Using a high-frequency identification methodology, we isolate exogenous shocks to order flow and measure their effects on prices. 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 factors affecting market liquidity have potentially first-order effects on the real risks facing investors.

When we condition our price-impact estimation on measures of funding liquidity conditions, we find modest support for the FLH in the form of economically small, but statistically significant positive effects of the government's policy rate and its interaction with the quantity of repo borrowing from the central bank upon price impact. Surprisingly, though, the marginal effect of repo borrowing goes the opposite way: higher funding demand is actually associated with more liquid government bond markets.

We document two channels that may partially explain this result. Liquidity demand is higher when the economy is doing well and intermediation seems less risky. Also there appears to be greater (uninformed) bond trading when liquidity conditions are tight.

When we examine the dynamics of the limit-order book at daily and longer frequency, higher funding demand makes the bond market more illiquid, consistent with FLH, although the effect is again economically small. Again, too, the positive effect of tighter funding liquidity conditions on uninformed trade mitigates the FLH response, since greater quantity of uninformed trade improves market depth.

Overall, the modest nature of the support we find for FLH poses something of a challenge for the belief in a tight linkage between funding liquidity and market liquidity. Our results suggest that there may be very limited scope for conventional monetary policy tools to affect bond market resilience.

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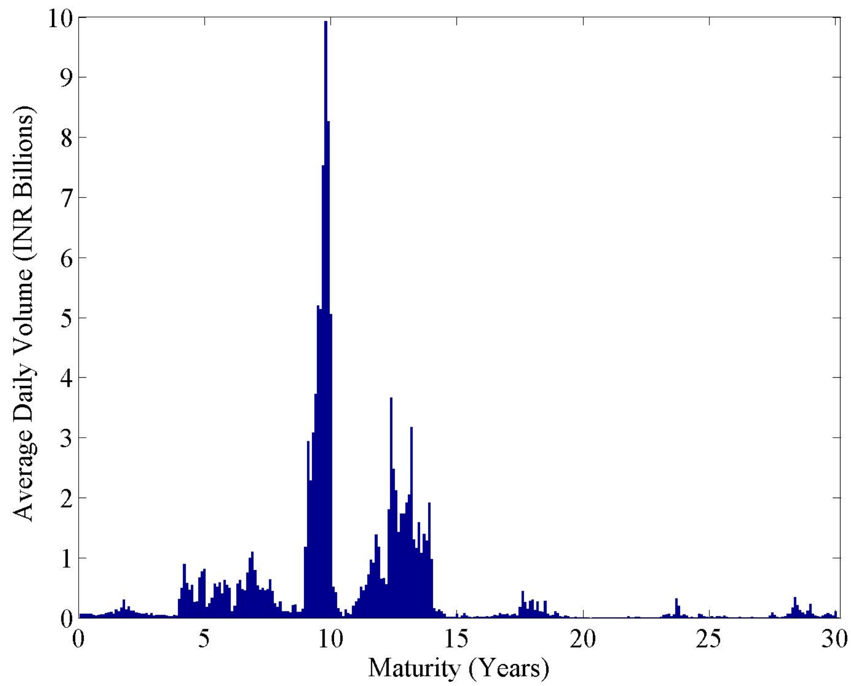
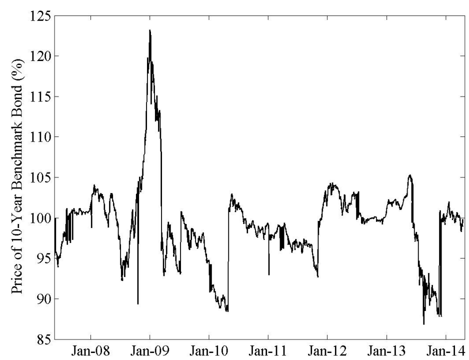
Figure 2
Daily trading volume by maturity



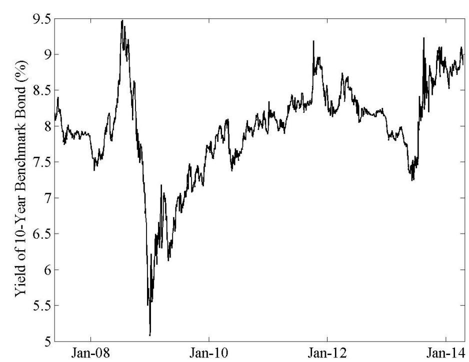
The figure plots average daily trading volume of the Government of India bonds, by maturity buckets, during the sample period of May 2007 to April 2014.

Figure 3
Time series of bond prices and volume

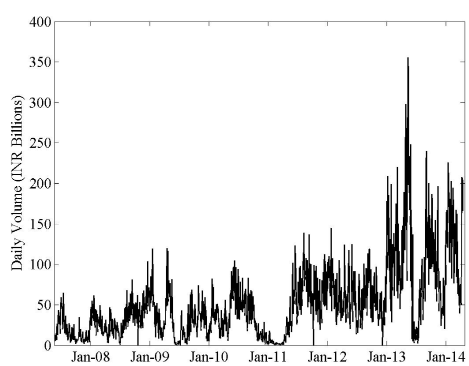
Panel A: Bond Prices



Panel B: Bond Yields



Panel C: Daily Trading Volume

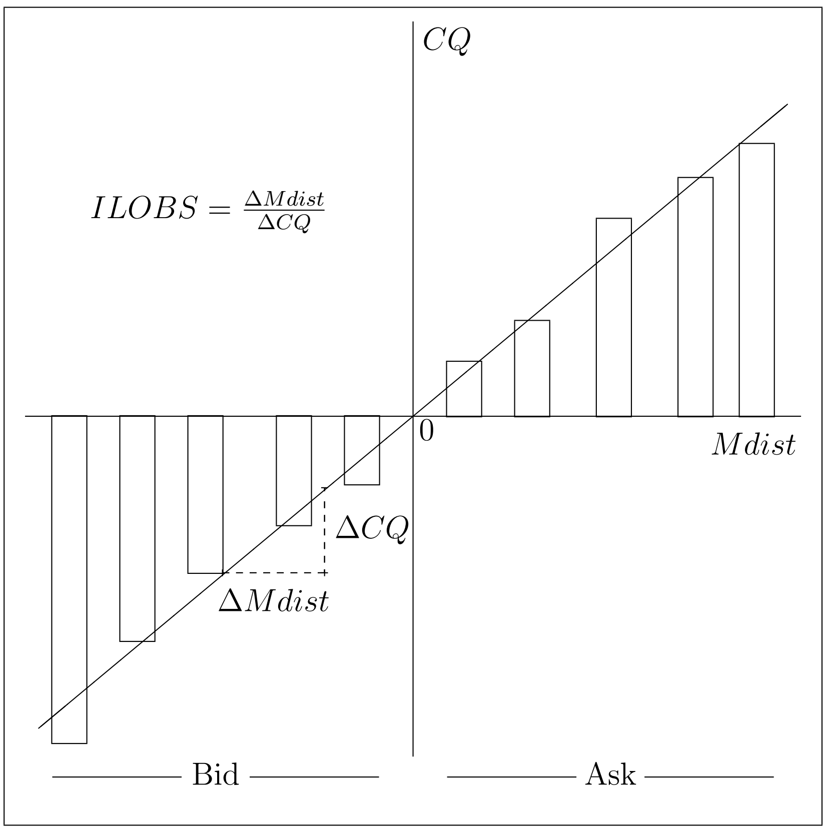


The figure shows prices, yields and trading volume for the benchmark 10-year maturity Government of India bond for the sample period May 21, 2007, to April 20, 2014. Panel A shows the time series of daily closing prices. Panel B shows the time series of daily closing yields. Panel C shows the time series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

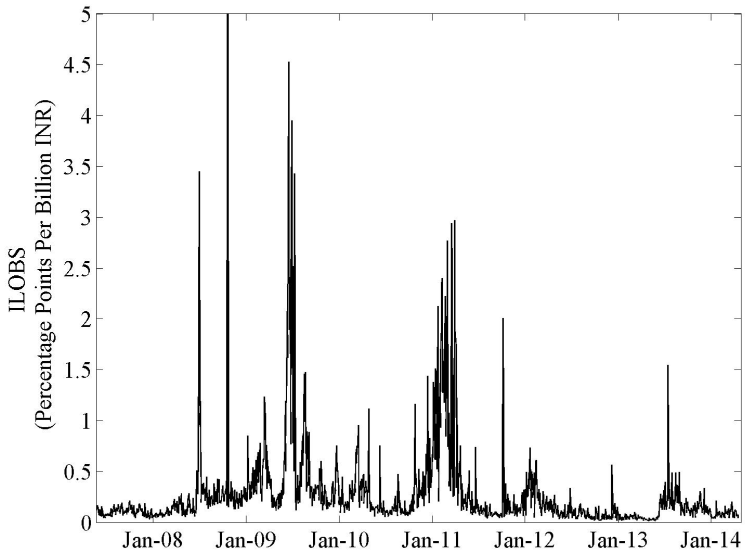
Panel A: Limit Order Book

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 $\Delta Mdist$.

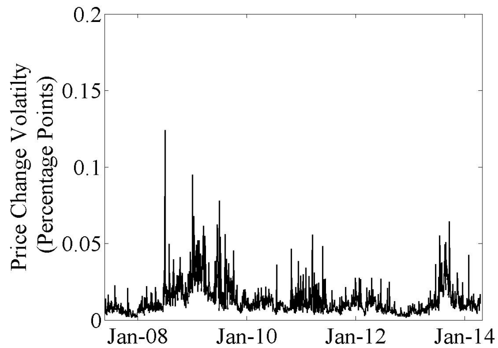
Figure 5
Time series of market illiquidity



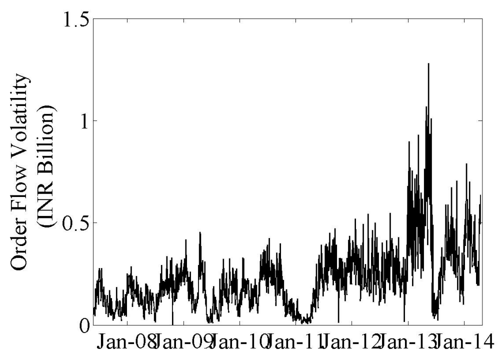
Market illiquidity is given by the inverse slope of the limit order book (ILOBS) for the benchmark 10-year maturity Government of India bond and is measured in percentage points per billion INR of bond face value. Section 2.2 and Figure 4 give details of the construction of ILOBS. Data are sampled at 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

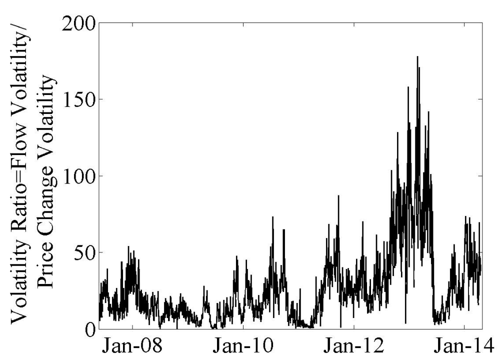
Panel A: Daily volatility of price changes



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.

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 2.2 and Figure 4 give the details of the construction of ILOBS. Data are sampled at one-minute intervals or one-day intervals over the period May 21, 2007, to April 20, 2014. Price changes and order flow are calculated as sum over the intervals. Bid-ask spreads and ILOBS are measured at the beginning of the 1-minute interval. They are daily medians for the 1-day intervals.

Panel A: 1-minute Intervals

Sample	Obs	Mean	Std Dev	Median	5th Percentile	95th Percentile
Price Changes	794890	-0.000	0.015	0.000	-0.015	0.014
Order Flow	855740	0.018	0.266	0.000	-0.200	0.300
Bid-Ask Spread	765880	0.048	0.073	0.030	0.010	0.140
ILOBS	797790	0.280	0.692	0.145	0.034	0.921

Panel B: 1-day Intervals

Sample	Obs	Mean	Std Dev	Median	5th Percentile	95th Percentile
Price Changes	1667	-0.022	0.414	-0.022	-0.606	0.599
Order Flow	1667	9.056	16.771	3.900	-8.172	39.642
Bid-Ask Spread	1666	0.043	0.057	0.030	0.013	0.102
ILOBS	1666	0.262	0.496	0.142	0.035	0.845

Table 3
Descriptive statistics: Funding liquidity

This table presents descriptive statistics and correlations of various funding liquidity variables. LAF borrowing is the total borrowing by the market participants from the RBI's liquidity adjustment facility (LAF). Liquidity deficit and liquidity need capture the funding liquidity shortage within a fortnightly cash reserve ratio maintenance cycle. Liquidity deficit is defined as LAF borrowing + (cumulative required reserves - cumulative actual reserves)/days past in the cycle. Liquidity need is defined as LAF borrowing + (total required reserves for the cycle - cumulative actual reserves)/days remaining in the cycle - current actual reserves. Cumulative reserves are the sum of daily reserves (required or actual) from the beginning of the cycle to the observation date. RBI repo rate is the RBI policy rate charged by the RBI for the LAF, measured as a fraction. Call rate is rate from the overnight uncollateralized interbank lending. Market repo rate is the rate for overnight interbank lending collateralized using repos. 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.

Panel A: Descriptive Statistics

	Obs	Mean	Std Dev	Median	5th Percentile	95th Percentile
LAF Borrowing - Rs Trillion	1667	0.301	0.796	0.387	-1.189	1.495
Liquidity Deficit - Rs Trillion	1667	0.225	0.789	0.320	-1.226	1.403
Liquidity Need - Rs Trillion	1667	0.116	0.802	0.200	-1.288	1.285
RBI Repo Rate	1667	0.070	0.013	0.077	0.048	0.085
Call Rate	1660	0.067	0.023	0.073	0.032	0.094
Market Repo Rate	1535	0.062	0.024	0.067	0.020	0.090
Net FPI Flows - Rs Trillion	1654	0.004	0.014	0.003	-0.016	0.026
US Fed Funds Rate	1607	0.008	0.015	0.002	0.001	0.049

Panel B: Correlations

	LAF Borrowing	Liquidity Deficit	Liquidity Need	RBI Repo Rate	Call Rate	Market Repo Rate	Net FPI Flows	US Fed Funds Rate
LAF Borrowing	1.00	0.99	0.96	0.63	0.72	0.73	0.01	-0.20
Liquidity Deficit	0.99	1.00	0.97	0.62	0.72	0.73	0.01	-0.20
Liquidity Need	0.96	0.97	1.00	0.61	0.72	0.73	0.01	-0.22
RBI Repo Rate	0.63	0.62	0.61	1.00	0.76	0.74	-0.07	0.31
Call Rate	0.72	0.72	0.72	0.76	1.00	0.93	-0.07	-0.13
Market Repo Rate	0.73	0.73	0.73	0.74	0.93	1.00	-0.03	-0.16
Net FPI Flows	0.01	0.01	0.01	-0.07	-0.07	-0.03	1.00	-0.06
US Fed Funds Rate	-0.20	-0.20	-0.22	0.31	-0.13	-0.16	-0.06	1.00

Table 4
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 (6) in Section 3.1. 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 2.2 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 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 4, 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
Conditioning on funding liquidity

This table presents price impact of order flow conditional on the funding liquidity variables estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades. Returns and order flow 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 $return = (b_0 + b_q Quantity + b_{rt} Rate)Flow$ and $Flow = b_f return$ in Panel A. Panel B has $return = (b_0 + b_q Quantity + b_{rt} Rate + b_{qrt} Quantity * Rate)Flow$ and $Flow = b_f return$ $Quantity$ measures borrowing via LAF. $Rate$ is cost of funding liquidity measured using the RBI repo rate. $Quantity$ and $Rate$ are standardized to have mean zero and standard deviation one. Each row gives results for ITH estimation using different length of a regime in days. The first row in each panel provides OLS estimates. Order flow is in billions of rupees of bond face value. The estimation controls for 10 lags of the dependent variables.

Panel A: Quantity and Rate

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
OLS	0.026	-0.0086	-0.0011	-	-
	(406.450)	(-130.9400)	(-12.9220)		
ITH 5 day	0.014	-0.0033	0.0010	-	4.65
	(39.808)	(-11.1750)	(2.8128)		(25.97)
ITH 10 days	0.013	-0.0032	0.0010	-	4.78
	(28.920)	(-7.6474)	(2.1975)		(19.45)
ITH 22 days	0.012	-0.0027	0.0010	-	5.44
	(21.099)	(-7.6595)	(2.2263)		(16.13)
ITH 66 days	0.011	-0.0025	0.0020	-	5.96
	(7.823)	(-3.3212)	(2.3461)		(9.04)

Panel B: Quantity, Rate, and Interaction

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
OLS	0.025	-0.0085	-0.0006	0.0015	-
	(291.550)	(-129.0000)	(-6.3126)	(18.4810)	
ITH 5 day	0.013	-0.0034	0.0013	0.0008	4.63
	(33.956)	(-11.1330)	(3.3296)	(2.2986)	(25.82)
ITH 10 days	0.013	-0.0033	0.0015	0.0011	4.75
	(24.756)	(-7.3126)	(2.7381)	(2.3915)	(19.47)
ITH 22 days	0.012	-0.0027	0.0015	0.0010	5.37
	(18.164)	(-7.5267)	(2.4531)	(1.8832)	(16.36)
ITH 66 days	0.010	-0.0028	0.0024	0.0016	5.89
	(6.884)	(-3.9016)	(2.4632)	(1.7466)	(9.15)

Table 7
Conditioning on funding liquidity - various measures

This table presents price impact of order flow conditional on the funding liquidity variables estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades. Returns and order flow 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 $return = (b_0 + b_q Quantity + b_{rt} Rate) Flow$ and $Flow = b_f return$ in Panel A. Panel B has $return = (b_0 + b_q Quantity + b_{rt} Rate + b_{qrt} Quantity * Rate) Flow$ and $Flow = b_f return$ *Quantity* is measured either as LAF borrowing, liquidity deficit or liquidity need. *Rate* is cost of funding liquidity measured using the RBI repo rate or the call rate or the market repo rate. Detailed definitions of the *Quantity* and *Rate* variables are in the caption of Table 3. *Quantity* and *Rate* are standardized to have mean zero and standard deviation one. Order flow is in billions of rupees of bond face value. The estimation uses 10-day regimes and controls for 10 lags of the dependent variables.

Panel A: Quantity and Rate

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
LAF Borrowing and Call Rate	0.014	-0.0033	0.0007	-	4.67
	(28.245)	(-7.1893)	(1.2208)		(18.92)
LAF Borrowing and Market Repo Rate	0.014	-0.0034	0.0003	-	4.47
	(28.722)	(-7.4346)	(0.5984)		(17.97)
Liquidity Deficit and RBI Repo Rate	0.013	-0.0033	0.0010	-	4.74
	(29.050)	(-7.8338)	(2.1496)		(19.39)
Liquidity Need and RBI Repo Rate	0.013	-0.0032	0.0010	-	4.72
	(28.968)	(-7.3544)	(2.1037)		(19.17)

Panel B: Quantity, Rate, and Interaction

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
LAF Borrowing and Call Rate	0.012	-0.0037	0.0016	0.0025	4.40
	(23.296)	(-7.2747)	(2.4251)	(4.5189)	(18.37)
LAF Borrowing and Market Repo Rate	0.013	-0.0039	0.0011	0.0018	4.35
	(21.995)	(-8.0426)	(1.6886)	(3.4985)	(17.84)
Liquidity Deficit and RBI Repo Rate	0.013	-0.0033	0.0015	0.0011	4.72
	(24.723)	(-7.4693)	(2.6533)	(2.3205)	(19.40)
Liquidity Need and RBI Repo Rate	0.013	-0.0033	0.0016	0.0012	4.69
	(23.772)	(-6.9592)	(2.6618)	(2.4124)	(19.17)

Table 8
Conditioning on funding liquidity - subsamples and frequency

This table presents price impact of order flow conditional on the funding liquidity variables estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades. Returns and order flow for the benchmark 10-year maturity Government of India bond are calculated over one-minute intervals or one-day interval. The sample period is May 21, 2007, to April 20, 2014. Different rows in each panel present results for different sample periods and different frequency of return-flow measurement. The table presents a linear specification where $return = (b_0 + b_q Quantity + b_{rt} Rate) Flow$ and $Flow = b_f return$ in Panel A. Panel B has $return = (b_0 + b_q Quantity + b_{rt} Rate + b_{qrt} Quantity * Rate) Flow$ and $Flow = b_f return$ *Quantity* measures borrowing via LAF. *Rate* is cost of funding liquidity measured using the RBI repo rate. *Quantity* and *Rate* are standardized to have mean zero and standard deviation one. Order flow is in billions of rupees of bond face value. The estimation use 10-day regimes. Specifications with 1-minute return and flow control for 10 lags of the dependent variables. Specifications at the daily level control for 5 lags.

Panel A: Quantity and Rate

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
May 2007-Oct 2010 - 1-minute	0.019	-0.0050	0.0031	-	3.33
	(19.137)	(-4.8588)	(4.7853)		(14.62)
Nov 2010-Apr 2014 - 1-minute	0.008	-0.0012	0.0048	-	6.44
	(6.058)	(-1.9051)	(3.0830)		(11.88)
May 2007-Apr 2014 - 1-day	0.012	-0.0046	0.0006	-	8.09
	(47.309)	(-23.7320)	(1.8772)		(20.31)

Panel B: Quantity, Rate, and Interaction

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_f
May 2007-Oct 2010 - 1-minute	0.022	0.0029	0.0059	0.0058	3.11
	(21.658)	(1.5759)	(8.3216)	(5.1514)	(15.08)
Nov 2010-Apr 2014 - 1-minute	0.009	-0.0019	0.0031	0.0016	6.24
	(3.984)	(-1.2739)	(0.9809)	(0.6482)	(10.98)
May 2007-Apr 2014 - 1-day	0.012	-0.0046	0.0006	0.0006	7.98
	(41.240)	(-20.9220)	(1.7588)	(1.9143)	(19.56)

Table 9
Conditioning on funding liquidity - additional controls

This table presents price impact of order flow conditional on the funding liquidity variables estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades. Returns and order flow for the benchmark 10-year maturity Government of India bond are calculated over one-minute intervals. The sample period is May 21, 2007, to April 20, 2014. Different rows in each panel presents result for different additional conditioning variable. The table presents a linear specification where $return = (b_0 + b_q Quantity + b_{rt} Rate + b_2 Control) Flow$ and $Flow = b_f return$ in Panel A. Panel B has $return = (b_0 + b_q Quantity + b_{rt} Rate + b_{qrt} Quantity * Rate + b_2 Control) Flow$ and $Flow = b_f return$ *Quantity* measures borrowing via LAF. *Rate* is cost of funding liquidity measured using the RBI repo rate. *Control* is either call money volume, Nifty 50 P/E ratio or Nifty 50 22-day standard deviation of daily returns. *Quantity*, *Rate*, and *Control* are standardized to have mean zero and standard deviation one. Order flow is in billions of rupees of bond face value. The estimation use 10-day regimes and controls for 10 lags of the dependent variables.

Panel A: Quantity and Rate

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_2	b_f
Call Money Volume	0.013	-0.0026	0.0012	-	-0.0012	4.73
	(29.420)	(-6.2082)	(2.6548)		(-2.8701)	(19.34)
Nifty P/E	0.014	-0.0038	0.0007	-	-0.0011	4.57
	(28.266)	(-7.8368)	(1.6061)		(-3.9372)	(18.54)
Nifty Std Dev	0.016	-0.0030	0.0008	-	0.0035	3.89
	(29.777)	(-7.0179)	(1.6710)		(6.3532)	(17.31)

Panel B: Quantity, Rate, and Interaction

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_2	b_f
Call Money Volume	0.012	-0.0025	0.0020	0.0016	-0.0016	4.69
	(24.771)	(-5.7057)	(3.8256)	(3.4278)	(-3.7439)	(19.38)
Nifty P/E	0.013	-0.0037	0.0011	0.0006	-0.0009	4.60
	(21.982)	(-7.4181)	(1.8633)	(1.3095)	(-2.5823)	(18.72)
Nifty Std Dev	0.015	-0.0030	0.0013	0.0015	0.0036	3.87
	(25.792)	(-6.5467)	(2.6587)	(3.1833)	(6.6352)	(17.38)

Table 10

Conditioning on additional funding liquidity measures

This table presents price impact of order flow conditional on the funding liquidity variables estimated using a simultaneous system of return and flow and identified through heteroskedasticity (ITH). Order flow denotes the quantity of buyer-initiated trades minus the quantity of seller-initiated trades. Returns and order flow for the benchmark 10-year maturity Government of India bond are calculated over one-minute intervals. The sample period is May 21, 2007, to April 20, 2014. Different rows in each panel present results conditioning on a different additional funding liquidity variable. The table presents a linear specification where $return = (b_0 + b_q Quantity + b_{rt} Rate + b_2 FundLiq) Flow$ and $Flow = b_f return$ in Panel A. Panel B has $return = (b_0 + b_q Quantity + b_{rt} Rate + b_{qrt} Quantity * Rate + b_2 FundLiq) Flow$ and $Flow = b_f return$ *Quantity* measures borrowing via LAF. *Rate* is cost of funding liquidity measured using the RBI repo rate. *FundLiq* are other variables capturing funding liquidity in the market - such as Net FPI Flows or Fed Funds Rate. Net FPI Flows are lagged net inflows 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. *Quantity*, *Rate*, and *FundLiq* are standardized to have mean zero and standard deviation one. Order flow is in billions of rupees of bond face value. The estimation use 10-day regimes and controls for 10 lags of the dependent variables.

Panel A: Quantity and Rate

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_2	b_f
Net FPI Flows	0.014	-0.0029	0.0007	-	-0.0012	4.68
	(30.078)	(-6.9082)	(1.5706)		(-2.9611)	(19.02)
Fed Funds Rate	0.014	-0.0032	0.0008	-	0.0005	4.58
	(29.236)	(-6.5501)	(1.5358)		(1.2002)	(19.00)

Panel B: Quantity, Rate, and Interaction

Estimation	b_0	b_q	b_{rt}	b_{qrt}	b_2	b_f
Net FPI Flows	0.013	-0.0029	0.0012	0.0012	-0.0013	4.63
	(25.960)	(-6.7023)	(2.2571)	(2.7510)	(-3.3926)	(18.95)
Fed Funds Rate	0.013	-0.0030	0.0013	0.0014	0.0009	4.54
	(23.927)	(-5.8234)	(2.3092)	(2.8881)	(2.2028)	(19.01)

Table 11
Funding Liquidity, Volatility of Shocks and ILOBS

This table presents results of vector autoregression at daily frequency of median ILOBS and volatilities of the return and order flow shocks with *Quantity*, *Rate* and *Quantity***Rate* as exogenous variables. *Quantity* measures borrowing via LAF. *Rate* is cost of funding liquidity measured using the RBI repo rate. 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 2.2 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. All the variables in the VAR are standardized to have mean zero and standard deviation one.

	ILOBS	$log(\sigma_r)$	$log(\sigma_f)$
ILOBS(-1)	0.244	0.028	0.010
	(9.961)	(1.330)	(0.639)
$log(\sigma_r)$(-1)	0.173	0.637	-0.077
	(7.519)	(31.733)	(-5.150)
$log(\sigma_f)$(-1)	-0.325	-0.047	0.804
	(-12.369)	(-2.041)	(46.980)
$Quantity(-1)$	0.102	0.039	0.061
	(3.534)	(1.540)	(3.249)
$Rate(-1)$	-0.043	-0.042	0.048
	(-1.415)	(-1.592)	(2.412)
$Quantity(-1)$*$Rate(-1)$	0.091	0.065	0.072
	(3.673)	(3.023)	(4.429)
Adj. R-squared	0.270	0.446	0.690