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ABSTRACT

We propose a new reserve-demand estimation strategy—a middle ground between atheoretical reduced-form econometric approaches and fully structural quantitative-theoretic approaches. The strategy consists of an econometric specification that satisfies core restrictions implied by theory and controls for changes in administered-rate spreads that induce rotations and shifts in reserve demand. The resulting approach is as user-friendly as existing reduced-form econometric methods but improves upon them by incorporating a minimal set of theoretical restrictions that any reserve demand must satisfy. We apply this approach to U.S. data and obtain reserve-demand estimates that are broadly consistent with the structural estimates in Lagos and Navarro (2023).

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1 Introduction

There are currently two approaches to reserve-demand estimation. The first specifies the interbank rate as a function of the quantity of reserves, and econometrically estimates the parameters of the function. Because the choice of functional form is typically not disciplined by economic theory, we refer to this approach as *no-theory estimation*. Examples include Hamilton (1996, 1997), Carpenter and Demiralp (2006), Afonso et al. (2022), and López-Salido and Vissing-Jorgensen (2023). The second approach, proposed by Lagos and Navarro (2023), is *structural*: it uses a fully specified equilibrium theory of interbank-rate determination in an over-the-counter market structure, estimates or calibrates the structural parameters using micro data, and produces a quantitative-theoretic estimate of the aggregate demand for reserves.

The no-theory approach is appealing for its simplicity but is pervaded by empirical challenges. First, it can have poor extrapolation properties, since the out-of-sample shape of the reserve demand is entirely determined by the arbitrary choice of functional form. Second, commonly used functional forms violate elementary theoretical shape restrictions. Third, due to the lack of theoretical guidance, this approach cannot identify the global shape of the reserve demand over periods in which the relationship is likely to have shifted or rotated due to structural changes in regulation or market structure.

The structural approach disciplines the global shape of the demand curve using economic theory and micro data, and identifies (e.g., via quantitative counterfactuals) the policy and microstructure variables that shift and rotate the demand for reserves. However, it can be computationally demanding for everyday use by practitioners.

We propose a new reserve-demand estimation strategy—a middle ground between the no-theory reduced-form and the quantitative-theoretic structural approaches. The strategy consists of an econometric specification that satisfies core restrictions implied by theory and controls for monetary-policy variables that induce rotations and shifts in the demand for reserves. The resulting approach is as user-friendly as no-theory reduced-form methods, while incorporating a minimal set of theoretical restrictions that any reserve demand ought to satisfy. We refer to it as the *minimal-theory approach*. We apply this approach to U.S. data and obtain reserve-demand estimates that are broadly consistent with the quantitative-theoretic structural estimates in Lagos and Navarro (2023).

2 Data

We use time-series data on five variables: effective fed funds rate (EFFR), quantity of reserves (Q), interest on reserves (IOR), discount-window rate (DWR), and overnight reverse repo rate (ONRRP). All data series are downloaded from FRED, whose respective codes are EFFR, WRESBAL, IOER (before August 2021) or IORB (after August 2021), DPCREDIT, and RRPONTSYAWARD. Figure 1 plots the five variables for the period 2010/01/01–2025/06/04.

Figure 2 displays a scatterplot of the weekly aggregate quantity of reserves (Q) against the EFFR–IOR spread for the period 2010/01/01–2025/06/04. This is the space in which one would seek to identify a tight, downward-sloping relationship resembling a reserve-demand schedule.

No such relationship is immediately evident in the raw data. This is not surprising given the large policy changes, motivated by concerns about financial stability, that materially altered banks' incentives to hold reserves during this period. Two prominent examples are the Liquidity Coverage Ratio (LCR), which was phased in between January 2015 and January 2017, and the Supplementary Leverage Ratio (SLR), which has been in effect since January 2018.

These large policy shifts suggest it is not reasonable to regard all the data points in Figure 2 as lying on a single reserve-demand schedule. The identification challenge is that capturing substantial variation in the supply of reserves necessarily entails spanning a long period of time, during which the demand for reserves is itself likely to have shifted due to structural changes, for example, in the market structure of interbank markets or in banks' incentives to hold reserves arising from changes in policy, regulation, or internal portfolio-allocation frameworks.

For this reason, when considering the sample period 2010/01/01–2025/06/04, which we refer to as the *full sample*, we divide it into four subsamples corresponding to distinct regulatory frameworks. The first subsample is 2010/01/01–2014/09/30, which corresponds to the period preceding the phase-in of GFC-inspired regulation. The second subsample is 2014/10/01–2016/12/31, which corresponds to the LCR (Liquidity Coverage Ratio) and SLR (Supplementary Leverage Ratio) phase-in period. The third subsample is 2017/01/01–2019/09/11, which corresponds to the period after GFC-inspired regulation was fully phased in, up to the money-market spikes of September 2019. The fourth subsample corresponds to the post-COVID period 2021/09/01–2025/06/04. Figure 3 displays a scatterplot of the weekly EFFR–IOR spread against the quantity of reserves, with observations color-coded by subsample.

To control for the *administered-rate regime*, we further divide each regulatory subsample according to the DWR–IOR and IOR–ONRRP spreads. Regime 0 corresponds to subsample 1 (the subsample preceding GFC-inspired regulation), during which DWR $-$ IOR $=$ 50 bps and IOR $-$ ONRRP $=$ 25 bps throughout. Regimes 1–4 consist of trading days from subsamples 2 and 3, sorted as follows. Regime 1: days with DWR $-$ IOR $=$ 50 bps and IOR $-$ ONRRP $=$ 25 bps. Regime 2: days with DWR $-$ IOR $=$ 55 bps and IOR $-$ ONRRP $=$ 20 bps. Regime 3: days with DWR $-$ IOR $=$ 60 bps and IOR $-$ ONRRP $=$ 15 bps. Regime 4: days with DWR $-$ IOR $=$ 65 bps and IOR $-$ ONRRP $=$ 10 bps. Regime 5 consists of trading days in subsample 4 with DWR $-$ IOR $=$ 10 bps and IOR $-$ ONRRP $=$ 10 bps. Figure 4 displays a scatterplot of the weekly EFFR–IOR spread against the quantity of reserves, with observations color-coded by administered-rate regime.

Our formal analysis focuses on subsamples 2 and 3 (2014/10/01–2019/09/11), which begins with the phase-in of GFC-inspired regulation and ends with the money-market spikes of September 2019. This is the period that Lagos and Navarro (2023) uses for their structural estimation, and it is the period during which the Fed's Trading Desk was not accommodating money-market conditions on a daily basis. For some of our estimations, we extend the sample back to 2010/01/01 to facilitate comparison with the recent literature.[1]

[1]Extending the analysis to periods in which the Trading Desk actively accommodates money-market conditions introduces well-known identification challenges that can be addressed as in Hamilton (1997), Carpenter and Demiralp (2006), or Afonso et al. (2022). Appendix A (Section A.5) in Lagos and Navarro (2023) contains a more detailed discussion of these issues, including a review of the three identification strategies.

3 Structural approach

In this section, we briefly review the quantitative-theoretic structural approach to reserve-demand estimation proposed in Lagos and Navarro (2023). The model consists of a large number of banks that start the trading day with given reserve balances, are subject to random payment shocks, and can borrow and lend reserves in a dynamic over-the-counter market to buffer payment shocks and maximize the end-of-day payoff from holding reserves. Lagos and Navarro (2023) calibrate the model to match a broad set of bank- and market-level statistics and compute the equilibrium, thereby obtaining the mapping $\iota = \mathcal{D}(Q)$ from the aggregate quantity of reserves, Q, to the equilibrium value-weighted interbank rate, ι. The mapping $\mathcal{D}(\cdot)$ constitutes the quantitative-theoretic estimate of reserve demand implied by the structural model.

Figure 5 illustrates the baseline structural estimates of aggregate reserve demand from Lagos and Navarro (2023). The vertical axis plots the EFFR–IOR spread, and the top horizontal axis plots *total reserves* (TOTRESNS from FRED). The bottom horizontal axis plots *active excess reserves*, the empirical reserve measure used by Lagos and Navarro (2023) to compute reserve demand in the quantitative theory.[2]

The dots in Figure 5 represent empirical observations of active excess reserves and the corresponding EFFR–IOR spread for each trading day in the sample period 2017/01/20–2019/09/11. Guided by the structural theory, which implies that reserve demand shifts and rotates with changes in administered-rate spreads, the sample is divided into four subsamples corresponding to the IOR–ONRRP spread: 10 bps (2019/05/02–2019/09/11, red dots), 15 bps (2018/12/20–2019/05/01, green dots), 20 bps (2018/06/14–2018/12/19, orange dots), and 25 bps (2017/01/20–2018/06/13, blue dots).[3]

Along with the data, the figure depicts four quantitative-theoretic reserve-demand curves. The solid (red) curve is generated by the baseline calibration, which targets an IOR–ONRRP spread of 10 bps. The fact that this curve fits the red data points in the subsample with IOR − ONRRP = 10 bps is not surprising, since the baseline calibration targets the average EFFR–IOR spread and the local slope of the empirical demand curve within this subsample. What is informative about the quantitative-theoretic structural approach is that it allows us to trace reserve demand over the full range of reserve levels, including regions beyond those observed in the narrow calibration subsample with IOR − ONRRP = 10 bps. The remaining three curves are counterfactual reserve demands obtained by changing only the IOR–ONRRP spread to 15 bps (green dashed curve), 20 bps (orange dash–dot curve), and 25 bps (blue long–short dashed curve). Despite the fact that no parameters other than the IOR–ONRRP spread were changed, these counterfactual reserve demands fit the data points in the corresponding subsamples reasonably well, thereby providing an out-of-sample validation of the quantitative predictions of the theory.[4]

[2] *Active excess reserves* are obtained from *total reserves* by subtracting reserves held by banks that did not participate in the interbank market during the baseline calibration year, as well as reserve requirements arising from Regulation D and the LCR. Lagos and Navarro (2023) (Appendix C, Section C.5.5) provide an empirical transformation that maps *active excess reserves* into *total reserves*.

[3] The DWR–ONRRP spread is constant at 75 bps throughout the sample period 2017/01/20–2019/09/11.

[4] In Appendix E (Section E.2), Lagos and Navarro (2023) extend this time-series validation exercise using

In $(Q, \text{EFFR} - \text{IOR})$ space, the structural demands in Figure 5 have two properties, which we regard as *minimal theoretical restrictions* that any reserve-demand estimate ought to satisfy:

1. Logistic shape, with:
   (a) upper asymptote at DWR − IOR.
   (b) lower asymptote at or above ONRRP − IOR.
2. Reaches the upper asymptote near $Q = 0$.

Properties 1 and 2 are minimal theoretical restrictions shared by a wide range of models of interbank markets. They arise not only in the dynamic over-the-counter equilibrium of Lagos and Navarro (2023), but also in the competitive static model of Poole (1968), which has long served as the canonical framework for studying the demand for reserves.

The equilibrium rate on day t in the model of Lagos and Navarro (2023), which we denote by r_t, admits a simple representation:

$$r_t = \omega_t \, i_t^W + (1 - \omega_t) \big[\underline{\omega} \, i_t^O + (1 - \underline{\omega}) \, i_t^R \big], \tag{1}$$

where $i_t^R = \text{IOR}$, $i_t^W = \text{DWR}$, $i_t^O = \text{ONRRP}$, and $\omega_t \in [0, 1]$ and $\underline{\omega} \in [0, 1]$ are determined in equilibrium by the structural model. Intuitively, the equilibrium interbank rate, r_t, is a convex combination of the maximum rate that participating institutions are willing to pay to borrow reserves, i_t^W, and the minimum rate they are willing to accept to lend reserves, which in the United States is i_t^R for some institutions, such as commercial banks, and i_t^O for others, such as Government Sponsored Enterprises (GSEs).[5]

In the structural model, the weights ω_t and $\underline{\omega}$ are complicated functions of parameters, which include the frequency and size of each bank's payment shocks, banks' trading frequency, their relative market power in bilateral lending operations, and the cross-sectional beginning-of-day distribution of reserves, which determines the aggregate supply of reserves, Q. Intuitively, however, ω_t tends to decrease with Q, reflecting the fact that most trades in a market with abundant reserves will involve borrowers and lenders whose marginal value of a unit of reserves is close to their minimum acceptable rates. And conversely, in a market with scarce reserves, most trades will involve borrowers and lenders whose marginal value of a unit of reserves is close to their maximum willingness-to-pay rate. The weight $\underline{\omega}$ tends to be very large (close to 1) if the equilibrium exhibits many lenders with minimum acceptable rate i_t^O and very low market power in bilateral negotiations. For example, if most excess reserves are held by GSEs, which

data from 2023—a representative post-COVID year with abundant reserves—and show that the model-generated demand fits the data well across the full range of reserves observed in the extended sample. We do not include this additional validation in Figure 5 (e.g., as done in Figure 26 in Lagos and Navarro (2023)) to simplify the exposition, as it requires recalibrating a structural parameter to match the average spread between the interbank rate and the IOR observed in 2023. This structural adjustment may reflect post-COVID changes in regulation and macro conditions, such as that Regulation D was operative in 2019 but not in 2023, and possibly lower inflation in 2019—two factors outside the model that would have shifted the demand for reserves.

[5] A "stigma premium" may be added to i_t^W to capture the fact that some institutions may be reluctant to borrow reserves from the Fed at the discount window.

are not eligible to earn the IOR and have very low market power in bilateral negotiations, then $\underline{\omega}$ will be close to 1, and the equilibrium interbank rate will be close to i_t^O when reserves are abundant.

Subtracting i_t^R from both sides of (1) yields a simple representation of the equilibrium spread $s_t \equiv r_t - i_t^R$, the theoretical counterpart of the empirical spread EFFR − IOR:

$$s_t = \omega_t \, \bar{s}_t + (1 - \omega_t) \, \underline{\omega} \, \underline{s}_t, \tag{2}$$

where $\bar{s}_t \equiv i_t^W - i_t^R$ and $\underline{s}_t \equiv i_t^O - i_t^R$.

4 No-theory estimation

There are currently two well-known no-theory estimation specifications for reserve demand. The first assumes that the EFFR–IOR spread is an affine function of the logarithm of the quantity of reserves (López-Salido and Vissing-Jorgensen (2023)). The second assumes that the EFFR–IOR spread is a sigmoid function of the quantity of reserves (Afonso et al. (2022)).

4.1 Semi-log demand

Consider the following baseline semi-log specification:

$$s_t = \sum_{i=0}^{4} c_i \, \mathbb{I}_{\{\text{regime } i\}} + b \, \ln(Q_t) + \varepsilon_t, \tag{3}$$

where $s_t = \text{EFFR} - \text{IOR}$ (in percentage points), Q_t denotes the quantity of reserves (in billions of dollars), and $\mathbb{I}_{\{\text{regime } i\}}$ is a dummy variable for administered-rate regime $i \in \{0, 1, 2, 3, 4\}$. The parameters b and $\{c_i\}_{i=0}^4$ are estimated by OLS. The data are weekly, and the sample period is 2010/06/01–2019/09/11. The coefficient of interest, b, is estimated to be -0.109, statistically significant at the 1% level.[6] In economic terms, a 10% increase in reserves lowers the EFFR–IOR spread by about 1.09 basis points.[7]

As illustrated in Figure 6, the semi-log specification has two shortcomings. First, the estimated demand does not have a logistic shape, does not have an upper asymptote at DWR − IOR, and does not have a lower asymptote at or above ONRRP − IOR, which violates restriction 1. Second, the demand curve does not reach the upper asymptote near $Q = 0$, which violates restriction 2.

[6] The standard error is 0.011 (Newey–West, robust to autocorrelation up to 13 lags).

[7] This estimate is similar in magnitude to the 1.83 basis points reported by López-Salido and Vissing-Jorgensen (2023) for the sample period 2009–2022. The semi-log specification in López-Salido and Vissing-Jorgensen (2023) differs from (3) in that it does not include administered-rate dummies and instead includes bank deposits as an additional control variable. We favor (3) because the administered-rate dummies control for shifts and rotations in reserve demand induced by changes in administered-rate spreads, consistent with the structural theory, and because this specification avoids the endogeneity concerns that arise when including bank deposits as a regressor. Another difference with López-Salido and Vissing-Jorgensen (2023) is that their sample extends past the money-market spikes of September 2019, which raises endogeneity concerns due to the fact that the Fed's Trading Desk has been actively accommodating money-market conditions since then.

Figure 7 compares the no-theory logistic demands with the structural demands from Lagos and Navarro (2023). While both are relatively similar in-sample, the no-theory semi-log demands do not match the shape of the structural demands well for very large or very low levels of reserves. In particular, the semi-log demands predict EFFR–IOR spreads that are unreasonably high as reserves become very scarce, and unreasonably low when reserves become very abundant. Because the out-of-sample predictions are so unreliable, this approach is not well suited for policy analysis that requires global estimates of the reserve demand, such as estimating the minimum level of reserves required for the Fed to operate a floor system.

4.2 Sigmoid demand

Consider the following logistic sigmoid specification:

$$s_t = D\left(Q_t\right)$$

with

$$D\left(Q_t\right) \equiv \omega\left(Q_t\right)\bar{s} + \left[1 - \omega\left(Q_t\right)\right]\underline{s},$$

and

$$\omega\left(Q_t\right) \equiv \frac{1}{1 + e^{\alpha\left(Q_t - Q_0\right)}}, \tag{4}$$

where $s_t \equiv \text{EFFR} - \text{IOR}$, Q_t is the quantity of reserves, and the parameters $(\alpha, Q_0, \bar{s}, \underline{s})$ are estimated separately by NLS for administered-rate regimes 1–4. The data are weekly, and the sample period is 2014/10/01–2019/09/11.[8] Table 1 reports the estimated parameter values.

As illustrated in Figure 8, the logistic specification has two shortcomings. First, it does not have an upper asymptote at DWR − IOR, violating restriction 1(a). Second, it does not reach the upper asymptote near $Q = 0$, violating restriction 2.

Figure 9 compares the no-theory logistic demands with the structural demands from Lagos and Navarro (2023). While both are relatively similar in-sample, the no-theory logistic demands do not match the shape of the structural demands well for intermediate and low levels of reserves. In particular, the no-theory logistic specification predicts EFFR–IOR spreads that are unreasonably low as reserves shrink. Because the out-of-sample predictions are so unreliable, this approach is not well suited for policy analysis that requires global estimates of the reserve demand.

[8] In their Appendix G, Afonso et al. (2022) follow this approach assuming $D(\cdot)$ is a transformation of the arctan function. Motivated by concerns about structural shifts in reserve demand, they split their full sample period (2010–2021/03/29) according to the different low-frequency cycles of expansion and contraction of the Federal Reserve balance sheet. Specifically, they consider the initial post-GFC expansionary period (2010–2014), the subsequent post-GFC and pre-COVID contractionary period (2015–2020/3/13), and the most recent post-COVID expansionary period (2020/03/16–2021/03/29). They do not, however, attempt to control for shifts and rotations caused by changes in administered-rate spreads. The sample we consider here, which is the union of subsamples 2 and 3 in Section 2, largely overlaps with their pre-COVID contractionary period, but we consider different administered-rate regimes to control for shifts and rotations induced by monetary-policy implementation decisions. See Lagos and Navarro (2023) (Appendix D) for other econometric specifications and sample periods.

5 Minimal-theory logistic

The demand representation (2) describes a broad class of interbank market models, whose relevant differences are summarized by the specifications of $\omega_t \in [0,1]$ and $\underline{\omega} \in [0,1]$. The structural model in Lagos and Navarro (2023) develops an equilibrium theory of ω_t and $\underline{\omega}$, grounded in over-the-counter trading frictions and bank-level heterogeneity and disciplined by micro data (such as the frequency and size of payment shocks, trading frequency, relative market power, and beginning-of-day reserve distributions). A practical challenge in Lagos and Navarro (2023) is that computing ω_t and $\underline{\omega}$ requires solving for the model equilibrium at every point on a grid of reserve levels, which can be computationally intensive.

The econometric strategy we propose here is to approximate (2) by using $\omega_t \approx \omega(Q_t)$ with $\omega(Q_t)$ given by (4), and to estimate $(\underline{\omega}, \alpha, Q_0)$ by NLS, subject to the restriction $\mathcal{D}(0; \bar{s}_t, \underline{s}_t) = k\bar{s}_t$ for some k close to 1, where $\mathcal{D}(Q_t; \bar{s}_t, \underline{s}_t) \equiv \omega(Q_t)\,\bar{s}_t + [1-\omega(Q_t)]\,\underline{\omega}\ \underline{s}_t$. This leads to a specification that is easy to estimate but still grounded in minimal theory, while sidestepping the computational burden of repeatedly solving the structural model to compute ω_t and $\underline{\omega}$.

The constraint $\mathcal{D}(0; \bar{s}_t, \underline{s}_t) = k\bar{s}_t$ ensures that the demand curve is close to its upper asymptote near $Q = 0$, consistent with restriction 2. According to the structural theory, k will be close to 1 if banks' required reserves are nonnegative and their trading frequencies are sufficiently high, that is, if the over-the-counter interbank market is sufficiently close to the perfectly competitive benchmark.[9] Here we adopt $k = 0.9$, which is the value consistent with the structural estimation in Lagos and Navarro (2023). The parameters $(\underline{\omega}, \alpha, Q_0)$ are estimated separately for each of administered-rate regimes 1–4 using weekly data for 2014/10/01–2019/09/11. Table 2 reports the results.[10]

Figure 10 illustrates the estimated minimal-theory logistic demands, which satisfy all the minimal theoretical restrictions. They have a logistic shape with upper asymptote at $\bar{s}_t$ and lower asymptote no smaller than $\underline{s}_t$, thus satisfying restriction 1. The NLS constraint $\mathcal{D}(0; \bar{s}_t, \underline{s}_t) = k\bar{s}_t$ with $k = 0.9$ ensures that the demands attain 90% of their upper asymptotes at $Q = 0$, thus satisfying restriction 2.

Figure 11 compares the minimal-theory logistic demands with the structural demands of Lagos and Navarro (2023). The global shapes of the two sets of demands are strikingly similar. For very large levels of reserves, the in-sample fit of the minimal-theory logistic demands is somewhat better than that of the structural demands because the latter tend to slightly over-predict the EFFR–IOR spread in this region. For intermediate and low levels of reserves outside the sample, the shapes of the two sets of demands are very similar, with both predicting reasonable values of the EFFR–IOR spread as reserves shrink.

[9] To visualize this, notice that the sigmoid demand is a smooth approximation to the perfectly competitive demand, which is a step correspondence given by $D^c(Q) = \mathbb{I}_{\{Q<Q_0\}}\bar{s} + \mathbb{I}_{\{Q_0<Q\}}\underline{s}$, and $D^c(Q_0) \in [\underline{s}, \bar{s}]$. Hence, $\mathcal{D}(0; \bar{s}_t, \underline{s}_t)$ is close to $\bar{s}_t$ for large enough α, provided that $0 \leq Q_0$.

[10] The estimated values of Q_0 for administered-rate regimes 1–4 are 936.6, 913.2, 892.6, and 874.2, respectively.

6 What is the minimum "ample" quantity of reserves?

The defining characteristic of a floor system is that the baseline quantity of reserves supplied by the central bank is "ample enough," i.e., no smaller than a level Q^*, so that the market operates on a region of the reserve-demand schedule that is sufficiently flat for the interbank rate to remain insensitive to autonomous variations in the supply of reserves. In this section, we use our reserve-demand estimates to determine the level of reserves Q^* required to implement alternative operational definitions of an interbank rate being "insensitive enough".

In the United States, the supply of reserves is largely determined by the Federal Reserve but it is also affected by autonomous variations ("supply shocks") generated by transactions in which the Fed is not a counterparty, such as transactions involving private-sector bank accounts and the account that the U.S. Treasury holds at the Fed.[11] Figure 12, taken from Lagos and Navarro (2023), shows the distribution of reserve-supply shocks over the period January 2011–July 2019. In what follows, we use this empirical distribution to define two notions of the minimum ample quantity of reserves and compute the corresponding estimates. The first is the minimum quantity of reserves that ensures sufficiently low volatility of the EFFR–IOR spread. The second is the minimum quantity of reserves that ensures the EFFR–IOR spread remains within a specified band with sufficiently high probability on any given day.

6.1 Rate volatility

One feature of floor systems that central banks view as desirable is that, when the supply of reserves is sufficiently ample, the central bank can keep the volatility of the interbank rate below a specified tolerance level on any given day.

In this section, we combine the empirical demand estimates from the previous sections with the estimated distribution of reserve-supply shocks to compute, for each aggregate quantity of reserves, the standard deviation of the EFFR–IOR spread. Figure 13 displays the standard deviation of the EFFR–IOR spread (in basis points) implied by the no-theory semi-log, the no-theory logistic, and the minimal-theory logistic specifications. As is clear from the figure, the relationship between the standard deviation of the spread and the quantity of reserves is quite different across the three specifications.

For example, suppose the central bank wishes to ensure that the standard deviation of the EFFR–IOR spread does not exceed half a basis point. Figure 13 shows that the minimum "ample" quantity of reserves required to achieve this objective is about \$2 tn under the minimal-theory logistic specification, and about \$2.5 tn under either of the no-theory specifications. Under the no-theory logistic specification, the same objective is also achieved with aggregate supplies of reserves below \$1.5 tn, which is not plausible. Under the no-theory semi-log specification, even \$3.5 tn would not be sufficient to reduce the standard deviation below a quarter of a basis point, reflecting the fact that the semi-log demand curve flattens too slowly.

[11] For example, whenever corporations or households pay taxes or purchase Treasury securities from the Treasury, reserves are transferred from private banks to the Treasury's account, which, from the perspective of domestic banks, constitutes an aggregate reserve-supply drain. Conversely, autonomous reserve-supply increases occur whenever the Treasury makes payments to the private sector.

6.2 Monetary Confidence Bands

Floor systems are appealing to central banks that implement monetary policy by targeting an interbank rate because by supplying a sufficiently ample quantity of reserves, the central bank can keep the interbank rate within a desired band. For instance, one of the Fed's operational objectives under a floor system may be to keep the EFFR–IOR spread within a specified range with sufficiently high probability on any given day.

In this section, we combine the empirical demand estimates from the previous sections with the estimated distribution of reserve-supply shocks to compute *Monetary Confidence Bands* (MCBs) for the EFFR–IOR spread. Intuitively, for each aggregate quantity of reserves, Q_t, the MCBs define a band around the estimated demand curve $s_t = D(Q_t)$ such that the EFFR–IOR spread s_t lies within the band for a specified confidence level. For example, the 99% MCB is a band around the demand curve such that the EFFR–IOR spread lies within the band with 99% probability on any given day, accounting for the randomness in the supply of reserves generated by reserve-supply shocks. MCBs provide an estimate of the minimum quantity of reserves required to keep the EFFR–IOR spread within a specified target range with a desired confidence level. For this reason, they are a useful tool for monetary-policy implementation.

The MCBs are constructed as follows. Let Z_p denote the p^{th} percentile of the empirical distribution of reserve-supply shocks reported in the bottom panel of Figure 12. We define the "p% MCB" as the pair of functions $(\underline{s}(Q), \overline{s}(Q))$, where $\underline{s}(Q) \equiv D\Big(Q + Z_{\frac{100+p}{2}}\Big)$ and $\overline{s}(Q) \equiv D\Big(Q + Z_{\frac{100-p}{2}}\Big)$. The idea is that supply shocks introduce randomness in reserve supply, which in turn induces randomness in the EFFR–IOR spread. For a given beginning-of-day reserve supply Q, the equilibrium rate lies within the 99% MCB $(D(Q + Z_{99.5}), D(Q + Z_{0.5}))$ with probability 99%.

The top-left panel of Figure 14 displays the 99% MCBs corresponding to the reserve demand estimated with the minimal-theory logistic specification, and to the structural demand from Lagos and Navarro (2023), both for administered-rate regime 1. The top-right, bottom-left, and bottom-right panels correspond to administered-rate regimes 2, 3, and 4, respectively. The data and the axes are the same as in Figures 7, 9, and 11. Figure 14 shows that, while not identical, there is a substantial overlap of the MCBs of the minimal-theory logistic demands and the structural demands of Lagos and Navarro (2023). For example, suppose the central bank wants the EFFR–IOR spread to remain below 10 basis points with 99% probability on any given day. The bottom-right panel of Figure 14 shows that the minimum "ample" quantity of reserves required to achieve this objective is about \$1.3 tn under the quantitative-theoretic structural estimation of Lagos and Navarro (2023), and about \$1.7 tn under the minimal-theory logistic estimation.

7 Conclusion

Existing reduced-form econometric approaches to reserve-demand estimation lack theoretical guidance, leading to poor out-of-sample extrapolation properties and violations of elementary theoretical shape restrictions. We have proposed a new approach to reserve-demand estimation—a middle ground between the no-theory reduced-form and quantitative-theoretic structural approaches. It is a nonstructural econometric specification that satisfies the two core restrictions implied by the theory, and controls for the monetary-policy variables that induce rotations and shifts in the demand for reserves, namely the DWR–IOR spread and the ONRRP–IOR spread. Our approach is as user-friendly as the no-theory approaches, but satisfies the minimal theoretical restrictions that any reserve-demand schedule ought to satisfy. We find that a little theory goes a long way. Unlike existing no-theory approaches, our new minimal-theory approach produces reserve-demand estimates for the U.S. that are broadly consistent with the structural estimates in Lagos and Navarro (2023).

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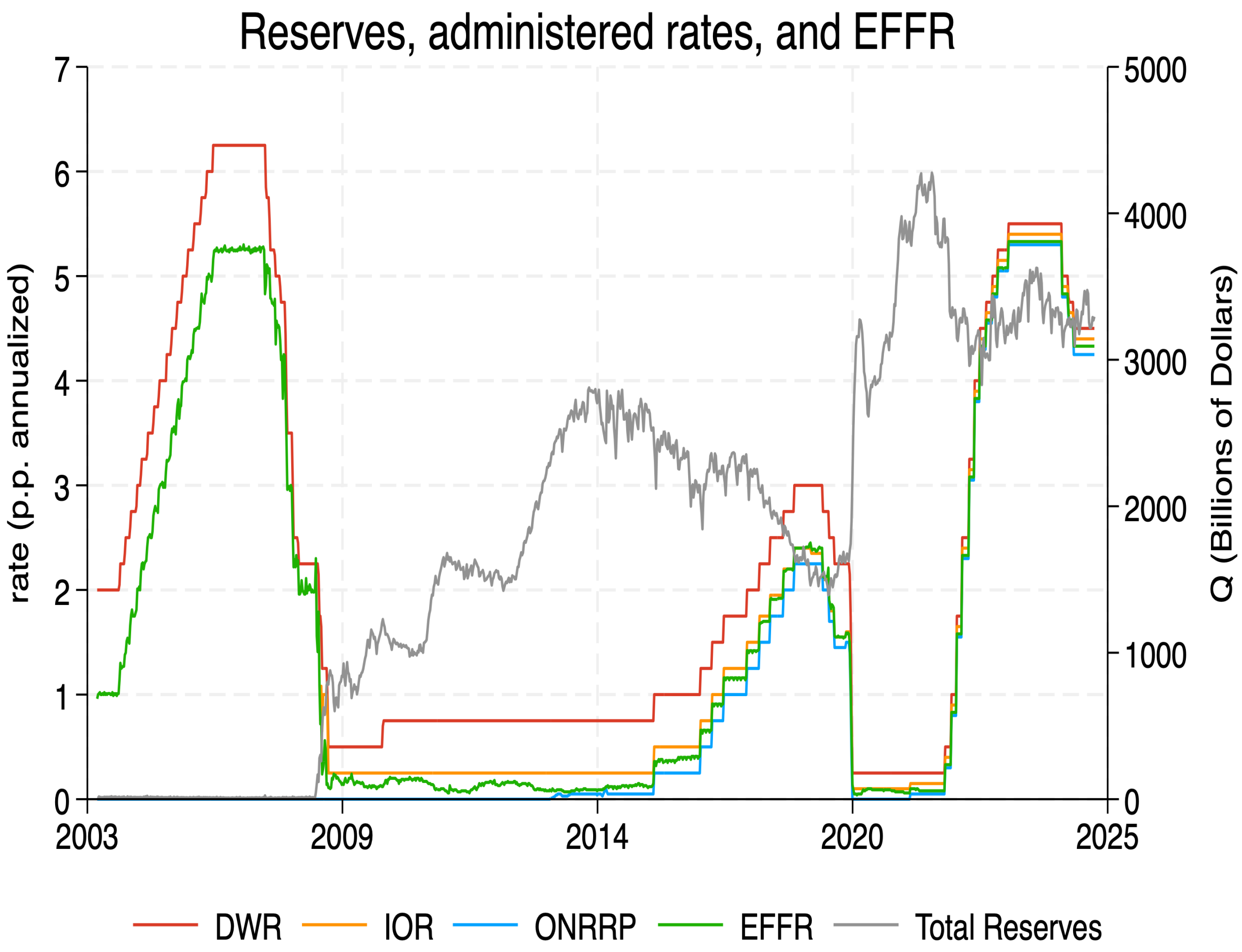

Figure 1: Time series of EFFR (green), Q (grey), and the administered rates, DWR (red), IOR (orange), and ONRRP (blue), for the period 2010/01/01–2025/06/04.

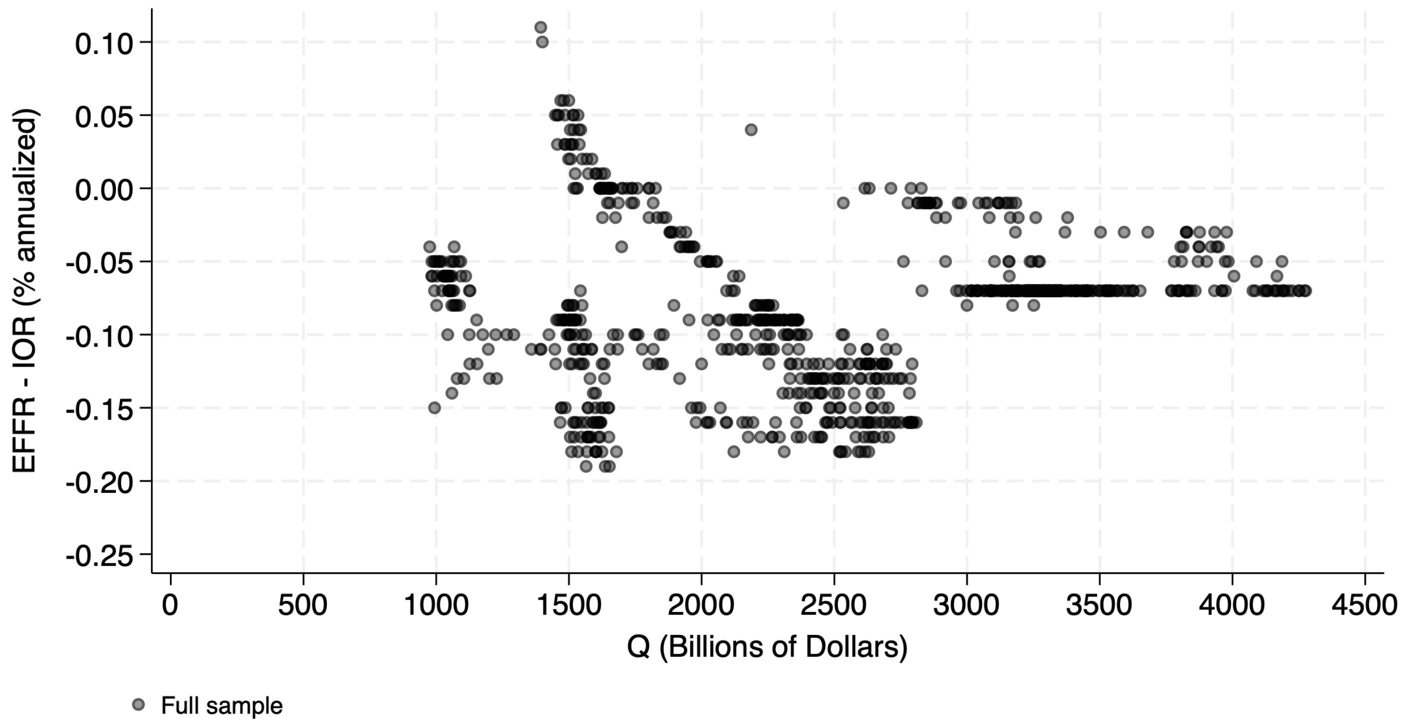

Figure 2: Scatterplot of weekly EFFR–IOR spread and quantity of reserves for the period 2010/01/01–2025/06/04.

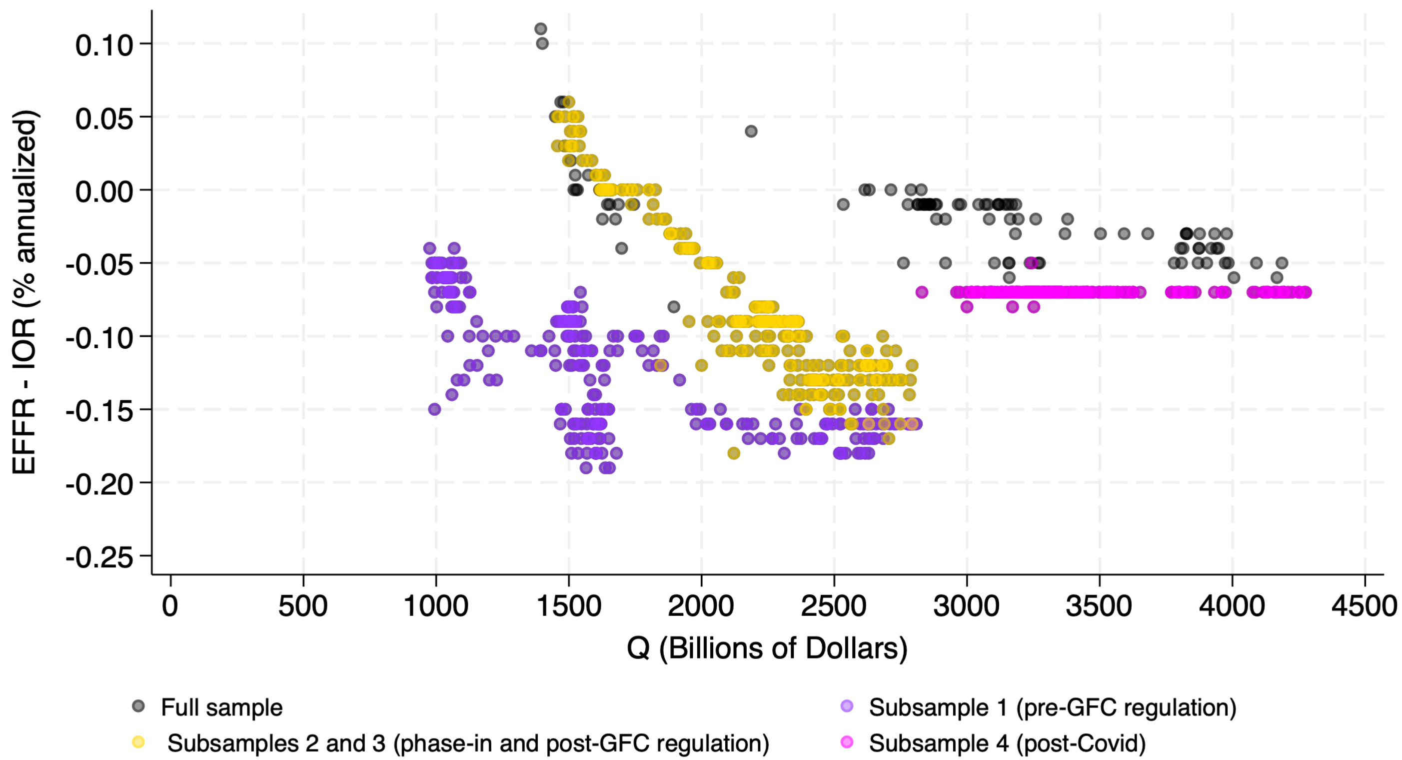

Figure 3: Scatterplot of weekly EFFR–IOR spread and quantity of reserves for the period 2010/01/01–2025/06/04, divided into four subsamples defined by regulatory regimes.

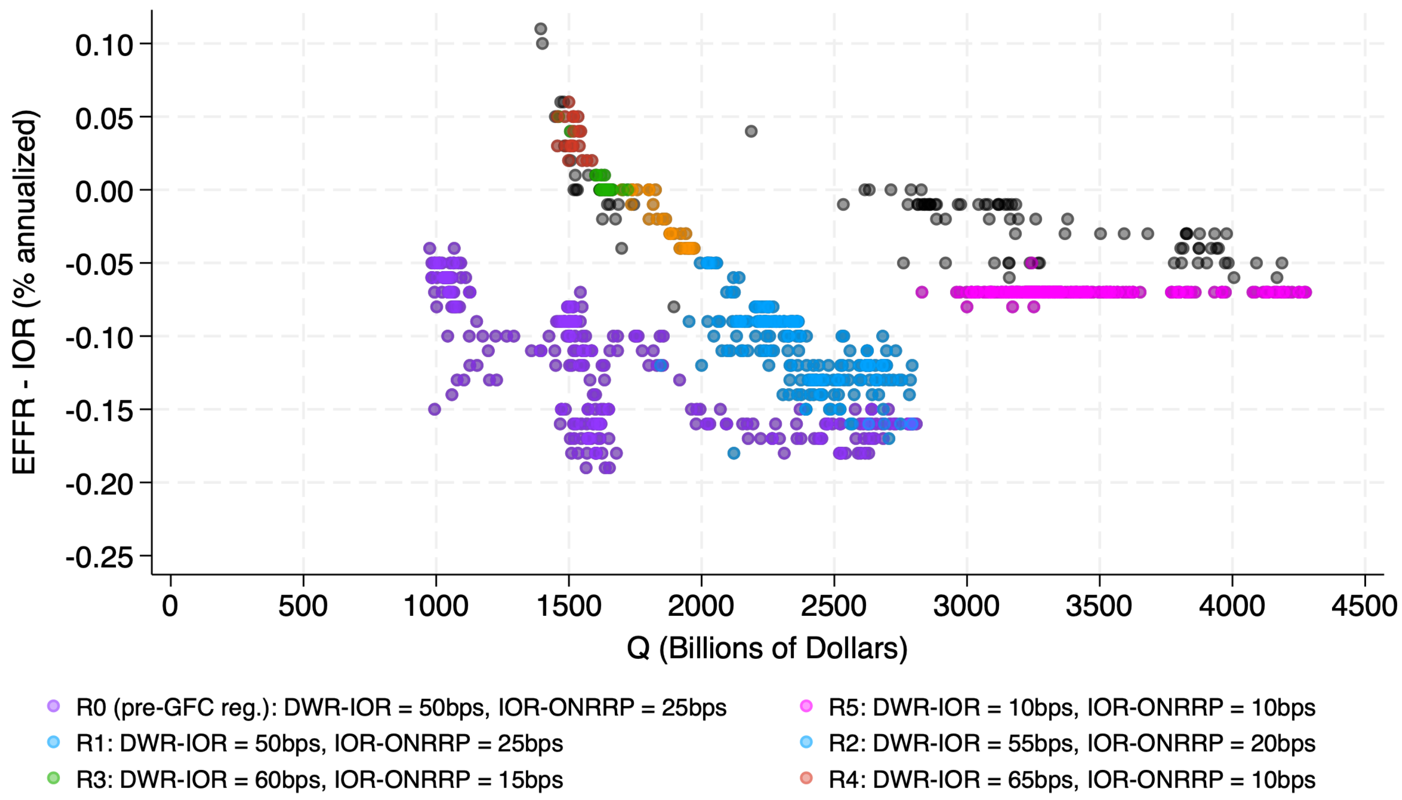

Figure 4: Scatterplot of weekly EFFR–IOR spread and quantity of reserves for the period 2010/01/01–2025/06/04, with subsamples divided into administered-rate regimes defined by the size of the IOR–ONRRP spread.

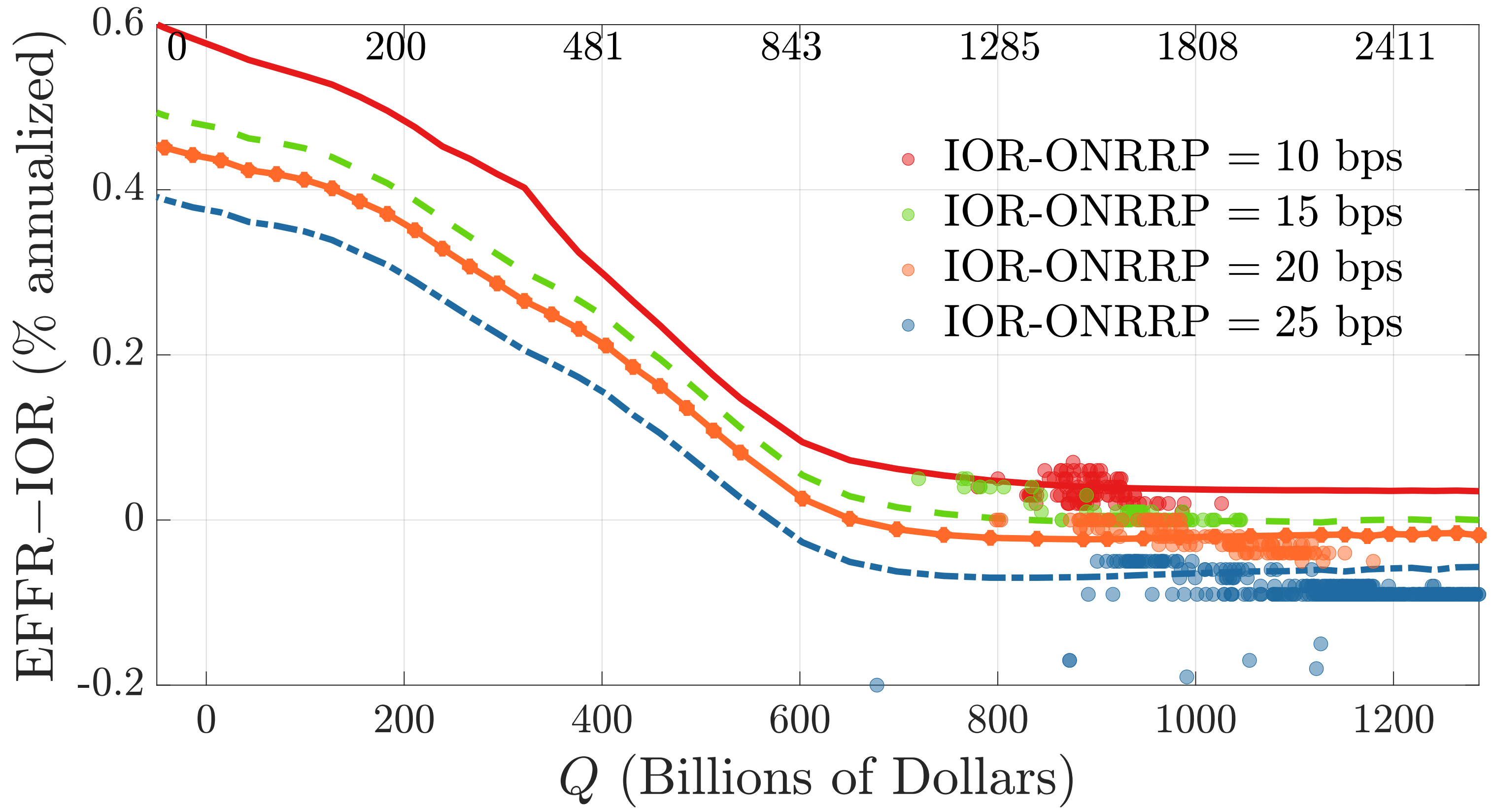

Figure 5: Structural reserve demands from Lagos and Navarro (2023), and empirical scatterplot of daily EFFR–ONRRP spread and quantity of reserves for each subsample defined by the IOR–ONRRP spread throughout the sample period 2017/01/20–2019/09/11.

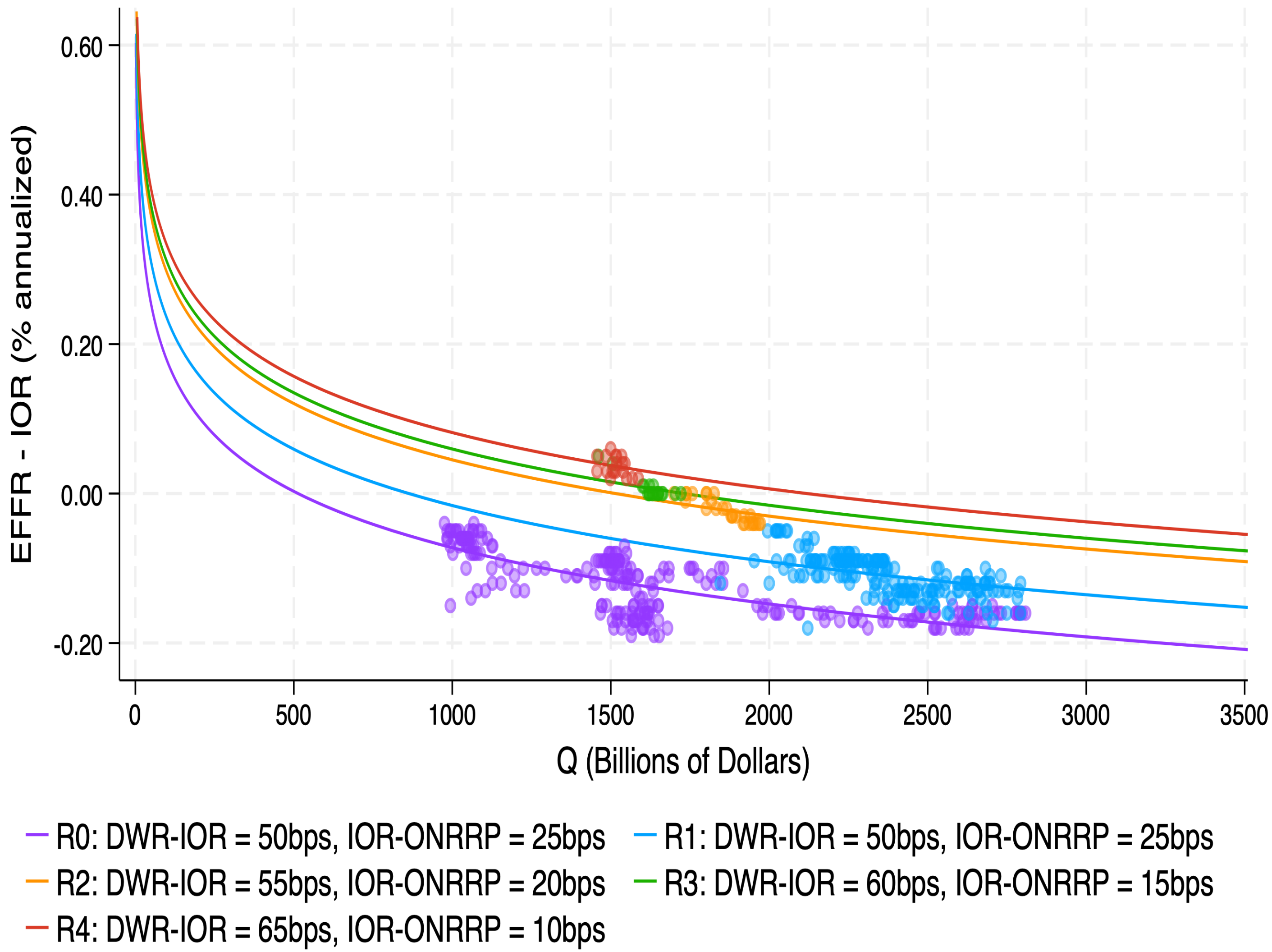

Figure 6: Semi-log demands by administered-rate regime, estimated over the sample period 2010/06/01 to 2019/09/11.

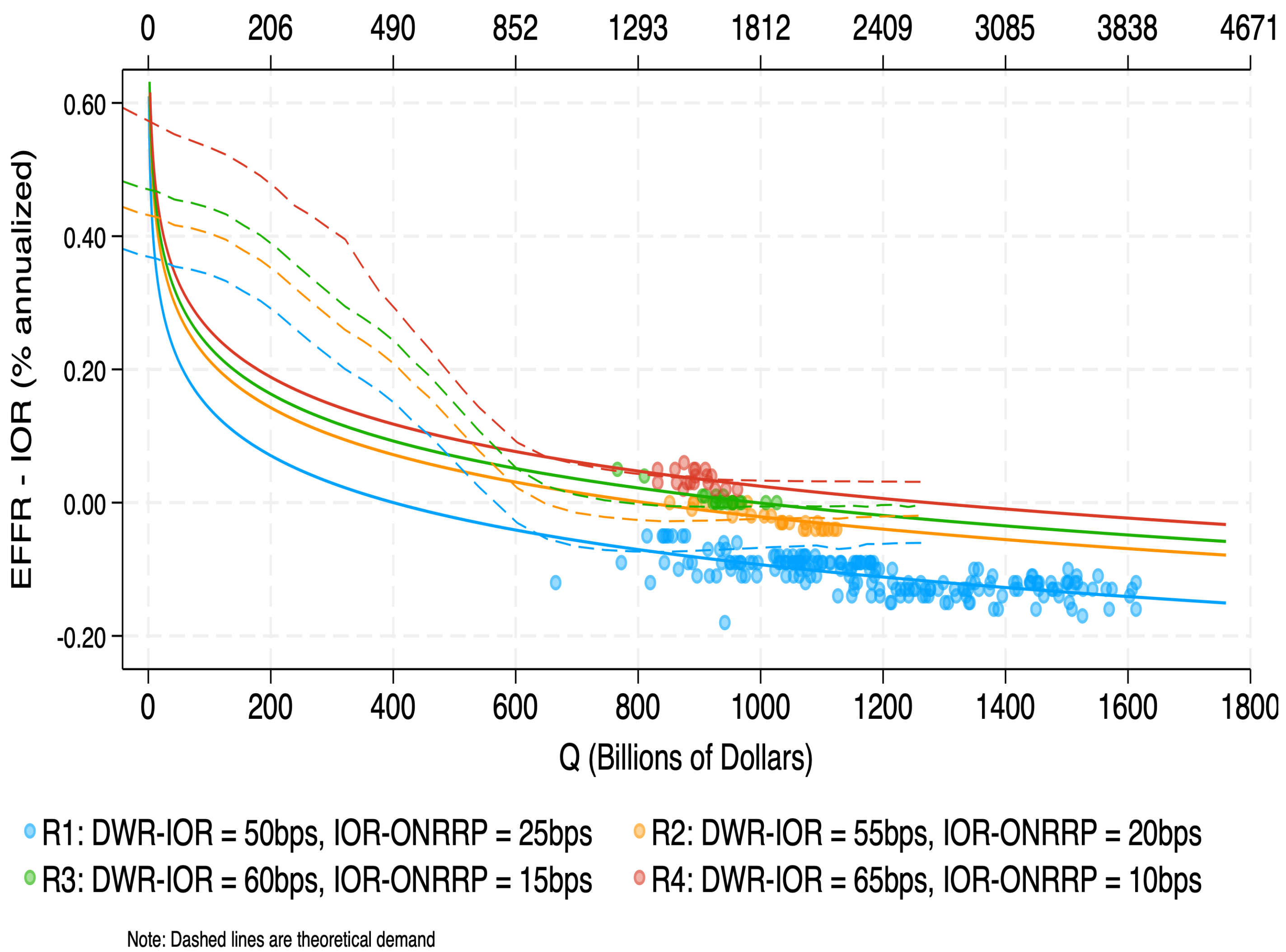

Figure 7: No-theory semi-log demands for the sample period 2010/06/01 to 2019/09/11 vs. structural demands from Lagos and Navarro (2023).

Table 1: No-theory logistic demand estimation

Coefficients	No-theory logistic
α	0.0033***
	(0.0011)
$\underline{s}$	-0.1460***
	(0.0140)
$\overline{s}$	0.1026
	(0.0631)
Q_0	1805.047***
	(163.101)
Observations	259
R-squared	0.967
Root MSE	0.018
Root MSE / $\lvert\text{mean}(s_t)\rvert$	0.224
Root MSE / s.e.(s_t)	0.325

Notes: Newey-West standard errors in parentheses (13 lags). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

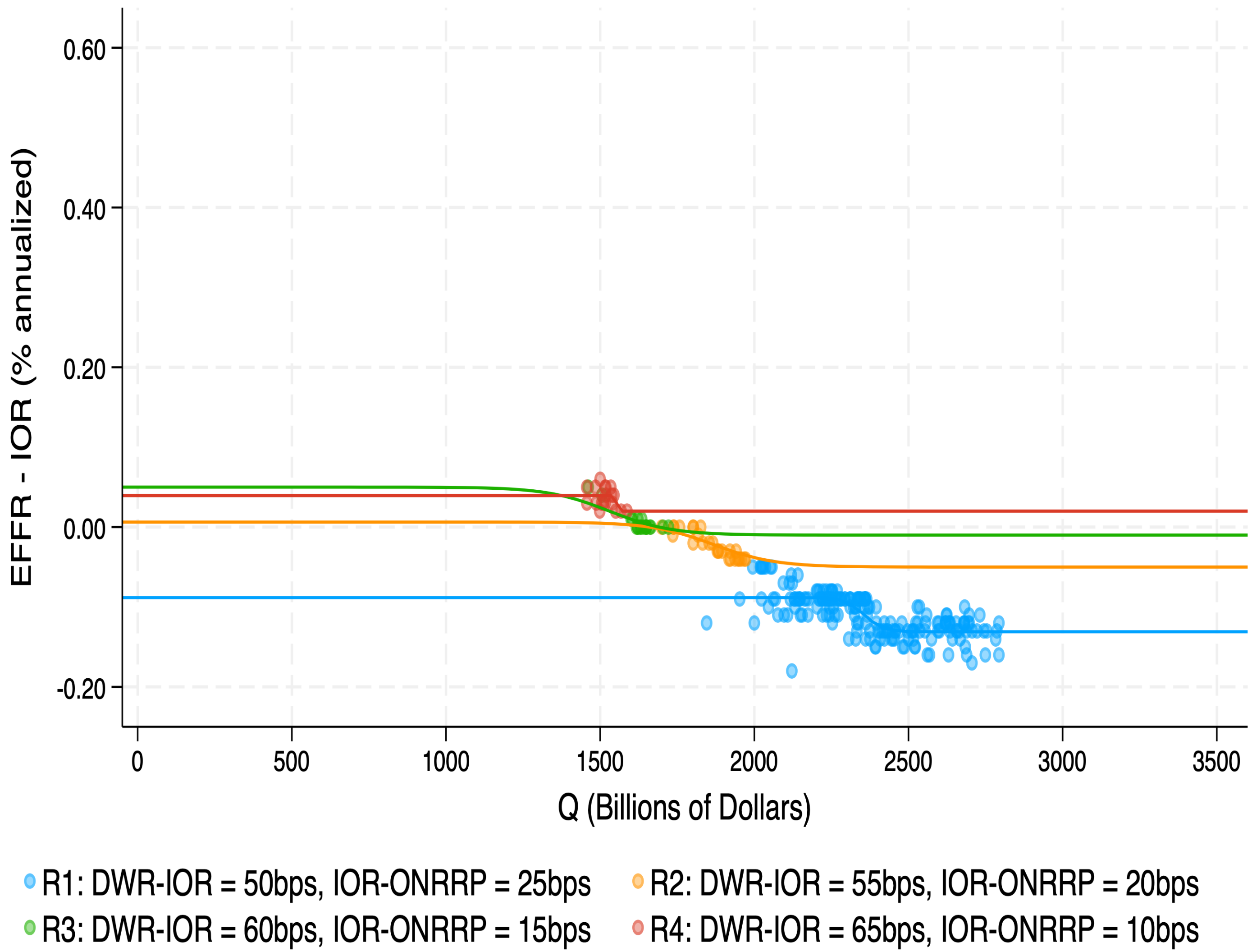

Figure 8: Logistic demands by administered-rate regime, estimated over the sample period 2014/10/01–2019/09/11.

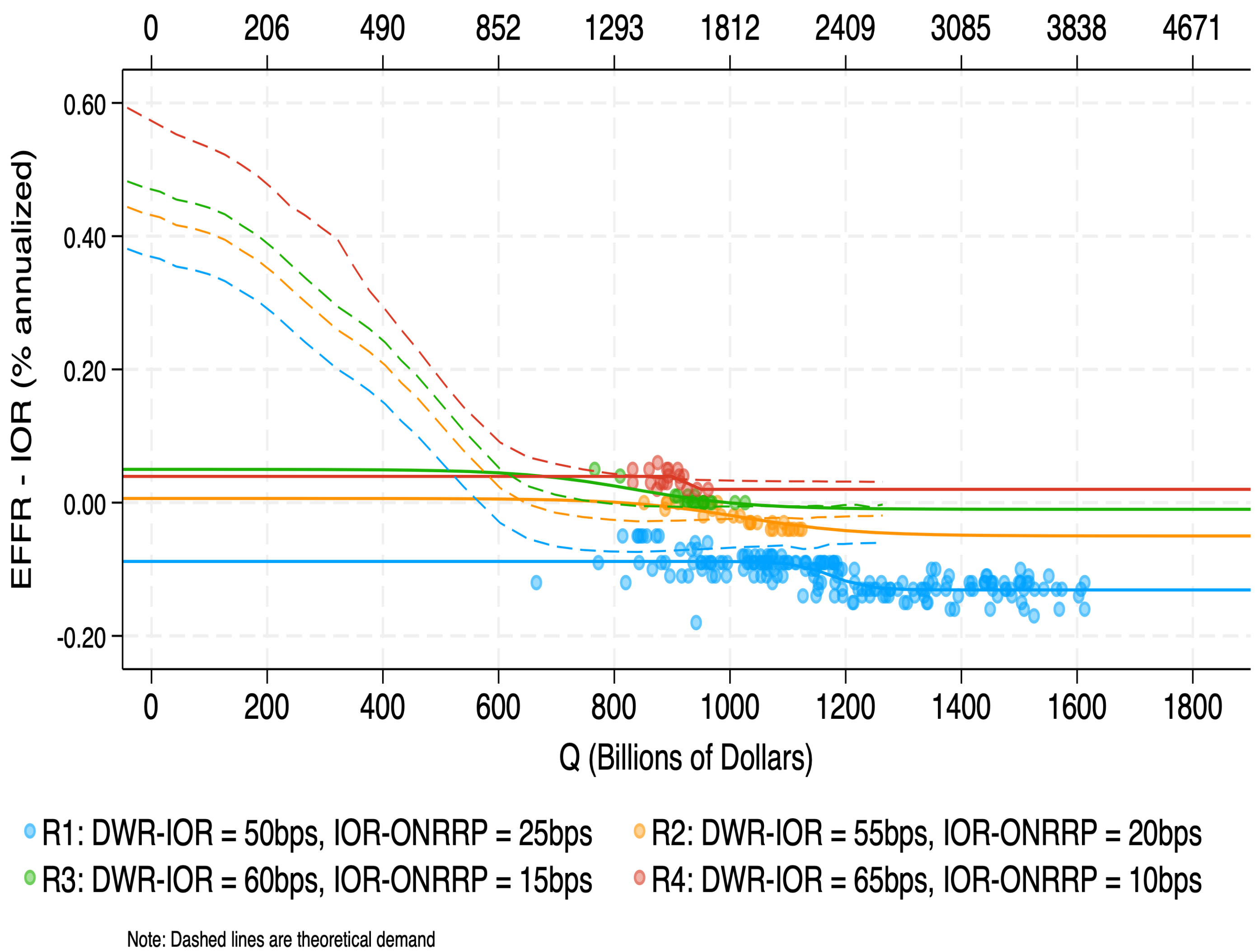

Figure 9: No-theory logistic demands for the sample period 2014/10/01–2019/09/11 vs. structural demands from Lagos and Navarro (2023).

Table 2: Minimal-theory logistic demand estimation

Coefficients	Minimal-theory logistic
α	0.0026***
	(0.000082)
$\underline{\omega}$	0.4985***
	(0.0241)
Observations	259
R-squared	0.845
Root MSE	0.022
Root MSE / $\lvert\text{mean}(s_t)\rvert$	0.270
Root MSE / s.e.(s_t)	0.392

Notes: Newey-West standard errors in parentheses (13 lags). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *** $p < 0.01$.

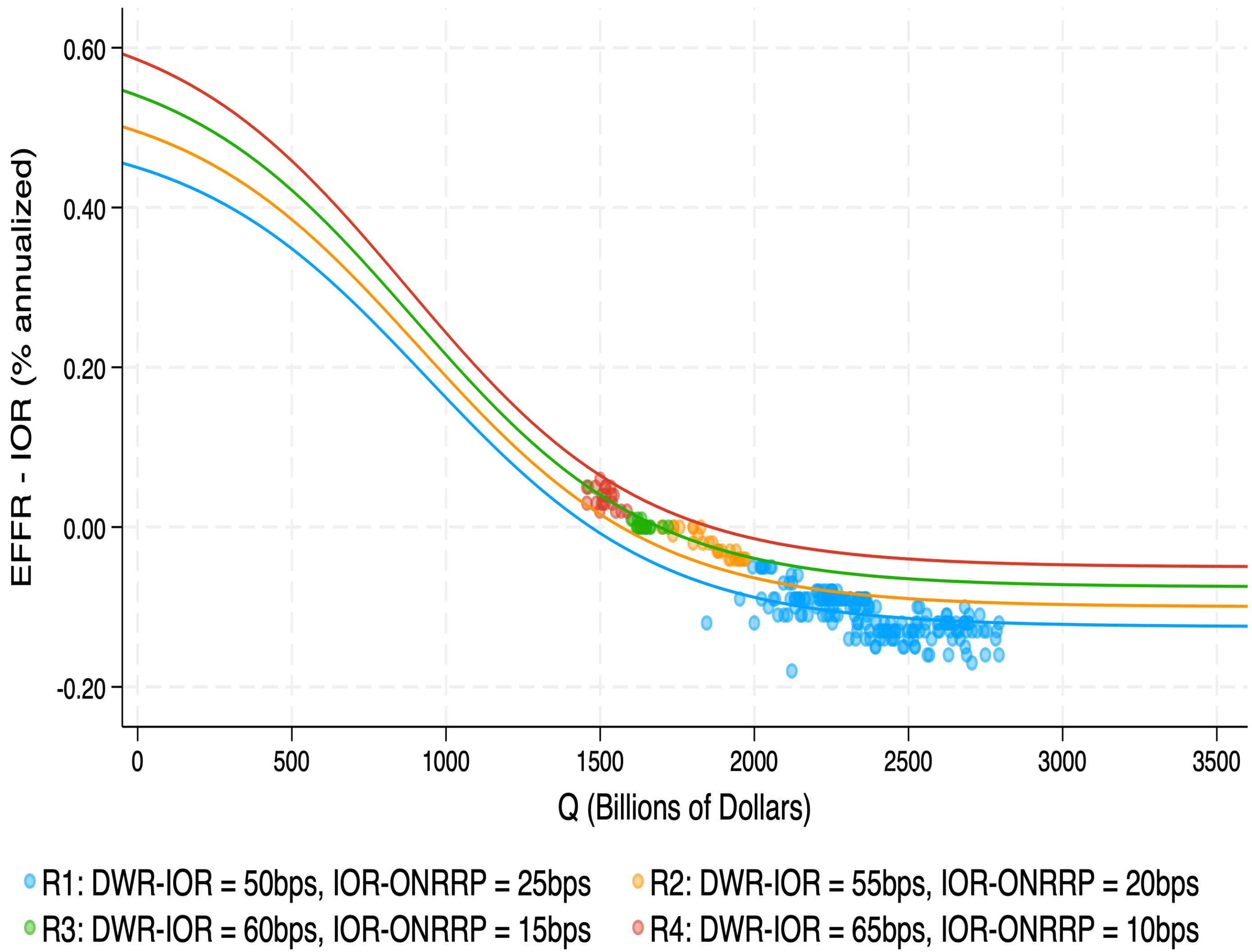

Figure 10: Minimal-theory demands by administered-rate regime, estimated for the sample period 2014/10/01–2019/09/11.

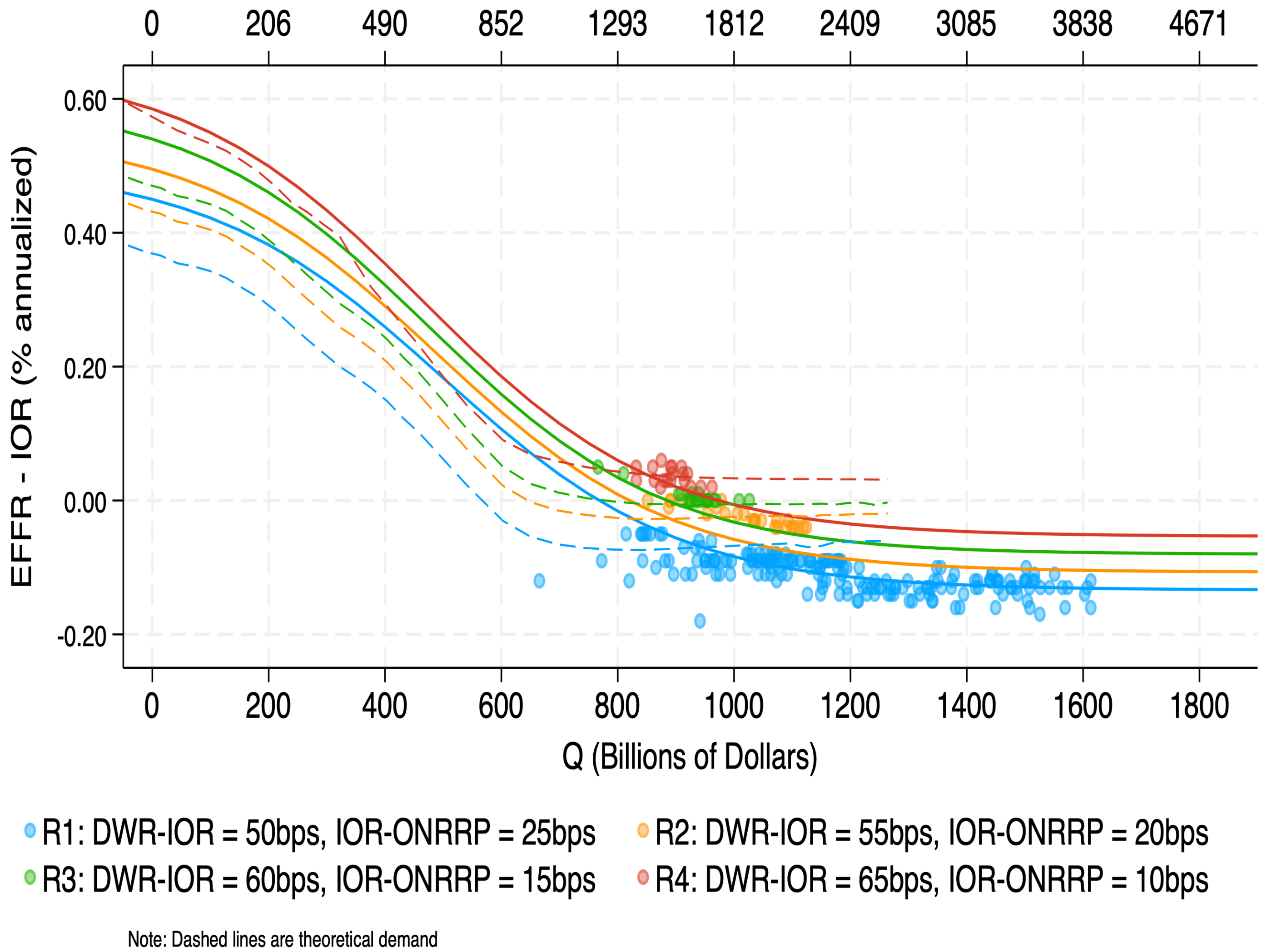

Figure 11: Minimal-theory logistic demands for the sample period 2014/10/01–2019/09/11 vs. structural demands from Lagos and Navarro (2023).

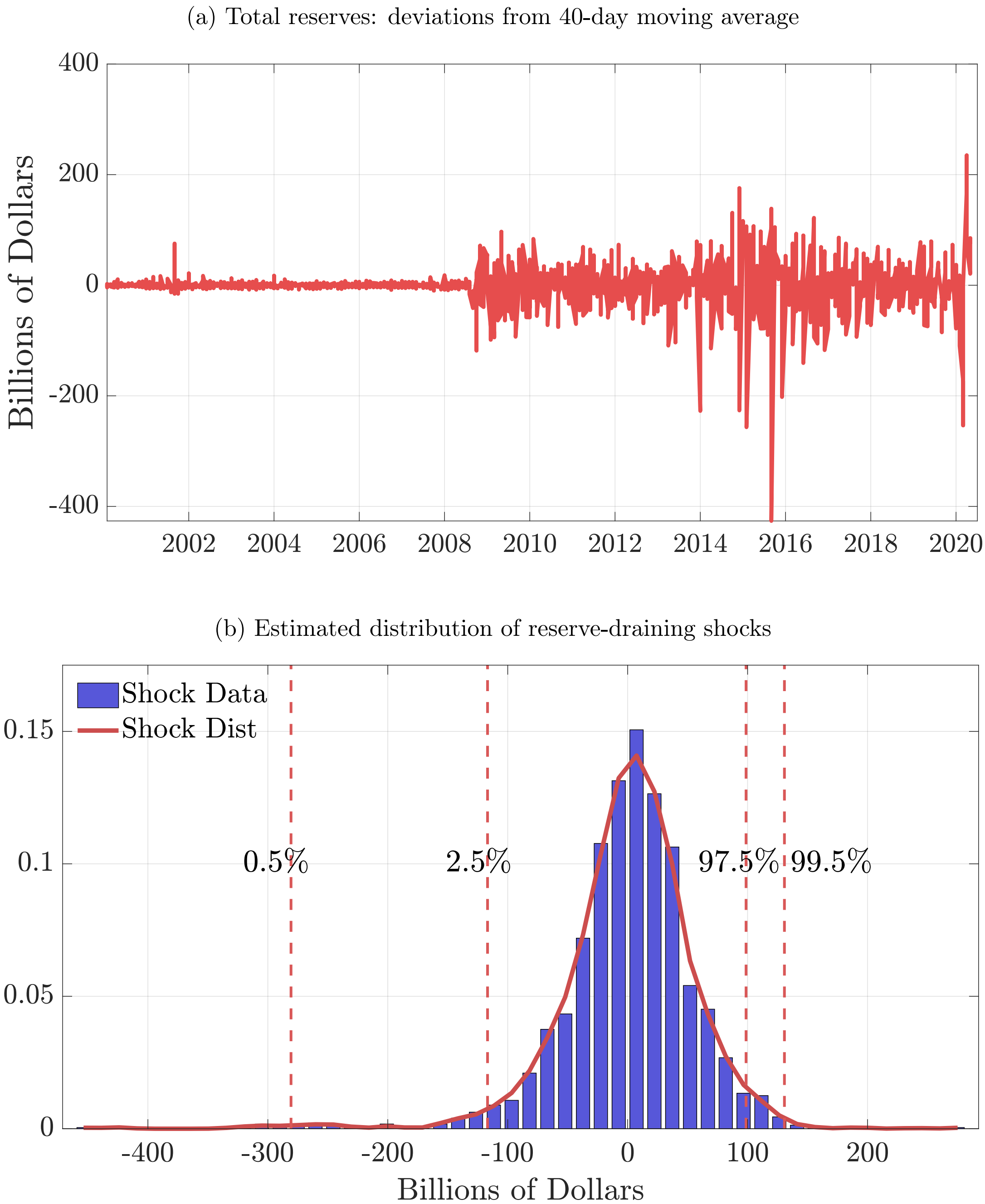

Figure 12: Reserve-supply shocks

Notes: Top panel: deviations of the weekly aggregate quantity of reserves from a 40-day two-sided moving average. Bottom panel: histogram of these deviations for January 2011–July 2019, together with the corresponding kernel density estimate. (See Appendix A.4 of Lagos and Navarro (2023) for details.)

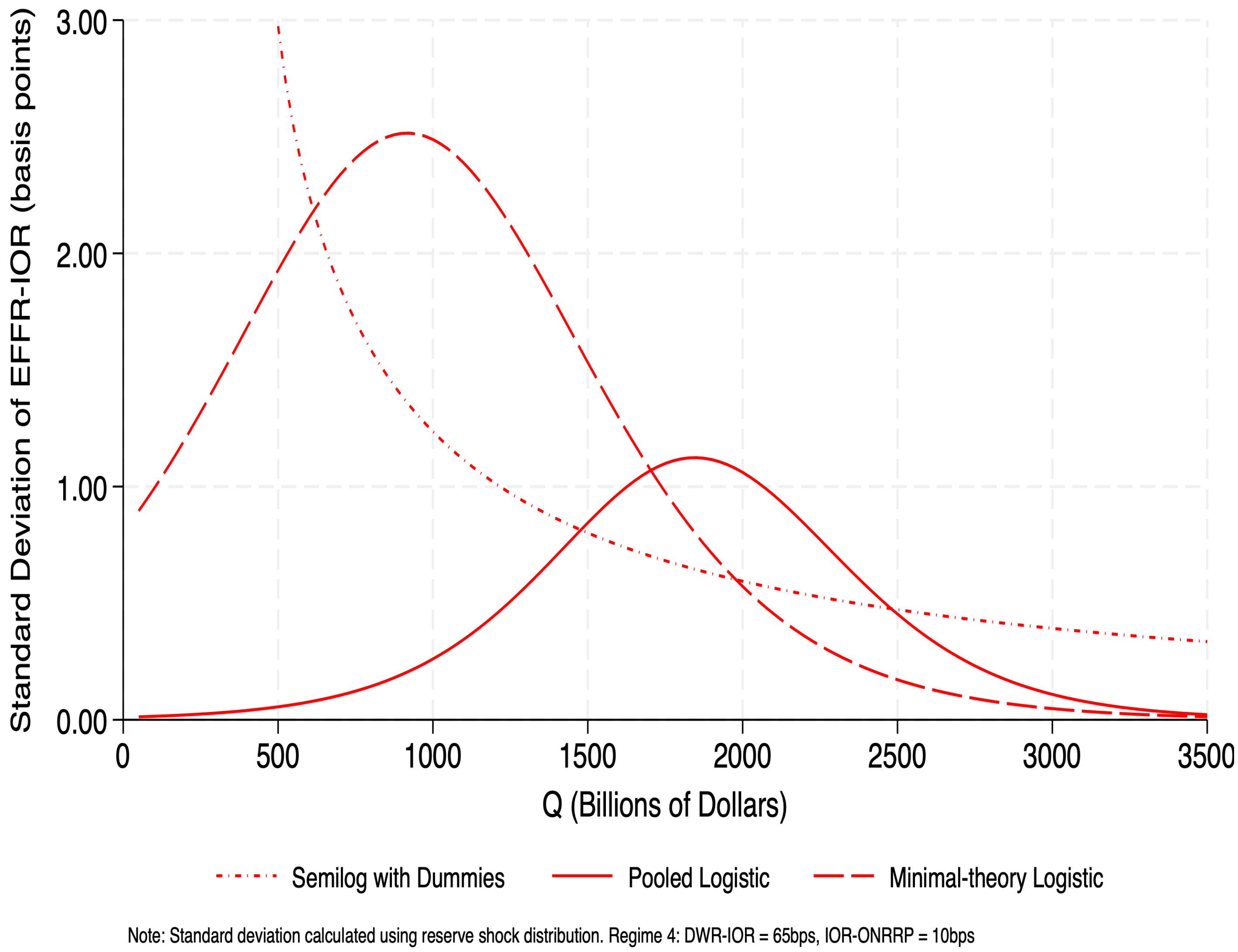

Figure 13: EFFR volatility comparisons across reduced-form models.

Notes: Sample corresponds to administered-rate regime 4, 2019/05/02–2019/09/11.

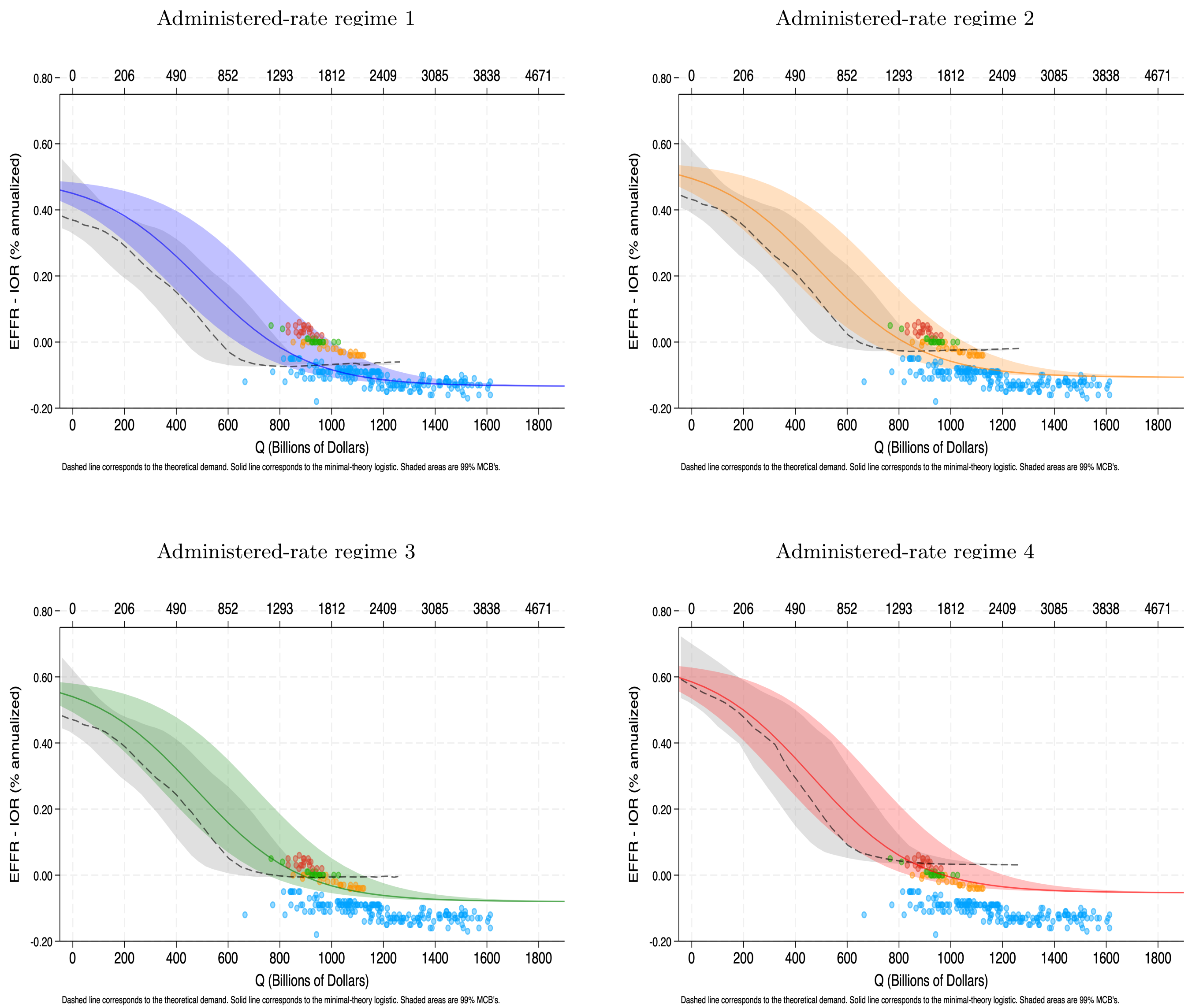

Figure 14: MCBs for minimal-theory logistic demands and for the structural demands from Lagos and Navarro (2023).