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Government Intervention and Strategic Trading in the U.S. Treasury Market

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Abstract

We study the impact of permanent open market operations (POMOs) by the Federal Reserve on U.S. Treasury market liquidity. Using a parsimonious model of speculative trading, we conjecture that i) this form of government intervention *improves* market liquidity, contrary to conclusions drawn by existing literature; and ii) the extent of this improvement depends on the market's information environment. Evidence from a novel sample of Federal Reserve POMOs during the 2000s indicates that bid–ask spreads of on-the-run Treasury securities *decline* when POMOs are executed, by an amount increasing in proxies for information heterogeneity among speculators, fundamental volatility, and POMO policy uncertainty, consistent with our model.

I. Introduction

During the recent financial crisis, several central banks (e.g., the Federal Reserve, the Bank of England, and the European Central Bank) traded large amounts of securities. While the motives and effectiveness of these trades continue to be intensely debated (e.g., see Acharya and Richardson (2009)), their potential externalities on the "quality" of the process of price formation have received much less attention.

In this article, we investigate, both theoretically and empirically, the effects of direct government intervention in a financial market (like central bank trades of

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securities) on that market's liquidity. We do so by studying one market in which monetary authorities have long been active, the secondary market for U.S. government bonds. U.S. Treasury securities are widely held and traded by domestic and foreign investors. The secondary market for these securities is among the largest, most liquid financial markets. There, the Federal Reserve (through the "Desk" of the Federal Reserve Bank of New York (FRBNY)) routinely buys or sells Treasury securities on an outright (i.e., definitive) basis, with trades known as permanent open market operations (POMOs), to permanently add or drain bank reserves toward a *nonpublic* target level consistent with the monetary policy stance (and accompanying federal funds target rate) previously set and publicly announced by the Federal Open Market Committee (FOMC).

The frequency and magnitude of POMO trades are nontrivial: Even prior to the recent crisis, between Jan. 2001 and Dec. 2007, the FRBNY executed POMOs nearly once every 8 working days, for an average daily principal amount of $1.11 billion. Importantly, while the FOMC's decisions are public and informative about its current and planned stance of monetary policy, the Federal Reserve's nonpublic targeted level of reserves has been *uninformative* about that stance since the mid-1990s (see Akhtar (1997), Edwards (1997), Harvey and Huang (2002), Sokolov (2009), and Cieslak, Morse, and Vissing-Jorgensen (2016), among others).[1] This constitutes a crucial difference between POMOs and government interventions in currency markets, the latter being typically deemed informative about economic policy or fundamentals (e.g., Sarno and Taylor (2001), Payne and Vitale (2003), and Dominguez (2006)).

To guide our analysis of the impact of POMOs on the Treasury market, we develop a parsimonious model of trading based on Kyle (1985). This model aims to capture an important feature of that market highlighted by several empirical studies (e.g., Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007), (2009)): namely, the role of informed trading in Treasury securities for their process of price formation. In the model's basic setting, strategic trading in a risky asset by heterogeneously informed speculators leads uninformed market-makers (MMs) to worsen that asset's equilibrium market liquidity. More valuable or diverse information among speculators magnifies this effect by making their trading activity more cautious and MMs more vulnerable to adverse selection.

The introduction of a stylized central bank consistent in spirit with the nature of the Federal Reserve's POMO policy in this setting significantly alters equilibrium market quality. We model the central bank as an informed agent facing a trade-off between policy motives (a nonpublic and uninformative price target for the risky asset) and the expected cost of its intervention, in the spirit of Stein (1989), Bhattacharya and Weller (1997), Vitale (1999), and Pasquariello (2010), (2018). In particular, the price target is a modeling device for the FRBNY's objective of targeting the supply of nonborrowed reserves by trading in Treasury securities in a market where demand for these securities is downward sloping (Krishnamurthy (2002), Vayanos and Vila (2009), Greenwood and Vayanos (2010), and Krishnamurthy and Vissing-Jorgensen (2012)). We then show that

[1] See also the FRBNY Web site at https://www.newyorkfed.org/markets/pomo/display/index.cfm.

allowing such a central bank to trade alongside noise traders and speculators *improves* equilibrium market liquidity. Intuitively, the presence of a central bank ameliorates adverse selection concerns for the MMs, not only because a portion of its trading activity is uninformative about fundamentals but also because that activity induces speculators to trade less cautiously on their private signals. This insight differs markedly from those in the aforementioned literature on the microstructure of government intervention in currency markets. In many of those studies (e.g., Bossaerts and Hillion (1991), Vitale (1999), and Naranjo and Nimalendran (2000)), the central bank is typically assumed to act as the *only* informed agent. Thus, its presence generally leads to deteriorating market liquidity.[2]

A further, interesting (and novel) insight of our model is that the magnitude of the improvement in market liquidity stemming from the central bank's trading activity is sensitive to the information environment of the market. Specifically, we show that this effect is greater when the economy's fundamentals are more volatile and when speculators' private signals about them are more heterogeneous. As discussed previously, either circumstance worsens market liquidity, but less so when the MMs perceive the threat of adverse selection as less serious because the central bank is intervening. Accordingly, we also show that greater uncertainty among market participants about the central bank's policy target magnifies the improvement in market liquidity accompanying its trades. Greater policy uncertainty both makes it more difficult for the MMs to learn about the policy target from the order flow and alleviates their perceived adverse selection from trading with informed speculators.[3]

We assess the empirical relevance of our model using a comprehensive, recently available sample of intraday price data for the secondary U.S. Treasury bond market from BrokerTec, the electronic platform where the majority of such trading migrated, since its inception, from the voice-brokered GovPX network (Mizrach and Neely (2006), (2009), Fleming, Mizrach, and Nguyen (2018)), and a novel data set of all POMOs conducted by the FRBNY during the 2000s. POMOs are typically aimed at all securities within specific maturity segments of the yield curve rather than at specific securities. However, most of these securities rarely trade, and assessing their liquidity is problematic (Fabozzi and Fleming (2004), Pasquariello and Vega (2009)). Thus, we study the effects of POMOs on the most liquid Treasury securities in those segments: on-the-run (i.e., most recently issued, or benchmark) 2-year, 3-year, 5-year, and 10-year Treasury notes and 30-year Treasury bonds.

Our empirical analysis provides support for our model's main prediction. Over the pre-crisis period, 2001–2007, we find that bid–ask price spreads for notes and bonds nearly uniformly *decline* from prior near-term levels, both on days when the FRBNY executed POMOs in the corresponding maturity bracket and on days when POMOs of any maturity occurred. The latter may be due to the relatively high degree of substitutability among Treasury securities documented in

[2]See also the surveys in Lyons (2001) and Neely (2005). Other studies (e.g., Evans and Lyons (2005), Chari (2007), and Pasquariello (2010)) postulate that government intervention in currency markets may worsen their liquidity because of inventory management considerations.

[3]We overview model extensions and robustness in Section II.C; for economy of space, further details and analysis are in Section 1 of the Supplementary Material.

prior studies (e.g., Cohen (1999), Greenwood and Vayanos (2010), and D'Amico and King (2013)). The estimated improvement in liquidity is both economically and statistically significant. For instance, on days when any POMO occurred, quoted bid–ask spreads decline by an average of 7% (for 3-year notes) to 16% (for 5-year notes) of their sample means and 25% (for 30-year bonds) to 46% (for 2-year notes) of the sample standard deviation of their daily changes. Only a portion of these effects takes place within the 90-minute morning interval during which the FRBNY executes its trades, suggesting that the impact of POMOs on MMs' adverse selection risk may not be short-lived.

Importantly, bid–ask spreads in the Treasury market do not affect the FRBNY's explicitly stated reserve policy, as implemented by the Desk with its outright operations (see, e.g., Akhtar (1997), Edwards (1997), and Federal Reserve Board of Governors (FRBG) FRBG (2005), among others). Our basic evidence is also unlikely to stem from interactions between POMOs and Treasury market conditions.[4] First, it is robust to (and often stronger when) controlling for various calendar effects and bond-specific characteristics as well as for changes in overnight repo specialness, the latest Treasury auction results, the latest pre-POMO on-the-run illiquidity, the Desk's repo trading activity, the reserve maintenance periods, the latest FOMC meetings, and the release of U.S. macroeconomic announcements. Second, it is obtained over a sample period when the FRBNY neither sold Treasury securities nor traded in "scarce" ones. Third, it is unaffected by extending our sample to the financial crisis of 2008 and 2009 and holds during that subperiod as well, despite the special nature of both the crisis period and the FRBNY's intervention activity in the Treasury market. Last, it is reproduced over a partly overlapping sample of quotes on the previously dominant GovPX platform.[5]

Further, more direct support for our model (hence further mitigating potential omitted variable biases) comes from tests of its unique, additional predictions about the effects of POMOs on Treasury market liquidity. In particular, our analysis also reveals that the magnitude of POMOs' positive liquidity externalities is related to the information environment of the Treasury market, consistent with our model. We find that bid–ask spreads decline significantly more when i) Treasury market liquidity is worse (especially in the earlier portion of the sample (2001–2004)); ii) the marketwide dispersion of beliefs about U.S. macroeconomic fundamentals (measured by the standard deviation of professional forecasts of macroeconomic news releases) is greater; iii) the marketwide uncertainty surrounding U.S. macroeconomic fundamentals (measured by Eurodollar or Treasury bond option implied volatility) is greater; and iv) marketwide uncertainty

[4]For instance, over our pre-crisis sample period, the Desk minimized the risk that those trades may disrupt Treasury market conditions by explicitly *avoiding* trading in such highly desirable and liquid securities as on-the-run notes and bonds or on days when important events for Treasury yields are scheduled (e.g., see FRBNY (2005), (2008)) but market liquidity tends to be high (Pasquariello and Vega (2007), (2009), except immediately around the event time; e.g., Green (2004)). Treasury market conditions are also related to alternative interpretations of our basic findings (based on inventory, search costs, reserves, or liquidity provision considerations), noted in Section IV.B and further discussed in Section 2.4 of the Supplementary Material.

[5]We summarize this robustness analysis in Section IV.B; for economy of space, its details and ensuing additional evidence are in Section 2 of the Supplementary Material.

surrounding the Federal Reserve's POMO policy (measured by federal funds rate volatility) is greater.

Open market operations (OMOs) have received surprisingly little attention in the literature.[6] In the only published empirical study on the topic of which we are aware, Harvey and Huang (2002) find that the FRBNY's OMOs between 1982 and 1988 (when those trades were still deemed informative about the Federal Reserve's monetary policy stance) are, on average, accompanied by higher intraday T-Bill, Eurodollar, and T-Bond futures return volatility. Inoue (1999) also finds that informative POMOs by the Bank of Japan are accompanied by higher intraday trading volume and price volatility in the secondary market for 10-year on-the-run Japanese government bonds. Harvey and Huang (2002) conjecture that such an increase may be attributed to the effect of OMOs on market participants' expectations. This evidence is consistent with that from several studies of the impact of potentially informative central bank interventions on the microstructure of currency markets (e.g., Dominguez (2003), (2006), Pasquariello (2007b)). As mentioned previously, the focus of our article is on the impact of uninformative central bank trades on the liquidity of government bond markets in the presence of strategic, informed speculation.[7]

We proceed as follows: In Section II, we construct a model of trading in the presence of an active central bank to guide our empirical analysis. In Section III, we describe the data. In Section IV, we present the empirical results. We conclude in Section V.

II. A Model of POMOs

The objective of this article is to analyze the impact of POMOs by the Federal Reserve on the liquidity of the secondary U.S. Treasury bond market. Trading in this market occurs in an interdealer, over-the-counter setting in which primary and nonprimary dealers act as market-makers, trading with customers on their own accounts and among themselves via interdealer brokers (for more details on the microstructure of the U.S. Treasury market, see Fabozzi and Fleming (2004), Mizrach and Neely (2009)). In this section, we develop a parsimonious

[6]One exception is recent studies of the *effectiveness* of unconventional monetary policy (including the auction-based purchase of extraordinarily large amounts of government bonds) at lowering long-term interest rates during the recent financial crisis (e.g., Gagnon, Raskin, Remache, and Sack (2011), Hamilton and Wu (2011), Krishnamurthy and Vissing-Jorgensen (2011), Christensen and Rudebusch (2012), D'Amico, English, Lopez-Salido, and Nelson (2012), D'Amico and King (2013), Eser and Schwaab (2016), and Krishnamurthy, Nagel, and Vissing-Jorgensen (2018)). Relatedly, Song and Zhu (2018) find that the Federal Reserve mitigated the execution costs of these extraordinary purchases between Nov. 2010 and Sept. 2011 by concentrating on undervalued Treasury securities (relative to an algorithm that includes, among others, *pre-auction* bid–ask spreads as a measure of bond illiquidity) even in the presence of strategic primary dealers partly predicting (and so profiting from) its demand (see also Kitsul (2013)). As noted earlier, we discuss the role of POMOs during the financial crisis period (2008–2009) and ascertain the robustness of our inference to pre-auction Treasury market illiquidity over the pre-crisis period (2001–2007) in Section IV.B and Sections 2.2 and 2.4 of the Supplementary Material.

[7]In a follow-up study, Pasquariello (2018) investigates the effect of government intervention pursuing a *partially* informative policy target in currency markets on violations of the law of one price (LOP) in the market for American depositary receipts (ADRs). Further discussion is in Section III.C and Section 1 of the Supplementary Material.

representation of the process of price formation in the Treasury bond market apt for our objective. First, we describe a model of trading in Treasury securities based on Kyle (1985) and derive closed-form solutions for the equilibrium depth as a function of the information environment of the market. Then, we enrich the model by introducing a central bank attempting to achieve a policy target while accounting for the cost of the intervention and consider the properties of the ensuing equilibrium. We test for the statistical and economic significance of our theoretical argument in the remainder of the article. All proofs are in the Appendix.

A. The Basic Model

The basic model is a 2-date ($t=0,1$) economy in which a single risky asset is exchanged. Trading occurs only at date $t=1$, after which the payoff of the risky asset, a normally distributed random variable v with mean p_0 and variance σ_v^2, is realized. The economy is populated by three types of risk-neutral traders: a discrete number (M) of informed, risk-neutral traders (henceforth speculators), liquidity traders, and perfectly competitive market-makers (MMs) in the risky asset. All traders know the structure of the economy and the decision process leading to order flow and prices.

At date $t=0$ there is neither information asymmetry about v nor trading, and the price of the risky asset is p_0. Recent studies provide evidence of privately and diversely informed trading in the secondary market for Treasury securities (e.g., see Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007), (2009)). Accordingly, some time between $t=0$ and $t=1$, we endow each speculator m with a private and noisy signal of v, $S_v(m)$. We assume that each signal $S_v(m)$ is drawn from a normal distribution with mean p_0 and variance σ_s^2 and that, for any two speculators m and j, $\operatorname{cov}\left[S_v(m), S_v(j)\right]=\operatorname{cov}\left[v, S_v(m)\right]=\sigma_v^2$. As in Pasquariello and Vega (2009), we also parameterize the dispersion of speculators' private information by imposing that $\sigma_s^2=\sigma_v^2/\rho$ and $\rho\in(0,1)$, such that each speculator's information advantage (or endowment) about v at $t=1$, before trading with the MMs, is given by $\delta_v(m)\equiv \mathrm{E}\left[v|S_v(m)\right]-p_0=\rho\left[S_v(m)-p_0\right]$ and that $\mathrm{E}\left[\delta_v(j)\,|\delta_v(m)\right]=\rho\delta_v(m)$. Thus, the parameter ρ represents the correlation between any two information endowments $\delta_v(m)$ and $\delta_v(j)$: The lower (higher) ρ is, the less (more) correlated (i.e., the more (less) *heterogeneous*) speculators' private information is.[8]

At date $t=1$, both liquidity traders and speculators submit their orders to the MMs before the equilibrium price p_1 has been set. We define the market order of each speculator m as $x(m)$, such that her profit is given by $\pi(m)=(v-p_1)\,x(m)$. Liquidity traders generate a random, normally distributed demand z, with mean 0 and variance σ_z^2. For simplicity, we assume that z is independent of all other random variables. The uninformed MMs observe the ensuing aggregate order flow $\omega_1=\sum_{m=1}^{M}x(m)+z$ and then set the market-clearing price $p_1=p_1(\omega_1)$. Consistently with Kyle (1985), we define a Bayesian Nash equilibrium of this

[8]Similar implications ensue from the (trivial) limiting case where speculators' private information is homogeneous (i.e., $\rho=1$ such that $S_v(m)=S_v(j)=v$) as well as from more general information structures (albeit at the cost of greater analytical complexity, e.g., as in Foster and Viswanathan (1996), Pasquariello (2007a), and Pasquariello and Vega (2007)).

economy as a set of $M+1$ functions $x(m)(\cdot)$ and $p_1(\cdot)$ such that the following two conditions hold:

1. *Utility maximization*: $x(m)(\delta_v(m)) = \arg\max \mathrm{E}[\pi(m)|\delta_v(m)]$;

2. *Semi-strong market efficiency*: $p_1(\omega_1) = \mathrm{E}(v|\omega_1)$.

The following proposition characterizes the unique linear, rational expectations equilibrium for this economy satisfying Conditions 1 and 2.

Proposition 1. There exists a unique linear equilibrium given by the price function

$$p_1 = p_0 + \lambda\omega_1 \tag{1}$$

and by each speculator m's demand strategy

$$x(m) = \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}\delta_v(m), \tag{2}$$

where

$$\lambda = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]} > 0. \tag{3}$$

In equilibrium, imperfectly competitive speculators are aware of the potential impact of their trades on prices; thus, despite being risk-neutral, they trade on their private information cautiously ($|x(m)| < \infty$) to dissipate less of it. Accordingly, speculators' optimal trading strategies depend both on their information endowments about the traded asset's payoff v ($\delta_v(m)$) and market liquidity (λ): $x(m) = \delta_v(m)/\{\lambda[2+(M-1)\rho]\}$ in equation (2). A positive λ allows MMs to offset losses from trading with speculators with profits from noise trading (z). As such, liquidity deteriorates (λ is greater) as the traded asset's payoff v (higher σ_v^2) becomes more uncertain, for speculators' information advantage becomes greater and MMs become more vulnerable to adverse selection.

Importantly, $x(m)$ and λ also depend on ρ, the correlation among speculators' information endowments. Intuitively, when speculators' private information is more heterogeneous (ρ closer to 0), each speculator perceives herself to have greater monopoly power on her signal because more of it is perceived to be known to her alone. Hence, each speculator trades on her signal more cautiously (i.e., her market order is lower: $\partial|x(m)|/\partial\rho = \left[\sigma_z/\left(2\sigma_v\rho\sqrt{M\rho}\right)\right]|\delta_v(m)| > 0$) to reveal less of it. Lower trading aggressiveness makes the aggregate order flow less informative and the adverse selection of MMs more severe, worsening equilibrium market liquidity (higher λ), except when accompanied by greater signal noise ($\partial\sigma_s^2/\partial\rho = -\sigma_v^2/\rho^2 < 0$) in the presence of few or very heterogeneously informed (thus already very cautious) speculators (low M or ρ) (see also Pasquariello and Vega (2015)). The following corollary summarizes these basic properties of λ of equation (3):

Corollary 1. Equilibrium market liquidity is decreasing in σ_v^2 and generally decreasing in ρ.

Pasquariello and Vega (2007), (2009) find strong empirical support for the predictions of our model in the U.S. Treasury market (see also Fleming (2003), Brandt and Kavajecz (2004), Green (2004), and Li, Wang, Wu, and He (2009)).

B. Central Bank Intervention

The Federal Reserve routinely intervenes in the secondary U.S. Treasury market via open market operations (OMOs) to implement its monetary policy.[9] OMOs are trades in previously issued U.S. Treasury securities executed by the Open Market Desk ("the Desk") at the Federal Reserve Bank of New York (FRBNY) on behalf of the entire Federal Reserve System, via an auction process with primary dealers (described in Section III.B), to ensure that the supply of nonborrowed reserves in the banking system is consistent with the target for the federal funds rate set by the FOMC.

The federal funds rate is the rate clearing the federal funds market, the market where financial institutions trade reserves (deposits held by those institutions at the Federal Reserve) on a daily basis.[10] Purchases (sales) of government bonds by the Desk expand (contract) the aggregate supply of nonborrowed reserves (i.e., those not originating from the Federal Reserve's discount window (which is meant as a source of last resort)) in the monetary system. *Permanent* OMOs (POMOs) are outright trades of government bonds affecting the supply of nonborrowed reserves permanently. *Temporary* OMOs (TOMOs) are repurchasing agreements by which the Desk either buys (repos) or sells (reverse repos or matched-sale purchases) government bonds with the agreement to an equivalent transaction of the opposite sign at a specified price and on a specified later date (overnight or term basis) affecting the supply of nonborrowed reserves only temporarily.

For many years, the FOMC did not publicly announce changes in its stance of monetary policy, forcing market participants to infer them from the Desk's OMOs and the observed level of the federal funds rate. Media reports would then publicize the resulting market consensus. As such, the Desk conducted outright operations (i.e., POMOs) only infrequently (e.g., a few times a year) and only when pursuing sizable permanent changes in the supply for reserves. According to Edwards ((1997), p. 862), this "could, and on a few occasions did, lead to misunderstandings about the stance of policy or to delays in recognizing changes." However, on Feb. 4, 1994, after the FOMC voted to tighten monetary policy for the first time in 5 years, Chairman Alan Greenspan decided to disclose that new

[9] Akhtar (1997), Edwards (1997), Harvey and Huang (2002), FRBG (2005), and Afonso, Kovner, and Schoar (2011) provide detailed discussions of U.S. monetary policy and its implementation. Further information is also available on the FRBNY Web site (https://www.newyorkfed.org/markets/domestic-market-operations).

[10] As noted in Section I, the main focus of our investigation is on FRBNY interventions prior to the 2008 financial crisis. The implementation process of U.S. monetary policy has significantly changed since then. For instance, the Federal Reserve has been paying interest on reserve balances since Oct. 1, 2008; those deposits were instead noninterest bearing over our sample period (2001–2007). Furfine (1999) provides a detailed analysis of the microstructure of the federal funds market prior to the 2008 financial crisis. We consider the implications of the financial crisis for our inference in Section 2.2 of the Supplementary Material (see also Section IV.B). For detailed information on the current U.S. monetary policy tools, see the FRBG Web site (https://www.federalreserve.gov/monetarypolicy/policytools.htm) and D'Amico and King (2013), Song and Zhu (2018), and references therein.

stance immediately and unequivocally to the public in a press release "to avoid any misunderstanding of the Committee's purposes" (see https://www.federalreserve.gov/fomc/19940204default.htm). Since then, the FOMC has made its monetary policy decisions increasingly transparent (e.g., by preannouncing its intentions and disclosing the federal funds target rate to all market participants), therefore making the Desk's OMOs virtually uninformative about the Federal Reserve's future monetary policy stance over our sample period (Akhtar (1997), Edwards (1997), Harvey and Huang (2002), Sokolov (2009), and Cieslak et al. (2016)).

Importantly, while uninformative about the FOMC's monetary policy stance, the actions by the Desk at the FRBNY are neither meaningless nor "mechanical" (Akhtar (1997), p. 34). Given that stance, the timing, direction, and magnitude of FRBNY trades along the Treasury maturity structure are driven by nonborrowed reserve paths (or targets) based on its projections of current and future reserve excesses or shortages (as well as by its assessment of current and future U.S. Treasury market conditions) in an environment in which those reserve imbalances are subject to many factors outside of the central bank's control (e.g., Edwards (1997), Harvey and Huang (2002), FRBG (2005), and FRBNY (2005), (2008)).[11] Every day, the FRBNY sets a nonborrowed reserve target consistent with the FOMC's monetary policy stance and the federal funds target rate (see, e.g., Edwards (1997)). If the FRBNY expects persistent imbalances between the demand and supply of nonborrowed reserves (e.g., due to trends in the demand for U.S. currency in circulation) leading to a persistent violation of its reserve target, it may affect the supply through POMOs.[12] If those imbalances are instead expected to be temporary, the FRBNY may enter TOMOs; accordingly, TOMOs occur much more frequently (nearly every trading day) than POMOs. These observations imply that at any point in time there may be considerable uncertainty among market participants as to the nature of the trading activity by the FRBNY in the secondary U.S. Treasury market (i.e., about its reserve targets).

In this article, we intend to analyze the process of price formation in the secondary Treasury market in the presence of outright trades (i.e., POMOs) by the FRBNY's Desk in that market. To that purpose, we amend the basic one-shot model of outright trading of Section II.A to allow for the presence of a stylized central bank alongside speculators and liquidity traders.

As noted earlier, the Desk also routinely executes short-lived round-trip trades (i.e., TOMOs) in the Treasury repo market. As such, our setting is inadequate at capturing TOMOs' transitory nature and heterogeneous holding-period intervals (i.e., overnight or term basis). TOMOs' significantly higher recurrence (e.g., virtually every day over 2001–2007) also makes it difficult to identify their effect on Treasury market liquidity. In addition, as we will discuss, uncertainty about government intervention plays an important role in our model.

[11] See https://www.newyorkfed.org/aboutthefed/fedpoint/fed32.html for a discussion of the FRBNY's review of financial conditions in advance of its OMOs.

[12] For instance, according to Akhtar ((1997), p. 18), "currency demand is the largest single factor requiring [nonborrowed] reserve injections [i.e., POMO purchases], because it has a strong growth trend which reflects, primarily, the growth trend of the economy."

According to Edwards (1997), temporary reserve imbalances (i.e., those leading the federal funds rate to temporarily move away from the FOMC's target and the Desk to execute TOMOs) are "more technical" (i.e., more mechanical in nature).[13] Thus, there may be considerably less uncertainty among market participants about the Desk's short-term reserve objectives behind its TOMOs. Nevertheless, in Section 2.4 of the Supplementary Material, we establish the robustness of our subsequent empirical analysis to explicitly controlling for any spillover effect of TOMOs on Treasury market liquidity (see also Section IV.B).

We model the main features of FRBNY's POMO policy in a parsimonious fashion by assuming that i) some time between $t=0$ and $t=1$, the central bank is given a *nonpublic* price target p_T for the traded asset, drawn from a normal distribution with mean $\overline{p}_T$ and variance σ_T^2; and ii) at date $t=1$, before the equilibrium price p_1 has been set, the central bank (CB) submits to the MMs an outright market order x_{CB} minimizing the expected value of the following separable loss function:

$$L = \gamma\,(p_1 - p_T)^2 + (1-\gamma)\,(p_1 - v)\,x_{\mathrm{CB}}, \tag{4}$$

where $\gamma \in (0,1)$ is known to all market participants.

The specification of equation (4) is similar in spirit to Stein (1989), Bhattacharya and Weller (1997), Vitale (1999), and Pasquariello (2010), (2018). The first component, $(p_1 - p_T)^2$, captures the FRBNY's policy motives in its trading activity by the squared distance between the traded asset's equilibrium price p_1 and the target p_T. The *price* target p_T captures the Desk's efforts to target the *supply* of nonborrowed reserves (via outright purchases or sales of Treasury securities affecting dealers' deposits at the Federal Reserve) while facing a downward-sloping *demand* for Treasury securities (e.g., Krishnamurthy (2002), Vayanos and Vila (2009), Greenwood and Vayanos (2010), and Krishnamurthy and Vissing-Jorgensen (2012)). Intuitively, in the presence of downward-sloping demand curves for Treasury securities, changes in their supply induced by the Desk's outright trades affect their prices. Hence, the Desk's reserve targets can be represented as either Treasury price targets or Treasury supply targets. In our setting, we choose the former for analytical convenience.

The second component, $(p_1 - v)\,x_{\mathrm{CB}}$, captures the cost of the intervention as any deviation from purely speculative trading motives (e.g., as in Bhattacharya and Weller (1997), eq. (1)). Intuitively, if $\gamma=0$ the central bank would trade as just another speculator (i.e., would maximize the expected profit from trading the risky asset at p_1 before its payoff v is realized). Hence, deviating from optimal speculation to pursue policy is costly. Accordingly, the Federal Reserve has often voiced concern about the effects of capital losses from its OMOs on its balance sheet and remittances to the U.S. Treasury.[14] The greater γ is, the more important is the first component relative to the second in the central bank's loss function (i.e., the more important it deems the pursuit of p_T relative to its cost). In other words,

[13] Accordingly, Harvey and Huang ((2002), p. 229) observe that "one might characterize [POMOs] as offensive operations whereas [TOMOs] are more defensively oriented operations."

[14] For example, see the published minutes of the FOMC meetings in Dec. 2012, Jan. 2013, and Mar. 2013 (https://www.federalreserve.gov/monetarypolicy/fomc.htm).

the coefficient γ can be interpreted as the relative preference weight placed by the central bank on its policy motives. The restriction that $0<\gamma<1$ in equation (4) then ensures that the central bank does not trade unlimited amounts of the risky asset to achieve its policy target p_T.

The FRBNY is likely to have first-hand knowledge of macroeconomic fundamentals. Thus, we assume that the central bank is also given a private signal of the risky asset's payoff v, S_{CB}, a normally distributed variable with mean p_0 and variance $\sigma_{\text{CB}}^2=\frac{1}{\psi}\sigma_v^2$, where the precision parameter $\psi \in (0,1)$ and $\text{cov}\left[S_v(m), S_{\text{CB}}\right]=\text{cov}(v, S_{\text{CB}})=\sigma_v^2$ (as for $S_v(m)$ in Section II.A). However, as noted earlier, since the mid-1990s, the FOMC no longer employs POMOs to communicate changes in its monetary policy stance to market participants. Hence, POMOs no longer convey payoff-relevant information about traded Treasury securities. We make this observation operational in our model by further imposing that the central bank's policy target p_T is *uninformative* about the traded asset's liquidation value v (i.e., that $\text{cov}(v, p_T)=\text{cov}\left[S_v(m), p_T\right]=\text{cov}(S_{\text{CB}}, p_T)=0$). Both uncertainty about and uninformativeness of p_T are meant to capture the unanticipated nature of FRBNY trades in government bonds following public, informational FOMC decisions. In our setting, we can think of these policy decisions as translating into the commonly known distribution of the risky asset's liquidation value v given at date $t=0$. This distribution is independent of the FRBNY's subsequent trading activity in that asset. Thus, our assumptions about p_T reflect the uncertainty surrounding the FRBNY's implementation of the announced informative FOMC policy in the marketplace (e.g., about the Desk's uninformative targets for nonborrowed reserves). These assumptions also imply that the central bank's information endowments about v and p_T at $t=1$, before trading with the MMs, are given by $\delta_{\text{CB}} \equiv \text{E}(v|S_{\text{CB}})-p_0=\psi(S_{\text{CB}}-p_0)$ and $\delta_T \equiv p_T-\overline{p}_T$, respectively.

As in Section II.A, the MMs set the equilibrium price p_1 at date $t=1$ after observing the aggregate order flow, composed of the market orders of liquidity traders, speculators, and the central bank, $\omega_1=x_{\text{CB}}+\sum_{m=1}^{M} x(m)+z$. Importantly, these simplifying assumptions about intervention activity x_{CB} and ensuing market clearing via ω_1 allow us to abstract from explicitly modeling the separate auction process through which the Desk actually executes its POMOs. As we further discuss in Section III.B, these auctions are attended exclusively by primary dealers, who play a crucial role in liquidity provision in the tightly linked secondary market for the auctioned Treasury securities and targeted maturities by intermediating their affected outright supply and aforementioned downward-sloping demand (see, e.g., Fabozzi and Fleming (2004)). Accordingly, prior research finds that both U.S. Treasury and FRBNY auction outcomes quickly and significantly affect price formation in the secondary Treasury market (Pasquariello and Vega (2009), D'Amico and King (2013), and references therein). Proposition 2 accomplishes the task of solving for the unique linear Bayesian Nash equilibrium of this economy.

Proposition 2. There exists a unique linear equilibrium given by the price function

$$(5) \qquad p_1 = \left[p_0+2d\lambda_{\text{CB}}\left(p_0-\overline{p}_T\right)\right]+\lambda_{\text{CB}}\omega_1,$$

by each speculator m's demand strategy

$$(6)\quad x(m) = \frac{2(1+d\lambda_{\text{CB}})-\psi}{\lambda_{\text{CB}}\{2[2+(M-1)\rho](1+d\lambda_{\text{CB}})-M\psi\rho(1+2d\lambda_{\text{CB}})\}}\delta_v(m),$$

and by the central bank's demand strategy

$$(7)\quad x_{\text{CB}} = 2d\left(\overline{p}_T-p_0\right)+\frac{d}{1+d\lambda_{\text{CB}}}\delta_T + \frac{[2+(M-1)\rho]-M\rho(1+2d\lambda_{\text{CB}})}{\lambda_{\text{CB}}\{2[2+(M-1)\rho](1+d\lambda_{\text{CB}})-M\psi\rho(1+2d\lambda_{\text{CB}})\}}\delta_{\text{CB}},$$

where the ratio $d\equiv\gamma/(1-\gamma)$ is the central bank's relative degree of commitment to its policy target and λ_{CB} is the unique positive real root of the sextic polynomial of equation (A-25) in the Appendix.

In equilibrium, each speculator m accounts not only for the potentially competing trading activity of the other speculators (via $\text{E}\left[\delta_v(j)|\delta_v(m)\right]$, as in the equilibrium of Proposition 1) but also for the trading activity of the central bank (via $\text{E}[\delta_{\text{CB}}|\delta_v(m)]$) when setting her cautious optimal demand strategy $x(m)$ to exploit her information advantage $\delta_v(m)$. As such, $x(m)$ of equation (6) also depends on the commonly known parameters controlling the government's intervention policy: the quality of its private information (ψ), the uncertainty surrounding its policy target (σ_T^2), and its commitment to it (d).

Similarly, the central bank uses its information advantage δ_{CB} to account for speculators' trading activity (via $\text{E}[\delta_v(m)|\delta_{\text{CB}}]$) when devising its optimal trading strategy x_{CB}. As such, x_{CB} of equation (7) also depends on the number of speculators (M) and the heterogeneity of their private information (ρ). According to Proposition 2, x_{CB} is composed of three terms. The first term depends on the expected deviation of the policy target p_T from the equilibrium price in absence of government intervention $\left(\overline{p}_T-p_0\right)$ and is fully anticipated by the MMs when setting the market-clearing price p_1 of equation (5). The second term depends on the portion of that target that is known exclusively to the central bank, δ_T; ceteris paribus, the more liquid the market (i.e., the lower λ_{CB} is), the more aggressively the central bank trades on δ_T to achieve its policy objectives — the more so the more important it is for the central bank to narrow the gap between p_1 and p_T in its loss function (the higher d is). The third term depends on the central bank's attempt to minimize the expected cost of the intervention given its private fundamental information, δ_{CB} ; as such, it may either amplify or dampen its magnitude.

One cannot solve for the unique equilibrium price impact λ_{CB} of Proposition 2 in closed form. Therefore, we characterize its properties by means of numerical examples rather than formal comparative statics. To that purpose, we select model parameters such that not only can the previous equilibrium be found (see the Appendix) but also the ensuing intervention x_{CB} of equation (7) neither closely resembles (otherwise already material) informed speculation in the secondary Treasury market (high M; e.g., Pasquariello and Vega (2007), (2009)) nor is nearly unbounded (i.e., d in Proposition 2 is nontrivially large; Pasquariello (2018)), consistent with the FRBNY's aforementioned policy motives and actions. In particular, we set $\sigma_v^2=\sigma_z^2=\sigma_T^2=1$, $\rho=0.5$, $\psi=0.5$,

$\gamma = 0.5$, and $M = 500$. Alternative such parameter selection generally affects only the scale of the economy; we discuss nonrobust, extreme exceptions and notable model extensions in Section 1 of the Supplementary Material (see also Section II.C). We then plot the ensuing difference between equilibrium price impact in the presence and in the absence of the central bank of equation (4), $\Delta\lambda \equiv \lambda_{CB} - \lambda = \lambda_{CB} - \left\{\sigma_v \sqrt{M\rho} / \{\sigma_z [2 + (M-1)\rho]\}\right\}$, as a function of either γ, σ_T^2, ρ, or σ_v^2, in Graphs A–D of Figure 1, respectively.

First, government intervention improves market liquidity: $\Delta\lambda < 0$ in Figure 1. Intuitively, the central bank's optimal trading strategy stems from the resolution of a trade-off between pursuing a nonpublic, uninformative target (p_T) and the cost of deviating from optimal informed speculation ($x_{CB} = \{(2-\rho) / \{\lambda_{CB} \{2[2 + (M-1)\rho] - M\psi\rho\}\}\} \delta_{CB}$ when $\gamma = 0$). The former leads the central bank to trade more (or less) to achieve its policy target than it otherwise would given the latter. Hence, a portion of its trading activity in equation (7) is uninformative about fundamentals (v). Further uninformative trading in the order flow also induces the speculators to trade more aggressively on their

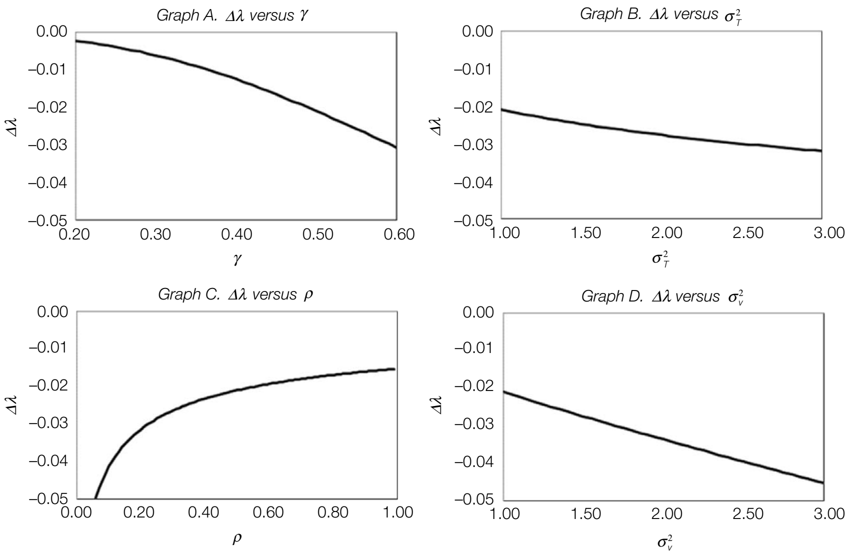
FIGURE 1

Market Liquidity and Central Bank Intervention

Figure 1 plots the difference between equilibrium price impact in the presence and in the absence of the central bank of equation (4),

$$\Delta\lambda \quad \equiv \quad \lambda_{CB} - \lambda \quad = \quad \lambda_{CB} - \left\{\sigma_v \sqrt{M\rho} / \{\sigma_z [2 + (M-1)\rho]\}\right\},$$

as a function of either γ (the central bank's commitment to achieve its policy, in Graph A), σ_T^2 (the uncertainty surrounding that policy, in Graph B), ρ (the degree of correlation of the speculators' private signals, in Graph C), or σ_v^2 (the fundamental uncertainty, in Graph D), when $\sigma_v^2 = \sigma_z^2 = \sigma_T^2 = 1$, $\rho = 0.5$, $\psi = 0.5$, $\gamma = 0.5$, and $M = 500$.



private signals.[15] Both in turn imply that the MMs perceive the threat of adverse selection to be less serious than in the absence of the central bank, thereby making the market more liquid.[16] Along those lines, equilibrium market liquidity is better (and $\Delta\lambda$ is more negative) as either the central bank's policy commitment (i.e., for higher γ in Graph A of Figure 1) or the uncertainty surrounding its policy (i.e., for higher σ_T^2 in Graph B of Figure 1) becomes greater, since in both circumstances the perceived intensity of uninformative government trading in the aggregate order flow is greater.

Second, the extent of this improvement in market liquidity is sensitive to the information environment of the market. In particular, $|\Delta\lambda|$ is increasing in the heterogeneity of speculators' signals (i.e., for lower ρ in Graph C of Figure 1) and in the economy's fundamental uncertainty (i.e., for higher σ_v^2 in Graph D of Figure 1). As discussed in Section II.A, less correlated (ρ closer to 0) or more valuable (higher σ_v^2) private information enhances speculators' incentives to behave cautiously when trading.[17] This worsens market liquidity regardless of whether the central bank is intervening or not, yet less so when it is doing so (i.e., when adverse selection is already less severe). Thus, the liquidity differential increases. The following conclusion summarizes these implications of our model.

Conclusion 1. The presence of a central bank improves market liquidity ($\Delta\lambda < 0$) by an extent ($|\Delta\lambda|$) increasing in γ, σ_T^2, and σ_v^2, and decreasing in ρ.

C. Model Extensions and Robustness

In Section 1 of the Supplementary Material, we discuss in detail both noteworthy model extensions and the robustness of their implications to parameter selection and key assumptions.

In particular, we show that government intervention would have no effect on market liquidity if its policy target p_T were *public*, would make the market infinitely deep for noise trading ($\lambda_{\text{CB}} = 0$) if p_T were *fully* informative about asset fundamentals (i.e., $p_T = v$), and would yield qualitatively similar implications for market liquidity if p_T were at least *partially* correlated with those fundamentals ($\text{cov}(v, p_T) > 0$, as in Pasquariello (2018)). As noted previously, we also find those implications to be broadly robust to parameter selection (with a noteworthy yet nonrobust and arguably implausible exception to Conclusion 1 arising from a central bank de facto acting as an *additional* speculator, that is, displaying low or 0 γ). Last, we argue that those implications are likely to be robust to any

[15]That is, Propositions 1 and 2 imply that $x(m)$ of equations (2) and (6) can be rewritten as $x(m) = B_1\rho\left[S_v(m) - p_0\right]$ and $x(m) = B_1^{\text{CB}}\rho\left[S_v(m) - p_0\right]$, respectively; it can then be shown numerically that

$$\Delta B_1 \equiv B_1^{\text{CB}} - B_1 = \frac{2(1+d\lambda_{\text{CB}}) - \psi}{\lambda_{\text{CB}}\{2[2+(M-1)\rho](1+d\lambda_{\text{CB}}) - M\psi\rho(1+2d\lambda_{\text{CB}})\}} - \frac{\sigma_z}{\sigma_v\sqrt{M\rho}} > 0.$$

Accordingly, unreported numerical analysis also shows that $\Delta\lambda$ is more negative in the presence of fewer speculators (i.e., for smaller M) since their trading activity is more cautious and the market in absence of government intervention less liquid.

[16]Consistently, Kumar and Seppi (1992) argue that uninformed futures-cash price manipulation may transfer liquidity from an infinitely deep futures market to a spot market plagued by adverse selection risk. See also the discussion in Pasquariello (2018).

[17]For instance, unreported numerical analysis shows that $|\Delta B_1 \rho|$ is increasing in ρ.

alternative loss function yielding nontrivial optimal intervention driven by at least partly uninformative policy goals, as for the stylized government of equation (4).

III. Data Description

We test the implications of the model of Section II in a comprehensive sample of intraday price formation in the secondary U.S. Treasury bond market and of open market operations executed by the Federal Reserve Bank of New York during the 2000s.

A. Bond Market Data

Our basic sample is made of intraday, interdealer U.S. Treasury bond price quotes from BrokerTec for the most recently issued (i.e., benchmark, or on-the-run) 2-year, 3-year, 5-year, and 10-year Treasury notes and 30-year Treasury bonds between Jan. 1, 2001, and Dec. 31, 2007 (i.e., immediately prior to the recent financial crisis). We analyze the more turbulent crisis period (2008–2009) in Section 2.2 of the Supplementary Material (see also Section IV.B). We focus on on-the-run issues because those securities display the greatest liquidity and informed trading (e.g., Fleming (1997), Brandt and Kavajecz (2004), Goldreich, Hanke, and Nath (2005), and Pasquariello and Vega (2007)). Trading in more seasoned (i.e., *off-the-run*) Treasury securities is scarce, and their liquidity is more difficult to assess (Fabozzi and Fleming (2004), Pasquariello and Vega (2009)).

Since the early 2000s, interdealer trading in benchmark Treasury securities has migrated from voice-assisted brokers (whose data are consolidated by GovPX) to either of two fully electronic trading platforms, BrokerTec (our data source) and eSpeed. BrokerTec accounts for nearly two-thirds of such trading activity (Mizrach and Neely (2006)). Fleming et al. (2018) find that liquidity and trading volume in BrokerTec are significantly greater than reported in earlier studies of the secondary Treasury bond market based on GovPX data. The BrokerTec's electronic interface displays, for each security (i), the best five bid (B_i) and ask (A_i) prices and accompanying quantities; traders either enter limit orders or hit these quotes anonymously. Our sample includes every quote posted during "New York trading hours," from 7:30AM ("open") to 5:00PM ("close") Eastern Time (ET).[18] To eliminate interdealer brokers' posting errors, we filter all quotes within this interval following the procedure described in Fleming (2003).[19] Last, we augment the BrokerTec database with information on important fundamental characteristics (daily modified duration, $D_{i,t}$, and convexity, $C_{i,t}$) of all notes and bonds in our sample (from Morgan Markets, JPMorgan's data portal).

[18] Although trading takes place nearly continuously during the week, 95% of trading volume occurs during those hours (e.g., Fleming (1997)). Outside that interval, fluctuations in bond prices are likely due to illiquidity.

[19] We also eliminate federal holidays, days in which BrokerTec recorded unusually low trading activity, and the days immediately following the terrorist attack to the World Trade Center (Sept. 11 to Sept. 21, 2001) because of the accompanying significant illiquidity in the Treasury market (e.g., Hu, Pan, and Wang (2013)).

Measuring Treasury Market Liquidity

The model of Section II yields implications of the occurrence of POMOs for the liquidity of the secondary U.S. Treasury bond market. These implications stem from the role of informed speculation for Treasury market liquidity. To better capture this role, we focus our analysis on *daily* measures of market liquidity for each security in our sample. The econometrician does not observe the precise timing and extent of informed speculation throughout the day; hence, narrowing the estimation window may lead us to underestimate its full effects on market liquidity around POMOs (e.g., since those effects may manifest nonuniformly over several hours after POMOs occurred).[20] In addition, noninformational microstructure frictions (e.g., bid–ask bounce, quote clustering, price staleness, inventory effects) affecting estimates of intraday market liquidity generally become immaterial over longer horizons (Hasbrouck (2007)). We nonetheless analyze *intraday* measures of liquidity in Section 2.3 of the Supplementary Material (see also Section IV.B).

In the context of our model, market liquidity for a traded asset i is defined as the marginal impact of unexpected aggregate order flow on its equilibrium price, λ_i. When transaction-level data are available, this variable is typically estimated as the slope $\lambda_{i,t}$ of the regression of intraday yield or price changes on the unexpected portion of intraday aggregate net volume. While our BrokerTec sample does not include such data, direct estimation of $\lambda_{i,t}$ suffers from several shortcomings. First, the occasional scarcity of trades at certain maturities may make the estimation of $\lambda_{i,t}$ at the daily frequency problematic. Even when possible, this estimation requires the econometrician to i) model expected intraday aggregate order flow and ii) explicitly control for the effect of the aforementioned noninformational microstructure frictions on its dynamics (e.g., Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007)). Thus, any ensuing inference may be subject to both misspecification and biases from measurement error in the dependent variable (e.g., Greene (1997)).

Accordingly, in this article we measure the liquidity of each on-the-run Treasury security i with $S_{i,t}$, the daily (i.e., from open to close) average of its quoted intraday *price* bid–ask spreads $S_i = A_i - B_i$. Treasury notes and bonds trade in units of par notional (i.e., of face value), which is set at \$1,000. Consistent with market conventions (e.g., Fleming (2003)), Treasury notes and bond prices A_i and B_i in our sample are in points (i.e., expressed as a percentage of par (where 1 point is 1% of par) multiplied by 100). Thus, bid–ask spreads S_i are in basis points (bps, where 1 basis point is 1% of 1 point) further multiplied by 100. Bid–ask spreads are virtually without measurement error. There is an extensive literature relating their magnitude and dynamics to informed trading (see O'Hara (1995) for a review). In addition, price spreads are comparable over time and across all Treasury securities in our sample since each security's spread is computed relative to the same face value. Accordingly, we show in Section 2.3 of the Supplementary Material that percentage spreads (e.g., Song and Zhu (2018)) yield nearly identical inference (see also Section IV.B). Last, when comparing several alternative measures of liquidity in the U.S. Treasury market, Fleming (2003) finds that the

[20]Neely (2005) and Pasquariello (2007b) further discuss these issues when surveying the vast empirical literature on central bank interventions in currency markets.

quoted bid–ask spread is the most highly correlated with both direct estimates of price impact and well-known episodes of poor liquidity in that market.[21] Panel A of Table 1 reports summary statistics over the basic sample period (2001–2007) for average daily quoted bid–ask spread ($S_{i,t}$) and daily trading volume ($V_{i,t}$) for each of the benchmark Treasury securities in our sample. We also plot the corresponding time series of $S_{i,t}$ in Figure 2.

The secondary market for on-the-run Treasury notes and bonds is extremely liquid. Average trading volumes are high and quoted bid–ask spreads are small; both are close to what is reported in other studies (e.g., Fleming (2003), Fleming et al. (2018), among others). Not surprisingly, bid–ask spreads display large, positive first-order autocorrelation ($\rho(1) > 0$). Notably, Figure 2 suggests that bid–ask spreads are wider in the earlier portion of the sample (2001–2004) before

TABLE 1

BrokerTec: Descriptive Statistics

Table 1 reports the mean (μ), standard deviation (σ), and first-order autocorrelation coefficient ($\rho(1)$) for variables of interest in the BrokerTec database of quotes for on-the-run 2-year, 3-year, 5-year, and 10-year U.S. Treasury notes and 30-year U.S. Treasury bonds (i). Summary statistics are computed over i) the basic sample period (Jan. 1, 2001, to Dec. 31, 2007, in Panel A); ii) the earlier subsample (Jan. 1, 2001, to Dec. 31, 2004, in Panel B); iii) the later subsample (Jan. 1, 2005, to Dec. 31, 2007, in Panel C); and iv) the crisis sample (Jan. 1, 2008, to Dec. 31, 2009, in Panel D). Data for 3-year notes are available only between May 7, 2003 and Mar. 30, 2007. N is the number of observations. Treasury note and bond prices are quoted in points (i.e., are reported as fraction of par multiplied by 100). $S_{i,t}$ is the average daily quoted bid–ask price spread in basis points (bps), that is, further multiplied by 100. $\Delta S^B_{i,t} \equiv S_{i,t} - S^B_{i,t}$, where $S^B_{i,t}$ is the average bid–ask price spread over the most recent previous 22 trading days when no permanent open market operation (POMO) occurred. $V_{i,t}$ is the daily trading volume, in billions of U.S. dollars. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

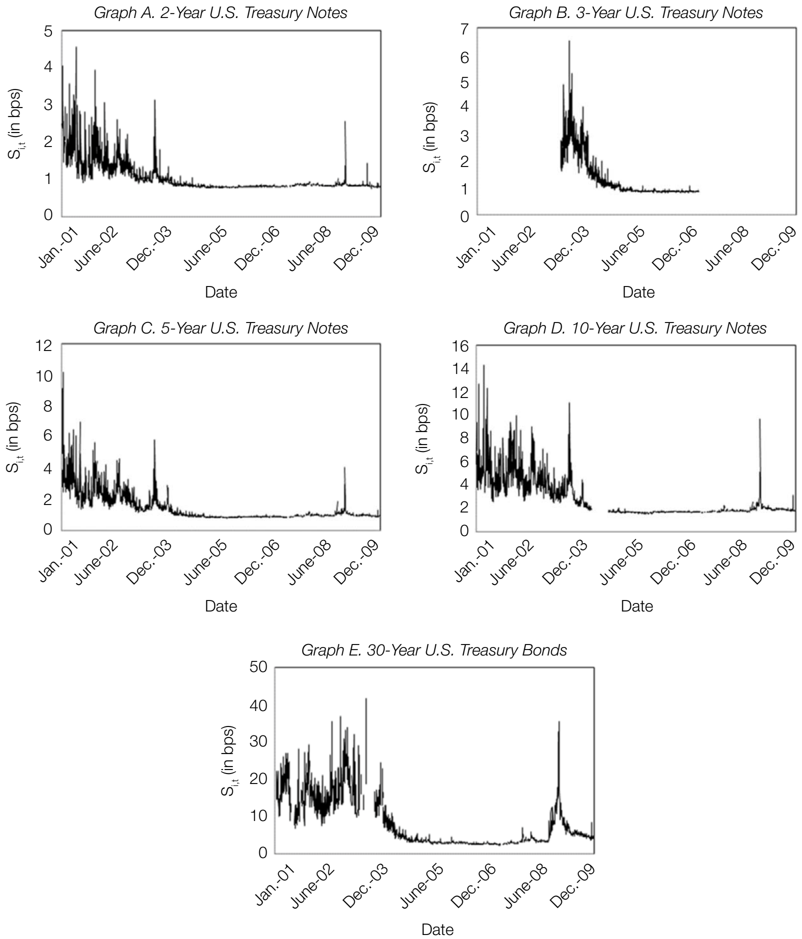
		$S_{i,t}$			$\Delta S^B_{i,t}$			$V_{i,t}$		
Segment	N	μ	σ	$\rho(1)$	μ	σ	$\rho(1)$	μ	σ	$\rho(1)$
Panel A. BrokerTec: 01/2001–12/2007										
2-year	1,680	1.096	0.46	0.97***	−0.030***	0.28	0.43***	$20.890	$15.21	0.93***
3-year	964	1.334	0.77	0.97***	−0.028***	0.30	0.33***	$7.829	$4.95	0.95***
5-year	1,684	1.535	0.97	0.95***	−0.064***	0.58	0.48***	$17.595	$12.99	0.95***
10-year	1,561	2.975	1.70	0.96***	−0.083***	0.91	0.39***	$15.243	$12.44	0.94***
30-year	1,514	8.322	6.97	0.96***	−0.237***	3.06	0.46***	$1.878	$1.82	0.93***
Panel B. BrokerTec: 01/2001–12/2004										
2-year	972	1.299	0.52	0.96***	−0.052***	0.37	0.43***	$11.790	$5.80	0.94***
3-year	407	1.947	0.88	0.97***	−0.058**	0.47	0.33***	$3.960	$1.97	0.94***
5-year	976	2.009	1.04	0.94***	−0.112***	0.76	0.48***	$9.025	$5.36	0.95***
10-year	854	4.036	1.67	0.95***	−0.153***	1.22	0.39***	$5.951	$4.47	0.94***
30-year	803	13.086	6.56	0.96***	−0.442***	4.18	0.46***	$0.525	$0.47	0.92***
Panel C. BrokerTec: 01/2005–12/2007										
2-year	708	0.816	0.03	0.99***	0.001**	0.01	0.35***	$33.383	$15.27	0.92***
3-year	557	0.886	0.04	0.99***	−0.006***	0.04	0.46***	$10.656	$4.55	0.95***
5-year	708	0.881	0.05	0.99***	0.001	0.03	0.58***	$29.409	$10.99	0.94***
10-year	707	1.693	0.07	0.99***	0.002	0.05	0.53***	$26.466	$9.34	0.94***
30-year	711	2.942	0.41	0.99***	−0.005	0.30	0.54***	$3.405	$1.55	0.93***
Panel D. BrokerTec: 01/2008–12/2009										
2-year	469	0.848	0.09	0.99***	−0.003	0.09	0.32***	$31.350	$16.47	0.93***
3-year	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
5-year	469	1.019	0.21	0.98***	−0.006	0.19	0.51***	$27.596	$12.61	0.95***
10-year	469	1.959	0.46	0.98***	−0.005	0.42	0.50***	$22.980	$9.03	0.95***
30-year	463	6.137	3.92	0.98***	−0.026***	2.44	0.79***	$3.531	$1.53	0.92***

[21] See also Chordia, Sarkar, and Subrahmanyam (2005) and Goldreich et al. (2005). Data availability considerations prevent us from estimating alternative measures of illiquidity or the portion of the bid–ask spread due to adverse selection, that is, net of order processing or inventory costs (see, e.g., Stoll (1989), George, Kaul, and Nimalendran (1991)).

FIGURE 2

U.S. Treasury Notes and Bonds: Bid–Ask Spreads

Figure 2 plots daily bid–ask price spreads $S_{i,t}$ for on-the-run 2-year (Graph A), 3-year (Graph B), 5-year (Graph C), and 10-year U.S. Treasury notes (Graph D), and 30-year U.S. Treasury bonds (Graph E) on the BrokerTec platform between Jan. 1, 2001, and Dec. 31, 2009. Data for 3-year notes are available only between May 7, 2003, and Mar. 30, 2007. Treasury note and bond prices are quoted in points (i.e., are reported as fraction of par multiplied by 100). $S_{i,t}$ is the average daily quoted bid–ask price spread for security i in basis points (bps) (i.e., further multiplied by 100).



sharply declining afterward (2005–2007). Corresponding summary statistics (in Panels B and C of Table 1, respectively) confirm this pattern in Treasury bond market liquidity. We further discuss this feature of the data and address its implications for our analysis in Section 2.1 of the Supplementary Material (see also Section IV.B). Since being discontinued in 1998, 3-year notes have been issued by the U.S. Treasury only between Feb. 2003 and May 2007 and from Nov. 2008 onward (e.g., see https://www.treasurydirect.gov/indiv/research/history/histtime/histtime_notes.htm.). Data for 3-year notes also have significant gaps in BrokerTec market coverage, restricting our analysis of that maturity segment to the subperiod

May 2003 to Mar. 2007 (see Graph B of Figure 2). Graphs D and E of Figure 2 reveal occasional gaps in coverage for 10-year notes and 30-year bonds as well; however, coverage is nearly continuous for 2-year and 5-year notes (Graphs A and C of Figure 2). Bid–ask spreads for Treasury securities are increasing (and their liquidity is generally decreasing) with their maturity. 2-year Treasury notes are characterized by the highest average daily trading volume ($20.9 billion) and the smallest average spread, 1.096 bps (i.e., 1.096% of 1 point). The latter implies an average round-trip cost of about $22,000 for trading $200 million par notional of these notes (i.e., $\$200{,}000{,}000 \times 1.096/10{,}000 = \$21{,}920$), an amount routinely available on BrokerTec at the best bid and ask prices (Fleming et al. (2018)). BrokerTec bid–ask spreads for 30-year Treasury bonds are not only the highest among the securities in our sample (8.322 bps, or $166,440 per $200 million face value) but also higher than those typically observed on the eSpeed platform (e.g., Mizrach and Neely (2006)). This may reflect the historical dominance of Cantor Fitzgerald (eSpeed's founder) in interdealer trading at the "long end" of the Treasury yield curve.

B. Permanent Open Market Operations

Our basic sample is a database of all permanent (outright) open market operations (POMOs) executed by the Federal Reserve Bank of New York (FRBNY) between Jan. 1, 2001, and Dec. 31, 2007 (available at https://www.newyorkfed.org/markets/OMO_transaction_data.html). As noted previously, we consider POMO activity during the crisis period (2008–2009) in Section 2.2 of the Supplementary Material (see also Section IV.B). POMOs are executed by the Desk through an auction with primary dealers usually taking place between 10:00AM and 11:30AM ET ("Fed Time;" see Akhtar (1997), Harvey and Huang (2002), and D'Amico and King (2013)), when intraday market liquidity is relatively high (Fleming (1997), Fleming et al. (2018)). This process consists of multiple steps. Between 10:00AM and 10:30AM ("Release Time"), the Desk announces a list of eligible Treasury securities (i.e., of CUSIPs) for the auction. This list typically includes all securities within a specific maturity segment targeted by the Desk (in order to "achieve a liquid and diversified portfolio structure;" FRBNY (2005), p. 20), with the exception of the cheapest-to-deliver in the futures market and any highly scarce (i.e., on special) security in the repo market. The auction closes between 10:45AM and 11:30AM ("Close Time"). Within a few minutes, the Desk selects from among the submitted bids using a proprietary algorithm and publishes the auction results. Following these trades, the reserve accounts of the Desk's counterparties (the dealers' banks) at the FRBNY are credited or debited accordingly, permanently altering the aggregate supply of nonborrowed reserves in the monetary system.

Our database contains salient information on the Desk's POMOs: their dates, release and close times, actual securities traded (CUSIPs), descriptions (coupon rate and maturity), and par amounts accepted at the auction. In order to capture the Desk's stated focus on broad maturity segments (rather than on specific securities), we group all auctioned securities based on their remaining maturity into five brackets centered around the maturities of the on-the-run securities available in the BrokerTec database: 2-year, 3-year, 5-year, 10-year, and 30-year POMOs.

Characterizing these maturity brackets is unavoidably subjective. As in D'Amico and King (2013), we label a FRBNY transaction as i) a 2-year POMO if the remaining maturity of the traded security is 0–4 years; ii) a 3-year POMO if the remaining maturity of the traded security is 1–5 years; iii) a 5-year POMO if the remaining maturity of the traded security is 3–7 years; iv) a 10-year POMO if the remaining maturity of the traded security is 8–12 years; and v) a 30-year POMO if the remaining maturity of the traded security is greater than 12 years. The first three brackets overlap partially because of the high substitutability of shorter-maturity Treasury securities (e.g., D'Amico and King (2013)). As we discuss subsequently, our inference is unaffected by this sorting procedure and robust to alternative and/or nonoverlapping bracket definitions. The extremely scarce liquidity of most off-the-run issues precludes a security-level analysis of price formation in the presence of POMOs. Our inference is likely only weakened by this aggregation.

Table 2 contains summary statistics of POMOs for each maturity bracket and for every intervention day (labeled Total), over three partitions of our basic sample: 2001–2007 (Panel A), 2001–2004 (Panel B), and 2005–2007 (Panel C). The FRBNY's Desk executed POMOs on 217 days between 2001 and 2007. When doing so, the Desk traded an average of about 25 different securities on any single day in which it intervened. As mentioned previously, this suggests that POMOs do not target (nor appear to significantly affect the supply of) any particular security within a maturity bracket. POMOs occur most frequently at the shortest, most liquid segments of the yield curve: the 2-year to 5-year maturities. As Table 2 shows, occasionally the Desk trades securities in more than one maturity bracket. Daily total par amounts accepted ($\text{POMO}_{i,t}$) average between \$343 million for 10-year notes and \$1.152 billion for 3-year notes. While sizeable, these amounts are significantly lower than sample average daily trading volume not only in the on-the-run Treasury securities in our data set (between \$1.9 billion and \$20.9 billion; see $V_{i,t}$ in Table 1) but also in the whole secondary U.S. Treasury market (\$469 billion).[22]

Figure 3 plots the daily total par amount of the FRBNY's POMOs (POMO_t, solid column), the end-of-day federal funds rate (dotted line), and the corresponding target rate set by the FOMC (solid line) over our sample period. POMOs appear to cluster in time, especially during the earlier, less liquid, and more volatile interval 2001–2004 (see Panel B of Tables 1 and 2), but still occur in every year of the sample. Importantly, the Desk executed exclusively purchases (POMO_t, $\text{POMO}_{i,t} > 0$) between 2001 and 2007, *regardless of the interest rate environment*, both in aggregate (Figure 3) and in each of the maturity brackets (Table 2). This behavior reflects the Desk's efforts to accommodate the persistent growth in the demand for U.S. money (mirroring the growth in the economy) by expanding the supply of nonborrowed reserves (Akhtar (1997), Edwards (1997)) and is consistent with our prior observation that POMOs are uninformative about the FOMC's monetary policy stance over our sample period.

[22]This average is computed from trading volume data reported by primary dealers to the FRBNY and available at https://www.newyorkfed.org/markets/gsds/search.html. Government interventions in currency markets are of similar relative magnitude (see, e.g., Neely (2005), Pasquariello (2007b)).

FIGURE 3

POMOs and Federal Funds Rates

Figure 3 plots the daily total principal amounts of U.S. Treasury securities purchased ($\text{POMO}_t > 0$) or sold ($\text{POMO}_t < 0$) by the Federal Reserve Bank of New York (FRBNY) as permanent open market operations (POMOs, left axis, in billions of dollars) as well as both the federal funds effective daily rate from overnight trading in the federal funds market (dotted line, right axis, in percentage terms (i.e., multiplied by 100)) and its corresponding target set by the Federal Open Market Committee (FOMC, solid line, right axis), between Jan. 1, 2001, and Dec. 31, 2009.

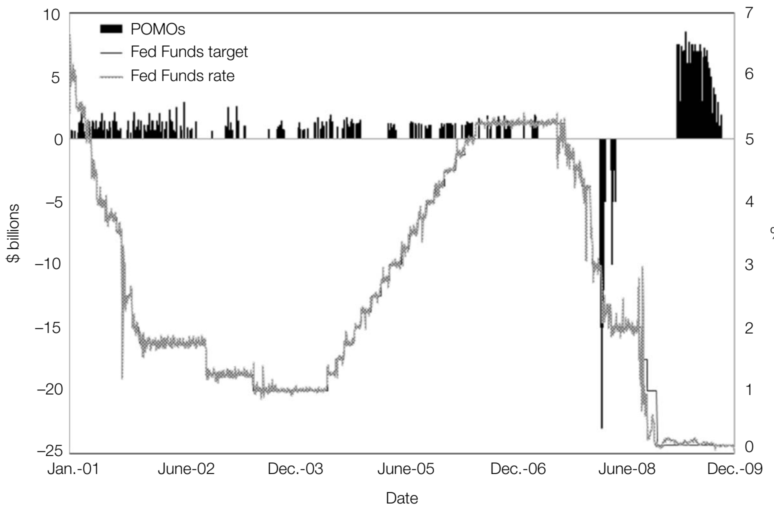


TABLE 2

POMOs: Descriptive Statistics

Table 2 reports summary statistics for all permanent open market operations (POMOs) conducted by the Federal Reserve Bank of New York (FRBNY) in the secondary U.S. Treasury market over i) the basic sample period (Jan. 1, 2001, to Dec. 31, 2007, in Panel A); ii) the earlier subsample (Jan. 1, 2001, to Dec. 31, 2004, in Panel B); iii) the later subsample (Jan. 1, 2005, to Dec. 31, 2007, in Panel C); and iv) the crisis sample (Jan. 1, 2008, to Dec. 31, 2009, in Panel D). All POMOs executed over this sample period were purchases of Treasury securities ($\text{POMO}_{i,t} > 0$). POMOs are sorted by the segment (i) of the yield curve targeted by the FRBNY, each centered around the maturities of the following *on-the-run* securities available in the BrokerTec database: 2-year, 3-year, 5-year, and 10-year U.S. Treasury notes and 30-year U.S. Treasury bonds. Specifically, we label a FRBNY transaction as i) a 2-year POMO if the remaining maturity of the traded security is between 0 and 4 years; ii) a 3-year POMO if the remaining maturity of the traded security is between 1 and 5 years; iii) a 5-year POMO if the remaining maturity of the traded security is between 3 and 7 years; iv) a 10-year POMO if the remaining maturity of the traded security is between 8 and 12 years; and v) a 30-year POMO if the remaining maturity of the traded security is greater than 12 years. N is the number of days when POMOs occurred over the sample period. N_d is the average number of intraday POMOs executed (i.e., of securities traded on POMO days) by the FRBNY. μ is the mean total daily principal traded, in billions of U.S. dollars; σ is the corresponding standard deviation.

	$\text{POMO}_{i,t}$															
	Panel A. 01/2001–12/2007				*Panel B.* 01/2001–12/2004				*Panel C.* 01/2005–12/2007				*Panel D.* 01/2008–12/2009			
Segment	N	N_d	μ	σ	N	N_d	μ	σ	N	N_d	μ	σ	N	N_d	μ	σ
Total	217	25	$1.108	$0.44	153	26	$1.073	$0.48	64	23	$1.194	$0.29	75	73	$2.020	$6.52
2-year	162	23	$1.152	$0.51	117	24	$1.136	$0.55	45	21	$1.194	$0.40	35	69	−$0.981	$7.98
3-year	120	20	$0.852	$0.39	80	19	$0.734	$0.34	40	22	$1.088	$0.38	40	63	$2.687	$4.86
5-year	78	16	$0.565	$0.40	50	15	$0.430	$0.30	28	19	$0.805	$0.45	39	53	$3.071	$4.04
10-year	36	10	$0.343	$0.25	24	10	$0.306	$0.21	12	11	$0.416	$0.32	21	32	$1.086	$1.33
30-year	32	15	$0.390	$0.24	23	16	$0.375	$0.17	9	13	$0.428	$0.38	16	49	$1.856	$1.03

IV. Empirical Analysis

In this section, we test the implications of our model for the impact of POMOs on the process of price formation in the secondary market for U.S. Treasury securities. We proceed in two steps. First, we test whether POMOs improve Treasury market liquidity. Second, we assess whether this effect depends on that market's information environment, as postulated by our model.

A. POMOs and Market Liquidity

The main prediction of our model is that outright trades by the FRBNY (POMOs) lower the equilibrium price impact of order flow ($\Delta\lambda \equiv \lambda_{\text{CB}} - \lambda < 0$, Conclusion 1). Intuitively, this outcome stems from uninformative POMOs alleviating adverse selection risk for the MMs. As discussed in Section III.A.1, in this article, we capture a Treasury security's daily market liquidity with that security's average daily bid–ask price spread, $S_{i,t}$. Accordingly, our model predicts a *tighter* bid–ask spread (i.e., a lower $S_{i,t}$) for the targeted maturity bracket on days when POMOs occur.

To test this prediction, we use an event-study methodology based on a well-established literature analyzing the impact of exogenous public announcements on asset prices (e.g., see Andersen, Bollerslev, Diebold, and Vega (2003), (2007), and references therein). These studies estimate that impact using only announcement days to mitigate omitted variable biases. We begin by defining liquidity changes on any POMO day as $\Delta S_{i,t}^{B} \equiv S_{i,t} - S_{i,t}^{B}$, the difference between the average bid–ask price spread on the day a POMO occurred, $S_{i,t}$, and a benchmark pre-intervention level, $S_{i,t}^{B}$. Because POMOs often cluster in time (e.g., see Figure 3), we do not compare $S_{i,t}$ to the average bid–ask price spread on the day before a POMO occurred (i.e., $S_{i,t}^{B} = S_{i,t-1}$). Instead, we compute $S_{i,t}^{B}$ as the average bid–ask price spread over the most recent previous 22 trading days when no POMO occurred (e.g., Pasquariello (2007b)). In Section 2.3 of the Supplementary Material, we show that alternative pre-intervention intervals lead to similar inference (see also Section IV.B). We then compute means of these differences for each on-the-run Treasury note and bond in our BrokerTec sample i) over days when POMOs occurred in the corresponding maturity bracket (i.e., when the event dummy $I_{i,t}^{\text{CB}} = 1$) and ii) over days when *any* POMO occurred (i.e., when the event dummy $I_{t}^{\text{CB}} = 1$) because of extant evidence of relatively high substitutability of on-the-run Treasury securities (e.g., Cohen (1999), Greenwood and Vayanos (2010), and D'Amico and King (2013)).[23] We report these averages, labeled $\overline{\Delta S_{i,t}^{B}}$, in Table 3.[24]

Consistent with our model, these univariate tests show that mean daily bid–ask spreads *decline* on both *same-maturity* and *any-maturity* POMO days. Estimates for $\overline{\Delta S_{i,t}^{B}}$ in Table 3 are always negative, much larger than their sample

[23]Spillover of the positive liquidity externalities of government intervention described in Conclusion 1 across highly substitutable assets would likely occur in any model of multi-asset trading in which adverse selection considerations affect equilibrium market liquidity (e.g., see Pasquariello (2007a) and references therein).

[24]The occasional gaps in BrokerTec coverage and the quote-filtering procedures described in Section III.A result in a loss of some event days in the merged BrokerTec/POMO sample, especially for on-the-run 3-year notes (the issuance of which only resumed in 2003 after a 5-year hiatus; see Section III.A.1).

TABLE 3
POMOs and Market Liquidity

Table 3 reports means of daily bid–ask price spread changes $\Delta S_{i,t}^{B} \equiv S_{i,t} - S_{i,t}^{B}$ (labeled $\overline{\Delta S_{i,t}^{B}}$, in basis points (bps)) for on-the-run Treasury notes and bonds (i) over days when permanent open market operations (POMOs) occurred in the *same* maturity bracket ($I_{i,t}^{\text{CB}} = 1$) and over days when *any* POMO occurred ($I_{t}^{\text{CB}} = 1$). $S_{i,t}$ is the average bid–ask price spread on day t; $S_{i,t}^{B}$ is the average bid–ask price spread over the most recent previous 22 trading days when no POMO occurred. We also report ordinary least squares (OLS) estimates of the following regression models:

$$\Delta S_{i,t}^{B} = \gamma_{i,\text{CB}} + \gamma_{i,T}\text{TREND}_{t} + \gamma_{i,\Delta D}\Delta D_{i,t}^{B} + \gamma_{i,\Delta C}\Delta C_{i,t}^{B} + \varepsilon_{i,t}, \tag{8}$$

where $\Delta S_{i,t}^{B}$ is computed over POMO days, TREND_{t} is a time-trend variable, $\Delta D_{i,t}^{B} \equiv D_{i,t} - D_{i,t}^{B}$, $\Delta C_{i,t}^{B} \equiv C_{i,t} - C_{i,t}^{B}$, $D_{i,t}$ and $C_{i,t}$ are the daily modified duration and convexity, and $D_{i,t}^{B}$ and $C_{i,t}^{B}$ are their averages over the most recent previous 22 trading days when no POMO occurred, respectively; and

$$\Delta S_{i,t}^{B} = \alpha_{i,0} + \alpha_{i,C}\text{CALENDAR}_{t} + \alpha_{i,\Delta D}\Delta D_{i,t}^{B} + \alpha_{i,\Delta C}\Delta C_{i,t}^{B} + \alpha_{i,\text{CB}}I_{t} + \varepsilon_{i,t}, \tag{9}$$

where $\Delta S_{i,t}^{B}$ is computed over all days and CALENDAR_{t} is a vector of day-of-the-week, month, and year dummies, for both same-maturity ($I_{t} = I_{i,t}^{\text{CB}}$) and any-maturity POMOs ($I_{t} = I_{t}^{\text{CB}}$). Means and regression coefficients are estimated over the basic BrokerTec sample period (Jan. 1, 2001, to Dec. 31, 2007). Data for 3-year notes are available only between May 7, 2003, and Mar. 30, 2007. N is the number of observations. R_{a}^{2} is the adjusted R^{2}. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using Newey–West standard errors for $\alpha_{i,\text{CB}}$.

Segment	Same-Maturity POMO						Any-Maturity POMOs					
	$\overline{\Delta S_{i,t}^{B}}$	$\gamma_{i,\text{CB}}$	N	$\alpha_{i,\text{CB}}$	R_{a}^{2}	N	$\overline{\Delta S_{i,t}^{B}}$	$\gamma_{i,\text{CB}}$	N	$\alpha_{i,\text{CB}}$	R_{a}^{2}	N
2-year	–0.125***	–0.306***	157	–0.085***	8%	1,682	–0.130***	–0.314***	211	–0.089***	9%	1,682
3-year	–0.046*	–0.115**	58	0.013	11%	964	–0.087***	–0.257***	102	–0.023	11%	964
5-year	–0.215**	–0.594***	75	–0.141*	8%	1,686	–0.248***	–0.579***	210	–0.149***	12%	1,686
10-year	–0.074	–0.002	33	0.028	9%	1,563	–0.366***	–0.776***	196	–0.257***	10%	1,563
30-year	–0.591	–1.316	28	–0.294	6%	1,516	–0.778***	–1.337***	200	–0.539**	7%	1,516

means (in Table 1), and both statistically and economically significant at most maturities. Same-maturity POMOs have a more discernible impact on the liquidity of Treasury notes than on the liquidity of Treasury bonds (for which the number of event days is much smaller). For instance, total round-trip costs per daily trading volume in benchmark 5-year Treasury notes ($V_{i,t}$, in Table 1) decline on average by about \$380,000 ($\overline{\Delta S_{i,t}^{B}} = (-0.215/10{,}000) \times \$17.6$ billion) (i.e., by 37% of the sample standard deviation of $\Delta S_{i,t}^{B}$ (0.580, in Table 1)) on days when the Desk is trading these securities. Table 3 also provides evidence of liquidity spillovers in correspondence with any outright trade by the FRBNY: On any-maturity POMO days, estimates for $\overline{\Delta S_{i,t}^{B}}$ are negative, large (e.g., amounting to 7%–16% of their mean bid–ask spreads $S_{i,t}$, in Table 1), and statistically significant at all maturities (perhaps due to the greater number of any-maturity POMO days for both notes and bonds), regardless of the segment of the yield curve targeted by the Desk.[25] As discussed in Section III.B, these estimates are obtained from on-the-run Treasury securities in the targeted segments rather than from the actual securities being traded by the Desk because of the often scarce liquidity of the latter. Thus, they are likely to underestimate the true extent of the impact of POMOs on Treasury market liquidity.[26]

[25] Of course, the any-maturity POMO evidence in Table 3 is unaffected by the POMO classification into maturity brackets described in Section III.B (based on D'Amico and King (2013)). Untabulated analysis shows that alternative (including nonoverlapping) maturity brackets yield similar or stronger same-maturity POMO evidence.

[26] As noted earlier, during our sample period, the Desk generally refrained from executing POMOs with "on-the-run Treasury securities, which have larger liquidity premia and are typically

Improvements in Treasury market liquidity in proximity to POMOs may be due to changes in bond characteristics and calendar effects unrelated to FRBNY interventions. For instance, changes in Treasury securities' sensitivity to yield dynamics (as proxied by modified duration, $D_{i,t}$, and convexity, $C_{i,t}$) may affect their perceived riskiness to dealers and investors (e.g., Strebulaev (2002), Goldreich et al. (2005), and Pasquariello and Vega (2009)). Bid–ask spreads and trading activity also display weekly seasonality and time trends (e.g., Fleming (1997), (2003), Pasquariello and Vega (2007)). In particular, as noted previously, bid–ask spreads on the BrokerTec platform have considerably tightened (and trading volume has likewise increased) over our sample period, especially from 2005 onward. These effects may either enhance or distort the impact of POMOs on the process of price formation in the Treasury bond market.

We assess the robustness of our univariate inference to these considerations by specifying a multiple regression event-study model of bid–ask price spread changes, that is, for only same-maturity ($I_{i,t}^{\mathrm{CB}}=1$) or any-maturity POMO days ($I_t^{\mathrm{CB}}=1$), as follows:

$$\text{(8)} \qquad \Delta S_{i,t}^B = \gamma_{i,CB} + \gamma_{i,T}\mathrm{TREND}_t + \gamma_{i,\Delta D}\Delta D_{i,t}^B + \gamma_{i,\Delta C}\Delta C_{i,t}^B + \varepsilon_{i,t},$$

where TREND_t is a time-trend variable, $\Delta D_{i,t}^B \equiv D_{i,t} - D_{i,t}^B$, $\Delta C_{i,t}^B \equiv C_{i,t} - C_{i,t}^B$, and $D_{i,t}^B$ and $C_{i,t}^B$ are average modified duration and convexity over the most recent previous 22 trading days when no POMO occurred, respectively. We consider additional explicit controls in Section 2.4 of the Supplementary Material (see also Section IV.B). Estimates of the intercept $\gamma_{i,\mathrm{CB}}$ in equation (8) measure average changes in Treasury bid–ask spreads on POMO days (i.e., relative to the prior 22 non-POMO days) net of calendar effects and contemporaneous changes in bond characteristics. We also specify a similar model using all trading days:

$$\text{(9)} \qquad \Delta S_{i,t}^B = \alpha_{i,0} + \alpha_{i,C}\mathrm{CALENDAR}_t + \alpha_{i,\Delta D}\Delta D_{i,t}^B + \alpha_{i,\Delta C}\Delta C_{i,t}^B + \alpha_{i,\mathrm{CB}} I_t + \varepsilon_{i,t},$$

where either $I_t = I_{i,t}^{\mathrm{CB}}$ or $I_t = I_t^{\mathrm{CB}}$ and $\mathrm{CALENDAR}_t$ is a vector of day-of-the-week, month, and year dummies.[27] Estimates of the event dummy coefficient $\alpha_{i,\mathrm{CB}}$ in equation (9) capture any additional effect of POMOs on $\Delta S_{i,t}^B$ relative to its average over all other trading days in the sample period (i.e., the constant $\alpha_{i,0}$).

We estimate equations (8) and (9) for each on-the-run maturity in our database separately using ordinary least squares (OLS). We evaluate the statistical significance of the coefficients' estimates, reported in Table 3, with Newey–West standard errors to correct for heteroskedasticity and serial correlation. The results in Table 3 provide further support for our model's main prediction. Consistent with the prior univariate evidence, bid–ask spreads tend to decline (i.e., $\gamma_{i,\mathrm{CB}} < 0$

most susceptible to liquidity squeezes, so as to avoid adverse market impact" (FRBNY (2005), p. 20). Specifically, the Desk never executed POMOs with on-the-run securities over the pre-crisis period (2001–2007) and purchased only six of them (one per separate POMO day) during the financial crisis period (2008–2009) (versus an average of 73 Treasury securities per POMO day over 75 POMO days; Panel D of Table 2) (see also the discussion in Sections 2.2 and 2.4 of the Supplementary Material).

[27]The time series $S_{i,t}$ are made of several on-the-run securities *stacked* on one another over the sample period (as in Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007), (2009)). Unreported analysis shows our inference to be insensitive to the inclusion of security fixed effects in equations (8) and (9).

and $\alpha_{i,\text{CB}} < 0$) both when same-maturity and any-maturity POMOs occur, and this decline is especially significant for the latter (i.e., in correspondence with liquidity spillovers and a greater number of any-maturity POMO days). Controlling for calendar effects and bond characteristics strengthens our inference: For instance, all estimated intercepts $\gamma_{i,\text{CB}}$ in equation (8) are larger (in absolute magnitude) than the corresponding means $\overline{\Delta S_{i,t}^{B}}$. As in prior event-study research, POMOs' liquidity externalities are instead smaller when estimated over all trading days (i.e., $\left|\alpha_{i,\text{CB}}\right| < \left|\gamma_{i,\text{CB}}\right|$). Regardless of the methodology used, the estimated decline in bid–ask spread accompanying POMO days remains both statistically and economically significant (e.g., amounting on average to 53% (14%) of the corresponding sample mean (in Table 1), and to more than 50% (25%) of the standard deviation of the corresponding spread change (also in Table 1), when measured by $\gamma_{i,CB}$ ($\alpha_{i,\text{CB}}$)).

Last, we note that our empirical strategy follows Harvey and Huang (2002) in that we use an indicator variable for POMO days rather than estimate the effect of the magnitude of POMOs on Treasury market liquidity. As Harvey and Huang emphasize, such an estimation is problematic since the econometrician does not know how much of each POMO trade is unexpected by market participants.[28] In addition, our model predicts that the mere presence of government intervention improves market liquidity (Conclusion 1). However, both the actual central bank trade (x_{CB}) and market depth ($1/\lambda_{\text{CB}}$) are endogenously determined in equilibrium, as for any strategic order flow in Kyle (1985). Accordingly, most empirical literature advocates the use of *order imbalance* (number of transactions per period, in the spirit of equations (8) and (9)) instead of trading volume when assessing the impact of order flow on price formation in financial markets (see, e.g., Hasbrouck (1991), (2007), Jones, Kaul, and Lipson (1994), Evans and Lyons (2002), Chordia and Subrahmanyam (2004), Green (2004), Pasquariello and Vega (2007), Chordia, Hu, Subrahmanyam, and Tong (2019), and Pasquariello (2018)).[29]

B. POMOs and Market Liquidity: Robustness

The evidence in Table 3 suggests that Treasury market liquidity improves on POMO days, consistent with the main prediction of our model. In Section 2 of the Supplementary Material, we assess the robustness of this evidence and its conformity to alternative interpretations.

[28]For instance, the FRBNY has only recently begun to preannounce monthly and daily expected POMO amounts, while executing extraordinary monetary policy measures in the aftermath of the 2008–2009 financial crisis (i.e., since Aug. 2010, at https://www.newyorkfed.org/markets/tot_operation_schedule.html; see also Section 2.2 of the Supplementary Material and Section IV.B). Estimating those amounts would introduce generated-regressor biased standard errors in our empirical analysis. We nonetheless develop a proxy for uncertainty surrounding POMO policy in Section IV.C.3. The ensuing evidence suggests that our baseline empirical results in Table 3 are only weakened by assuming uniform POMO policy uncertainty on every POMO day in our sample.

[29]For example, when studying the microstructure of the U.S. stock market, (Jones et al. (1994), p. 631) find that "it is the occurrence of transactions per se, and not their size, that generates [price] volatility; trade size has no information beyond that contained in the frequency [i.e., number] of transactions." (Hasbrouck (2007), p. 90) attributes such findings to the fact that, as in our model of Section II, "agents trade large amounts when price impact is low, and small amounts when price impact is high." See also the discussion in Pasquariello (2018).

In particular, we find our inference to be qualitatively similar yet stronger within the earlier portion of our sample (2001–2004), when bid–ask spreads are much wider and more volatile, than in the calmer latter period (2005–2007), as well as robust to extending our analysis to all available GovPX data within our sample period (i.e., over 2001–2004) to account for the aforementioned gradual migration of most trading in on-the-run Treasury securities from voice-brokered (GovPX) to electronic intermediation (BrokerTec and eSpeed) (see Section 2.1 and Table IA1 of the Supplementary Material). We also find that the estimated liquidity externalities of the more numerous and larger POMOs executed during the recent financial crisis (2008–2009; Panel D of Table 2 and Figure 3) are consistent with our model's main prediction in Conclusion 1, despite the ensuing economic and financial turmoil (see, e.g., Figure 4) and likely effects on both liquidity provision (otherwise worsening; Figure 2 and Panel D of Table 1) and the Federal Reserve's policy goals in the Treasury market (see Section 2.2 and Table IA2 of the Supplementary Material).

We then ascertain that our inference is robust to such alternative specifications as the estimation of $\overline{\Delta S^{B}_{i,t}}$, $\gamma_{i,\mathrm{CB}}$, and $\alpha_{i,\mathrm{CB}}$ over *different* pre-intervention periods, during the *intraday* 90-minute Fed Time interval when the FRBNY typically announces and executes its POMOs (10:00AM to 11:30AM; see Section III.B) as well as for percentage bid–ask spreads $S_i \equiv (A_i - B_i) / \left[\frac{1}{2}(A_i + B_i)\right]$ (see Section 2.3 and Table IA3 of the Supplementary Material). Last, we consider several alternative interpretations of the evidence in Table 3 related to Treasury market conditions during POMO activity (like dealers' inventory levels, pre-auction illiquidity, bank reserves, or relative security supply) and show that our inference is robust to explicitly controlling for such additional factors related to those conditions as repo specialness, Treasury auction outcomes, pre–Fed Time and end-of-year on-the-run illiquidity, the Desk's repo-trading activity, reserve maintenance periods, dates of and distance from FOMC meetings, and the release of important U.S. macroeconomic announcements (listed in Section IV.C.1), hence mitigating potential omitted variable biases in that inference (notwithstanding the discussion in Section I) (see Section 2.4 and Table IA4 of the Supplementary Material).

C. POMOs and the Information Environment of the Market

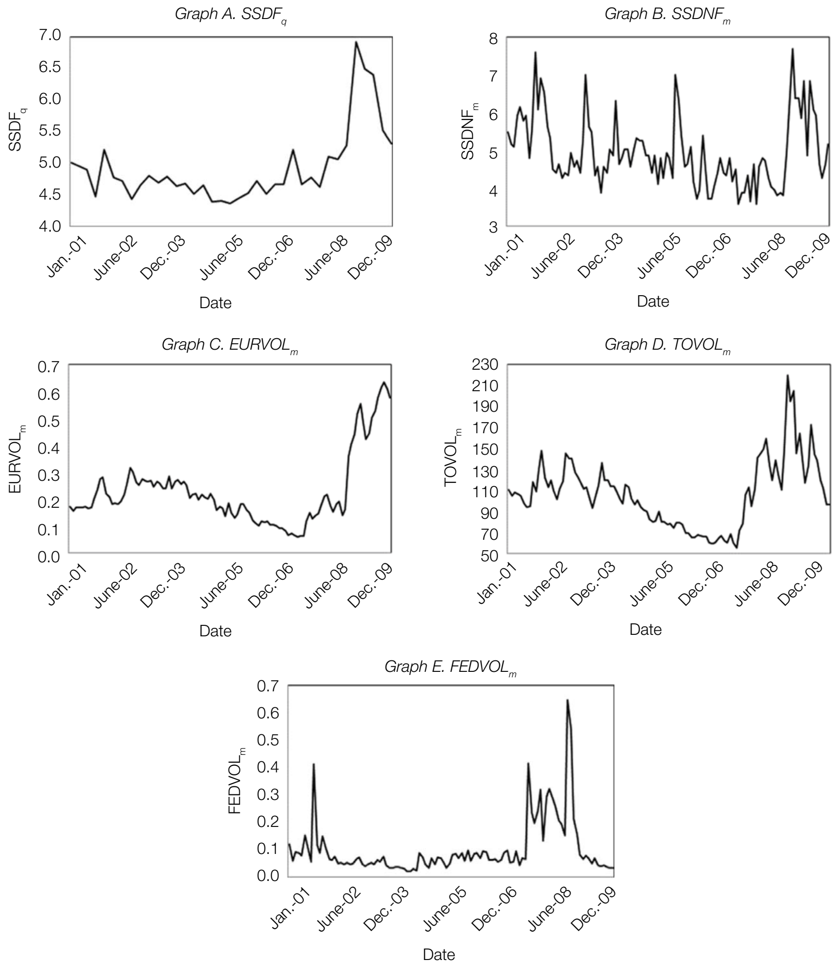
The evidence in Table 3 provides support for our model's main prediction (in Conclusion 1): POMOs executed by the FRBNY's Desk in the secondary market for Treasury securities meaningfully improve Treasury market liquidity. Our model attributes this effect to the impact of government intervention on the Treasury market's information environment. In this section, we assess more directly this basic, novel premise of our theory by testing its unique, additional predictions for Treasury market liquidity (also in Conclusion 1).

1. Information Heterogeneity

The first prediction from Conclusion 1 states that, ceteris paribus, greater information heterogeneity among speculators (i.e., lower ρ) magnifies the positive liquidity externalities of government intervention (i.e., a more negative $\Delta\lambda$, as in Graph C of Figure 1). Intuitively, more heterogeneously informed speculators trade more cautiously to protect their perceived private information monopoly.

FIGURE 4
Marketwide Information Variables

Figure 4 plots $SSDF_q$ (Graph A), the scaled simple average of standardized standard deviation of professional forecasts of six U.S. macroeconomic variables (unemployment, nonfarm payroll, nominal gross domestic product (GDP), consumer price index (CPI), industrial production, and housing starts) from the Survey of Professional Forecasters (SPF, see Section IV.C.1); $SSDNF_m$ (Graph B), the scaled standardized standard deviation of professional forecasts of nonfarm payroll from Bloomberg (Section IV.C.1); $EURVOL_m$ (Graph C), the monthly average of daily Eurodollar implied volatility (in percentage) from Bloomberg (Section IV.C.2); $TOVOL_m$ (Graph D), the monthly average of daily implied volatility on 1-month Treasury options from Merrill Lynch (Section IV.C.2); $FEDVOL_m$ (Graph E), the monthly average of daily volatility of the federal funds rate (in percentage) from the Federal Reserve Bank of New York (FRBNY) (Section IV.C.3), between Jan. 2001 and Dec. 2009.



The ensuing greater adverse selection risk for the MMs worsens market liquidity (i.e., increases the equilibrium price impact of aggregate order flow). In those circumstances, central bank trades attempting to achieve a nonpublic, uninformative policy target more significantly mitigate the more severe threat of adverse selection in market-making.

Testing for this prediction requires measurement of the heterogeneity of private information about fundamentals among sophisticated Treasury market participants. Marketwide information heterogeneity is commonly proxied by the standard deviation across professional forecasts of economic and financial variables (e.g., Diether, Malloy, and Scherbina (2002), Green (2004), and Yu (2011)). In this article we consider two proxies for ρ based on the notion that U.S. macroeconomic variables may contain payoff-relevant information for U.S. Treasury securities; accordingly, numerous studies find that government bond returns and market quality are sensitive to the release of these variables to the public (e.g., see Pasquariello and Vega (2007), Brenner, Pasquariello, and Subrahmanyam (2009), and references therein). These proxies employ the only continuously available surveys of U.S. macroeconomic forecasts over our sample period, namely those collected by the Federal Reserve Bank of Philadelphia (the Survey of Professional Forecasters (SPF)) and by Bloomberg.

The SPF, initiated in 1968 by the American Statistical Association and the National Bureau of Economic Research, is commonly used in empirical research on the formation of macroeconomic expectations. Croushore (1993) provides a detailed description of the SPF database. SPF data are available exclusively at the quarterly frequency. For each quarter q, the SPF database contains tens of individual forecasts by private sector economists (working at financial firms, banks, economic consulting firms, university research centers, and Fortune 500 companies) for various macroeconomic variables and at various future horizons. We focus on next-quarter forecasts for the most important of them: nonfarm payroll, unemployment, nominal gross domestic product (GDP), consumer price index (CPI), industrial production, and housing starts (e.g., Andersen and Bollerslev (1998), Andersen et al. (2003), (2007), Pasquariello and Vega (2007), Brenner et al. (2009), and Gilbert, Scotti, Strasser, and Vega (2017); see also Section 2.4 of the Supplementary Material and Section IV.B). Bloomberg surveys professional forecasts of U.S. macroeconomic announcements at the frequency of their release to the public. These data are available to us only for nonfarm payroll, which is released monthly and is labeled by (Andersen and Bollerslev (1998), p. 240) as the "king" of macroeconomic announcements because of its significant impact on financial markets.

We define the dispersion of beliefs among speculators for each macroeconomic variable p in the SPF data set in quarter q as the standard deviation of all of that variable's next-quarter forecasts available in that quarter, $\text{SDF}_{p,q}$. We similarly compute the monthly standard deviation of all of the nonfarm payroll forecasts available in Bloomberg in month m, SDNF_m. Since units of measurement differ across macroeconomic variables, we then divide the difference between each $\text{SDF}_{p,q}$ (or SDNF_m) and its sample mean by its sample standard deviation (e.g., Pasquariello and Vega (2007)) and then add 5 (to ensure that each information variable is always positive). This yields time series of scaled, standardized dispersion of analyst forecasts, $\text{SSDF}_{p,q}$ and SSDNF_m. Last, we compute our proxies for the *aggregate* degree of information heterogeneity about U.S. macroeconomic fundamentals as either SSDF_q (the simple average of all available $\text{SSDF}_{p,q}$; see Graph A of Figure 4) or SSDNF_m (see Graph B), such that the greater either proxy is, the lower ρ may be in the U.S. Treasury market.

As in Section IV.A, we assess the impact of marketwide information heterogeneity on POMOs' positive liquidity externalities in several ways. We estimate univariate regressions of average bid–ask spread changes $\Delta S^B_{i,t}$ over (same-maturity or any-maturity) POMO days alone ($I^{\mathrm{CB}}_{i,t}=1$ or $I^{\mathrm{CB}}_{t}=1$) on the contemporaneous realizations of either $X_t=\mathrm{SSDF}_q$ or $X_t=\mathrm{SSDNFP}_m$:

$$\text{(10)} \qquad \Delta S^B_{i,t} \quad = \quad \beta_{i,\mathrm{CB}}+\beta^x_{i,\mathrm{CB}}X_t+\varepsilon_{i,t}.$$

We also amend the multiple regression models of equations (8) and (9) to include either the information variable X_t (SSDF_q or SSDNFP_m) using only POMO days:

$$\text{(11)} \qquad \Delta S^B_{i,t} \quad = \quad \gamma_{i,CB}+\gamma_{i,T}\mathrm{CALENDAR}_t+\gamma_{i,\Delta D}\Delta D^B_{i,t} + \gamma_{i,\Delta C}\Delta C^B_{i,t}+\gamma^x_{i,CB}X_t+\varepsilon_{i,t},$$

or both X_t and its cross-products with same-maturity and any-maturity POMO dummies ($I_t=I^{\mathrm{CB}}_{i,t}$ and $I_t=I^{\mathrm{CB}}_{t}$) using all trading days:

$$\text{(12)} \quad \Delta S^B_{i,t} \quad = \quad \alpha_{i,0}+\alpha_{i,C}\mathrm{CALENDAR}_t+\alpha_{i,\Delta D}\Delta D^B_{i,t}+\alpha_{i,\Delta C}\Delta C^B_{i,t}+\alpha_{i,x}X_t + \alpha_{i,\mathrm{CB}}I_t+\alpha^x_{i,\mathrm{CB}}I_tX_t+\varepsilon_{i,t}.$$

Estimates of the slope coefficient $\beta^x_{i,\mathrm{CB}}$ in equation (10) capture any state dependency (from X_t) in bid–ask spread changes on POMO days alone. Estimates of the interaction coefficient $\gamma^x_{i,\mathrm{CB}}$ in equation (11) capture that state dependency while controlling for calendar effects and changes in bond characteristics. Estimates of the interaction coefficient $\alpha^x_{i,\mathrm{CB}}$ in equation (12) capture that state dependency with respect to changes over the whole sample period.[30]

The linear specifications of equations (10)–(12) are standard in the literature (e.g., see Pasquariello and Vega (2015), Pasquariello (2018)) and allow us to estimate the statistical significance of the continuous effect of any state variable X_t on POMOs' liquidity externalities. However, the scale of X_t affects the scale of the resulting OLS estimates for $\beta^x_{i,\mathrm{CB}}$, $\gamma^x_{i,\mathrm{CB}}$, and $\alpha^x_{i,\mathrm{CB}}$. Thus, exclusively to ease their interpretation and assess their economic significance, we multiply each of those coefficients by a hypothetical discrete increase in the information variable X_t from the bottom (i.e., "low") 30th percentile ($X^{30\mathrm{th}}_t$) to the top (i.e., "high") 70th percentile ($X^{70\mathrm{th}}_t$) of its empirical distribution. We report these scaled estimates $\overline{\Delta\Delta S^{B,x}_{i,t}}\equiv\beta^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$, $\Delta\gamma^x_{i,\mathrm{CB}}\equiv\gamma^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$, and $\Delta\alpha^x_{i,\mathrm{CB}}\equiv\alpha^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$ for either $X_t=\mathrm{SSDF}_q$ or $X_t=\mathrm{SSDNFP}_m$ in Panels A and B of Table 4, respectively. By construction, $\overline{\Delta\Delta S^{B,x}_{i,t}}$, $\Delta\gamma^x_{i,\mathrm{CB}}$, and $\Delta\alpha^x_{i,\mathrm{CB}}$ are in the same unit as the dependent variable $\Delta S^B_{i,t}$ (i.e., bps); their sign and statistical significance are unaffected by alternative scaling factors (e.g., different high–low ranges for X_t or the sample standard deviation of X_t).

[30] According to our basic model (see Proposition 1, in Section II.A) and extant empirical evidence (e.g., Pasquariello and Vega (2007)), the Treasury market's information environment may affect its equilibrium liquidity (λ of equation (3)) even in the absence of central bank interventions (i.e., even on non-POMO days). Thus, our low-frequency information measures X_t are likely to impact both $S_{i,t}$ and $S^B_{i,t}$, such that these effects may cancel out in $\Delta S^B_{i,t}\equiv S_{i,t}-S^B_{i,t}$. Consistently, untabulated estimates of $\alpha_{i,x}$ in equation (12) reveal $\Delta S^B_{i,t}$ to be largely insensitive to X_t on non-POMO days.

TABLE 4
POMOs and Information Heterogeneity

Table 4 reports ordinary least squares (OLS) slope coefficients $\beta^x_{i,\mathrm{CB}}$ of the following regression of average daily bid–ask spread and price changes $\Delta S^B_{i,t}$ (in basis points (bps), defined in Section IV.A) for on-the-run Treasury notes and bonds (i) over *same* -maturity or *any*-maturity permanent open market operation (POMO) days ($I^{\mathrm{CB}}_{i,t}=1$ or $I^{\mathrm{CB}}_t=1$) on the contemporaneous realizations of either $X_t=\mathrm{SSDF}_q$ (the simple scaled average of the standardized dispersion of analyst forecasts of six macroeconomic variables from the Survey of Professional Forecasters (SPF), see Section IV.C.1; in Panel A) or $X_t=\mathrm{SSDNF}_m$ (the scaled standardized dispersion of analyst forecasts of nonfarm payroll from Bloomberg, see Section IV.C.1; in Panel B) multiplied by the difference between $X^{70\mathrm{th}}_t$ (the top 70th percentile of its empirical distribution) and $X^{30\mathrm{th}}_t$ (the bottom 30th percentile of its empirical distribution):

$$\Delta S^B_{i,t} = \beta_{i,\mathrm{CB}}+\beta^x_{i,\mathrm{CB}}X_t+\varepsilon_{i,t}. \tag{10}$$

We label these differences as $\overline{\Delta\Delta S^{B,x}_{i,t}}\equiv\beta^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$. We also estimate, again by OLS, both the effect of either $X_t=\mathrm{SSDF}_q$ or $X_t=\mathrm{SSDNF}_m$ on $\Delta S^B_{i,t}$ in event time (slope $\gamma^x_{i,\mathrm{CB}}$):

$$\Delta S^B_{i,t} = \gamma_{i,CB}+\gamma_{i,T}\mathrm{TREND}_t+\gamma_{i,\Delta D}\Delta D^B_{i,t}+\gamma_{i,\Delta C}\Delta C^B_{i,t}+\gamma^x_{i,\mathrm{CB}}X_t+\varepsilon_{i,t}, \tag{11}$$

as well as the interaction of either $I_t=I^{\mathrm{CB}}_{i,t}$ or $I_t=I^{\mathrm{CB}}_t$ with either $X_t=\mathrm{SSDF}_q$ or $X_t=\mathrm{SSDNF}_m$ over the full sample (interaction $\alpha^x_{i,\mathrm{CB}}$):

$$\Delta S^B_{i,t} = \alpha_{i,0}+\alpha_{i,C}\mathrm{CALENDAR}_t+\alpha_{i,\Delta D}\Delta D^B_{i,t}+\alpha_{i,\Delta C}\Delta C^B_{i,t}+\alpha_{i,x}X_t+\alpha_{i,\mathrm{CB}}I_t+\alpha^x_{i,\mathrm{CB}}I_tX_t+\varepsilon_{i,t}. \tag{12}$$

We report these slope and interaction coefficients as $\Delta\gamma^x_{i,\mathrm{CB}}\equiv\gamma^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$ and $\Delta\alpha^x_{i,\mathrm{CB}}\equiv\alpha^x_{i,\mathrm{CB}}\left(X^{70\mathrm{th}}_t-X^{30\mathrm{th}}_t\right)$, again in bps. Means and regression coefficients are estimated over the basic BrokerTec sample period (Jan. 1, 2001, to Dec. 31, 2007). Data for 3-year notes are available only between May 7, 2003, and Mar. 30, 2007. N is the number of observations. R^2_a is the adjusted R^2. *, **, and *** indicate statistical significance at the 10%, 5%, or 1% levels, respectively, using Newey–West standard errors for $\alpha^x_{i,\mathrm{CB}}$.

Segment	Same-Maturity POMOs						Any-Maturity POMOs					
	$\overline{\Delta\Delta S^{B,x}_{i,t}}$	$\Delta\gamma^x_{i,\mathrm{CB}}$	N	$\Delta\alpha^x_{i,\mathrm{CB}}$	R^2_a	N	$\overline{\Delta\Delta S^{B,x}_{i,t}}$	$\Delta\gamma^x_{i,\mathrm{CB}}$	N	$\Delta\alpha^x_{i,\mathrm{CB}}$	R^2_a	N
Panel A. $X_t=SSDF_q$												
2-year	−0.099***	−0.061***	157	−0.086***	9%	1,682	−0.107***	−0.067***	211	−0.092***	11%	1,682
3-year	0.011	0.003	58	0.014	10%	964	−0.023	−0.047**	102	−0.017	11%	964
5-year	−0.220***	−0.150	75	−0.172	9%	1,686	−0.206***	−0.137***	210	−0.167***	13%	1,686
10-year	−0.274*	−0.461*	33	−0.297*	9%	1,563	−0.361***	−0.248***	196	−0.295***	11%	1,563
30-year	−1.537**	−1.897*	28	−1.664**	7%	1,516	−0.247	−0.051	200	−0.373	7%	1,516
Panel B. $X_t=SSDNF_m$												
2-year	−0.064***	−0.065***	157	−0.056**	9%	1,682	−0.068***	−0.015**	211	−0.058**	10%	1,682
3-year	0.002	0.008	58	0.006	11%	964	−0.008	−0.028*	102	0.018	11%	964
5-year	0.080	0.096	75	0.059	9%	1,686	−0.074*	−0.051	210	−0.062	12%	1,686
10-year	−0.337*	−0.329	33	−0.282	9%	1,563	−0.117**	−0.011	196	−0.118**	10%	1,563
30-year	−0.425	−0.541	28	−0.223	6%	1,516	−0.098	−0.069	200	0.075	7%	1,516

Consistent with Conclusion 1, POMOs' positive liquidity externalities are increasing in our proxies for marketwide information heterogeneity (i.e., decreasing in ρ) ($\overline{\Delta\Delta S^{B,x}_{i,t}}$, $\Delta\gamma^x_{i,\mathrm{CB}}$, and $\Delta\alpha^x_{i,\mathrm{CB}}$ are negative and statistically significant) in correspondence with both same-maturity ($I^{\mathrm{CB}}_{i,t}=1$) and any-maturity POMOs ($I^{\mathrm{CB}}_t=1$) for both on-the-run Treasury notes and bonds. For instance, Panel A of Table 4 shows that, on average, bid–ask spreads for 2-year, 5-year, and 10-year Treasury notes on any-maturity POMO days when our broad-based proxy for marketwide dispersion of beliefs $X_t=\mathrm{SSDF}_q$ is high decline by roughly 110% (of the baseline effect in Table 3) more (or about 0.185 bps more) than when SSDF_q is low (i.e., mean significant $\Delta\alpha^x_{i,\mathrm{CB}}/\alpha_{i,\mathrm{CB}}=1.10$). Panel A of Table 4 further indicates that, in correspondence with government intervention at the long-end of the yield curve, bid–ask spreads for 30-year Treasury bonds when SSDF_q is high are nearly 2 bps lower than when SSDF_q is low (i.e., $\overline{\Delta\Delta S^{B,x}_{i,t}}=-1.537$, $\Delta\gamma^x_{i,\mathrm{CB}}=-1.897$, and $\Delta\alpha^x_{i,\mathrm{CB}}=-1.664$). Those estimates are qualitatively similar, albeit smaller and less often statistically significant, when obtained from the (noisier) monthly series of dispersion of nonfarm payroll forecasts alone (i.e., when $X_t = \text{SSDNF}_m$; see Graph B of Figure 4) in Panel B. This evidence suggests that government interventions have a greater impact on the process of price formation in the secondary market for Treasury securities when information heterogeneity among speculators is high, as postulated by our model.

2. Fundamental Uncertainty

The second prediction from Conclusion 1 states that, ceteris paribus, greater uncertainty about the traded asset's payoff (i.e., higher σ_v^2) amplifies the impact of government intervention on market liquidity (i.e., leads to higher $|\Delta\lambda|$ (Graph D of Figure 1)). Greater fundamental uncertainty worsens equilibrium market liquidity because it makes speculators' private information more valuable and the accompanying adverse selection risk for the MMs more severe. As discussed previously, this enhances the positive liquidity externalities of central bank trades.

To evaluate this implication of our model, we use two proxies for σ_v^2. The first is EURVOL_m (plotted in Graph C of Figure 4), the monthly average (to smooth daily variability) of daily Eurodollar implied volatility from Bloomberg. The second is TOVOL_m (in Graph D of Figure 4), the monthly average of daily realizations of the yield-curve-weighted MOVE index of the normalized implied volatility on 1-month Treasury options from Merrill Lynch. Both EURVOL_m and TOVOL_m are commonly used as measures of market participants' perceived uncertainty surrounding U.S. macroeconomic fundamentals (e.g., Bernanke and Kuttner (2005), Pasquariello and Vega (2009)). We then run the same univariate and multiple regressions for spread change differentials described in Section IV.C.1, which yield scaled estimates $\overline{\Delta\Delta S_{i,t}^{B,x}}$ for the former, $\Delta\gamma_{i,\text{CB}}^x$ and $\Delta\alpha_{i,\text{CB}}^x$ for the latter, after imposing that either $X_t = \text{EURVOL}_m$ or $X_t = \text{TOVOL}_m$. We report these estimates in Panels A and B of Table 5, respectively.

Consistent with Conclusion 1, $\overline{\Delta\Delta S_{i,t}^{B,x}}$, $\Delta\gamma_{i,\text{CB}}^x$, and $\Delta\alpha_{i,\text{CB}}^x$ are always negative in Table 5 and nearly always statistically significant when proxying for fundamental uncertainty with $X_t = \text{TOVOL}_m$. For example, Panel B of Table 5 shows that during any-maturity POMO days when TOVOL_m is historically high, the bid–ask spreads for 10-year Treasury notes decline by roughly 0.3 bps more than when TOVOL_m is low (i.e., a statistically significant $\overline{\Delta\Delta S_{i,t}^{B,x}} = -0.309$, $\Delta\gamma_{i,\text{CB}}^x = -0.271$, and $\Delta\alpha_{i,\text{CB}}^x = -0.295$). This effect is economically significant as well because it amounts to roughly 32% of the sample standard deviation of $\Delta S_{i,t}^B$ in Table 1. Those estimates are rarely statistically significant for $X_t = \text{EURVOL}_m$, in Panel A of Table 5. However, in those circumstances bid–ask spreads tighten much more pronouncedly on POMO days characterized by higher Eurodollar volatility (e.g., by no less than 100% of the baseline decline in spread reported in Table 3). This evidence suggests that government interventions are accompanied by a greater improvement in Treasury market liquidity when fundamental uncertainty is greater, as implied by our model.

3. POMO Policy Uncertainty

The last prediction from Conclusion 1 states that, ceteris paribus, greater uncertainty about the central bank's uninformative policy target p_T among market

TABLE 5
POMOs and Fundamental Uncertainty

Table 5 reports ordinary least squares (OLS) estimates of the slope coefficient $\beta^{x}_{i,\mathrm{CB}}$ from equation (10) and the interaction coefficients $\gamma^{x}_{i,\mathrm{CB}}$ and $\alpha^{x}_{i,\mathrm{CB}}$ from equations (11) and (12) for on-the-run Treasury notes and bonds and *same*-maturity or *any*-maturity permanent open market operations (POMOs, as in Table 4) over the basic BrokerTec sample period (Jan. 1, 2001, to Dec. 31, 2007) when either $X_t = \mathrm{EURVOL}_m$ (the monthly average of daily Eurodollar implied volatility from Bloomberg, see Section IV.C.2; in Panel A) or $X_t = \mathrm{TOVOL}_m$ (the monthly average of daily implied volatility on Treasury options from Merrill Lynch, see Section IV.C.2; in Panel B), multiplied by the difference between $X_t^{70\mathrm{th}}$ (the top 70th percentile of its empirical distribution) and $X_t^{30\mathrm{th}}$ (the bottom 30th percentile of its empirical distribution). We label these differences (in basis points (bps)) as $\overline{\Delta\Delta S^{B,x}_{i,t}} \equiv \beta^{x}_{i,\mathrm{CB}}\,(X_t^{70\mathrm{th}} - X_t^{30\mathrm{th}})$, $\Delta\gamma^{x}_{i,CB} \equiv \gamma^{x}_{i,\mathrm{CB}}\,(X_t^{70\mathrm{th}} - X_t^{30\mathrm{th}})$, and $\Delta\alpha^{x}_{i,\mathrm{CB}} \equiv \alpha^{x}_{i,\mathrm{CB}}\,(X_t^{70\mathrm{th}} - X_t^{30\mathrm{th}})$. N is the number of observations. R^2_a is the adjusted R^2. *, **, and *** indicate statistical significance at the 10%, 5%, or 1% levels, respectively, using Newey–West standard errors for $\alpha^{x}_{i,\mathrm{CB}}$.

Segment	Same-Maturity POMOs						Any-Maturity POMOs					
	$\overline{\Delta\Delta S^{B,x}_{i,t}}$	$\Delta\gamma^{x}_{i,\mathrm{CB}}$	N	$\Delta\alpha^{x}_{i,\mathrm{CB}}$	R^2_a	N	$\overline{\Delta\Delta S^{B,x}_{i,t}}$	$\Delta\gamma^{x}_{i,\mathrm{CB}}$	N	$\Delta\alpha^{x}_{i,\mathrm{CB}}$	R^2_a	N
Panel A. $X_t = EURVOL_m$												
2-year	−0.015	−0.091***	157	−0.027	9%	1,682	−0.026	−0.076***	211	−0.034	10%	1,682
3-year	−0.051*	−0.008	58	−0.025	10%	964	−0.130***	0.024	102	−0.086**	11%	964
5-year	−0.039	−0.154	75	−0.060	9%	1,686	−0.023	−0.182***	210	−0.049	13%	1,686
10-year	−0.398	−0.513	33	−0.323***	9%	1,563	−0.123	0.192	196	−0.154**	11%	1,563
30-year	−0.898	−1.171	28	−0.479	7%	1,516	−0.452	−0.246	200	−0.340	8%	1,516
Panel B. $X_t = TOVOL_m$												
2-year	−0.102***	−0.107***	157	−0.093***	9%	1,682	−0.117***	−0.123***	211	−0.102***	10%	1,682
3-year	−0.076**	−0.069*	58	−0.049	11%	964	−0.159***	−0.150***	102	−0.126***	12%	964
5-year	−0.198*	−0.206*	75	−0.176**	9%	1,686	−0.185***	−0.176**	210	−0.147***	12%	1,686
10-year	−0.355	−0.301	33	−0.372***	9%	1,563	−0.309***	−0.271***	196	−0.295***	11%	1,563
30-year	−1.500	−1.959	28	−1.407**	6%	1,516	−0.584	−0.652*	200	−0.578**	7%	1,516

participants (i.e., higher σ^2_T) enhances the improvement in equilibrium market liquidity accompanying its trades ($\Delta\lambda$, as in Graph B of Figure 1). Greater policy uncertainty complicates the MMs' attempt at accounting for the extent of uninformative government intervention in the aggregate order flow before setting the equilibrium price p_1. However, it also lowers their perceived adverse selection risk from trading with informed speculators.

As discussed in Sections II.B and III.B, the FRBNY's Desk targets the aggregate level of nonborrowed reserves available in the banking system via uninformative POMOs to ensure that conditions in the federal funds rate market are "consistent" with the publicly known target rate set by the FOMC.[31] Thus, uncertainty among market participants about the FRBNY's nonpublic and uninformative reserve target for POMOs may manifest itself in the federal funds market. Accordingly, we measure marketwide policy uncertainty surrounding the Desk's POMOs with FEDVOL_m (plotted in Graph E of Figure 4), the monthly average (to smooth daily variability) of daily standard deviation of the federal funds rate, from the FRBNY (these data are available at https://apps.newyorkfed.org/markets/autorates/fed%20funds). Importantly, in unreported analysis we find FEDVOL_m to be virtually unrelated to our proxies for marketwide dispersion of beliefs (ρ) and uncertainty (σ^2_v) about U.S. macroeconomic fundamentals described in Sections IV.C.1 and IV.C.2. We then assess the sensitivity of spread changes in

[31]For example, the Web site of the FRBNY (https://www.newyorkfed.org/markets/pomo_landing.html) states that "purchases or sales of Treasury securities on an outright basis have been used historically to manage the supply of reserves in the banking system…to maintain conditions in the market for bank reserves consistent with the federal funds target rate set by the [FOMC]."

correspondence with POMOs to $X_t = \text{FEDVOL}_m$ by means of the same univariate and multiple regressions of Section IV.C.1.

Both sets of tests in Table 6 provide further support for our model. As postulated by Conclusion 1, once again the resulting scaled estimates $\overline{\Delta\Delta S_{i,t}^{B,x}}$, $\Delta\gamma_{i,\text{CB}}^{x}$, and $\Delta\alpha_{i,\text{CB}}^{x}$ are negative for most maturities and in correspondence with both same-maturity ($I_{i,t}^{\text{CB}} = 1$) and any-maturity POMOs ($I_t^{\text{CB}} = 1$). Hence, these estimates suggest that liquidity improves more pronouncedly on POMO days when uncertainty about the Desk's policy (proxied by FEDVOL_m) is greater. This effect is especially strong for 30-year Treasury bonds. According to Table 6, those bonds' bid–ask price spreads on same-maturity POMO days when FEDVOL_m is historically high are about 1.7 bps ($\overline{\Delta\Delta S_{i,t}^{B,x}} = -1.657$ and $\Delta\alpha_{i,\text{CB}}^{x} = -1.740$, or about 20% of its sample mean in Table 1) lower than when FEDVOL_m is low. Table 6 also shows that, when negative and statistically significant, the estimated slope and cross-product coefficients $\Delta\gamma_{i,\text{CB}}^{x}$ and $\Delta\alpha_{i,\text{CB}}^{x}$ for Treasury securities of shorter maturity are also large (e.g., 14%–63% of the baseline estimated decline of their bid–ask spreads on any-maturity POMO days in Table 3 (i.e., of $\gamma_{i,\text{CB}}$ and $\alpha_{i,\text{CB}}$ of equations (8) and (9), respectively)).

TABLE 6

POMOs and POMO Policy Uncertainty

Table 6 reports ordinary least squares (OLS) estimates of the slope coefficient $\beta_{i,\text{CB}}^{x}$ from equation (10) and the interaction coefficients $\gamma_{i,\text{CB}}^{x}$ and $\alpha_{i,\text{CB}}^{x}$ from equations (11) and (12) for on-the-run Treasury notes and bonds and *same*-maturity or *any*-maturity permanent open market operations (POMOs, as in Table 4) over the basic BrokerTec sample period (Jan. 1, 2001, to Dec. 31, 2007) when $X_t = \text{FEDVOL}_m$ (the monthly average of daily volatility of the federal funds rate, from the Federal Reserve Bank of New York (FRBNY), see Section IV.C.3), multiplied by the difference between $X_t^{70\text{th}}$ (the top 70th percentile of its empirical distribution) and $X_t^{30\text{th}}$ (the bottom 30th percentile of its empirical distribution). We label these differences (in basis points (bps)) as $\overline{\Delta\Delta S_{i,t}^{B,x}} \equiv \beta_{i,\text{CB}}^{x}\left(X_t^{70\text{th}} - X_t^{30\text{th}}\right)$, $\Delta\gamma_{i,\text{CB}}^{x} \equiv \gamma_{i,\text{CB}}^{x}\left(X_t^{70\text{th}} - X_t^{30\text{th}}\right)$, and $\Delta\alpha_{i,\text{CB}}^{x} \equiv \alpha_{i,\text{CB}}^{x}\left(X_t^{70\text{th}} - X_t^{30\text{th}}\right)$. N is the number of observations. R_a^2 is the adjusted R^2. *, **, and *** indicate statistical significance at the 10%, 5%, or 1% levels, respectively, using Newey–West standard errors for $\alpha_{i,\text{CB}}^{x}$.

	$X_t = \text{FEDVOL}_m$											
	Same-Maturity POMOs						Any-Maturity POMOs					
Segment	$\overline{\Delta\Delta S_{i,t}^{B,x}}$	$\Delta\gamma_{i,\text{CB}}^{x}$	N	$\Delta\alpha_{i,\text{CB}}^{x}$	R_a^2	N	$\overline{\Delta\Delta S_{i,t}^{B,x}}$	$\Delta\gamma_{i,\text{CB}}^{x}$	N	$\Delta\alpha_{i,\text{CB}}^{x}$	R_a^2	N
2-year	−0.061***	−0.062***	157	−0.046*	9%	1,682	−0.076***	−0.076***	211	−0.056**	10%	1,682
3-year	0.048**	0.041	58	0.012	11%	964	0.082***	0.073***	102	0.044***	12%	964
5-year	−0.183*	−0.174*	75	−0.157	9%	1,686	−0.094**	−0.083***	210	−0.055	12%	1,686
10-year	0.157	0.071	33	0.039	9%	1,563	−0.105**	−0.106***	196	−0.111***	10%	1,563
30-year	−1.657*	−1.627	28	−1.740***	7%	1,516	0.012	0.004	200	−0.124	7%	1,516

In short, the evidence in Tables 4–6 indicates that the Treasury market's information environment importantly affects the impact of government interventions on its process of price formation, as uniquely predicated by our model, thus also further alleviating the aforementioned concerns about alternative interpretations and potential omitted variable biases plaguing our inference from Table 3.

V. Conclusions

The many severe episodes of financial turmoil affecting the global economy in the past decade have led to increasing calls for greater, more direct involvement of governments and monetary authorities in the process of price formation in financial markets. The objective of this article is to shed light on the implications of this involvement for financial market quality.

To that purpose, we investigate the impact of permanent open market operations (POMOs) by the Federal Reserve Bank of New York (FRBNY) (on behalf of the Federal Reserve System) on the liquidity of the secondary U.S. Treasury bond market. POMOs are outright (i.e., definitive) trades in previously issued U.S. Treasury securities (i.e., permanently affecting the supply of nonborrowed reserves in the banking system) to accomplish a nonpublic, uninformative reserve target consistent with the monetary policy stance set and publicly announced by the Federal Open Market Committee (FOMC). To guide our analysis, we construct a parsimonious model of trading in the Treasury market in which (consistent with much recent empirical evidence) the presence of strategic, heterogeneously informed speculators enhances adverse selection risk for uninformed market-makers (MMs). In this basic setting, we introduce a stylized central bank facing a trade-off between a nonpublic, uninformative policy goal and its expected cost. The main novel insight of our model is twofold. First, contrary to existing literature, the central bank's trading activity *improves* equilibrium market liquidity because it alleviates MMs' adverse selection concerns when facing the aggregate order flow, thanks to the uninformativeness of its nonpublic target. Second, the extent of this improvement is sensitive to the market's information environment.

Our subsequent empirical analysis of a comprehensive sample of price formation and FRBNY trades in the secondary U.S. Treasury market during the 2000s provides support for these predictions. Our evidence shows that i) bid–ask spreads for on-the-run Treasury notes and bonds *decline* on days when the FRBNY executes POMOs and ii) the estimated magnitude of this decline on POMO days is greater when Treasury market liquidity is lower, and it is increasing in measures of volatility of U.S. economic fundamentals, marketwide dispersion of beliefs about them, and uncertainty about the FRBNY's POMO policy, as implied by our model.

Overall, these findings indicate that the externalities of government intervention in financial markets for their process of price formation may be economically and statistically significant as well as crucially related to the information environment of the targeted markets. We believe these are important contributions to current and future research on official trading activity and market manipulation.

Appendix

Proof of Proposition 1. The proof is by construction: We first conjecture general linear functions for the pricing rule and speculators' demands; we then solve for their parameters satisfying Conditions 1 and 2; finally, we show that these parameters and functions represent a rational expectations equilibrium. We start by guessing that equilibrium p_1 and $x(m)$ are given by $p_1 = A_0 + A_1\omega_1$ and $x(m) = B_0 + B_1\delta_v(m)$, respectively, where $A_1 > 0$. Those expressions and the definition of ω_1 imply that, for each speculator m,

$$\text{(A-1)}\qquad E\left[p_1|\delta_v(m)\right] = A_0 + A_1x(m) + A_1B_0(M-1) + A_1B_1(M-1)\rho\delta_v(m).$$

Using equation (A-1), the first-order condition of the maximization of each speculator m's expected profit $\mathrm{E}[\pi(m)|\delta_v(m)]$ with respect to $x(m)$ is given by

$$\text{(A-2)}\quad p_0 + \delta_v(m) - A_0 - (M+1)A_1B_0 - 2A_1B_1\delta_v(m) - (M-1)A_1B_1\rho\delta_v(m) = 0.$$

The second-order condition is satisfied since $2A_1 > 0$. For equation (A-2) to be true, it must be that

$$\text{(A-3)} \qquad p_0 - A_0 = (M+1)\, A_1 B_0,$$
$$\text{(A-4)} \qquad 2A_1 B_1 = 1 - (M-1)\, A_1 B_1 \rho.$$

The distributional assumptions of Section II.A imply that the order flow ω_1 is normally distributed with mean $\mathrm{E}(\omega_1) = M B_0$ and variance $\mathrm{var}(\omega_1) = M B_1^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2$. Since $\mathrm{cov}(v, \omega_1) = M B_1 \rho \sigma_v^2$, it ensues that

$$\text{(A-5)} \qquad E(v|\omega_1) = p_0 + \frac{M B_1 \rho \sigma_v^2}{M B_1^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2} (\omega_1 - M B_0).$$

According to the definition of a Bayesian Nash equilibrium in this economy (Section II.A), $p_1 = \mathrm{E}(v|\omega_1)$. Therefore, our conjecture for p_1 yields

$$\text{(A-6)} \qquad A_0 = p_0 - M A_1 B_0,$$
$$\text{(A-7)} \qquad A_1 = \frac{M B_1 \rho \sigma_v^2}{M B_1^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2}.$$

The expressions for A_0, A_1, B_0, and B_1 in Proposition 1 must solve the system made of equations (A-3), (A-4), (A-6), and (A-7) to represent a linear equilibrium. Defining $A_1 B_0$ from equation (A-3) and plugging it into equation (A-6) leads us to $A_0 = p_0$. Thus, it must be that $B_0 = 0$ to satisfy equation (A-3). We are left with the task of finding A_1 and B_1. Solving equation (A-4) for A_1, we get

$$\text{(A-8)} \qquad A_1 = \frac{1}{B_1 [2 + (M-1)\rho]}.$$

It then follows from equating equation (A-8) to equation (A-7) that $B_1^2 = \sigma_z^2 / \left(\sigma_v^2 M \rho\right)$, (i.e., that $B_1 = \sigma_z / \left(\sigma_v \sqrt{M\rho}\right)$). Substituting this expression back into equation (A-8) implies that $A_1 = \sigma_v \sqrt{M\rho} / \{\sigma_z [2 + (M-1)\rho]\}$. Finally, we observe that Proposition 1 is equivalent to a symmetric Cournot equilibrium with M speculators. Therefore, the "backward reaction mapping" introduced by Novshek (1984) to find n-firm Cournot equilibriums can be used to prove that, given any linear pricing rule, the symmetric linear strategies $x(m)$ of equation (2) indeed represent the unique Bayesian Nash equilibrium of the Bayesian game among speculators (Caballé and Krishnan (1994)). □

Proof of Corollary 1. The first part of the statement stems from the fact that $\partial\lambda/\partial\sigma_v = \sqrt{M\rho}/\{\sigma_z[2 + (M-1)\rho]\} > 0$. Furthermore, $\partial\lambda/\partial\rho = -\sigma_v \sqrt{M}[(M-1)\rho - 2]/\{2\sigma_z \sqrt{\rho}\,[2 + (M-1)\rho]^2\} < 0$ except in the small region of $\{M, \rho\}$ where $\rho \leq 2/(M-1)$. □

Proof of Proposition 2. The outline of the proof is similar to that of Proposition 1 (see also the proof of Proposition 2 in Pasquariello (2018)). We begin by conjecturing the following functional forms for the equilibrium price and trading activity of speculators and the central bank: $p_1 = A_0 + A_1\omega_1$, $x(m) = B_0 + B_1\delta_v(m)$ and $x_{\mathrm{CB}} = C_0 + C_1\delta_{\mathrm{CB}} + C_2\delta_T$, respectively, where $A_1 > 0$. Since $\mathrm{E}[\delta_{\mathrm{CB}}|\delta_v(m)] = \psi\delta_v(m)$ and $\mathrm{E}[\delta_v(m)|\delta_{\mathrm{CB}}] = \rho\delta_{\mathrm{CB}}$, the previous expressions and the definition of ω_1 imply that, for each speculator m and the central bank,

$$\text{(A-9)} \qquad E\left[p_1|\delta_v(m)\right] = A_0 + A_1 x(m) + A_1 B_0 (M-1) + A_1 B_1 (M-1)\rho\delta_v(m) + A_1 C_0 + A_1 C_1 \psi \delta_v(m),$$

$$\text{(A-10)} \qquad E\left[p_1|\delta_{\mathrm{CB}}, \delta_T\right] = A_0 + A_1 x_{\mathrm{CB}} + M A_1 B_0 + M A_1 B_1 \rho \delta_{\mathrm{CB}},$$

respectively. Equation (A-9) leads to the following expression for the first-order condition of the maximization of each speculator m's $\mathrm{E}[\pi(m)|\delta_v(m)]$:

$$\text{(A-11)} \qquad p_0+\delta_v(m)-A_0-2A_1x(m)-(M-1)A_1B_0 - (M-1)A_1B_1\rho\delta_v(m)-A_1C_0-A_1C_1\psi\delta_v(m) = 0.$$

The second-order condition is satisfied as $-2A_1<0$. For equation (A-11) to be true, it must be that

$$\text{(A-12)} \qquad p_0-A_0 = (M+1)A_1B_0+A_1C_0,$$

$$\text{(A-13)} \qquad 2A_1B_1 = 1-(M-1)A_1B_1\rho-A_1C_1\psi.$$

The distributional assumptions of Sections II.A and II.B imply that

$$\text{(A-14)} \qquad \arg\min_{x_{\text{CB}}} E[L|\delta_{\text{CB}},\delta_T] = \arg\min_{x_{\text{CB}}}\big[\gamma A_1^2x_{\text{CB}}^2+2\gamma A_1^2MB_0x_{\text{CB}} +2\gamma A_1^2MB_0\rho\delta_{\text{CB}}x_{\text{CB}}+2\gamma A_0A_1x_{\text{CB}}-2\gamma p_TA_1x_{\text{CB}}+(1-\gamma)A_0x_{\text{CB}} +(1-\gamma)A_1x_{\text{CB}}^2+(1-\gamma)MA_1B_0x_{\text{CB}}+(1-\gamma)MA_1B_1\rho\delta_{\text{CB}}x_{\text{CB}} -(1-\gamma)p_0x_{\text{CB}}-(1-\gamma)\delta_{\text{CB}}x_{\text{CB}}\big].$$

The first-order condition of this minimization is then given by

$$\text{(A-15)} \qquad 2\gamma A_1^2x_{\text{CB}}+2\gamma A_1^2MB_0+2\gamma A_1^2MB_0\rho\delta_{\text{CB}}+2\gamma A_0A_1-2\gamma p_TA_1 +(1-\gamma)A_0+2(1-\gamma)A_1x_{\text{CB}}+(1-\gamma)MA_1B_0 +(1-\gamma)MA_1B_1\rho\delta_{\text{CB}}-(1-\gamma)p_0-(1-\gamma)\delta_{\text{CB}} = 0.$$

The second-order condition is also satisfied as $2\gamma A_1^2+2(1-\gamma)A_1>0$. Equation (A-15) and $d\equiv\gamma/(1-\gamma)$ imply that

$$\text{(A-16)} \qquad p_0-A_0 = 2A_1C_0+MA_1B_0+2dA_1^2C_0+2dA_1^2MB_0+2dA_0A_1-2d\overline{p}_TA_1,$$

$$\text{(A-17)} \qquad 2A_1C_1 = 1-MA_1B_1\rho-2dA_1^2C_1-2dA_1^2MB_1\rho,$$

$$\text{(A-18)} \qquad A_1C_2 = dA_1-dA_1^2C_2,$$

for our conjectures to be true. It ensues from equation (A-18) that $C_2=d/(1+dA_1)$. We further observe that those conjectures also imply that the order flow ω_1 must be normally distributed with mean $\mathrm{E}(\omega_1)=MB_0+C_0$ and variance

$$\text{(A-19)} \qquad \mathrm{var}(\omega_1) = MB_1^2\rho\sigma_v^2[1+(M-1)\rho]+C_1^2\psi\sigma_v^2 +2MB_1C_1\psi\rho\sigma_v^2+\sigma_z^2+C_2^2\sigma_T^2.$$

Since $\mathrm{cov}(v,\omega_1)=MB_1\rho\sigma_v^2+C_1\psi\sigma_v^2$ and $p_1=\mathrm{E}(v|\omega_1)$ in equilibrium (Condition 2), it follows that

$$\text{(A-20)} \qquad p_1 = p_0+\frac{\left(MB_1\rho\sigma_v^2+C_1\psi\sigma_v^2\right)(\omega_1-MB_0-C_0)}{MB_1^2\rho\sigma_v^2[1+(M-1)\rho]+C_1^2\psi\sigma_v^2+2MB_1C_1\psi\rho\sigma_v^2+\sigma_z^2+C_2^2\sigma_T^2}.$$

Thus, our conjecture for p_1 yields

$$\text{(A-21)} \qquad A_0 = p_0-MA_1B_0-A_1C_0,$$

$$\text{(A-22)} \qquad A_1 = \frac{MB_1\rho\sigma_v^2+C_1\psi\sigma_v^2}{MB_1^2\rho\sigma_v^2[1+(M-1)\rho]+C_1^2\psi\sigma_v^2+2MB_1C_1\psi\rho\sigma_v^2+\sigma_z^2+C_2^2\sigma_T^2}.$$

The expressions for A_0, A_1, B_0, B_1, C_0, and C_1 in Proposition 2 must solve the system made of equations (A-12), (A-13), (A-16), (A-17), (A-21), and (A-22) to represent a linear equilibrium. For both equations (A-12) and (A-21) to be true, it must be that $B_0=0$.

Defining $A_1 C_0 = p_0 - A_0$ from equation (A-12) and plugging it into equation (A-16) leads us to $A_0 = p_0 + 2dA_1 \left(p_0 - \overline{p}_T\right)$ and $C_0 = 2d\left(\overline{p}_T - p_0\right)$. We are left with the task of finding A_1, B_1, and C_1. Solving equation (A-13) for B_1 and equation (A-17) for C_1 we get

$$\text{(A-23)} \qquad B_1 = \frac{1 - A_1 C_1 \psi}{A_1 \left[2 + (M-1)\rho\right]},$$

$$\text{(A-24)} \qquad C_1 = \frac{1 - M A_1 B_1 \rho \left(1 + 2dA_1\right)}{2A_1 \left(1 + dA_1\right)},$$

respectively. The system made of equations (A-23) and (A-24) implies that $B_1 = \left[2\left(1 + dA_1\right) - \psi\right] / \left[A_1 f\left(A_1\right)\right]$ and $C_1 = \{\left[2 + (M-1)\rho\right] - M\rho\left(1 + 2dA_1\right)\} / \left[A_1 f\left(A_1\right)\right]$, where $f\left(A_1\right) = 2\left[2 + (M-1)\rho\right]\left(1 + dA_1\right) - M\psi\rho\left(1 + 2dA_1\right)$. Next, we replace the previous expressions for B_1 and C_1 in equation (A-22) to get the following sextic polynomial in A_1,

$$\text{(A-25)} \qquad g_6 A_1^6 + g_5 A_1^5 + g_4 A_1^4 + g_3 A_1^3 + g_2 A_1^2 + g_1 A_1 + g_0 = 0,$$

where it is a straightforward but tedious exercise to show that, for the parameter restrictions in Sections II.A and II.B,

$$\text{(A-26)} \qquad g_0 = -\sigma_v^2 \left[M\rho\left(2-\psi\right)^2 + \psi\left(2-\rho\right)^2\right] < 0,$$

$$\text{(A-27)} \qquad g_1 = -2\sigma_v^2 d\left\{M\rho\left[8 - 6\psi - \psi^2\left(1-\rho\right)\right] + 2\psi\left(2-\rho\right)^2\right\} < 0,$$

$$\begin{aligned} \text{(A-28)} \qquad g_2 = {} & \sigma_z^2 M\rho\left[M\rho\left(2-\psi\right)^2 + 4\left(2-\rho\right)\left(2-\psi\right)\right] \\ & + \sigma_T^2 d^2 \left[M\rho\left(2-\psi\right) + 2\left(2-\rho\right)\right]^2 \\ & + \sigma_v^2 d^2 \left\{M\rho\left[4M\rho\psi\left(1-\psi\right) + \psi^2\left(7-4\rho\right) + 5\psi\left(4-\rho\right) - 24\right] \right. \\ & \left. + 5\psi\rho\left(4-\rho\right) - 20\psi\right\}, \end{aligned}$$

$$\begin{aligned} \text{(A-29)} \qquad g_3 = {} & 2\sigma_z^2 d M\rho \{M\rho\left[8 - \psi\left(10-3\psi\right)\right] + 2\left[16 - 5\psi\left(2-\rho\right) + 8\rho\right]\} \\ & + 2\sigma_v^2 d^3 \left\{4M^2\rho^2\psi\left(1-\psi\right) + 2M\rho\left[\psi^2\left(1-\rho\right)\right.\right. \\ & \left.\left. + \psi\left(5-2\rho\right) - 4\right] - \psi\left(2-\rho\right)^2\right\} \\ & + 4\sigma_T^2 d^3 \left\{M^2\rho^2\left[2 - \psi\left(3-\psi\right)\right]\right. \\ & \left. + M\rho\left[8 - 3\psi\left(2-\rho\right) - 4\rho\right] + 2\left(2-\rho\right)^2\right\}, \end{aligned}$$

$$\begin{aligned} \text{(A-30)} \qquad g_4 = {} & 4\sigma_T^2 d^4 \left[M\rho\left(1-\psi\right) + \left(2-\rho\right)\right]^2 \\ & + 4\sigma_v^2 d^4 M\rho\left[M\rho\psi\left(1-\psi\right) + \psi\left(2-\rho\right) - 1\right] \\ & + \sigma_z^2 d^2 \left\{M^2\rho^2\left[24 + \psi\left(13\psi - 36\right)\right]\right. \\ & \left. + 12M\rho\left[8 - 3\psi\left(2-\rho\right) - 4\rho\right] + 24\left(2-\rho\right)^2\right\}, \end{aligned}$$

$$\begin{aligned} \text{(A-31)} \qquad g_5 = {} & 4\sigma_z^2 d^3 \left\{M^2\rho^2\left[4 - \psi\left(7-3\psi\right)\right]\right. \\ & \left. + M\rho\left[16 - 7\psi\left(2-\rho\right) - 8\rho\right] + 4\left(2-\rho\right)^2\right\} > 0, \end{aligned}$$

$$\text{(A-32)} \qquad g_6 = 4\sigma_z^2 d^4 \left[M\rho\left(1-\psi\right) + \left(2-\rho\right)\right]^2 > 0,$$

as well as (by numerical inspection) that $\text{sign}\left(g_3\right) = \text{sign}\left(g_2\right) = \text{sign}\left(g_1\right)$ and $\text{sign}\left(g_4\right) = \text{sign}\left(g_5\right)$, $\text{sign}\left(g_4\right) = \text{sign}\left(g_3\right) = \text{sign}\left(g_2\right)$, or $\text{sign}\left(g_3\right) = \text{sign}\left(g_4\right) = \text{sign}\left(g_5\right)$ and $\text{sign}\left(g_2\right) = \text{sign}\left(g_1\right)$ (i.e., that only one change of sign is possible while proceeding from the lowest to the highest power). Descartes' Rule then implies that the polynomial of equation (A-25) has only one positive real root satisfying the second-order conditions for both the speculators' and the central bank's optimization problems. This root, λ_{CB}, is therefore the unique linear Bayesian Nash equilibrium of the amended economy of Section II.B. According to

Abel's Impossibility Theorem, the polynomial of equation (A-25) cannot be solved with rational operations and finite root extractions. In the numerical examples of Figure 1, we find λ_{CB} using the 3-stage algorithm proposed by Jenkins and Traub (1970a), (1970b). Unfortunately, this algorithm does not always identify all roots of the polynomial of equation (A-25). Thus, those examples are based on exogenous parameter values such that λ_{CB} can be found. For instance, this is the case under most model parameterizations when the central bank is nontrivially concerned about the cost of pursuing its uninformative policy target p_T (i.e., γ is sufficiently lower than 1). □

Supplementary Material

Supplementary Material for this article is available at https://doi.org/10.1017/S0022109018001552.

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