Government Intervention and Arbitrage

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Direct government intervention in a market may induce violations of the law of one price in other, arbitrage-related markets. I show that a government pursuing a nonpublic, partially informative price target in a model of strategic market-order trading and segmented dealership generates equilibrium price differentials among fundamentally identical assets by clouding dealers' inference about the targeted asset's payoff from its order flow, to an extent complexly dependent on existing price formation. I find supportive evidence using a sample of American Depositary Receipts and other cross-listings traded in the major U.S. exchanges, along with currency interventions by developed and emerging countries between 1980 and 2009. (*JEL* F31, G14, G15)

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Modern finance rests on the law of one price (LOP). The LOP states that unimpeded arbitrage activity should eliminate price differences for identical assets in well-functioning markets. The study of frictions leading to LOP violations is crucial to understanding the forces affecting the *quality* of the process of price formation in financial markets—their ability to price assets correctly on an absolute and relative basis. Accordingly, the literature reports evidence of LOP violations in several financial markets, often explains their occurrence and intensity with unspecified behavioral or (less often and anecdotally) rational demand shocks unrelated to asset fundamentals, and attributes their persistence to various limits to arbitrageurs' efforts to fully absorb those shocks (e.g., Shleifer 2000; Lamont and Thaler 2003; Gromb and Vayanos 2010). I contribute to this understanding by investigating the role of a specific and empirically observable form of rational demand shocks—*direct* government intervention—in the emergence of LOP violations, ceteris paribus for limits to arbitrage.

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Central banks and governmental agencies ("governments" for brevity) routinely trade securities in pursuit of economic and financial policy.[1] Recently, both the scale and frequency of this activity have soared in the aftermath of the financial crisis of 2008–2009. The pursuit of policy via "official" trading in financial assets has long been found both to be effective and to yield welfare gains, for example, by achieving "intermediate" monetary targets (Rogoff 1985; Corrigan and Davis 1990; Edison 1993; Sarno and Taylor 2001; Hassan, Mertens, and Zhang 2016). I model and document the novel notion that such government intervention may also induce LOP violations and so *worsen* financial market quality. My analysis indicates that these price distortions in the affected markets may be nontrivial and hence may have nontrivial effects on their allocational and risk-sharing roles. The insight that direct government intervention in financial markets can create negative externalities on their quality has important implications for the broader debate on financial stability, optimal financial regulation, and unconventional policy making (e.g., Acharya and Richardson 2009; Hanson, Kashyap, and Stein 2011; Bernanke 2012).[2]

I illustrate this notion within a standard, parsimonious one-period model of strategic multiasset trading based on Kyle (1985) and Chowdhry and Nanda (1991). In the economy's basic setting, two fundamentally identical, or linearly related risky assets—labeled 1 and 2—are exchanged by three types of risk-neutral market participants: a discrete number of heterogeneously informed multiasset speculators, single-asset noise traders, and competitive market makers. If the dealership sector is segmented, market makers in one asset do not observe order flow in the other asset (e.g., Subrahmanyam 1991a; Baruch, Karolyi, and Lemmon 2007; Boulatov, Hendershott, and Livdan 2013). Then liquidity demand differentials from less-than-perfectly correlated noise trading in assets 1 and 2 yield equilibrium LOP violations (i.e., less-than-perfectly correlated equilibrium prices of these assets) despite semi-strong efficiency in either market and fundamentally informed, hence perfectly correlated speculation across both (e.g., like in Chowdhry and Nanda 1991). Intuitively, those relative mispricings—nonzero price differentials—can occur in equilibrium because speculators can only submit *camouflaged*

[1] Responsibility for direct intervention either is shared by various governmental bodies or is the exclusive purview of one of them. For instance, the European Central Bank (ECB) and the Swiss National Bank (SNB) use open market operations and foreign exchange interventions as instruments of their independently set monetary policies (see, e.g., https://www.ecb.europa.eu/ecb/tasks/forex/html/index.en.html; https://www.snb.ch/en/iabout/monpol/id/monpol_instr). However, in the United States, "[t]he Treasury, in consultation with the Federal Reserve System, has responsibility for setting U.S. exchange rate policy, while the Federal Reserve Bank [of] New York [FRBNY] is responsible for executing [foreign exchange] intervention" (see, e.g., https://www.newyorkfed.org/aboutthefed/fedpoint/fed44.html). Similarly, in Japan, the Ministry of Finance is in charge of planning, and the Bank of Japan (BOJ) of executing foreign exchange intervention operations (see, e.g., https://www.boj.or.jp/en/about/outline/data/foboj10.pdf).

[2] For instance, when discussing the costs and benefits of the large-scale asset purchases (LSAPs) by the Federal Reserve in the wake of the recent financial crisis, its then-chairman (Ben Bernanke 2012, p. 12) observed that "[o]ne possible cost of conducting additional LSAPs is that these operations could impair the functioning of securities markets."

market orders in each asset, that is, together with noise traders and before market-clearing prices are set. Accordingly, when both markets are more illiquid, noise trading in either asset has a greater impact on its equilibrium price, yielding larger LOP violations. Dealership segmentation, speculative market-order trading, and liquidity demand differentials in the model serve as a reduced-form representation of existing forces behind LOP violations and impediments to arbitrage activity in financial markets.

In this setting, I introduce a stylized government submitting camouflaged market orders (e.g., Vitale 1999; Naranjo and Nimalendran 2000) in only one of the two assets, asset 1, in pursuit of policy—a *nonpublic*, *partially informative* price target (e.g., Bhattacharya and Weller 1997). I then show that such government intervention increases equilibrium LOP violations, that is, lowers the equilibrium price correlation of assets 1 and 2, ceteris paribus for those limits to arbitrage and even in the absence of liquidity demand differentials. An intuitive explanation for this result is that the uncertainty surrounding the government's intervention policy in asset 1 clouds the inference of the market makers about its fundamentals when setting the equilibrium price of that asset from its order flow. Consistently, the magnitude of this effect is increasing in government policy uncertainty and generally, yet not uniformly decreasing in pre-intervention market quality. In particular, intervention-induced LOP violations are larger when market liquidity is low, for example, in the presence of more heterogeneously informed speculators or less intense noise trading, since in those circumstances official trading has a greater impact on the equilibrium price of asset 1. However, intervention-induced LOP violations may also be complexly related to extant such violations. For example, they may be larger in the presence of fewer speculators yet smaller in the presence of less correlated noise trading, since in the former circumstances official trading has a greater impact on the already low equilibrium price correlation of assets 1 and 2 than in the latter.

I test the model's main implications by examining the impact of government interventions in the foreign exchange ("forex") market on LOP violations in the U.S. market for American Depositary Receipts and other cross-listed stocks ("ADRs" for brevity). The forex market is one of the largest, most liquid financial markets in the world (e.g., Bank for International Settlements 2016). The major U.S. exchanges (the "ADR market") are the most important venue for international cross-listings (e.g., Karolyi 1998, 2006). These markets also serve as a setting that is as close as possible in spirit to the assumptions in my model. First, an ADR is a dollar-denominated security, traded in the United States, representing a set number of shares in a foreign stock held in deposit by a U.S. financial institution; hence, its price is linked to the underlying exchange rate by an arbitrage relation, the "ADR parity" (ADRP; e.g., Gagnon and Karolyi 2010; Pasquariello, Roush, and Vega 2014). This fundamental linkage can be described in my setting as a linear relation between the terminal payoff of asset 1, the exchange rate (traded in the forex market), and the terminal payoff of asset 2, the ADR (traded in the U.S. stock market). My model then predicts that, ceteris paribus, forex intervention (government intervention targeting the price of asset 1) may induce ADRP violations, that is, lowers the equilibrium correlation between the price of the actual ADR (asset 2) and its *synthetic*, arbitrage-free price implied by the ADRP (a linear function of the price of asset 1). Second, forex and ADR dealership sectors are arguably less-than-perfectly integrated, as market makers in either market are less likely to observe order flow in the other market. Third, according to the literature (surveyed in Edison 1993; Sarno and Taylor 2001; Neely 2005; Menkhoff 2010; Engel 2014), government intervention in currency markets is common and often secret; its policy objectives are often nonpublic; its effectiveness is statistically robust and often attributed to their perceived informativeness about fundamentals. Fourth, most forex interventions are sterilized (i.e., do not affect the money supply of the targeted currencies), and all of them are unlikely to be prompted by ADRP violations.

I construct a sample that includes ADRs traded in the major U.S. exchanges as well as official trading activity of developed and emerging countries in the currency markets between 1980 and 2009. Its salient features are in line with the aforementioned literature. Average absolute percentage ADRP violations are large (e.g., a 2% [200 basis points, bps] deviation from the arbitrage-free price), generally decline as financial integration increases, but display meaningful intertemporal dynamics (e.g., spiking during periods of financial instability). Forex interventions are also nontrivial, albeit small relative to average turnover in the currency markets, are especially frequent between the mid-1980s and the mid-1990s, and typically involve exchange rates relative to the dollar.

The empirical analysis of this sample provides support for my model. I find that measures of the actual and historically abnormal intensity of ADRP violations increase in measures of the actual and historically abnormal intensity of forex interventions. This relation is both statistically and (plausibly) economically significant. For instance, a one-standard-deviation increase in forex intervention activity in a month is accompanied by a material average cumulative increase in absolute ADRP violations of up to 10 bps, which is as much as 45% of the sample volatility of their monthly changes. This relation is also robust to controlling for several proxies for market conditions that are commonly associated with LOP violations, limits to arbitrage, and/or forex intervention (e.g., Pontiff 1996, 2006; Pasquariello 2008, 2014; Gagnon and Karolyi 2010; Garleanu and Pedersen 2011; Engel 2014), as well as to removing ADRs from emerging countries from the analysis when affected by the imposition of capital controls (e.g., Edison and Warnock 2003; Auguste et al. 2006). Importantly, those same official currency trades are not accompanied by larger LOP violations in the much more closely integrated currency and international money markets in many respects, including dealership (e.g., McKinnon 1977; Dufey and Giddy 1994; Bekaert and Hodrick 2012), as they are unrelated to violations of the covered interest rate parity (CIRP), an arbitrage relation between interest rates and spot and forward exchange rates commonly used to proxy for currency market quality (e.g., Frenkel and Levich 1975, 1977; Coffey et al. 2009; Griffoli and Ranaldo 2011). This finding not only is consistent with my model but also suggests that my results are unlikely to stem from a dislocation in currency markets leading to both forex interventions and ADRP violations (e.g., Neely and Weller 2007).

Further cross-sectional and time-series analysis indicates that poor, deteriorating price formation in the ADR arbitrage-linked markets magnify ADRP violations both directly and through its possibly complex linkage with forex intervention activity, as postulated by my model. In particular, I find LOP violations to be larger and the linkage to be stronger not only for ADRs from emerging economies but also for markets and portfolios of ADRs of high underlying quality, as well as in correspondence with high or greater ADRP illiquidity (as measured by the average fraction of zero returns in the currency, U.S., and foreign stock markets), greater dispersion of beliefs about common fundamentals (as measured by the standard deviation of professional forecasts of U.S. macroeconomic news releases), and greater uncertainty about governments' currency policy (as measured by real-time intervention volatility). For example, the positive estimated impact of high forex intervention activity on ADRP violations is more than three times larger when in correspondence with high information heterogeneity among market participants.

In summary, my study highlights novel, and potentially important, adverse implications of direct government intervention, a frequently employed instrument of policy with well-understood benefits, for financial market quality.

1. Theory

I am interested in the effects of government intervention on relative mispricings, that is, on LOP violations. To that purpose, I first describe, in Section 1.1, a standard noisy rational expectations equilibrium (REE) model of multiasset informed trading. The model, based on Kyle (1985), is a straightforward extension of Chowdhry and Nanda (1991) to imperfectly competitive speculation and nondiscretionary liquidity trading that allows for relative mispricings in equilibrium. I then contribute to the literature on limits to arbitrage, in Section 1.2, by introducing in this setting a stylized government and considering the implications of its official trading activity for LOP violations. The Appendix contains all proofs.

1.1 The basic model of multiasset trading

The basic model is based on Kyle (1985) and Chowdhry and Nanda (1991). The model's standard framework has often been used to study price formation in many financial markets and for many asset classes (see, e.g., the surveys in

O'Hara 1995; Vives 2008; Foucault, Pagano, and Röell 2013). It is a two-date ($t=0,1$) economy in which two risky assets ($i=1,2$) are exchanged. Trading occurs only at date $t=1$, after which each asset's payoff v_i is realized. The two assets are fundamentally related in that $v_i \equiv a_i + b_i v$, where v is normally distributed with mean p_0 and variance σ_v^2, and a_i and b_i are constants. Fundamental commonality in payoffs is meant to parsimoniously represent a wide range of LOP relations between the two assets; linearity of their payoffs in v ensures that the model can be solved in closed form. I discuss one particular such representation for the ADR parity in Section 2.1. For simplicity and without loss of generality, I assume that the two assets are fundamentally identical in that $a_i=0$ and $b_i=1$, such that $v_i=v$. There are three types of risk-neutral traders: a discrete number (M) of informed traders (labeled speculators) in both assets (e.g., Foucault and Gehrig 2008; Pasquariello and Vega 2009), as well as nondiscretionary liquidity traders and competitive market makers (MMs) in each asset. All traders know the structure of the economy and the decision-making process leading to order flow and prices.

At date $t=0$, there is neither information asymmetry about v nor trading. Sometime between $t=0$ and $t=1$, each speculator m receives a private and noisy signal of v, $S_v(m)$. I 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 $S_v(m)$ and $S_v(j)$, $cov[v, S_v(m)] = cov[S_v(m), S_v(j)] = \sigma_v^2$. Each speculator's information endowment about v is defined as $\delta_v(m) \equiv E[v|S_v(m)] - p_0$. I characterize speculators' private information heterogeneity by further imposing that $\sigma_s^2 = \frac{1}{\rho}\sigma_v^2$ and $\rho \in (0,1)$. This parsimonious parametrization implies that $\delta_v(m) = \rho[S_v(m) - p_0]$ and $E[\delta_v(j)|\delta_v(m)] = \rho\delta_v(m)$, i.e., that ρ is the unconditional correlation between any two $\delta_v(m)$ and $\delta_v(j)$. Intuitively, as ρ declines, speculators' private information about v becomes more dispersed, thus is less precise and correlated.[3]

At date $t=1$, speculators and liquidity traders submit their orders in assets 1 and 2 to the MMs before their equilibrium prices $p_{1,1}$ and $p_{1,2}$ have been set. The market order of each speculator m in each asset i is defined as $x_i(m)$, such that her profit is given by $\pi(m) = (v - p_{1,1})x_1(m) + (v - p_{1,2})x_2(m)$. Liquidity traders generate random, normally distributed demands z_1 and z_2, with mean zero, variance σ_z^2, and covariance σ_{zz}, where $\sigma_{zz} \in (0, \sigma_z^2]$.[4] For simplicity, z_1 and z_2 are assumed to be independent from all other random variables. Competitive MMs in each asset i do not receive any information about its terminal payoff v, and observe only that asset's aggregate order flow,

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3 Without loss of generality, the distributional assumptions for $S_v(m)$ also imply that $S_v(m) = S_v(j) = v$ in the limiting case in which $\rho = 1$ (i.e., private information homogeneity). More general, yet analytically complex, information structures for $S_v(m)$ (e.g., like in Caballé and Krishnan 1994; Pasquariello 2007a; Pasquariello and Vega 2007; Albuquerque and Vega 2009) lead to similar implications.

4 Chowdhry and Nanda (1991) study the impact of the relative concentration of large, exogenous, and perfectly correlated liquidity traders versus small, discretionary, and uncorrelated liquidity traders on monopolistic speculation and price formation in multiple markets for the same asset.

$\omega_i = \sum_{m=1}^{M} x_i(m) + z_i$, before setting the market-clearing price, $p_{1,i} = p_{1,i}(\omega_i)$, like in Chowdhry and Nanda (1991), Subrahmanyam (1991a), Baruch, Karolyi, and Lemmon (2007), Pasquariello and Vega (2009), and Boulatov, Hendershott, and Livdan (2013). Segmentation in market making is an important feature of the model, as it allows for the possibility that $p_{1,1}$ and $p_{1,2}$ might be different in equilibrium despite assets 1 and 2's identical payoffs.[5]

1.1.1 Equilibrium. A Bayesian Nash equilibrium of this economy is a set of $2(M+1)$ functions, $x_i(m)(\cdot)$ and $p_{1,i}(\cdot)$, satisfying the following conditions:

1. *Utility maximization*: $x_i(m)(\delta_v(m)) = \arg\max E[\pi(m)|\delta_v(m)]$;
2. *Semi-strong market efficiency*: $p_{1,i} = E(v|\omega_i)$.[6]

Proposition 1 describes the unique linear REE that obtains.

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

$$p_{1,i} = p_0 + \lambda\omega_i, \tag{1}$$

where $\lambda = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]} > 0$; and by each speculator's orders:

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

In this class of models, MMs in each market i learn about the traded asset i's terminal payoff from its order flow, ω_i; hence, each imperfectly competitive, risk-neutral speculator trades cautiously in both assets ($|x_i(m)| < \infty$, Equation (2)) to protect the information advantage stemming from her private signal, $S_v(m)$. Like in Kyle (1985), positive equilibrium price impact or lambda ($\lambda > 0$) compensates the MMs for their expected losses from speculative trading in ω_i with expected profits from noise trading (z_i). The ensuing comparative statics are intuitive and standard in the literature (e.g., Subrahmanyam 1991b; Pasquariello and Vega 2009). MMs' adverse selection risk is more severe and equilibrium liquidity lower in both markets (higher λ) when: (1) the traded assets' identical terminal payoff v is more uncertain (higher σ_v^2), since speculators' private information advantage is greater; (2) their private signals are less correlated (lower ρ), since each of them, perceiving to have greater monopoly power on her private information, trades more cautiously with it

[5] Relaxing this assumption to allow for partial dealership segmentation—for example, by endowing MMs in each asset with a noisy signal of the order flow in the other asset or by allowing for more than one round of trading and cross-market observability over time (like in Chowdhry and Nanda 1991)—would significantly complicate the analysis without qualitatively altering its implications. Without loss of generality, the distributional assumptions for z_i also imply that if $\sigma_{zz} = \sigma_z^2$, then $z_1 = z_2$.

[6] Condition 2 can also be interpreted as the outcome of competition among MMs that forces their expected profits to zero in both markets (Kyle 1985).

(lower $|x_i(m)|$); (3) noise trading is less intense (lower σ_z^2), since MMs need to be compensated for less camouflaged speculation in the order flow; or (4) there are fewer speculators in the economy (lower M), since imperfect competition among them magnifies their cautious aggregate trading behavior (lower $\left|\sum_{m=1}^{M} x_i(m)\right|$).[7]

1.1.2 LOP violations. The literature defines and measures LOP violations either as nonzero price differentials or as less-than-perfect price correlations among identical assets (e.g., Karolyi 1998, 2006; Auguste et al. 2006; Pasquariello 2008, 2014; Gagnon and Karolyi 2010; Gromb and Vayanos 2010; Griffoli and Ranaldo 2011). As I further discuss in Section 2.1.1, the two representations are conceptually equivalent in the economy. An examination of Equations (1) and (2) in Proposition 1 reveals that less-than-perfectly correlated noise trading in assets 1 and 2 ($\sigma_{zz} < \sigma_z^2$) may lead to nonzero realizations of liquidity demand ($z_1 \neq z_2$) and price differentials ($p_{1,1} \neq p_{1,2}$) in equilibrium, by at least partly offsetting fundamentally informed (i.e., perfectly correlated) trading in those assets ($x_1(m) = x_2(m)$). Of course, this may occur only with segmented market making allowing for $E(v|\omega_1) \neq E(v|\omega_2)$. If MMs observe order flow in both assets (i.e., with perfectly integrated market making), no price differential can arise in equilibrium since semi-strong market efficiency in Condition 2 implies that $p_{1,1} = E(v|\omega_1, \omega_2) = p_{1,2}$. I formalize these observations in Corollary 1 by measuring LOP violations in the economy using the unconditional correlation of the equilibrium prices of assets 1 and 2, $corr(p_{1,1}, p_{1,2})$, like in Gromb and Vayanos (2010).

Corollary 1. In the presence of less-than-perfectly correlated noise trading, the LOP is violated in equilibrium:

$$corr(p_{1,1}, p_{1,2}) = 1 - \frac{\sigma_z^2 - \sigma_{zz}}{\sigma_z^2 [2 + (M-1)\rho]} < 1. \tag{3}$$

There are no LOP violations under perfectly integrated market making or perfectly correlated noise trading.

Figures 1 and 2 illustrate the intuition behind Corollary 1. I consider a baseline economy in which $\sigma_v^2 = 1$, $\sigma_z^2 = 1$, $\sigma_{zz} = 0.5$, $\rho = 0.5$, and $M = 10$. I then plot the equilibrium price correlation of Equation (3) as a function of σ_{zz}, ρ, M, or σ_z^2 in Figures 1A to 1D, respectively (solid lines). Figure 2A displays

[7] For example, $\frac{\partial|x_i(m)|}{\partial\rho} = \frac{\sigma_z}{2\sigma_v\sqrt{M\rho}} > 0$, whereas $\frac{\partial\left|\sum_{m=1}^{M} x_i(m)\right|}{\partial M} = \frac{\sigma_z|v - p_0|}{2\sigma_v\sqrt{M}} > 0$ in the limiting case in which $\rho = 1$; see also Pasquariello and Vega (2007). Accordingly, $\frac{\partial\lambda}{\partial\rho} = -\frac{\sigma_v M[(M-1)\rho - 2]}{2\sigma_z\sqrt{M\rho}[2+(M-1)\rho]^2} < 0$ and $\frac{\partial\lambda}{\partial M} = -\frac{\sigma_v \rho[(M-1)\rho - 2]}{2\sigma_z\sqrt{M\rho}[2+(M-1)\rho]^2} < 0$, except in the small region of $\{M, \rho\}$ in which $\rho \leq \frac{2}{M-1}$. In addition, $\frac{\partial\lambda}{\partial\sigma_v^2} = \frac{\sqrt{M\rho}}{2\sigma_v\sigma_z[2+(M-1)\rho]} > 0$ and $\frac{\partial\lambda}{\partial\sigma_z} = -\frac{\sigma_v\sqrt{M\rho}}{2\sigma_z^3[2+(M-1)\rho]} < 0$.

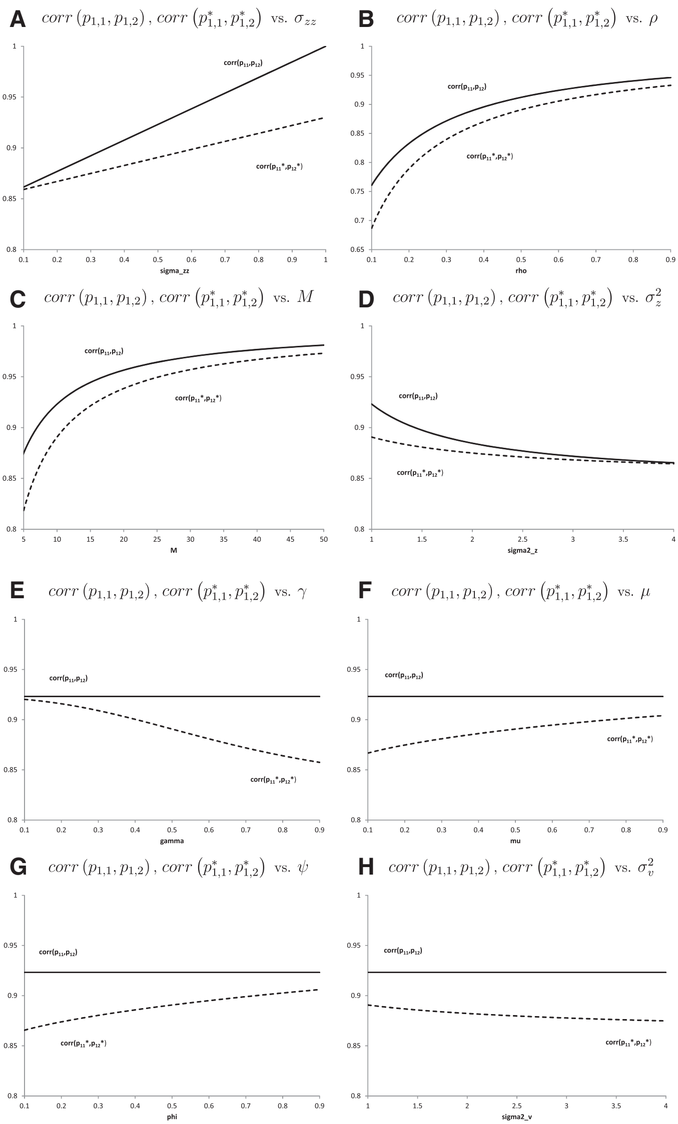

Figure 1
LOP violations and model parameters
This figure plots the unconditional correlation between the equilibrium prices of assets 1 and 2 in the absence ($corr(p_{1,1},p_{1,2})$ of Equation (3), solid lines) and in the presence of government intervention ($corr(p^*_{1,1},p^*_{1,2})$ of Equation (10), dashed lines), as a function of either σ_{zz} (the covariance of noise trading in those assets, in Figure 1A), ρ (the correlation of speculators' private signals $S_v(m)$ about v, the identical terminal payoff of assets 1 and 2, in Figure 1B), M (the number of speculators, in Figure 1C), σ_z^2 (the intensity of noise trading, in Figure 1D), γ (the government's commitment to its policy target $p^T_{1,1}$ for the equilibrium price of asset 1 in its loss function $L(gov)$ of Equation (4)), μ (the correlation of the government's policy target $p^T_{1,1}$ with its private signal $S_v(gov)$ about the identical terminal payoff v of assets 1 and 2), ψ (the precision of the government's private signal of v, $S_v(gov)$), and σ_v^2 (the uncertainty about v, the identical terminal payoff of assets 1 and 2, in Figure 1H), when $\sigma_v^2=1$, $\sigma_z^2=1$, $\sigma_{zz}=0.5$, $\rho=0.5$, $\psi=0.5$, $\gamma=0.5$, $\mu=0.5$, and $M=10$.

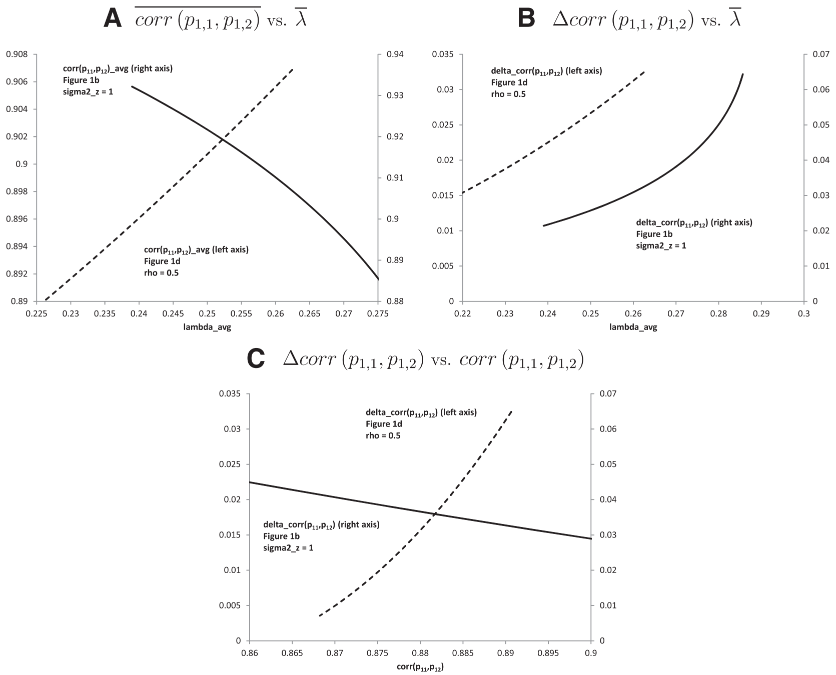

Figure 2
LOP violations and other equilibrium outcomes
This figure plots the average unconditional equilibrium correlation between the equilibrium prices of assets 1 and 2 in the absence ($corr(p_{1,1}, p_{1,2})$ of Equation (3)) and in the presence of government intervention ($corr(p^*_{1,1}, p^*_{1,2})$ of Equation (10)), $\overline{corr(p_{1,1}, p_{1,2})} = \frac{1}{2}[corr(p_{1,1}, p_{1,2}) + corr(p^*_{1,1}, p^*_{1,2})]$, as a function of the corresponding average equilibrium price impact $\overline{\lambda} = \frac{1}{2}(\lambda + \lambda^*)$ (in Figure 2A) as well as their difference, $\Delta corr(p_{1,1}, p_{1,2}) \equiv corr(p_{1,1}, p_{1,2}) - corr(p^*_{1,1}, p^*_{1,2})$, as a function of either the corresponding $\overline{\lambda}$ (in Figure 2B) or the corresponding $corr(p_{1,1}, p_{1,2})$ (in Figure 2C), for both the relation between $corr(p_{1,1}, p_{1,2})$ and ρ of Figure 1B for $\sigma^2_z = 1$ and $\rho \approx 0.5$ (solid line, right axis) and the relation between $corr(p_{1,1}, p_{1,2})$ and σ^2_z of Figure 1D for $\rho = 0.5$ and $\sigma^2_z \approx 1$ (dashed line, left axis), when $\sigma^2_v = 1$, $\sigma^2_z = 1$, $\sigma_{zz} = 0.5$, $\rho = 0.5$, $\psi = 0.5$, $\gamma = 0.5$, $\mu = 0.5$, and $M = 10$.

(average) $corr\left(p_{1,1}, p_{1,2}\right)$ as a function of the corresponding (average) λ for both the relation between $corr\left(p_{1,1}, p_{1,2}\right)$ and ρ of Figure 1B (solid line, right axis, for $\sigma^2_z = 1$ and $\rho \approx 0.5$) and the relation between $corr\left(p_{1,1}, p_{1,2}\right)$ and σ^2_z of Figure 1D (dashed line, left axis, for $\rho = 0.5$ and $\sigma^2_z \approx 1$).[8]

LOP violations are larger when noise trading in assets 1 and 2 is less correlated (lower σ_{zz} in Figure 1A), since liquidity demand and price differentials are more likely in equilibrium (e.g., like in Chowdhry and Nanda 1991). LOP violations are also larger when equilibrium liquidity in both markets

[8] Averages include both economies without and with government intervention; see also the discussion in Section 1.2. Plots of equilibrium outcomes based on Figures 1A (for σ_{zz}) and 1C (for M) yield similar insights. Solid and dashed lines in Figure 2 are plotted on different axes to adjust for differences in the scale of the corresponding equilibriums.

is lower (i.e., the higher is λ), since the impact of noise trading on equilibrium prices is greater and the price differentials stemming from liquidity demand differentials in Equation (1) are larger. Thus, $corr\left(p_{1,1}, p_{1,2}\right)$ is greater when there are fewer speculators in the economy (lower M in Figure 1B) or when their private information is more dispersed (lower ρ in Figures 1C and 2A), since the more cautious is their (aggregate or individual) trading activity and the more serious is the threat of adverse selection for MMs.[9] Lastly, more intense noise trading (higher σ_z^2 in Figures 1D and 2A) amplifies LOP violations by increasing both the likelihood and magnitude of liquidity demand differentials, despite its lesser impact (via lower λ) on equilibrium prices. I summarize these observations in Corollary 2.

Corollary 2. LOP violations increase in speculators' information heterogeneity and the intensity of noise trading, as well as decrease in the number of speculators and the covariance of noise trading.

LOP violations do not necessarily imply riskless arbitrage opportunities. While the former occur whenever nonzero price differences between two assets with identical liquidation value arise, the latter require that those differences be exploitable with no risk. In my setting, only speculators can and do trade strategically and simultaneously in both assets 1 and 2 (see Equation (2)). Hence, only they can attempt to profit from any price difference they anticipate to observe. However, the unconditional expected prices of assets 1 and 2 are identical in equilibrium ($E\left(p_{1,1}\right) = E\left(p_{1,2}\right)$) since, by Condition 2, both $p_{1,1}$ and $p_{1,2}$ incorporate all individual private information about their identical terminal value v (i.e., all private signals $S_v(m)$ in Equation (1)). Further, speculators cannot place limit orders and, in the noisy REE of Proposition 1, neither observe nor can accurately predict the market-clearing prices of assets 1 and 2 when submitting their market orders, $x_i(m)$. Thus, there is no feasible riskless arbitrage opportunity in the economy.[10]

Segmentation in market making, speculative market-order trading, and less-than-perfectly correlated noise trading in the basic model are a reduced-form representation of existing forces affecting the ability of financial markets to correctly price assets that are fundamentally linked by an arbitrage parity.

1.2 Government intervention

Governments often intervene in financial markets. The trading activity of central banks and various governmental agencies has been argued and shown both to affect price levels and dynamics of exchange rates, sovereign bonds,

[9] However, greater fundamental uncertainty (higher σ_v^2) does not affect $corr\left(p_{1,1}, p_{1,2}\right)$, since lower market liquidity is offset by greater price volatility in Equation (3).

[10] See also the discussions in Subrahmanyam (1991a), Shleifer and Vishny (1997), and Pasquariello and Vega (2009).

derivatives, and stocks, as well as to yield often conflicting microstructure externalities. Recent studies include Bossaerts and Hillion (1991), Dominguez and Frankel (1993), Bhattacharya and Weller (1997), Vitale (1999), Naranjo and Nimalendran (2000), Lyons (2001), Dominguez (2003), 2006), Evans and Lyons (2005), and Pasquariello (2007b, 2010) for the spot and forward currency markets, Harvey and Huang (2002), Ulrich (2010), Brunetti, di Filippo, and Harris (2011), D'Amico and King (2013), Pasquariello, Roush, and Vega (2014), and Pelizzon et al. (2016) for the money and bond markets, and Sojli and Tham (2010) and Dyck and Morse (2011) for the stock markets.[11] As such, this "official" trading activity may have an impact on the ability of the affected markets to price assets correctly. I explore this possibility by introducing a stylized government in the multiasset economy of Section 1.1.

The literature identifies several recurring features of direct government intervention in financial markets (e.g., Edison 1993; Vitale 1999; Sarno and Taylor 2001; Neely 2005; Menkhoff 2010; Engel 2014; Pasquariello, Roush, and Vega 2014): (1) governments tend to pursue nonpublic price targets in those markets; (2) governments often intervene in secret in the targeted markets; (3) governments are likely or perceived to have an information advantage over most market participants about the fundamentals of the traded assets; (4) the observed ex post effectiveness of governments at pursuing their price targets is often attributed to that actual or perceived information advantage; (5) those price targets may be related to governments' fundamental information; and (6) governments are sensitive to the potential costs of their interventions. I parsimoniously capture these features using the following assumptions about the stylized government.

First, the government is given a private and noisy signal of v, $S_v(gov)$, a normally distributed variable with mean p_0, variance $\sigma_{gov}^2 = \frac{1}{\psi}\sigma_v^2$, and precision $\psi \in (0,1)$. I further impose that $cov\left[S_v(m), S_v(gov)\right] = cov\left[v, S_v(gov)\right] = \sigma_v^2$, as for speculators' private signals $S_v(m)$ in Section 1.1. Accordingly, the government's information endowment about v is defined as $\delta_v(gov) \equiv E\left[v|S_v(gov)\right] - p_0 = \psi\left[S_v(gov) - p_0\right]$.

Second, the government is given a nonpublic target for the price of asset 1, $p_{1,1}^T$, drawn from a normal distribution with mean $\overline{p}_{1,1}^T$ and variance σ_T^2. The government's information endowment about $p_{1,1}^T$ is then $\delta_T(gov) \equiv p_{1,1}^T - \overline{p}_{1,1}^T$.[12] This policy target is some unspecified function of $S_v(gov)$, such that $\sigma_T^2 = \frac{1}{\mu}\sigma_{gov}^2 = \frac{1}{\mu\psi}\sigma_v^2$, $cov\left[p_{1,1}^T, S_v(gov)\right] = \sigma_{gov}^2$, and

11 However, direct government intervention in stock markets is currently less common, and evidence of this activity remains largely anecdotal. For example, see media coverage of the actions by the Chinese government in support of the plunging Shanghai Composite Index in 2015 (Hong 2016). Other studies focus on the implications of government policies affecting the fundamental payoffs of traded securities for financial market outcomes (e.g., Pastor and Veronesi 2012, 2013; Bond and Goldstein 2015).

12 In a model of currency trading based on Kyle (1985), Vitale (1999) shows that central bank intervention cannot effectively achieve an uninformative price target known to all market participants.

$cov\left[S_v(m), p^T_{1,1}\right] = cov\left(v, p^T_{1,1}\right) = \sigma^2_v$. Hence, when $\mu \in (0,1)$ is higher, the government's price target is more correlated to its fundamental information and market participants are less uncertain about its policy. For example, this assumption captures the observation that government interventions in currency markets either "chase the trend" (if μ is high) to reinforce market participants' beliefs about fundamentals as reflected by observed exchange rate dynamics (e.g., Edison 1993; Sarno and Taylor 2001; Engel 2014) or more often "lean against the wind" (if μ is low) to resist those beliefs and dynamics (e.g., Lewis 1995; Kaminsky and Lewis 1996; Bonser-Neal, Roley, and Sellon 1998; Pasquariello 2007b).[13]

Third, the government can only trade in asset 1; at date $t=1$, before the equilibrium price $p_{1,1}$ has been set, it submits to the MMs a market order $x_1(gov)$ minimizing the expected value of its loss function:

$$L(gov) = \gamma\left(p_{1,1} - p^T_{1,1}\right)^2 + (1-\gamma)\left(p_{1,1} - v\right)x_1(gov), \tag{4}$$

where $\gamma \in (0,1)$. This specification is based on Stein (1989), Bhattacharya and Weller (1997), Vitale (1999), and Pasquariello, Roush, and Vega (2014). The first term in Equation (4) is meant to capture the government's attempts to achieve its policy objectives for asset 1 by trading to minimize the squared distance between asset 1's equilibrium price, $p_{1,1}$, and the target, $p^T_{1,1}$. The second term in Equation (4) accounts for the costs of that intervention, namely, deviating from pure profit-maximizing speculation in asset 1 ($\gamma = 0$). When γ is higher, the government is more committed to policy making in asset 1, relative to its cost. Imposing that $\gamma < 1$ then ensures that the government does not implausibly trade unlimited amounts of asset 1 in pursuit of $p^T_{1,1}$. This feature of Equation (4) is further discussed in Section 1.2.1.

At date $t=1$, MMs in each asset i clear their market after observing its aggregate order flow, ω_i, like in Section 1.1. However, while $\omega_2 = \sum_{m=1}^{M} x_2(m) + z_2$, ω_1 now consists of the market orders of noise traders, speculators, and the government: $\omega_1 = x_1(gov) + \sum_{m=1}^{M} x_1(m) + z_1$. In this amended economy, MMs in each asset i attempt to learn from ω_i about that asset's terminal payoff v when setting its equilibrium price $p_{1,i}$, like in Section 1.1. However, each speculator now uses her private signal, $S_v(m)$, to learn not only about v and the other speculators' private signals but also about the government's intervention policy in asset 1 before choosing her optimal trading strategy, $x_i(m)$, in both assets 1 and 2. In addition, the government uses its private information, $S_v(gov)$, to learn about what speculators may know about v and trade in asset 1 when choosing its optimal intervention strategy, $x_1(gov)$. I solve for the ensuing unique linear Bayesian Nash equilibrium in Proposition 2.

13 Accordingly, in their REE model of currency trading, Bhattacharya and Weller (1997) also assume that the central bank's nonpublic price target is partially correlated to the payoff of the traded asset, forward exchange rates.

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

$$p^*_{1,1} = \left[p_0 + 2d\lambda^*\left(p_0 - \overline{p}^T_{1,1}\right)\right] + \lambda^* \omega_1, \tag{5}$$

$$p^*_{1,2} = p_0 + \lambda \omega_2, \tag{6}$$

where $d = \frac{\gamma}{1-\gamma}$, λ^* is the unique positive real root of the sextic polynomial of Equation (A33) in the Appendix, and $\lambda = \frac{\sigma_v \sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]} > 0$ (like in Proposition 1); by each speculator's orders

$$x^*_1(m) = B^*_{1,1} \delta_v(m), \tag{7}$$

$$x^*_2(m) = \frac{\sigma_z}{\sigma_v \sqrt{M\rho}} \delta_v(m), \tag{8}$$

where $B^*_{1,1} = \frac{2-\psi}{\lambda^*\{2[2+(M-1)\rho](1+d\lambda^*) - M\rho\psi(1+2d\lambda^*)\}} > 0$; and by the government intervention:

$$x_1(gov) = 2d\left(\overline{p}^T_{1,1} - p_0\right) + C^*_{1,1}\delta_v(gov) + C^*_{2,1}\delta_T(gov), \tag{9}$$

where $C^*_{1,1} = \frac{[2+(M-1)\rho]\left(1+d\lambda^*\right) - M\rho\left(1+2d\lambda^*\right)}{\lambda^*(1+d\lambda^*)\{2[2+(M-1)\rho](1+d\lambda^*) - M\rho\psi(1+2d\lambda^*)\}}$ and $C^*_{2,1} = \frac{d}{1+d\lambda^*} > 0$.

In Corollary 3, I examine the effect of government intervention in asset 1, $x_1(gov)$ of Equation (9), on the extent of LOP violations in the economy (i.e., on the unconditional comovement of equilibrium asset prices $p^*_{1,1}$ and $p^*_{1,2}$ of Equations (5) and (6)), like in Corollary 1.

Corollary 3. In the presence of government intervention, the unconditional correlation of the equilibrium prices of assets 1 and 2 is given by:

$$corr(p^*_{1,1}, p^*_{1,2}) = \frac{\sigma_{zz} + \sigma_z \sigma_v \sqrt{M\rho}\{B^*_{1,1}[1+(M-1)\rho] + \psi C^*_{1,1} + C^*_{2,1}\}}{\sigma_z \sqrt{[2+(M-1)\rho]\{\sigma_z^2 + \sigma_v^2\{M\rho B^{*2}_{1,1}[1+(M-1)\rho] + D^*_1 + E^*_1\}\}}}, \tag{10}$$

where $D^*_1 = 2M\rho\left[B^*_{1,1}\left(\psi C^*_{1,1} + C^*_{2,1}\right)\right]$ and $E^*_1 = \psi C^{*2}_{1,1} + \frac{1}{\mu\psi} C^{*2}_{2,1} + 2C^*_{1,1}C^*_{2,1}$. There are no LOP violations under perfectly integrated market making.

In the above economy, the equilibrium price impact of order flow in asset 1 (λ^* of Proposition 2) cannot be solved in closed form (see the Appendix). Thus, I characterize the equilibrium properties of $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Equation (10) via numerical analysis. To that purpose, I introduce the stylized government, with starting parameters $\gamma = 0.5$, $\psi = 0.5$, and $\mu = 0.5$, in the baseline economy of Section 1.1.2, where $\sigma_v^2 = 1$, $\sigma_z^2 = 1$, $\sigma_{zz} = 0.5$, $\rho = 0.5$, and $M = 10$. Most parameter selection only affects the relative magnitude of the effects described below. I examine limiting cases and nonrobust exceptions of interest in Section 1.2.1; see also the discussion in the proof of Proposition

2. I then plot the ensuing equilibrium price correlation $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ in Figure 1 (dashed lines), alongside its corresponding level in the absence of government intervention ($corr\left(p_{1,1}, p_{1,2}\right)$ of Equation (3), solid lines), as a function of σ_{zz}, ρ, M, or σ^2_z (Figures 1A to 1D, like in Section 1.1.2), and γ, μ, ψ, or σ^2_v (Figure 1E to 1H). Figures 2B and 2C display their difference, $\Delta corr\left(p_{1,1}, p_{1,2}\right) \equiv corr\left(p_{1,1}, p_{1,2}\right) - corr\left(p^*_{1,1}, p^*_{1,2}\right)$, as a function of the corresponding average λ (i.e., $\overline{\lambda} = \frac{1}{2}(\lambda + \lambda^*)$) and $corr\left(p_{1,1}, p_{1,2}\right)$ (i.e., $\overline{corr\left(p_{1,1}, p_{1,2}\right)} = \frac{1}{2}\left[corr\left(p_{1,1}, p_{1,2}\right) + corr\left(p^*_{1,1}, p^*_{1,2}\right)\right]$), respectively, for both their relation with ρ of Figure 1B (solid line, right axis, for $\sigma^2_z = 1$ and $\rho \approx 0.5$) and their relation with σ^2_z of Figure 1D (dashed line, left axis, for $\rho = 0.5$ and $\sigma^2_z \approx 1$).

Like in Corollary 1, if MMs observe order flow in both assets 1 and 2, once again no LOP violation can arise in equilibrium under semi-strong market efficiency, regardless of government intervention: $corr\left(p^*_{1,1}, p^*_{1,2}\right) = corr\left(p_{1,1}, p_{1,2}\right) = 1$. However, insofar as the dealership sector is segmented and multiasset speculators submit market orders (i.e., ceteris paribus for existing limits to arbitrage), government intervention makes LOP violations more likely in equilibrium, even in the absence of liquidity demand differentials. According to Figure 1, official trading activity in asset 1 lowers the unconditional correlation of the equilibrium prices of the otherwise identical assets 1 and 2 (i.e., $corr\left(p^*_{1,1}, p^*_{1,2}\right) < corr\left(p_{1,1}, p_{1,2}\right)$) even when noise trading in those assets is perfectly correlated (i.e., $\sigma_{zz} = \sigma^2_z = 1$ such that $corr\left(p_{1,1}, p_{1,2}\right) = 1$ in Figure 1A). Intuitively, the camouflage provided by the aggregate order flow allows the stylized government of Equation (4) to trade in asset 1 to push its equilibrium price $p^*_{1,1}$ toward a target $p_{1,T}$ that is at most only partially informative about fundamentals, that is, only partially correlated with both assets' identical terminal payoff v: $corr\left(v, p^T_{1,1}\right) = \sqrt{\mu\psi} < 1$ (see also Vitale 1999; Naranjo and Nimalendran 2000). To that end, the government optimally chooses to bear some costs, that is, to tolerate some trading losses or forego some trading profits in asset 1, given its private information of precision ψ. For instance, at the economy's baseline parametrization, not only is $C^*_{2,1} > 0$ but also $0 < C^*_{1,1} < B^*_{1,1}$ in $x_1(gov)$ of Equation (9): $C^*_{2,1} = 0.85$ and $C^*_{1,1} = 0.34$ versus $B^*_{1,1} = 0.69$ in $x^*_1(m)$ of Equation (7).

Since $p^T_{1,1}$ is also nonpublic (i.e., policy uncertainty $\sigma^2_T = \frac{\sigma^2_v}{\mu\psi} > 0$), the uninformed MMs in asset 1 cannot fully account for the government's trading activity when setting $p^*_{1,1}$ from the observed aggregate order flow in that asset, ω_1 (i.e., $E(v|\omega_1)$). As such, camouflaged government intervention in asset 1 is at least partly effective at pushing that asset's equilibrium price $p^*_{1,1}$ toward its partly uninformative policy target $p^T_{1,1}$—ceteris paribus, $\frac{\partial p^*_{1,1}}{\partial p^T_{1,1}} = \frac{d\lambda^*}{1+d\lambda^*} > 0$ in Proposition 2—hence away from the equilibrium price of asset 2, $p^*_{1,2}$, despite occurring in a deeper market. For instance, in the baseline economy, $\lambda^* = 0.18$ versus $\lambda = 0.34$. Intuitively, $\lambda^* < \lambda$ because at least partly uninformative official trading activity in asset 1 both alleviates dealers' adverse selection risk and induces more aggressive informed (i.e., perfectly correlated) speculation in that asset (Subrahmanyam 1991b; Pasquariello, Roush, and Vega 2014): $B^*_{1,1} > \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$ in Equations (7) and (8), respectively; for example, $B^*_{1,1}=0.69$ versus $\frac{\sigma_z}{\sigma_v\sqrt{M\rho}}=0.45$.

This liquidity differential mitigates the differential impact of less-than-perfectly correlated noise trading shocks on $p^*_{1,1}$ and $p^*_{1,2}$.[14] However, ceteris paribus for $p^*_{1,2}$, the former effect of government intervention on $p^*_{1,1}$ prevails on its latter effect on asset 1's liquidity, leading to greater LOP violations in equilibrium (i.e., allowing for further $E(v|\omega_1)\neq E(v|\omega_2)$). For instance, in the baseline economy, $corr\left(p^*_{1,1},p^*_{1,2}\right)=0.89$ versus $corr\left(p_{1,1},p_{1,2}\right)=0.92$, which amounts to a 19% increase in the expected absolute difference between $p_{1,1}$ and $p_{1,2}$, $E\left(\left|p_{1,1}-p_{1,2}\right|\right)$.[15] Consistently, so-induced LOP violations increase (lower $corr\left(p^*_{1,1},p^*_{1,2}\right)$) not only when the government is more committed to achieve its policy target $p^T_{1,1}$ for asset 1 (higher γ, Figure 1E), but also when the target is less correlated to its private signal of v, $S_v(gov)$ (lower μ, Figure 1F), or that signal is less precise (lower ψ, Figure 1G) such that its official trading activity in that asset is more costly yet less predictable. I further investigate this trade-off in Section 1.2.1.

The implications of government intervention for LOP violations also depend on extant market conditions. Figures 1 and 2 suggest that official trading activity leads to larger LOP violations when the affected markets are less liquid and LOP violations are more severe in the government's absence. In particular, equilibrium $corr\left(p^*_{1,1},p^*_{1,2}\right)$ is lower (and lower than $corr\left(p_{1,1},p_{1,2}\right)$) in the presence of fewer speculators (lower M, Figure 1C) or when their private information is more dispersed (lower ρ, Figure 1B and Figures 2B and 2C [solid lines]). Ceteris paribus, as discussed in Section 1.1.1, fewer or more heterogeneous speculators trade (as a group or individually) more cautiously with their private signals, making MMs' adverse selection problem more severe and the equilibrium price impact of order flow (Kyle (1985) lambda) higher in both assets 1 (λ) and 2 (λ^*), thereby lowering liquidity in both markets and amplifying the impact of liquidity demand differentials on their price correlation. In those circumstances, government intervention in asset 1 is more effective at driving its equilibrium price $p^*_{1,1}$ of Equation (5) toward the partially uninformative policy target, $p^T_{1,1}$—ceteris paribus, $\frac{\partial^2 p^*_{1,1}}{\partial p^T_{1,1}\partial\lambda^*}=$

[14] Accordingly, the dashed lines of $corr\left(p^*_{1,1},p^*_{1,2}\right)$ as a function of σ_{zz} (Figure 1A) and σ^2_z (Figure 1D) are less steep than the corresponding solid lines of $corr\left(p_{1,1},p_{1,2}\right)$ in the absence of official trading activity.

[15] Propositions 1 and 2 and well-known properties of half-normal distributions (e.g., Vives 2008, p. 149) imply that $E\left(\left|p_{1,1}-p_{1,2}\right|\right)=2\lambda\sqrt{\frac{1}{\Pi}\left(\sigma^2_z-\sigma_{zz}\right)}$ and $E\left(\left|p^*_{1,1}-p^*_{1,2}\right|\right)=\sqrt{\frac{2}{\Pi}var\left(p^*_{1,1}-p^*_{1,2}\right)}$, where $\Pi\equiv\arccos(-1)$ and $var\left(p^*_{1,1}\right)$, $var\left(p^*_{1,2}\right)$, and $covar\left(p^*_{1,1},p^*_{1,2}\right)$ are in the proof of Corollary 3; their close relation with $corr\left(p_{1,1},p_{1,2}\right)$ and $corr\left(p^*_{1,1},p^*_{1,2}\right)$ is discussed in Section 2.1.1 below and Section 3 of the Internet Appendix.

$\frac{d}{(1+d\lambda^*)^2} > 0$—hence farther away from the equilibrium price of asset 2 ($p^*_{1,2}$ of Equation (6)).

This effect, however, is less pronounced in correspondence with greater fundamental uncertainty (higher σ^2_v, Figure 1H). When private fundamental information is more valuable, both market liquidity deteriorates (see Section 1.1.1) and the pursuit of policy motives becomes more costly for the government in the loss function of Equation (4). The latter partly offsets the former, leading to a nearly unchanged $corr\left(p^*_{1,1}, p^*_{1,2}\right)$. Similarly, Figures 1 and 2 also suggest that government intervention may amplify LOP violations more conspicuously (greater $\Delta corr\left(p_{1,1}, p_{1,2}\right) > 0$) even when those violations are not as severe in its absence (high $corr\left(p_{1,1}, p_{1,2}\right)$). This may occur when noise trading in assets 1 and 2 (z_1 and z_2) is less intense, lowering liquidity in both markets (lower σ^2_z, Figure 1B and Figures 2B and 2C [dashed lines]), or when z_1 and z_2 are more positively correlated (higher σ_{zz}, Figure 1A). For instance, in the baseline economy with perfectly correlated noise trading shocks ($\sigma_{zz} = \sigma^2_z = 1$), $corr\left(p^*_{1,1}, p^*_{1,2}\right) = 0.93$ (and $E\left(\left|p^*_{1,1} - p^*_{1,2}\right|\right) = 0.27$) versus $corr\left(p_{1,1}, p_{1,2}\right) = 1$ (and $E\left(\left|p_{1,1} - p_{1,2}\right|\right) = 0$). Hence, the observed relation between the impact of government intervention on LOP violations and their extant severity may be positive, negative, or possibly nonmonotonic. I summarize these novel, robust observations about the impact of government intervention on the LOP in Conclusions 1 and 2.[16]

Conclusion 1. Under less-than-perfectly integrated market making, government intervention results in greater LOP violations in equilibrium, even in the absence of liquidity demand differentials.

Conclusion 2. Government-induced LOP violations increase in the government's policy commitment, speculators' information heterogeneity, policy (but not fundamental) uncertainty, and the covariance of noise trading, as well as decrease in the quality of the government's private fundamental information, the covariance of its policy target with fundamentals, the number of speculators, and the intensity of noise trading.

1.2.1 Limiting cases and exceptions. In this section, I examine the implications of notable limiting cases of the model of Section 1.2 for the positive relation between government intervention and LOP violations postulated in Conclusion 1. All of these circumstances are arguably less plausible relative

[16] As noted for the economy of Section 1.1, despite this impact, the unconditional expected prices of assets 1 and 2 remain identical ($E\left(p^*_{1,1}\right) = E\left(p^*_{1,2}\right)$) and no feasible riskless arbitrage opportunity arises in equilibrium.

to the aforementioned literature on official trading activity, and some of them may yield nonrobust exceptions to Conclusion 1. Yet, their examination allows me to further illustrate the intuition behind the model's main predictions.

To begin with, if $\gamma = 0$ in the loss function of Equation (4), the government in the model would act exclusively as an additional, privately informed trader in asset 1. The equilibrium of the resulting economy can be shown to closely mimic the one in Proposition 1 except in that such intervention would make only asset 1 both more liquid ($\lambda^* < \lambda$) and more informationally efficient ($var\left(p^*_{1,1}\right) > var\left(p_{1,1}\right)$), like by increasing the total number of speculators M by one unit only in asset 1 (see Section 1.1.1), and especially when M is small; thus, it would lower asset 1's equilibrium price correlation with asset 2 relative to Corollary 1 ($corr\left(p^*_{1,1}, p^*_{1,2}\right) < corr\left(p_{1,1}, p_{1,2}\right)$), even in the presence of perfectly correlated noise trading shocks ($\sigma_{zz} = \sigma^2_z$). See, for example, Figure IA-1A in the Internet Appendix. The equilibrium $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Corollary 3 and Figure 1E converges to this limiting case for $\gamma \to 0$. Relatedly, there are also circumstances when the dispersion of the information endowments of a sufficiently small number of speculators is so high (i.e., when the precision and correlation of their private signals of v are so low, $\rho \approx 0$) that the government is practically the only informed trader in the targeted asset, thus worsening its dealers' adverse selection risk such that $\lambda^* > \lambda$ (e.g., like in Vitale 1999; Naranjo and Nimalendran 2000) and $corr\left(p^*_{1,1}, p^*_{1,2}\right) \ll corr\left(p_{1,1}, p_{1,2}\right)$, like in Conclusion 1.

Conclusion 1 is also robust to imposing that the government's policy target $p_{1,T}$ is independent of asset 1's terminal payoff v (i.e., $cov\left(v, p^T_{1,1}\right) = 0$, like in Pasquariello, Roush, and Vega 2014), or when $\mu \to 0$ such that $corr\left(v, p^T_{1,1}\right) = \sqrt{\mu\psi} \to 0$. See, for example, Figure IA-1B in the Internet Appendix. This is true even if the government is uninformed about asset fundamentals, that is, even in the absence of $S_v(gov)$, or when $\psi \to 0$ such that $corr\left[v, S_v(gov)\right] = \sqrt{\psi} \to 0$. Intuitively, in either case the pursuit of policy may be not only more costly for the government in terms of expected trading losses in asset 1, but also more effective as less predictable to other market participants. It can be shown that the equilibrium $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Corollary 3 and Figures 1F and 1G converges to either of these limiting cases for either $\mu \to 0$ (but $\psi > 0$) or $\mu = \psi \to 0$, respectively. Relatedly, there are also circumstances when an informed government may optimally trade in asset 1 against its private information ("leaning against the wind") to achieve its at least partly informative policy objectives. For instance, consider parametrizations of the baseline economy for which the equilibrium price impact of order flow in either asset 1 or 2 is relatively low (e.g., $\rho = 0.9$ such that $\lambda = 0.29$) and the government's price target is both relatively important in its loss function ($\gamma = 0.5$ in $L(gov)$ of Equation (4)) and only partially correlated to its fundamental information ($\mu = 0.5$ such that $corr\left[p^T_{1,1}, S_v(gov)\right] = \sqrt{\mu} = 0.71$). In such economies, the resulting $C^*_{1,1} < 0$

in $x_1(gov)$ of Equation (9), while $B^*_{1,1} > 0$ in $x^*_1(m)$ of Equation (7): $C^*_{1,1} = -0.04$ versus $B^*_{1,1} = 0.55$.

Lastly, government intervention in asset 1 may reduce LOP violations in equilibrium when σ_{zz} is close to zero or negative (such that liquidity trading in the fundamentally identical assets 1 and 2 is weakly or negatively correlated), or when both ψ and μ are close to one (such that a nearly fully informed government is in pursuit of a nearly fully informative policy target). In those more extreme circumstances—but only under some market conditions, like a relatively large number of speculators, and even if the government is uninformed and/or in pursuit of an uninformative target—such intervention may increase equilibrium price correlation ($corr\left(p^*_{1,1}, p^*_{1,2}\right) > corr\left(p_{1,1}, p_{1,2}\right)$), in exception to Corollary 1, by at least partly offsetting the impact of highly divergent noise trading shocks on $p^*_{1,1}$. See, for example, Figure IA-1C in the Internet Appendix.

1.3 Empirical implications

The stylized model of Sections 1.1 and 1.2 represents a plausible channel through which direct government intervention may affect the relative prices of fundamentally linked securities in markets with less-than-perfectly integrated dealership. This channel depends crucially on various facets of government policy and the information environment of those markets. Yet, measuring such intervention characteristics and market conditions is challenging, and often unfeasible. Under these premises, I identify from Corollary 1, Proposition 2, Figures 1 and 2, and Conclusions 1 and 2 the following subset of plausibly testable implications of official trading activity for relative mispricings: *H1)* government intervention does not affect extant LOP violations, if any, in markets with perfectly integrated dealership; *H2)* government intervention induces, or increases extant LOP violations in markets with less-than-perfectly integrated dealership; *H3)* this effect is more pronounced when market liquidity is low; *H4)* this effect is more pronounced when information heterogeneity is high; and *H5)* this effect is more pronounced when government policy uncertainty is high.

2. Empirical Analysis

I test the implications of my model by analyzing the impact of government intervention in currency markets on the relative pricing of American Depositary Receipts and other U.S. cross-listings ("ADRs" for brevity). An ADR is a dollar-denominated security, traded in the United States, representing ownership of a pre-specified amount ("bundling ratio") of stocks of a foreign company, denominated in a foreign currency, held on deposit at a U.S. depositary banks (e.g., Karolyi 1998, 2006). In Section 2.1, I motivate the use of this setting to that purpose. I describe the data in Section 2.2. Sections 2.3 to 2.5 contain the econometric analysis.

2.1 ADRs and forex intervention in the model

The market for U.S. cross-listings (the "ADR market") represents an ideal setting to test my model, since its interaction with the foreign exchange ("forex") market is consistent in spirit with the model's basic premises.

First, exchange rates and ADRs are fundamentally linked by an arbitrage parity. Depositary banks facilitate the convertibility between ADRs and their underlying foreign shares (Gagnon and Karolyi 2010) such that the unit price of an ADR i, $P_{i,t}$, should at any time t be equal to the dollar (USD) price of the corresponding amount (bundling ratio) q_i of foreign shares, $P_{i,t}^{LOP}$:

$$P_{i,t}^{LOP} = S_{t,USD/FOR} \times q_i \times P_{i,t}^{FOR}, \tag{11}$$

where $P_{i,t}^{FOR}$ is the unit foreign stock price denominated in a foreign currency FOR, and $S_{t,USD/FOR}$ is the exchange rate between USD and FOR. I interpret the fundamental commonality in the terminal payoffs of assets 1 and 2 in the model (v_1 and v_2) as a stylized representation of the LOP relation between currency and ADR markets in Equation (11). In particular, Equation (11) suggests that one can think of asset 1 as the exchange rate—with payoff $v_1 = v$—traded in the forex market at a price $p_{1,1}$ (i.e., $S_{t,USD/FOR}$); and of asset 2 as an ADR—whose payoff v_2 is a linear function of the exchange rate: $v_2 = a_2 + b_2 v$, where $a_2 = 0$ and $b_2 = q_i \times P_{i,t}^{FOR} > 0$, that is, ceteris paribus for the corresponding foreign stock price—traded in the U.S. stock market at a *tilded* price $\widetilde{p}_{1,2} = b_2 p_{1,2}$ (i.e., $P_{i,t}$). Ignoring the market for an ADR's underlying foreign shares is for simplicity only and without loss of generality. In Section 1 and Figure IA-2 of the Internet Appendix, I show that extending the model to a third such asset—with payoff v_3 such that the ADR's log-linearized payoff $v_2 = a_2 + v_1 + v_3$, where $a_2 = \ln(q_i)$—requires more involved analysis but yields similar implications.

In the above setting, the LOP relation between actual ($P_{i,t}$) and *synthetic* ($P_{i,t}^{LOP}$) ADR prices in Equation (11) can then be represented by the unconditional correlation between $\widetilde{p}_{1,2}$ and $p_{1,2}^{LOP} = b_2 p_{1,1}$, respectively (e.g., Gromb and Vayanos 2010), such that in equilibrium: $corr\left(\widetilde{p}_{1,2}, p_{1,2}^{LOP}\right) = corr\left(p_{1,1}, p_{1,2}\right)$ of Equation (3). Accordingly, I postulate in Conclusion 1 that, ceteris paribus, government intervention in the forex market—that is, targeting the exchange rate $p_{1,1}$—lowers the unconditional correlation between exchange rates and actual ADR prices—that is, between $p_{1,1}$ and $\widetilde{p}_{1,2}$: $corr\left(p_{1,1}^*, \widetilde{p}_{1,2}^*\right) = corr\left(p_{1,1}^*, p_{1,2}^*\right)$ of Equation (10), such that $corr\left(p_{1,1}^*, \widetilde{p}_{1,2}^*\right) < corr\left(\widetilde{p}_{1,2}, p_{1,2}^{LOP}\right)$. Hence, forex intervention may yield larger price differentials between actual and synthetic ADRs—that is, it lowers the unconditional correlation between $\widetilde{p}_{1,2}$ and $p_{1,2}^{LOP}$: $corr\left(\widetilde{p}_{1,2}^*, p_{1,2}^{LOP*}\right) = corr\left(p_{1,1}^*, p_{1,2}^*\right)$, such that $corr\left(\widetilde{p}_{1,2}^*, p_{1,2}^{LOP*}\right) < corr\left(\widetilde{p}_{1,2}, p_{1,2}^{LOP}\right)$.

Second, market making in currency and ADR markets is arguably less-than-perfectly integrated, in that market makers in one market are less likely to directly observe, and set prices based on, trading activity in the other market than within their own.[17] I interpret segmented market making in assets 1 and 2 in the model as a stylized representation of this observation. Third, as mentioned in Section 1.2, the stylized representation of the government in the model is consistent with the consensus in the literature that government intervention in currency markets, although typically secret and in pursuit of nonpublic policy, is often effective at moving exchange rates because it is deemed at least partly informative about fundamentals.[18] Fourth, the same literature suggests that forex intervention is unlikely to be motivated by relative mispricings in the ADR market. This observation alleviates reverse causality concerns when estimating and interpreting any empirical relation between government intervention and the arbitrage parity of Equation (11). I further assess this and other potential sources of endogeneity in Section 2.3.1.

Overall, according to the model, these features of currency and ADR markets raise the possibility that government intervention in the former may lead to LOP violations in the latter, that is, to "ADR parity" (ADRP) violations. I measure these violations as nonzero absolute log percentage differences, in basis points (bps), between actual ($P_{i,t}$) and theoretical ADR prices ($P_{i,t}^{LOP}$ of Equation (11)):

$$ADRP_{i,t} = \left|\ln\left(P_{i,t}\right) - \ln\left(P_{i,t}^{LOP}\right)\right| \times 10{,}000 \tag{12}$$

(e.g., Gagnon and Karolyi 2010; Pasquariello, Roush, and Vega 2014), and assess their empirical relation with forex intervention in the reminder of the paper.

2.1.1 Alternative model interpretations and measures of ADRP violations. My investigation of the effects of forex interventions on ADRP violations is qualitatively unaffected when considering alternative interpretations of the traded assets in the model, relative to actual and synthetic ADRs in Equation (11), or alternative measures of LOP violations both in the model and in the ADR market, relative to their absolute price differentials in Equation (12).

To begin with, I show in Section 2 of the Internet Appendix that the linearity of asset payoffs and equilibrium prices in the model implies that one can also think of asset 1 as the actual exchange rate traded in the forex markets and of asset 2 as either: (1) an ADR-specific synthetic, or shadow exchange rate implied by Equation (11) implicitly traded in the ADR market at $S_{t,USD/FOR}^{i,LOP} = P_{i,t} \times \left(q_i \times P_{i,t}^{FOR}\right)^{-1}$ (e.g., Auguste et al. 2006; Eichler, Karmann, and Maltritz 2009); or (2) an actual ADR traded in the U.S. stock market at $P_{i,t}$ implying a synthetic exchange rate $S_{t,USD/FOR}^{i,LOP}$. Although less common and intuitive, these

17 See Lyons (2001) and Gagnon and Karolyi (2010) for investigations of the microstructure of currency and ADR markets, respectively.

18 Recent examples include Bhattacharya and Weller (1997), Peiers (1997), Vitale (1999), Naranjo and Nimalendran (2000), Payne and Vitale (2003), and Pasquariello (2007b). See also the comprehensive surveys in Edison (1993), Sarno and Taylor (2001), Neely (2005), Menkhoff (2010), and Engel (2014).

representations of the LOP relation between currency and ADR markets are conceptually and empirically equivalent to the one discussed in Section 2.1 since any violation of the ADR parity of Equation (11) yields both $P_{i,t} \neq P_{i,t}^{LOP}$ and $S_{t,USD/FOR} \neq S_{t,USD/FOR}^{i,LOP}$—that is, not only the same equilibrium price correlation in the model but also the same absolute percentage LOP violation in Equation (12).

In addition, as noted in Section 1.1.2, the notion of LOP violations in the ADR market as nonzero unsigned relative, that is, log percentage, price differentials $ADRP_{i,t}$ of Equation (12) is both common in the literature and conceptually equivalent to the notion of LOP violations as less-than-one equilibrium unconditional price correlation $corr(p_{1,1}, p_{1,2})$ in the model. For instance, I show in Section 3 of the Internet Appendix that the expected absolute differential between equilibrium actual and synthetic ADR prices described in Section 2.1 (i.e., $E\left(\left|\widetilde{p}_{1,2} - p_{1,2}^{LOP}\right|\right)$) is a, ceteris paribus decreasing, function of their unconditional correlation whose scale depends on the magnitude of the ADR's fundamental payoff. Both $corr(p_{1,1}, p_{1,2})$ and $ADRP_{i,t}$ are instead price-scale invariant and display similar comparative statics (see also Auguste et al. 2006; Pasquariello 2008; Gagnon and Karolyi 2010). Accordingly, the empirical analysis of several measures of the correlation between actual and synthetic ADR prices, although computationally less convenient than for $ADRP_{i,t}$ in my setting, yields qualitatively similar inference. See, for example, Figure IA-3 and Tables IA-1 and IA-2 in the Internet Appendix.

2.2 Data

For the empirical investigation of my model, I construct a sample of ADRs traded in U.S. stock exchanges and official intervention activity in currency markets over the past three decades.

2.2.1 ADRs. I begin by obtaining from Thomson Reuters Datastream (Datastream) its entire sample of foreign stocks cross-listed in the United States between January 1, 1973 and December 31, 2009.[19] Following standard practice in the literature, I then remove ADRs trading over-the-counter (Level I), Securities and Exchange Commission (SEC) Regulation S shares, private placement ADRs (Rule 144A), and preferred shares. In addition, I also conservatively exclude any identifiable cross-listing with ambiguous, incomplete, or missing descriptive, listing, or pairing information in the Datastream sample. This leaves a subset of 410 viable Level II and Level III ADRs from developed and emerging countries (with bundling ratios q_i) and mostly Canadian ordinary shares (ordinaries, with $q_i = 1$) listed on the three major U.S. stock exchanges (NYSE,

[19] I complement this sample with the directory of depositary receipts compiled by Bank of New York Mellon (BNY Mellon), available at https://www.adrbnymellon.com/directory/dr-directory.

Table 1
ADRP violations: Summary statistics

				ADRP violations								ADRP illiquidity	
				$ADRP_m$		$ADRP^z_m$		$\Delta ADRP_m$		$\Delta ADRP^z_m$		$ILLIQ_m$	
Country (Currency)	N_v	N_u	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Australia (AUD)	30	23	269	217.26	112.57	−0.23	0.32	−3.39	53.91	−0.002	0.280	11.0%	9.0%
Argentina (ARS)	9	6	198	187.70	114.41	0.40	1.15	0.44	81.45	−0.001	0.840	19.2%	12.5%
Brazil (BRL)	23	18	178	165.06	104.49	−0.08	0.36	−1.60	40.57	0.003	0.307	9.1%	7.2%
Canada (CAD)	67	46	360	103.13	46.08	−0.18	0.27	−0.08	26.14	−0.000	0.189	13.4%	7.7%
Chile (CLP)	5	5	168	185.16	67.26	−0.33	0.38	0.41	50.94	−0.006	0.338	14.9%	7.1%
Euro area (EUR)	58	51	287	352.29	287.90	−0.41	0.64	−0.87	60.98	−0.001	0.421	6.5%	3.8%
Hong Kong (HKD)	54	39	198	166.78	65.22	0.07	0.33	−0.69	40.03	−0.002	0.282	15.0%	5.9%
India (INR)	10	9	143	248.34	141.33	−0.07	0.38	−0.42	64.99	−0.004	0.359	4.7%	3.1%
Indonesia (IDR)	5	2	168	181.19	79.67	−0.04	0.48	−0.93	67.90	−0.010	0.408	9.7%	4.9%
Japan (JPY)	24	19	360	149.34	75.33	−0.04	0.42	−0.31	29.46	−0.001	0.289	9.3%	3.8%
Mexico (MXN)	9	9	198	275.74	78.37	−0.16	0.35	−0.24	54.34	−0.005	0.285	16.6%	5.4%
Russia (RUB)	7	7	140	189.70	114.27	−0.05	0.46	−1.66	86.89	−0.004	0.400	10.0%	8.7%
S. Africa (ZAR)	14	13	231	324.28	185.28	0.06	0.63	−0.77	66.61	−0.000	0.297	11.2%	5.9%
S. Korea (KRW)	8	7	141	328.73	187.75	−0.10	0.44	−0.86	74.53	−0.004	0.285	6.9%	4.4%
Switzerland (CHF)	4	2	116	253.67	141.83	−0.55	0.39	−1.98	37.30	−0.015	0.261	4.1%	2.6%
Turkey (TRY)	7	3	74	227.50	174.99	0.21	0.99	−1.30	104.33	−0.005	0.619	7.8%	4.0%
United Kingdom (GBP)	43	34	360	200.59	73.82	−0.21	0.31	−0.48	34.07	0.000	0.211	4.7%	2.6%
Other (Other)	33	26	250	261.15	112.06	−0.18	0.40	−0.26	85.10	0.005	0.371	17.3%	14.1%
Total	410	319	360	194.33	41.34	−0.17	0.19	−0.28	21.47	−0.001	0.153	10.6%	3.3%

This table reports the composition of the sample of U.S. cross-listings by the country or most recent currency area of listing (i.e., most recent currency of denomination) of the underlying foreign stocks, as well as summary statistics on the country-level and marketwide measures of their usable mispricings and illiquidity in the analysis. These measures are constructed by first obtaining all viable Level II and Level III ADRs and ordinaries ("ADRs") listed on the NYSE, AMEX, or NASDAQ from the entire Datastream sample of U.S. cross-listings between January 1, 1973 and December 31, 2009; N_v is their number in each grouping (where all those with available actual mispricings in the 1970s are usable afterward). $ADRP_m$ and $ADRP^z_m$ are then computed from Datastream and Pacific data as the monthly averages of daily equal-weighted means of available, filtered actual (in basis points [bps], i.e., multiplied by 10,000) and historically standardized absolute log violations of the ADR parity (ADRP; Equations (11) and (12)); $\Delta ADRP_m = ADRP_m - ADRP_{m-1}$ and $\Delta ADRP^z_m = ADRP^z_m - ADRP^z_{m-1}$. $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 2.2.1 as the equal-weighted mean (in percentage) of monthly averages of Z^{FOR}_t, Z_t, and Z^{FX}_t, the daily fractions of ADRs in $ADRP_m$ whose underlying foreign stock, ADR, or exchange rate experiences a zero return on day t. For each grouping, I list the ensuing total number of usable ADRs (N_u), as well as available months (N), mean, and standard deviation for each measure over the sample period 1980–2009. The "Other" grouping includes Colombia (COP), Denmark (DKK), Egypt (EGP), Hungary (HUF), Israel (ILS), New Zealand (NZD), Norway (NOK), Philippines (PHP), Singapore (SGD), Sweden (SEK), Taiwan (TWD), Thailand (THB), and Venezuela (VEF).

AMEX, or NASDAQ).[20] Because of my focus on forex interventions, Table 1 reports the composition of this sample by the country or most recent currency area of listing (i.e., most recent currency of denomination) of the underlying foreign stocks. Most viable cross-listed stocks are traded in developed, highly liquid and higher-quality equity markets, and denominated in highly liquid currencies: Canada (CAD, $N_v = 67$), Euro area (EUR, 58), United Kingdom (GBP, 43), Australia (AUD, 30), and Japan (JPY, 24); emerging, often less liquid and lower-quality equity markets and currencies of local listing comprise Hong Kong (HKD, 54 including H-shares of firms incorporated in mainland China), Brazil (BRL, 23), and South Africa (ZAR, 14), among others.

Daily closing prices for these U.S. cross-listings, $P_{i,t}$, and their underlying foreign stocks, $P^{FOR}_{i,t}$, are also from Datastream. The corresponding exchange

20 This is the sample used in Pasquariello, Roush, and Vega (2014); see also Baruch, Karolyi, and Lemmon (2007), Pasquariello (2008), Gagnon and Karolyi (2010), and the references therein.

rates in Equation (11), $S_{t,USD/FOR}$, are daily indicative spot mid-quotes, as observed at 12 p.m. Eastern Standard Time (EST), from Pacific Exchange Rate Service (Pacific) and Datastream. Although commonly used, the resulting dataset allows to measure the extent of LOP violations in the ADR market only imprecisely (see, e.g., Ince and Porter 2006; Xie 2009; Gagnon and Karolyi 2010; Pasquariello, Roush, and Vega 2014). For instance, the trading hours in many of the foreign stock and currency markets listed in Table 1 are partly overlapping or nonoverlapping with those in New York, yielding nonsynchronous closing prices. Individual ADRP violations often differ in scale, making cross-sectional comparisons problematic, and either persist or display discernible trends. Paired closing foreign stock, currency, or ADR prices may also be stale (e.g., reflecting sparse trading), incorrectly reported (e.g., due to inaccurate data entry or around delistings), partly unavailable, or sometimes altogether missing.

Pasquariello, Roush, and Vega (2014) proposes two measures of the marketwide (i.e., aggregate), low-frequency extent of violations of the ADR parity of Equation (11) addressing these concerns. The first measure, $ADRP_m$, is the monthly average of daily equal-weighted means of all available, filtered realizations of $ADRP_{i,t}$ of Equation (12), that is, of daily mean absolute percentage ADRP violations. In particular, I conservatively remove from these averages any available $ADRP_{i,t}$ deemed "too large" ($ADRP_{i,t} > 1,000$ bps) or stemming from "too extreme" ADR prices ($P_{i,t} < \$5$ or $P_{i,t} > \$1,000$). These requirements and the aforementioned data limitations reduce the number of usable ADRs to 319 in total and roughly uniformly across most groupings in Table 1, except for Turkey ($N_u = 3$), Indonesia (3), Hong Kong (39), and Canada (46).[21] Yet, filtering and daily averaging across individual ADRs minimize the impact of any idiosyncratic parity violations (or lack thereof), for example, due to quoting errors, missing data, or other data issues in the sample. Monthly averaging further smooths any spurious daily variability in observed ADRP violations, for example, due to bid-ask bounce, price staleness, nonsynchronicity, or data gaps, among others. The second measure, $ADRP^z_m$, is the monthly average of daily equal-weighted means of all historically normalized ADRP violations, $ADRP^z_{i,t}$—that is, after each usable realization of $ADRP_{i,t}$ has been standardized by its earliest available historical distribution on day t since 1973.[22] Up-to-current normalization allows me to identify individual abnormal ADRP violations—that is, innovations in each observed $ADRP_{i,t}$ relative to its time-varying, potentially spurious mean—without look-ahead bias, while making these violations comparable in scale across ADRs. As such,

[21] The analysis and inference are unaffected by this filtering procedure or by excluding all Canadian ordinaries, whose fungibility and propensity to delist from U.S. exchanges differ from those of ADRs and other ordinaries (Witmer 2008; Gagnon and Karolyi 2010).

[22] Specifically, I standardize each available, filtered absolute ADR parity violation, $ADRP_{i,t}$, by its historical mean and standard deviation over at least 22 observations up to (and including) its current realization.

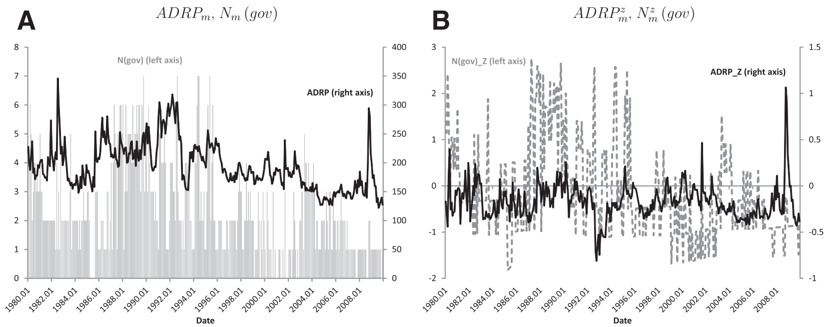

Figure 3
ADRP violations and forex intervention
This figure plots the aggregate measures of LOP violations in the ADR market, defined in Section 2.2.1 as the monthly averages of daily equal-weighted means of available actual ($ADRP_m$, Figure 3A, right axis, solid line, in basis points [bps], i.e., multiplied by 10,000) and standardized ($ADRP^z_m$, Figure 3B, right axis, solid line) absolute log violations of the ADR parity of Equation (11), as well as the aggregate measures of government intervention in the forex market, defined in Section 2.2.2 as the number of government intervention-exchange rates pairs in each month m ($N_m\,(gov)$, Figure 3A, left axis, histogram) and the number of those pairs standardized by its historical distribution in month m ($N^z_m\,(gov)$, Figure 3B, left axis, dashed line), over the sample period 1980–2009.

$ADRP^z_m$ is positive (higher) in correspondence with historically large (larger) LOP violations in the ADR market.

Foreign companies rarely issued ADRs before the 1980s (e.g., Karolyi 2006; Sarkissian and Schill 2016; Karolyi and Wu Forthcoming). When they did, their local and cross-listed stock prices in my sample—although frequently associated with usable mispricings for all of them afterward—are often either stale or suspect then, yielding extreme LOP violations. Accordingly, the filtering and aggregation procedure described above results in several missing observations between 1973 and 1979. Thus, I focus the empirical analysis on the interval 1980–2009, the longest portion of the sample with the greatest aggregate and country-level continuous coverage. Inference from the full sample is qualitatively similar. Summary statistics for marketwide and country-level $ADRP_m$ and $ADRP^z_m$ for the sample period 1980–2009 are in Table 1; their marketwide plots are in Figures 3A and 3B (right axis, solid line).

Consistent with the aforementioned literature, absolute ADR parity violations $ADRP_m$ in the past three decades are large (e.g., a sample mean of nearly 2% [194 bps]). They are also volatile, although not exceedingly so (e.g., a sample standard deviation of 41 bps), and declining, perhaps reflecting improving quality and integration of the world financial markets. Once controlling for this trend, scaled such violations ($ADRP^z_m$), while often statistically significant, display more discernible cycles and spikes, especially during periods of financial turmoil.[23] Both measures also display nontrivial

[23] In particular, $ADRP^z_m$ is statistically significant at the 10% level in 76% of all months over the sample period 1980–2009; $ADRP^z_m$ is highest in October 2008, in correspondence with the global financial crisis initiated by

cross-country heterogeneity. LOP violations in Table 1 are on average most pronounced for ADRs from Europe, Australia, and emerging markets (e.g., Mexico, South Africa, and South Korea), and least pronounced for Canadian ordinaries, which have long been trading synchronously and (as noted earlier) on a one-to-one basis in both Canada and the United States.

The model of Section 1 relates extant ($corr\left(p_{1,1}, p_{1,2}\right) < 1$) and intervention-induced equilibrium LOP violations ($corr\left(p^*_{1,1}, p^*_{1,2}\right) < corr\left(p_{1,1}, p_{1,2}\right)$) to common, exogenous forces affecting the equilibrium liquidity of the underlying, arbitrage-linked markets (λ and λ^*), such as the number of multiasset speculators (M, in Figure 1C) or the correlation of their private fundamental information (ρ, in Figure 1B). In light of this observation, Equation (11) suggests that ADR parity violations may be related to exogenous commonality in the liquidity of the U.S. stock market where an ADR is exchanged, the listing market for the underlying foreign stock, and the corresponding currency market. Those violations may also be caused by such illiquidity increasing the cost of ADR arbitrage activity (e.g., Gagnon and Karolyi 2010; Gromb and Vayanos 2010). Data availability considerations make measurement of liquidity in many of these venues over long sample periods challenging, especially in emerging markets (e.g., Lesmond 2005; Lyons and Moore 2009; Mancini, Ranaldo, and Wrampelmeyer 2013). Lesmond, Ogden, and Trzcinka (1999) and Lesmond (2005) propose to measure a security's (or a market's) illiquidity by its incidence of zero returns, as the relative frequency of its price changes may depend on transaction costs and other impediments to trade; they then show that so-constructed estimates are highly correlated with popular measures of liquidity like quoted or effective bid-ask spreads (when available; see also Bekaert, Harvey, and Lundblad 2007).

Accordingly, I define and compute composite marketwide and country-level illiquidity measures, $ILLIQ_m$ (Figure 4A), for both $ADRP_m$ and $ADRP^z_m$ as the equal-weighted means of monthly averages of Z^{FOR}_t, Z_t, and Z^{FX}_t—the daily fractions of ADRs in the corresponding grouping whose underlying foreign stock, ADR, or exchange rate experiences a zero return on day t ($P^{FOR}_{i,t} = P^{FOR}_{i,t-1}$, $P_{i,t} = P_{i,t-1}$, or $S_{t,USD/FOR} = S_{t-1,USD/FOR}$), respectively. This procedure allows to capture any commonality in ADR parity-level liquidity parsimoniously, over the full sample, and without look-ahead bias. Summary statistics for $ILLIQ_m$ (in percentage) are in Table 1. Perhaps unsurprisingly, the so-defined ADRP illiquidity of cross-listings from developed economies is lower than in emerging markets; for example, the average fraction of zero returns across U.S., foreign stock, and currency markets $ILLIQ_m$ is as low as 4.1% for Switzerland and 4.7% for the United Kingdom, and as high as 19.2% for Argentina and 16.6% for Mexico. However, there is also significant heterogeneity in ADRP illiquidity across both sets of markets; for example, $ILLIQ_m$ for cross-listings from South

Lehman Brothers' default (on September 15, 2008). Qualitatively similar inference ensues from excluding the subperiod 2008–2009 from the analysis.

Korea (6.9%) or Turkey (7.8%) is lower than for those from Canada (13.4%) or Australia (11%).

Interestingly, Table 1 further suggests that large ADRP violations tend to be associated with both extremes of the cross-sectional distribution of ADRP illiquidity. For instance, mean $ADRP_m$ and $ADRP^z_m$ are relatively high for cross-listings not only from Argentina and Mexico (whose $ILLIQ_m$ are high) but also from the Euro area and South Korea (whose $ILLIQ_m$ is instead low).[24] This preliminary observation is consistent with my model's basic premise, as summarized in Corollary 2. In the basic model of multiasset trading without government intervention of Section 1.1, LOP violations are likely to be larger (i.e., $corr\left(p_{1,1}, p_{1,2}\right)$ is lower) not only when (the commonality in) asset liquidity is low—because the price impact of less-than-perfectly correlated noise trading is greater—but also when it is high—because the intensity of less-than-perfectly correlated noise trading is greater. See, for example, the plots of $\overline{corr\left(p_{1,1}, p_{1,2}\right)}$ versus $\overline{\lambda}$ in Figure 2A. I investigate this relation and, more generally, the relevance of extant market quality for the LOP externality of government intervention, in greater detail in Sections 2.4 and 2.5.

2.2.2 Forex interventions. As noted earlier, the forex market is not only one of the largest and deepest financial markets but also one where government interventions occur most often.[25] According to the literature (surveyed in Edison 1993; Sarno and Taylor 2001; Neely 2005; Menkhoff 2010; Engel 2014), monetary authorities, like central banks, and other government agencies frequently engage in secret, generally small, nearly always sterilized currency transactions (i.e., accompanied by offsetting actions on the domestic money supply), normally in a coordinated fashion, to accomplish their habitually nonpublic policy objectives for exchange rate dynamics, at least in the short-run, by virtue of their actual or perceived informativeness about market fundamentals.

As discussed in Section 1.2, the stylized government of Equation (4) captures in spirit those features of observed official currency trading activity. To measure this activity, I use the database of government intervention in currency markets available on the Federal Reserve Economic Data (FRED) website of the Federal Reserve Bank of St. Louis.[26] This database contains daily amounts of domestic and/or foreign currencies traded by the governments of Australia, Germany, Italy, Japan, Mexico, Switzerland, Turkey, and the United States for policy

[24] Accordingly, Gagnon and Karolyi (2010) find that estimates of the price impact of order flow in the foreign (U.S.) stock market are positively related to relative ADR parity violations for cross-listings from markets with relatively high (low) levels of economic and capital market development. See also Baruch, Karolyi, and Lemmon (2007) and Levy Yeyati, Schmukler, and Van Horen (2009).

[25] For an overview of the main characteristics of the global currency markets, see the 2016 triennal survey by the Bank for International Settlements (BIS 2016).

[26] See https://fred.stlouisfed.org/categories/32145.

reasons—that is, to influence exchange rates—over the past several decades, in some cases as early as in 1973 or as late as in 2009.[27] Where currency-specific intervention data are missing, I augment the FRED database using various official government sources (when possible).[28] As for the sample of ADR parity violations, the resulting sample has the broadest continuous coverage of currency intervention activity between 1980 and 2009.[29]

Panel A of Table 2 reports summary statistics for these interventions, aggregated at the monthly frequency over this period, by country and foreign exchange involved. All governments in the sample intervene by purchasing or selling their domestic currencies. Most often, they do so against USD, the currency of denomination of ADRs; less so via cross-rates, exchange rates not involving vehicle currencies like USD or EUR.[30] Cross-rates are however kept in line with the corresponding USD-denominated exchange rates by triangular arbitrage (Bekaert and Hodrick 2012); thus, any intervention in the former must reverberate in the latter. Excluding those interventions from the sample does not affect the inference; see, for example, Tables IA-3 and IA-4 in the Internet Appendix.

According to Table 2, and consistent with the aforementioned literature, the absolute amounts of currency traded by these governments in the sample, while nontrivial, are small relative to the average monthly trading volume in the forex market (e.g., USD 111 trillions, according to BIS 2016) and heterogeneous across currencies and governments. Yet, scaling and aggregating these amounts is impeded by cross-currency turnover heterogeneity and sparsity of historical currency turnover data. Furthermore, in my model, like in all models based on Kyle (1985), optimal strategic and noise trading activity in general, and optimal intervention intensity in particular (i.e., sign and magnitude of $x_1(gov)$ of Equation (9)), are separately unobservable by dealers and endogenously determined in equilibrium. However, the presence of an active government is exogenous and known to all market participants. Both the presence and optimal intensity of an intervention contribute to its impact on equilibrium price formation. Relatedly, the effect of $x_1(gov)$ on equilibrium outcomes depends not only on the realizations of unobservable variables controlling

27 Accordingly, as is standard, I remove from the sample all customer transactions, that is, central banks' infrequent passive forex trades triggered not by policy motives but by their domestic governments' mundane requests for foreign currencies (e.g., Payne and Vitale 2003; Pasquariello 2007b).

28 More detailed information on the intervention activity of any of these governments (e.g., time-stamped trades or transaction prices) is rarely available over extended sample periods, with the exception of the Swiss National Bank (SNB; Fischer and Zurlinden 1999).

29 Official trades in the sample may have been executed in the spot and/or forward currency markets, although the former is much more common than the latter (e.g., Neely 2000). Only in the case of Australia, the FRED database explicitly mentions consolidating spot and forward transactions by the Reserve Bank of Australia (RBA).

30 Japan and Switzerland occasionally trade on exchange rates between foreign currencies and USD. In the case of either Italy and the United States or Germany, the FRED database also reports official trades in their domestic currencies relative to either unspecified "other" currencies or unspecified currencies in the European Monetary System (EMS).

Table 2
Government interventions in the forex market: Summary statistics

A. Forex intervention by country and foreign exchange

Country	Foreign exchange		Absolute amount ($1M) N	Mean	SD
Australia	AUD	USD	184	394	460
Germany	DEM	USD	115	534	688
Germany	DEM	Other	66	2,603	8,293
Italy	ITL	Other	111	1,168	1,655
Japan	JPY	DEM, EUR	10	930	1,296
Japan	JPY	USD	64	9,092	12,012
Japan	DEM	USD	1	101	na
Japan	INR	USD	1	568	na
Mexico	MXN	USD	84	601	492
Switzerland	CHF	DEM	1	0.44	na
Switzerland	CHF	USD	39	163	164
Switzerland	DEM	USD	2	70	78
Switzerland	JPY	USD	6	98	73
Turkey	TRL, TRY	USD	16	1,728	1,460
United States	USD	DEM, EUR	76	626	641
United States	USD	JPY	60	537	755
United States	USD	Other	12	90	88

B. Aggregate measures of forex intervention

Variable			N	Mean	SD
$N_m(gov)$	na	na	360	2.36	1.61
$N_m^z(gov)$	na	na	360	−0.13	1.03
$\Delta N_m(gov)$	na	na	360	−0.006	1.402
$\Delta N_m^z(gov)$	na	na	360	−0.004	0.911

This table reports summary statistics on the database of government interventions in the foreign exchange ("forex") market between January 1, 1980 and December 31, 2009 used in the analysis. This database is compiled by the Federal Reserve Bank of St. Louis. For each country for which intervention data is available, I list in panel A the foreign exchange involved, the number of months in the sample when official trades were executed (N), as well as the mean and standard deviation of their absolute total monthly amounts (USD millions); "na" indicates not applicable. In the case of Italy (Germany) and the United States, the database reports official trades in the domestic currency relative to unspecified "other" currencies (in the European Monetary System [EMS]). This table also reports summary statistics for $N_m(gov)$, the number of nonzero government intervention-exchange rate pairs in a month, $N_m^z(gov)$, the number of those pairs standardized by its earliest available historical distribution in month m since 1973, as defined in Section 2.2.2; $\Delta N_m(gov) = N_m(gov) - N_{m-1}(gov)$ and $\Delta N_m^z(gov) = N_m^z(gov) - N_{m-1}^z(gov)$. I list their total number of available months, mean, and standard deviation over the sample period 1980–2009 in panel B.

the government's information and policy but also on market participants' unobservable expectations of them (i.e., on $E\left[x_1(gov)\right] = 2d\left(\overline{p}_{1,1}^T - p_0\right)$ in $p_{1,1}^*$ of Equation (5)). Comprehensive survey data on forex intervention expectations is typically unavailable, and their estimation raises considerable econometric challenges (e.g., Dominguez and Frankel 1993; Naranjo and Nimalendran 2000; Sarno and Taylor 2001).

Thus, my model does not postulate any easily testable relation between realized intervention sign and/or magnitude and LOP violations (see also Bhattacharya and Weller 1997). Consistently, since Kyle (1985), there is strong empirical support in the literature for the use of order imbalance—that is, the total or net signed number of transactions over a period of time—rather than signed or unsigned trading volume, to measure the intensity of order flow and estimate its impact 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 et al. 2017).[31]

In addition, as mentioned above, most currency interventions are coordinated among multiple governments for greatest effectiveness (e.g., Dominguez and Frankel 1993; Sarno and Taylor 2001); however, individual transactions within a concerted forex policy may not be contemporaneous, as they are executed in different time zones and often coordinated through informal discussions. Accordingly, many of the official currency trades in Table 2 tend to cluster in time but often are not perfectly synchronous at high frequency. Lastly, Tables 1 and 2 suggest that there is relative scarcity of currency-matched intervention-ADR pairs and events in the sample. For instance, forex interventions in Table 2 can be feasibly matched to only 105 usable ADRs in Table 1 whose underlying foreign stocks are denominated in the involved currencies (AUD, EUR, JPY, MXN, or TRY), and only over the portions of the sample period 1980–2009 when both are contemporaneously available.[32] Yet, portfolio rebalancing, price pressure, and triangular arbitrage effects may induce significant cross-currency spillovers of interventions involving vehicle currencies (e.g., Dominguez 2006; Beine, Bos, and Laurent 2007; Beine, Laurent, and Palm 2009; Chortareas, Jiang, and Nankervis 2013; Gerlach-Kristen, McCauley, and Ueda 2016). Analysis of this smaller dataset (in Section 2.4) yields noisier but qualitatively similar inference.

In light of these observations, I propose two aggregate, low-frequency measures of the presence and intensity of government intervention in the forex market. The first measure, $N_m(gov)$, is the number of nonzero government intervention-exchange rates pairs in a month. The second measure, $N_m^z(gov)$, is such a number standardized by its earliest available historical distribution in month m since 1973, as in Section 2.2.1. Hence, as for normalized ADRP violations $ADRP_m^z$, a positive (negative) $N_m^z(gov)$ indicates an abnormally large (small) number of government interventions—that is, historically high (low) intensity of official trading activity—in the forex market during month m. Consistent with the aforementioned literature, replacing $N_m(gov)$ and $N_m^z(gov)$ in the ensuing analysis with the actual and normalized sums of unsigned and unscaled observed government trades (in USD millions at concurrent exchange rates) yields similar but weaker evidence, while augmenting that analysis by

[31] For instance, in their seminal empirical investigation of the U.S. stock market, Jones, Kaul, and Lipson (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." According to Hasbrouck (2007, p. 90), time-averaged price formation is relatively unaffected by order size because of time variation in liquidity since, like in my model, "agents trade large amounts when price impact is low, and small amounts when price impact is high."

[32] For example, I observe no interventions in CHF or INR over the portions of the sample period when I can compute ADRP violations for cross-listed stocks denominated in CHF or INR; in addition, USD interventions by the United States in unspecified "other" currencies (see Table 2) cannot be matched to any ADR.

those measures does not affect the inference. See, for example, Figure IA-4A and Tables IA-5 and IA-7 in the Internet Appendix.

I plot $N_m(gov)$ and $N_m^z(gov)$ in Figures 3A (left axis, histogram) and 3B (left axis, dashed line), alongside $ADRP_m$ and $ADRP_m^z$, respectively. Their summary statistics are in panel B of Table 2. Forex interventions (i.e., $N_m(gov) \geq 1$ in Figure 3A) occur in almost every month of the sample; thus, identification of their impact on LOP violations may come from their time-varying intensity. Official trading activity in the currency markets is especially intense in the late 1980s and mid-1990s, before abating afterward. In those circumstances, both $N_m(gov)$ and $N_m^z(gov)$ experience frequent sharp spikes, suggesting that episodes of coordinated forex intervention are often short-lived but not isolated.[33] Figure 3 also suggests that more frequent forex intervention is often accompanied by larger LOP violations in the ADR market. I formally investigate this possibility next.

2.3 Marketwide ADRP violations

Table 2 and Figure 3 indicate that the market for ADRs experiences nontrivial LOP violations between 1980 and 2009. According to the model of Section 1 (see, e.g., H2 in Section 1.3), government intervention in currency markets may induce their occurrence or increase their intensity.

I test this prediction by specifying the following regression model for changes in monthly averages of measures of those LOP violations (e.g., Neely 2005; Pasquariello 2007b; Garleanu and Pedersen 2011):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \tag{13}$$

where LOP_m is either $ADRP_m$ or $ADRP_m^z$, $\Delta LOP_m = LOP_m - LOP_{m-1}$, I_m is either $N_m(gov)$ or $N_m^z(gov)$, and $\Delta I_m = I_m - I_{m-1}$. Both ADR parity violations and the intensity of forex interventions tend to persist; for instance, the time series of $ADRP_m$ and $N_m(gov)$ in Figure 3A ($ADRP_m^z$ and $N_m^z(gov)$ in Figure 3B) have a first-order serial correlation of 0.86 and 0.62 (0.68 and 0.61), respectively. Regressions in changes mitigate biases caused by potential non-stationarity (e.g., Hamilton 1994). In unreported analysis, regressions in levels yield similar or stronger results. Year and month fixed effects (or linear and quadratic time trends) are nearly always statistically insignificant and their inclusion does not affect the inference. The coefficient β_0 in Equation (13) captures the contemporaneous impact of forex intervention activity ($\Delta I_m > 0$) on ADRP violations (ΔLOP_m) predicted by the model of Section 1.2 and discussed in Section 2.1, that is, $\Delta corr(p_{1,1}, p_{1,2}) > 0$ in Figures 1, 2B, and 2C. Currency market participants may anticipate the nature and/or extent of forex intervention and react prior to its actual occurrence ($\Delta I_{m+1} > 0$), for

[33] Nonetheless, $N_m^z(gov)$ is nearly always statistically significant, for example, at the 10% level in 91% of all months over the sample period 1980-2009.

instance, if its policy objectives and/or accompanying trades are pre-announced by government officials or leaked to the media (Payne and Vitale 2003; Beine, Janssen, and Lecourt 2009). In Equation (13), the impact of any such anticipation in currency markets on the LOP relation between current actual and synthetic ADR prices of Equation (11) is captured by the lead coefficient β_1. The effects of past forex intervention ($\Delta I_{m-1} > 0$) on LOP violations in the ADR market may persist or ebb, for example, depending on the extent to which currency market participants learn about the government's prior trades and policy objectives (Jansen and De Haan 2005; Fratzscher 2006). In Equation (13), the impact of any such persistence or reversal in currency markets on current ADRP violations is captured by the lag coefficient β_{-1}.

I estimate Equation (13) by ordinary least squares (OLS) over the sample period 1980-2009 and report these coefficients, as well as their cumulative sums, $\beta_1^0 = \beta_1 + \beta_0$ and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$, in panel A of Table 3.[34] According to Dimson (1979), estimates of β_1^{-1} can also be interpreted as correcting for any bias in the contemporaneous coefficient β_0 due to nonsynchronous or sparse trading (e.g., price staleness).

The results in Table 3 provide support for the main prediction of my model (H2). Estimates of both the contemporaneous and up-to-current impact of forex interventions on ADR parity violations are positive and statistically significant: $\beta_0 > 0$ and $\beta_1^0 > 0$. These estimates are (plausibly) economically significant as well. For example, a one-standard-deviation increase in the monthly change in the number of forex interventions $\Delta N_m(gov)$—1.402, in panel B of Table 2—is accompanied by a contemporaneous (up-to-current) increase in average ADR parity violations $ADRP_m$ in (up to) that month by $3.505 \times 1.402 = 4.9$ bps ($4.830 \times 1.402 = 6.8$ bps), which is nearly 23% (32%) of the sample standard deviation of $\Delta ADRP_m$—21.47 bps, in Table 1. According to panel A of Table 3, the estimated impact of government intervention in currency markets on ADRP violations is seldom due to its anticipation ($\beta_1 > 0$ but small); yet it is often persistent ($\beta_{-1} > 0$ and nontrivial), perhaps because of its secrecy and slow information diffusion. These estimates imply that forex interventions continue to have a discernible cumulative impact on the average intensity of LOP violations in the ADR market within a month of their occurrence: β_1^{-1} is always positive, large, and statistically significant. For example, normalized ADR parity violations $ADRP_m^z$ increase on average by 34% of their sample standard deviation over the three-month window in correspondence with historically high intensity of official trading activity in a month—that is, in response to a one-standard-deviation increase in the monthly change in the normalized number of government interventions $\Delta N_m^z(gov)$: $0.057 \times 0.911 \div 0.153 = 0.34$. Their cumulative effect on actual ADR parity violations $ADRP_m$ is even larger, for example, amounting to $10.631 \times 0.911 = 9.7$ bps or 45% of the standard

34 The inference is unaffected by using Newey-West standard errors to correct for (mild or absent) residual serial correlation and heteroscedasticity.

Table 3
Marketwide ADRP violations and forex intervention

	$I=N(gov)$						$I=N^z(gov)$						
	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N
A. 1980–2009													
$\Delta ADRP_m$	1.325	3.505***	1.831**	4.830***	6.661***	4%	2.259*	5.314***	3.059**	7.573***	10.631***	4%	359
	(1.52)	(3.73)	(2.10)	(3.17)	(3.31)		(1.68)	(3.66)	(2.27)	(3.22)	(3.42)		
$\Delta ADRP_m^z$	0.002	0.026***	0.009	0.028**	0.036**	5%	0.004	0.039***	0.014	0.043**	0.057**	4%	359
	(0.31)	(3.87)	(1.37)	(2.56)	(2.54)		(0.45)	(3.75)	(1.44)	(2.57)	(2.57)		
$\Delta ADRP_t$	−0.488	1.371*	0.944	0.883	1.826	0%	−0.438	1.399*	0.915	0.961	1.876	0%	7,827
	(−0.69)	(1.78)	(1.34)	(0.70)	(1.08)		(−0.64)	(1.86)	(1.33)	(0.78)	(1.13)		
$\Delta ADRP_t^z$	−0.003	0.009	0.002	0.006	0.008	0%	−0.002	0.010*	0.002	0.007	0.009	0%	7,827
	(−0.51)	(1.59)	(0.33)	(0.68)	(0.65)		(−0.47)	(1.69)	(0.32)	(0.77)	(0.71)		
$\Delta ADRP_m^-$	1.329	3.484***	1.763**	4.812***	6.575***	4%	2.265*	5.281***	2.957**	7.546***	10.503***	4%	359
	(1.51)	(3.69)	(2.01)	(3.15)	(3.26)		(1.67)	(3.62)	(2.19)	(3.19)	(3.37)		
$\Delta ADRP_m^{-z}$	0.002	0.026***	0.009	0.028**	0.036**	4%	0.005	0.039***	0.014	0.043**	0.057**	4%	359
	(0.33)	(3.83)	(1.37)	(2.55)	(2.53)		(0.47)	(3.71)	(1.44)	(2.56)	(2.56)		
B. 1990–2009													
$\Delta ADRP_m$	0.939	4.032***	0.641	4.971***	5.612***	8%	1.534	6.625***	1.077	8.160***	9.237***	8%	234
	(1.04)	(4.26)	(0.71)	(3.29)	(2.83)		(1.04)	(4.29)	(0.73)	(3.31)	(2.86)		
$\Delta CIRP_m$	−0.214	0.568	0.462	0.354	0.816	2%	−0.346	0.943	0.723	0.596	1.319	2%	234
	(−0.62)	(1.57)	(1.34)	(0.61)	(1.08)		(−0.62)	(1.60)	(1.29)	(0.63)	(1.07)		
$\Delta ADRP_m^z$	0.000	0.032***	0.003	0.032***	0.035**	9%	0.001	0.052***	0.004	0.053***	0.058**	9%	233
	(0.06)	(4.32)	(0.36)	(2.74)	(2.26)		(0.07)	(4.37)	(0.39)	(2.78)	(2.30)		
$\Delta CIRP_m^z$	−0.006	0.028*	0.020	0.022	0.042	2%	−0.010	0.046*	0.032	0.036	0.068	2%	233
	(−0.39)	(1.65)	(1.26)	(0.80)	(1.19)		(−0.39)	(1.68)	(1.21)	(0.82)	(1.18)		

This table reports OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (13):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \tag{13}$$

where LOP_m are LOP violations in month m; $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m(gov)$ or $N_m^z(gov)$ defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Panel A reports estimates of Equation (13) for (absolute and normalized) ADR parity violations either at the monthly frequency ($LOP_m = ADRP_m$ or $ADRP_m^z$, as defined in Section 2.2.1; or $LOP_m = ADRP_m^-$ or $ADRP_m^{-z}$, that is, after removing ADRs from emerging countries where and when capital controls were introduced, as defined in Section 2.3.1) or at the daily frequency ($LOP_t = ADRP_t$ or $ADRP_t^z$ and $I_t = N_t(gov)$ or $N_t^z(gov)$) over the sample period 1980–2009. Panel B reports estimates of Equation (13) for either ADR parity violations or CIRP violations ($LOP_m = CIRP_m$ or $CIRP_m^z$, as defined in Section 2.3.1) at the monthly frequency over the subsample period 1990–2009 during which both are contemporaneously available. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $\{\beta_1, \beta_0, \beta_{-1}\}$. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

deviation of $\Delta ADRP_m$. In unreported analysis, I find the estimation of Equation (13) to yield qualitatively similar inference within each decade of the sample period.

2.3.1 Endogeneity bias. Coefficient estimates from the regression model of Equation (13) may be plagued by possible endogeneity bias. As shown in Equation (11), violations of the ADR parity ($P_{i,t} \neq P_{i,t}^{LOP}$) may originate from the U.S. stock market where the ADR is traded ($P_{i,t}$), the market for the underlying foreign stock ($P_{i,t}^{FOR}$), and/or the market for the relevant exchange rate relative to USD ($S_{t,USD/FOR}$). As discussed earlier, official trading activity in currency markets is unlikely to be motivated by the intensity of LOP violations in the ADR market. Accordingly, while forex interventions occasionally may be anticipated by currency market participants, estimates of their lead effect β_1 on ADRP violations in Equation (13) are always small and rarely significant in panel A of Table 3. Forex interventions are also most often sterilized, that is, do not affect money supply or funding liquidity conditions; hence, they are unlikely to be aimed at mitigating otherwise deteriorating (foreign and/or U.S.) stock market quality. However, forex interventions are likely to occur in correspondence with, or in response to high exchange rate volatility (e.g., Neely 2006) and tend to be accompanied by deteriorating currency market quality (e.g., Dominguez 2003, 2006; Pasquariello 2007b). Thus, ADRP violations may be large in months when currency market quality is low (e.g., Pasquariello 2008, 2014)—which is exactly when governments are more likely to intervene—rather than as a consequence of forex interventions (e.g., Neely and Weller 2007). Unfortunately, those properties of forex interventions also make it extremely difficult to find covariates of I_m that are uncorrelated with the error term ε_t in Equation (13) to obtain consistent estimates of the impact coefficients (β_1, β_0, β_{-1}) in Equation (13) via an instrumental variable (IV) approach (e.g., Fatum and Hutchison 2003; Neely 2005, 2006; Engel 2014).

I assess the relevance of these considerations for the inference in various ways. First, I estimate Equation (13) for daily changes in actual or historically abnormal ADR parity violations ($ADRP_t$ or $ADRP_t^z$) and the actual or historically abnormal number of forex interventions in a day ($N_t(gov)$ or $N_t^z(gov)$). Omitted variable bias may be mitigated at higher, for example, daily frequencies (see, e.g., Humpage and Osterberg 1992; Andersen et al. 2003, 2007; and references therein). However, as discussed in Section 2.1, daily ADR parity violations are also significantly more volatile and more likely to be spurious because of microstructure frictions (see also Gagnon and Karolyi 2010);[35] forex interventions are often executed and coordinated over

[35] For instance, the daily (monthly) sample standard deviation of $ADRP_t$ ($ADRP_m$) is 92 bps (41 bps in Table 1), or 42% (21%) of its daily (monthly) sample mean. Gagnon and Karolyi (2010) address one such microstructure friction—nonsynchronicity between foreign stock and ADR prices—by employing intraday price and quote data for the latter (from TAQ) observed at the closing time of the equity market for the former, as long as their trading

several clustered days or even weeks, rather than on single, less salient event days; market participants may learn about such official trading activity, and its full effects on the targeted currency may manifest, only with considerable delay (see, e.g., Neely 2000; Pasquariello 2007b). All are likely to weaken the estimated relation between forex interventions and ADRP violations. Nonetheless, the resulting estimates of β_1, β_0, and β_{-1} in panel A of Table 3 indicate that daily official trading activity in the currency market still has a positive and weakly significant (but unanticipated and short-lived) impact on $\Delta ADRP_t$ and $\Delta ADRP_t^z$, consistent with the model.

Second, I use Equation (13) to estimate the impact of forex interventions on violations of the covered interest rate parity (CIRP). The CIRP is perhaps the most popular textbook no-arbitrage condition. According to the CIRP, in the absence of arbitrage, spot and forward exchange rates between two currencies and their nominal interest rates in international money markets should ensure that riskless borrowing in one currency and lending in another, while hedging currency risk, generates no riskless profit. The literature documents frequent, albeit generally small violations of the CIRP over the past three decades and attributes their occurrence and magnitude to numerous observable and unobservable frictions to price formation in both currency and international money markets (see, e.g., Frenkel and Levich 1975, 1977; Coffey et al. 2009; Griffoli and Ranaldo 2011; Pasquariello, Roush, and Vega 2014; and the references therein). Since both markets have long been nearly perfectly integrated in many respects, including dealership (e.g., McKinnon (1977); Dufey and Giddy 1994; Bekaert and Hodrick 2012), my model predicts that government intervention in currency markets should have no impact on the extent of CIRP violations—that is, $\Delta corr\left(p_{1,1}, p_{1,2}\right) = 0$; see H1 in Section 1.3. However, the aforementioned literature also argues that greater CIRP violations may be due to deteriorating currency market quality—an omitted variable that, as I noted above, may be linked to forex intervention and so bias upward the estimates of its impact on ADR parity violations in Equation (13). Hence, the strength of the relation between forex intervention and CIRP violations may hint at the importance of this bias for those estimates.

To that purpose, I obtain the time series of actual and normalized monthly CIRP violations, $CIRP_m$ and $CIRP_m^z$, constructed by Pasquariello, Roush, and Vega (2014). Both measures of CIRP violations are monthly averages of actual and normalized daily absolute log differences (in bps, as in Equation (12) and Section 2.2.1) between daily indicative (short- and long-term maturity) forward exchange rates for five of the most actively traded and liquid currencies in the forex market (CHF, EUR, GBP, USD, JPY; from Datastream) and the

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hours are at least partially overlapping. However, this is not the case for Asian stock markets. In addition, TAQ data are available only from 1993 onward, while much forex intervention activity is concentrated in the 1980s and early 1990s (see, e.g., Figure 3A). Lastly, both the level and dynamics of ADRP violations in my sample are consistent with what is reported in Gagnon and Karolyi (2010) over their sample period 1993-2004.

corresponding synthetic forward exchange rates implied by the CIRP. Because of data limitations, either series is exclusively available over a portion of my sample period, between either May ($CIRP_m$) or June 1990 ($CIRP^z_m$) and December 2009. Pasquariello, Roush, and Vega (2014) reports that CIRP violations within this subperiod are small, for example, averaging roughly 21 bps (versus a concurrent mean $ADRP_m$ of 187 bps), but are also volatile and often much larger in correspondence with well-known episodes of financial turmoil (like ADRP violations in Figure 3).[36]

I then estimate the regression model of Equation (13) over the subperiod 1990-2009 for monthly changes in both ADRP ($\Delta LOP_m = \Delta ADRP_m$ or $\Delta ADRP^z_m$) and CIRP violations ($\Delta LOP_m = \Delta CIRP_m$ or $\Delta CIRP^z_m$). The resulting estimated coefficients β_1, β_0, and β_{-1} in panel B of Table 3 suggest that during that common interval of data availability, forex interventions have little or no impact on CIRP violations, that is, on LOP violations within the more closely integrated currency and international money markets. However, those interventions continue to be accompanied by a large and persistent increase in ADRP violations, that is, in LOP violations within the less closely integrated currency and ADR markets. This evidence not only provides further support for the model but also suggests that deteriorating currency market quality, as proxied by CIRP violations, is unlikely to be related to periods of intensifying forex intervention and ADR parity violations.

Lastly, government interventions in emerging currency markets during times of distress are occasionally accompanied by the imposition of capital controls (e.g., East Asia in the 1990s; Argentina in 2001–2002; Brazil in 2008–2009), which may impede ADR arbitrage activity by restricting foreign ownership of local shares or local ownership of foreign shares as well as by introducing uncertainty about either (see Edison and Warnock 2003; Auguste et al. 2006; Gagnon and Karolyi 2010; Garleanu and Pedersen 2011). Nonetheless, panel A of Table 3 shows that the exclusion of cross-listings from so-affected countries in the sample from both measures of marketwide ADRP violations over the portion of the sample period when these restrictions were in place ($ADRP^-_m$ and $ADRP^{-z}_m$) has no effect on the inference from Equation (13).

2.4 The cross-section of ADRP violations

According to Table 3, there is a positive and economically and statistically significant relation between changes in ADR parity violations and changes in the intensity of forex intervention, as postulated in Conclusion 1.

I also postulate in Conclusion 2 that the impact of government intervention in one asset on LOP violations—that is, on the equilibrium correlation between its price and the price of another, otherwise identical or arbitrage-linked asset ($corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Equation (10))—may depend on such variables affecting the

[36] For further details on the construction of these series and their properties, see Pasquariello (2014; Section 1.1.1).

underlying quality of the markets in which those assets are traded as the intensity and correlation of noise trading, or the extent of and adverse selection risk from informed, strategic speculation. These variables, although intrinsically conceptual and difficult to measure for each ADR or within each ADR market, may be plausibly related to such observable market characteristics as each ADR's country of listing (e.g., Gagnon and Karolyi 2010), as well as to such observable ADR market quality outcomes as each ADR's illiquidity and no-arbitrage parity violations (e.g., Pasquariello 2008, 2014). Investigating the cross-section of the impact of forex intervention on ADRP violations along those dimensions may shed further light on its theoretical determinants, and thus further alleviate the aforementioned endogeneity concerns plaguing the inference from Table 3.

To this end, I estimate the regression model of Equation (13) separately for each country of listing in Table 1, for each of the five countries for which currency-matched intervention-ADR pairs are available within the sample (Australia, Euro area, Japan, Mexico, and Turkey; see Table 2 and Section 2.2.2), as well as for each tercile portfolio of cross-listings sorted by either their sample mean ADRP illiquidity $ILLIQ_m$ or their sample mean actual absolute ADRP violations $ADRP_m$ (as defined in Section 2.2.1, from the lowest to the highest), when correspondingly available.[37] I then report the resulting coefficients of interest for either actual or normalized absolute ADRP violations ($LOP_m = ADRP_m$ or $ADRP^z_m$) in panels A and B of Tables 4 to 7, respectively. Noisier but qualitatively similar inference ensues from (unreported) cross-sectional estimates of Equation (13) at the daily frequency ($LOP_t = ADRP_t$ or $ADRP^z_t$) and/or for quintile sorts.

My model suggests that estimates of the positive relation between forex intervention and ADR parity violations may be complexly linked to underlying ADR market quality. For instance, as noted in Section 1.2, government intervention may yield larger LOP violations (larger $\Delta corr(p_{1,1}, p_{1,2})$) when the underlying, arbitrage-linked markets are less liquid (higher λ and λ^*)—indicating low underlying market quality; for example, for less intense noise trading (see Figure 1D; H3 in Section 1.3). However, $\Delta corr(p_{1,1}, p_{1,2})$ may also be larger when underlying LOP violations are either smaller (larger $corr(p_{1,1}, p_{1,2})$)—indicating high market quality; for example, for more correlated noise trading (Figure 1A)—or larger (smaller $corr(p_{1,1}, p_{1,2})$)—indicating low market quality; for example, for fewer and/or more heterogeneously informed speculators (Figures 1B and 1C). On the other hand, $\Delta corr(p_{1,1}, p_{1,2})$ may be smaller not only when $corr(p_{1,1}, p_{1,2})$ is smaller—indicating low market quality; for example, for less correlated noise trading—but also when it is larger—indicating high market quality; for

[37] Despite uneven sample coverage across usable ADRs (see, e.g., Table 1), actual and normalized LOP violation data for each of the ensuing sorts are always available over the sample period 1980-2009, with the exception of the high-$ADRP_m$ tercile, which is only populated since either November ($ADRP_m$) or December 1985 ($ADRP^z_m$).

Table 4
Country-level ADRP violations and forex intervention

A. $LOP_m = ADRP_m$

Country	$I_m = N_m(gov)$						$I_m = N_m^z(gov)$						N
	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N
Australia	0.691	1.711	−4.463*	2.403	−2.061	2%	2.184	2.872	−7.834*	5.056	−2.778	2%	264
	(0.27)	(0.60)	(−1.69)	(0.53)	(−0.35)		(0.53)	(0.63)	(−1.83)	(0.69)	(−0.29)		
Argentina	4.240	1.220	2.263	5.460	7.722	0%	6.929	2.281	3.884	9.210	13.094	0%	196
	(0.84)	(0.23)	(0.45)	(0.63)	(0.68)		(0.84)	(0.26)	(0.47)	(0.65)	(0.70)		
Brazil	1.268	5.095*	−0.720	6.363	5.644	2%	2.183	8.453*	−1.138	10.636	9.498	2%	175
	(0.45)	(1.66)	(−0.26)	(1.27)	(0.85)		(0.47)	(1.69)	(−0.25)	(1.29)	(0.87)		
Canada	−0.739	1.531	−0.787	0.793	0.006	1%	−1.244	2.175	−1.371	0.931	−0.440	1%	359
	(−0.69)	(1.32)	(−0.73)	(0.42)	(0.00)		(−0.75)	(1.22)	(−0.83)	(0.32)	(−0.11)		
Chile	1.765	5.527	−4.640	7.291	2.651	3%	2.940	8.988	−7.437	11.927	4.490	3%	166
	(0.42)	(1.20)	(−1.11)	(0.96)	(0.26)		(0.43)	(1.20)	(−1.10)	(0.97)	(0.27)		
Euro area	4.046	9.323***	2.501	13.370***	15.871**	4%	6.165	14.002***	3.586	20.167***	23.752**	3%	283
	(1.49)	(3.23)	(0.92)	(2.86)	(2.55)		(1.44)	(3.08)	(0.84)	(2.73)	(2.42)		
Hong Kong	2.270	5.707**	3.541	7.977*	11.518**	3%	3.772	9.442**	5.926	13.214*	19.140**	3%	196
	(0.93)	(2.17)	(1.45)	(1.88)	(2.07)		(0.94)	(2.20)	(1.48)	(1.91)	(2.11)		
India	−1.702	3.753	1.981	2.051	4.031	1%	−2.724	6.452	3.502	3.729	7.231	1%	141
	(−0.30)	(0.58)	(0.35)	(0.19)	(0.28)		(−0.29)	(0.62)	(0.38)	(0.22)	(0.31)		
Indonesia	5.885	10.649*	2.757	16.534	19.291	2%	9.722	17.578*	4.685	27.301	31.986	2%	164
	(1.05)	(1.72)	(0.49)	(1.63)	(1.42)		(1.07)	(1.75)	(0.51)	(1.65)	(1.45)		
Japan	0.422	2.893**	2.445**	3.315	5.761**	2%	0.795	4.537**	4.084**	5.332	9.416**	2%	359
	(0.35)	(2.22)	(2.02)	(1.57)	(2.07)		(0.43)	(2.26)	(2.19)	(1.64)	(2.19)		
Mexico	−2.417	4.028	4.331	1.611	5.942	2%	−4.052	6.589	6.925	2.537	9.462	2%	196
	(−0.73)	(1.13)	(1.30)	(0.28)	(0.78)		(−0.74)	(1.13)	(1.27)	(0.27)	(0.77)		
Russia	−14.417	−2.952	−7.335	−17.368	−24.703	4%	−23.425*	−4.805	−11.957	−28.231	−40.188	4%	136
	(−1.88)	(−0.35)	(−0.97)	(−1.24)	(−1.31)		(−1.88)	(−0.35)	(−0.98)	(−1.24)	(−1.32)		
South Africa	4.493	6.266	−4.315	10.760	6.445	3%	7.762	11.881*	−5.326	19.642*	14.316	3%	222
	(1.15)	(1.47)	(−1.10)	(1.56)	(0.71)		(1.27)	(1.77)	(−0.87)	(1.82)	(1.02)		
South Korea	−12.901	5.019	9.055	−7.881	1.173	7%	−20.839**	8.047	14.488	−12.792	1.696	7%	133
	(−1.99)	(0.69)	(1.42)	(−0.65)	(0.07)		(−1.98)	(0.68)	(1.39)	(−0.65)	(0.07)		
Switzerland	4.227	8.324*	4.874	12.551*	17.425*	3%	6.792	13.418*	7.880	20.209*	28.089*	3%	114
	(1.11)	(1.95)	(1.28)	(1.78)	(1.84)		(1.10)	(1.94)	(1.27)	(1.76)	(1.82)		
Turkey	26.600	−3.601	−14.702	22.999	8.296	8%	42.931	−5.777	−23.774	37.155	13.381	8%	71
	(1.42)	(−0.21)	(−0.77)	(0.74)	(0.19)		(1.43)	(−0.21)	(−0.78)	(0.75)	(0.19)		
United Kingdom	0.598	4.000***	1.825	4.598*	6.423**	2%	1.097	6.209***	3.086	7.306*	10.392**	2%	359
	(0.43)	(2.66)	(1.30)	(1.89)	(2.00)		(0.51)	(2.67)	(1.43)	(1.94)	(2.09)		
Other	6.121	15.917***	−1.072	22.038***	20.967**	6%	9.996	25.957***	−1.698	35.953***	34.255**	6%	245
	(1.44)	(3.58)	(−0.26)	(3.06)	(2.22)		(1.44)	(3.59)	(−0.25)	(3.07)	(2.22)		

(*continued*)

Table 4
Continued

B. $LOP_m = ADRP^z_m$

Country	$I_m = N_m\,(gov)$						$I_m = N^z_m\,(gov)$						
	β_1	β_0	β_{-1}	β^0_1	β^{-1}_1	R^2	β_1	β_0	β_{-1}	β^0_1	β^{-1}_1	R^2	N
Australia	−0.009	0.021	−0.005	0.012	0.007	2%	−0.012	0.035	−0.007	0.023	0.016	2%	259
	(−0.64)	(1.42)	(−0.37)	(0.52)	(0.23)		(−0.54)	(1.45)	(−0.32)	(0.61)	(0.32)		
Argentina	0.050	0.022	0.020	0.072	0.092	1%	0.081	0.039	0.035	0.120	0.155	1%	195
	(0.95)	(0.40)	(0.39)	(0.80)	(0.78)		(0.95)	(0.42)	(0.41)	(0.82)	(0.80)		
Brazil	0.003	0.044*	−0.001	0.047	0.045	3%	0.006	0.074*	−0.002	0.080	0.078	3%	173
	(0.11)	(1.84)	(−0.07)	(1.17)	(0.86)		(0.15)	(1.89)	(−0.05)	(1.22)	(0.91)		
Canada	0.000	0.012	−0.009	0.013	0.004	2%	0.001	0.017	−0.015	0.018	0.004	2%	359
	(0.03)	(1.49)	(−1.13)	(0.94)	(0.22)		(0.09)	(1.33)	(−1.22)	(0.87)	(0.13)		
Chile	0.004	0.021	−0.042	0.025	−0.016	3%	0.008	0.035	−0.067	0.042	−0.024	3%	165
	(0.16)	(0.68)	(−1.50)	(0.50)	(−0.24)		(0.17)	(0.70)	(−1.48)	(0.52)	(−0.22)		
Euro area	0.008	0.036*	0.003	0.044	0.047	1%	0.015	0.055*	0.002	0.069	0.071	1%	280
	(0.43)	(1.78)	(0.14)	(1.35)	(1.08)		(0.49)	(1.71)	(0.06)	(1.34)	(1.03)		
Hong Kong	0.008	0.054***	0.016	0.062**	0.078**	5%	0.013	0.089***	0.027	0.102**	0.130**	5%	195
	(0.46)	(2.96)	(0.95)	(2.10)	(2.01)		(0.47)	(2.99)	(0.98)	(2.12)	(2.05)		
India	−0.021	0.062*	0.023	0.041	0.064	5%	−0.034	0.102*	0.038	0.067	0.105	5%	140
	(−0.69)	(1.80)	(0.74)	(0.71)	(0.83)		(−0.69)	(1.80)	(0.75)	(0.72)	(0.84)		
Indonesia	0.036	0.060	0.012	0.096	0.108	2%	0.059	0.099	0.021	0.158	0.179	2%	163
	(1.06)	(1.61)	(0.36)	(1.56)	(1.32)		(1.08)	(1.64)	(0.39)	(1.59)	(1.35)		
Japan	−0.004	0.023*	0.024**	0.019	0.044	2%	−0.005	0.036*	0.040**	0.030	0.070*	2%	359
	(−0.32)	(1.81)	(2.05)	(0.93)	(1.60)		(−0.29)	(1.81)	(2.18)	(0.95)	(1.67)		
Mexico	−0.021	0.031*	0.014	0.011	0.024	3%	−0.034	0.052*	0.022	0.017	0.039	4%	195
	(−1.18)	(1.69)	(0.78)	(0.36)	(0.62)		(−1.20)	(1.70)	(0.77)	(0.35)	(0.61)		
Russia	−0.034	0.001	−0.030	−0.032	−0.062	2%	−0.054	0.003	−0.048	−0.051	−0.099	2%	135
	(−0.94)	(0.03)	(−0.84)	(−0.49)	(−0.70)		(−0.92)	(0.04)	(−0.85)	(−0.47)	(−0.69)		
South Africa	0.014	0.038**	0.001	0.052*	0.052	2%	0.026	0.066**	0.006	0.092*	0.098	2%	222
	(0.81)	(1.97)	(0.03)	(1.68)	(1.30)		(0.93)	(2.22)	(0.20)	(1.91)	(1.55)		
South Korea	−0.030	0.014	0.017	−0.016	0.001	3%	−0.048	0.023	0.028	−0.025	0.003	3%	132
	(−1.18)	(0.49)	(0.69)	(−0.34)	(0.02)		(−1.16)	(0.50)	(0.68)	(−0.33)	(0.03)		
Switzerland	0.032	0.078***	0.058**	0.110**	0.168**	7%	0.053	0.128***	0.095**	0.181**	0.276**	7%	113
	(1.23)	(2.65)	(2.20)	(2.27)	(2.57)		(1.25)	(2.68)	(2.22)	(2.29)	(2.60)		
Turkey	0.152	−0.055	−0.098	0.096	−0.001	9%	0.245	−0.089	−0.158	0.156	−0.002	9%	70
	(1.35)	(−0.53)	(−0.86)	(0.52)	(−0.01)		(1.36)	(−0.53)	(−0.87)	(0.52)	(−0.00)		
United Kingdom	−0.003	0.023**	0.002	0.020	0.022	2%	−0.003	0.034**	0.003	0.031	0.034	2%	359
	(−0.29)	(2.43)	(0.24)	(1.33)	(1.11)		(−0.23)	(2.34)	(0.22)	(1.31)	(1.09)		
Other	0.022	0.085***	0.001	0.107***	0.108***	9%	0.036	0.138***	0.002	0.174***	0.176***	9%	244
	(1.22)	(4.43)	(0.04)	(3.45)	(2.65)		(1.22)	(4.43)	(0.06)	(3.45)	(2.65)		

This table reports OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (13):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \qquad (13)$$

where LOP_m are LOP violations in month m; $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m\,(gov)$ or $N^z_m\,(gov)$ defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta^0_1 = \beta_1 + \beta_0$; and $\beta^{-1}_1 = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Equation (13) is estimated separately, at the monthly frequency, for each of the 18 countries listed in Table 1 (Australia, Argentina, Brazil, Canada, Chile, Euro area, Hong Kong, India, Indonesia, Japan, Mexico, Russia, South Africa, South Korea, Switzerland, Turkey, United Kingdom, and Other) over the portion of the sample period 1980–2009 over which ADRP violation data are correspondingly available. In panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in panel B, $LOP_m = ADRP^z_m$ (normalized ADRP violations), as defined in Section 2.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β^0_1 and β^{-1}_1 are computed from the asymptotic covariance matrix of $\{\beta_1, \beta_0, \beta_{-1}\}$. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

example, for more numerous and/or less heterogeneously informed speculators. See also the plots of $\Delta corr\left(p_{1,1}, p_{1,2}\right)$ versus $\overline{\lambda}$ and $corr\left(p_{1,1}, p_{1,2}\right)$ in Figures 2B and 2C, respectively.

Accordingly, country-level estimates of the contemporaneous (β_0) and cumulative impact (β_1^0 and β_1^{-1}) of changes in either $N_m(gov)$ or $N_m^z(gov)$ on absolute percentage ADR parity violations in Table 4 tend to be more often positive, large, and/or significant for cross-listings from emerging markets, which typically have a lower quality information environment (e.g., Bekaert and Harvey 1995, 1997, 2000, 2003; Lesmond 2005; Pasquariello 2008), as well as for cross-listings whose samplewide mean ADRP violations ($ADRP_m$) and/or illiquidity ($ILLIQ_m$) in Table 1 tend to be either high (like in Figure 2C [solid line] and H3) or low (like in Figure 2C [dashed line], yet unlike H3). For instance, panel A of Table 4 shows that, on average, a one-standard-deviation increase in $\Delta N_m^z(gov)$ is accompanied by a large cumulative increase in LOP violations for cross-listings both from markets with high mean $ADRP_m$ and/or $ILLIQ_m$—for example, South Africa (13 bps, i.e., 20% of the corresponding standard deviation of $\Delta ADRP_m$ in Table 1), Hong Kong (13 bps, 44%), and Other (mostly emerging countries, listed in Table 1; 31 bps, 37%)—as well as from markets with low mean $ADRP_m$ and/or $ILLIQ_m$—for example, Japan (9 bps, 29%), Euro area (22 bps, 35%), and Switzerland (26 bps, 69%).[38]

While generally consistent with the model's predictions, the evidence in Table 4 is only suggestive. Especially emerging country-level groupings consist of fewer usable ADRs over shorter periods (see Table 1), such that both their measures of ADRP violations and their estimated relation with forex intervention are noisier. Country-level sorting may also subsume additional, albeit possibly nonexclusive interpretations. For instance, greater or lower illiquidity in emerging markets may be both unrelated to adverse selection risk and still associated with more limited arbitrage activity in the presence of government-induced LOP violations. Estimates of the impact of currency-matched intervention on ADRP violations in Table 5 yield similar insight, as they are mostly positive (except for Turkey, as in Table 4) and generally large, but are statistically significant only Australia, the Euro area, and (to a lesser extent) Mexico, which have a relatively large number of interventions (see Tables 1 and 2).

Further estimation of Equation (13) for illiquidity-sorted and LOP violation-sorted ADRP portfolios in Tables 6 and 7 confirms that the observed relation between the negative arbitrage externality of forex intervention and ADRs' underlying market quality may be rather complex—broadly, albeit weakly and once again only suggestively consistent with the model. For instance, estimates

38 The Hong Kong dollar (HKD) has been pegged against USD at different levels over my sample period. Since $N_m(gov)$ and $N\tilde{m}(gov)$ measure the intensity of government intervention in the forex market, the evidence in Table 4 is consistent with the notion that ADR prices, $P_{i,t}$, may reflect ensuing expectations that a peg for $S_{FOR/USD,t}$ may be altered or abandoned in the future (e.g., Auguste et al. 2006; Eichler, Karmann, and Maltritz 2009).

Table 5
Country-level ADRP violations and currency-matched forex intervention

	$I_m = N_m(gov)$							$I_m = N_m^z(gov)$						
Country	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N
A: $LOP_m = ADRP_m$														
Australia	2.822	7.626	−2.134	10.448	8.314	1%	264	1.361	3.657	−0.364	5.018	4.654	1%	260
	(0.43)	(1.02)	(−0.32)	(0.85)	(0.50)			(0.55)	(1.29)	(−0.15)	(1.08)	(0.74)		
Euro area	4.535	11.064**	1.495	15.599*	17.094	2%	283	4.609	11.206**	1.362	15.815*	17.177	2%	283
	(0.90)	(2.06)	(0.30)	(1.77)	(1.45)			(0.89)	(2.03)	(0.26)	(1.75)	(1.42)		
Japan	−0.911	0.305	2.864	−0.605	2.258	0%	359	−0.453	−0.233	1.805	−0.686	1.119	1%	359
	(−0.34)	(0.11)	(1.08)	(−0.13)	(0.37)			(−0.34)	(−0.16)	(1.35)	(−0.29)	(0.36)		
Mexico	12.094	5.355	13.716	17.449	31.165	2%	144	2.321	0.616	2.895	2.937	5.832	0%	133
	(1.08)	(0.46)	(1.22)	(0.90)	(1.20)			(0.37)	(0.10)	(0.45)	(0.28)	(0.42)		
Turkey	18.331	−33.876	−58.037	−15.545	−73.582	10%	50	8.544	−14.862	−26.087	−6.137	−32.404	10%	50
	(0.48)	(−0.83)	(−1.53)	(−0.22)	(−0.74)			(0.50)	(−0.80)	(−1.51)	(−0.19)	(−0.71)		
B: $LOP_m = ADRP_m^z$														
Australia	0.028	0.086**	0.004	0.114*	0.118	3%	259	0.012	0.035**	0.003	0.047*	0.050	3%	258
	(0.83)	(2.23)	(0.11)	(1.79)	(1.38)			(0.86)	(2.25)	(0.19)	(1.83)	(1.43)		
Euro area	−0.004	0.000	−0.039	−0.004	−0.043	1%	280	−0.004	−0.000	−0.040	−0.004	−0.044	1%	280
	(−0.11)	(0.01)	(−1.10)	(−0.06)	(−0.51)			(−0.11)	(−0.01)	(−1.12)	(−0.06)	(−0.52)		
Japan	−0.024	−0.003	0.029	−0.027	0.002	1%	359	−0.014	−0.006	0.019	−0.021	−0.001	1%	359
	(−0.94)	(−0.10)	(1.11)	(−0.60)	(0.03)			(−1.09)	(−0.45)	(1.48)	(−0.90)	(−0.04)		
Mexico	0.029	0.120*	0.074	0.149	0.223	2%	144	0.031	0.048	0.020	0.079	0.098	1%	133
	(0.44)	(1.73)	(1.11)	(1.30)	(1.46)			(0.84)	(1.25)	(0.52)	(1.28)	(1.20)		
Turkey	0.058	−0.292	−0.454*	−0.234	−0.689	13%	49	0.028	−0.129	−0.205*	−0.101	0.306	13%	49
	(0.24)	(−1.16)	(−1.95)	(−0.52)	(−1.09)			(0.25)	(−1.12)	(−1.92)	(−0.49)	(−1.06)		

This table reports OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (13):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \tag{13}$$

where LOP_m are LOP violations in month m; $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m(gov)$ or $N_m^z(gov)$ defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Equation (13) is estimated separately, at the monthly frequency, for each of the five countries listed in Section 2.2.2 (Australia, Euro area, Japan, Mexico, and Turkey) for which both ADRP violations (see Table 1) and currency-matched interventions (i.e., involving the currency of denomination of the underlying foreign stocks; see Table 2) are contemporaneously available over the sample period 1980–2009. In panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 2.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $\{\beta_1, \beta_0, \beta_{-1}\}$. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

Table 6
Illiquidity-level ADRP violations and forex intervention

	$I_m = N_m(gov)$						$I_m = N_m^z(gov)$						
$ILLIQ_m$ tercile	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N
A: $LOP_m = ADRP_m$													
Low	1.588	6.040***	1.671	7.628***	9.299***	4%	2.502	9.193***	2.833	11.695***	14.528***	4%	359
	(1.10)	(3.88)	(1.15)	(3.02)	(2.79)		(1.12)	(3.82)	(1.27)	(3.00)	(2.82)		
Medium	0.505	1.917	2.345*	2.422	4.767*	1%	0.981	2.918	3.983**	3.899	7.882*	1%	359
	(0.42)	(1.48)	(1.94)	(1.15)	(1.72)		(0.53)	(1.46)	(2.14)	(1.20)	(2.57)		
High	0.730	3.891***	0.213	4.622**	4.835*	3%	1.318	5.840***	0.093	7.158**	7.251*	3%	359
	(0.62)	(3.09)	(0.18)	(2.27)	(1.80)		(0.73)	(3.00)	(0.05)	(2.27)	(1.74)		
B: $LOP_m = ADRP_m^z$													
Low	0.003	0.034***	0.003	0.037**	0.040**	4%	0.005	0.050***	0.005	0.055**	0.060*	4%	359
	(0.31)	(3.60)	(0.35)	(2.40)	(1.97)		(0.34)	(3.45)	(0.35)	(2.32)	(1.91)		
Medium	0.001	0.024***	0.015*	0.024*	0.040**	2%	0.002	0.036***	0.026**	0.038*	0.064**	2%	359
	(0.07)	(2.64)	(1.82)	(1.67)	(2.06)		(0.15)	(2.60)	(1.97)	(1.69)	(2.13)		
High	−0.001	0.018**	−0.002	0.017	0.015	2%	0.001	0.026*	−0.005	0.027	0.022	2%	359
	(−0.09)	(2.07)	(−0.27)	(1.22)	(0.81)		(0.05)	(1.95)	(−0.40)	(1.23)	(0.76)		

This table reports OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (13):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \tag{13}$$

where LOP_m are LOP violations in month m; $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m(gov)$ or $N_m^z(gov)$ defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Equation (13) is estimated separately, at the monthly frequency, for each tercile of ADRs sorted by their sample mean ADRP illiquidity $ILLIQ_m$ (as defined in Section 2.2.1, from the lowest to the highest), over the sample period 1980–2009. In panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 2.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $\{\beta_1, \beta_0, \beta_{-1}\}$. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

Table 7
LOP violation-level ADRP violations and forex intervention

	$I_m = N_m(gov)$						$I_m = N_m^z(gov)$						
$ADRP_m$ tercile	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	N
A. $LOP_m = ADRP_m$													
Low	−0.176	2.724***	0.037	2.548*	2.586	4%	−0.239	4.111***	0.012	3.872*	3.883	4%	359
	(−0.22)	(3.11)	(0.05)	(1.80)	(1.38)		(−0.19)	(3.04)	(0.01)	(1.76)	(1.34)		
Medium	2.898*	6.098***	3.536**	8.996***	12.531***	3%	4.934*	9.428***	6.269**	14.363***	20.632***	3%	359
	(1.70)	(3.32)	(2.07)	(3.02)	(3.19)		(1.88)	(3.33)	(2.39)	(3.13)	(3.40)		
High	0.323	4.584**	2.890	4.907	7.797*	3%	0.381	6.852**	4.411	7.233	11.644*	2%	288
	(0.18)	(2.44)	(1.64)	(1.61)	(1.93)		(0.14)	(2.32)	(1.59)	(1.50)	(1.82)		
B. $LOP_m = ADRP_m^z$													
Low	−0.001	0.024***	0.002	0.023	0.024	3%	−0.001	0.036***	0.002	0.035	0.037	3%	359
	(−0.18)	(2.82)	(0.20)	(1.63)	(1.32)		(−0.11)	(2.71)	(0.16)	(1.61)	(1.29)		
Medium	0.009	0.030***	0.018*	0.040**	0.058**	2%	0.018	0.046**	0.033*	0.063**	0.096**	2%	359
	(0.87)	(2.60)	(1.69)	(2.11)	(2.33)		(1.06)	(2.57)	(1.96)	(2.19)	(2.51)		
High	0.001	0.022*	0.010	0.023	0.033	2%	0.001	0.032*	0.016	0.033	0.049	1%	287
	(0.09)	(1.96)	(1.02)	(1.26)	(1.40)		(0.05)	(1.84)	(0.98)	(1.16)	(1.30)		

This table reports OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (13):

$$\Delta LOP_m = \alpha + \beta_{-1}\Delta I_{m-1} + \beta_0 \Delta I_m + \beta_1 \Delta I_{m+1} + \varepsilon_m, \tag{13}$$

where LOP_m are LOP violations in month m; $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m(gov)$ or $N_m^z(gov)$ defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Equation (13) is estimated separately, at the monthly frequency, for each tercile of ADRs sorted by their sample mean ADRP violations $ADRP_m$ (as defined in Section 2.2.1, from the lowest to the highest), over the sample period 1980–2009 (except for the high-ADRP-violation tercile, only populated since late 1985). In panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 2.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $\{\beta_1, \beta_0, \beta_{-1}\}$. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

of the positive, contemporaneous and cumulative impact of forex intervention on ADRP violations are nonmonotonic, instead of increasing (e.g., Figure 2B; H3), in unconditional ADRP illiquidity $ILLIQ_m$ (e.g., panel A of Table 6), perhaps because of the concurrent effect of other frictions and forces impeding both liquidity provision and arbitrage activity in the ADR market. However, these estimates are also nonmonotonic in unconditional ADR parity violations $ADRP_m$ (e.g., panel B of Table 7), as hinted by the discussion in Section 1.2 (e.g., Figure 2C), and up to twice as large for higher underlying market quality (e.g., low or medium $ILLIQ_m$ or $ADRP_m$) as for lower underlying market quality (high $ILLIQ_m$ or $ADRP_m$).

2.5 ADRP violations and market conditions

Tables 3 to 7 indicate that government intervention in currency markets is accompanied by a large and statistically significant increase in LOP violations in ADR markets. This evidence is consistent with the main empirical implication of my model (H2 in Section 1.3). Yet, as noted earlier, this interpretation may be clouded by the possible endogeneity of forex interventions and ADRP violations, a concern that the additional time-series and cross-sectional analysis in Sections 2.3.1 and 2.4 can only mitigate. For instance, directly linking the cross-sectional tests in Tables 4 to 7 to the model of Section 1 may be problematic since their conditioning variables (country of home listing, ADRP illiquidity, or ADRP violations) are plausibly related to alternative frictions and theories as well. Unfortunately, most primitive parameters in the model—like the intensity and correlation of noise trading (σ_z^2 and σ_{zz}) or the number of multiasset speculators (M)—are directly unobservable (like in all models based on Kyle 1985), their indirect estimation involves significant risk of measurement error, and the relevant data is typically unavailable for most currency and/or foreign stock markets (e.g., Allen and Taylor 1990; Madhavan 2000; Caballé and Krishnan 2004; Lesmond 2005; Cong, Hoitash, and Krishnan 2010).

In addition, the above evidence may also be consistent with another, albeit possibly complementary interpretation related to trading risk—that is, one that does not play a role in my model, where all market participants are risk-neutral. Forex intervention, rather than only constituting a source of LOP violations in the ADR market given existing limits to arbitrage (as implied by the model; see Section 1.1), may itself also impede arbitrage activity, for instance, by introducing a new source of unhedgeable convergence risk, in the spirit of Pontiff (1996), 2006), for speculators and arbitrageurs exploiting extant ADRP violations. However, these market participants are also more likely to be able to manage such a risk, and its severity is more likely to be attenuated—thus, their trading activity in the ADR market is less likely to be affected—at the low, monthly frequency of my analysis.

In this section, I assess these notions more directly, by explicitly testing for additional, unique predictions of the model, hence more difficult to reconcile with endogeneity or alternative interpretations—such as those relating the negative arbitrage externalities of government intervention to plausibly measurable market conditions affecting asset liquidity or policy uncertainty (H3 to H5)—as well as explicitly controlling for plausibly measurable state variables that may affect the time-varying intensity of limits to arbitrage and/or of forex intervention activity. To that purpose, I amend the regression model of Equation (13) for monthly changes in LOP violations (ΔLOP_m) as follows:

$$\begin{aligned}\Delta LOP_m = &\alpha + \beta_0 \Delta I_m + \beta_{ILQ} \Delta ILLIQ_m + \beta_{ILQ}^2 \left(\Delta ILLIQ_m\right)^2 \\ &+ \beta_0^{ILQ} \Delta I_m \Delta ILLIQ_m + \beta_{DSP} \Delta DISP_m + \beta_0^{DSP} \Delta I_m \Delta DISP_m \\ &+ \beta_{SDI} \Delta STD(I_m) + \beta_0^{SDI} \Delta I_m \Delta STD(I_m) + \Gamma \Delta X_m + \varepsilon_m,\end{aligned} \tag{14}$$

where LOP_m is either $ADRP_m$ or $ADRP_m^z$, and I_m is either $N_m(gov)$ or $N_m^z(gov)$. The inference is insensitive to introducing lead-lag effects of forex intervention and calendar fixed effects (or time trends), as well as robust to numerous plausible extensions and alternative specifications, some of which are noted below. Equation (14) allows for changes in ADRP illiquidity ($\Delta ILLIQ_m$), marketwide information heterogeneity ($\Delta DISP_m$), and policy uncertainty ($\Delta STD(I_m)$) to affect the extent of LOP violations in the ADR market both directly and through their interaction with forex intervention, as postulated by my model.

As discussed in Section 2.2.1, $ILLIQ_m$, the equal weighted average of the marketwide fraction of zero returns in the arbitrage-linked ADR, foreign stock, and currency markets (Figure 4A), is designed to capture marketwide ADR parity-level illiquidity. The model predicts that either $\beta_{ILQ} > 0$ or $\beta_{ILQ} < 0$ (Corollary 2), but $\beta_0^{ILQ} > 0$ (Conclusion 2; H3), i.e., that ADRP violations may depend on, but their positive sensitivity to forex intervention ($\beta_0 > 0$) is likely greater in correspondence with, deteriorating ADRP liquidity ($\Delta ILLIQ_m > 0$). Intuitively, ceteris paribus, when markets are less deep in equilibrium (higher λ and λ^*; e.g., when there are fewer speculators, see Figure 1C), noise trading shocks and government intervention in the aggregate order flow have a greater impact on equilibrium prices, yielding larger LOP violations (lower $corr\left(p_{1,1}, p_{1,2}\right)$, e.g., Figure 2A [solid line]; and greater $\Delta corr\left(p_{1,1}, p_{1,2}\right)$, e.g., Figure 2B). However, as noted in Section 1.1.2, the observed relation between ΔLOP_m and $\Delta ILLIQ_m$ may also be negative, or possibly nonmonotonic. For instance, according to Corollary 2, LOP violations may also be greater in the presence of more intense noise trading, despite its lower price impact (lower λ and λ^*, see Figure 1D and Figure 2A [dashed line]). Thus, Equation (14) includes a quadratic term for $\Delta ILLIQ_m$ as well.

Among the determinants of market liquidity in the model, speculators' information heterogeneity (ρ) plays an important role as it affects their

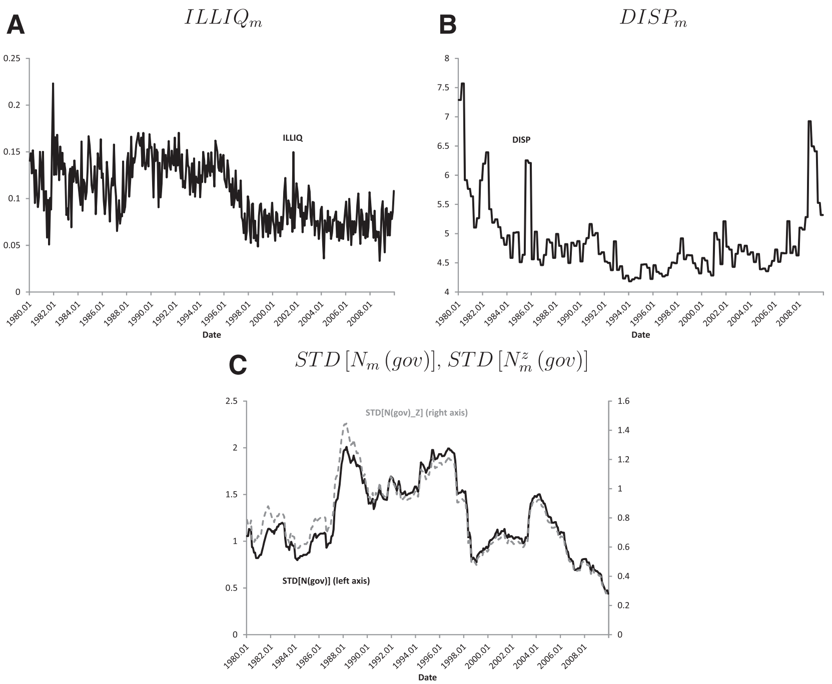

Figure 4
Proxies for market conditions
This figure plots the measures of market conditions described in Section 2.5: $ILLIQ_m$ (Figure 4A, left axis, solid line), a measure of ADRP illiquidity defined in Section 2.2.1 as the simple average (in percentage) of the fraction of ADRs in LOP_m whose underlying foreign stock, ADR, or exchange rate experience zero returns; $DISP_m = DISP_q$ (for each $m \in q$; Figure 4B, left axis, solid line), a measure of information heterogeneity defined in Section 2.5 as the simple average of the standardized dispersion of analyst forecasts of six U.S. macroeconomic variables; and $STD(I_m)$, a measure of forex intervention policy uncertainty defined in Section 2.5 as the historical volatility (over a three-year rolling window) of either $I_m = N_m(gov)$ (Figure 4C, left axis, solid line) or $I_m = N_m^z(gov)$ (Figure 4C, right axis, dashed line), over the sample period 1980–2009.

informed, strategic trading in all markets, hence both the extent of adverse selection risk faced by MMs and the depth they are willing to provide to all market participants, including noise traders and the government. The dispersion of private information among sophisticated traders in a market is commonly measured by the standard deviation of professional forecasts of economic and financial variables that are relevant to the fundamental payoffs of the assets traded in that market, such as corporate earnings, macroeconomic aggregates, or policy decisions (e.g., Diether, Malloy, and Scherbina 2002; Green 2004; Pasquariello and Vega 2007, 2009; Yu 2011).

I measure the heterogeneity of private fundamental information in the ADR arbitrage-linked markets using the aggregate dispersion of professional forecasts of U.S. macroeconomic variables collected by the Federal Reserve Bank of Philadelphia in its Survey of Professional Forecasters (SPF). Those variables contain payoff-relevant information not only for the U.S. markets where ADRs are traded, but also for the markets for their underlying foreign stocks and currencies (e.g., Chen, Roll, and Ross 1986; Bekaert, Harvey, and Ng 2005; Albuquerque and Vega 2009; Evans and Lyons 2013). Thus, they are plausibly related to the fundamental commonality in USD-denominated exchange rates and ADRs implied by Equation (12) in the model (i.e., the common v in their payoffs v_1 and v_2, respectively; see also Section 2.1). The SPF is the only continuously available survey of expert forecasts of those variables, by hundreds of private-sector economists, over the sample period 1980–2009; however, it is available only at the quarterly frequency (Croushore 1993; Beber, Brandt, and Luisi 2014; Pasquariello, Roush, and Vega 2014). Data of similar quality are typically unavailable for most other countries in the sample (see, e.g., Dovern, Fritsche, and Slacalek 2012). Following the literature, I construct the measure of marketwide dispersion of beliefs, $DISP_m$, in three steps. First, for each quarter q, I compute the standard deviation of next-quarter forecasts for each of the most important of the surveyed variables: *Nonfarm payroll*, *Unemployment*, *Nominal GDP*, *CPI*, *Industrial production*, and *Housing starts* (Andersen and Bollerslev 1998; Andersen et al. 2003, 2007; Pasquariello and Vega 2007). Second, I standardize each time series of dispersions to adjust for their different units of measurement. Third, I compute their equal-weighted average, $DISP_q$, and impose—without loss of generality, since the scale is irrelevant—that $DISP_m = DISP_q$ (Figure 4B) and $\Delta DISP_m = \Delta DISP_q$ for each month m within q. As noted earlier (e.g., Figure 1B), my model predicts that when ρ is lower (higher $DISP_m$), $corr\left(p_{1,1}, p_{1,2}\right)$ (Corollary 2) and $\Delta corr\left(p_{1,1}, p_{1,2}\right)$ are greater (Conclusion 2; H4), thus $\beta_{DSP} > 0$ and $\beta_0^{DSP} > 0$ in Equation (14).

The model also predicts that government intervention may be accompanied by larger LOP violations (greater $\Delta corr\left(p_{1,1}, p_{1,2}\right)$) when there is greater uncertainty among market participants about its policy motives (lower μ and higher $\sigma_T^2 = \frac{1}{\mu}\sigma_{gov}^2$; Conclusion 2; H5). Intuitively, greater uncertainty about its policy target ($p_{1,1}^T$) makes official trading activity in one asset more effective at moving its equilibrium price away from its fundamentals, hence away from the price of another, otherwise identical asset, by further obfuscating the MMs' inference from the order flow. As noted earlier, many governments do not disclose their policy objectives when intervening in currency markets, and market expectations of those objectives are typically unavailable. In my model, ceteris paribus, the unconditional variance of the government's optimal intervention strategy in equilibrium ($x_1(gov)$ of Equation (9)) is increasing in the variance of its information advantage about $p_{1,1}^T$ ($\delta_T(gov) \equiv p_{1,1}^T - \overline{p}_{1,1}^T$), that is, in policy uncertainty σ_T^2 via the coefficient $C_{2,1}^{*2}$. Equilibrium $var\left[x_1(gov)\right]$ also depends on fundamental uncertainty σ_v^2 via the coefficient $C_{1,1}^{*2}$. However, the distributional assumptions for $p_{1,1}^T$ in Section 1.2 imply that its variance $\sigma_T^2 = \frac{1}{\mu\psi}\sigma_v^2 > \sigma_v^2$. In addition, $C_{2,1}^{*2} > C_{1,1}^{*2}$ both on average and in correspondence with nearly all parametrizations associated with the plots in Figure 1.

For instance, constant $C^{*2}_{2,1}=0.725$ and $C^{*2}_{1,1}=0.014$ in Figure 1A, while average $C^{*2}_{2,1}=0.727$ and $C^{*2}_{1,1}=0.509$ in Figure 1B. Accordingly, in a first-order sense, $\Delta var\left[x_1(gov)\right]\approx C^{*2}_{2,1}\Delta\sigma^2_T$.

As noted in Section 2.2.2, the literature recommends to measure order flow variability by order imbalance variability, since transaction frequency dynamics have been found to be significantly more influential than trading volume dynamics in explaining asset price movements (e.g., Jones, Kaul, and Lipson 1994; Chordia et al. 2017). Hence, I proxy for currency policy uncertainty using the historical standard deviation of either one of my measures of forex intervention I_m ($N_m(gov)$ or $N^z_m(gov)$), $STD(I_m)$, over a three-year rolling window to allow for short-term variation (Figure 4C). I then consider the impact of monthly changes in both the intensity and volatility of observed intervention activity and their cross-product on observed ADRP violations in Equation (14). The model predicts that $\beta_{SDI}>0$ and $\beta_0^{SDI}>0$ (see Figure 1F). Consistent with the aforementioned literature, replacing I_m and/or $STD(I_m)$ in Equation (14) with changes in the level and/or volatility of actual and normalized measures of unsigned observed intervention amounts yields similar but weaker evidence, while including both of these variables and their associated cross-products in Equation (14) does not affect the inference. See, for example, Figure IA-4B and Tables IA-6, IA-8, and IA-9 in the Internet Appendix.

Lastly, Equation (14) includes a vector ΔX_m of changes in several common measures of market conditions linked by the literature to the intensity of limits to arbitrage and/or observed LOP violations, especially in the ADR market—for instance, unhedgeable risk and opportunity cost of arbitrage, scarcity of arbitrage capital, or noise trader sentiment (Pontiff 1996, 2006; Baker and Wurgler 2006, 2007; Pasquariello 2008, 2014; Gagnon and Karolyi 2010; Garleanu and Pedersen 2011; Baker, Wurgler, and Yuan 2012)—but also to forex intervention (see Edison 1993; Sarno and Taylor 2001; Engel 2014). These proxies include: U.S. and world stock market volatility (from CRSP and MSCI); average exchange rate volatility (from Datastream and Pacific); an NBER recession dummy; U.S. risk-free rate (from Ken French's website); Pastor and Stambaugh's (2003) measure of U.S. equity market liquidity (based on volume-related return reversals, from Pastor's website); Adrian, Etula, and Muir's (2014) measure of U.S. funding liquidity (aggregating broker-dealer leverage, from Muir's website); and Baker and Wurgler's (2006, 2007) measure of U.S. investor sentiment (from Wurgler's website).

Table 8 reports scaled OLS estimates of the coefficients of interest β_0, β_{ILQ}, β^2_{ILQ}, β_0^{ILQ}, β_{DSP}, β_0^{DSP}, β_{SDI} in Equation (14) for $I_m=N_m(gov)$ (panel A) and $I_m=N_m(gov)$ (panel B). Different units for the regressors in Equation (14) affect the scale of their estimated slope and interaction coefficients. Thus, to facilitate the economic interpretation of these estimates, I multiply each one by the standard deviation of the corresponding original regressor(s) such that

Table 8
Marketwide ADRP violations: Forex intervention and market conditions

A. $I_m = N_m(gov)$

	β_0	β_{ILQ}	β_{ILQ}^2	β_0^{ILQ}	β_{DSP}	β_0^{DSP}	β_{SDI}	β_0^{SDI}	Controls	R^2	N
$\Delta ADRP_m$	3.251***								No	2%	360
	(2.90)										
$\Delta ADRP_m^z$	0.031***								No	4%	360
	(3.86)										
$\Delta ADRP_m$	2.856**								Yes	8%	360
	(2.57)										
$\Delta ADRP_m^z$	0.027***								Yes	12%	360
	(3.47)										
$\Delta ADRP_m$	3.368***	3.497***	−0.323	−0.084					Yes	10%	360
	(3.02)	(3.15)	(−0.43)	(−0.07)							
$\Delta ADRP_m^z$	0.029***	0.016**	−0.002	0.003					Yes	13%	360
	(3.71)	(2.09)	(−0.31)	(0.35)							
$\Delta ADRP_m$	2.937***				−1.065	6.077***			Yes	14%	360
	(2.73)				(−0.95)	(4.97)					
$\Delta ADRP_m^z$	0.027***				−0.010	0.023***			Yes	14%	360
	(3.56)				(−1.25)	(2.60)					
$\Delta ADRP_m$	3.205***						3.391***	−3.345***	Yes	12%	360
	(2.91)						(2.98)	(−3.28)			
$\Delta ADRP_m^z$	0.029***						0.017**	−0.017**	Yes	14%	360
	(3.69)						(2.12)	(−2.39)			
$\Delta ADRP_m$	3.705***	3.344***	0.154	1.343	−1.011	6.134***	2.783**	−3.232***	Yes	20%	360
	(3.45)	(3.15)	(0.22)	(1.22)	(−0.93)	(4.94)	(2.54)	(−3.30)			
$\Delta ADRP_m^z$	0.031***	0.016**	0.000	0.008	−0.010	0.023**	0.015*	−0.017**	Yes	17%	360
	(3.98)	(2.05)	(0.04)	(1.04)	(−1.23)	(2.58)	(1.82)	(−2.32)			

(*continued*)

Table 8
Continued

B. $I_m = N_m^z(gov)$

	β_0	β_{ILQ}	β_{ILQ}^2	β_0^{ILQ}	β_{DSP}	β_0^{DSP}	β_{SDI}	β_0^{SDI}	Controls	R^2	N
$\Delta ADRP_m$	3.008***								No	2%	360
	(2.68)										
$\Delta ADRP_m^z$	0.029***								No	4%	360
	(3.64)										
$\Delta ADRP_m$	2.596**								Yes	8%	360
	(2.33)										
$\Delta ADRP_m^z$	0.025***								Yes	12%	360
	(3.23)										
$\Delta ADRP_m$	3.117***	3.471***	−0.330	−0.081					Yes	10%	360
	(2.79)	(3.12)	(−0.44)	(−0.07)							
$\Delta ADRP_m^z$	0.027***	0.016**	−0.002	0.003					Yes	13%	360
	(3.48)	(2.06)	(−0.31)	(0.39)							
$\Delta ADRP_m$	2.653**				−1.147	5.945***			Yes	14%	360
	(2.46)				(−1.02)	(5.14)					
$\Delta ADRP_m^z$	0.025***				−0.010	0.021**			Yes	13%	360
	(3.30)				(−1.27)	(2.58)					
$\Delta ADRP_m$	3.123***						3.658***	−3.382***	Yes	12%	360
	(2.82)						(3.22)	(−3.33)			
$\Delta ADRP_m^z$	0.028***						0.022***	−0.019***	Yes	14%	360
	(3.59)						(2.70)	(−2.65)			
$\Delta ADRP_m$	3.615***	3.335***	0.191	1.322	−1.019	6.003***	3.076***	−3.322***	Yes	20%	360
	(3.36)	(3.15)	(0.27)	(1.20)	(−0.93)	(5.12)	(2.82)	(−3.40)			
$\Delta ADRP_m^z$	0.030***	0.016**	0.000	0.008	−0.009	0.022**	0.019**	−0.018***	Yes	17%	360
	(3.87)	(2.03)	(0.07)	(1.01)	(−1.19)	(2.55)	(2.40)	(−2.60)			

This table reports *scaled* OLS estimates of interest, as well as t-statistics in parentheses, for the regression model in Equation (14):

$$\begin{aligned}\Delta LOP_m = &\alpha + \beta_0 \Delta I_m + \beta_{ILQ} \Delta ILLIQ_m + \beta_{ILQ}^2 \left(\Delta ILLIQ_m\right)^2 + \beta_0^{ILQ} \Delta I_m \Delta ILLIQ_m \\ &+ \beta_{DSP} \Delta DISP_m + \beta_0^{DSP} \Delta I_m \Delta DISP_m \\ &+ \beta_{SDI} \Delta STD(I_m) + \beta_{SDI}^0 \Delta I_m \Delta STD(I_m) + \Gamma \Delta X_m + \varepsilon_m,\end{aligned} \tag{14}$$

where $LOP_t = ADRP_m$ or $ADRP_m^z$ are the absolute or normalized ADR parity violations in month m (as defined in Section 2.2.1); $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m(gov)$ (in panel A) or $N_m^z(gov)$ (in panel B) defined in Section 2.2.2; $\Delta I_m = I_m - I_{m-1}$; $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 2.2.1 as the simple average (in percentage) of the fractions of ADRs in LOP_m whose underlying foreign stock, ADR, or exchange rate experiences zero returns; $\Delta DISP_m = \Delta DISP_q$ for each month m within quarter q; $DISP_q$ is a measure of information heterogeneity, defined in Section 2.5 as the simple average of the standardized dispersion of analyst forecasts of six U.S. macroeconomic variables; $STD(I_m)$ is a measure of forex intervention policy uncertainty, defined in Section 2.5 as the historical volatility of I_m over a three-year rolling window; and X_m is a matrix of control variables (defined in Section 2.5) including U.S. and world stock market volatility, global exchange rate volatility, official NBER recession dummy, U.S. risk-free rate, U.S. equity market liquidity, U.S. funding liquidity, and U.S. investor sentiment. Equation (14) is estimated over the sample period 1980–2009; each estimate is then multiplied by the standard deviation of the corresponding original regressor(s). N is the number of observations; R^2 is the coefficient of determination. *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

each scaled coefficient in Table 8 is in the same unit as the dependent variable ΔLOP_m.

The evidence in Table 8 provides additional support for my model. First, the estimated positive contemporaneous impact of forex intervention on ADR parity violations ($\beta_0 > 0$) is robust to the inclusion of controls for changes in market conditions potentially related to limits to arbitrage and/or forex intervention activity as well as to the exclusion of its lead-lag effects, for example, ranging between 2.6 bps (t=2.33; panel B) and 2.9 bps (t=2.57; panel A) in correspondence with a one-standard-deviation shock to ΔI_m. Augmenting Equation (14) with additional control variables related to such alternative sources of relative mispricings as marketwide financial distress, dislocations, foreign equity flows, or capital account liberalizations in emerging markets (e.g., Edison and Warnock 2003; Hu, Pan, and Wang 2013; Pasquariello 2008, 2014; Brusa, Ramadorai, and Verdelhan 2015), when available, yields qualitatively similar inference. See, for example, Tables IA-10 to IA-13 in the Internet Appendix.

Second, estimates of β_{ILQ} in Table 8 are always positive and both economically and statistically significant. Consistent with Corollary 2 (e.g., Figure 2A [solid line])—but also with the literature on arbitrage trading costs as determinants of LOP violations in general, and ADRP violations in particular (see, e.g., Gagnon and Karolyi 2010; Gromb and Vayanos 2010)—deteriorating ADRP liquidity is accompanied by larger ADRP violations (e.g., by as much as 16% of the sample standard deviation of ΔLOP_m) even in the absence of forex intervention. I nonetheless find no evidence of the potential nonmonotonicity in this relation also hinted by Corollary 2 (e.g., Figure 2A [dashed line]): $\beta_{ILQ}^2 \approx 0$ in panels A and B of Table 8. Shocks to the average fraction of zero returns do not weaken, yet only weakly magnify the impact of forex interventions on ADR parity violations: Estimates of β_0 remain large and significant; estimates of β_0^{ILQ} are often positive, consistent with H3, but small and never significant. However, the total effect of ADRP illiquidity alone on the relation between forex interventions and ADRP violations ($\beta_0 + \beta_0^{ILQ}$) is both positive and large, for example, about 18% of the baseline scaled estimates of β_0 in Table 8. Relatedly, amending Equation (14) to include the interaction of ΔI_m and $(\Delta ILLIQ_m)^2$ reveals some nonmonotonicity in the sensitivity of β_0 to ADRP illiquidity (β_0^{ILQ}), as hinted by Table 6. Likewise, as noted in Section 2.4, this evidence—in Table IA-14 in the Internet Appendix—cannot be explained by the model (i.e., via H3; e.g., Figure 2B), and may be related to other concurrent limits to ADRP liquidity provision and trading (e.g., such as those in X_m); yet it does not otherwise affect the inference.

When I allow each of the components of my measure of ADRP illiquidity, $ILLIQ_m$ (Z_m^{FOR}, Z_m, and Z_m^{FX}) in Equation (14), its estimates in Table IA-15 in the Internet Appendix suggest that, consistent with the literature, illiquidity in the U.S. market for international cross-listings (ΔZ_m) is a more important determinant of ADRP violations than illiquidity in the foreign markets for the underlying stocks (ΔZ_t^{FOR}; e.g., Pasquariello 2008, 2014; Gagnon and Karolyi 2010). The interaction of ΔZ_m with forex intervention intensity (ΔI_m) is also generally positive and statistically significant, as postulated by the model (H3; e.g., Figure 2B). The effect of forex illiquidity (ΔZ_t^{FX}) on ADRP violations is instead weaker and its cross-product with ΔI_m has more difficult interpretation, since both my model and many extant studies find forex interventions to have a significant impact on the liquidity of the targeted currencies (e.g., Bossaerts and Hillion 1991; Vitale 1999; Naranjo and Nimalendran 2000; Pasquariello 2007b, 2010). Accordingly, the samplewide correlation between ΔZ_t^{FX} and either $\Delta N_m(gov)$ or $\Delta N_m^z(gov)$ is weakly negative, consistent with the model ($\lambda^* < \lambda$ in Section 1.2) and potentially weakening the estimated aggregate interaction effect β_0^{ILQ} in Table 8. Nevertheless, the inference from Equation (14) is otherwise unaffected.

Third, the relation between forex interventions and ADRP violations is sensitive to more direct measures of the specific determinants of market liquidity in the model. In particular, forex intervention has a significantly greater impact on ADRP violations in correspondence with greater dispersion of beliefs among market participants: $\beta_0^{DSP} > 0$, as predicted by my model (H4; e.g., Figure 1B). For instance, ceteris paribus, a large increase in the number of interventions in a month (i.e., a one-standard-deviation shock to $\Delta N_m(gov) > 0$) is accompanied by more than three times larger ADRP violations when information heterogeneity is high in that month (i.e., in conjunction with a one-standard-deviation shock to $\Delta DISP_m$), that is, by nearly 10 bps ($\beta_0 + \beta_0^{DSP} = 3.705 + 6.134$, in panel A of Table 8) versus an unconditional average increase of less than 3 bps ($\beta_0 = 2.856$). Estimates of β_{DSP} are instead always negative, but small and statistically insignificant, suggesting that the positive direct effect of information heterogeneity on the extent of LOP violations postulated in Corollary 2 may be subsumed by changes in other market conditions in Equation (14). Therefore, the total joint effect of ΔI_m and $\Delta DISP_m$ alone on ΔLOP_m ($\beta_0 + \beta_{DSP} + \beta_0^{DSP}$) is still positive and more than twice as large, on average, as the baseline effect of ΔI_m alone (β_0) in Table 8.

Fourth, scaled estimates of the policy uncertainty coefficient β_{SDI} in Equation (14) are always positive, statistically significant, and almost as large as (or larger than) the corresponding coefficient for the intensity of forex intervention β_0. For example, panel B of Table 8 shows that a one-standard-deviation increase in normalized forex policy uncertainty in a month ($\Delta STD\left[N_m^z(gov)\right] > 0$) is accompanied by between 12% and 17% greater ADR parity violations in that month than their sample variation in Table 1, consistent with my model (H5; e.g., Figure 1F), even in the absence of an increase in the standardized number of forex interventions ($\Delta N_m^z(gov) = 0$). Estimates of the interaction coefficient β_0^{SDI} are, however, negative, suggesting that the positive impact of historical intervention volatility on ADRP violations ($\beta_{SDI} > 0$) is weaker in months when intervention policy uncertainty may have been partially resolved by further intervention activity. Nonetheless, the total joint effect of greater intervention intensity and policy uncertainty alone on ADRP violations ($\beta_0 + \beta_{SDI} + \beta_0^{SDI}$) remains positive and between 6% and 31% larger than the corresponding baseline scaled estimates of β_0, in line with H5.

Alternatively, some studies argue that government intervention in currency markets may reflect actual and expected violations of the absolute purchasing power parity (APPP, a relation between exchange rates and inflation rates equating currency-adjusted prices of goods and services across countries), especially during periods of relatively high inflation (e.g., Naranjo and Nimalendran 2000; Sarno and Taylor 2001; Neely 2005). Thus, the latter may proxy for intensity and uncertainty in the former. However, inflation differentials are relatively low over my sample period. In addition, large APPP violations often stem from multilateral international agreements (e.g., the Plaza and Louvre Accords in the 1980s), and hence may not translate into more intense and uncertain intervention activity. I use monthly CPI inflation data from the Organisation for Economic Co-operation and Development (OECD) to compute the actual or historically normalized average or three-year rolling volatility of absolute percentage APPP violations in the exchange rates targeted by government interventions in Table 2 (see, e.g., Bekaert and Hodrick 2012). These variables are often positively, yet weakly correlated to my measures of forex intervention intensity (ΔI_m) and forex policy uncertainty ($\Delta STD(I_m)$), including during the portion of the sample when inflation differentials across countries were the highest (1980–1989). Accordingly, estimates of Equation (14) when replacing $\Delta STD(I_m)$ with shocks to APPP violation intensity yields noisier but qualitatively similar inference. See, for example, Figure IA-5 and Tables IA-16 and IA-17 in the Internet Appendix.

3. Conclusions

In this study, I propose and report evidence of the novel notion that direct government intervention in a market may induce LOP violations in other, arbitrage-related markets.

I illustrate the intuition for this negative externality of policy in two steps. I first construct a standard multiasset model of strategic, heterogeneously informed speculation, based on Kyle (1985) and Chowdhry and Nanda (1991), in which segmentation in the dealership sector, speculative market-order trading, and less-than-perfectly correlated noise trading yield less-than-perfectly correlated equilibrium prices of two fundamentally identical, or linearly related assets (i.e., equilibrium LOP violations). I then introduce a stylized government pursuing a nonpublic, partially informative price target for only one of the two assets and consider the equilibrium implications of its policy-motivated, camouflaged trading activity. I show that, given existing limits to arbitrage, such intervention lowers those assets' equilibrium price correlation (i.e., increases equilibrium LOP violations) by clouding dealers' inference about the targeted asset's payoff, with an intensity that depends in a complex manner on extant price formation.

My empirical analysis provides support for this effect. I find that more intense forex intervention activity between 1980 and 2009 is accompanied by meaningfully larger LOP violations in the arbitrage-linked, yet arguably less-than-perfectly integrated U.S. market for ADRs, but not in the arbitrage-linked, yet arguably perfectly integrated international money markets for exchange-risk-covered deposits and loans. This estimated relation is unaffected by changes in market conditions typically associated with level and dynamics of LOP violations, limits to arbitrage, and/or forex intervention. I also find it to be stronger for ADRs from both emerging economies and high-quality markets, as well as in correspondence with low or deteriorating liquidity in the ADR arbitrage-linked markets, greater dispersion of U.S. macroeconomic forecasts, and greater uncertainty about official currency policy, consistent with my model.

These findings suggest that direct government intervention—an increasingly popular policy tool in the aftermath of the recent financial crisis—may not only yield welfare gains but also have nontrivial, undesirable implications for financial market quality. This is an important insight both for the understanding of the forces driving price formation, hence resource allocation and risk sharing, in financial markets and for the debate on optimal financial policy and regulation.

Appendix

Proof of Proposition 1. The proof is by construction and proceeds in three steps (e.g., Kyle 1985; Pasquariello and Vega 2009). In the first, I conjecture general linear functions for prices and trading strategies. In the second, I solve for the parameters of those functions satisfying Conditions 1 and 2 in Section 1.1. In the third, I verify that those parameters and functions represent a rational expectations equilibrium. I begin by assuming that, in equilibrium, $p_{1,i}=A_{0,i}+A_{1,i}\omega_i$ and $x_i(m)=B_{0,i}+B_{1,i}\delta_v(m)$, where $A_{1,i}>0$ and $i=\{1,2\}$. These assumptions and the definitions of $\delta_v(m)$ and ω_i imply that:

$$E\left[p_{1,i}|\delta_v(m)\right]=A_{0,i}+A_{1,i}x_i(m)+A_{1,i}B_{0,i}(M-1)+A_{1,i}B_{1,i}(M-1)\rho\delta_v(m). \tag{A1}$$

Using Equation (A1), maximization of each speculator's expected profit $E[\pi(m)|\delta_v(m)]$ with respect to $x_i(m)$ yields the following first-order conditions:

$$0=p_0+\delta_v(m)-A_{0,i}-(M+1)A_{1,i}B_{0,i}-A_{1,i}B_{1,i}\delta_v(m)[2+(M-1)\rho]. \tag{A2}$$

The second-order conditions are satisfied, since $-2A_{1,i}<0$. Equation (A2) is true iff:

$$p_0-A_{0,i}=(M+1)A_{1,i}B_{0,i}, \tag{A3}$$

$$2A_{1,i}B_{1,i}=1-(M-1)A_{1,i}B_{1,i}\rho. \tag{A4}$$

Because of the distributional assumptions in Section 1.1, ω_i are normally distributed with means $E(\omega_i)=MB_{0,i}$, variances $var(\omega_i)=MB_{1,i}^2\rho\sigma_v^2[1+(M-1)\rho]+\sigma_z^2$, and covariances

$cov(v,\omega_i)=MB_{1,i}\rho\sigma_v^2$. It then ensues from the properties of conditional normal distributions (e.g., Greene 1997, p. 90) that:

$$E(v|\omega_i)=p_0+\frac{MB_{1,i}\rho\sigma_v^2}{MB_{1,i}^2\rho\sigma_v^2[1+(M-1)\rho]+\sigma_z^2}\left(\omega_i-MB_{0,i}\right). \tag{A5}$$

According to Condition 2 (semi-strong market efficiency), $p_{1,i}=E(v|\omega_i)$. Therefore, the prior conjectures for $p_{1,i}$ are correct iff:

$$A_{0,i}=p_0-MA_{1,i}B_{0,i}, \tag{A6}$$

$$A_{1,i}=\frac{MB_{1,i}\rho\sigma_v^2}{MB_{1,i}^2\rho\sigma_v^2[1+(M-1)\rho]+\sigma_z^2}. \tag{A7}$$

The expressions for $A_{0,i}$, $A_{1,i}$, $B_{0,i}$, and $B_{1,i}$ in Proposition 1 must solve the system made of Equations (A3), (A4), (A6), and (A7) to constitute a linear equilibrium. Defining $A_{1,i}B_{0,i}$ from Equation (A3) and plugging it into Equation (A6) leads to $A_{0,i}=p_0$. Since $A_{1,i}>0$, only $B_{0,i}=0$ satisfies Equation (A3). Next, I solve Equation (A4) for $A_{1,i}$:

$$A_{1,i}=\frac{1}{B_{1,i}[2+(M-1)\rho]}. \tag{A8}$$

Equating Equation (A7) to Equation (A8) implies that $B_{1,i}^2=\frac{\sigma_z^2}{M\rho\sigma_v^2}$, i.e., that $B_{1,i}=\frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$. I then substitute this expression back into Equation (A8), yielding $A_{1,i}=\frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]}$, and define $\lambda\equiv A_{1,i}$. Lastly, I follow Caballé and Krishnan (1994) to note that the equilibrium of Proposition 1 with M speculators is equivalent to a symmetric n-firm Cournot equilibrium. As such, the "backward reaction mapping" technique in Novshek (1984) proves that, given a linear pricing rule (like the one of Equation (1)), the symmetric linear strategies $x_i(m)$ of Equation (2) represent the unique Bayesian-Nash equilibrium of the Bayesian game among speculators. ■

Proof of Corollary 1. The equilibrium pricing rule of Equation (1) implies that $var(p_{1,i})=\lambda^2 var(\omega_i)$ and $covar(p_{1,1},p_{1,2})=\lambda^2 covar(\omega_1,\omega_2)$, where $var(\omega_i)=\sigma_z^2[2+(M-1)\rho]$ and $covar(\omega_1,\omega_2)=\sigma_{zz}+\sigma_z^2[1+(M-1)\rho]$. It is then straightforward to substitute these moments into the expression for the unconditional correlation of the equilibrium prices $p_{1,1}$ and $p_{1,2}$, $corr(p_{1,1},p_{1,2})=\frac{covar(p_{1,1},p_{1,2})}{\sqrt{var(p_{1,1})var(p_{1,2})}}$, so yielding Equation (3). Under perfectly integrated market making, MMs observe the aggregate order flow in both assets 1 and 2. Condition 2 (semi-strong market efficiency) then implies that $p_{1,1}=E(v|\omega_1,\omega_2)=p_{1,2}$ (e.g., Caballé and Krishnan 1994, p. 697) and $corr(p_{1,1},p_{1,2})=1$. Under (less-than-) perfectly correlated noise trading, $\sigma_{zz}=\sigma_z^2$ ($\sigma_{zz}<\sigma_z^2$). Equation (3) then implies that $corr(p_{1,1},p_{1,2})=1$ ($corr(p_{1,1},p_{1,2})<1$). ■

Proof of Corollary 2. Given the distributional assumptions in Section 1.1 (and $\sigma_{zz}\geq 0$), the statement stems from observing that under less-than-perfectly correlated noise trading ($\sigma_{zz}<\sigma_z^2$): $\frac{\partial corr(p_{1,1},p_{1,2})}{\partial\rho}=\frac{\sigma_z^2(M-1)(\sigma_z^2-\sigma_{zz})}{[2+(M-1)\rho]^2}>0$, $\frac{\partial corr(p_{1,1},p_{1,2})}{\partial\sigma_z^2}=-\frac{\sigma_{zz}}{\sigma_z^4[2+(M-1)\rho]}\leq 0$, $\frac{\partial corr(p_{1,1},p_{1,2})}{\partial M}=\frac{\sigma_z^2\rho(\sigma_z^2-\sigma_{zz})}{[2+(M-1)\rho]^2}>0$, and $\frac{\partial corr(p_{1,1},p_{1,2})}{\partial\sigma_{zz}}=\frac{1}{\sigma_z^2[2+(M-1)\rho]}>0$. ■

Proof of Proposition 2. As noted above, the proof is by construction. Its outline is based on Pasquariello and Vega (2009) and Pasquariello, Roush, and Vega (2014). First, I conjecture linear functions for equilibrium prices and the trading activity of speculators (in assets 1 and 2) and the stylized government of Equation (4) (in asset 1 alone): $p_{1,i}=A_{0,i}+A_{1,i}\omega_i$, $x_i(m)=B_{0,i}+B_{1,i}\delta_v(m)$, where $A_{1,i}>0$ and $i=\{1,2\}$, and $x_1(gov)=C_{0,1}+C_{1,1}\delta_v(gov)+C_{2,1}\delta_T(gov)$.

Since $E[\delta_v(gov)|\delta_v(m)]=\psi\delta_v(m)$ and $E[\delta_T(gov)|\delta_v(m)]=\delta_v(m)$ under the parametrization in Section 1.2, these conjectures imply that:

$$E\left[p_{1,1}|\delta_v(m)\right]=A_{0,1}+A_{1,1}x_1(m)+A_{1,1}B_{0,1}(M-1)+A_{1,1}B_{1,1}(M-1)\rho\delta_v(m)$$
$$+A_{1,1}C_{0,1}+A_{1,1}C_{1,1}\psi\delta_v(m)+A_{1,1}C_{2,1}\delta_v(m), \tag{A9}$$
$$E\left[p_{1,2}|\delta_v(m)\right]=A_{0,2}+A_{1,2}x_2(m)+A_{1,2}B_{0,2}(M-1)$$
$$+A_{1,2}B_{1,2}(M-1)\rho\delta_v(m), \tag{A10}$$
$$E\left[p_{1,1}|\delta_v(gov),\delta_T(gov)\right]=A_{0,1}+MA_{1,1}B_0+MA_{1,1}B_{1,1}\rho\delta_v(gov)+A_{1,1}x_1(gov). \tag{A11}$$

Given Equations (A9) and (A10), the first-order conditions for maximizing each speculator's expected profit $E[\pi(m)|S_v(m)]$ relative to $x_i(m)$ are:

$$0=p_0+\delta_v(m)-A_{0,1}-(M+1)A_{1,1}B_{0,1}-A_{1,1}B_{1,1}\delta_v(m)[2+(M-1)\rho]$$
$$-A_{1,1}C_{0,1}-A_{1,1}C_{1,1}\psi\delta_v(m)-A_{1,1}C_{2,1}\delta_v(m), \tag{A12}$$
$$0=p_0+\delta_v(m)-A_{0,2}-(M+1)A_{1,2}B_{0,2}-A_{1,2}B_{1,2}\delta_v(m)[2+(M-1)\rho]. \tag{A13}$$

Because $-2A_{1,i}<0$, the second-order conditions are satisfied. For Equations (A12) and (A13) to be true, it must be that:

$$p_0-A_{0,1}=(M+1)A_{1,1}B_{0,1}+A_{1,1}C_{0,1}, \tag{A14}$$
$$2A_{1,1}B_{1,1}=1-(M-1)A_{1,1}B_{1,1}\rho-A_{1,1}C_{1,1}\psi-A_{1,1}C_{2,1}, \tag{A15}$$
$$p_0-A_{0,2}=(M+1)A_{1,2}B_{0,2}, \tag{A16}$$
$$2A_{1,2}B_{1,2}=1-(M-1)A_{1,2}B_{1,2}\rho. \tag{A17}$$

The government's optimal intervention strategy is the one minimizing its expected loss function of Equation (4), $E[L(gov)|\delta_v(gov),\delta_T(gov)]$, with respect to $x_1(gov)$. Given the distributional assumptions of Sections 1.1. and 1.2, removing all terms not interacting with the latter from the former implies that $x_1(gov)=\operatorname{argmin} E[L(gov)|\delta_v(gov),\delta_T(gov)]$ is equal to:

$$\begin{aligned}&\operatorname{argmin}\Big[\gamma A_{1,1}^2x_1^2(gov)+2\gamma A_{1,1}^2MB_{0,1}x_1(gov)+2\gamma A_{1,1}^2MB_{0,1}\rho\delta_v(gov)x_1(gov)\\&+2\gamma A_{0,1}A_{1,1}x_1(gov)-2\gamma p_{1,1}^TA_{1,1}x_1(gov)+(1-\gamma)A_{0,1}x_1(gov)\\&+(1-\gamma)A_{1,1}x_1^2(gov)+(1-\gamma)MA_{1,1}B_{0,1}x_1(gov)\\&+(1-\gamma)MA_{1,1}B_{1,1}\rho\delta_v(gov)x_1(gov)-(1-\gamma)p_0x_1(gov)-(1-\gamma)\delta_v(gov)x_1(gov)\Big].\end{aligned} \tag{A18}$$

The first-order condition from Equation (A18) is:

$$\begin{aligned}0=&2\gamma A_{1,1}^2x_1(gov)+2\gamma A_{1,1}^2MB_{0,1}+2\gamma A_{1,1}^2MB_{0,1}\rho\delta_v(gov)+2\gamma A_{0,1}A_{1,1}-2\gamma p_{1,1}^TA_{1,1}\\&+(1-\gamma)A_{0,1}+2(1-\gamma)A_{1,1}x_1(gov)+(1-\gamma)MA_{1,1}B_{0,1}\\&+(1-\gamma)MA_{1,1}B_{1,1}\rho\delta_v(gov)-(1-\gamma)p_0-(1-\gamma)\delta_v(gov).\end{aligned} \tag{A19}$$

The second-order condition is satisfied, since $2\gamma A_{1,1}^2 + 2(1-\gamma)A_{1,1} > 0$. Let us define $d \equiv \frac{\gamma}{1-\gamma}$. Given Equation (A19), the prior conjecture for $x_1(gov)$ is then correct iff:

$$p_0 - A_{0,1} = 2A_{1,1}C_{0,1} + MA_{1,1}B_{0,1} + 2dA_{1,1}^2 C_{0,1}$$
$$+2dA_{1,1}^2 MB_{0,1} + 2dA_{0,1}A_{1,1} - 2d\overline{p}_{1,1}^T A_{1,1}, \tag{A20}$$

$$2A_{1,1}C_{1,1} = 1 - MA_{1,1}B_{1,1}\rho - 2dA_{1,1}^2 C_{1,1} - 2dA_{1,1}^2 MB_{1,1}\rho, \tag{A21}$$

$$A_{1,1}C_{2,1} = dA_{1,1} - dA_{1,1}^2 C_{2,1}. \tag{A22}$$

Equation (A22) implies that $C_{2,1} = \frac{d}{1+dA_{1,1}} > 0$. The prior conjectures for $x_i(m)$ and $x_1(gov)$ also imply that the aggregate order flows ω_1 and ω_2 are normally distributed with means $E(\omega_1) = MB_{0,1} + C_{0,1}$ and $E(\omega_2) = MB_{0,2}$, the following variances:

$$var(\omega_1) = MB_{1,1}^2 \rho\sigma_v^2 [1 + (M-1)\rho] + C_{1,1}^2 \psi\sigma_v^2 + C_{2,1}^2 \frac{\sigma_v^2}{\mu\psi}$$
$$+2MB_{1,1}C_{1,1}\psi\rho\sigma_v^2 + 2MB_{1,1}C_{2,1}\rho\sigma_v^2 + 2C_{1,1}C_{2,1}\sigma_v^2 + \sigma_z^2, \tag{A23}$$

$$var(\omega_2) = MB_{1,2}^2 \rho\sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2, \tag{A24}$$

and covariances $cov(v,\omega_1) = MB_{1,1}\rho\sigma_v^2 + C_{1,1}\psi\sigma_v^2 + C_{2,1}\sigma_v^2$ and $cov(v,\omega_2) = MB_{1,2}\rho\sigma_v^2$. From the market-clearing Condition 2 ($p_{1,i} = E(v|\omega_i)$), it then ensues that:

$$p_{1,1} = p_0 + \frac{\left(MB_{1,1}\rho + C_{1,1}\psi + C_{2,1}\right)\sigma_v^2}{\sigma_z^2 + \sigma_v^2 \left\{MB_{1,1}^2 \rho[1+(M-1)\rho] + D_1 + E_1\right\}}\left(\omega_1 - MB_{0,1} - C_{0,1}\right), \tag{A25}$$

$$p_{1,2} = p_0 + \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2\rho\sigma_v^2[1+(M-1)\rho] + \sigma_z^2}\left(\omega_2 - MB_{0,2}\right), \tag{A26}$$

where $D_1 = 2M\rho[B_{1,1}(\psi C_{1,1} + C_{2,1})]$ and $E_1 = \psi C_{1,1}^2 + \frac{1}{\mu\psi}C_{2,1}^2 + 2C_{1,1}C_{2,1}$. Thus, the conjectures for $p_{1,i}$ are true iff

$$A_{0,1} = p_0 - MA_{1,1}B_{0,1} - A_{1,1}C_{0,1}, \tag{A27}$$

$$A_{1,1} = \frac{\left(MB_{1,1}\rho + C_{1,1}\psi + C_{2,1}\right)\sigma_v^2}{\sigma_z^2 + \sigma_v^2\left\{MB_{1,1}^2\rho[1+(M-1)\rho] + D_1 + E_1\right\}}, \tag{A28}$$

$$A_{0,2} = p_0 - MA_{1,2}B_{0,2}, \tag{A29}$$

$$A_{1,2} = \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2\rho\sigma_v^2[1+(M-1)\rho] + \sigma_z^2}. \tag{A30}$$

Next, I verify that the expressions for $A_{0,i}$, $A_{1,i}$, $B_{0,i}$, $B_{1,i}$, $C_{0,1}$, and $C_{1,1}$ in the linear equilibrium of Proposition 2 solve the system made of Equations (A14) to (A17), (A20), (A21), and (A27) to (A30). As shown in the proof of Proposition 1, Equations (A16), (A17), (A29), and (A30) imply that $B_{0,2} = 0$, $A_{0,2} = 0$, $B_{1,2} = \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$, and $A_{1,2} = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]}$. For both Equations (A14) and (A27) to be true, it must be that $B_{0,1} = 0$. Because of the latter, Equation (A14) implies that $p_0 - A_{0,1} = A_{1,1}C_{0,1}$. Substituting $A_{1,1}C_{0,1}$ into Equation (A20) yields $A_{0,1} = p_0 + 2dA_{1,1}$

$(p_0-\overline{p}_{1,1}^T)$ and $C_{0,1}=2d(\overline{p}_{1,1}^T-p_0)$. I am left to find $A_{1,1}$, $B_{1,1}$, and $C_{1,1}$. I first extract $B_{1,1}$ from Equation (A15) and $C_{1,1}$ from Equation (A21):

$$B_{1,1}=\frac{1-A_{1,1}C_{1,1}\psi-A_{1,1}C_{2,1}}{A_{1,1}[2+(M-1)\rho]}, \tag{A31}$$

$$C_{1,1}=\frac{1-MA_{1,1}B_{1,1}\rho\left(1+2dA_{1,1}\right)}{2A_{1,1}\left(1+dA_{1,1}\right)}. \tag{A32}$$

I then solve the system made of Equations (A31) and (A32) to get $B_{1,1}=\frac{2-\psi}{A_{1,1}f(A_{1,1})}>0$ and $C_{1,1}=\frac{[2+(M-1)\rho](1+dA_{1,1})-M\rho(1+2dA_{1,1})}{A_{1,1}(1+dA_{1,1})f(A_{1,1})}$, where $f(A_{1,1})=2[2+(M-1)\rho](1+dA_{1,1})-M\psi\rho(1+2dA_{1,1})$ is clearly positive. Lastly, I substitute these expressions for $B_{1,1}$ and $C_{1,1}$ in Equation (A28), yielding a *sextic* polynomial in $A_{1,1}$,

$$g_{1,6}A_{1,1}^6+g_{1,5}A_{1,1}^5+g_{1,4}A_{1,1}^4+g_{1,3}A_{1,1}^3+g_{1,2}A_{1,1}^2+g_{1,1}A_{1,1}+g_{0,1}=0, \tag{A33}$$

whose coefficients can be shown to be (via tedious algebra and the parameter restrictions in Sections 1.1 and 1.2):

$$g_{0,1}=-\mu\psi\sigma_v^2\left[M\rho(2-\psi)^2+\psi(2-\rho)^2\right]<0, \tag{A34}$$

$$g_{1,1}=-2\mu\psi\sigma_v^2 d\left\{M\rho\left[2(2-\psi)-\psi^2(1-\rho)-\rho\psi\right]+2\psi(2-\rho)^2\right\}<0, \tag{A35}$$

$$\begin{aligned}g_{2,1}=&\mu\psi\sigma_z^2\left\{4(2-\rho)^2+M\rho\left[M\rho(2-\psi)^2+4(2-\rho)(2-\psi)\right]\right\}\\&+\sigma_v^2d^2\left\{4(1-\mu\psi)(2-\rho)^2+4M\rho[M\rho(1-\psi)+2(2-\psi-\rho)+\psi\rho]\right.\\&+4\mu\psi\rho\left[3M(\rho+\psi)-M\left(7+\rho\psi+\rho\psi^2\right)+5\psi\right]\\&\left.+M^2\rho^2\psi[\mu\psi(11-4\psi)+\psi-8\mu]+\mu\psi^2[\rho(7M\psi-5\rho)-20]\right\},\end{aligned} \tag{A36}$$

$$\begin{aligned}g_{3,1}=&2\sigma_v^2d^3\left\{(2-\rho)^2\left[4(1-\mu\psi)-\mu\psi^2\right]+M\rho(2-\rho)\left[\mu\psi\left(7\psi-10+\psi^2\right)\right.\right.\\&\left.\left.+2(4-3\psi)\right]+2M^2\rho^2\left[\mu\psi^2(5-2\psi)-\psi(3-\psi)+(2-3\mu\psi)\right]\right\}\\&+2\mu\psi\sigma_z^2d\left\{8(2-\rho)^2+M^2\rho^2[8-\psi(10-3\psi)]+2M\rho(2-\rho)(8-5\psi)\right\},\end{aligned} \tag{A37}$$

$$\begin{aligned}g_{4,1}=&4(1-\mu\psi)\sigma_v^2d^4[(2-\rho)+M\rho(1-\psi)]^2\\&+\mu\psi\sigma_z^2d^2\left\{12(2-\rho)[2(2-\rho)+M\rho(4-3\psi)]+M^2\rho^2[24+\psi(13\psi-36)]\right\}>0,\end{aligned} \tag{A38}$$

$$g_{5,1}=4\mu\psi\sigma_z^2d^3\left\{M^2\rho^2[4-\psi(7-3\psi)]+M\rho[16-7\psi(2-\rho)-8\rho]+4(2-\rho)^2\right\}>0, \tag{A39}$$

$$g_{6,1}=4\mu\psi\sigma_z^2d^4[M\rho(1-\psi)+(2-\rho)]^2>0, \tag{A40}$$

where either $sign(g_{3,1})=sign(g_{2,1})=sign(g_{1,1})$, $sign(g_{4,1})=sign(g_{3,1})=sign(g_{2,1})$, or $sign(g_4,1)=sign(g_{3,1})$ and $sign(g_{2,1})=sign(g_{1,1})$, such that only one change of sign is possible while proceeding from the lowest to the highest power term in the polynomial of Equation (A33). According to Descartes' rule, under these conditions there exists only one positive real root λ^* of Equation (A33). Hence, this root implies the unique linear Bayesian Nash equilibrium of Proposition 2. By Abel's impossibility theorem, Equation (A33) cannot be solved with rational operations and finite root extractions. In the numerical examples of Figure 1, I find λ^* using the three-stage algorithm proposed by Jenkins and Traub (1970a, 1970b) under some mild restrictions on exogenous parameter values to ensure its convergence to a solution, for example, such that the government is "reasonably committed" to a "reasonably uncertain" policy target p_T (i.e., γ is sufficiently lower than 1, while ψ and μ are sufficiently higher than 0). ■

Proof of Corollary 3. As for the proof of Corollary 1, I start by observing that $corr(p^*_{1,1}, p^*_{1,2}) = \frac{covar(p^*_{1,1}, p^*_{1,2})}{\sqrt{var(p^*_{1,1})var(p^*_{1,2})}}$, where Equations (5) and (6) imply that $var(p^*_{1,1}) = \lambda^{*2} var(\omega^*_1)$, $var(p^*_{1,2}) = \lambda^2 var(\omega^*_2)$, and $covar(p^*_{1,1}, p^*_{1,2}) = \lambda\lambda^* covar(\omega^*_1, \omega^*_2)$. Because of the distributional assumptions of Sections 1.1 and 1.2, it is straightforward to show that $var(\omega^*_1) = \sigma^2_z + \sigma^2_v \{M\rho B^{*2}_{1,1}[1+(M-1)\rho] + D^*_1 + E^*_1\}$, $var(\omega^*_2) = \sigma^2_z[2+(M-1)\rho]$, and $covar(\omega^*_1, \omega^*_2) = \sigma_{zz} + \sigma_z\sigma_v\sqrt{M\rho}\{B^*_{1,1}[1+(M-1)\rho] + \psi C^*_{1,1} + C^*_{2,1}\}$. Substituting these expressions into the one for $corr(p^*_{1,1}, p^*_{1,2})$ yields Equation (10). Once again, if MMs observe order flow in both assets 1 and 2, Condition 2 (semi-strong market efficiency) implies that $p^*_{1,1} = E(v|\omega^*_1, \omega^*_2) = p^*_{1,2}$ (e.g., Caballé and Krishnan 1994, p. 697) and $corr(p^*_{1,1}, p^*_{1,2}) = 1$. ■

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