MICHIGAN
ROSS SCHOOL OF BUSINESS

Working Paper

Government Intervention and Arbitrage

Paolo Pasquariello
Stephen M. Ross School of Business
University of Michigan

Ross School of Business Working Paper
Working Paper No. 1240
May 2014

Government Intervention and Arbitrage

Paolo Pasquariello[1]

May 23, 2014

[1]Department of Finance, Ross School of Business, University of Michigan, ppasquar@umich.edu. I benefited from the comments of Sugato Bhattacharyya and Andrew Karolyi. Any remaining errors are my own.

Abstract

We model and document the novel notion that direct government intervention in a market — e.g., central bank trading in exchange rates — may induce violations of the law of one price (LOP) in other, arbitrage-related markets — e.g., the market for American Depositary Receipts (ADRs, dollar-denominated securities fully convertible in a preset amount of foreign shares). We show that the introduction of a stylized government pursuing a non-public, partially informative price target in a model of strategic, multi-asset trading and segmented dealership generates equilibrium price differentials among fundamentally identical assets — even in absence of liquidity demand differentials, and especially when markets are less liquid, speculators are more heterogeneously informed, or uncertainty about government policy is greater. We find empirical evidence consistent with these predictions in a sample of all ADRs traded in U.S. exchanges and available intervention activity of developed and emerging countries in the currency markets between 1980 and 2009.

JEL classification: F31; G14; G15

Keywords: Arbitrage; Law of One Price; Central Bank; Government Intervention; Currency Market; ADR; Liquidity; Strategic Trading

1 Introduction

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 the understanding of 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.[1] We contribute to this understanding by investigating the role of *direct* government intervention for LOP violations.

Central banks and government agencies routinely trade securities in pursuit of economic and financial policy. More recently, both the scale and frequency of this activity have soared in the aftermath of the financial crisis of 2008-2009. We establish and test the novel notion that such form of government intervention in financial markets may induce LOP violations and so *worsen* financial market quality.[2] The insight that policy pursued via direct government intervention in financial markets may create *negative* arbitrage externalities has important implications for the intense debate on financial stability and optimal financial regulation (e.g., Acharya and Richardson, 2009; Hanson et al., 2011).

We illustrate this notion in a parsimonious one-period model of strategic multi-asset trading based on Kyle (1985). In the economy's basic setting, two identical risky assets are exchanged by three types of risk-neutral market participants: A discrete number of (heterogeneously informed) multi-asset speculators, single-asset noise traders, and competitive market-makers. If the dealership sector is segmented — market-makers in each asset do not observe order flow in the other asset (e.g., Subrahmanyam, 1991a; Boulatov et al., 2013) — liquidity demand differentials (i.e., less-than-perfectly correlated noise trading) yield equilibrium LOP violations

[1] Accordingly, there is a vast literature reporting violations of various arbitrage parities in financial markets as well as attributing those violations to numerous "limits" to arbitrage activity. Comprehensive surveys of this research can be found in Shleifer (2000), Lamont and Thaler (2003), and Gromb and Vayanos (2010), among others.

[2] A well-established body of research, briefly discussed in Section 2.2, examines the implications of official trading activity targeting asset price levels and volatility for the microstructure of the targeted currency, bond, and stock markets. Other studies focus on the implications of government policies affecting the fundamental payoffs of traded securities for financial market outcomes (e.g., Bond and Goldstein, 2010; Pastor and Veronesi, 2012, 2013).

(i.e., less-than-perfectly correlated equilibrium prices) despite both markets being semi-strong efficient. Intuitively, those relative mispricings (nonzero price differentials) can occur in equilibrium because speculators can only submit market orders in each asset, i.e., together with noise traders and before market clearing prices are set. Accordingly, as both markets are more illiquid, noise trading in either asset has a greater impact on its equilibrium price, yielding larger LOP violations.

The introduction of a stylized government submitting market orders in only one of the two assets in pursuit of policy — a *non-public*, *partially informative* price target (e.g., Bhattacharya and Weller, 1997) — *lowers* their equilibrium price correlations (i.e., increases equilibrium LOP violations), even if noise trading is identical in both markets. An intuitive explanation for this result is that the uncertainty surrounding the government's policy clouds the inference of the market-makers in the targeted asset when setting the equilibrium price of that asset from its order flow. Consistently, the magnitude of this effect is increasing in policy uncertainty and generally decreasing in pre-intervention market quality. In particular, intervention-induced LOP violations are larger when market liquidity is lower — e.g., in the presence of more heterogeneously informed speculators — since in those circumstances "official" trading has a greater impact on the targeted asset's equilibrium price.

We test our model's main implications by examining the impact of government interventions in the foreign exchange (forex) market on LOP violations in the market for American Depositary Receipts (ADRs). These markets serve as a setting that is as close as possible in spirit to the assumptions of our model. First, an ADR is a dollar-denominated security, traded in the U.S., 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 (and foreign stock price) by an arbitrage relationship (the ADR parity [ADRP]; e.g., Gagnon and Karolyi 2010; Pasquariello, 2014). Second, according to a vast literature (surveyed in Edison, 1993; Sarno and Taylor, 2001; Neely, 2005a; Menkhoff, 2010; Engel, 2014), forex intervention is common; its policy objectives are often non-public; its effectiveness is statistically robust and often attributed to their perceived informativeness about fundamentals. Third, 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. Lastly, 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.

We construct a sample of all ADRs traded in U.S. exchanges and available official trading activity of developed and emerging countries in the currency markets between 1980 and 2009. Average absolute (i.e., unsigned) ADRP violations are large (e.g., about a 2% [200 basis points, bps] deviation from the arbitrage-free price) and generally declining (as financial integration increases), but display meaningful intertemporal dynamics (e.g., spiking during periods of financial instability). Forex interventions are also non-trivial (albeit small relative to average turnover in the currency markets), especially frequent between the mid-1980s and the mid-1990s, and typically involve exchange rates relative to the dollar.

Our empirical analysis provides support for our model. We find that (various measures of) the intensity of ADRP violations are increasing in (various measures of) the intensity of forex interventions. This relationship is both (economically and statistically) significant and unaffected by controlling for (various measures of) market conditions that are commonly associated with LOP violations and limits to arbitrage (e.g., Pontiff, 1996; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Garleanu and Pedersen, 2011; Baker et al., 2012). For instance, a one standard deviation increase in (i.e., high) forex intervention activity in a month is accompanied by an average cumulative increase in absolute ADRP violations of nearly 10 bps — or more than 45% of the sample volatility of their monthly changes. Importantly, those same official currency trades do *not* affect LOP violations in the much more closely integrated forward currency and international money markets — i.e., do not affect the arbitrage-free, Covered Interest Rate parity (CIRP) between borrowing, lending, and hedging interest and exchange rates (e.g., Griffoli and Ranaldo, 2011). This finding not only is consistent with our model but also suggests that our evidence is unlikely to stem from a dislocation in currency markets leading to both forex interventions and ADRP violations (e.g., Neely and Weller, 2007).

Our analysis also suggests that poor, deteriorating conditions in the ADR arbitrage-linked markets magnify ADRP violations both directly and through their linkage with forex intervention activity, as postulated by our model. In particular, we find those LOP violations to be larger and that linkage to be stronger *i)* for ADRs from emerging markets; as well as in correspondence with *ii)* greater ADRP illiquidity (measured by the average fraction of zero returns in the currency, U.S., and foreign stock markets); *iii)* greater marketwide dispersion of beliefs about common fundamentals (measured by the standard deviation of professional forecasts of U.S. macroeconomic news releases); and *iv)* greater marketwide uncertainty about governments' currency policy (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.

We proceed as follows. In Section 2, we construct a model of multi-asset trading in the presence of an active central bank. In Section 3, we describe the data and present the empirical results. We conclude in Section 4.

2 Theory

We are interested in the effects of government intervention on relative mispricings, i.e., on violations of the law of one price (LOP). To that purpose, we first describe a noisy rational expectations equilibrium (REE) model of multi-asset trading in the presence of better informed speculators and derive its equilibrium in closed-form. We then introduce a stylized government and consider the implications of its official trading activity for LOP violations. All proofs are in the Appendix.

2.1 The Benchmark Model of Multi-Asset Trading

The basic model is based on Kyle (1985) and Pasquariello and Vega (2009). It is a two-date ($t = 0, 1$) economy in which two identical risky assets ($i = 1, 2$) are exchanged. Trading occurs only at date $t = 1$, after which the identical payoff v of both assets is realized; it is assumed that v is normally distributed with mean p_0 and variance σ_v^2. Three types of risk-neutral traders populate the economy: a discrete number (M) of informed traders (labeled speculators) in both assets, as well as liquidity traders and competitive market-makers (MMs) in each asset. All traders know the structure of the economy and the decision process leading to order flow and prices.

At date $t = 0$, there is neither information asymmetry about v nor trading. Sometime between $t = 0$ and $t = 1$, each speculator m receives a private and noisy signal of v, $S_v(m)$. We assume that each signal $S_v(m)$ is drawn from a normal distribution with mean p_0 and variance $\sigma_s^2 = \frac{1}{\rho}\sigma_v^2$ and that, for any two $S_v(m)$ and $S_v(j)$, $cov[v, S_v(m)] = cov[S_v(m), S_v(j)] = \sigma_v^2$. We define each speculator's information endowment about v as $\delta_v(m) \equiv E[v|S_v(m)] - p_0$ and 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, the lower is ρ, the more dispersed (i.e., the less precise and correlated) is speculators' private information about v.[3]

At date $t = 1$, liquidity traders and speculators submit their orders in assets 1 and 2 to the MMs before the equilibrium prices $p_{1,1}$ and $p_{1,2}$ have been set. We define the market order of each speculator m in each asset i 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, we assume that z_1 and z_2 are independent from all other random variables. Competitive MMs in each

[3] More general (yet analytically complex) information structures for $S_v(m)$ (e.g., as in Caballé and Krishnan, 1994; Pasquariello, 2007a; Albuquerque and Vega, 2009) lead to qualitatively similar implications.

[4] Allowing for negatively correlated noise trading ($\sigma_{zz} < 0$) is immaterial for our analysis.

asset i do not receive any information about its terminal payoff v, and observe only that asset's aggregate order flow $\omega_i = \sum_{m=1}^{M} x_i(m) + z_i$ before setting the market-clearing price $p_{1,i} = p_{1,i}(\omega_i)$, as in Subrahmanyam (1991a) and Boulatov et al. (2013). *Segmentation* in market-making is an important feature of our model, for it allows for the possibility that $p_{1,1}$ and $p_{1,2}$ be different in equilibrium despite identical terminal payoffs. We return to this issue below.

2.1.1 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*: $p_{1,i} = E(v|\omega_i)$.[5]

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, imperfectly competitive, risk-neutral speculators trade cautiously in both assets ($|x_i(m)| < \infty$, Eq. (2)) to protect the information advantage stemming from their private signals $S_v(m)$. As 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

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

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 market liquidity worse in both markets (higher λ): *i)* the more uncertain is the traded assets' identical terminal payoff v (higher σ_v^2), since speculators' private information advantage is greater; *ii)* the less correlated are their private signals (lower ρ), since each speculator, perceiving to have greater monopoly power on her private information, trades more cautiously with it; *iii)* the less intense is noise trading (lower σ_z^2), since MMs need to be compensated for less camouflaged speculation in the order flow; and *iv)* the fewer speculators are in the economy (lower M), since imperfect competition among them magnifies their cautious trading behavior.[6]

2.1.2 LOP violations

A well-established empirical literature measures LOP violations either as nonzero (absolute or square, arithmetic or percentage) price differences or as less than perfectly correlated price changes among identical assets (e.g., Karolyi, 1998, 2006; Auguste et al., 2006; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Griffoli and Ranaldo, 2011). In our economy, the two representations are conceptually equivalent. An examination of Eqs. (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. Of course, this may occur only in the presence of segmented market-making. If MMs observe order flow in both assets, no price differential can arise in equilibrium since semi-strong market efficiency (Condition 2) implies that $p_{1,1} = E\left(v|\omega_1, \omega_2\right) = p_{1,2}$. We formalize these observations in Corollary 1 by measuring LOP violations in the economy with the unconditional correlation of the equilibrium prices of assets 1 and 2, $corr\left(p_{1,1}, p_{1,2}\right)$.

Corollary 1 *In the presence of less than perfectly correlated noise trading, the LOP is violated*

[6]Specifically, it can be shown that $\frac{\partial\lambda}{\partial\sigma_v} = \frac{\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]} > 0$; $\frac{\partial\lambda}{\partial\rho} = -\frac{\sigma_v M[(M-1)\rho-2]}{2\sigma_z\sqrt{M\rho}[2+(M-1)\rho]^2} < 0$ 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 $\{M, \rho\}$ where $\rho \leq \frac{2}{M-1}$; and $\frac{\partial\lambda}{\partial\sigma_z} = -\frac{\sigma_v\sqrt{M\rho}}{\sigma_z^2[2+(M-1)\rho]} < 0$.

in equilibrium:

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

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

We illustrate the intuition behind Corollary 1 with a numerical example. We consider an economy in which $\sigma_v^2 = 1$, $\sigma_z^2 = 1$, $\sigma_{zz} = 0.5$, $\rho = 0.5$, and $M = 10$. We then plot the equilibrium price correlation of Eq. (3) as a function of σ_{zz}, ρ, M, or σ_z^2 in Figures 1a to 1d, respectively (solid lines). LOP violations are larger the less correlated is noise trading in assets 1 and 2 (lower σ_{zz} in Figure 1a), since liquidity demand and price differentials are more likely in equilibrium. LOP violations are also larger the worse is equilibrium liquidity in both markets (i.e., the higher is λ), since the greater is the impact of noise trading on equilibrium prices and the larger are the price differentials stemming from liquidity demand differentials in Eq. (1). Thus, $corr\left(p_{1,1}, p_{1,2}\right)$ is greater the fewer are speculators in the economy (lower M in Figure 1b) and the more dispersed is their private information (lower ρ in Figure 1c), since the more cautious is their trading activity and the more serious is the threat of adverse selection for MMs.[7] Lastly, more intense noise trading (higher σ_z^2 in Figure 1d) amplifies LOP violations by increasing both the likelihood and magnitude of liquidity demand differentials, despite its lesser impact (via lower λ) on equilibrium prices.

Remark 1 *LOP violations are increasing in speculators' information heterogeneity and intensity of noise trading, decreasing in the number of speculators and 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 our setting, only speculators can and do trade strategically and simultaneously in both assets 1 and 2 (see Eq. (2)). Hence, only they can attempt to profit from any price difference they anticipate to observe.

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

However, unconditional expected prices of assets 1 and 2 are identical in equilibrium ($E(p_{1,1}) = E(p_{1,2})$), 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 Eq. (1)). Further, in the noisy REE of Proposition 1, speculators 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.[8]

2.2 Government Intervention

Governments often intervene in financial markets. A large literature documents both the attempts of central banks and various governmental agencies to affect price levels and dynamics of especially exchange rates, but also sovereign bonds, derivatives, and even stocks, by directly trading in those assets in the marketplace, as well as their microstructure externalities.[9] As such, this "official" trading activity may have an impact on the ability of the affected markets to price assets correctly. We explore this possibility by introducing a stylized government in the multi-asset economy of Section 2.1.

The aforementioned literature identifies three recurring features of government intervention in financial markets (e.g., see Sarno and Taylor, 2001; Neely, 2005a; Menkhoff, 2010; Engel, 2014; Pasquariello et al., 2014; and references therein): *i)* governments tend to pursue *non-public* price targets in those markets; *ii)* governments are likely (or perceived) to have an *information advantage* over most market participants about the fundamentals of the traded assets; and *iii)* those price targets *may be related* to governments' fundamental information. We capture these features parsimoniously by the following assumptions about our stylized government.

First, the government is given a private and noisy signal of v, $S_v(gov)$, a normally distributed

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

[9] A comprehensive survey of this literature is beyond the scope of this paper. Recent studies include Bossaerts and Hillion (1991), Dominguez and Frankel (1993), 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), and Pasquariello et al. (2014) for the bond markets, and Sojli and Tham (2010) and Dyck and Morse (2011) for the stock markets.

variable with mean p_0, variance $\sigma^2_{gov} = \frac{1}{\psi}\sigma^2_v$, and precision $\psi \in (0,1)$; we further impose that $cov\left[S_v(m), S_v(gov)\right] = cov\left[v, S_v(gov)\right] = \sigma^2_v$, as for speculators' private signals $S_v(m)$ in Section 2.1. Accordingly, we define the government's information endowment about v 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 non-public target for the price of asset 1, $p^T_{1,1}$, drawn from a normal distribution with mean $\overline{p}^T_{1,1}$ and variance σ^2_T. The government's information endowment about $p^T_{1,1}$ is then $\delta_T(gov) \equiv p^T_{1,1} - \overline{p}^T_{1,1}$. This policy target is some unspecified function of $S_v(gov)$ such that $\sigma^2_T = \frac{1}{\mu}\sigma^2_{gov} = \frac{1}{\mu\psi}\sigma^2_v$, $cov\left[p^T_{1,1}, S_v(gov)\right] = \sigma^2_{gov}$, and $cov\left[S_v(m), p^T_{1,1}\right] = cov\left[v, p^T_{1,1}\right] = \sigma^2_v$. Hence, the higher is $\mu \in (0,1)$ the more correlated is the government's price target to its fundamental information and the less uncertain are market participants about its policy. For example, this assumption captures the observation that central bank 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., Sarno and Taylor, 2001) or more often "lean against the wind" (if μ is low, to resist those beliefs and dynamics; e.g., Edison, 1993; Lewis, 1995).[10]

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 et al. (2014). The first term in Eq. (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

[10] Accordingly, in their REE model of currency trading, Bhattacharya and Weller (1997) also assume that the central bank's price target is partially correlated to the payoff of the traded asset (forward exchange rates). It can be shown that qualitatively similar inference ensues from imposing that $p_{1,T}$ is independent of asset 1's terminal payoff v ($cov\left[v, p^T_{1,1}\right] = 0$, as in Pasquariello et al., 2014).

Eq. (4) accounts for the costs of that intervention, namely, deviating from pure profit-maximizing speculation in asset 1 ($\gamma = 0$). The higher is γ, the more committed is the government to policy-making in market 1 relative to its cost.

At date $t = 1$, MMs in each asset i clear their market after observing the corresponding aggregate order flow, ω_i, as in Section 2.1. However, while $\omega_2 = \sum_{m=1}^{M} x_2(m) + z_2$, ω_1 is now made 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 asset 1 attempt to learn from ω_1 not only about asset 1's terminal payoff v but also about the government's policy target $p_{1,1}^T$ when setting the equilibrium price $p_{1,1}$; each speculator 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 before choosing her optimal trading strategy $x_i(m)$; the government uses its private information $S_v(gov)$ to learn about what speculators know when choosing its optimal intervention strategy $x_1(gov)$. Proposition 2 solves for the ensuing unique linear Bayesian Nash equilibrium.

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

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

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

where $d = \frac{\gamma}{1-\gamma}$, λ^* is the unique positive real root of the sextic polynomial of Eq. (A-33) in the Appendix, and $\lambda = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]} > 0$ (as 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

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

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

Corollary 2 examines the effect of government intervention in asset 1, $x_1(gov)$ of Eq. (9), on the extent of LOP violations in the economy by the unconditional comovement of equilibrium asset prices $p_{1,1}^{*}$ and $p_{1,2}^{*}$ of Eqs. (5) and (6), as in Section 2.1.

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

$$corr\left(p_{1,1}^{*},p_{1,2}^{*}\right)=\frac{\sigma_{zz}+\sigma_{z}\sigma_{v}\sqrt{M\rho}\left\{B_{1,1}^{*}\left[1+(M-1)\rho\right]+C_{1,1}^{*}\psi+C_{1,2}^{*}\right\}}{\sigma_{z}\sqrt{\left[2+(M-1)\rho\right]\left\{\sigma_{z}^{2}+\sigma_{v}^{2}\left\{M\rho B_{1,1}^{*2}\left[1+(M-1)\rho\right]+D_{1}^{*}+E_{1}^{*}\right\}\right\}}},\qquad(10)$$

where $D_{1}^{*}=2M\rho\left[B_{1,1}^{*}\left(\psi C_{1,1}^{*}+C_{1,2}^{*}\right)\right]$ *and* $E_{1}^{*}=\psi C_{1,1}^{*2}+\frac{1}{\mu\psi}C_{1,2}^{*2}+2C_{1,1}^{*}C_{1,2}^{*}.$

In the above economy, the equilibrium price impact of order flow in market 1 (λ^{*} of Proposition 2) cannot be solved in closed form (see the Appendix). Thus, we characterize the equilibrium properties of $corr\left(p_{1,1}^{*},p_{1,2}^{*}\right)$ of Eq. (10) via numerical analysis. To that purpose, we introduce our stylized government, with starting parameters $\gamma=0.5$, $\psi=0.5$, and $\mu=0.5$, in the simple economy of Section 2.1 — the one where $\sigma_{v}^{2}=1$, $\sigma_{z}^{2}=1$, $\sigma_{zz}=0.5$, $\rho=0.5$, and $M=10$. Parameter selection only affects the relative magnitude of the effects described below. We then plot the ensuing equilibrium price correlation $corr\left(p_{1,1}^{*},p_{1,2}^{*}\right)$ (dashed lines), alongside its corresponding level in absence of government intervention ($corr\left(p_{1,1},p_{1,2}\right)$ of Eq. (3), solid lines), as a function of σ_{zz}, ρ, M, or σ_{z}^{2} (Figures 1a to 1d, as in Section 2.1.2), and γ, μ, ψ, or σ_{v}^{2} (Figure 1e to 1h).

Insofar as the dealership sector is segmented (Corollary 1), government intervention makes LOP violations more likely in equilibrium. According to Figure 1, official trading activity in asset 1 *lowers* the unconditional correlation of the equilibrium prices of (the 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 is perfectly correlated in both markets ($\sigma_{zz}=\sigma_{z}^{2}=1$ and $corr\left(p_{1,1},p_{1,2}\right)=1$ in Figure 1a; see Section 2.1.2). Intuitively, the stylized government of Eq. (4) trades 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, i.e., only partially correlated with both assets' identical terminal payoff v: $corr\left(v, p_{1,1}^T\right) = \sqrt{\mu\psi} < 1$. Since $p_{1,1}^T$ is also non-public (i.e., policy uncertainty $\sigma_T^2 = \frac{\sigma_v^2}{\mu\psi} > 0$), MMs in market 1 cannot fully account for the government's trading activity when setting $p_{1,1}^*$ from the observed aggregate order flow in asset 1, ω_1. As such, government intervention is at least partly effective at accomplishing its policy in the equilibrium of Proposition 2, in that $cov\left(p_{1,1}^*, p_{1,1}^T\right) = \frac{d\lambda^*\sigma_v^2}{\mu\psi(1+d\lambda^*)} > 0$. Thus, (at least partly) effective government efforts at achieving an (at least partly) uninformative and non-public policy target lead to greater LOP violations in equilibrium. Consistently, so-induced LOP violations increase (lower $cov\left(p_{1,1}^*, p_{1,1}^T\right)$) the more committed is the government to its policy target $p_{1,1}^T$ (higher γ, Figure 1e), the less correlated is the target to its private signal of v, $S_v\left(gov\right)$ (i.e., the greater uncertainty surrounds its target; lower μ, Figure 1f), and the less precise is its signal (lower ψ, Figure 1g).

The implications of government intervention for LOP violations also depend on existing market conditions. Figure 1 suggests that official trading activity leads to larger LOP violations the less liquid is the affected asset (1). 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). Ceteris paribus (as discussed in Section 2.1.1), fewer, more heterogeneous speculators trade more cautiously with their private signals, making MMs' adverse selection problem more severe and equilibrium price impact of order flow (Kyle's (1985) lambda) higher in both markets 1 (λ) and 2 (λ^*) — i.e., worsening liquidity in both markets. In those circumstances, government intervention in asset 1 is more effective at driving its equilibrium price $p_{1,1}^*$ toward the partially uninformative policy target $p_{1,1}^T$ ($\frac{\partial cov\left(p_{1,1}^*, p_{1,1}^T\right)}{\partial\lambda^*} = \frac{\mu\psi d\sigma_v^2}{\mu^2\psi^2(1+d\lambda^*)^2} > 0$), hence away from the informationally efficient equilibrium price of asset 2 ($p_{1,2}^*$ of Eq. (6)).

This effect is however less pronounced in correspondence with greater fundamental uncertainty (higher σ_v^2, Figure 1h). When private fundamental information is more valuable, both market liquidity deteriorates (see Section 2.1.1) and the pursuit of policy motives becomes more costly for the government (in the loss function of Eq. (4)). The latter partly offsets the former, leading to a nearly unchanged $corr\left(p^*_{1,1}, p^*_{1,2}\right)$. Similarly, Figure 1 also suggests that government intervention amplifies LOP violations less conspicuously (i.e., the difference between $corr\left(p_{1,1}, p_{1,2}\right)$ and $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ is smaller) when those violations are already severe in its absence, e.g., when noise trading in assets 1 and 2 is either more intense (higher σ^2_z, Figure 1d, improving liquidity in both markets) or more weakly correlated (lower σ_{zz}, Figure 1a), consistent with Remark 1. The following conclusions summarize these novel observations about the impact of government intervention on the law of one price.[11]

Conclusion 1 *Government intervention results in greater LOP violations in equilibrium, even with perfectly correlated noise trading.*

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

2.3 Empirical Implications

The stylized model of Sections 2.1 and 2.2 is meant to represent in a parsimonious fashion a plausible channel through which government intervention may affect the relative prices of fundamentally linked securities in less than fully integrated markets. This channel depends crucially on various facets of the information environment of those markets. Yet, measuring such market characteristics is challenging, and often unfeasible. Under these premises, we identify from Corollary 1, Proposition 2, Figure 1, and Conclusions 1 and 2 the following subset of *feasibly* testable implications of official trading activity for relative mispricings:

[11] As noted for the economy of Section 2.1, despite this impact, 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.

H1 *Government intervention does not affect pre-existing LOP violations (if any) in fully integrated markets;*

H2 *Government intervention induces (or magnifies pre-existing) LOP violations in less than fully integrated markets;*

H3 *This effect is more pronounced when pre-existing LOP violations are small;*

H4 *This effect is more pronounced when pre-existing market liquidity is low;*

H5 *This effect is more pronounced when information heterogeneity is high;*

H6 *This effect is more pronounced when government policy uncertainty is high.*

3 Empirical Analysis

In this section, we test the implications of our model by analyzing the impact of government intervention in currency markets on the relative pricing of American Depositary Receipts (ADRs). An ADR is a U.S. dollar-denominated security, traded in the U.S., representing ownership of a pre-specified amount ("bundling ratio") of stocks of a foreign company held on deposit at a U.S. depositary banks (e.g., Karolyi, 1998; 2006).

The market for ADRs represents an ideal setting to test our 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 in its foreign currency FOR, and $S_{t,USD/FOR}$ is the exchange rate between USD and FOR. We interpret the common terminal payoff v of assets 1 and 2 in our model as a stylized representation of the LOP relationship between ADR prices and the corresponding exchange rates in Eq. (11).

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.[12] We interpret segmented market-making in assets 1 and 2 in our model as a stylized representation of this observation.

Third, as mentioned in Section 2.2, the stylized representation of the government in our model is consistent with the consensus in the literature that government intervention in currency markets is often effective at moving exchange rates because it is (deemed) at least partly informative about fundamentals.[13]

Lastly, the same literature suggests that forex intervention is unlikely to be motivated by relative mispricings in the ADR market (or by the frictions leading to their occurrence; see Gagnon and Karolyi, 2010). This observation alleviates endogeneity concerns when estimating and interpreting the empirical relationship (if any) between government intervention and arbitrage parities.

According to our model, these features of currency and ADR markets raise the possibility that government intervention in the former may lead to violations of the law of one price in the latter — for instance, nonzero absolute log percentage differences (in basis points, bps) between actual ($P_{i,t}$) and theoretical ADR prices ($P_{i,t}^{LOP}$ of Eq. (11)):

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

(as in Pasquariello, 2014) — i.e., to ADR parity (ADRP) violations. We assess this possibility

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

[13] Recent examples include Peiers (1997), Naranjo and Nimalendran (2000), Payne and Vitale (2003), and Pasquariello (2007b). See also the comprehensive surveys in Sarno and Taylor (2001), Neely (2005b), Menkhoff (2010), and Engel (2014).

in the reminder of the paper.[14]

3.1 Data

In this section we construct a comprehensive sample of all ADRs traded in U.S. exchanges and available official intervention activity in currency markets over the last three decades.

3.1.1 American Depositary Receipts

We begin by obtaining from Thomson Reuters Datastream (Datastream) the complete sample of all foreign stocks cross-listed in the U.S., either as ADRs or as ordinary shares, between January 1, 1973 and December 31, 2009. Following standard practice in the literature (e.g., Gagnon and Karolyi, 2010), we 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.[15] This leaves us with a final sample of daily closing prices (and bundling ratios q_i) for 410 pairs of foreign stocks from developed and emerging countries, $P_{i,t}^{FOR}$, and their (Levels II and III) ADRs listed on the NYSE, AMEX, or NASDAQ, $P_{i,t}$. The corresponding exchange rates $S_{t,USD/FOR}$ in Eq. (11) are daily indicative spot mid-quotes (as observed at 12 p.m. Eastern Standard Time [EST]), from Pacific Exchange Rate Service (Pacific) and Datastream. Because of our focus on forex interventions, Table 1 reports summary statistics on this sample by the most recent country of listing (and currency of denomination) of the underlying foreign stocks.

[14] The notion of LOP violations in the ADR market as nonzero absolute price (relative) differentials ($ADRP_{i,t} > 0$) is both common in the aforementioned literature and conceptually equivalent to the notion of LOP violations in our model (an equilibrium unconditional price correlation $corr\,(p_{1,1}, p_{1,2}) < 1$). For instance, Proposition 1, Corollary 2, and well-known properties of half-normal distributions (e.g., Vives, 2008, p. 149) imply that the expected absolute differential between the equilibrium prices of assets 1 and 2 is a linear function of their unconditional correlation: $E\left[|p_{1,1} - p_{1,2}|\right] = H\left[1 - corr\,(p_{1,1}, p_{1,2})\right]$, where the scaling factor $H = \sqrt{\frac{2\sigma_z^2\sigma_v^2 M\rho}{pi(\sigma_z^2 - \sigma_{zz})}}$ depends on the magnitude of the assets' terminal payoff v (σ_v^2), and $pi \equiv \arccos(-1)$. Both $corr\,(p_{1,1}, p_{1,2})$ of Section 2 and $ADRP_{i,t}$ of Eq. (12) are instead price-scale independent. Accordingly, Auguste et al. (2006), Pasquariello (2008), and Gagnon and Karolyi (2010) note that the null hypothesis that the LOP holds in the ADR market at any point in time implies that both $\ln(P_{i,t}) = \ln\left(P_{i,t}^{LOP}\right)$ and $a_i = 0$ and $b_i = 1$ in $\Delta\ln(P_{i,t}) = a_i + b_i\Delta\ln\left(P_{i,t}^{LOP}\right) + \varepsilon_{i,t}$, where $\Delta\ln(P_{i,t}) = \ln(P_{i,t}) - \ln(P_{i,t-1})$ and $\Delta\ln\left(P_{i,t}^{LOP}\right) = \ln\left(P_{i,t}^{LOP}\right) - \ln\left(P_{i,t-1}^{LOP}\right)$.

[15] We also exclude any ADR and foreign stock with missing Datastream pair codes. We verify the accuracy of the Datastream sample by cross-checking its pairings with those compiled by the Bank of New York Mellon in its Depositary Receipts Directory (see http://www.adrbnymellon.com/dr_directory.jsp).

Most cross-listed stocks in the sample are listed in developed, highly liquid equity markets (and denominated in highly liquid currencies): Canada (in CAD, 67), Euro area (EUR, 58), the United Kingdom (GBP, 43), Australia (AUD, 30), and Japan (JPY, 24); emerging, often less liquid equity markets (and currencies) include Hong Kong (HKD, 54), Brazil (BRL, 23), and South Africa (ZAR, 14), among others.[16]

While comprehensive, this dataset allows to measure the extent of LOP violations in the ADR market only imprecisely. Gagnon and Karolyi (2010) discuss its structural limitations in detail. For instance, the trading hours in many of the foreign stock and currency markets listed in Table 1 are partly- or non-overlapping with those in New York. Individual ADR parity violations often differ in scale, making cross-sectional comparisons problematic, and either persist or display discernible trends. Closing foreign stock, currency, or ADR prices may be stale, e.g., reflecting sparse trading. Pasquariello (2014) proposes two measures of the *marketwide* extent of violations of the ADR parity of Eq. (11) addressing these concerns. The first one, labeled $ADRP_m$, is the monthly average of daily equal-weighted means of all available, filtered realizations of $ADRP_{i,t}$ of Eq. (12) — i.e., of daily mean absolute percentage ADR parity violations.[17] Filtering and monthly averaging smooth potentially spurious daily variability in observed parity violations, e.g., due to quoting errors, price staleness, or non-synchronicity. The second one, labeled $ADRP^z_m$, is the monthly average of daily equal-weighted means of all normalized ADRP violations, $ADRP^z_{i,t}$ — i.e., after each has been standardized by its historical distribution on day t. Normalization allows to identify individual *abnormal* ADR parity violations, i.e., innovations in each observed $ADRP_{i,t}$ relative to its time-varying trend (without look-ahead bias), while making these violations comparable across ADRs. As such, $ADRP^z_m$ is positive (higher) in correspondence with historically large (larger) LOP violations in the ADR market.

Foreign companies rarely issued ADRs in the 1970s; when they did, their ADR and local

[16] For a detailed overview of the main characteristics of the global currency markets, see the latest triennal survey by the Bank for International Settlements (2013). The "other" category in Table 1 includes Colombia, Denmark, Egypt, Hungary, Israel, New Zealand, Norway, Philippines, Singapore, Sweden, Thailand, and Venezuela.

[17] Specifically, Pasquariello (2014) excludes from these averages any observed absolute ADR parity violation $ADRP_{i,t}$ deemed either "too large" ($ADRP_{i,t} \geq 1,000$ bps) or stemming from "too extreme" ADR prices ($P_{i,t} <$ \$5 or $P_{i,t} >$ \$1,000).

stock prices in our sample are often either stale or suspect, yielding extreme LOP violations. Accordingly, the filtering and aggregation procedure described above results in several missing observations between 1973 and 1979. Thus, we focus our empirical analysis on the interval 1980-2009, the longest portion of our 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 $ADRP_m^z$ over the sample period 1980-2009 are in Table 1; their plots are in Figures 2a and 2b (right axis, solid line). As discussed in Pasquariello (2008, 2014), absolute ADR parity violations $ADRP_m$ in the past three decades are large and volatile, but also declining — perhaps reflecting improving quality and integration of the world financial markets over the sample period. Once controlling for this trend, scaled such violations ($ADRP_m^z$) display more discernible cycles and spikes, especially during periods of financial turmoil.[18] Both measures also display non-trivial cross-country heterogeneity. Consistent with Gagnon and Karolyi (2010), LOP violations in Table 1 are on average most pronounced for ADRs from Europe, Australia, and emerging markets (e.g., Mexico, South Africa, South Korea), and least pronounced for Canadian stocks ("ordinaries"), which have long been trading synchronously and on a one-to-one basis (i.e., $q_i = 1$ in Eq. (11)) in both Canada and the U.S.

The model of Section 2 relates LOP violations to common forces affecting the liquidity of the underlying, arbitrage-linked markets. In light of this observation, Eq. (11) suggests that ADR parity violations may be related to commonality in the liquidity of the U.S. stock market where an ADR is exchanged, the foreign listing market for the underlying stock, and the corresponding currency market. 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). Lesmond et al. (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

[18] In particular, $ADRP_m^z$ is highest in October 2008, in correspondence with the global financial crisis initiated by Lehman Brothers' default (on September 15, 2008). Qualitatively similar inference ensues from excluding this recent period of turmoil (2008-2009) from our analysis.

estimates are highly correlated with such popular measures of liquidity as quoted or effective bid-ask spreads (when available; see also Bekaert et al., 2007).

Accordingly, we compute composite marketwide and country-level illiquidity measures $ILLIQ_m$ for both $ADRP_m$ and $ADRP_m^z$ as the equal-weighted averages of monthly averages of Z_t^{FOR}, Z_t, and Z_t^{FX} — the daily fractions of ADRs in the corresponding grouping whose underlying foreign stock, ADR, and exchange rate experience a zero return on day t ($P_{i,t}^{FOR} = P_{i,t-1}^{FOR}$, $P_{i,t} = P_{i,t-1}$, and $S_{t,USD/FOR} = S_{t-1,USD/FOR}$), respectively. This procedure allows us to capture any commonality in ADR parity-level liquidity parsimoniously, over our full sample, and without look-ahead bias. Summary statistics for $ILLIQ_m$ (in percentage) are also in Table 1. Perhaps unsurprisingly, the so-defined *ADRP illiquidity* of cross-listings from developed economies is lower than in emerging markets: E.g., 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 U.K., 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: E.g., $ILLIQ_m$ for cross-listings from South 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 $ADRP_m^z$ 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 $ILLIQ_m$ are instead low).[19] This preliminary observation is consistent with our model's basic premise (as summarized in Remark 1). In the benchmark model of multi-asset trading of Section 2.1 (i.e., in absence of government intervention), LOP violations are likely to be larger (i.e., the unconditional correlation of the equilibrium prices of two identical assets is lower) not only when (the commonality in their) liquidity is low (because adverse selection risk is greater and so is the price impact of less-than-perfectly correlated noise trading) but also when it is high (because the

[19] 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) level of economic and capital market development. See also Levy Yeyati et al. (2009).

intensity of less-than-perfectly correlated noise trading is greater). We investigate this relationship (and its relevance for the LOP externality of government intervention) in greater detail in Section 3.4.

3.1.2 Foreign Exchange Interventions

The forex market is not only among the largest, most liquid financial markets (Bank for International Settlements, 2013) but also one where government interventions occur most often. According to a well-established literature (surveyed in Edison, 1993; Sarno and Taylor, 2001; Neely, 2005a; Menkhoff, 2010; Engel, 2014), monetary authorities (like central banks) and other government agencies frequently engage in *sterilized* currency transactions — i.e., accompanied by offsetting actions on the domestic money supply — normally in a coordinated fashion, to accomplish their (habitually non-public) policy objectives for exchange rate dynamics. Despite a robust theoretical and empirical debate, there is consensus that these interventions are effective, at least in the short-run, by virtue of their (actual or perceived) informativeness about market fundamentals (e.g., Dominguez, 2006; Pasquariello, 2007b; and references therein).

As discussed in Section 2.2, the stylized government of Eq. (4) captures in spirit those features of observed official exchange rate trading activity. To measure this activity, we use the database of government intervention in currency markets available on the Web site of the Federal Reserve Bank of St. Louis (FRED).[20] This database contains daily amounts of domestic and foreign currencies traded by the governments of Australia, Germany, Italy, Japan, Mexico, Switzerland, Turkey, and the United States for policy reasons (i.e., to influence exchange rates) over the past several decades.[21] When currency-specific intervention data is missing, we augment

[20]See http://research.stlouisfed.org/fred2. 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 (Fischer and Zurlinden, 1999).

[21]Those official trades may have been executed in the spot and/or forward currency markets, although the former is likely 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. Monetary authorities also execute *customer transactions* in the spot forex market. Customer transactions are passive trades triggered not by policy motives but by the domestic government's requests for foreign currencies (e.g., Payne and Vitale, 2003; Pasquariello, 2007b). Hence, we exclude them from our sample.

the FRED database using various official government sources. As for our sample of ADR parity violations, the resulting sample has the broadest continuous coverage of currency intervention activity between 1980 and 2009. More recent intervention data is not currently available. Panel A of Table 2 reports summary statistics for these interventions, aggregated at the monthly frequency, by country and exchange rate affected over this period. All governments in the sample intervene by purchasing or selling their domestic currencies — most often against USD, the currency of denomination of ADRs; less so via cross-rates (exchange rates not involving vehicle currencies like USD or EUR). Cross-rates are however kept in line with USD-quoted exchange rates by triangular arbitrage (Bekaert and Hodrick, 2009). Japan and Switzerland occasionally trade on exchange rates between foreign currencies and USD.

According to Table 2, the absolute amounts of currency traded by governments, while non-trivial, are small relative to the average monthly trading volume in the forex market (118 trillions of dollars, according to the Bank for International Settlements, 2013). In our model optimal intervention amounts ($x_1\,(gov)$ of Eq. (9)) are endogenously determined in equilibrium and depend on the realizations of unobservable variables controlling the information environment of the market, liquidity trading, or policy. Thus, our theory does not postulate any clear relationship between the magnitude of the intervention and LOP violations. In addition, most currency interventions are *coordinated* among multiple central banks for greatest effectiveness (e.g., 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, the official trades in different exchange rates in Table 2 tend to cluster in time but often are not perfectly synchronous at high frequency. Lastly, Tables 1 and 2 suggest there is relative scarcity of currency-matched intervention-ADR pairs in our sample.

In light of these observations, we propose two aggregate measures of the presence of government intervention in the forex market. The first one, labeled $N_m\,(gov)$, is the number of nonzero government intervention-exchange rates pairs in a month. The second one, labeled $N_m^z\,(gov)$, is such number standardized by its historical distribution on month m. As for normalized ADRP violations $ADRP_m^z$ in Section 3.1.1, a positive (negative) $N_m^z\,(gov)$ indicates an *abnormally* large (small) number of government interventions — i.e., historically high (low) intensity of official trading activity — in the forex market on month m. Computing both variables using exclusively interventions in exchange rates relative to USD yields similar inference.

We plot $N_m\,(gov)$ and $N_m^z\,(gov)$ in Figures 2a (left axis, histogram) and 2b (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 2a) 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 somehow 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. Visual inspection of Figure 2 also suggests that more frequent forex intervention is often accompanied by larger LOP violations in the ADR market. We formally explore this possibility next.

3.2 Marketwide LOP Violations

Table 2 and Figure 2 indicate that the market for ADRs experiences non-trivial LOP violations between 1980 and 2009. According to the model of Section 2 (e.g., see H2 in Section 2.3), government intervention in currency markets may either explain their occurrence or magnify their intensity.

We test this prediction by specifying the following regression model for changes in monthly averages of (various measures of) those LOP violations (LOP_m):

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

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 2a have a first-order serial correlation of 0.86 and 0.61, respectively. Regressions in changes have better small-sample properties and mitigate biases caused by potential non-stationarity. 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 our inference. The coefficient β_0 in Eq. (13) captures the contemporaneous impact of intervention activity ($\Delta I_m > 0$) on LOP violations. Market participants may anticipate the nature and/or extent of this activity, e.g., if its policy objectives are preannounced by the government or leaked to the media ($\Delta I_{m+1} > 0$). In Eq. (13), any such anticipation is captured by the coefficient β_1. The effects of past intervention activity ($\Delta I_{m-1} > 0$) on LOP violations may persist (or ebb), e.g., depending on the extent to which market participants learn about the government's prior trades and policy objectives. In Eq. (13), any such persistence (or reversal) is captured by the coefficient β_{-1}. We estimate Eq. (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.[22]

The results in Table 3 provide support for our model's main prediction (in H2). Estimates of both the contemporaneous and cumulative impact of forex interventions on ADR parity violations are positive and statistically significant: $\beta_0 > 0$ and $\beta_1^0 > 0$. These estimates are economically significant as well; for example, a one standard deviation increase in the monthly change in the number of forex interventions $\Delta ADRP_m$ (1.40, in Panel B of Table 2) is accompanied by a contemporaneous (cumulative) increase in average ADR parity violations $ADRP_m$ in (up to) that month by $3.505 \times 1.40 = 4.9$ bps ($4.830 \times 1.40 = 6.8$ bps), i.e., by nearly 23% (32%) of the sample-wide standard deviation of $\Delta ADRP_m$ (21.47, in Table 1). According to Panel A of Table 3, the estimated impact of forex interventions on LOP violations is seldom anticipated ($\beta_1 > 0$ but small), yet often persistent ($\beta_{-1} > 0$ and non-trivial). These estimates imply that forex

[22]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 non-synchronous trading (e.g., price staleness). Our inference is unaffected by using Newey-West standard errors to correct for (mild or absent) residual serial correlation and heteroskedasticity.

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. E.g., normalized ADR parity violations $ADRP_m^z$ increase on average by 34% of their sample-wide standard deviation over the three-month window in correspondence with historically high intensity of official trading activity in a month — i.e., in response to a one standard deviation increase in the monthly change in the normalized number of government interventions $\Delta ADRP_m^z$ $[0.057 \times 0.91 \div 0.153]$.

Coefficient estimates from the regression model of Eq. (13) may be plagued by possible endogeneity bias. As shown in Eq. (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. Forex interventions are also most often sterilized — i.e., 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 intervention is likely to occur in correspondence with (or in response to) high exchange rate volatility (e.g., Neely, 2005b) and has been shown to be accompanied by deteriorating currency market quality (e.g., see Dominguez, 2003, 2006; Pasquariello, 2007). Thus, LOP violations may be high in months when currency market quality is low — which is exactly when governments are more likely to intervene — rather than as a consequence of forex intervention (e.g., Neely and Weller, 2007).[23] Unfortunately, those properties of forex intervention also make it extremely difficult to find covariates of I_m that are uncorrelated with the error term ε_t in Eq. (13) to obtain consistent estimates of the impact coefficients (β_1, β_0, β_{-1}) in Eq. (13) via an instrumental variable (IV) approach (e.g., Engel, 2014).[24]

[23]Neely and Weller (2007) argue that, in a model of risk-arbitrage based on Shleifer and Vishny (1997), decreasing availability of arbitrage capital may magnify both observed mispricings in currency markets and forex intervention activity aimed at stabilizing the exchange rate. See also Garleanu and Pedersen (2011) and Gabaix and Maggiori (2014). We highlight the robustness of our evidence to controlling for funding liquidity conditions in Eq. (13) in Section 3.4.

[24]See also the discussion in Fatum and Hutchison (2003) and Neely (2005b). Nonetheless, estimates of the

We assess the relevance of these considerations for our inference in several ways. First, we estimate Eq. (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, e.g., daily frequencies (e.g., see Humpage and Osterberg, 1992; Andersen et al., 2003, 2007; and references therein). However, as discussed in Section 3.1, daily ADR parity violations are also significantly more volatile and more likely to be spurious or affected by microstructure frictions, while forex interventions often cluster over several days. Nonetheless, the resulting estimates of β_1, β_0, β_{-1} (in Panel A of Table 3) indicate that daily official trading activity in the currency market has a (weakly significant and short-lived but) positive impact on $\Delta ADRP_t$ and $\Delta ADRP_t^z$, consistent with our model.

Second, we use Eq. (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 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. A well-developed literature provides evidence of 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 money markets (e.g., see Griffoli and Ranaldo, 2011; Pasquariello, 2014; and references therein). Since both markets are (virtually) fully integrated (e.g., Bekaert and Hodrick, 2009), our model predicts that government intervention in the currency markets should have *no* impact on the extent of CIRP violations (see H1 in Section 2.3). However, the aforementioned literature suggests that greater CIRP violations may be due to deteriorating currency market quality — an omitted variable that, as we noted above, may be linked to forex intervention and

coefficients of interest in Table 3 (β_0, β_1^0, and β_1^{-1}) are significant and with the expected sign relative not only to the actual ($N_m\,(gov)$) but also to the historically abnormal number of forex interventions in a month — $N_m^z\,(gov)$, i.e., the portion of $N_m\,(gov)$ that could not have been anticipated by market participants via a naive prediction model based on average scaled prior intervention activity.

so bias upward our estimates of its impact on ADR parity violations in Eq. (13). Hence, the strength of the relationship between forex intervention and CIRP violations may hint at the importance of this bias for those estimates.

To that purpose, we obtain the time series of actual and normalized monthly CIRP violations, $CIRP_m$ and $CIRP_m^z$, constructed by Pasquariello (2014). Both measures of CIRP violations are monthly averages of (actual and normalized [as in Section 3.1.1]) daily absolute log differences (in bps, as in Eq. (12)) 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 corresponding synthetic forward exchange rates implied by the CIRP. Because of data limitations, these series are available exclusively over a portion of our sample period, between May 1990 and December 2009. Pasquariello (2014) reports that CIRP violations within this sub-period are small (e.g., averaging roughly 21 bps) but also volatile, e.g., often much larger in correspondence with well-known episodes of financial turmoil (like ADRP violations in Figure 2).[25] We then estimate the regression model of Eq. (13) over the subperiod 1990-2009 for monthly changes in both ADRP ($\Delta LOP_m = \Delta ADRP_m$ or $\Delta ADRP_m^z$) and CIRP violations ($\Delta LOP_m = \Delta CIRP_m$ or $\Delta CIRP_m^z$). The resulting estimated coefficients β_1, β_0, and β_{-1} (and their cumulative sums β_1^0 and β_1^{-1}; in Panel B of Table 3) indicate that forex interventions have little or no impact on LOP violations within the more closely integrated currency and money markets but are accompanied by a large and persistent increase in LOP violations within the less closely integrated currency and international stock markets. This evidence not only provides further support for our model but also suggests that deteriorating currency market quality is unlikely to be related to periods of intensifying forex intervention and ADR parity violations.

Lastly, we use our model's guidance to explicitly consider the effect of additional, potentially important economic and financial aggregates on currency and stock market conditions in proximity of official currency trading activity. We do so in Sections 3.3 and 3.4 next.

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

3.3 The Cross-Section of LOP Violations

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

Our model also postulates (in Conclusion 2) that the impact of forex intervention in one asset on LOP violations — i.e., on the equilibrium correlation between its price and the price of another, otherwise identical asset ($corr\left(p_{1,1}^{*}, p_{1,2}^{*}\right)$ of Eq. (10)) — may depend on variables affecting the information environment of the markets in which those assets are traded. The cross-section of this impact may shed light on its theoretical determinants. We estimate the regression model of Eq. (13) separately for each country of listing in Table 1 and report the resulting coefficients of interest for either actual or normalized absolute ADRP violations ($ADRP_m$ or $ADRP_m^z$) in Panels A and B of Table 4, respectively.

Table 4 provides evidence of meaningful heterogeneity in the estimated relationship between country-level LOP violations and official trading activity in currency markets. In particular, our model predicts that forex intervention may yield larger ADR parity violations when the underlying, arbitrage-linked markets are less liquid (see H4 in Section 2.3), but also when those violations are unconditionally small (e.g., if liquidity trading is high; H3). Accordingly, estimates of the contemporaneous (β_0) and cumulative impact (β_1^0 and β_1^{-1}) of changes in either $N_m\left(gov\right)$ or $N_m^z\left(gov\right)$ on absolute percentage ADR parity violations in Table 4 tend to be larger and more often significant: *i)* for cross-listings from emerging markets (i.e., markets whose information environment is generally deemed to be of lower quality; e.g., Bekaert and Harvey, 1993, 1997, 2000, 2003; Lesmond, 2005; Pasquariello, 2008); *ii)* for cross-listings whose measure of ADRP illiquidity $ILLIQ_m$ of Section 3.1.1 (in Table 1) tends to be higher; and *iii)* for cross-listings whose samplewide mean LOP violations (also in Table 1) tend to be smaller. For instance, Panel A of Table 4 shows that, on average, a one standard deviation increase in $\Delta N\left(gov\right)_m$ is accompanied by a cumulative increase in ADR parity violations for cross-listings from Other (mostly emerging markets), Hong Kong, and Japan by 29, 19, and 8 bps, respectively — i.e., by more than 34%, 40%, and 27% of the standard deviation of $\Delta ADRP_m$.

3.4 LOP Violations and Market Conditions

Overall, the evidence in Tables 3 and 4 is consistent with the main empirical implication of our stylized model of multi-market trading in the presence of government intervention (see H2 in Section 2.3): Official trading activity in currency markets is accompanied by nontrivial negative arbitrage externalities — namely by a large and statistically significant increase in LOP violations in the arbitrage-linked ADR markets. Importantly, our model relates this effect to such existing market conditions as those affecting the liquidity of the traded arbitrage-linked assets or the uncertainty surrounding government intervention among market participants. These additional implications are also listed in Section 2.3 (H3 to H6). For instance, our model postulates that greater dispersion of speculators' private information (or fewer of them) may amplify government-induced LOP violations by lowering market depth (i.e., worsening market liquidity) and magnifying the potential impact of official trading activity on equilibrium prices and price correlation (see Conclusion 2 [in Section 2.2] and H5), as it does greater policy uncertainty (H6). However, deteriorating market conditions may also be related to intensifying forex interventions and LOP violations. As noted earlier, the evidence in Tables 3 and 4 provides preliminary support for the former notion but not for the latter.

In this section, we assess both notions more directly. To that purpose, we amend parsimoniously the regression model of Eq. (13) for monthly changes in LOP violations (ΔLOP_m) as follows:

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

where LOP_m is either $ADRP_m$ or $ADRP_m^z$, and I_m is either $N_m\left(gov\right)$ or $N_m^z\left(gov\right)$. Our inference is insensitive to introducing lead-lag effects of forex intervention and/or calendar fixed effects. Eq.

(14) allows for changes in ADRP illiquidity ($ILLIQ_m$) and marketwide information heterogeneity ($DISP_m$) to affect the extent of LOP violations in the ADR market both directly and through their interaction with forex intervention, as postulated by our model. As discussed in Section 3.1.1, the variable $ILLIQ_m$ — the equal weighted average of the marketwide fraction of zero returns in the arbitrage-linked ADR, foreign stock, and currency markets — is designed to capture marketwide ADR parity-level illiquidity. Our model predicts that $\beta_{ILQ} > 0$ (Remark 1) and $\beta_0^{ILQ} > 0$ (Conclusion 2; H4), i.e., that ADRP violations and their positive sensitivity to forex intervention ($\beta_0 > 0$) are likely greater in correspondence with deteriorating ADRP liquidity (i.e., $\Delta ILLIQ_m > 0$). Intuitively, ceteris paribus, when markets are less deep (higher λ and λ^*), noise trading shocks and government intervention in the aggregate order flow have greater impact on equilibrium prices, yielding larger LOP violations. The relationship between ΔLOP_m and $\Delta ILLIQ_m$ may be non-linear — for instance, according to Remark 1, LOP violations may also be greater in the presence of more intense liquidity trading; thus, Eq. (14) includes a quadratic term for $\Delta ILLIQ_m$ as well.

Among the determinants of market liquidity in our model, speculators' information heterogeneity (ρ) plays an important role for it affects the extent of their 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 participants (including noise traders and the government) in each market. The dispersion of private information among sophisticated market participants in a market is commonly measured by the standard deviation of professional forecasts of economic and financial variables that are relevant to the fundamental payoff of the asset(s) traded in that market, such as corporate earnings, macroeconomic aggregates, or policy decisions (e.g., Diether et al., 2002; Green, 2004; Pasquariello and Vega, 2007, 2009; Yu, 2011).

In the spirit of our model, we measure the heterogeneity of private information about fundamentals in the arbitrage-linked ADR market with 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 may (and have been shown to) contain payoff-relevant information not only for the U.S. stock market where ADRs are traded, but also for the stock and currency markets for the underlying foreign stocks and exchange rates (e.g., Chen et al., 1986; Bekaert et al., 1995; Albuquerque and Vega, 2009; Evans and Lyons, 2013). The SPF is the only continuously available survey of professional forecasts (by hundreds of private-sector economists) for U.S. macroeconomic variables over our sample period. However, it is available exclusively at the quarterly frequency.[26] Following the literature, we construct our measure of ADRP dispersion of beliefs $DISP_m$ in three steps. First, in each quarter q we 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).[27] Second, we standardize each time series of dispersions to adjust for their different units of measurement. Third, we compute an equal-weighted average of them, $DISP_q$, and impose that $\Delta DISP_m = \Delta DISP_q$ for each month m within q. As noted earlier, our model predicts that $\beta_{DSP} > 0$ (Remark 1) and $\beta_0^{DSP} > 0$ (Conclusion 2; H5) in Eq. (14).

Our model also postulates that government intervention may be accompanied by larger LOP violations the greater is the uncertainty among market participants about its policy motives (lower μ and higher $\sigma_T^2 = \frac{1}{\mu}\sigma_{gov}^2$; Conclusion 2; H6). Intuitively, ceteris paribus, 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 the other, otherwise identical asset) by further obfuscating the MMs' inference from the order flow. As noted earlier, many central banks do not disclose their policy objectives when intervening in the currency markets, nor market expectations of those objectives are typically available. Within our model, ceteris paribus, the unconditional variance of the government's optimal intervention strategy in equilibrium ($x_1(gov)$ of Eq. (9)) is increasing in the variance of its information advantage about its policy target ($\delta_T(gov) \equiv p_{1,1}^T - \overline{p}_{1,1}^T$), i.e., in the uncertainty surrounding that

[26] See Croushore (1993) for a detailed description of the SPF database. Popular sources of monthly surveys of economist-level forecasts either have long been discontinued (e.g., MMS in 2003; Pasquariello et al., 2014) or are not available prior to the late 1990s (e.g., Bloomberg before 1997; Beber et al., 2013).

[27] According to several studies, these macroeconomic news releases have the greatest impact on U.S. and international stock, bond, and currency markets (e.g., Andersen and Bollerslev, 1998; Andersen et al., 2003, 2007; Pasquariello and Vega, 2007).

target (σ_T^2) — such that, in a first order sense, $\Delta var\left[x_1(gov)\right] \approx \left(C_{1,2}^*\right)^2 \Delta\sigma_T^2$. Accordingly, we proxy for the latter by the historical standard deviation of the former, $STD(I_m)$, and consider the impact of monthly changes in both the intensity and volatility of observed intervention activity on observed ADRP violations in Eq. (14). Our model then predicts that $\beta_{SDI} > 0$.

Lastly, Eq. (14) includes a vector ΔX_m of changes in several measures of market conditions linked by the literature to the intensity of limits to arbitrage and ensuing LOP violations, especially in the ADR market (e.g., unhedgeable risk and opportunity cost of arbitrage, scarcity of arbitrage capital, or noise trader sentiment; see Pontiff, 1996; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Garleanu and Pedersen, 2011; Baker et al., 2012), but also to forex intervention (see Edison, 1993; Sarno and Taylor, 2001; Engel, 2014): U.S. and world stock market volatility (from MSCI); global exchange rate volatility (from Datastream and Pacific); official NBER recession dummy; U.S. risk-free rate (from Kenneth French's Web site); Pastor and Stambaugh's (2003) measure of U.S. equity market liquidity (based on volume-related return reversals, from Pastor's Web site); Adrian et al.'s (2014) measure of U.S. funding liquidity (aggregating broker-dealer leverage, from Muir's Web site); and Baker and Wurgler's (2006, 2007) measure of U.S. investor sentiment (from Wurgler's Web site).

Table 5 reports *scaled* OLS estimates of the coefficients of interest β_0, β_{ILQ}, β_{ILQ}^2, β_0^{ILQ}, β_{DSP}, β_0^{DSP}, β_{SDI} in Eq. (14) for $I_m = N_m(gov)$ (Panel A) and $I_m = N_m(gov)$ (Panel B). Different units for the regressors in Eq. (14) affect the scale of their estimated slope and interaction coefficients. Thus, to facilitate the economic interpretation of these estimates, we multiply each of them by the standard deviation of the corresponding regressor(s) such that each scaled coefficient in Table 5 is in the same unit as the dependent variable ΔLOP_m. The evidence in Table 5 provides additional support for our 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, e.g., ranging between 2.6 bps ($t = 2.32$; Panel B) and 2.8 bps ($t = 2.56$; Panel A) in correspondence with a one standard deviation shock to ΔI_m.

Second, estimates of β_{ILQ} are always positive and both economically and statistically significant: Consistent with Remark 1, 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 absence of forex intervention.[28] 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 H4, but small and never significant.

Third, this relationship is nevertheless sensitive to more direct measures of the specific determinants of market liquidity in our 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 our model (H5). For instance, ceteris paribus, a large increase in the standardized number of interventions in a month (i.e., a one standard deviation shock to $\Delta N_m^z\,(gov) > 0$) leads to three times larger ADRP violations if information heterogeneity is high in that month (i.e., in conjunction with a one standard deviation shock to $\Delta DISP_m$) — i.e., by more than 9 bps ($= 2.959 + 6.147$, in Panel B of Table 5) versus an unconditional average increase by nearly 3 bps.[29]

Finally, scaled estimates of the policy uncertainty coefficient β_{SDI} in Eq. (14) are always positive, and often both statistically significant and as large as (or larger than) the corresponding coefficient for the intensity of forex intervention β_0. For example, Panel B of Table 5 shows that a one standard deviation increase in forex policy uncertainty in a month ($\Delta STD\,(N_m^z\,(gov)) > 0$) is accompanied by between 10% and 12% greater ADR parity violations in that month than their sample variation (in Table 1), consistent with our model (H6), even in absence of an increase in the standardized number of forex interventions ($\Delta N_m^z\,(gov) = 0$).

In short, the evidence in Table 5 indicates that, as postulated by the model of Section 2, shocks to conditions affecting price formation in arbitrage-linked markets may affect the extent of LOP violations in those markets both directly and by magnifying the negative externalities

[28] However, we find no evidence of nonlinearity in this relationship: $\beta_{ILQ}^2 \approx 0$ in Panels A and B of Table 5.

[29] Yet, Table 5 does not provide support for the notion (postulated in Remark 1) that information heterogeneity may be positively related to the extent of LOP violations even in absence of government intervention: Estimates of β_{DSP} in Eq. (14) are always negative, small, and statistically insignificant.

of government intervention on market quality.

4 Conclusions

In this study we propose, and provide evidence of the novel notion that direct government intervention in a market — e.g., central bank trading in exchange rates — may induce violations of the law of one price (LOP) in other, arbitrage-related markets — e.g., the market for American Depositary Receipts (ADRs).

We illustrate the intuition for this negative externality of policy in two steps. We first construct a multi-asset model of strategic speculation in which segmentation in the dealership sector and less-than-perfectly correlated noise trading yield less-than-perfectly correlated equilibrium prices of two fundamentally identical assets. We then introduce a stylized government pursuing a non-public, partially informative price target for only one of the two assets and show that its policy-motivated trading activity lowers those assets' equilibrium price correlation by effectively clouding dealers' inference — even in the presence of common liquidity shocks, and especially when market quality is otherwise poor.

Our empirical analysis provides support for these effects. We find that more intense foreign exchange 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 — dollar-denominated assets convertible at any time in a preset amount of foreign shares — but not in the (arbitrage-linked, yet arguably perfectly integrated) currency and money markets for exchange-risk-covered deposits and loans. We also find these effects to be *i)* unaffected by changes in market conditions typically associated with LOP violations; as well as stronger *ii)* for ADRs from emerging markets, and in correspondence with *iii)* deteriorating liquidity in the ADR arbitrage-linked markets; *iv)* greater marketwide dispersion of beliefs; *v)* and greater uncertainty about governments' currency policy, consistent with our model.

These findings suggest that direct government intervention — an increasingly popular policy tool in the aftermath of the recent financial crisis — may have non-trivial, undesirable implications for financial market quality. This is an important insight both for the understanding of the forces driving price formation in financial markets and for the debate on optimal financial policy and regulation.

5 Appendix

Proof of Proposition 1. The search for a linear equilibrium in this class of models is standard in the literature (e.g., see Kyle, 1985; Pasquariello and Vega, 2009). It proceeds in three steps. In the first, we conjecture general linear functions for prices and trading strategies. In the second, we solve for the parameters of those functions satisfying Conditions 1 and 2 in Section 2.1. In the third, we verify that those parameters and functions represent a rational expectations equilibrium. We 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

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

Using Eq. (A-1), maximization of each speculator's expected profit $E[\pi(m)|S_v(m)]$ with respect to $x_i(m)$ yields the following first-order conditions:

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

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

$$p_0 - A_{0,i} = (M+1)A_{1,i}B_{0,i}, \tag{A-3}$$

$$2A_{1,i}B_{1,i} = 1 - (M-1)A_{1,i}B_{1,i}\rho. \tag{A-4}$$

Because of the distributional assumptions in Section 2.1, 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 properties of conditional normal distributions (e.g., Greene, 1997, p. 90) that

$$E(v|\omega_i) = p_0 + \frac{MB_{1,i}\rho\sigma_v^2}{MB_{1,i}^2\rho\sigma_v^2[1+(M-1)\rho]+\sigma_z^2}(\omega_i - MB_{0,i}). \tag{A-5}$$

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

$$A_{0,i} = p_0 - MA_{1,i}B_{0,i}, \tag{A-6}$$

$$A_{1,i} = \frac{MB_{1,i}\rho\sigma_v^2}{MB_{1,i}^2\rho\sigma_v^2[1+(M-1)\rho]+\sigma_z^2}. \tag{A-7}$$

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 Eqs. (A-3), (A-4), (A-6), and (A-7) to constitute a linear equilibrium. Defining $A_{1,i}B_{0,i}$ from Eq. (A-3) and plugging it into Eq. (A-6) leads to $A_{0,i} = p_0$. Since $A_{1,i} > 0$, only $B_{0,i} = 0$ satisfies Eq. (A-3). Next, we solve Eq. (A-4) for $A_{1,i}$:

$$A_{1,i} = \frac{1}{B_{1,i}[2+(M-1)\rho]}. \tag{A-8}$$

Equating Eq. (A-7) to Eq. (A-8) implies that $B_{1,i}^2 = \frac{\sigma_z^2}{M\rho\sigma_v^2}$, i.e., that $B_{1,i} = \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$. We then substitute this expression back into Eq. (A-8), yielding $A_{1,i} = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]}$, and define $\lambda \equiv A_{1,i}$. Lastly, we 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 Eq. (1)), the symmetric linear strategies $x_i(m)$ of Eq. (2) represent the unique Bayesian-Nash equilibrium of the Bayesian game among speculators. ■

Proof of Corollary 1. The equilibrium pricing rule of Eq. (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 in 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 Eq. (3). Under integrated market-making, MMs observe the aggregate order flow in both markets 1 and 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), i.e., that $corr(p_{1,1}, p_{1,2}) = 1$. Under (less than) perfectly correlated noise trading, $\sigma_{zz} = \sigma_z^2$ ($\sigma_{zz} < \sigma_z^2$); Eq. (3) then implies $corr(p_{1,1}, p_{1,2}) = 1$ ($corr(p_{1,1}, p_{1,2}) < 1$). ■

Proof of Remark 1. Given the distributional assumptions in Section 2.1 (and $\sigma_{zz} \geq 0$), the statement stems from observing that under less than perfectly correlated noise trading ($\sigma_{zz} < \sigma_z^2$): $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial \rho} = \frac{\sigma_z^2(M-1)\left(\sigma_z^2 - \sigma_{zz}\right)}{[2+(M-1)\rho]^2} > 0$, $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial \sigma_z^2} = -\frac{\sigma_{zz}}{\sigma_z^4[2+(M-1)\rho]} \leq 0$, $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial M} = \frac{\sigma_z^2\rho\left(\sigma_z^2 - \sigma_{zz}\right)}{[2+(M-1)\rho]^2} < 0$, 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 et al. (2014). First, we conjecture linear functions for equilibrium prices and trading activity of speculators (in assets 1 and 2) and the stylized government of Eq. (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 $x_1(gov) = C_{0,1} + C_{1,1}\delta_v(gov) + C_{1,2}\delta_T(gov)$. These assumptions imply that

$$
\begin{aligned}
E[p_{1,1}|S_v(m)] &= A_{0,1} + A_{1,1}x_1(m) + A_{1,1}B_{0,1}(M-1) + A_{1,1}B_{1,1}(M-1)\rho\delta_v(m) \\
&\quad + A_{1,1}C_{0,1} + A_{1,1}C_{1,1}\psi\delta_v(m) + A_{1,1}C_{1,2}\delta_v(m), \qquad \text{(A-9)} \\
E[p_{1,2}|S_v(m)] &= A_{0,2} + A_{1,2}x_2(m) + A_{1,2}B_{0,2}(M-1) \\
&\quad + A_{1,2}B_{1,2}(M-1)\rho\delta_v(m), \qquad \text{(A-10)} \\
E\left[p_{1,1}|S_v(gov), p_{1,1}^T\right] &= A_{0,1} + MA_{1,1}B_0 + MA_{1,1}B_{1,1}\rho\delta_v(gov). \qquad \text{(A-11)}
\end{aligned}
$$

Given Eqs. (A-9) and (A-10), the first-order conditions for maximizing each speculator's expected profit $E\left[\pi\left(m\right)|S_v\left(m\right)\right]$ relative to $x_i\left(m\right)$ are:

$$\begin{aligned} 0 &= p_0+\delta_v\left(m\right)-A_{0,1}-\left(M+1\right)A_{1,1}B_{0,1}-A_{1,1}B_{1,1}\delta_v\left(m\right)\left[2+\left(M-1\right)\rho\right] \quad \text{(A-12)} \\ &\quad -A_{1,1}C_{0,1}-A_{1,1}C_{1,1}\psi\delta_v\left(m\right)-A_{1,1}C_{1,2}\delta_v\left(m\right), \\ 0 &= p_0+\delta_v\left(m\right)-A_{0,2}-\left(M+1\right)A_{1,2}B_{0,2}-A_{1,2}B_{1,2}\delta_v\left(m\right)\left[2+\left(M-1\right)\rho\right]. \quad \text{(A-13)} \end{aligned}$$

Because $-2A_{1,i}<0$, the second order conditions are satisfied. For Eqs. (A-12) and (A-13) to be true, it must be that

$$\begin{aligned} p_0-A_{0,1} &= \left(M+1\right)A_{1,1}B_{0,1}+A_{1,1}C_{0,1}, \quad \text{(A-14)} \\ 2A_{1,1}B_{1,1} &= 1-\left(M-1\right)A_{1,1}B_{1,1}\rho-A_{1,1}C_{1,1}\psi-A_{1,1}C_{1,2}, \quad \text{(A-15)} \\ p_0-A_{0,2} &= \left(M+1\right)A_{1,2}B_{0,2}, \quad \text{(A-16)} \\ 2A_{1,2}B_{1,2} &= 1-\left(M-1\right)A_{1,2}B_{1,2}\rho. \quad \text{(A-17)} \end{aligned}$$

The government's optimal intervention strategy is the one minimizing its expected loss function of Eq. (4), i.e., $E\left[L\left(gov\right)|S_v\left(gov\right),p_{1,1}^T\right]$, with respect to $x_1\left(gov\right)$. Given the distributional assumptions of Sections 2.1. and 2.2, removing all terms not interacting with the latter from the former implies that $\arg\min_{x_1(gov)} E\left[L\left(gov\right)|S_v\left(gov\right),p_{1,1}^T\right]$ is equal to

$$\begin{aligned} &\arg\min_{x_1(gov)}\left[\gamma A_{1,1}^2x_1^2\left(gov\right)+2\gamma A_{1,1}^2MB_{0,1}x_1\left(gov\right)+2\gamma A_{1,1}^2MB_{0,1}\rho\delta_v\left(gov\right)x_1\left(gov\right)\right. \\ &+2\gamma A_{0,1}A_{1,1}x_1\left(gov\right)-2\gamma p_{1,1}^TA_{1,1}x_1\left(gov\right)+\left(1-\gamma\right)A_{0,1}x_1\left(gov\right) \quad \text{(A-18)} \\ &+\left(1-\gamma\right)A_{1,1}x_1^2\left(gov\right)+\left(1-\gamma\right)MA_{1,1}B_{0,1}x_1\left(gov\right) \\ &\left.+\left(1-\gamma\right)MA_{1,1}B_{1,1}\rho\delta_v\left(gov\right)x_1\left(gov\right)-\left(1-\gamma\right)p_0x_1\left(gov\right)-\left(1-\gamma\right)\delta_v\left(gov\right)x_1\left(gov\right)\right]. \end{aligned}$$

The first order condition from Eq. (A-18) is

$$
\begin{aligned}
0 &= 2\gamma A_{1,1}^2 x_1(gov) + 2\gamma A_{1,1}^2 M B_{0,1} + 2\gamma A_{1,1}^2 M B_{0,1} \rho \delta_v (gov) + 2\gamma A_{0,1} A_{1,1} - 2\gamma p_{1,1}^T A_{1,1} \\
&\quad + (1-\gamma) A_{0,1} + 2(1-\gamma) A_{1,1} x_1(gov) + (1-\gamma) M A_{1,1} B_{0,1} \qquad \text{(A-19)} \\
&\quad + (1-\gamma) A_{0,1} + 2(1-\gamma) A_{1,1} x_1(gov) + (1-\gamma) M A_{1,1} B_{0,1}.
\end{aligned}
$$

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 Eq. (A-19), our prior conjecture for $x_1(gov)$ is correct iff

$$
\begin{aligned}
p_0 - A_{0,1} &= 2A_{1,1}C_{0,1} + MA_{1,1}B_{0,1} + 2dA_{1,1}^2 C_{0,1} \qquad \text{(A-20)} \\
&\quad + 2dA_{1,1}^2 M B_{0,1} + 2dA_{0,1}A_{1,1} - 2d\overline{p}_{1,1}^T A_{1,1}, \\
2A_{1,1}C_{1,1} &= 1 - MA_{1,1}B_{1,1}\rho - 2dA_{1,1}^2 C_{1,1} - 2dA_{1,1}^2 M B_{1,1}\rho, \qquad \text{(A-21)} \\
A_{1,1}C_{1,2} &= dA_{1,1} - dA_{1,1}^2 C_{1,2}. \qquad \text{(A-22)}
\end{aligned}
$$

Eq. (A-22) implies that $C_{1,2} = \frac{d}{1+dA_{1,1}} > 0$. Our 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 $E(\omega_2) = MB_{0,2}$, variances

$$
\begin{aligned}
var(\omega_1) &= MB_{1,1}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + + C_{1,1}^2 \psi \sigma_v^2 + C_{1,2}^2 \frac{\sigma_v^2}{\mu\psi} \qquad \text{(A-23)} \\
&\quad + 2MB_{1,1}C_{1,1}\psi\rho\sigma_v^2 + 2MB_{1,1}C_{1,2}\rho\sigma_v^2 + 2C_{1,1}C_{1,2}\sigma_v^2 + \sigma_z^2, \\
var(\omega_2) &= MB_{1,2}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2, \qquad \text{(A-24)}
\end{aligned}
$$

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

$$
\begin{aligned}
p_{1,1} &= p_0 + \frac{(MB_{1,1}\rho + C_{1,1}\psi + C_{1,2})\sigma_v^2}{\sigma_z^2 + \sigma_v^2 \left\{ MB_{1,1}^2 \rho [1 + (M-1)\rho] + D_1 + E_1 \right\}} (\omega_1 - MB_{0,1} - C_{0,1}), \qquad \text{(A-25)} \\
p_{1,2} &= E(v|\omega_i) = p_0 + \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2} (\omega_2 - MB_{0,2}). \qquad \text{(A-26)}
\end{aligned}
$$

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

$$\begin{aligned}
A_{0,1} &= p_0 - MA_{1,1}B_{0,1} - A_{1,1}C_{0,1}, && \text{(A-27)}\\
A_{1,1} &= \frac{\left(MB_{1,1}\rho + C_{1,1}\psi + C_{1,2}\right)\sigma_v^2}{\sigma_z^2 + \sigma_v^2\left\{MB_{1,1}^2\rho\left[1 + (M-1)\rho\right] + D_1 + E_1\right\}}, && \text{(A-28)}\\
A_{0,2} &= p_0 - MA_{1,2}B_{0,2}, && \text{(A-29)}\\
A_{1,2} &= \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2\rho\sigma_v^2\left[1 + (M-1)\rho\right] + \sigma_z^2}. && \text{(A-30)}
\end{aligned}$$

Next, we 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 Eqs. (A-14) to (A-17), (A-20), (A-21), (A-27) to (A-30). As shown in the proof of Proposition 1, Eqs. (A-16), (A-17), (A-29), and (A-30) 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 Eqs. (A-14) and (A-27) to be true, it must be that $B_{0,1} = 0$. Because of the latter, Eq. (A-14) implies that $p_0 - A_{0,1} = A_{1,1}C_{0,1}$. Substituting $A_{1,1}C_{0,1}$ into Eq. (A-20) yields $A_{0,1} = p_0 + 2dA_{1,1}\left(p_0 - \overline{p}_{1,1}^T\right)$. We are left to find $A_{1,1}$, $B_{1,1}$, and $C_{1,1}$. We first extract $B_{1,1}$ from Eq. (A-15) and $C_{1,1}$ from Eq. (A-21):

$$\begin{aligned}
B_{1,1} &= \frac{1 - A_{1,1}C_{1,1}\psi - A_{1,1}C_{1,2}}{A_{1,1}\left[2 + (M-1)\rho\right]}, && \text{(A-31)}\\
C_{1,1} &= \frac{1 - MA_{1,1}B_{1,1}\rho\left(1 + 2dA_{1,1}\right)}{2A_{1,1}\left(1 + dA_{1,1}\right)}. && \text{(A-32)}
\end{aligned}$$

We then solve the system made of Eqs. (A-31) and (A-32) 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 $f\left(A_{1,1}\right) = 2\left[2 + (M-1)\rho\right]\left(1 + dA_{1,1}\right) - M\psi\rho\left(1 + 2dA_{1,1}\right)$ is clearly positive. Lastly, we substitute these expressions for $B_{1,1}$ and $C_{1,1}$ in Eq. (A-28), yielding a *sextic* polynomial in $A_{1,1}$,

$$g_{1,6}A_{1,1}^6 + g_{1,5}A_{1,1}^5 + g_{1,4}A_{1,1}^4 + g_{1,3}A_{1,1}^3 + g_{1,2}A_{1,1}^2 + g_{1,1}A_{1,1} + g_{0,1} = 0, \qquad \text{(A-33)}$$

whose coefficients can be shown to be (via tedious algebra and the parameter restrictions in Sections 2.1 and 2.2)

$$g_{0,1} = -\mu\psi\sigma_v^2\left[M\rho\left(2-\psi\right)^2+\psi\left(2-\rho\right)^2\right]<0, \tag{A-34}$$

$$g_{1,1} = -2\mu\psi\sigma_v^2 d\left\{M\rho\left[2\left(2-\psi\right)-\psi^2\left(1-\rho\right)-\rho\psi\right]+2\psi\left(2-\rho\right)^2\right\}<0, \tag{A-35}$$

$$\begin{aligned}
&g_{2,1} = \mu\psi\sigma_z^2\left\{4\left(2-\rho\right)^2+M\rho\left[M\rho\left(2-\psi\right)^2+4\left(2-\rho\right)\left(2-\psi\right)\right]\right\}\\
&+\sigma_v^2 d^2\left\{4\left(1-\mu\psi\right)\left(2-\rho\right)^2+4M\rho\left[M\rho\left(1-\psi\right)+2\left(2-\psi-\rho\right)+\psi\rho\right]\right.\\
&+4\mu\psi\rho\left[3M\left(\rho+\psi\right)-M\left(7+\rho\psi+\rho\psi^2\right)+5\psi\right]\\
&\left.+M^2\rho^2\psi\left[\mu\psi\left(11-4\psi\right)+\psi-8\mu\right]+\mu\psi^2\left[\rho\left(7M\psi-5\rho\right)-20\right]\right\},
\end{aligned} \tag{A-36}$$

$$\begin{aligned}
&g_{3,1} = 2\sigma_v^2 d^3\left\{\left(2-\rho\right)^2\left[4\left(1-\mu\psi\right)-\mu\psi^2\right]+M\rho\left(2-\rho\right)\left[\mu\psi\left(7\psi-10+\psi^2\right)\right.\right.\\
&\left.\left.+2\left(4-3\psi\right)\right]+2M^2\rho^2\left[\mu\psi^2\left(5-2\psi\right)-\psi\left(3-\psi\right)+\left(2-3\mu\psi\right)\right]\right\}\\
&+2\mu\psi\sigma_z^2 d\left\{8\left(2-\rho\right)^2+M^2\rho^2\left[8-\psi\left(10-3\psi\right)\right]+2M\rho\left(2-\rho\right)\left(8-5\psi\right)\right\},
\end{aligned} \tag{A-37}$$

$$\begin{aligned}
&g_{4,1} = 4\left(1-\mu\psi\right)\sigma_v^2 d^4\left[\left(2-\rho\right)+M\rho\left(1-\psi\right)\right]^2\\
&+\mu\psi\sigma_z^2 d^2\left\{12\left(2-\rho\right)\left[2\left(2-\rho\right)+M\rho\left(4-3\psi\right)\right]+M^2\rho^2\left[24+\psi\left(13\psi-36\right)\right]\right\}>0,
\end{aligned} \tag{A-38}$$

$$g_{5,1} = 4\mu\psi\sigma_z^2 d^3\left\{M^2\rho^2\left[4-\psi\left(7-3\psi\right)\right]+M\rho\left[16-7\psi\left(2-\rho\right)-8\rho\right]+4\left(2-\rho\right)^2\right\}>0, \tag{A-39}$$

$$g_{6,1} = 4\mu\psi\sigma_z^2 d^4\left[M\rho\left(1-\psi\right)+\left(2-\rho\right)\right]^2>0, \tag{A-40}$$

where either $sign\left(g_{3,1}\right) = sign\left(g_{2,1}\right) = sign\left(g_{1,1}\right)$, $sign\left(g_{4,1}\right) = sign\left(g_{3,1}\right) = sign\left(g_{2,1}\right)$, or $sign\left(g_4,1\right) = sign\left(g_{3,1}\right)$ and $sign\left(g_{2,1}\right) = sign\left(g_{1,1}\right)$, such that only one change of sign is possible while proceeding from the lowest to the highest power term in the polynomial of Eq. (A-33). According to Descartes' Rule, under these conditions there exists only one positive real root λ^* of Eq. (A-33). Hence, this root implies the unique linear Bayesian Nash equilibrium of Proposition 2. By Abel's Impossibility Theorem, Eq. (A-33) cannot be solved with rational operations and finite root extractions. In the numerical examples of Figure 1, we find λ^* using the three-stage algorithm proposed by Jenkins and Traub (1970a, b). Unfortunately, this algorithm does not always identify all roots of Eq. (A-33). Thus, those examples are based on exogenous parameter values such that λ^* can be found. ■

Proof of Corollary 2. As for the proof of Corollary 1, we start by observing that $corr\left(p_{1,1}^*, p_{1,2}^*\right) = \frac{covar\left(p_{1,1}^*, p_{1,2}^*\right)}{\sqrt{var\left(p_{1,1}^*\right) var\left(p_{1,2}^*\right)}}$, where Eqs. (5) and (6) imply that $var\left(p_{1,1}^*\right) = \lambda^{*2} var\left(\omega_1^*\right)$, $var\left(p_{1,2}^*\right) = \lambda^2 var\left(\omega_2^*\right)$, and $covar\left(p_{1,1}^*, p_{1,2}^*\right) = \lambda\lambda^* covar\left(\omega_1^*, \omega_2^*\right)$. Because of the distributional assumptions of Sections 2.1 and 2.2, it is straightforward to show that $var\left(\omega_1^*\right) = \sigma_z^2 + \sigma_v^2 \left\{M\rho B_{1,1}^{*2}\left[1 + (M-1)\rho\right] + D_1^* + E_1^*\right\}$, $var\left(\omega_2^*\right) = \sigma_z^2\left[2 + (M-1)\rho\right]$, and $covar\left(\omega_1^*, \omega_2^*\right) = \sigma_{zz} + \sigma_z\sigma_v\sqrt{M\rho}\left\{B_{1,1}^*\left[1 + (M-1)\rho\right] + C_{1,1}^*\psi + C_{1,2}^*\right\}$. Substituting these expressions in the one for $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ yields Eq. (10). ■

References

Acharya, V., and Richardson, M. (Eds.), 2009, *Restoring Financial Stability: How to Repair a Failed System — An Independent View from New York University Stern School of Business*, John Wiley & Sons.

Adrian, T., Etula, E., and Muir, T., 2013, Financial Intermediaries and the Cross Section of Asset Returns, *Journal of Finance*, forthcoming.

Albuquerque, R., and Vega, C., 2009, Economic News and International Stock Market Co-Movement, *Review of Finance*, 13, 401-465.

Andersen, T., and Bollerslev, T., 1998, Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies, *Journal of Finance*, 53, 219-265.

Andersen, T., Bollerslev, T., Diebold, F., and Vega, C., 2003, Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange, *American Economic Review*, 93, 38-62.

Andersen, T., Bollerslev, T., Diebold, F., and Vega, C., 2007, Real-Time Price Discovery in Stock, Bond, and Foreign Exchange Markets," *Journal of International Economics*, 73, 251-277.

Auguste, S., Dominguez, K., Kamil, H., and Tesar, L., 2006, Cross-Border Trading as a Mechanism for Capital Flight: ADRs and the Argentine Crisis, *Journal of Monetary Economics*, 53, 1259-1295.

Baker, M., and Wurgler, J., 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance*, 61, 1645-1680.

Baker, M., and Wurgler, J., 2007, Investor Sentiment and the Stock Market, *Journal of Economic Perspectives*, 21, 129-151.

Baker, M., Wurgler, J., and Yuan, Y., 2012, Global, Local, and Contagious Investor Sentiment, *Journal of Financial Economics*, 104, 272-287.

Bank for International Settlements, 2013, *Foreign Exchange and Derivatives Market Activity in 2013*, Triennial Central Bank Survey.

Beber, A., Brandt, M., and Luisi, M., Distilling the Macroeconomic News Flow, Working Paper, Duke University.

Bekaert, G., and Harvey, C., 1995, Time-Varying World Market Integration, *Journal of Finance*, 50, 403-444.

Bekaert, G., and Harvey, C., 1997, Emerging Equity Market Volatility, *Journal of Financial Economics*, 43, 29-78.

Bekaert, G., and Harvey, C., 2000, Foreign Speculators and Emerging Equity Markets, *Journal of Finance*, 55, 565-613.

Bekaert, G., and Harvey, C., 2003, Emerging Markets Finance, *Journal of Empirical Finance*, 10, 3-55.

Bekaert, G., Harvey, C., and Lundblad, C., 2007, Liquidity and Expected Returns: Lessons from Emerging Markets, *Review of Financial Studies*, 20, 1783-1831.

Bekaert, G., Harvey, C., and Ng, A., 2005, Market Integration and Contagion, *Journal of Business*, 75, 39-69.

Bekaert, G., and Hodrick, R., 2009, *International Financial Management*, Pearson-Prentice Hall.

Bhattacharya, U., and Weller, P., 1997, The Advantage of Hiding One's Hand: Speculation and Central Bank Intervention in the Foreign Exchange Market, *Journal of Monetary Economics*, 39, 251-277.

Bond, P., and Goldstein, I., 2010, Government Intervention and Information Aggregation by Prices, Working Paper, University of Pennsylvania.

Bossaerts, P., and Hillion, P., 1991, Market Microstructure Effects of Government Intervention in the Foreign Exchange Market, *Review of Financial Studies*, 4, 513-541.

Boulatov, A., Hendershott, T., and Livdan, D., 2013, Informed Trading and Portfolio Returns, *Review of Economic Studies*, 80, 35-72.

Caballé, J., and Krishnan, M., 1994, Imperfect Competition in a Multi-Security Market with Risk Neutrality, *Econometrica*, 62, 695-704.

Chen, N., Roll, R., and Ross, S., 1986, Economic Forces and the Stock Market, *Journal of Business*, 59, 383-403.

Diether, K., Malloy, C., and Scherbina, A., 2002, Differences of Opinion and the Cross-Section of Stock Returns, *Journal of Finance*, 57, 2113-2141.

Dimson, E., 1979, Risk Measurement When Shares Are Subject to Infrequent Trading, *Journal of Financial Economics*, 7, 197-226.

Dominguez, K., 2003, The Market Microstructure of Central Bank Intervention, *Journal of International Economics*, 59, 25-45.

Dominguez, K., 2006, When Do Central Bank Interventions Influence Intra-Daily and Longer-Term Exchange Rate Movements? *Journal of International Money and Finance*, 25, 1051-1071.

Dominguez, K., and Frankel, J., 1993, Does Foreign Exchange Intervention Matter? The Portfolio Effect, *American Economic Review*, 83, 1356-1369.

Dyck, A., and Morse, A., 2011, Sovereign Wealth Fund Portfolios, Working Paper, University of Chicago.

Edison, H., 1993, The Effectiveness of Central-Bank Intervention: A Survey of the Literature After 1982, *Special Papers in International Economics*, 18, 1-63.

Engel, C., 2014, Exchange Rates and Interest Parity, In: Gopinath, G., Helpman, E., and Rogoff, K. (Eds.), *Handbook of International Economics, Volume 4*, Elsevier.

Evans, M., and Lyons, R., 2005, Are Different-Currency Assets Imperfect Substitutes? In: De Grauwe, P. (Ed.), *Exchange Rate Economics: Where Do We Stand?* MIT Press.

Evans, M., and Lyons, R., 2013, Exchange Rate Fundamentals and Order Flow, *Quarterly Journal of Finance*, 2, 1-63.

Fatum, R., and Hutchison, M., 2003, Is Sterilised Foreign Exchange Intervention Effective After All? An Event Study Approach, *Economic Journal*, 113, 390–411.

Fischer, A., and Zurlinden, M., 1999, Exchange Rate Effects of Central Bank Interventions: An Analysis of Transaction Prices, *Economic Journal*, 109, 662-676.

Gabaix, X., and Maggiori, M., 2014, International Liquidity and Exchange Rate Dynamics, Working Paper, New York University.

Gagnon, L., and Karolyi, A., 2010, Multi-Market Trading and Arbitrage, *Journal of Financial Economics*, 97, 53-80.

Garleanu, N., and Pedersen, L., 2011, Margin-Based Asset Pricing and Deviations from the Law of One Price, *Review of Financial Studies*, 24, 1980-2022.

Green, C., 2004, Economic News and the Impact of Trading on Bond Prices, *Journal of Finance*, 59, 1201-1233.

Greene, W., 1997, *Econometric Analysis*, Prentice Hall.

Griffoli, T., and Ranaldo, A., 2011, Limits to Arbitrage during the Crisis: Funding Liquidity Constraints and Covered Interest Parity, Working Paper, Swiss National Bank.

Gromb, D., and Vayanos, D., 2010, Limits to Arbitrage: The State of the Theory, *Annual Review of Financial Economics*, 2, 251-275.

Hanson, S., Kashyap, A., and Stein, J., 2011, A Macroprudential Approach to Financial Regulation, *Journal of Economic Perspectives*, 25, 3-28.

Harvey, C., and Huang, R., 2002, The Impact of the Federal Reserve Bank's Open Market Operations, *Journal of Financial Markets*, 5, 223-257.

Humpage, O., and Osterberg, W., 1992, Intervention and the Foreign Exchange Risk Premium: An Empirical Investigation of Daily Effects, *Global Finance Journal*, 3, 23–50.

Jenkins, M., and Traub, J., 1970a, A Three-Stage Variables-Shift Iteration for Polynomial Zeros and Its Relation to Generalized Rayleigh Iteration, *Numerishe Mathematik*, 14, 252-263.

Jenkins, M., and Traub, J., 1970b, A Three-Stage Algorithm for Real Polynomials Using Quadratic Iteration, *SIAM Journal of Numerical Analysis*, 7, 545-566.

Kallberg, J., and Pasquariello, P., 2008, Time-Series and Cross-Sectional Excess Comovement in Stock Indexes, *Journal of Empirical Finance*, 15, 481-502.

Karolyi, A., 1998, Why Do Companies List Shares Abroad? A Survey of the Evidence and Its Managerial Implications, *Financial Markets, Institutions & Money*, 7, 1–60.

Karolyi, A., 2006, The World of Cross-Listings and Cross-Listings of the World: Challenging Conventional Wisdom, *Review of Finance*, 10, 73-115.

Kyle, A., 1985, Continuous Auctions and Insider Trading, *Econometrica*, 53, 1315-1335.

Lamont, O., and Thaler, R., 2003, Anomalies: The Law of One Price in Financial Markets, *Journal of Economic Perspectives*, 17, 191-202.

Lesmond, D., 2005, Liquidity of Emerging Markets, *Journal of Financial Economics*, 77, 411–452.

Lesmond, D., Ogden, J., and Trzcinka, C., 1999, A New Estimate of Transaction Costs, *Review of Financial Studies*, 12, 1113-1141.

Levy Yeyati, E., Schmukler, S., and Van Horen, N., 2009, International Financial Integration Through the Law of One Price: The Role of Liquidity and Capital Controls, *Journal of Financial Intermediation*, 18, 432-463.

Lewis, K., 1995, Occasional Intervention to Target Rates, *American Economic Review*, 85, 691-715.

Lyons, R., 2001, *The Microstructure Approach to Exchange Rates*, MIT Press.

Menkhoff, L., 2010, High-Frequency Analysis of Foreign Exchange Interventions: What Do We Learn? *Journal of Economic Surveys*, 24, 85-112.

Naranjo, A., and Nimalendran, M., 2000, Government Intervention and Adverse Selection Costs in Foreign Exchange Markets, *Review of Financial Studies*, 13, 453-477.

Neely, C., 2000, The Practice of Central Bank Intervention: Looking Under the Hood, *Central Banking*, 11, 24-37.

Neely, C., 2005a, An Analysis of Recent Studies of the Effect of Foreign Exchange Intervention, Federal Reserve Bank of St. Louis Working Paper No. 2005-030B.

Neely, C., 2005b, Identifying the Effects of U.S. Intervention on the Levels of Exchange Rates, Reserve Bank of St. Louis Working Paper No. 2005-031C.

Neely, C., and Weller, P., 2007, Central Bank Intervention with Limited Arbitrage, *International Journal of Finance and Economics*, 12, 249-260.

Pasquariello, P., 2007a, Imperfect Competition, Information Heterogeneity, and Financial Contagion, *Review of Financial Studies*, 20, 391-426.

Pasquariello, P., 2007b, Informative Trading or Just Costly Noise? An Analysis of Central Bank Interventions, *Journal of Financial Markets*, 10, 107-143.

Pasquariello, P., 2008, The Anatomy of Financial Crises: Evidence from the Emerging ADR Market, *Journal of International Economics*, 76, 193-207.

Pasquariello, P., 2010, Central Bank Intervention and the Intraday Process of Price Formation in the Currency Markets, *Journal of International Money and Finance*, 29, 1045-1061.

Pasquariello, P., 2014, Financial Market Dislocations, *Review of Financial Studies*, forthcoming.

Pasquariello, P., and Vega, C., 2009, The On-The-Run *Liquidity* Phenomenon, *Journal of Financial Economics*, 92, 1-24.

Pasquariello, P., Roush, J., and Vega, C., 2014, Government Intervention and Strategic Trading in the U.S. Treasury Market, Working Paper, University of Michigan.

Pastor, L., and Stambaugh, R., 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111, 642-685.

Pastor, L., and Veronesi, P., 2012, Uncertainty about Government Policy and Stock Prices, *Journal of Finance*, 67, 1219-1264.

Pastor, L., and Veronesi, P., 2013, Political Uncertainty and Risk Premia, *Journal of Financial Economics*, 110, 520-545.

Payne, R., and Vitale, P., 2003, A Transaction Level Study of the Effects of Central Bank Intervention on Exchange Rates, *Journal of International Economics*, 61, 331-352.

Peiers, B., 1997, Informed Traders, Intervention and Price Leadership: A Deeper View of the Microstructure of the Foreign Exchange Market, *Journal of Finance*, 52, 1589-1614.

Pontiff, J., 1996, Costly Arbitrage: Evidence from Closed-End Funds, *Quarterly Journal of Economics*, 111, 1135-1151.

Sarno, L., and Taylor, M., 2001, Official Intervention in the Foreign Exchange Market: Is it Effective, and if So, How Does it Work? *Journal of Economic Literature*, 39, 839-868.

Shleifer, A., 2000, *Inefficient Markets: An Introduction to Behavioral Finance*, Oxford University Press.

Shleifer, A., and Vishny, R., 1997, The Limits of Arbitrage, *Journal of Finance*, 52, 35-55.

Sojli, E., and Tham, W., 2010, The Impact of Foreign Government Investments on Corporate Performance: Evidence from the U.S., Working Paper, Erasmus University.

Subrahmanyam, A., 1991a, A Theory of Trading in Stock Index Futures, *Review of Financial Studies*, 4, 17-51.

Subrahmanyam, A., 1991b, Risk Aversion, Market Liquidity, and Price Efficiency, *Review of Financial Studies*, 4, 417-441.

Ulrich, M., 2010, How Does the Bond Market Perceive FOMC Interventions? Working Paper, Columbia University.

Vives, X., 2008, *Information and Learning in Markets*, Princeton University Press.

Yu, J., 2011, Disagreement and Return Predictability of Stock Portfolios, *Journal of Financial Economics*, 99, 162-183.

Table 1. ADRs: Summary Statistics

This table reports the composition of our sample of ADRs by the country of listing of the underlying foreign stocks, as well as summary statistics on their observed relative mispricings and measures of market liquidity. Our sample is obtained by filtering the complete Datastream sample of all U.S. cross-listings between January 1, 1973 and December 31, 2009, to include Levels II and III ADRs listed on the NYSE, AMEX, or NASDAQ. "Other" countries include Colombia, Denmark, Egypt, Hungary, Israel, New Zealand, Norway, Philippines, Singapore, Sweden, Thailand, and Venezuela. $ADRP_m$ and $ADRP^z_m$ are computed as monthly averages of daily equal-weighted means of available observed (in basis points, i.e., multiplied by 10,000) and standardized absolute log violations (Eq. (12)) of the ADR parity described in Section 3 (Eq. (11)); $\Delta ADRP_m = ADRP_m - ADRP_{m-1}$ and $\Delta ADRP^z_m = ADRP^z_m - ADRP^z_{m-1}$. $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 3.1.1 as the (country-level or marketwide) equal-weighted average (in percentage) of the 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 experience 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. We list each series' total number of available ADRs (N_i) and months (N), mean, and standard deviation over 1980-2009.

			Measures of LOP violations in the ADR market								ADRP illiquidity	
			$ADRP_m$		$ADRP^z_m$		$\Delta ADRP_m$		$\Delta ADRP^z_m$		$ILLIQ_m$	
Country	N_i	N	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Australia	30	269	217.26	112.57	-0.23	0.32	-3.39	53.91	-0.002	0.278	11.0%	9.0%
Argentina	9	198	187.70	114.41	0.40	1.15	0.44	81.45	-0.000	0.834	19.2%	12.5%
Brazil	23	178	165.06	104.49	-0.08	0.36	-1.60	40.57	0.001	0.308	9.1%	7.2%
Canada	67	360	103.13	46.08	-0.18	0.27	-0.08	26.14	-0.000	0.189	13.4%	7.7%
Chile	5	168	185.16	67.26	-0.33	0.38	0.41	50.94	-0.002	0.341	14.9%	7.1%
Euro area	58	287	352.29	287.90	-0.41	0.64	-0.87	60.98	0.001	0.421	6.5%	3.8%
Hong Kong	54	198	166.78	65.22	0.07	0.33	-0.69	40.03	-0.002	0.281	15.0%	5.9%
India	10	143	248.34	141.33	-0.07	0.38	-0.42	64.99	-0.006	0.358	4.7%	3.1%
Indonesia	5	168	181.19	79.67	-0.04	0.48	-0.93	67.90	-0.010	0.406	9.7%	4.9%
Japan	24	360	149.34	75.33	-0.06	0.42	-0.31	29.46	-0.001	0.289	9.3%	3.8%
Mexico	9	198	275.74	78.37	-0.16	0.35	-0.24	54.34	-0.004	0.284	16.6%	5.4%
Russia	7	140	189.70	114.27	-0.05	0.46	-1.66	86.89	-0.004	0.399	10.0%	8.7%
S. Africa	14	231	324.28	185.28	0.06	0.63	-0.77	66.61	-0.000	0.297	11.2%	5.9%
S. Korea	8	141	328.73	187.75	-0.10	0.43	-0.86	74.53	-0.003	0.284	6.9%	4.4%
Switzerland	4	116	253.67	141.83	-0.55	0.39	-1.98	37.30	-0.012	0.261	4.1%	2.6%
Turkey	7	74	227.50	174.99	0.21	0.98	-1.30	104.33	-0.006	0.615	7.8%	4.0%
U.K.	43	360	200.59	73.82	-0.21	0.31	-0.48	34.07	0.000	0.211	4.7%	2.6%
Other	33	250	261.15	112.06	-0.18	0.40	-0.26	85.10	0.003	0.372	17.3%	14.1%
Total	410	360	194.33	41.34	-0.17	0.19	-0.28	21.47	-0.001	0.153	10.6%	3.3%

Table 2. Government Intervention in the Forex Market: Summary Statistics

This table reports summary statistics on the database of government interventions in currency markets between 1980 and 2009, compiled by Neely (2005). This database is available on the Web site of the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2). For each country for which intervention data is available, we list in Panel A the currency pair 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 (in millions of USD). In some circumstances, the database only reports official trades in a currency relative to unspecified "other" currencies. This table also reports summary statistics for $N_m\left(gov\right)$, the number of nonzero government intervention-exchange rates pairs in a month, $N_m^z\left(gov\right)$, the number of those pairs standardized by its historical distribution on month m; $\Delta N_m\left(gov\right) = N_m\left(gov\right) - N_{m-1}\left(gov\right)$ and $\Delta N_m^z\left(gov\right) = N_m^z\left(gov\right) - N_{m-1}^z\left(gov\right)$. We list their total number of months, mean, and standard deviation over 1980-2009 in Panel B.

Panel A: Forex Intervention by Exchange Rates					
			Absolute amount ($1M)		
Country	Currency Pair		N	Mean	Stdev
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	n.a.
Japan	INR	USD	1	568	n.a.
Mexico	MXN	USD	84	601	492
Switzerland	CHF	DEM	1	0.44	n.a.
Switzerland	CHF	USD	39	163	164
Switzerland	USD	DEM	2	70	78
Switzerland	USD	JPY	6	98	73
Turkey	TRL	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
Panel B: Aggregate Measures of Forex Intervention					
Variable			N	Mean	Stdev
$N_m\left(gov\right)$	n.a.	n.a.	360	2.36	1.61
$N_m^z\left(gov\right)$	n.a.	n.a.	360	-0.13	1.03
$\Delta N_m\left(gov\right)$	n.a.	n.a.	360	-0.006	1.40
$\Delta N_m^z\left(gov\right)$	n.a.	n.a.	360	-0.004	0.91

Table 3. Marketwide LOP Violations and Forex Intervention

This table reports OLS estimates of the following regression model of Eq. (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 3.1.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. In Panel A, Eq. (13) is estimated for (absolute and normalized) ADR parity violations either at the monthly frequency ($LOP_m = ADRP_m$ or $ADRP_m^z$, as defined in Section 3.1.1) 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 full sample period 1980-2009. In Panel B, Eq. (13) is estimated for either ADR parity violations or CIRP violations ($LOP_m = CIRP_m$ or $CIRP_m^z$, as defined in Section 3.2) at the monthly frequency over the sub-sample 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 (β_1, β_0, β_{-1}). A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% levels, respectively.

	$I = N\,(gov)$						$I = N^z\,(gov)$						
	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
	Panel 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)		
	Panel 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)		
$\Delta ADRP_m^z$	-0.002	0.032***	0.003	0.032***	0.035**	9%	0.001	0.052***	0.004	0.053***	0.053***	9%	233
	(-0.27)	(4.32)	(0.36)	(2.74)	(2.26)		(0.07)	(4.37)	(0.39)	(2.78)	(2.78)		
$\Delta CIRP_m^z$	-0.007	0.028*	0.020	0.022	0.042	2%	-0.010	0.046*	0.032	0.036	0.068	2%	233
	(-0.40)	(1.65)	(1.26)	(0.80)	(1.19)		(-0.39)	(1.68)	(1.21)	(0.82)	(1.18)		

Table 4. The Cross-Section of LOP Violations and Forex Intervention

This table reports OLS estimates of the following regression model of Eq. (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 3.1.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Eq. (13) is estimated separately, at the monthly frequency, for each of the eighteen 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, Other) over the portion of the full sample period 1980-2009 over which ADRP violation data is correspondingly available. 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 3.1.1. 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 $(\beta_1, \beta_0, \beta_{-1})$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% levels, respectively.

Table 4. (*Continued*)

	Panel A: $LOP_m = ADRP_m$												
	$I_m = N_m\,(gov)$						$I_m = N_m^z\,(gov)$						
Country	β_1	β_0	β_{-1}	β_1^0	β_1^{-1}	R^2	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)		

Table 4. (*Continued*)

	Panel B: $LOP_m = ADRP^z_m$												
	$I_m = N_m\,(gov)$						$I_m = N^z_m\,(gov)$						
Country	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	0.034	-0.007	0.021	0.015	2%	264
	(-0.68)	(1.41)	(-0.36)	(0.50)	(0.22)		(-0.58)	(1.43)	(-0.31)	(0.57)	(0.29)		
Argentina	0.048	0.022	0.020	0.070	0.090	0%	0.079	0.038	0.034	0.117	0.151	0%	196
	(0.93)	(0.40)	(0.38)	(0.78)	(0.76)		(0.93)	(0.42)	(0.40)	(0.80)	(0.79)		
Brazil	0.011	0.053**	0.003	0.064*	0.066	4%	0.019	0.088**	0.005	0.107*	0.112	4%	175
	(0.52)	(2.27)	(0.13)	(1.68)	(1.32)		(0.56)	(2.31)	(0.15)	(1.72)	(1.36)		
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	0.007	0.026	-0.039	0.033	-0.006	3%	0.011	0.043	-0.063	0.054	-0.009	3%	166
	(0.24)	(0.85)	(-1.41)	(0.65)	(-0.09)		(0.25)	(0.86)	(-1.39)	(0.66)	(-0.08)		
Euro area	0.007	0.037*	0.004	0.044	0.048	1%	0.013	0.055*	0.004	0.068	0.072	1%	283
	(0.39)	(1.82)	(0.21)	(1.35)	(1.11)		(0.44)	(1.74)	(0.13)	(1.33)	(1.06)		
Hong Kong	0.009	0.054***	0.017	0.063**	0.079**	5%	0.014	0.089***	0.028	0.104**	0.132**	5%	196
	(0.51)	(2.96)	(0.98)	(2.13)	(2.05)		(0.52)	(3.00)	(1.01)	(2.16)	(2.09)		
India	-0.022	0.063*	0.025	0.041	0.066	5%	-0.035	0.103*	0.041	0.067	0.109	5%	141
	(-0.71)	(1.83)	(0.82)	(0.72)	(0.86)		(-0.71)	(1.83)	(0.83)	(0.73)	(0.87)		
Indonesia	0.036	0.060	0.012	0.096	0.108	2%	0.059	0.099	0.021	0.158	0.179	2%	164
	(1.06)	(1.62)	(0.37)	(1.57)	(1.33)		(1.08)	(1.65)	(0.39)	(1.60)	(1.36)		
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*	0.013	0.010	0.024	4%	-0.035	0.052*	0.021	0.017	0.038	4%	196
	(-1.22)	(1.69)	(0.77)	(0.34)	(0.60)		(-1.24)	(1.70)	(0.76)	(0.34)	(0.59)		
Russia	-0.034	0.001	-0.030	-0.032	-0.062	2%	-0.054	0.003	-0.048	-0.051	-0.099	2%	136
	(-0.95)	(0.04)	(-0.85)	(-0.49)	(-0.71)		(-0.93)	(0.04)	(-0.86)	(-0.48)	(-0.70)		
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%	133
	(-1.19)	(0.49)	(0.69)	(-0.34)	(0.02)		(-1.17)	(0.50)	(0.68)	(-0.33)	(0.03)		
Switzerland	0.031	0.076**	0.055**	0.107**	0.162**	6%	0.052	0.125**	0.090**	0.176**	0.266**	6%	114
	(1.19)	(2.59)	(2.08)	(2.21)	(2.48)		(1.21)	(2.61)	(2.10)	(2.23)	(2.50)		
Turkey	0.143	-0.059	-0.103	0.083	-0.020	9%	0.231	-0.095	-0.166	0.136	-0.031	9%	71
	(1.30)	(-0.58)	(-0.92)	(0.46)	(-0.08)		(1.31)	(-0.58)	(-0.93)	(0.47)	(-0.07)		
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	0.021	0.084***	-0.001	0.104***	0.103**	9%	0.033	0.136***	-0.001	0.169***	0.168**	8%	245
	(1.12)	(4.36)	(-0.05)	(3.35)	(2.53)		(1.11)	(4.35)	(-0.04)	(3.34)	(2.53)		

Table 5. Marketwide LOP Violations: Forex Intervention and Market Conditions

This table reports OLS estimates of the following regression model of Eq. (14):

$$\Delta LOP_m = \alpha + \beta_0 \Delta I_m + \beta_{ILQ} ILLIQ_m + \beta_{ILQ}^2 (\Delta ILLIQ_m)^2 + \beta_0^{ILQ} \Delta I_m \Delta ILLIQ_m \quad (14)$$
$$+\beta_{DSP} \Delta DISP_m + \beta_0^{DSP} \Delta I_m \Delta DISP_m + \beta_{SDI} \Delta STD(I_m) + \Gamma \Delta X_m + \varepsilon_m,$$

where $LOP_t = ADRP_m$ or $ADRP_m^z$ are the absolute or normalized ADR parity violations in month m (as defined in Section 3.1.1); $\Delta LOP_m = LOP_m - LOP_{m-1}$; 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 3.1.2; $\Delta I_m = I_m - I_{m-1}$; $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 3.1.1 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; $DISP_m$ is a measure of information heterogeneity, defined in Section 3.4 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 3.4 as the historical volatility of I_m; and X_m is a matrix of control variables (defined in 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. Eq. (14) is estimated over the full sample period 1980-2009; each estimate is then multiplied by the standard deviation of the corresponding regressor(s). N is the number of observations; R^2 is the coefficient of determination. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% levels, respectively.

	Panel A: $I_m = N_m(gov)$									
	β_0	β_{ILQ}	β_{ILQ}^2	β_0^{ILQ}	β_{DSP}	β_0^{DSP}	β_{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)									
$\Delta ADRP_m$	2.839**							Yes	8%	360
	(2.56)									
$\Delta ADRP_m^z$	0.027***							Yes	12%	360
	(3.49)									
$\Delta ADRP_m$	3.362***	3.512***	-0.329	-0.174				Yes	11%	360
	(3.02)	(3.16)	(-0.44)	(-0.16)						
$\Delta ADRP_m^z$	0.029***	0.016**	-0.001	0.002				Yes	13%	360
	(3.74)	(2.11)	(-0.23)	(0.31)						
$\Delta ADRP_m$	2.928***				-0.987	6.121***		Yes	14%	360
	(2.72)				(-0.88)	(5.02)				
$\Delta ADRP_m^z$	0.027***				-0.009	0.023***		Yes	14%	360
	(3.58)				(-1.18)	(2.62)				
$\Delta ADRP_m$	2.701**						2.334**	Yes	9%	360
	(2.44)						(2.10)			
$\Delta ADRP_m^z$	0.026***						0.012	Yes	13%	360
	(3.40)						(1.49)			
$\Delta ADRP_m$	3.227***	3.279***	0.083	1.219	-1.148	6.303***	1.761	Yes	17%	360
	(3.00)	(3.05)	(0.11)	(1.09)	(-1.04)	(5.01)	(1.64)			
$\Delta ADRP_m^z$	0.029***	0.016**	0.000	0.008	-0.010	0.024***	0.009	Yes	16%	360
	(3.70)	(2.00)	(0.05)	(0.97)	(-1.29)	(2.66)	(1.20)			

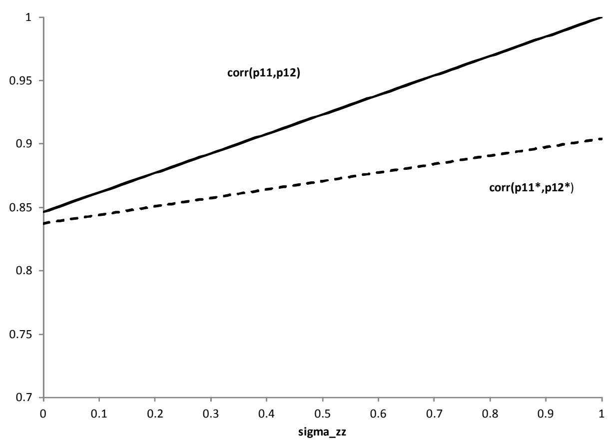
Table 5. (*Continued*)

	Panel B: $I_m = N_m^z\,(gov)$									
	β_0	β_{ILQ}	β_{ILQ}^2	β_0^{ILQ}	β_{DSP}	β_0^{DSP}	β_{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)									
$\Delta ADRP_m$	2.579**							Yes	8%	360
	(2.32)									
$\Delta ADRP_m^z$	0.025***							Yes	12%	360
	(3.25)									
$\Delta ADRP_m$	3.109***	3.486***	-0.337	-0.159				Yes	10%	360
	(2.79)	(3.13)	(-0.45)	(-0.14)						
$\Delta ADRP_m^z$	0.027***	0.016**	-0.001	0.003				Yes	13%	360
	(3.50)	(2.08)	(-0.24)	(0.35)						
$\Delta ADRP_m$	2.640**				-1.068	5.979***		Yes	14%	360
	(2.45)				(-0.95)	(5.17)				
$\Delta ADRP_m^z$	0.026***				-0.010	0.021**		Yes	14%	360
	(3.32)				(-1.20)	(2.60)				
$\Delta ADRP_m$	2.462**						2.625**	Yes	9%	360
	(2.23)						(2.37)			
$\Delta ADRP_m^z$	0.024***						0.016**	Yes	13%	360
	(3.17)						(2.05)			
$\Delta ADRP_m$	2.959***	3.211***	0.063	1.279	-1.165	6.147***	2.066*	Yes	18%	360
	(2.76)	(2.99)	(0.09)	(1.14)	(-1.05)	(5.17)	(1.94)			
$\Delta ADRP_m^z$	0.027***	0.015*	0.000	0.008	-0.010	0.023***	0.013*	Yes	16%	360
	(3.45)	(1.94)	(0.01)	(1.00)	(-1.27)	(2.63)	(1.75)			

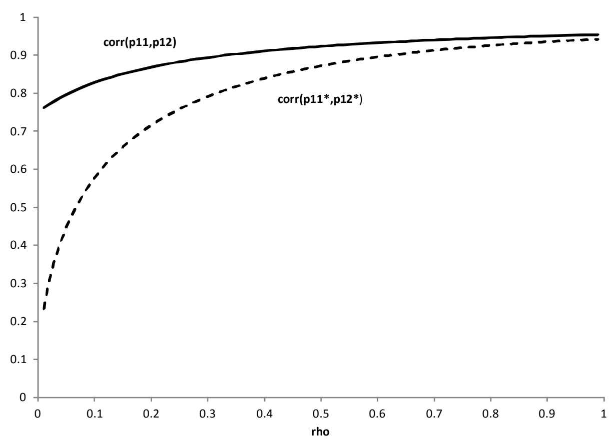
Figure 1. Law of One Price Violations

This figure plots the unconditional correlation between the equilibrium prices of assets 1 and 2 in the absence ($corr\left(p_{1,1}, p_{1,2}\right)$ of Eq. (3), solid lines) and in the presence of government intervention ($corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Eq. (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 $S_v\left(m\right)$ about v, the identical terminal payoff of assets 1 and 2, in Figure 1b), M (the number of speculators, in Figure 1c), σ^2_z (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 $L\left(gov\right)$ of Eq. (4)), μ (the correlation of the government's policy target $p^T_{1,1}$ with its private signal $S_v\left(gov\right)$ about the identical terminal payoff v of assets 1 and 2), ψ (the precision of the government's private signal of v, $S_v\left(gov\right)$), and σ^2_v (the uncertainty about v, the identical terminal payoff of assets 1 and 2, in Figure 1h), 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 $M = 10$.

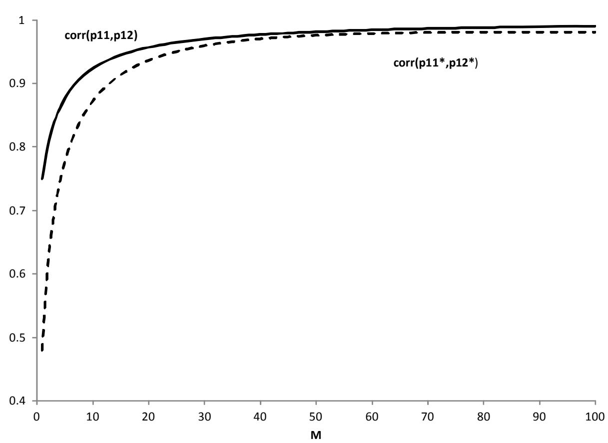
a) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus σ_{zz}



b) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus ρ



c) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus M



d) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus σ^2_z

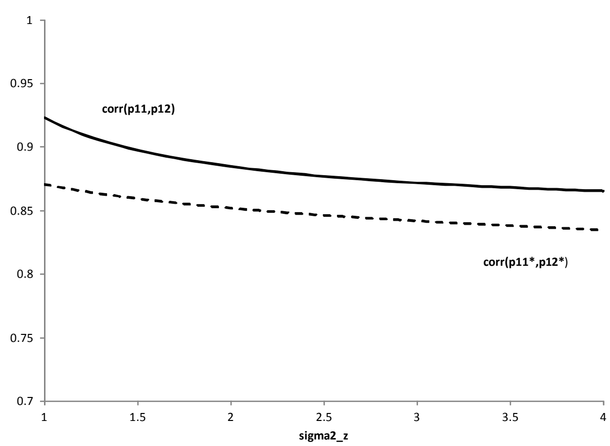
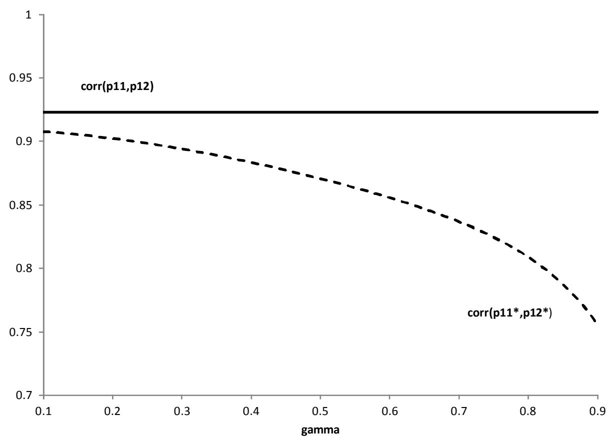
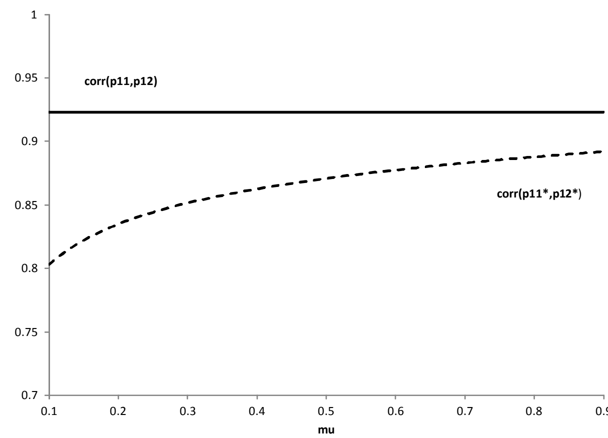


Figure 1 (*Continued*).

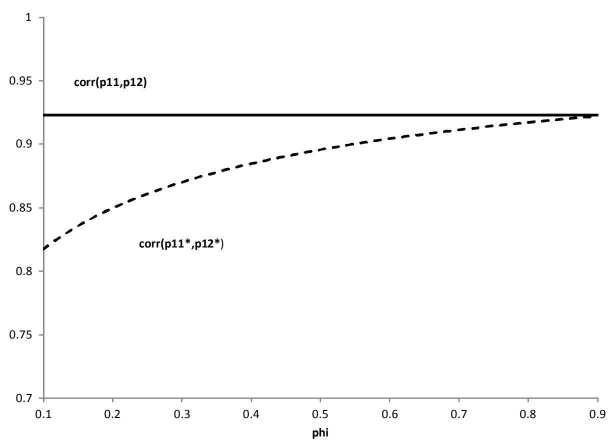
e) $corr\left(p_{1,1},p_{1,2}\right), corr\left(p^*_{1,1},p^*_{1,2}\right)$ versus γ



f) $corr\left(p_{1,1},p_{1,2}\right), corr\left(p^*_{1,1},p^*_{1,2}\right)$ versus μ



g) $corr\left(p_{1,1},p_{1,2}\right), corr\left(p^*_{1,1},p^*_{1,2}\right)$ versus ψ



h) $corr\left(p_{1,1},p_{1,2}\right), corr\left(p^*_{1,1},p^*_{1,2}\right)$ versus σ^2_v

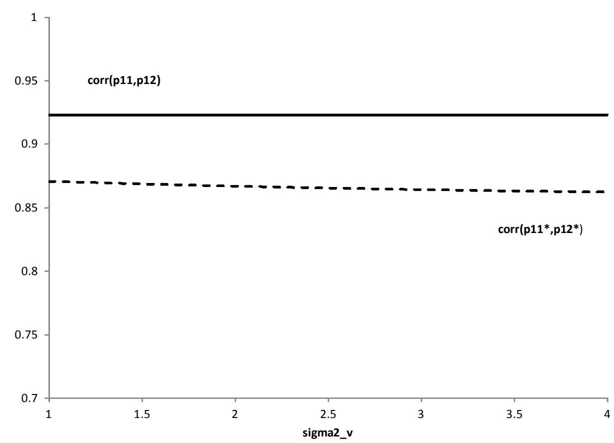
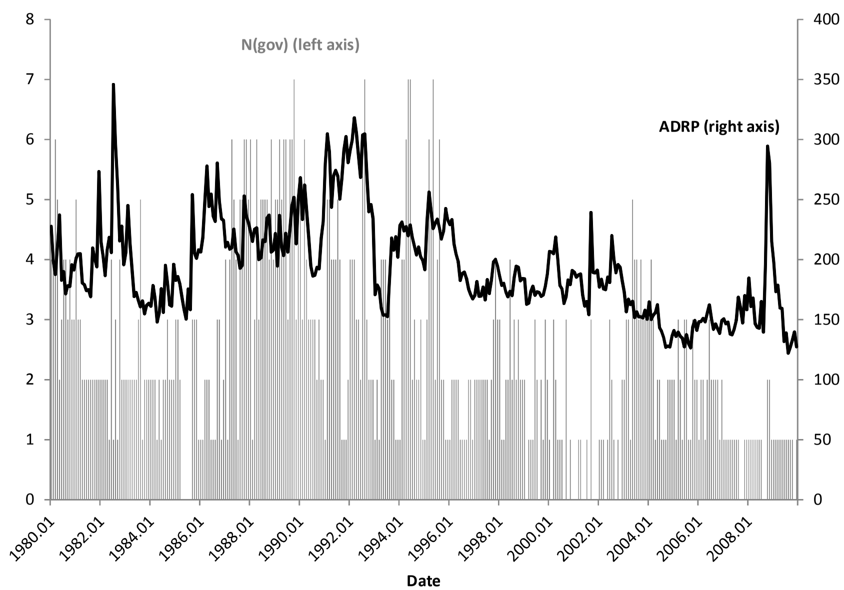


Figure 2. ADR Parity Violations and Forex Interventions

This figure plots the aggregate measures of LOP violations in the ADR market defined in Section 3.1.1 — the monthly averages of daily equal-weighted means of available observed ($ADRP_m$, Figure 2a, right axis, solid line [in basis points, i.e., multiplied by 10,000]) and standardized ($ADRP_m^z$, Figure 2b, right axis, solid line) absolute log violations of the ADR parity of Eq. (11) — as well as the aggregate measures of government intervention in the forex market defined in Section 3.1.2 — the number of government intervention-exchange rates pairs in each month m ($N_m\,(gov)$, Figure 2a, left axis, histogram) and the number of those pairs standardized by its historical distribution on month m ($N_m^z\,(gov)$, Figure 2b, left axis, dashed line) — over our sample period 1980-2009.

a) $ADRP_m$, $N_m\,(gov)$



b) $ADRP_m^z$, $N_m^z\,(gov)$