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Government Intervention and Arbitrage

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

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Paolo Pasquariello[1]

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[1]Department of Finance, Ross School of Business, University of Michigan, ppasquar@umich.edu. I benefited from the comments of Sugato Bhattacharyya, Bernard Dumas, Michael Goldstein, Andrew Karolyi, Pete Kyle, Bruce Lehmann, Dmitry Livdan, Ananth Madhavan, Stefan Nagel, Francesco Saita, Clara Vega, an anonymous referee, and seminar participants at the NBER Market Microstructure meetings, University of Michigan, New York University, Università Bocconi, INSEAD, HEC, Federal Reserve Bank of New York, and AFA meetings. Any remaining errors are my own.

Abstract

We model and document the novel notion that direct government intervention in a market may induce violations of the law of one price (LOP) in other, arbitrage-related markets. We show that the introduction of a government pursuing a non-public, partially informative price target in a model of strategic trading and segmented dealership generates equilibrium price differentials among fundamentally identical (or linearly related) assets — especially when markets are illiquid, LOP violations are small, speculators are heterogeneously informed, or policy uncertainty is high. We find supportive evidence in a sample of ADRs traded in U.S. exchanges and currency interventions by developed and emerging countries between 1980 and 2009.

JEL classification: F31; G14; G15

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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 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* externalities on their quality has important implications for the broader debate on financial stability, optimal financial regulation, and unconventional policy-making (e.g., Acharya and Richardson, 2009; Hanson et al., 2011; Bernanke, 2012).[3]

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 fundamentally identical (or linearly related) risky assets (labeled assets 1 and 2) 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 —

[1] Accordingly, there is a vast literature reporting evidence of violations of various arbitrage parities in financial markets as well as attributing their occurrence, intensity, and persistence 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 (often conflicting) 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., Pastor and Veronesi, 2012, 2013; Bond and Goldstein, 2015).

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

market-makers in each asset do not observe order flow in the other asset (e.g., Subrahmanyam, 1991a; Baruch et al., 2007; Boulatov et al., 2013) — liquidity demand differentials (i.e., less-than-perfectly correlated noise trading in assets 1 and 2) yield equilibrium LOP violations (i.e., less-than-perfectly correlated equilibrium prices of assets 1 and 2) despite both markets being semi-strong efficient. Intuitively, those relative mispricings (nonzero price differentials) can occur in equilibrium because speculators can only submit *camouflaged* market orders in each asset, i.e., together with noise traders and before market-clearing prices are set. Accordingly, when both markets are more illiquid, noise trading in either asset has a greater impact on its equilibrium price, yielding larger LOP violations. Dealership segmentation and liquidity demand differentials in the model serve as a reduced-form representation of existing forces behind LOP violations and impediments to arbitrage activity in financial markets.

The introduction of a stylized government submitting camouflaged market orders (e.g., Vitale, 1999; Naranjo and Nimalendran, 2000) in only one of the two assets (asset 1) in pursuit of policy — a *non-public*, *partially informative* price target (e.g., Bhattacharya and Weller, 1997) — *increases* equilibrium LOP violations (i.e., *lowers* the equilibrium price correlation of assets 1 and 2), ceteris paribus for existing limits to arbitrage and even in absence of liquidity demand differentials. An intuitive explanation for this result is that the uncertainty surrounding the government's intervention policy in asset 1 clouds the inference of the market-makers about asset 1's fundamentals when setting the equilibrium price of that asset from its order flow. Consistently, the magnitude of this effect is increasing in government policy uncertainty and generally, yet not uniformly decreasing in pre-intervention market quality. In particular, intervention-induced LOP violations are larger not only when market liquidity is lower (e.g., in the presence of less intense noise trading or more heterogeneously informed speculators) but also when pre-existing LOP violations are smaller (e.g., in the presence of more correlated noise trading) — since in those circumstances "official" trading has a greater impact on asset 1's equilibrium price and price correlation with asset 2.

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). The forex market is one of the largest, most liquid financial markets in the world (e.g., Bank for International Settlements, 2013); the ADR market is the most important venue for internationally cross-listed stocks (e.g., Karolyi, 1998, 2006). These markets also 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). This fundamental linkage can be described in our setting as a linear relationship between the terminal payoff of asset 1 (the exchange rate, traded in the forex market) and the terminal payoff of asset 2 (the ADR, traded in the U.S. stock market). Our model then predicts that, ceteris paribus, forex intervention — i.e., government intervention targeting the price of asset 1 (the exchange rate) — may induce ADRP violations — i.e., lowers the equilibrium correlation between the price of asset 2 (the actual ADR) and its *synthetic* (arbitrage-free) price implied by the ADRP (a linear function of the price of asset 1). Second, forex and ADR dealership sectors are arguably less-than-perfectly integrated, as market-makers in either market are less likely to observe order flow in the other market. Third, according to a vast literature (surveyed in Edison, 1993; Sarno and Taylor, 2001; Neely, 2005; Menkhoff, 2010; Engel, 2014), government intervention in currency markets is common and often secret; its policy objectives are often non-public; its effectiveness is statistically robust and often attributed to their perceived informativeness about fundamentals. 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 ADRs traded in the major U.S. exchanges and official trading activity of developed and emerging countries in the currency markets between 1980 and 2009. Its salient features are in line with the aforementioned literature. Average absolute (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 involving exchange rates relative to the dollar.

Our empirical analysis of this sample 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 statistically and (plausibly) economically significant. 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 (up to) nearly 10 bps — i.e., (as much as) 45% of the sample volatility of their monthly changes. This relationship is also robust to controlling for (several proxies for) market conditions that are commonly associated with LOP violations, limits to arbitrage, and/or forex intervention (e.g., Pontiff, 1996, 2006; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Garleanu and Pedersen, 2011; Engel, 2014). Importantly, those same official currency trades are *not* accompanied by greater LOP violations in the much more closely integrated currency and international money markets — i.e., are unrelated to violations of the (arbitrage-free) covered interest rate parity (CIRP; between interest rates and spot and forward exchange rates), a common proxy for currency market quality (e.g., Frenkel and Levich, 1975, 1977; 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).

Further cross-sectional and time-series analysis also indicates that poor, deteriorating conditions in the ADR arbitrage-linked markets magnify ADRP violations both directly and through their (possibly nonlinear) 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 (but also in markets and portfolios of ADRs of high underlying quality);

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 dispersion of beliefs about common fundamentals (measured by the standard deviation of professional forecasts of U.S. macroeconomic news releases); and *iv)* greater 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 almost four 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). The model's standard framework has often been used to study price formation in many financial markets and for many asset classes (e.g., see the surveys in O'Hara, 1995; Vives, 2008; Foucault et al., 2013). It is a two-date ($t = 0, 1$) economy in which two risky assets ($i = 1, 2$) are exchanged. Trading occurs only at date $t = 1$, after which each asset's payoff v_i is realized. The two assets are fundamentally *related* in that $v_i \equiv a_i + b_i v$, where v is normally distributed with mean p_0 and variance σ_v^2, and a_i

and b_i are constants. Fundamental commonality in payoffs is meant to parsimoniously represent a wide range of LOP relationships between the two assets; linearity of their payoffs in v ensures that the model can be solved in closed form. We discuss one particular such representation for the ADR parity in Section 3.1. For simplicity and without loss of generality, in what follows we assume that the two assets are fundamentally *identical* in that $a_i = 0$ and $b_i = 1$ such that $v_i = v$. 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 σ_s^2 and that, for any two $S_v(m)$ and $S_v(j)$, $cov[v, S_v(m)] = cov[S_v(m), S_v(j)] = \sigma_v^2$. 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.[4]

At date $t = 1$, speculators and liquidity traders submit their orders in assets 1 and 2 to the MMs before their equilibrium prices $p_{1,1}$ and $p_{1,2}$ have been set. 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 $\sigma_{zz} \in (0, \sigma_z^2]$. For simplicity, we assume that z_1 and z_2 are independent from all other random variables. Competitive MMs in each asset i do not receive any information about its terminal payoff v,

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

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), Baruch et al. (2007), 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 assets 1 and 2's identical payoffs.[5] 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*: $p_{1,i} = E(v|\omega_i)$.[6]

Proposition 1 describes the unique linear REE that obtains.

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

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

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

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

In this class of models, MMs in each market i learn about the traded asset i's terminal payoff from its order flow ω_i; hence, imperfectly competitive, risk-neutral speculators trade cautiously in both assets ($|x_i(m)| < \infty$, Eq. (2)) to protect the information advantage stemming from their

[5]Relaxing this assumption to allow for *partial* dealership segmentation (e.g., by endowing MMs in each asset with a noisy signal of the order flow in the other asset) would significantly complicate the analysis without qualitatively altering its implications. Without loss of generality, the distributional assumptions for z_i also imply that if $\sigma_{zz} = \sigma_z^2$ then $z_1 = z_2$.

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

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 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.[7]

2.1.2 LOP violations

A well-established empirical literature measures LOP violations either as nonzero (absolute or square, arithmetic or percentage) price differentials 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). As we further discuss in Section 3.1, the two representations are conceptually equivalent in our economy. 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 $p_{1,1} = E(v|\omega_1, \omega_2) = p_{1,2}$. We formalize these observations in Corollary 1 by measuring LOP violations

[7] 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 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 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.[8] 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

[8] 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).

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. 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.[9]

Segmentation in market-making and less-than-perfectly correlated noise trading in our basic model are a reduced-form representation of existing forces affecting the ability of financial markets to correctly price assets that are fundamentally linked by an arbitrage parity. Next, we introduce a government in this setting and examine the effects of its intervention activity on the extent of equilibrium LOP violations.

2.2 Government Intervention

Governments often intervene in financial markets. A large literature models and 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.[10] 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.

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

[10] A comprehensive survey of this literature is beyond the scope of this paper. Recent studies include Bossaerts and Hillion (1991), Dominguez and Frankel (1993), Bhattacharya and Weller (1997), Vitale (1999), Naranjo and Nimalendran (2000), Lyons (2001), Dominguez (2003, 2006), Evans and Lyons (2005), and Pasquariello (2007b, 2010) for the spot and forward currency markets, Harvey and Huang (2002), Ulrich (2010), and Pasquariello et al. (2014) for the bond markets, and Sojli and Tham (2010) and Dyck and Morse (2011) for the stock markets.

The aforementioned literature identifies several recurring features of government intervention in financial markets (e.g., see Edison, 1993; Vitale, 1999; Sarno and Taylor, 2001; Neely, 2005; 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 often intervene *in secret* in the targeted markets; *iii)* governments are likely (or perceived) to have an *information advantage* over most market participants about the fundamentals of the traded assets; *iv)* the effectiveness of governments at pursuing their price targets is often attributed to that (perceived) information advantage; and *v)* 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 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 $cov[S_v(m), S_v(gov)] = cov[v, S_v(gov)] = \sigma^2_v$, as for speculators' private signals $S_v(m)$ in Section 2.1. Accordingly, we define the government's information endowment about v as $\delta_v(gov) \equiv E[v|S_v(gov)] - p_0 = \psi[S_v(gov) - p_0]$.

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 $\delta_T(gov) \equiv p^T_{1,1} - \overline{p}^T_{1,1}$.[11] 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;

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

e.g., Edison, 1993; Lewis, 1995).[12]

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:

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

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 $p_{1,1}^T$. The second term in 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 asset 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.

[12] Accordingly, in their REE model of currency trading, Bhattacharya and Weller (1997) also assume that the central bank's non-public 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 ($cov\left(v, p_{1,1}^T\right) = 0$, as in Pasquariello et al., 2014).

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 — i.e., on 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:*

$$corr\left(p_{1,1}^*, p_{1,2}^*\right) = \frac{\sigma_{zz} + \sigma_z\sigma_v\sqrt{M\rho}\left\{B_{1,1}^*\left[1+(M-1)\rho\right] + C_{1,1}^*\psi + C_{1,2}^*\right\}}{\sigma_z\sqrt{\left[2+(M-1)\rho\right]\left\{\sigma_z^2 + \sigma_v^2\left\{M\rho B_{1,1}^{*2}\left[1+(M-1)\rho\right] + D_1^* + E_1^*\right\}\right\}}}, \tag{10}$$

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 asset 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 2.1.2 (where $\sigma^2_v = 1$, $\sigma^2_z = 1$, $\sigma_{zz} = 0.5$, $\rho = 0.5$, 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^2_z (Figures 1a to 1d, as in Section 2.1.2), and γ, μ, ψ, or σ^2_v (Figure 1e to 1h).

Insofar as the dealership sector is segmented (Corollary 1) — i.e., ceteris paribus for existing limits to arbitrage — government intervention makes LOP violations more likely in equilibrium — even in absence of liquidity demand differentials. According to Figure 1, official trading activity in asset 1 *lowers* the unconditional correlation of the equilibrium prices of (the 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 (i.e., $\sigma_{zz} = \sigma^2_z = 1$ such that $corr\left(p_{1,1}, p_{1,2}\right) = 1$ in Figure 1a). Intuitively, the camouflage provided by the aggregate order flow allows the stylized government of Eq. (4) to trade in asset 1 to push its equilibrium price $p^*_{1,1}$ toward a target $p_{1,T}$ that is at most only partially informative about fundamentals — i.e., only partially correlated with both assets' identical terminal payoff v: $corr\left(v, p^T_{1,1}\right) = \sqrt{\mu\psi} < 1$ (see also Vitale, 1999; Naranjo and Nimalendran, 2000). Since $p^T_{1,1}$ is also non-public (i.e., policy uncertainty $\sigma^2_T = \frac{\sigma^2_v}{\mu\psi} > 0$), MMs in asset 1 cannot fully account for the government's trading activity when setting $p^*_{1,1}$ from the observed aggregate order flow in that asset, ω_1.

As such, so-camouflaged government intervention is at least partly effective at accomplishing its policy in the equilibrium of Proposition 2 (in that $cov\left(p^*_{1,1}, p^T_{1,1}\right) = \frac{d\lambda^*\sigma^2_v}{\mu\psi(1+d\lambda^*)} > 0$), despite occurring in a deeper market ($\lambda^* < \lambda$, because at least partly uninformative official trading activity in ω_1 alleviates dealers' adverse selection risk in the market for asset 1; see also Pasquariello et al., 2014). 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.[13] Con-

[13]This effect prevails over the aforementioned liquidity differential between the two markets from government intervention in one market mitigating the differential impact of (less than perfectly correlated) noise trading

sistently, 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 are the affected markets. 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 assets 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 $p_{1,1}^*$ of Eq. (5) toward the partially uninformative policy target $p_{1,1}^T$ (ceteris paribus, $\frac{\partial cov\left(p_{1,1}^*, p_{1,1}^T\right)}{\partial \lambda^*} = \frac{\mu\psi d\sigma_v^2}{\mu^2\psi^2(1+d\lambda^*)^2} > 0$), hence further away from the 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_z^2, Figure 1d,

shocks on their asset prices $p_{1,1}^*$ and $p_{1,2}^*$ (e.g., see the dashed plots of $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ as a function of σ_{zz} and σ_z^2 being less steep than the corresponding solid plots of $corr\left(p_{1,1}, p_{1,2}\right)$ in absence of official trading activity in Figures 1a and 1d, respectively), as well as over such partly uninformative intervention also inducing more aggressive informed (hence perfectly correlated) speculation in asset 1 (i.e., $B_{1,1}^* > \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$ in Eqs. (7) and (8), respectively, because of greater competition and opportunity for camouflage from official trading activity; e.g., see Subrahmanyam, 1991b; Pasquariello et al., 2014).

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.[14]

Conclusion 1 *Government intervention results in greater LOP violations in equilibrium, even in absence of liquidity demand differentials.*

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 direct 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 both that government policy and the information environment of those markets. Yet, measuring such intervention characteristics and market conditions is challenging, and often unfeasible. Under these premises, we identify from Corollary 1, Proposition 2, Figure 1, and Conclusions 1 and 2 the following subset of *plausibly* testable implications of official trading activity for relative mispricings:

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

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

[14] 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.

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

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 dollar-denominated security, traded in the U.S., representing ownership of a pre-specified amount ("bundling ratio") of stocks of a foreign company (denominated in a foreign currency) held on deposit at a U.S. depositary banks (e.g., Karolyi, 1998, 2006).

3.1 ADRs and Foreign Exchange Intervention in the Model

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 denominated in a foreign currency FOR, and $S_{t,USD/FOR}$ is the exchange rate between USD and FOR. We interpret the fundamental commonality in the terminal payoffs of assets 1 and 2 in our model (v_1 and v_2) as a stylized representation of the

LOP relationship between currency and ADR markets in Eq. (11). In particular, Eq. (11) suggests that one can think of asset 1 as the exchange rate (with payoff $v_1 = v$) — traded in the forex market at a price $p_{1,1}$ (i.e., $S_{t,USD/FOR}$) — and of asset 2 as an ADR (whose payoff v_2 is a linear function of the exchange rate: $v_2 = a_2 + b_2 v$, where $a_2 = 0$ and $b_2 = q_i \times P_{i,t}^{FOR} > 0$) — traded in the U.S. stock market at a price $p_{1,2}$ (i.e., $P_{i,t}$). In this setting, the LOP relationship between actual ($P_{i,t}$) and *synthetic* ($P_{i,t}^{LOP}$) ADR prices in Eq. (11) can be represented by the unconditional correlation between $p_{1,2}$ and $p_{1,2}^{LOP} = b_2 p_{1,1}$, respectively, such that in equilibrium: $corr\left(p_{1,2}, p_{1,2}^{LOP}\right) = corr\left(p_{1,2}, b_2 p_{1,1}\right) = corr\left(p_{1,1}, p_{1,2}\right)$ of Eq. (3).[15] Accordingly, our model postulates (in Conclusion 1) that, ceteris paribus, government intervention in the forex market (i.e., targeting the exchange rate $p_{1,1}$) lowers the unconditional correlation between exchange rates and actual ADR prices (i.e., between $p_{1,1}$ and $p_{1,2}$: $corr\left(p_{1,1}^*, p_{1,2}^*\right) < corr\left(p_{1,1}, p_{1,2}\right)$), hence may yield larger price differentials between actual and synthetic ADRs — i.e., lowers the unconditional correlation between $p_{1,2}$ and $p_{1,2}^{LOP}$: $corr\left(p_{1,2}^*, p_{1,2}^{LOP*}\right) = corr\left(p_{1,2}^*, b_2 p_{1,1}^*\right) = corr\left(p_{1,1}^*, p_{1,2}^*\right)$ of Eq. (10), such that $corr\left(p_{1,2}^*, p_{1,2}^{LOP*}\right) < corr\left(p_{1,2}, p_{1,2}^{LOP}\right)$.[16]

Second, market-making in currency and ADR markets is arguably less-than-perfectly integrated, in that market-makers in one market are less likely to directly observe (and set prices based on) trading activity in the other market than within their own.[17] 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

[15] Alternatively, one can also think of asset 1 as the actual exchange rate (with payoff $v_1 = v$) — traded in the forex markets at a price $p_{1,1}$ (i.e., $S_{t,USD/FOR}$) — and of asset 2 as the ADR-specific synthetic (or *shadow*) exchange rate implied by Eq. (11) (with payoff $v_2 = v$) — implicitly traded in the ADR market at a price $p_{1,2}$ (i.e., $S_{t,USD/FOR}^{i,LOP} = P_{i,t} \times \left(q_i \times P_{i,t}^{FOR}\right)^{-1}$; e.g., see Auguste et al., 2006; Eichler et al., 2009). While less common and intuitive, this representation of the LOP relationship between currency and ADR markets within our model is conceptually (as well as empirically) equivalent to the one in the main text since any violation of the ADR parity of Eq. (11) yields both $P_{i,t} \neq P_{i,t}^{LOP}$ and $S_{t,USD/FOR} \neq S_{t,USD/FOR}^{i,LOP}$ (as well as the same absolute percentage LOP violation $\left|\ln\left(P_{i,t}\right) - \ln\left(P_{i,t}^{LOP}\right)\right| = \left|\ln\left(S_{t,USD/FOR}\right) - \ln\left(S_{t,USD/FOR}^{i,LOP}\right)\right|$ in Eq. (12) next).

[16] More generally, it can be shown that if the two assets' terminal payoffs are $v_i \equiv a_i + b_i v$, their (tilded) equilibrium prices are then given by $\widetilde{p}_{1,i} = a_i + b_i p_{1,i}$ and $\widetilde{p}_{1,i}^* = a_i + b_i p_{1,i}^*$ (where $p_{1,i}$ and $p_{1,i}^*$ are those in Proposition 1 and 2, respectively), such that $corr\left(\widetilde{p}_{1,1}, \widetilde{p}_{1,2}\right) = sgn\left(b_1 b_2\right) corr\left(p_{1,1}, p_{1,2}\right)$, $corr\left(\widetilde{p}_{1,1}^*, \widetilde{p}_{1,2}^*\right) = sgn\left(b_1 b_2\right) corr\left(p_{1,1}^*, p_{1,2}^*\right)$ (where $sgn\left(\cdot\right)$ is the sign function, and $corr\left(p_{1,1}, p_{1,2}\right)$ and $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ are those in Corollary 1 and 2, respectively), and $\left|corr\left(\widetilde{p}_{1,1}^*, \widetilde{p}_{1,2}^*\right)\right| < \left|corr\left(\widetilde{p}_{1,1}, \widetilde{p}_{1,2}\right)\right|$.

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

model is consistent with the consensus in the literature that government intervention in currency markets, while typically secret and in pursuit of non-public policy, is often effective at moving exchange rates because it is (deemed) at least partly informative about fundamentals.[18]

Lastly, the same literature suggests that forex intervention is unlikely to be motivated by relative mispricings in the ADR market. This observation alleviates reverse causality concerns when estimating and interpreting the empirical relationship (if any) between government intervention and arbitrage parities. We further assess this and other potential sources of endogeneity in Section 3.3.1.

Overall, 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 in the reminder of the paper.[19]

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

[19] As noted in Section 2.1.2, the notion of LOP violations in the ADR market as nonzero absolute relative price differentials ($ADRP_{i,t} > 0$) is both common in the literature and conceptually equivalent to the notion of LOP violations in our model (an equilibrium unconditional price correlation $corr\left(p_{1,2}, p_{1,2}^{LOP}\right) = corr\left(p_{1,1}, p_{1,2}\right) < 1$). 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 actual and synthetic ADR prices $p_{1,2}$ and $p_{1,2}^{LOP}$ described above is a function of their unconditional correlation: $E\left[\left|p_{1,2} - p_{1,2}^{LOP}\right|\right] = H\sqrt{1 - corr\left(p_{1,1}, p_{1,2}\right)}$, where the scaling factor $H = \sqrt{\frac{4b_2^2\sigma_v^2 M\rho}{pi[2+(M-1)\rho]}}$ depends on the magnitude of the ADR's fundamental payoff $b_2 v$ ($b_2^2\sigma_v^2$), and $pi \equiv \arccos(-1)$. Both $corr\left(p_{1,1}, p_{1,2}\right)$ of Section 2 and $ADRP_{i,t}$ of Eq. (12) are instead price-scale invariant. 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 $\ln\left(P_{i,t}\right) = \ln\left(P_{i,t}^{LOP}\right)$ and $r_{i,t} = r_{i,t}^{FOR} + r_{t,USD/FOR}$, where $\ln\left(P_{i,t}^{LOP}\right) = \ln\left(S_{t,USD/FOR}\right) + \ln\left(q_i\right) + \ln\left(P_{i,t}^{FOR}\right)$, $r_{i,t} = \ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right)$, $r_{i,t}^{FOR} = \ln\left(P_{i,t}^{FOR}\right) - \ln\left(P_{i,t-1}^{FOR}\right)$, and $r_{t,USD/FOR} = \ln\left(S_{t,USD/FOR}\right) - \ln\left(S_{t-1,USD/FOR}\right)$.

3.2 Data

Next, we construct a sample of ADRs traded in U.S. exchanges and official intervention activity in currency markets over the last three decades.

3.2.1 American Depositary Receipts

We begin by obtaining from Thomson Reuters Datastream (Datastream) the complete sample of foreign stocks cross-listed in the U.S. between January 1, 1973 and December 31, 2009.[20] Following standard practice in the literature, we then remove ADRs trading over-the-counter (Level I), Securities and Exchange Commission (SEC) Regulation S shares, private placement ADRs (Rule 144A), preferred shares, and (conservatively) any cross-listing with ambiguous, incomplete, or missing descriptive information in the Datastream sample. This leaves us with a subset of 410 (Level II and III) ADRs (from developed and emerging countries, with bundling ratios q_i) and (mostly Canadian) ordinary shares (ordinaries, with $q_i = 1$) listed on the NYSE, AMEX, or NASDAQ.[21] Daily closing prices for these U.S. cross-listings, $P_{i,t}$, and their underlying foreign stocks, $P_{i,t}^{FOR}$, are also from Datastream. The corresponding exchange rates in Eq. (11), $S_{t,USD/FOR}$, are daily indicative spot mid-quotes (as observed at 12 p.m. Eastern Standard Time [EST]), from Pacific Exchange Rate Service (Pacific) and Datastream. Because of our focus on forex interventions, Table 1 reports the composition of this sample of ADRs by the country or most recent currency area of listing (i.e., most recent currency of denomination) of the underlying foreign stocks. Most cross-listed stocks in the sample are listed in developed, highly liquid (and

[20]When possible, we verify the accuracy of this sample (and fill in any missing information) by cross-checking it with the directory of U.S. cross-listings compiled by Bank of New York Mellon (BNY Mellon), the leading U.S. depositary bank (available at http://www.adrbnymellon.com/dr_directory.jsp).

[21]This is the ADR sample used in Pasquariello (2014); see also Baruch et al. (2007), Pasquariello (2008), Gagnon and Karolyi (2010), and references therein. While prevalent in the literature, the inclusion of Canadian ordinaries makes the size and composition of any ADR sample from Datastream both more time-period dependent and more sensitive to ADR delistings — since Datastream does not clearly identify all ADRs that trade over-the-counter after being delisted from any of the major U.S. exchanges (Ince and Porter, 2006), these delistings have become increasingly common, especially in the latter part of our sample period (Xie, 2009), and Canadian ordinaries have a high (the highest among U.S. cross-listings) and time-varying propensity to delist (Witmer, 2008). The inference that follows is robust to (and stronger when) excluding all Canadian ordinaries from our sample.

high-quality) equity markets (and denominated in highly liquid currencies): Canada (CAD, 67), Euro area (EUR, 58), the United Kingdom (GBP, 43), Australia (AUD, 30), and Japan (JPY, 24); emerging, often less liquid (and lower-quality) equity markets (and currencies) of local listing comprise Hong Kong (HKD, 54 [including H-shares of firms incorporated in mainland China]), Brazil (BRL, 23), and South Africa (ZAR, 14), among others.

While commonly used, this dataset allows to measure the extent of LOP violations in the ADR market only imprecisely.[22] 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, yielding non-synchronous closing prices. Individual ADR parity violations often differ in scale, making cross-sectional comparisons problematic, and either persist or display discernible trends. Paired closing foreign stock, currency, or ADR prices may also be stale (e.g., reflecting sparse trading), incorrectly reported (e.g., because of inaccurate data entry), or frequently altogether missing. 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.[23] Filtering and daily averaging across individual ADRs minimize the impact of idiosyncratic parity violations (e.g., due to quoting errors). Monthly averaging smooths potentially spurious daily variability in observed parity violations (e.g., due to bid-ask bounce, price staleness, or non-synchronicity). The second one, labeled $ADRP_m^z$, is the monthly average of daily equal-weighted means of all normalized ADRP violations, $ADRP_{i,t}^z$ — i.e., after each $ADRP_{i,t}$ has been standardized by its historical distribution on day t.[24] Up-to-current normalization allows to identify individual *abnormal* ADR parity violations (i.e., innovations in each observed $ADRP_{i,t}$ relative to its [potentially spurious]

[22]E.g., see Xie (2009), Gagnon and Karolyi (2010), and Pasquariello (2014) for detailed discussions of the limitations of the Datastream sample of U.S. cross-listings.

[23]In particular, we (conservatively) exclude from these averages any observed absolute ADR parity violation $ADRP_{i,t}$ deemed "too large" ($ADRP_{i,t} \geq 1,000$ bps) or stemming from "too extreme" ADR prices ($P_{i,t} < \$5$ or $P_{i,t} > \$1,000$). The ensuing analysis and inference are unaffected by this filtering procedure.

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

time-varying mean) without look-ahead bias, while making these violations comparable in scale 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 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 $ADRP^z_m$ over the sample period 1980-2009 are in Table 1; their marketwide plots are in Figures 2a and 2b (right axis, solid line). Consistent with the aforementioned literature, absolute ADR parity violations $ADRP_m$ in the past three decades are large (e.g., a sample mean of nearly 2% [194 bps]) and volatile (although not exceedingly so; e.g., a sample standard deviation of 41 bps), 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 ($ADRP^z_m$), while often statistically significant, display more discernible cycles and spikes, especially during periods of financial turmoil.[25] Both measures also display non-trivial cross-country heterogeneity. LOP violations in Table 1 are on average most pronounced for ADRs from Europe, Australia, and emerging markets (e.g., Mexico, South Africa, South Korea), and least pronounced for Canadian ordinaries, which have long been trading synchronously and (as noted earlier) on a one-to-one basis in both Canada and the 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 listing market for the underlying foreign stock, and the corresponding

[25] In particular, $ADRP^z_m$ is statistically significant at the 10% level in 76% of all months over the sample period 1980-2009; $ADRP^z_m$ is highest in October 2008, in correspondence with the global financial crisis initiated by Lehman Brothers' default (on September 15, 2008). Qualitatively similar inference ensues from excluding this recent period of turmoil (2008-2009) from our analysis.

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 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 define and 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, or exchange rate experiences a zero return on day t ($P_{i,t}^{FOR} = P_{i,t-1}^{FOR}$, $P_{i,t} = P_{i,t-1}$, or $S_{t,USD/FOR} = S_{t-1,USD/FOR}$), 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; see also Figure 3a) are 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).[26] This preliminary observation is consistent with our model's basic premise (as

[26] 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

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 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 3.5.

3.2.2 Foreign Exchange Interventions

As noted earlier, the forex market is not only among the biggest and deepest financial markets but also one where government interventions occur most often.[27] According to a well-established literature (surveyed in Edison, 1993; Sarno and Taylor, 2001; Neely, 2005; Menkhoff, 2010; Engel, 2014), monetary authorities (like central banks) and other government agencies frequently engage in (nearly always) *sterilized* currency transactions — i.e., accompanied by offsetting actions on the domestic money supply — normally in a coordinated fashion, to accomplish their (habitually 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., Payne and Vitale, 2003; 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 currency trading activity. To measure this activity, we use the database of government intervention in currency markets available on the Federal Reserve Economic Data (FRED) Web site of the Federal Reserve Bank of St. Louis.[28] This database contains daily amounts of domestic and foreign currencies traded by the governments of Australia, Germany,

relatively high (low) level of economic and capital market development. See also Levy Yeyati et al. (2009).

[27] For an overview of the main characteristics of the global currency markets, see the latest triennal survey by the Bank for International Settlements (BIS, 2013).

[28] See http://research.stlouisfed.org/fred2/categories/32145.

Italy, Japan, Mexico, Switzerland, Turkey, and the United States for policy reasons (i.e., to influence exchange rates) over the past several decades — in same cases, as early as in 1973 or as late as in 2009.[29] Where currency-specific intervention data is missing, we augment the FRED database using various official government sources (when possible). As for our sample of ADR parity violations, the resulting sample has the broadest continuous coverage of currency intervention activity between 1980 and 2009.[30] 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 traded foreign exchange 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 the corresponding USD-quoted exchange rates by triangular arbitrage (Bekaert and Hodrick, 2009); thus, any intervention in the former must reverberate in the latter. Excluding those interventions from the sample does not affect our inference. 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 BIS, 2013). In our model, optimal intervention amounts ($x_1\,(gov)$ of Eq. (9)) are endogenously determined in equilibrium; both these amounts and their effect on equilibrium outcomes depend not only on the realizations of unobservable variables controlling informed speculation, liquidity trading, or policy but also on market participants' unobservable

[29] 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).

[30] Official trades in our sample may have been executed in the spot and/or forward currency markets, although the former is much more common than the latter (e.g., Neely, 2000). Only in the case of Australia, the FRED database explicitly mentions consolidating spot and forward transactions by the Reserve Bank of Australia. In the case of Italy (Germany) and the United States, the FRED database reports official trades in the domestic currency relative to unspecified "other" currencies (in the European Monetary System [EMS]). 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.

expectations of them. Thus, our theory does not postulate any clearly testable relationship between realized intervention magnitude and LOP violations.[31] In addition, as mentioned above, 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 and events in our sample. For instance, forex interventions in Table 2 can be feasibly matched only to 128 ADRs in Table 1 whose underlying foreign stocks are denominated in the involved currencies (AUD, EUR, JPY, CHF, or TRY) — and only over the portions of the sample period 1980-2009 when both are contemporaneously available.[32] Yet, portfolio rebalancing, price pressure, and triangular arbitrage effects may induce significant cross-currency spillovers of interventions involving vehicle currencies (e.g., Dominguez, 2006; Beine et al., 2007, 2009; Gerlach-Kristen et al., 2012; Chortareas et al., 2013).

In light of these observations, we propose two *aggregate*, *lower-frequency* measures of the presence of government intervention in the forex market. The first one, labeled $N_m\left(gov\right)$, is the number of nonzero government intervention-exchange rates pairs in a month. The second one, labeled $N_m^z\left(gov\right)$, is such number standardized by its historical distribution on month m. As for normalized ADRP violations $ADRP_m^z$ in Section 3.2.1, a positive (negative) $N_m^z\left(gov\right)$ 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.

We plot $N_m\left(gov\right)$ and $N_m^z\left(gov\right)$ in Figures 2a (left axis, histogram) and 2b (left axis, dashed

[31] Similarly, our model does not make sharp or plausibly testable predictions about the sign of the effect of government intervention on LOP violations, for it critically depends on market participants' unobservable expectations of government intervention activity, i.e., on the sign of $x_1\left(gov\right) - 2d\left(\overline{p}_{1,1}^T - p_0\right)$ in Eq. (5). See also the discussion in Bhattacharya and Weller (1997).

[32] E.g., we observe no interventions in CHF or INR over the portions of the sample period when we can compute ADRP violations for cross-listed stocks denominated in CHF or INR; in addition, USD interventions by the United States in unspecified "other" currencies (see Table 2) cannot be matched to any ADR. Analysis of this smaller dataset (in Section 3.4) yields qualitatively similar inference.

line), alongside $ADRP_m$ and $ADRP^z_m$, respectively. Their summary statistics are in Panel B of Table 2. Forex interventions (i.e., $N_m\left(gov\right) \geq 1$ 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 $N_m\left(gov\right)$ and $N^z_m\left(gov\right)$ experience frequent sharp spikes, suggesting that episodes of (coordinated) forex intervention are often short-lived but not isolated.[33] 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.

3.3 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 induce their occurrence or increase 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 $ADRP^z_m$, $\Delta LOP_m = LOP_m - LOP_{m-1}$, I_m is either $N_m\left(gov\right)$ or $N^z_m\left(gov\right)$, 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 $N_m\left(gov\right)$ in Figure 2a ($ADRP^z_m$ and $N^z_m\left(gov\right)$ in Figure 2b) have a first-order serial correlation of 0.86 and 0.62 (0.68 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

[33] Nonetheless, $N^z_m\left(gov\right)$ is nearly always statistically significant, e.g., at the 10% level in 91% of all months over the sample period 1980-2009.

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 (ΔLOP_m). 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.[34]

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 (plausibly) economically significant as well; for example, a one standard deviation increase in the monthly change in the number of forex interventions $\Delta N_m\,(gov)$ (1.40, 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 standard deviation of $\Delta ADRP_m$ (21.47 bps, 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 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 $ADRP_m^z$ in-

[34] According to Dimson (1979), estimates of β_1^{-1} can also be interpreted as correcting for any bias in the contemporaneous coefficient β_0 due to 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.

crease on average by 34% of their sample standard deviation over the three-month window in correspondence with historically high intensity of official trading activity in a month — i.e., in response to a one standard deviation increase in the monthly change in the normalized number of government interventions $\Delta N_m^z(gov)$ $(0.057 \times 0.91 \div 0.153)$. Their cumulative effect on actual ADR parity violations $ADRP_m$ is even larger, e.g., amounting to 9.6 bps (10.631×0.91) or 45% of the standard deviation of $\Delta ADRP_m$. In unreported analysis, we further find these estimates to be broadly consistent in sign, magnitude, and statistical significance within each decade of our sample period.

3.3.1 Endogeneity Bias

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 interventions are likely to occur in correspondence with (or in response to) high exchange rate volatility (e.g., Neely, 2006) and tend to be accompanied by deteriorating currency market quality (e.g., Dominguez, 2003, 2006; Pasquariello, 2007b). Thus, ADRP violations may be large in months when currency market quality is low (e.g., Pasquariello, 2008, 2014) — which is exactly when governments are more likely to intervene — rather than as a consequence of forex interventions (e.g., Neely and Weller, 2007).[35] Unfortunately, those properties of forex

[35] 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 (2015). We highlight the robustness of our evidence to controlling for funding liquidity conditions in Eq. (14) of Section 3.5.

interventions 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).[36]

We assess the relevance of these considerations for our inference in various 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 (because of microstructure frictions; see also Gagnon and Karolyi, 2010);[37] forex interventions are often executed and coordinated over several clustered days (or even weeks), rather than on single, less salient (event) days; market participants may learn about such official trading activity — and its full effects on the targeted currency may manifest — only with considerable delay (e.g., see Neely, 2000; Pasquariello, 2007b). All are likely to weaken the estimated relationship between forex interventions and ADRP violations. 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 still has a positive and (weakly) significant (but short-lived) 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

[36] See also the discussion in Fatum and Hutchison (2003) and Neely (2005, 2006). Nonetheless, estimates of the 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.

[37] For instance, the daily (monthly) sample standard deviation of $ADRP_t$ ($ADRP_m$) is 92 bps (41 bps in Table 1), or 42% (21%) of its daily (monthly) sample mean. Gagnon and Karolyi (2010) address one such microstructure friction — non-synchronicity between foreign stock and ADR prices — by employing intraday price and quote data for the latter (from TAQ) observed at the closing time of the equity market for the former — as long as their trading hours are at least partially overlapping. However, this is not the case for Asian stock markets. In addition, TAQ data is available only from 1993 onward, while much forex intervention activity concentrates in the 1980s and early 1990s (e.g., see Figure 2). Lastly, both the level and dynamics of ADRP violations in our sample are consistent with what reported in Gagnon and Karolyi (2010) over their sample period 1993-2004.

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 Frenkel and Levich, 1975, 1977; Coffey et al., 2009; 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 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 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 3.2.1]) 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, either series is available exclusively over a portion of our sample period, between either May ($CIRP_m$) or June 1990 ($CIRP_m^z$) 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).[38] We then

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

estimate the regression model of Eq. (13) over the sub-period 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, during that common interval of data availability, forex interventions have little or no impact on CIRP violations (i.e., on LOP violations within the more closely integrated currency and money markets) but continue to be accompanied by a large and persistent increase in ADRP violations (i.e., 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 (as proxied by CIRP violations) is unlikely to be related to periods of intensifying forex intervention *and* ADR parity violations.[39]

Lastly, we use our model's guidance to explicitly consider the (cross-sectional and time-series) 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 3.4 and 3.5 next.

3.4 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 government intervention in

[39] Government interventions in emerging currency markets during times of distress are occasionally accompanied by the imposition of capital controls (e.g., East Asia in the 1990s; Argentina in 2001-2002; Brazil in 2008-2009) which may impede ADR arbitrage activity by restricting foreign ownership of local shares or local ownership of foreign shares as well as by introducing uncertainty about either (see Edison and Warnock, 2003; Auguste et al., 2006; Gagnon and Karolyi, 2010; Garleanu and Pedersen, 2011). Nonetheless, the exclusion of cross-listings from so-affected countries in our sample from both measures of marketwide ADRP violations ($ADRP_m$ and $ADRP_m^z$) over the portion of the sample period when these restrictions were in place has no effect on our inference. We discuss evidence from the country-level estimation of Eq. (13) in Section 3.4; we also amend Eq. (13) to control for explicit measures of financial distress and time-varying capital controls in Section 3.5.

one asset on LOP violations — i.e., on the equilibrium correlation between its price and the price of another, otherwise identical (or arbitrage-linked) asset ($corr\left(p_{1,1}^{*}, p_{1,2}^{*}\right)$ of Eq. (10)) — may depend on such variables affecting the underlying quality of the markets in which those assets are traded as the intensity (and correlation) of noise trading or the intensity of (and adverse selection risk from) informed, strategic speculation. These variables — while intrinsically conceptual and difficult to measure for each ADR or within each ADR market — may however be plausibly related to such observable market characteristics as each ADR's country of listing (e.g., Gagnon and Karolyi, 2010) as well as to such observable market outcomes as each ADR's illiquidity and no-arbitrage parity violations (e.g., Pasquariello, 2008, 2014). Investigating the cross-section of the impact of forex intervention on ADRP violations along those dimensions may shed further light on its theoretical determinants.

To this end, we estimate the regression model of Eq. (13) separately for each country of listing in Table 1, for each of the five countries for which currency-matched intervention-ADR pairs are available within our sample (Australia, Euro area, Japan, Mexico, and Turkey; see Table 2 and Section 3.2.2), as well as for each tercile portfolio of cross-listings sorted by either their samplewide ADRP illiquidity $ILLIQ_m$ or their samplewide actual absolute ADRP violations $ADRP_m$ (as defined in Section 3.2.1, from the lowest to the highest). We then report the resulting coefficients of interest for either actual or normalized absolute ADRP violations ($LOP_m = ADRP_m$ or $ADRP_m^z$) in Panels A and B of Tables 4 to 7, respectively. Noisier but qualitatively similar inference ensues from (unreported) cross-sectional estimates of Eq. (13) at the daily frequency ($LOP_t = ADRP_t$ or $ADRP_t^z$) or for quintile sorts. Our model predicts that forex intervention may yield larger ADR parity violations not only when the underlying, arbitrage-linked markets are less liquid (i.e., in the presence of less severe adverse selection risk from speculation; see H4 in Section 2.3 and Figures 1b to 1d) — e.g., because of low underlying market quality — but also when those violations are unconditionally smaller (i.e., in the presence of less correlated noise trading; see H3 and Figure 1a) — e.g., because of high underlying market quality.

Accordingly, country-level estimates of the contemporaneous (β_0) and cumulative impact (β_1^0 and β_1^{-1}) of changes in either $N_m\,(gov)$ or $N_m^z\,(gov)$ on absolute percentage ADR parity violations in Table 4 tend to be 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, 1995, 1997, 2000, 2003; Lesmond, 2005; Pasquariello, 2008); *ii)* for cross-listings whose ADRP illiquidity $ILLIQ_m$ (in Table 1) tends to be high; but also *iii)* for cross-listings whose samplewide mean LOP violations (also in Table 1) tend to be small. For instance, Panel A of Table 4 shows that, on average, a one standard deviation increase in $\Delta N_m^z\,(gov)$ is accompanied by a large cumulative increase in ADR parity violations for cross-listings both from markets with high average $ADRP_m$ and/or $ILLIQ_m$ — e.g., South Africa and Hong Kong: 13 and 17 bps (i.e., 20% and 44% of the corresponding standard deviation of $\Delta ADRP_m$ in Table 1), respectively — as well as from markets with low average $ADRP_m$ and/or $ILLIQ_m$ — e.g., Japan and Switzerland: 9 and 26 bps (i.e., 29% and 69% of the standard deviation of $\Delta ADRP_m$).[40] Estimates of the impact of currency-matched intervention on ADRP violations in Table 5 yield similar insight — e.g., are mostly positive (with the exception of Turkey, as in Table 4) and generally large — but are statistically significant only for countries with a relatively large number of intervention events over their available sub-sample period (see Tables 1 and 2) — i.e., Australia, the Euro area, and (to a lesser extent) Mexico.

Further estimation of Eq. (13) for illiquidity-sorted and LOP violation-sorted ADRP portfolios in Tables 6 and 7 confirms that the relationship between the negative arbitrage externality of forex intervention and ADRs' underlying market quality may be nonlinear. For example, estimates of the positive (contemporaneous and cumulative) impact of forex intervention on ADRP violations are roughly U-shaped in unconditional ADRP illiquidity ($ILLIQ_m$; e.g., see Panel A of Table 6), inverted U-shaped in unconditional LOP violations ($ADRP_m$; e.g., see Panel B of Table 7), and up to twice as large for higher underlying market quality (e.g., low or medium

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

$ILLIQ_m$ or $ADRP_m$) as for lower underlying market quality (high $ILLIQ_m$ or $ADRP_m$).

Overall, Tables 4 to 7 provide evidence of meaningful cross-sectional heterogeneity in the estimated effects of official trading activity in currency markets on LOP violations in the arbitrage-linked ADR markets — one that is both dispersed across country and market quality groupings and broadly consistent with our model's predictions.

3.5 LOP Violations and Market Conditions

The findings presented so far are supportive of 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 trades in currency markets are accompanied by non-trivial 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 both intensifying forex interventions and LOP violations. As noted earlier (in Section 3.3.1), the evidence in Tables 3 to 7 provides preliminary support for the former notion but not for the latter.

This evidence may also be consistent with another (albeit possibly complementary) interpretation related to trading risk — i.e., one that does not play a role in our model (where all market participants are risk-neutral) by construction. Forex intervention, rather than (only) constituting a source of LOP violations in the ADR market given existing limits to arbitrage (as implied by our model; see Section 2.1), may itself (also) limit existing arbitrage activity — e.g., by introducing a new source of unhedgeable convergence risk (e.g., in the spirit of Pontiff, 1996, 2006) for speculators and arbitrageurs exploiting existing ADRP violations. Yet, these market participants are also more likely to be able to manage such a risk, and its severity is more likely to be attenuated — hence their trading activity in the ADR market is less likely to be affected — at the low (monthly) frequency of our analysis.

In this section, we attempt to assess all of these notions more directly, by both explicitly testing for those *unique* comparative statics of the model (hence more difficult to reconcile with endogeneity or alternative interpretations) and explicitly controlling for state variables affecting the time-varying intensity of limits to arbitrage and/or of forex intervention activity. To that purpose, we amend the regression model of Eq. (13) for monthly changes in LOP violations (ΔLOP_m) as follows:

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

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 calendar fixed effects (or time trends). Eq. (14) allows for changes in ADRP illiquidity ($\Delta ILLIQ_m$), marketwide information heterogeneity ($\Delta DISP_m$), and policy uncertainty ($\Delta STD\left(I_m\right)$) 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 3.2.1, 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 (Figure 3a) — 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 ($\Delta ILLIQ_m > 0$; e.g., see Figures 1b and 1c). 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 — e.g., according to Remark 1, LOP violations may also be greater in the presence of more intense noise trading, despite its lesser price impact (lower λ and λ^*); see also Figure 1d. 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 market participants (including noise traders and the government). The dispersion of private information among sophisticated traders in a market is commonly measured by the standard deviation of professional forecasts of economic and financial variables that are relevant to the fundamental 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 fundamental information in the ADR arbitrage-linked markets 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 have been shown to contain payoff-relevant information not only for the U.S. markets where ADRs are traded, but also for the markets for their underlying foreign stocks and currencies (e.g., Chen et al., 1986; Bekaert et al., 2005; Albuquerque and Vega, 2009; Evans and Lyons, 2013); thus, they are plausibly related to the fundamental commonality in exchange rates and ADRs in our model (i.e., the common v in their payoffs v_1 and v_2, respectively; see Section 3.1). The SPF is the only continuously available survey of expert forecasts of those variables (by hundreds of private-sector economists) over our sample period. However, it is available only at the quarterly frequency.[41] Following the literature, we construct our measure of marketwide 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).[42] Second, we standardize each time series of dispersions to adjust for their different units of measurement. Third, we compute their equal-weighted average, $DISP_q$, and impose (without loss of generality, since the scale is irrelevant) that $DISP_m = DISP_q$ (Figure 3b) and $\Delta DISP_m = \Delta DISP_q$ for each month m within q. As noted earlier (e.g., see Figure 1b), 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, greater uncertainty about its policy target ($p_{1,1}^T$) makes official trading activity in one asset more effective at moving its equilibrium price away from its fundamentals (hence, away from the price of another, otherwise identical asset) by further obfuscating the MMs' inference from the order flow. As noted earlier, many central banks do not disclose their policy objectives when intervening in currency markets, nor market expectations of those objectives are typically available. In 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 $p_{1,1}^T$ ($\delta_T(gov) \equiv p_{1,1}^T - \overline{p}_{1,1}^T$), i.e., in policy uncertainty σ_T^2 — such that, in a first order sense, $\Delta var[x_1(gov)] \approx \left(C_{1,2}^*\right)^2 \Delta\sigma_T^2$. Accordingly, we proxy for the latter by the historical standard deviation of the former, $STD(I_m)$ (over a three-year rolling window to allow for short-term variation; Figure 3c), and consider the impact of monthly changes in both the intensity and

[41] 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., 2014).

[42] 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).

volatility of observed intervention activity and their cross-product on observed ADRP violations in Eq. (14). Our model then predicts that $\beta_{SDI} > 0$ and $\beta_0^{SDI} > 0$ (e.g., see Figure 1f).

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, 2006; 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). These proxies (many of which available only at low frequency) include: U.S. and world stock market volatility (from CRSP and MSCI); average 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 8 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 8 is in the same unit as the dependent variable ΔLOP_m. The evidence in Table 8 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 potentially related to limits to arbitrage and/or forex intervention activity, e.g., ranging between 2.6 bps ($t = 2.33$; Panel B) and 2.9 bps ($t = 2.57$; Panel A) in correspondence with a one standard deviation shock to ΔI_m.[43]

[43] In unreported analysis, similar inference can be drawn from augmenting Eq. (14) with additional control variables related to marketwide financial distress or dislocations (as a potential source of relative mispricings;

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.[44] 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. However, the total effect of ADRP illiquidity on the relationship between forex interventions and ADRP violations is both positive and large, e.g., about 20% of the baseline scaled estimates of β_0 in Table 8.

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 $\Delta N_m^z(gov) > 0$) is accompanied by nearly four 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 9.6 bps ($= 3.615 + 6.003$, in Panel B of Table 8) versus an unconditional average increase of 2.6 bps.[45]

Finally, scaled estimates of the policy uncertainty coefficient β_{SDI} in Eq. (14) are always positive, statistically significant, and almost as large as (or larger than) the corresponding coefficient for the intensity of forex intervention β_0. For example, Panel B of Table 8 shows that a one

e.g., see Hu et al.; 2013; Pasquariello, 2014; and references therein), when available: Monthly U.S. and world stock market returns, as well as monthly changes in VIX (over 1990-2009), Chauvet and Piger's (2008) real-time U.S. recession probability, slope of U.S. Treasury yield curve, U.S. Treasury bond yield volatility, "TED" spread (between LIBOR and Treasury yields; over 1982-2009), U.S. "default" spread (between Baa and Aaa corporate bond yields), Federal Reserve Bank of St. Louis' "financial stress" index (over 1994-2009), and Edison and Warnock's (2003) proxy for intensity of capital controls in emerging markets (over 1989-2006).

[44] However, we find no evidence of nonlinearity in this relationship: $\beta_{ILQ}^2 \approx 0$ in Panels A and B of Table 8.

[45] Estimates of β_{DSP} in Eq. (14) are instead always negative, small, and statistically insignificant, suggesting that the positive direct effect of information heterogeneity on the extent of LOP violations (i.e., even in absence of government intervention) postulated in Remark 1 may be subsumed by changes in other market conditions in Eq. (14).

standard deviation increase in forex policy uncertainty in a month ($\Delta STD\left(N_m^z\left(gov\right)\right) > 0$) is accompanied by between 14% and 17% 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 ($\Delta N_m^z\left(gov\right) = 0$). Estimates of the interaction coefficient β_0^{SDI} are, however, negative, suggesting that the positive impact of historical intervention volatility on ADRP violations ($\beta_{SDI} > 0$) is weaker in months when intervention policy uncertainty may have been partially resolved by further intervention activity.[46] Nonetheless, the total joint effect of greater intervention intensity and policy uncertainty on ADRP violations remains positive and (between 6% and 31%) larger than the corresponding baseline scaled estimates of β_0 (in line with H6).

In short, the evidence in Table 8 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 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, heterogeneously informed 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 (or linearly related)

[46] Table 8 also suggests caution when including the cross-product of ΔI_m and $\Delta STD\left(I_m\right)$ in Eq. (14) since both estimates of their direct effect on ΔLOP_m (β_0 and β_{SDI}) are positive and statistically significant, $\Delta STD\left(I_m\right)$ is a continuous function of ΔI_m (see Figure 3c), and ΔI_m itself is often enough equal to zero (or close to zero; e.g., see Figure 2) to cloud the interpretation of β_0^{SDI} relative to H6. In unreported analysis, our inference from Table 8 is unaffected by this inclusion.

assets (i.e., equilibrium LOP violations). We then introduce a stylized government pursuing a non-public, partially informative price target for only one of the two assets and show that (given existing limits to arbitrage) its policy-motivated, camouflaged trading activity lowers those assets' equilibrium price correlation (i.e., increases equilibrium LOP violations) by effectively clouding dealers' inference about the targeted asset's fundamentals — 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 further find these effects to be *i)* unaffected by changes in market conditions typically associated with level and dynamics of LOP violations, limits to arbitrage, and/or forex intervention; as well as stronger *ii)* for ADRs not only from emerging (and lower-quality) markets but also from developed (and higher-quality) ones, and in correspondence with *iii)* deteriorating aggregate liquidity in the ADR arbitrage-linked markets; *iv)* greater dispersion of U.S. macroeconomic forecasts; *v)* and greater uncertainty about official 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

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

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

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

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 $p_{1,2}$,

$corr\left(p_{1,1},p_{1,2}\right)=\frac{covar(p_{1,1},p_{1,2})}{\sqrt{var(p_{1,1})var(p_{1,2})}}$, so yielding Eq. (3). Under integrated market-making, MMs observe the aggregate order flow in both assets 1 and 2; semi-strong market efficiency then implies that $p_{1,1}=E\left(v|\omega_1,\omega_2\right)=p_{1,2}$ (e.g., Caballé and Krishnan, 1994, p. 697), i.e., that $corr\left(p_{1,1},p_{1,2}\right)=1$. Under (less-than-) perfectly correlated noise trading, $\sigma_{zz}=\sigma_z^2$ ($\sigma_{zz}<\sigma_z^2$); Eq. (3) then implies that $corr\left(p_{1,1},p_{1,2}\right)=1$ ($corr\left(p_{1,1},p_{1,2}\right)<1$). ■

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): $p_{1,i}=A_{0,i}+A_{1,i}\omega_i$, $x_i\left(m\right)=B_{0,i}+B_{1,i}\delta_v\left(m\right)$, where $A_{1,i}>0$ and $i=\{1,2\}$, and $x_1\left(gov\right)=C_{0,1}+C_{1,1}\delta_v\left(gov\right)+C_{1,2}\delta_T\left(gov\right)$. Since $E\left[\delta_v\left(gov\right)|\delta_v\left(m\right)\right]=\psi\delta_v\left(m\right)$ and $E\left[\delta_T\left(gov\right)|\delta_v\left(m\right)\right]=\delta_v\left(m\right)$ under the parametrization in Section 2.2, these conjectures imply that:

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

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:

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

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

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

The government's optimal intervention strategy is the one minimizing its expected loss function of Eq. (4), i.e., $E\left[L\left(gov\right)|\delta_v\left(gov\right),\delta_T\left(gov\right)\right]$, 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 $\arg\min_{x_1(gov)}E\left[L\left(gov\right)|\delta_v\left(gov\right),\delta_T\left(gov\right)\right]$ is equal to

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

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

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

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

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

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

$$
\begin{aligned}
var(\omega_{1}) &= MB_{1,1}^{2}\rho\sigma_{v}^{2}\left[1 + (M-1)\rho\right] + + C_{1,1}^{2}\psi\sigma_{v}^{2} + C_{1,2}^{2}\frac{\sigma_{v}^{2}}{\mu\psi} \qquad \text{(A-23)} \\
& \quad +2MB_{1,1}C_{1,1}\psi\rho\sigma_{v}^{2} + 2MB_{1,1}C_{1,2}\rho\sigma_{v}^{2} + 2C_{1,1}C_{1,2}\sigma_{v}^{2} + \sigma_{z}^{2}, \\
var(\omega_{2}) &= MB_{1,2}^{2}\rho\sigma_{v}^{2}\left[1 + (M-1)\rho\right] + \sigma_{z}^{2}, \qquad \text{(A-24)}
\end{aligned}
$$

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

$$
\begin{aligned}
p_{1,1} &= p_{0} + \frac{\left(MB_{1,1}\rho + C_{1,1}\psi + C_{1,2}\right)\sigma_{v}^{2}}{\sigma_{z}^{2} + \sigma_{v}^{2}\left\{MB_{1,1}^{2}\rho\left[1 + (M-1)\rho\right] + D_{1} + E_{1}\right\}}\left(\omega_{1} - MB_{0,1} - C_{0,1}\right), \qquad \text{(A-25)} \\
p_{1,2} &= E(v|\omega_{i}) = p_{0} + \frac{MB_{1,2}\rho\sigma_{v}^{2}}{MB_{1,2}^{2}\rho\sigma_{v}^{2}\left[1 + (M-1)\rho\right] + \sigma_{z}^{2}}\left(\omega_{2} - MB_{0,2}\right). \qquad \text{(A-26)}
\end{aligned}
$$

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). ■

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 $var\left(\omega^*_1\right) = \sigma^2_z + \sigma^2_v \left\{M\rho B^{*2}_{1,1}\left[1 + (M-1)\rho\right] + D^*_1 + E^*_1\right\}$, $var\left(\omega^*_2\right) = \sigma^2_z\left[2 + (M-1)\rho\right]$, 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). ■

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Table 1. ADRP Violations: Summary Statistics

This table reports the composition of our sample of ADRs by the country or most recent currency area of listing (i.e., most recent currency of denomination) of the underlying foreign stocks, as well as summary statistics on the (country-level and marketwide) measures of their available, filtered relative mispricings and illiquidity used in the analysis. Those measures are constructed by first obtaining all Level II and III ADRs listed on the NYSE, AMEX, or NASDAQ from the complete Datastream sample of U.S. cross-listings between January 1, 1973 and December 31, 2009; N_i is the resulting number of ADRs in each grouping. The "Other" grouping includes Colombia, Denmark, Egypt, Hungary, Israel, New Zealand, Norway, Philippines, Singapore, Sweden, Taiwan, Thailand, and Venezuela. $ADRP_m$ and $ADRP^z_m$ are then computed as monthly averages of daily equal-weighted means of available, filtered actual (in basis points [bps], i.e., multiplied by 10,000) and (historically) standardized absolute log violations of the ADR parity (ADRP) described in Section 3 (Eqs. (11) and (12)); $\Delta ADRP_m = ADRP_m - ADRP_{m-1}$ and $\Delta ADRP^z_m = ADRP^z_m - ADRP^z_{m-1}$. $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 3.2.1 as the 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. For each grouping, we report the number of available months (N), as well as the mean and standard deviation for each measure of ADRP violations and illiquidity over the analyzed sample period 1980-2009.

			ADRP violations								ADRP illiquidity	
			$ADRP_m$		$ADRP^z_m$		$\Delta ADRP_m$		$\Delta ADRP^z_m$		$ILLIQ_m$	
Country (Currency)	N_i	N	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Australia (AUD)	30	269	217.26	112.57	-0.23	0.32	-3.39	53.91	-0.002	0.280	11.0%	9.0%
Argentina (ARS)	9	198	187.70	114.41	0.40	1.15	0.44	81.45	-0.001	0.840	19.2%	12.5%
Brazil (BRL)	23	178	165.06	104.49	-0.08	0.36	-1.60	40.57	0.003	0.307	9.1%	7.2%
Canada (CAD)	67	360	103.13	46.08	-0.18	0.27	-0.08	26.14	0.000	0.189	13.4%	7.7%
Chile (CLP)	5	168	185.16	67.26	-0.33	0.38	0.41	50.94	-0.006	0.338	14.9%	7.1%
Euro area (EUR)	58	287	352.29	287.90	-0.41	0.64	-0.87	60.98	-0.001	0.421	6.5%	3.8%
Hong Kong (HKD)	54	198	166.78	65.22	0.07	0.33	-0.69	40.03	-0.002	0.282	15.0%	5.9%
India (INR)	10	143	248.34	141.33	-0.07	0.38	-0.42	64.99	-0.004	0.359	4.7%	3.1%
Indonesia (IDR)	5	168	181.19	79.67	-0.04	0.48	-0.93	67.90	-0.010	0.408	9.7%	4.9%
Japan (JPY)	24	360	149.34	75.33	-0.04	0.42	-0.31	29.46	-0.001	0.289	9.3%	3.8%
Mexico (MXN)	9	198	275.74	78.37	-0.16	0.35	-0.24	54.34	-0.005	0.285	16.6%	5.4%
Russia (RUB)	7	140	189.70	114.27	-0.05	0.46	-1.66	86.89	-0.004	0.400	10.0%	8.7%
S. Africa (ZAR)	14	231	324.28	185.28	0.06	0.63	-0.77	66.61	0.000	0.297	11.2%	5.9%
S. Korea (KRW)	8	141	328.73	187.75	-0.10	0.44	-0.86	74.53	-0.004	0.285	6.9%	4.4%
Switzerland (CHF)	4	116	253.67	141.83	-0.55	0.39	-1.98	37.30	-0.015	0.261	4.1%	2.6%
Turkey (TRY)	7	74	227.50	174.99	0.21	0.99	-1.30	104.33	-0.005	0.619	7.8%	4.0%
U.K. (GBP)	43	360	200.59	73.82	-0.21	0.31	-0.48	34.07	0.000	0.211	4.7%	2.6%
Other (Other)	33	250	261.15	112.06	-0.18	0.40	-0.26	85.10	0.005	0.371	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 January 1, 1980 and December 31, 2009, compiled by the Federal Reserve Bank of St. Louis on its Federal Reserve Economic Data (FRED) Web site (http://research.stlouisfed.org/fred2/categories/32145). For each country for which intervention data is available, we list in Panel A the foreign exchange involved, the number of months in the sample when official trades were executed (N), as well as the mean and standard deviation of their absolute total monthly amounts (in millions of USD). In the case of Italy (Germany) and the United States, the database reports official trades in the domestic currency relative to unspecified "other" currencies (in the European Monetary System [EMS]). This table also reports summary statistics for $N_m\left(gov\right)$, the number of nonzero government intervention-exchange rate 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 Country and Foreign Exchange					
			Absolute Amount ($1M)		
Country	Foreign Exchange		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	DEM	USD	2	70	78
Switzerland	JPY	USD	6	98	73
Turkey	TRL, TRY	USD	16	1,728	1,460
United States	USD	DEM, EUR	76	626	641
United States	USD	JPY	60	537	755
United States	USD	Other	12	90	88
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 ADRP Violations and Forex Intervention

This table reports OLS estimates (and bracketed t-statistics) of the 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 $N^z_m\,(gov)$ defined in Section 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta^0_1 = \beta_1 + \beta_0$; and $\beta^{-1}_1 = \beta_1 + \beta_0 + \beta_{-1}$. In Panel A, Eq. (13) is estimated for (absolute and normalized) ADR parity violations either at the monthly frequency ($LOP_m = ADRP_m$ or $ADRP^z_m$, as defined in Section 3.2.1) or at the daily frequency ($LOP_t = ADRP_t$ or $ADRP^z_t$ and $I_t = N_t\,(gov)$ or $N^z_t\,(gov)$) over the sample period 1980-2009. In Panel B, Eq. (13) is estimated for either ADR parity violations or CIRP violations ($LOP_m = CIRP_m$ or $CIRP^z_m$, as defined in Section 3.3) 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^0_1 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% level, respectively. Estimates of the intercept α are not reported.

	$I = N\,(gov)$						$I = N^z\,(gov)$						
	β_1	β_0	β_{-1}	β^0_1	β^{-1}_1	R^2	β_1	β_0	β_{-1}	β^0_1	β^{-1}_1	R^2	N
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)		
$\Delta ADRP^z_m$	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)		
$\Delta ADRP^z_t$	-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)		
$\Delta ADRP^z_m$	-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)		
$\Delta CIRP^z_m$	-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 Country-Level Cross-Section of ADRP Violations and Forex Intervention

This table reports OLS estimates (and bracketed t-statistics) of the 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 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, 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 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 3.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $(\beta_1, \beta_0, \beta_{-1})$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively. Estimates of the intercept α are not reported.

Table 4. (*Continued*)

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

Table 5. Country-Level ADRP Violations and Currency-Matched Forex Intervention

This table reports OLS estimates (and bracketed t-statistics) of the 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 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Eq. (13) is estimated separately, at the monthly frequency, for each of the five countries listed in Section 3.2.2 (Australia, Euro area, Japan, Mexico, and Turkey) for which both ADRP violations (see Table 1) and currency-matched interventions (i.e., involving the currency of denomination of the underlying foreign stocks; see Table 2) are contemporaneously available over the sample period 1980-2009. In Panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in Panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 3.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of $(\beta_1, \beta_0, \beta_{-1})$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively. Estimates of the intercept α are not reported.

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

Table 6. The Illiquidity-Level Cross-Section of ADRP Violations and Forex Intervention

This table reports OLS estimates (and bracketed t-statistics) of the 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 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Eq. (13) is estimated separately, at the monthly frequency, for each tercile of ADRs sorted by their samplewide ADRP illiquidity $ILLIQ_m$ (as defined in Section 3.2.1, from the lowest to the highest), over the sample period 1980-2009. In Panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in Panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 3.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of (β_1, β_0, β_{-1}). A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively. Estimates of the intercept α are not reported.

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

Table 7. The LOP Violation-Level Cross-Section of ADRP Violations and Forex Intervention

This table reports OLS estimates (and bracketed t-statistics) of the 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 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $\beta_1^0 = \beta_1 + \beta_0$; and $\beta_1^{-1} = \beta_1 + \beta_0 + \beta_{-1}$. Specifically, Eq. (13) is estimated separately, at the monthly frequency, for each tercile of ADRs sorted by their samplewide ADRP violations $ADRP_m$ (as defined in Section 3.2.1, from the lowest to the highest), over the sample period 1980-2009 (except for the High tercile, populated only over 1986-2009). In Panel A, $LOP_m = ADRP_m$ (absolute ADRP violations); in Panel B, $LOP_m = ADRP_m^z$ (normalized ADRP violations), as defined in Section 3.2.1. N is the number of observations; R^2 is the coefficient of determination; t-statistics for the cumulative effects β_1^0 and β_1^{-1} are computed from the asymptotic covariance matrix of (β_1, β_0, β_{-1}). A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively. Estimates of the intercept α are not reported.

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

Table 8. Marketwide ADRP Violations: Forex Intervention and Market Conditions

This table reports *scaled* OLS estimates (and bracketed t-statistics) of the regression model of Eq. (14):

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

where $LOP_t = ADRP_m$ or $ADRP_m^z$ are the absolute or normalized ADR parity violations in month m (as defined in Section 3.2.1); $\Delta LOP_m = LOP_m - LOP_{m-1}$; I_m is the measure of actual or normalized government intervention $N_m\left(gov\right)$ (in Panel A) or $N_m^z\left(gov\right)$ (in Panel B) defined in Section 3.2.2; $\Delta I_m = I_m - I_{m-1}$; $ILLIQ_m$ is a measure of ADRP illiquidity, defined in Section 3.2.1 as the simple average (in percentage) of the fraction of ADRs in LOP_m whose underlying foreign stock, ADR, or exchange rate experience zero returns; $\Delta DISP_m = \Delta DISP_q$ for each month m within quarter q; $DISP_q$ is a measure of information heterogeneity, defined in Section 3.5 as the simple average of the standardized dispersion of analyst forecasts of six U.S. macroeconomic variables; $STD\left(I_m\right)$ is a measure of forex intervention policy uncertainty, defined in Section 3.5 as the historical volatility of I_m over a three-year rolling window; and X_m is a matrix of control variables (defined in 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 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% level, respectively. Estimates of the intercept α and control coefficients Γ are not reported.

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

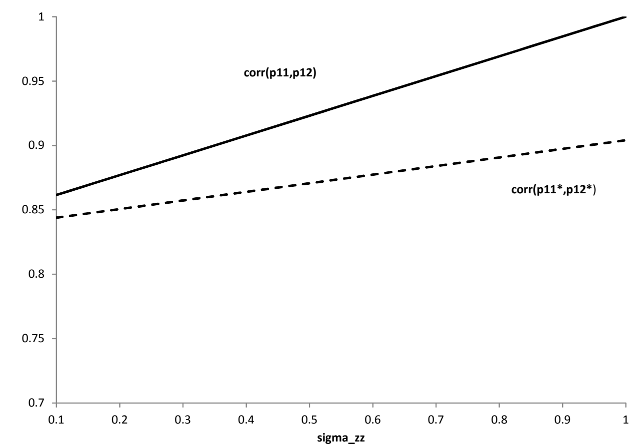
Table 8. (*Continued*)

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

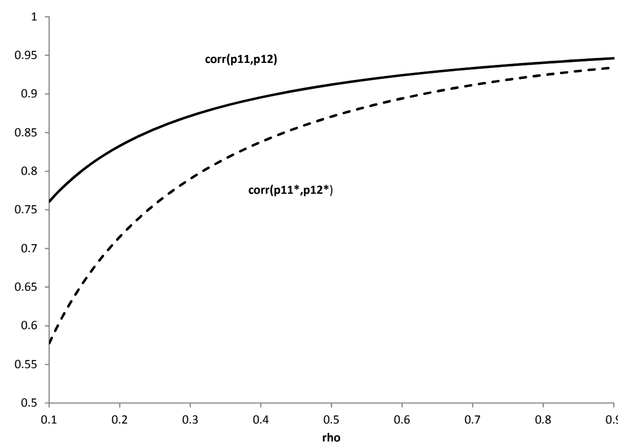
Figure 1. Law of One Price Violations

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 $M = 10$.

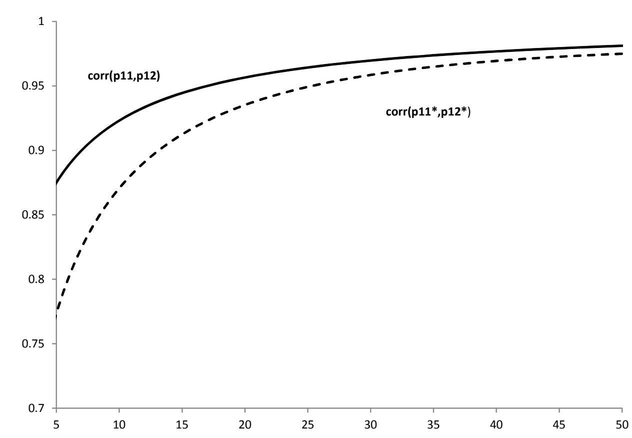
a) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus σ_{zz}



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

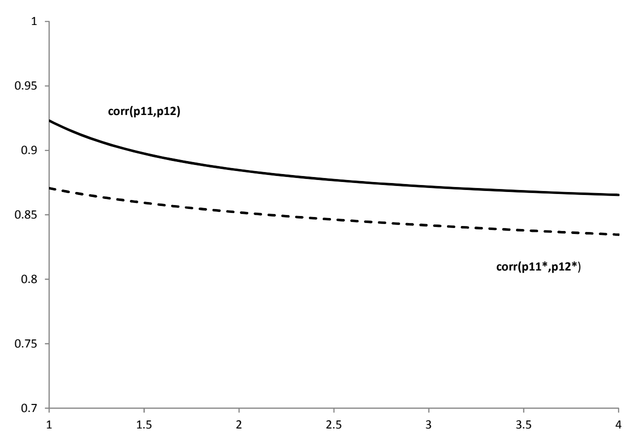
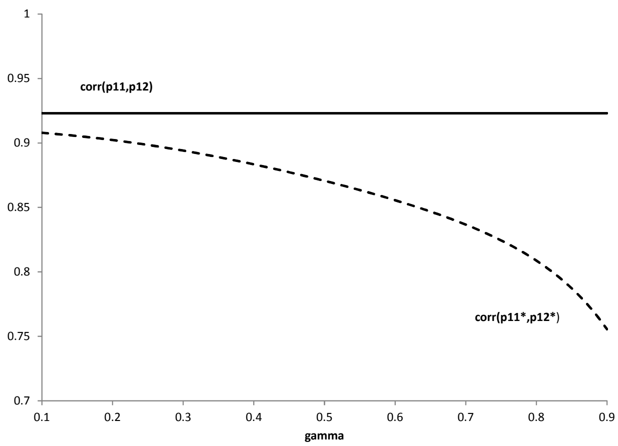
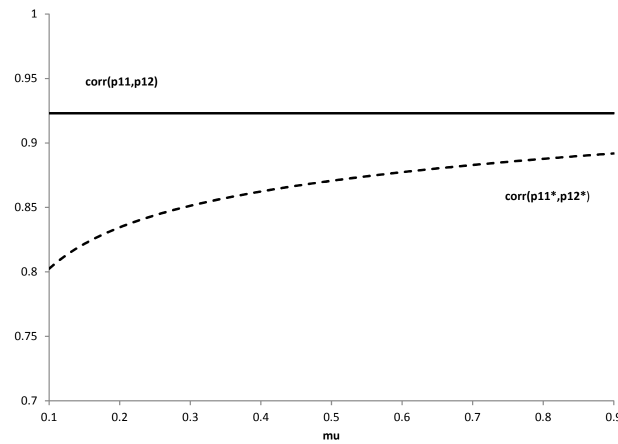


Figure 1 (*Continued*).

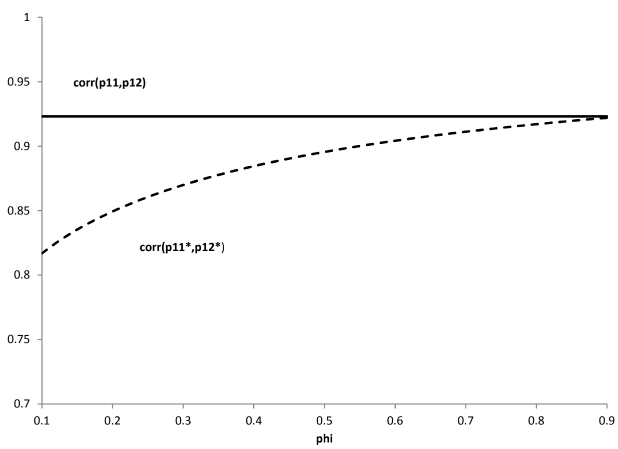
e) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus γ



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

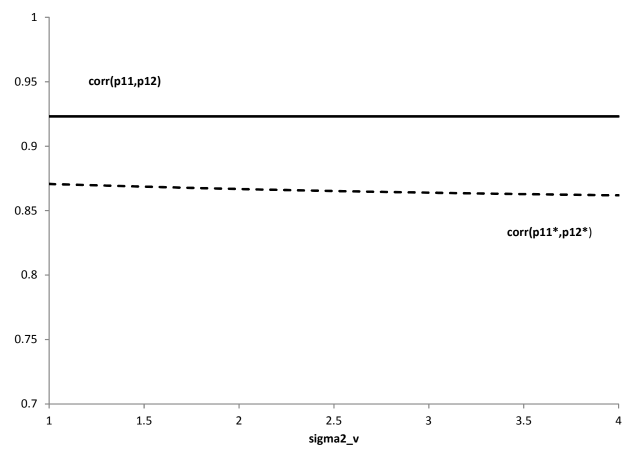
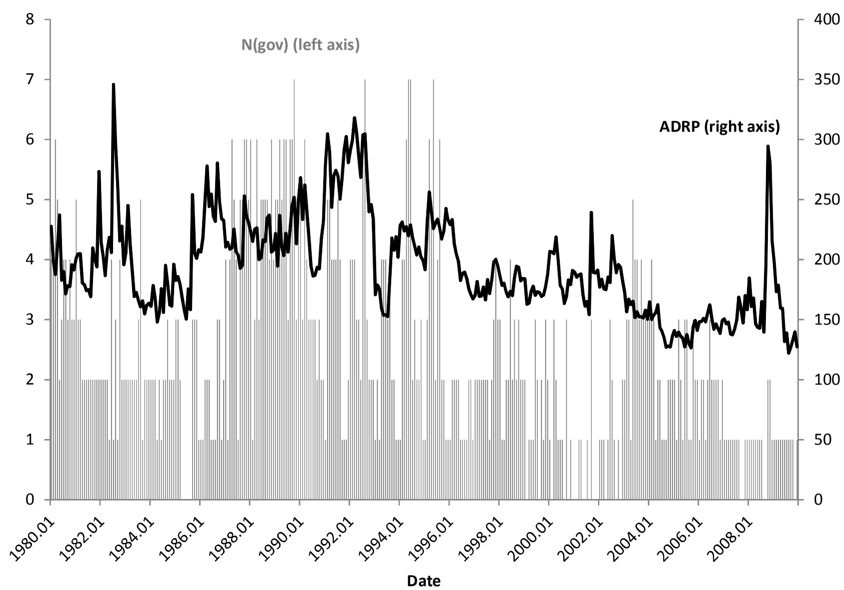


Figure 2. ADR Parity Violations and Forex Interventions

This figure plots the aggregate measures of LOP violations in the ADR market defined in Section 3.2.1 — the monthly averages of daily equal-weighted means of available observed ($ADRP_m$, Figure 2a, right axis, solid line [in basis points [bps], i.e., multiplied by 10,000]) and standardized ($ADRP^z_m$, 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 3.2.2 — 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 ($N^z_m\,(gov)$, Figure 2b, left axis, dashed line) — over the sample period 1980-2009.

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



b) $ADRP^z_m$, $N^z_m\,(gov)$

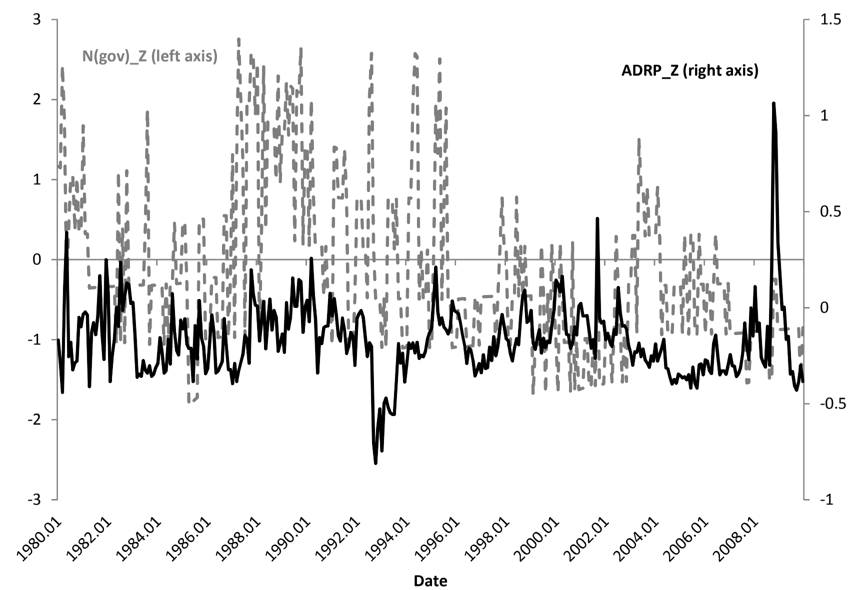
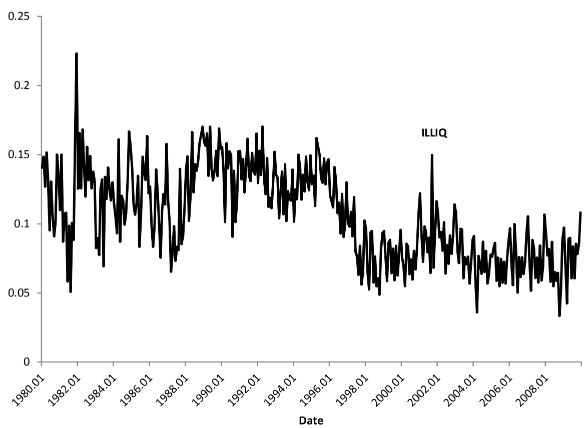


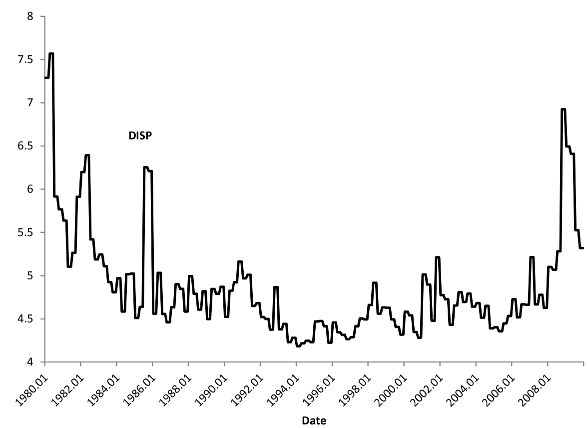
Figure 3. Proxies for Market Conditions

This figure plots the measures of market conditions described in Section 3.5 — $ILLIQ_m$ (Figure 3a, left axis, solid line), a measure of ADRP illiquidity defined in Section 3.2.1 as the simple average (in percentage) of the fraction of ADRs in LOP_m whose underlying foreign stock, ADR, or exchange rate experience zero returns; $DISP_m = DISP_q$ (for each $m \in q$; Figure 3b, left axis, solid line), a measure of information heterogeneity defined in Section 3.5 as the simple average of the standardized dispersion of analyst forecasts of six U.S. macroeconomic variables; and $STD\left(I_m\right)$, a measure of forex intervention policy uncertainty defined in Section 3.5 as the historical volatility (over a three-year rolling window) of either $I_m = N_m\left(gov\right)$ (Figure 3c, left axis, solid line) or $I_m = N_m^z\left(gov\right)$ (Figure 3c, right axis, dashed line) — over the sample period 1980-2009.

a) $ILLIQ_m$



b) $DISP_m$



c) $STD\left(N_m\left(gov\right)\right)$, $STD\left(N_m^z\left(gov\right)\right)$