Government Intervention and Arbitrage

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Abstract

We model and document the 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 market-order trading and segmented dealership generates equilibrium price differentials among fundamentally identical assets by further clouding dealers' inference about the targeted asset's fundamentals from its order flow — especially when markets are illiquid, speculators are heterogeneously informed, or policy uncertainty is high, but non-monotonically in extant LOP violations. We find supportive evidence in a sample of American Depositary Receipts and other cross-listings traded in the major U.S. exchanges and currency interventions by developed and emerging countries between 1980 and 2009.

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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. Accordingly, a vibrant literature reports evidence of LOP violations in several financial markets, often explains their occurrence and intensity with unspecified behavioral — or less often, and anecdotally, with rational — demand shocks unrelated to asset fundamentals, and attributes their persistence to various limits to arbitrageurs' efforts to fully absorb those shocks (e.g., Shleifer, 2000; Lamont and Thaler, 2003; Gromb and Vayanos, 2010). We contribute to this understanding by explicitly investigating the role of a specific and empirically observable form of rational demand shocks — *direct* government intervention — for the emergence of LOP violations, ceteris paribus for limits to arbitrage.

Central banks and governmental agencies ("governments" for brevity) routinely trade securities in pursuit of economic and financial policy.[1] More recently, both the scale and frequency of this activity have soared in the aftermath of the financial crisis of 2008-2009. The pursuit of policy via "official" trading in financial assets has long been found both to be effective and to yield welfare gains, e.g., by achieving "intermediate" monetary targets (Rogoff, 1985; Corrigan and Davis, 1990; Edison, 1993; Sarno and Taylor, 2001; Hassan et al., 2015). We establish and test the novel notion that such form of government intervention may also induce LOP violations and so *worsen* financial market quality. Our analysis indicates that these price distortions in the

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

affected markets may be non-trivial — hence may have non-trivial effects on their allocational and risk-sharing roles. The insight that direct government intervention in financial markets can create *negative* externalities on their quality has important implications for the broader debate on financial stability, optimal financial regulation, and unconventional policy-making (e.g., Acharya and Richardson, 2009; Hanson et al., 2011; Bernanke, 2012).[2]

We illustrate this notion in a standard, parsimonious one-period model of strategic multi-asset trading based on Kyle (1985) and Chowdhry and Nanda (1991). In the economy's basic setting, two fundamentally identical, or linearly related risky assets — labeled 1 and 2 — are exchanged by three types of risk-neutral market participants: a discrete number of heterogeneously informed multi-asset speculators, single-asset noise traders, and competitive market-makers. If the dealership sector is segmented, market-makers in each asset do not observe order flow in the other asset (e.g., Subrahmanyam, 1991a; Baruch et al., 2007; Boulatov et al., 2013). Then 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 semi-strong efficiency in either market and informed — i.e., perfectly correlated — speculation across both (e.g., as in Chowdhry and Nanda, 1991). 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, speculative market-order trading, and liquidity demand differentials in the model serve as a reduced-form representation of existing forces behind LOP violations and impediments to arbitrage activity in financial markets.

In this setting, we introduce a stylized government submitting camouflaged market orders (e.g., Vitale, 1999; Naranjo and Nimalendran, 2000) in only one of the two assets, asset 1,

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

in pursuit of policy — a *non-public*, *partially informative* price target (e.g., Bhattacharya and Weller, 1997). We then show that such government intervention *increases* equilibrium LOP violations — i.e., *lowers* the equilibrium price correlation of assets 1 and 2 — ceteris paribus for those 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 further clouds the inference of the market-makers about its fundamentals when setting the equilibrium price of that asset from its order flow. Consistently, the magnitude of this effect is increasing in government policy uncertainty and generally, yet not uniformly decreasing in pre-intervention market quality. In particular, intervention-induced LOP violations are larger when market liquidity is low, e.g., in the presence of more heterogeneously informed speculators or less intense noise trading — since in those circumstances official trading has a greater impact on the equilibrium price of asset 1. However, intervention-induced LOP violations are also non-monotonically related to extant such violations, e.g., are larger in the presence of fewer speculators yet smaller in the presence of less correlated noise trading — since in the former circumstances official trading has a greater impact on the already low equilibrium price correlation of assets 1 and 2 than in the latter.

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 U.S. market for American Depositary Receipts and other cross-listed stocks ("ADRs" for brevity). The forex market is one of the largest, most liquid financial markets in the world (e.g., Bank for International Settlements, 2016). The major U.S. exchanges (the "ADR market") are the most important venue for international cross-listings (e.g., Karolyi, 1998, 2006). These markets also serve as a setting that is as close as possible in spirit to the assumptions 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 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 percentage ADRP violations are large — e.g., 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 measures of the actual and historically abnormal intensity of ADRP violations are increasing in measures of the actual and historically abnormal intensity of forex interventions. This relationship is both statistically and (plausibly) economically significant. For instance, a one standard deviation increase in forex intervention activity in a month is accompanied by a material average cumulative increase in absolute ADRP violations of up to 10 bps — i.e., of 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), as well as to removing from the analysis ADRs from emerging countries when affected by the imposition of capital controls (e.g., Edison and Warnock, 2003; Auguste et al., 2006). Importantly, those same official currency trades are *not* accompanied by larger LOP violations in the much more closely integrated currency and international money markets in many respects, including dealership (e.g., McKinnon, 1977; Dufey and Giddy, 1994; Bekaert and Hodrick, 2012) — i.e., are unrelated to violations of the covered interest rate parity (CIRP), an arbitrage relationship between interest rates and spot and forward exchange rates commonly used to proxy for currency market quality (e.g., Frenkel and Levich, 1975, 1977; Coffey et al., 2009; Griffoli and Ranaldo, 2011). This finding not only is consistent with 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 indicates that poor, deteriorating price formation in the ADR arbitrage-linked markets magnify ADRP violations both directly and through its possibly non-monotonic 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 more than three times larger when in correspondence with high information heterogeneity among market participants.

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

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, in Section 2.1, a standard noisy rational expectations equilibrium (REE) model of multi-asset informed trading and derive its equilibrium in closed-form. The model, based on Kyle (1985), is a straightforward extension of Chowdhry and Nanda (1991) to *imperfectly competitive* speculation and *non-discretionary* liquidity trading that allows us to represent, in reduced form, extant sources of LOP violations in the literature on limits to arbitrage. We then contribute to this literature, in Section 2.2, by introducing in this setting a stylized government and considering 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 Chowdhry and Nanda (1991). The model's standard framework has often been used to study price formation in many financial markets and for many asset classes (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 (e.g., Foucault and Gehrig, 2008; Pasquariello and Vega, 2009), as well as non-discretionary 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.[3]

At date $t = 1$, speculators and liquidity traders submit their orders in assets 1 and 2 to the MMs before their equilibrium prices $p_{1,1}$ and $p_{1,2}$ have been set. We define the market order of each speculator m in each asset i as $x_i(m)$, such that her profit is given by $\pi(m) = (v - p_{1,1})x_1(m) + (v - p_{1,2})x_2(m)$. Liquidity traders generate random, normally distributed demands z_1 and z_2, with mean zero, variance σ_z^2, and covariance σ_{zz}, where $\sigma_{zz} \in (0, \sigma_z^2]$.[4]

[3]Without loss of generality, the distributional assumptions for $S_v(m)$ also imply that $S_v(m) = S_v(j) = v$ in the limiting case where $\rho = 1$ — i.e., private information *homogeneity*. 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.

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

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, 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 Chowdhry and Nanda (1991), Subrahmanyam (1991a), Baruch et al. (2007), Pasquariello and Vega (2009), 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*

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

[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, or by allowing for more than one round of trading and cross-market observability over time (as in Chowdhry and Nanda, 1991) — would significantly complicate the analysis without qualitatively altering its implications. Without loss of generality, the distributional assumptions for z_i also imply that if $\sigma_{zz} = \sigma_z^2$ then $z_1 = z_2$.

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

In this class of models, MMs in each market i learn about the traded asset i's terminal payoff from its order flow ω_i; hence, each imperfectly competitive, risk-neutral speculator trades cautiously in both assets ($|x_i(m)| < \infty$, Eq. (2)) to protect the information advantage stemming from her private signal $S_v(m)$. 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 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 of them, perceiving to have greater monopoly power on her private information, trades more cautiously with it (lower $|x_i(m)|$); *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 aggregate trading behavior (lower $\left|\sum_{m=1}^{M} x_i(m)\right|$).[7]

2.1.2 LOP violations

A well-established literature defines and measures LOP violations either as nonzero price differentials or as less-than-perfect price correlations among identical assets (e.g., Karolyi, 1998, 2006; Auguste et al., 2006; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Gromb and Vayanos, 2010; Griffoli and Ranaldo, 2011). As we further discuss in Section 3.1.1, 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 equi-

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

librium — by at least partly offsetting informed, i.e., perfectly correlated trading in those assets ($x_1(m) = x_2(m)$). Of course, this may occur only with segmented market-making allowing for $E(v|\omega_1) \neq E(v|\omega_2)$. If MMs observe order flow in both assets — i.e., with perfectly integrated market-making — no price differential can arise in equilibrium since semi-strong market efficiency in Condition 2 implies that $p_{1,1} = E(v|\omega_1, \omega_2) = p_{1,2}$. We formalize these observations in Corollary 1 by measuring LOP violations in the economy with the unconditional correlation of the equilibrium prices of assets 1 and 2, $corr(p_{1,1}, p_{1,2})$, e.g., as in Gromb and Vayanos (2010).

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

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

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

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 (e.g., as in Chowdhry and Nanda, 1991). 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, $corr(p_{1,1}, p_{1,2})$ is greater the fewer are speculators in the economy (lower M in Figure 1b) or the more dispersed is their private information (lower ρ in Figure 1c), since the more cautious is their (aggregate or individual) 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

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

liquidity demand differentials, despite its lesser impact (via lower λ) on equilibrium prices. See also Figure IA-1a of the Internet Appendix to this study.

Corollary 2 *LOP violations are increasing in speculators' information heterogeneity and intensity of noise trading, decreasing in the number of speculators and covariance of noise trading.*

LOP violations do not necessarily imply riskless arbitrage opportunities. While the former occur whenever nonzero price differences between two assets with identical liquidation value arise, the latter require that those differences be exploitable with no risk. In our setting, only speculators can and do trade strategically and simultaneously in both assets 1 and 2 (see Eq. (2)). Hence, only they can attempt to profit from any price difference they anticipate to observe. 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, speculators cannot place limit orders and, in the noisy REE of Proposition 1, neither observe nor can accurately predict the market-clearing prices of assets 1 and 2 when submitting their market orders $x_i(m)$. Thus, there is no feasible riskless arbitrage opportunity in the economy.[9]

Segmentation in market-making, speculative market-order trading, 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

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

directly trading in those assets in the marketplace, as well as their often conflicting microstructure externalities. 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), Brunetti et al. (2011), D'Amico and King (2013), Pasquariello et al. (2014), and Pelizzon et al. (2016) for the money and bond markets, and Sojli and Tham (2010) and Dyck and Morse (2011) for the stock markets.[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.

The literature identifies several recurring features of direct 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): *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 observed ex-post *effectiveness* of governments at pursuing their price targets is often attributed to that actual or perceived information advantage; *v)* those price targets *may be related* to governments' fundamental information; and *vi)* governments are sensitive to the potential *costs* of their interventions. 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

[10] However, direct government intervention in stock markets is currently less common, and evidence of this activity remains largely anecdotal. E.g., see media coverage of the actions by the Chinese government in support of the plunging Shanghai Composite Index in 2015 (at http://www.wsj.com/articles/chinas-national-team-plays-defense-when-stocks-decline-1452686207). 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).

$cov\left[S_v(m), S_v(gov)\right] = cov\left[v, S_v(gov)\right] = \sigma_v^2$, as for speculators' private signals $S_v(m)$ in Section 2.1. Accordingly, we define the government's information endowment about v as $\delta_v(gov) \equiv E\left[v|S_v(gov)\right] - p_0 = \psi\left[S_v(gov) - p_0\right]$.

Second, the government is given a non-public target for the price of asset 1, $p_{1,1}^T$, drawn from a normal distribution with mean $\overline{p}_{1,1}^T$ and variance σ_T^2. The government's information endowment about $p_{1,1}^T$ is then $\delta_T(gov) \equiv p_{1,1}^T - \overline{p}_{1,1}^T$.[11] This policy target is some unspecified function of $S_v(gov)$ such that $\sigma_T^2 = \frac{1}{\mu}\sigma_{gov}^2 = \frac{1}{\mu\psi}\sigma_v^2$, $cov\left[p_{1,1}^T, S_v(gov)\right] = \sigma_{gov}^2$, and $cov\left[S_v(m), p_{1,1}^T\right] = cov\left(v, p_{1,1}^T\right) = \sigma_v^2$. 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 government interventions in currency markets either "chase the trend" (if μ is high) to reinforce market participants' beliefs about fundamentals as reflected by observed exchange rate dynamics (e.g., Edison, 1993; Sarno and Taylor, 2001; Engel, 2014) or more often "lean against the wind" (if μ is low) to resist those beliefs and dynamics (e.g., Lewis, 1995; Kaminsky and Lewis, 1996; Bonser-Neal et al., 1998; Pasquariello, 2007b).[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:

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

where $\gamma \in (0,1)$. This specification is based on Stein (1989), Bhattacharya and Weller (1997), Vitale (1999), and Pasquariello et al. (2014). The first term in Eq. (4) is meant to capture the government's attempts to achieve its policy objectives for asset 1 by trading to minimize the squared distance between asset 1's equilibrium price $p_{1,1}$ and the target $p_{1,1}^T$. The second term in

[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.

[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.

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. Imposing that $\gamma < 1$ then ensures that the government does not implausibly trade unlimited amounts of asset 1 in pursuit of $p_{1,1}^{T}$. We further discuss this feature of Eq. (4) in Section 2.2.1.

At date $t = 1$, MMs in each asset i clear their market after observing its 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 each asset i attempt to learn from ω_i about that asset's terminal payoff v when setting its equilibrium price $p_{1,i}$, as in Section 2.1. However, each speculator now uses her private signal $S_v(m)$ to learn not only about v and the other speculators' private signals but also about the government's intervention policy in asset 1 before choosing her optimal trading strategy $x_i(m)$ in both assets 1 and 2. In addition, the government uses its private information $S_v(gov)$ to learn about what speculators may know about v and trade in asset 1 when choosing its optimal intervention strategy $x_1(gov)$. Proposition 2 solves for the ensuing unique linear Bayesian Nash equilibrium.

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

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

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

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

$$x_1^{*}(m) = B_{1,1}^{*}\delta_v(m), \tag{7}$$

$$x_2^{*}(m) = \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}\delta_v(m), \tag{8}$$

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

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

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

Corollary 3 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 Corollary 1.

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

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

where $D^*_1 = 2M\rho\left[B^*_{1,1}\left(\psi C^*_{1,1} + C^*_{2,1}\right)\right]$ *and* $E^*_1 = \psi C^{*2}_{1,1} + \frac{1}{\mu\psi}C^{*2}_{2,1} + 2C^*_{1,1}C^*_{2,1}$.

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 $M = 10$). Most parameter selection only affects the relative magnitude of the effects described below; we examine non-robust exceptions and limiting cases in Section 2.2.1. We then plot the ensuing equilibrium price correlation $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ in Figure 1 (dashed lines), alongside its corresponding level in 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 and multi-asset speculators submit market orders, as in 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 otherwise identical assets 1 and 2 — i.e., $corr\left(p^*_{1,1}, p^*_{1,2}\right) < corr\left(p_{1,1}, p_{1,2}\right)$ — even when noise trading in those assets is perfectly correlated — i.e., $\sigma_{zz} = \sigma^2_z = 1$ such that $corr\left(p_{1,1}, p_{1,2}\right) = 1$ in Figure 1a. Intuitively, the camouflage provided by the aggregate order flow allows the stylized government of 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). To that end, the government optimally chooses to bear some costs — i.e., to tolerate some trading losses or forego some trading profits in asset 1, given its private information of precision ψ. For instance, at the economy's baseline parametrization, not only $C^*_{2,1} > 0$ but also $0 < C^*_{1,1} < B^*_{1,1}$ in $x_1\left(gov\right)$ of Eq. (9): $C^*_{2,1} = 0.85$ and $C^*_{1,1} = 0.34$ versus $B^*_{1,1} = 0.69$ in $x^*_1\left(m\right)$ of Eq. (7).

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

This liquidity differential mitigates the differential impact of less-than-perfectly correlated noise trading shocks on $p^*_{1,1}$ and $p^*_{1,2}$.[13] However, ceteris paribus for $p^*_{1,2}$, the former effect of

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

government intervention on $p_{1,1}^*$ prevails upon its latter effect on asset 1's liquidity, leading to greater LOP violations in equilibrium — i.e., allowing for further $E(v|\omega_1) \neq E(v|\omega_2)$. For instance, in the baseline economy, $corr\left(p_{1,1}^*, p_{1,2}^*\right) = 0.89$ versus $corr\left(p_{1,1}, p_{1,2}\right) = 0.92$ — which can be shown to amount to a 19% increase in the expected absolute difference between $p_{1,1}$ and $p_{1,2}$, $E\left(|p_{1,1} - p_{1,2}|\right)$.[14] Consistently, so-induced LOP violations increase (lower $corr\left(p_{1,1}^*, p_{1,2}^*\right)$) 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 otherwise costlier target (lower μ, Figure 1f) — and the less precise is that signal — i.e., the costlier but less predictable is its intervention (lower ψ, Figure 1g). We further investigate this trade-off in Section 2.2.1.

The implications of government intervention for LOP violations also depend on extant market conditions. Figure 1 suggests that official trading activity leads to larger LOP violations the less liquid are the affected markets — and the more severe are LOP violations in the government's absence. In particular, equilibrium $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ is lower (and lower than $corr\left(p_{1,1}, p_{1,2}\right)$) in the presence of fewer speculators (lower M, Figure 1c) or when their private information is more dispersed (lower ρ, Figure 1b). Ceteris paribus, as discussed in Section 2.1.1, fewer or more heterogeneous speculators trade (as a group or individually) more cautiously with their private signals, making MMs' adverse selection problem more severe and 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 — and amplifying the impact of liquidity demand differentials on their price correlation. In those circumstances, government intervention in asset 1 is more effective at driving its equilibrium price $p_{1,1}^*$ of Eq. (5) toward the partially uninformative policy target $p_{1,1}^T$ — ceteris paribus, $\frac{\partial^2 p_{1,1}^*}{\partial p_{1,1}^T \partial \lambda^*} = \frac{d}{(1+d\lambda^*)^2} > 0$ — hence further away from the equilibrium price of asset 2 ($p_{1,2}^*$ of Eq. (6)); e.g., see also Figures IA-1b and IA-1c of the Internet Appendix.

[14] Propositions 1 and 2 and well-known properties of half-normal distributions (e.g., Vives, 2008, p. 149) imply that $E\left(|p_{1,1} - p_{1,2}|\right) = 2\lambda\sqrt{\frac{1}{\Pi}\left(\sigma_z^2 - \sigma_{zz}\right)}$ and $E\left(\left|p_{1,1}^* - p_{1,2}^*\right|\right) = \sqrt{\frac{2}{\Pi} var\left(p_{1,1}^* - p_{1,2}^*\right)}$, where $\Pi \equiv \arccos(-1)$ and $var\left(p_{1,1}^*\right)$, $var\left(p_{1,2}^*\right)$, and $covar\left(p_{1,1}^*, p_{1,2}^*\right)$ are in the Proof to Corollary 3; their close relationship with $corr\left(p_{1,1}, p_{1,2}\right)$ and $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ is discussed in Section 3.1.1 and Section 3 of the Internet Appendix.

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 may amplify LOP violations more conspicuously — i.e., the difference $\Delta corr\left(p_{1,1}, p_{1,2}\right) \equiv corr\left(p_{1,1}, p_{1,2}\right) - corr\left(p_{1,1}^*, p_{1,2}^*\right) > 0$ is greater — even when those violations are not as severe in its absence, e.g., when noise trading in assets 1 and 2 is either less intense, worsening liquidity in both markets (lower σ_z^2, Figure 1d and Figure IA-1b), or more positively correlated (higher σ_{zz}, Figure 1a). For instance, in the baseline economy with perfectly correlated noise trading shocks ($\sigma_{zz} = \sigma_z^2 = 1$), $corr\left(p_{1,1}^*, p_{1,2}^*\right) = 0.93$ (and $E\left(\left|p_{1,1}^* - p_{1,2}^*\right|\right) = 0.27$) versus $corr\left(p_{1,1}, p_{1,2}\right) = 1$ (and $E\left(\left|p_{1,1} - p_{1,2}\right|\right) = 0$). Hence, the relationship between the impact of government intervention on LOP violations ($\Delta corr\left(p_{1,1}, p_{1,2}\right)$) and their extant severity ($corr\left(p_{1,1}, p_{1,2}\right)$) may be non-monotonic; e.g., see also Figure IA-1c. The following conclusions summarize these novel, robust observations about the impact of government intervention on the law of one price.[15]

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.*

[15] 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.

2.2.1 Limiting Cases and Exceptions

In this section, we examine the implications of notable limiting cases of the model of Section 2.2 for the positive relationship between government intervention and LOP violations postulated in Conclusion 1. All of these circumstances are arguably less plausible relative to the aforementioned literature on official trading activity, and some of them may yield non-robust exceptions to Conclusion 1. Yet, their study allows us to further illustrate the intuition behind the model's main predictions.

To begin with, if $\gamma = 0$ in the loss function of Eq. (4), the government in our model would act exclusively as an *additional*, privately informed trader in asset 1. The equilibrium of the resulting economy can be shown to closely mimic the one of Proposition 1 except in that such intervention would make only asset 1 both more liquid ($\lambda^* < \lambda$) and more informationally efficient ($var\left(p_{1,1}^*\right) > var\left(p_{1,1}\right)$), like by increasing the total number of speculators M by one unit only in asset 1 (see Section 2.1.1), and especially when M is small; thus, it would lower asset 1's equilibrium price correlation with asset 2 relative to Corollary 1 ($corr\left(p_{1,1}^*, p_{1,2}^*\right) < corr\left(p_{1,1}, p_{1,2}\right)$), even in the presence of perfectly correlated noise trading shocks ($\sigma_{zz} = \sigma_z^2$). See, e.g., Figure IA-2a of the Internet Appendix. The equilibrium $corr\left(p_{1,1}^*, p_{1,2}^*\right)$ of Corollary 3 and Figure 1e converges to this limiting case for $\gamma \to 0$. Relatedly, there are also circumstances when the dispersion of the information endowments of a sufficiently small number of speculators is so high — i.e., when the precision and correlation of their private signals of v are so low ($\rho \approx 0$) — that the government is practically the *only* informed trader in the targeted asset, thus *worsening* its dealers' adverse selection risk such that $\lambda^* > \lambda$ (e.g., as in Vitale, 1999; Naranjo and Nimalendran, 2000) and $corr\left(p_{1,1}^*, p_{1,2}^*\right) \ll corr\left(p_{1,1}, p_{1,2}\right)$, as in Conclusion 1.

Conclusion 1 is also robust to imposing that the government's policy target $p_{1,T}$ is *independent* of asset 1's terminal payoff v — i.e., $cov\left(v, p_{1,1}^T\right) = 0$, as in Pasquariello et al. (2014), or when $\mu \to 0$ such that $corr\left(v, p_{1,1}^T\right) = \sqrt{\mu\psi} \to 0$. See, e.g., Figure IA-2b of the Internet Appendix. This is true even if the government is uninformed about asset fundamentals — i.e., even in absence of $S_v\left(gov\right)$ or when $\psi \to 0$ such that $corr\left[v, S_v\left(gov\right)\right] = \sqrt{\psi} \to 0$. Intuitively, in either case the pursuit of policy may be both more costly for the government in terms of expected trading losses in asset 1, but especially more effective as less predictable to other sophisticated market participants. It can be shown that the equilibrium $corr\left(p^*_{1,1}, p^*_{1,2}\right)$ of Corollary 3 and Figures 1f and 1g converges to either of these limiting cases for either $\mu \to 0$ (but $\psi > 0$) or $\mu = \psi \to 0$, respectively. Relatedly, there are also some circumstances when an informed government may optimally trade in asset 1 *against* its private information — i.e., "leaning against the wind" — to achieve its at least partly informative policy objectives. For instance, at the economy's baseline parametrization for which the equilibrium price impact of order flow in either asset 1 or 2 is relatively low — e.g., $\rho = 0.9$ such that $\lambda = 0.29$ — and the government's price target is both relatively important in its loss function — $\gamma = 0.5$ in $L\left(gov\right)$ of Eq. (4) — and only partially correlated to its fundamental information — $\mu = 0.5$ such that $corr\left[p^T_{1,1}, S_v\left(gov\right)\right] = \sqrt{\mu} = 0.71$ — the resulting $C^*_{1,1} < 0$ in $x_1\left(gov\right)$ of Eq. (9) while $B^*_{1,1} > 0$ in $x^*_1\left(m\right)$ of Eq. (7): $C^*_{1,1} = -0.04$ versus $B^*_{1,1} = 0.55$.

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

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 markets with less-than-perfectly integrated dealership. This channel depends crucially on various facets of both that government policy and the information environment of those markets. Yet, as we further discuss next, 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 extant LOP violations, if any, in markets with perfectly integrated dealership; *H2)* government intervention induces, or increases extant LOP violations in markets with less-than-perfectly integrated dealership; *H3)* this effect may be non-monotonic in extant LOP violations; *H4)* this effect is more pronounced when 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 and other U.S. cross-listings ("ADRs" for brevity). 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 Forex Intervention in the Model

The market for U.S. cross-listings (the "ADR market") 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 $b_2 = q_i \times P_{i,t}^{FOR} > 0$, i.e., ceteris paribus for the corresponding foreign stock price — traded in the U.S. stock market at a *tilded* price $\widetilde{p}_{1,2} = b_2 p_{1,2}$ (i.e., $P_{i,t}$). Ignoring the market for an ADR's underlying foreign shares is for simplicity only and without loss of generality. In Section 1 and Figure IA-3 of the Internet Appendix, we show that extending our model to a third such asset — e.g., with payoff v_3 such that the ADR's log-linearized payoff $v_2 = a_2 + v_1 + v_3$, where $a_2 = \ln(q_i)$ — requires more involved analysis but yields similar implications.

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

and $p_{1,2}^{LOP}$: $corr\left(\widetilde{p}_{1,2}^{*}, p_{1,2}^{LOP*}\right) = corr\left(p_{1,1}^{*}, p_{1,2}^{*}\right)$, such that $corr\left(\widetilde{p}_{1,2}^{*}, p_{1,2}^{LOP*}\right) < corr\left(\widetilde{p}_{1,2}, p_{1,2}^{LOP}\right)$.

Second, market-making in currency and ADR markets is arguably less-than-perfectly integrated, in that market-makers in one market are less likely to directly observe, and set prices based on, trading activity in the other market than within their own.[16] We interpret segmented market-making in assets 1 and 2 in our model as a stylized representation of this observation. Third, as mentioned in Section 2.2, the stylized representation of the government in our model is consistent with the consensus in the literature that government intervention in currency markets, 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.[17] 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 any empirical relationship between government intervention and the arbitrage parity of Eq. (11). 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)):

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

(e.g., Gagnon and Karolyi, 2010; Pasquariello, 2014) — i.e., "ADR parity" (ADRP) violations. We assess this possibility in the reminder of the paper.

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

[17] 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).

3.1.1 Alternative Model Interpretations and Measures of ADRP Violations

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

To begin with, we show in Section 2 of the Internet Appendix that linearity of asset payoffs and equilibrium prices in our model implies that one can also think of asset 1 as the actual exchange rate traded in the forex markets and of asset 2 as: *i)* either an ADR-specific synthetic, or *shadow* exchange rate implied by Eq. (11) *implicitly* traded in the ADR market at $S_{t,USD/FOR}^{i,LOP} = P_{i,t} \times \left(q_i \times P_{i,t}^{FOR}\right)^{-1}$ (e.g., see Auguste et al., 2006; Eichler et al., 2009); *ii)* or an actual ADR traded in the U.S. stock market at $P_{i,t}$ implying a synthetic exchange rate $S_{t,USD/FOR}^{i,LOP}$. While less common and intuitive, these representations of the LOP relationship between currency and ADR markets within our model are conceptually and empirically equivalent to the one discussed in Section 3.1 since any violation of the ADR parity of Eq. (11) yields both $P_{i,t} \neq P_{i,t}^{LOP}$ and $S_{t,USD/FOR} \neq S_{t,USD/FOR}^{i,LOP}$ — i.e., not only the same equilibrium price correlation in the model but also the same absolute percentage LOP violation in Eq. (12).

In addition, as noted in Section 2.1.2, the notion of LOP violations in the ADR market as nonzero unsigned relative, i.e., log percentage, price differentials $ADRP_{i,t}$ of Eq. (12) is both common in the literature and conceptually equivalent to the notion of LOP violations as less-than-one equilibrium unconditional price correlation $corr\left(p_{1,1}, p_{1,2}\right)$ in our model. For instance, we show in Section 3 of the Internet Appendix that the expected absolute differential between equilibrium actual and synthetic ADR prices described in Section 3.1 (i.e., $E\left(\left|\widetilde{p}_{1,2} - p_{1,2}^{LOP}\right|\right)$) is a, ceteris paribus decreasing, function of their unconditional correlation whose scale depends on the magnitude of the ADR's fundamental payoff. Both $corr\left(p_{1,1}, p_{1,2}\right)$ and $ADRP_{i,t}$ are instead *price-scale invariant* and display similar comparative statics (see also Auguste et al., 2006; Pasquariello, 2008; Gagnon and Karolyi, 2010). Accordingly, the empirical analysis of several measures of the correlation between actual and synthetic ADR prices, while computationally less convenient than for $ADRP_{i,t}$ in our setting, yields qualitatively similar inference. See, e.g., Figure IA-4 and Tables IA-1 and IA-2 of the Internet Appendix.

3.2 Data

3.2.1 ADRs

We begin by obtaining from Thomson Reuters Datastream (Datastream) its entire sample of foreign stocks cross-listed in the U.S. between January 1, 1973 and December 31, 2009.[18] 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 Level III ADRs from developed and emerging countries (with bundling ratios q_i) and mostly Canadian ordinary shares (ordinaries, with $q_i = 1$) listed on the three major U.S. exchanges (NYSE, AMEX, or NASDAQ).[19]

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 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

[18] We complement this sample with the directory of depositary receipts compiled by Bank of New York Mellon (BNY Mellon), the leading U.S. depositary bank (available at http://www.adrbnymellon.com/dr_directory.jsp).

[19] This is the sample used in Pasquariello (2014); see also Baruch et al. (2007), Pasquariello (2008), Gagnon and Karolyi (2010), and references therein.

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 (e.g., see Ince and Porter, 2006; Xie, 2009; Gagnon and Karolyi, 2010; Pasquariello, 2014). 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 around delistings), 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.[20] 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 $ADRP^z_m$, is the monthly average of daily equal-weighted means of all normalized ADRP violations, $ADRP^z_{i,t}$ — i.e., after each $ADRP_{i,t}$ has been standardized by its earliest available historical distribution on day t since 1973.[21] 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) time-varying mean — without look-ahead bias,

[20]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 or by further excluding all Canadian ordinaries — whose fungibility and propensity to delist from U.S. exchanges differ from that of ADRs and other ordinaries (Witmer, 2008; Gagnon and Karolyi, 2010).

[21]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.

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 (e.g., Karolyi, 2006; Karolyi and Wu, 2016; Sarkissian and Schill, 2016). When they did, their ADR and local stock prices in our sample, while available for all of them afterwards, are often either stale or suspect then, yielding extreme LOP violations. Accordingly, the filtering and aggregation procedure described above results in several missing observations between 1973 and 1979. Thus, 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.[22] 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 extant ($corr\,(p_{1,1}, p_{1,2}) < 1$) and intervention-induced equilibrium LOP violations ($corr\left(p^*_{1,1}, p^*_{1,2}\right) < corr\,(p_{1,1}, p_{1,2})$) to common, *exogenous* forces affecting the equilibrium liquidity of the underlying, arbitrage-linked markets (λ and λ^*) — e.g., the num-

[22] 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.

ber of multi-asset speculators (M, in Figure 1c) or the correlation of their private fundamental information (ρ, in Figure 1b). In light of this observation, Eq. (11) suggests that ADR parity violations may be *related* to exogenous commonality in the liquidity of the U.S. stock market where an ADR is exchanged, the listing market for the underlying foreign stock, and the corresponding currency market. Those violations may also be *caused* by such illiquidity increasing the cost of ADR arbitrage activity (e.g., Gagnon and Karolyi, 2010; Gromb and Vayanos, 2010). Data availability considerations make measurement of liquidity in many of these venues over long sample periods challenging, especially in emerging markets (e.g., Lesmond, 2005; Lyons and Moore, 2009; Mancini et al., 2013). 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 $ILLIQ_m$ is instead low).[23] This preliminary observation is consistent with our model's basic premise, as summarized in Corollary 2. In the benchmark model of multi-asset trading without government intervention of Section 2.1, 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 in both markets 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 in both markets is greater; see, e.g., Figure IA-1a of the Internet Appendix. We investigate this relationship — and, more generally, the relevance of extant market quality for the LOP externality of government intervention — in greater detail in Sections 3.4 and 3.5.

3.2.2 Forex 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.[24] 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 secret, generally small, nearly always *sterilized* currency transactions — i.e., accompanied by offsetting actions on the domestic money supply — normally in a coordinated fashion, to accomplish their habitually non-public policy objectives for exchange rate dynamics. Despite a robust theoretical and empirical debate, there is consensus that these interventions are effective,

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

[24] 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).

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.[25] This database contains daily amounts of domestic and/or foreign currencies traded by the governments of Australia, Germany, Italy, Japan, Mexico, Switzerland, Turkey, and the United States for *policy* 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.[26] Where currency-specific intervention data is missing, we augment the FRED database using various official government sources (when possible).[27] As for our sample of ADR parity violations, the resulting sample has the broadest continuous coverage of currency intervention activity between 1980 and 2009.[28] Panel A of Table 2 reports summary statistics for these interventions, aggregated at the monthly frequency over this period, by country and foreign exchange involved. All governments in the sample intervene by purchasing or selling their domestic currencies — most often against USD, the currency of denomination of ADRs; less so via *cross-rates*, exchange rates not involving *vehicle* currencies like USD or EUR.[29] Cross-rates are however kept in line with the corresponding USD-denominated exchange rates by triangular arbitrage (Bekaert and Hodrick, 2012); thus, any intervention in the former must reverberate in

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

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

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

[28] 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 (RBA).

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

the latter. Excluding those interventions from the sample does not affect our inference; see, e.g., Tables IA-3 and IA-4 of the Internet Appendix.

According to Table 2, and consistent with the aforementioned literature, the absolute amounts of currency traded by governments in our sample, while non-trivial, are small relative to the average monthly trading volume in the forex market (e.g., 111 trillions of dollars, according to BIS, 2016) and heterogeneous across currencies and governments. Yet, scaling and aggregating these amounts is impeded by cross-currency turnover heterogeneity and sparsity of historical currency turnover data. Furthermore, in our model — as in all models based on Kyle (1985) — optimal strategic and noise trading activity in general, and optimal intervention *intensity* in particular (i.e., sign and magnitude of $x_1(gov)$ of Eq. (9)), are separately unobservable by dealers and endogenously determined in equilibrium. However, the *presence* of an active government is exogenous and known to all market participants. Both the presence and optimal intensity of intervention contribute to its impact on equilibrium price formation. Relatedly, the effect of $x_1(gov)$ on equilibrium outcomes depends not only on the realizations of unobservable variables controlling the government's information and policy but also on market participants' unobservable expectations of them (i.e., on $E[x_1(gov)] = 2d\left(\overline{p}_{1,1}^T - p_0\right)$ in $p_{1,1}^*$ of Eq. (5)). Comprehensive survey data on forex intervention expectations is typically unavailable, and their estimation raises considerable econometric challenges (e.g., Dominguez and Frankel, 1993; Naranjo and Nimalendran, 2000; Sarno and Taylor, 2001).

Thus, our theory does not postulate any easily testable relationship between *realized* intervention sign and/or magnitude and LOP violations (see also Bhattacharya and Weller, 1997). Consistently, since Kyle (1985), the market microstructure literature has long advocated and provided strong empirical support for the use of order imbalance — i.e., the total or net signed number of transactions over a period of time — rather than signed or unsigned trading volume, to measure the intensity of order flow and estimate its impact on price formation in financial markets (e.g., see Hasbrouck, 1991, 2007; Jones et al., 1994; Evans and Lyons, 2002; Chordia and Subrahmanyam, 2004; Green, 2004; Pasquariello and Vega, 2007; Chordia et al., 2016).[30]

In addition, as mentioned above, most currency interventions are coordinated among multiple governments for greatest effectiveness (e.g., Dominguez and Frankel, 1993; Sarno and Taylor, 2001); however, individual transactions within a concerted forex policy may not be contemporaneous, as they are executed in different time zones and often coordinated through informal discussions. Accordingly, many of the official currency trades in Table 2 tend to cluster in time but often are not perfectly synchronous at high frequency. Lastly, Tables 1 and 2 suggest 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.[31] 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, 2009b; Gerlach-Kristen et al., 2012; Chortareas et al., 2013). Analysis of this smaller dataset (in Section 3.4) yields noisier but qualitatively similar inference.

In light of these observations, we propose two *aggregate*, *lower-frequency* measures of the presence and intensity of government intervention in the forex market. The first one, labeled $N_m\,(gov)$, is the number of nonzero government intervention-exchange rates pairs in a month. The second one, labeled $N_m^z\,(gov)$, is such number standardized by its earliest available historical distribution on month m since 1973, as in Section 3.2.1. Hence, as for normalized ADRP violations $ADRP_m^z$, a positive (negative) $N_m^z\,(gov)$ indicates an *abnormally* large (small) number

[30] For instance, in their seminal empirical investigation of the U.S. stock market, Jones et al. (1994, p. 631) find that "*it is the occurrence of transactions per se, and not their size, that generates* [price] *volatility; trade size has no information beyond that contained in the frequency* [i.e., number] *of transactions.*" According to Hasbrouck (2007, p. 90), time-averaged price formation is relatively unaffected by order size because of time variation in liquidity since, as in our model, "*agents trade large amounts when price impact is low, and small amounts when price impact is high.*"

[31] 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.

of government interventions — i.e., historically high (low) intensity of official trading activity — in the forex market on month m. Consistent with the aforementioned literature, replacing $N_m(gov)$ and $N_m^z(gov)$ in the ensuing analysis with the actual and normalized sums of unsigned and unscaled observed government trades (in millions of USD at concurrent exchange rates) yields similar but weaker evidence, while augmenting that analysis by those measures does not affect our inference. See, e.g., Figure IA-5a and Tables IA-5 and IA-7 of the Internet Appendix.

We plot $N_m(gov)$ and $N_m^z(gov)$ in Figures 2a (left axis, histogram) and 2b (left axis, dashed line), alongside $ADRP_m$ and $ADRP_m^z$, respectively. Their summary statistics are in Panel B of Table 2. Forex interventions (i.e., $N_m(gov) \geq 1$ in Figure 2a) occur in almost every month of the sample; thus, identification of their impact on LOP violations may come from their time-varying intensity. Official trading activity in the currency markets is especially intense in the late 1980s and mid-1990s, before abating somehow afterward. In those circumstances, both $N_m(gov)$ and $N_m^z(gov)$ experience frequent sharp spikes, suggesting that episodes of coordinated forex intervention are often short-lived but not isolated.[32] 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 ADRP 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 measures of those LOP violations (e.g., Neely, 2005; Pasquariello, 2007b; Garleanu

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

and Pedersen, 2011):

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

where LOP_m is either $ADRP_m$ or $ADRP^z_m$, $\Delta LOP_m = LOP_m - LOP_{m-1}$, I_m is either $N_m\,(gov)$ or $N^z_m\,(gov)$, and $\Delta I_m = I_m - I_{m-1}$. Both ADR parity violations and the intensity of forex interventions tend to persist; for instance, the time series of $ADRP_m$ and $N_m\,(gov)$ in Figure 2a ($ADRP^z_m$ and $N^z_m\,(gov)$ 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 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 forex intervention activity ($\Delta I_m > 0$) on ADRP violations (ΔLOP_m) predicted by our model of Section 2.2 and discussed in Section 3.1 — i.e., $\Delta corr\,(p_{1,1}, p_{1,2}) > 0$ in Figure 1 and Figures IA-1b and IA-1c of the Internet Appendix. Currency market participants may anticipate the nature and/or extent of forex intervention and react prior to its actual occurrence ($\Delta I_{m+1} > 0$), e.g., if its policy objectives and/or accompanying trades are pre-announced by government officials or leaked to the media (Payne and Vitale, 2003; Beine et al., 2009a). In Eq. (13), the impact of any such anticipation in currency markets on the LOP relationship between current actual and synthetic ADR prices of Eq. (11) is captured by the lead coefficient β_1. The effects of past forex intervention ($\Delta I_{m-1} > 0$) on LOP violations in the ADR market may persist or ebb, e.g., depending on the extent to which currency market participants learn about the government's prior trades and policy objectives (Jansen and De Haan, 2005; Fratzscher, 2006). In Eq. (13), the impact of any such persistence or reversal in currency markets on current ADRP violations is captured by the lag 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 $\beta^0_1 = \beta_1 + \beta_0$ and $\beta^{-1}_1 = \beta_1 + \beta_0 + \beta_{-1}$, in Panel A of Table 3.[33] 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 or sparse trading (e.g., price staleness).

The results in Table 3 provide support for our model's main prediction (in H2). Estimates of both the contemporaneous and up-to-current impact of forex interventions on ADR parity violations are positive and statistically significant: $\beta_0 > 0$ and $\beta_1^0 > 0$. These estimates are (plausibly) economically significant as well. For example, a one standard deviation increase in the monthly change in the number of forex interventions $\Delta N_m\,(gov)$ — 1.402, in Panel B of Table 2 — is accompanied by a contemporaneous (up-to-current) increase in average ADR parity violations $ADRP_m$ in (up to) that month by $3.505 \times 1.402 = 4.9$ bps ($4.830 \times 1.402 = 6.8$ bps), 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 government intervention in currency markets on ADRP violations is seldom due to its anticipation ($\beta_1 > 0$ but small) yet is often persistent ($\beta_{-1} > 0$ and non-trivial), perhaps because of its secrecy and slow information diffusion. These estimates imply that forex interventions continue to have a discernible cumulative impact on the average intensity of LOP violations in the ADR market within a month of their occurrence: β_1^{-1} is always positive, large, and statistically significant. E.g., normalized ADR parity violations $ADRP_m^z$ increase on average by 34% of their sample standard deviation over the three-month window in correspondence with historically high intensity of official trading activity in a month — i.e., in response to a one standard deviation increase in the monthly change in the normalized number of government interventions $\Delta N_m^z\,(gov)$: $0.057 \times 0.911 \div 0.153 = 0.34$. Their cumulative effect on actual ADR parity violations $ADRP_m$ is even larger, e.g., amounting to $10.631 \times 0.911 = 9.7$ bps or 45% of the standard deviation of $\Delta ADRP_m$. In unreported analysis, we further find the estimation of Eq. (13) to yield qualitatively similar inference within each decade of our sample period.

[33] Our inference is unaffected by using Newey-West standard errors to correct for (mild or absent) residual serial correlation and heteroskedasticity.

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. Accordingly, while forex interventions may occasionally be anticipated by currency market participants, estimates of their lead effect β_1 on ADRP violations in Eq. (13) are always small and rarely significant in Panel A of Table 3. 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). Unfortunately, those properties of forex interventions also make it extremely difficult to find covariates of I_m that are uncorrelated with the error term ε_t in 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., Fatum and Hutchison, 2003; Neely, 2005, 2006; Engel, 2014).

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);[34] 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 unanticipated and 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 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 international 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 have long been nearly perfectly integrated in many respects — including dealership (e.g., McKinnon, 1977; Dufey and Giddy, 1994; Bekaert and Hodrick, 2012) — our model predicts that government intervention in currency markets should have *no* impact on the extent of CIRP violations — i.e., $\Delta corr\,(p_{1,1}, p_{1,2}) = 0$; see H1 in Section 2.3. However, the aforementioned

[34] 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.

literature also argues 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 daily absolute log differences (in bps, as in Eq. (12) and Section 3.2.1) between daily indicative (short- and long-term maturity) forward exchange rates for five of the most actively traded and liquid currencies in the forex market (CHF, EUR, GBP, USD, JPY; from Datastream) and the 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 (versus a concurrent mean $ADRP_m$ of 187 bps) — but also volatile — e.g., often much larger in correspondence with well-known episodes of financial turmoil (like ADRP violations in Figure 2).[35] We then 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} in Panel B of Table 3 suggest that during that common interval of data availability, forex interventions have little or no impact on CIRP violations — i.e., on LOP violations within the more closely integrated currency and international 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 ADR 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

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

intensifying forex intervention *and* ADR parity violations.

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

3.4 The Cross-Section of ADRP 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 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 extent 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 ADR market quality outcomes as each ADR's illiquidity and no-arbitrage parity violations (e.g., Pasquariello, 2008, 2014). Investigating the cross-section of the impact of forex intervention on ADRP violations along those dimensions may shed further light on its theoretical determinants — and so further alleviate the aforementioned endogeneity concerns plaguing the inference from Table 3.

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 suggests that estimates of the positive relationship between forex intervention and ADR parity violations may be non-monotonic in underlying ADR market quality. For instance, as noted in Section 2.2, government intervention may yield larger LOP violations (i.e., larger $\Delta corr\,(p_{1,1}, p_{1,2})$) not only when the underlying, arbitrage-linked markets are less liquid (i.e., higher λ and λ^*) — *low* underlying market quality; e.g., for less intense noise trading (see Figure 1d; H4 in Section 2.3) but also when underlying LOP violations are either smaller (i.e., larger $corr\,(p_{1,1}, p_{1,2})$) — *high* market quality; e.g., for more correlated noise trading (Figure 1a; H3) — or larger (i.e., smaller $corr\,(p_{1,1}, p_{1,2})$) — *low* market quality; e.g., for fewer and/or more heterogeneously informed speculators (Figures 1b and 1c; H3). Vice versa, $\Delta corr\,(p_{1,1}, p_{1,2})$ may be smaller not only when $corr\,(p_{1,1}, p_{1,2})$ is smaller — *low* market quality; e.g., for less correlated noise trading — but also when it is larger — *high* market quality; e.g., for more numerous and/or less heterogeneously informed speculators. See, e.g., Figures IA-1b and IA-1c of the Internet Appendix.

Accordingly, country-level estimates of the contemporaneous (β_0) and cumulative impact (β_1^0 and β_1^{-1}) of changes in either $N_m\,(gov)$ or $N_m^z\,(gov)$ on absolute percentage ADR parity violations in Table 4 tend to be more often positive, large, and/or significant *i)* for cross-listings from emerging markets, i.e., 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 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 $\Delta ADRP_m$).[36]

While generally consistent with our model's predictions, the evidence in Table 4 is only suggestive. Especially emerging country-level groupings are made of fewer ADRs over shorter periods (see Table 1), such that both their measures of ADRP violations and their estimated relationship with forex intervention are noisier. Country-level sorting may also subsume additional, albeit possibly non-exclusive interpretations. For instance, greater illiquidity in emerging markets may be both unrelated to adverse selection risk and associated with more limited arbitrage activity in the presence of government-induced LOP violations. Estimates of the impact of currency-matched intervention on ADRP violations in Table 5 yield similar insight — 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 non-monotonic — broadly

[36]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).

consistent with our model, albeit once again only suggestively. For example, estimates of the positive, contemporaneous and cumulative impact of forex intervention on ADRP violations are roughly U-shaped — rather than increasing (e.g., Figure IA-1b) — in unconditional ADRP illiquidity $ILLIQ_m$ (e.g., Panel A of Table 6) — perhaps because of the concurrent effect of other frictions and forces impeding both liquidity provision and arbitrage activity in the ADR market. However, those estimates are also roughly inverted U-shaped in unconditional ADR parity violations $ADRP_m$ (e.g., Panel B of Table 7) — in line with the above discussion (e.g., Figure IA-1c) — and up to twice as large for higher underlying market quality (e.g., low or medium $ILLIQ_m$ or $ADRP_m$) as for lower underlying market quality (high $ILLIQ_m$ or $ADRP_m$).

3.5 ADRP Violations and Market Conditions

Tables 3 to 7 indicate that government intervention in currency markets is accompanied by a large and statistically significant increase in LOP violations in ADR markets. This evidence is consistent with the main empirical implication of our model (see H2 in Section 2.3). Yet, as noted earlier, this interpretation may be clouded by the possible endogeneity of forex interventions and ADRP violations — a concern that our additional time-series and cross-sectional analysis in Sections 3.3.1 and 4 can only mitigate. For instance, directly linking the cross-sectional tests in Tables 4 to 7 to the model of Section 2 may be problematic since, as noted earlier, their conditioning variables (country of home listing, ADRP illiquidity, or ADRP violations) are plausibly related to alternative frictions and theories as well. Unfortunately, most primitive parameters in our model — like the intensity and correlation of noise trading (σ_z^2 and σ_{zz}) or the number of multi-asset speculators (M) — are directly unobservable (as in all models based on Kyle, 1985), their indirect estimation involves significant risk of measurement error, and the relevant data is typically unavailable for most currency and/or foreign stock markets (e.g., Allen and Taylor, 1990; Madhavan, 2000; Caballé and Krishnan, 2004; Lesmond, 2005; Cong et al., 2010).

In addition, the above 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 impede arbitrage activity — e.g., by introducing a new source of unhedgeable convergence risk, in the spirit of Pontiff (1996, 2006), for speculators and arbitrageurs exploiting extant ADRP violations. However, these market participants are also more likely to be able to manage such a risk, and its severity is more likely to be attenuated — thus, their trading activity in the ADR market is less likely to be affected — at the low, monthly frequency of our analysis.

In this section, we assess these notions more directly, by both *i)* explicitly testing for additional, *unique* predictions of the model, hence more difficult to reconcile with endogeneity or alternative interpretations — such as those relating the negative arbitrage externalities of government intervention to plausibly measurable market conditions affecting asset liquidity or policy uncertainty (H3 to H6); and *ii)* explicitly controlling for plausibly measurable 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:

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

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), as well as robust to numerous plausible extensions and alternative specifications, some of which are noted below. 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 $\beta_{ILQ} > 0$ (Corollary 2) 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 ($\Delta ILLIQ_m > 0$). Intuitively, ceteris paribus, when markets are less deep in equilibrium — i.e., higher λ and λ^*, e.g., in the presence of fewer speculators (Figure 1c) — noise trading shocks and government intervention in the aggregate order flow have greater impact on equilibrium prices, yielding larger LOP violations — i.e., greater $corr\,(p_{1,1}, p_{1,2})$ and $\Delta corr\,(p_{1,1}, p_{1,2})$; see also Figure IA-1b of the Internet Appendix. As noted in Section 2.1.2, the relationship between ΔLOP_m and $\Delta ILLIQ_m$ may be non-monotonic — e.g., according to Corollary 2, 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 and Figure IA-1a of the Internet Appendix. 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 payoffs of the assets 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 USD-denominated exchange rates and ADRs implied by Eq. (12) 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 (see Croushore, 1993; Beber et al., 2014; Pasquariello et al., 2014). Data of similar quality is typically unavailable for most other developed and emerging countries in our sample (e.g., see Dovern et al., 2012). 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 (see Andersen and Bollerslev, 1998; Andersen et al., 2003, 2007; Pasquariello and Vega, 2007). 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 the lower is ρ — i.e., the higher is $DISP_m$ — the greater are $corr\left(p_{1,1}, p_{1,2}\right)$ (Corollary 2) and $\Delta corr\left(p_{1,1}, p_{1,2}\right)$ (Conclusion 2; H5) — i.e., $\beta_{DSP} > 0$ and $\beta_0^{DSP} > 0$ in Eq. (14).

Our model also postulates that government intervention may be accompanied by larger LOP violations — i.e., greater $\Delta corr\left(p_{1,1}, p_{1,2}\right)$ — the greater is the uncertainty among market participants about its policy motives — i.e., 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 governments 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 $p^T_{1,1}$ ($\delta_T(gov) \equiv p^T_{1,1} - \overline{p}^T_{1,1}$), i.e., in policy uncertainty σ^2_T via the coefficient $C^{*2}_{2,1}$. Equilibrium $var[x_1(gov)]$ also depends on fundamental uncertainty σ^2_v via the coefficient $C^{*2}_{1,1}$. However, the distributional assumptions for $p^T_{1,1}$ in Section 2.2 imply that its variance $\sigma^2_T = \frac{1}{\mu\psi}\sigma^2_v > \sigma^2_v$. In addition, $C^{*2}_{2,1} > C^{*2}_{1,1}$ both on average and in correspondence with nearly all parametrizations associated with the plots in Figure 1. For instance, constant $C^{*2}_{2,1} = 0.725$ and $C^{*2}_{1,1} = 0.014$ in Figure 1a, while average $C^{*2}_{2,1} = 0.727$ and $C^{*2}_{1,1} = 0.509$ in Figure 1b. Accordingly, in a first order sense, $\Delta var[x_1(gov)] \approx C^{*2}_{2,1}\Delta\sigma^2_T$.

As noted in Section 3.2.2, the market microstructure literature recommends to measure order flow variability by order imbalance variability, since transaction frequency dynamics have been found to be significantly more influential than trading volume dynamics in explaining asset price movements (e.g., see Jones et al., 1994; Chordia et al., 2016). Hence, we proxy for currency policy uncertainty by the historical standard deviation of either of our measures of forex intervention I_m, $N_m(gov)$ or $N^z_m(gov)$ — $STD(I_m)$, over a three-year rolling window to allow for short-term variation (Figure 3c). We then consider the impact of monthly changes in both the intensity and volatility of observed intervention activity and their cross-product on observed ADRP violations in Eq. (14). Our model then predicts that $\beta_{SDI} > 0$ and $\beta^{SDI}_0 > 0$ (e.g., see Figure 1f). Consistent with the aforementioned literature, replacing I_m and/or $STD(I_m)$ in Eq. (14) with changes in the level and/or volatility of actual and normalized measures of unsigned observed intervention amounts yields similar but weaker evidence, while including both of those variables and their associated cross-products in Eq. (14) does not affect our inference below. See, e.g., Figure IA-5b and Tables IA-6, IA-8, and IA-9 of the Internet Appendix.

Lastly, Eq. (14) includes a vector ΔX_m of changes in several common measures of market conditions linked by the literature to the intensity of limits to arbitrage and/or observed LOP violations, especially in the ADR market — e.g., unhedgeable risk and opportunity cost of arbitrage, scarcity of arbitrage capital, or noise trader sentiment (Pontiff, 1996, 2006; Baker and Wurgler, 2006, 2007; Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010; Garleanu and Pedersen, 2011; Baker 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 original 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 as well as to the exclusion of its lead-lag effects, 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. Augmenting Eq. (14) with additional control variables related to such alternative sources of relative mispricings as marketwide financial distress, dislocations, foreign equity flows, or capital account liberalizations in emerging markets (e.g., Edison and Warnock, 2003; Hu et al.; 2013; Pasquariello, 2008, 2014; Brusa et al., 2015), when available, yields qualitatively similar inference. See, e.g., Tables IA-10 to IA-13 of the Internet Appendix.

Second, estimates of β_{ILQ} are always positive and both economically and statistically significant. Consistent with Corollary 2 — but also with extant literature on the determinants of LOP violations in general, and ADRP violations in particular (e.g., Gagnon and Karolyi, 2010; Gromb and Vayanos, 2010) — deteriorating ADRP liquidity is accompanied by larger ADRP violations (e.g., by as much as 16% of the sample standard deviation of ΔLOP_m) even in absence of forex intervention. We nonetheless find no evidence of non-monotonicity in this relationship: $\beta_{ILQ}^2 \approx 0$ in Panels A and B of Table 8. Shocks to the average fraction of zero returns do not weaken, yet only weakly magnify the impact of forex interventions on ADR parity violations: Estimates of β_0 remain large and significant; estimates of β_0^{ILQ} are often positive, consistent with H4, but small and never significant. However, the total effect of ADRP illiquidity alone on the relationship between forex interventions and ADRP violations ($\beta_0 + \beta_0^{ILQ}$) is both positive and large, e.g., about 18% of the baseline scaled estimates of β_0 in Table 8. Relatedly, amending Eq. (14) to include the interaction of ΔI_m and $(\Delta ILLIQ_m)^2$ reveals some non-monotonicity in the sensitivity of β_0 to ADRP illiquidity (β_0^{ILQ}), as hinted by Table 6. This evidence cannot be explained by our model, and may be related to other concurrent limits to ADRP liquidity provision and trading (e.g., such as those in X_m); yet, it does not otherwise affect our inference. See, e.g., Figure IA-1b and Table IA-14 of the Internet Appendix.

Further analysis allowing for each of the components of our measure of ADRP illiquidity $ILLIQ_m$ at the monthly frequency (Z_m^{FOR}, Z_m, and Z_m^{FX}) in Eq. (14) — in Table IA-15 of the Internet Appendix — suggests that, consistent with the literature, illiquidity in the U.S. market for international cross-listings (ΔZ_m) is a more important determinant of ADRP violations than illiquidity in the foreign markets for the underlying stocks (ΔZ_t^{FOR}; e.g., Pasquariello, 2008, 2014; Gagnon and Karolyi, 2010). The interaction of ΔZ_m with forex intervention intensity (ΔI_m) is also generally positive and statistically significant, as postulated by our model (H4). The effect of forex illiquidity (ΔZ_t^{FX}) on ADRP violations is instead weaker and its cross-product with ΔI_m of more difficult interpretation, since both our theory (as noted earlier) and many extant studies find forex interventions to have a significant impact on the liquidity of the targeted currencies (e.g., Bossaerts and Hillion, 1991; Vitale, 1999; Naranjo and Nimalendran, 2000; Pasquariello, 2007b, 2010). Accordingly, the samplewide correlation between ΔZ_t^{FX} and either $\Delta N_m(gov)$ or $\Delta N_m^z(gov)$ is weakly negative, consistent with our model ($\lambda^* < \lambda$ in Section 2.2) and potentially weakening the estimated aggregate interaction effect β_0^{ILQ} in Table 8. Nevertheless, our inference from Eq. (14) is otherwise unaffected.

Third, the relationship between forex interventions and ADRP violations is 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 number of interventions in a month — i.e., a one standard deviation shock to $\Delta N_m(gov) > 0$ — is accompanied by more than three times larger ADRP violations if information heterogeneity is high in that month — i.e., in conjunction with a one standard deviation shock to $\Delta DISP_m$ — that is, by nearly 10 bps ($\beta_0 + \beta_0^{DSP} = 3.705 + 6.134$, in Panel A of Table 8) versus an unconditional average increase of less than 3 bps ($\beta_0 = 2.856$). Estimates of β_{DSP} are instead always negative, but small and statistically insignificant, suggesting that the positive direct effect of information heterogeneity on the extent of LOP violations postulated in Corollary 2 may be subsumed by changes in other market conditions in Eq. (14). Therefore, the total joint effect of ΔI_m and $\Delta DISP_m$ alone on ΔLOP_m ($\beta_0 + \beta_{DSP} + \beta_0^{DSP}$) is still positive and more than twice as large, on average, as the baseline effect of ΔI_m alone (β_0) in Table 8.

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 standard deviation increase in normalized forex policy uncertainty in a month

($\Delta STD\left[N_m^z\left(gov\right)\right] > 0$) is accompanied by between 12% and 17% greater ADR parity violations in that month than their sample variation in Table 1, consistent with 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. Nonetheless, the total joint effect of greater intervention intensity and policy uncertainty alone on ADRP violations ($\beta_0 + \beta_{SDI} + \beta_0^{SDI}$) remains positive and between 6% and 31% larger than the corresponding baseline scaled estimates of β_0, in line with H6.

Alternatively, some studies argue that government intervention in currency markets may reflect actual and expected violations of the absolute purchasing power parity — APPP, a relationship between exchange rates and inflation rates equating currency-adjusted prices of goods and services across countries — especially during times of relatively high inflation (e.g., Naranjo and Nimalendran, 2000; Sarno and Taylor, 2001; Neely, 2005). Thus, the latter may proxy for intensity and uncertainty in the former. However, inflation differentials are relatively low over our sample period. In addition, large APPP violations often stem from multilateral international agreements (e.g., the Plaza and Louvre Accords in the 1980s), and hence may not translate into more intense and uncertain intervention activity. We use monthly CPI inflation data from the OECD to compute the actual or historically normalized average or three-year rolling volatility of absolute percentage APPP violations in the exchange rates targeted by government intervention in Table 2 (e.g., see Bekaert and Hodrick, 2012). These variables are often positively, yet weakly correlated to our measures of forex intervention intensity (ΔI_m) and forex policy uncertainty ($\Delta STD\left(I_m\right)$) — including during the portion of our sample when inflation differentials across countries were the highest (1980-1989). Accordingly, estimates of Eq. (14) when replacing $\Delta STD\left(I_m\right)$ with shocks to APPP violation intensity yields noisier but qualitatively similar inference. See, e.g., Figure IA-6 and Tables IA-16 and IA-17 of the Internet Appendix.

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 major U.S. exchanges for American Depositary Receipts and other cross-listings ("ADRs").

We illustrate the intuition for this negative externality of policy in two steps. We first construct a standard multi-asset model of strategic, heterogeneously informed speculation, based on Kyle (1985) and Chowdhry and Nanda (1991), in which segmentation in the dealership sector, speculative market-order trading, and less-than-perfectly correlated noise trading yield less-than-perfectly correlated equilibrium prices of two fundamentally identical, or linearly related assets (i.e., equilibrium LOP violations). 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 further clouding dealers' inference about the targeted asset's fundamentals — even in the presence of common liquidity shocks, especially when market depth is low, but non-monotonically when LOP violations are otherwise extreme.

Our empirical analysis provides support for these effects. We find that more intense foreign exchange ("forex") intervention activity between 1980 and 2009 is accompanied by meaningfully larger LOP violations in the arbitrage-linked, yet arguably less-than-perfectly integrated U.S. market for ADRs — dollar-denominated assets convertible at any time in a preset amount of foreign shares — but not in the arbitrage-linked, yet arguably perfectly integrated international 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 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 not only yield welfare gains but also have non-trivial, undesirable implications for financial market quality. This is an important insight both for the understanding of the forces driving price formation, hence resource allocation and risk sharing, in financial markets and for the debate on optimal financial policy and regulation.

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

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

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:

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

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

$$\begin{aligned} p_0 - A_{0,i} &= (M+1) A_{1,i} B_{0,i}, & \text{(A-3)} \\ 2A_{1,i} B_{1,i} &= 1 - (M-1) A_{1,i} B_{1,i} \rho. & \text{(A-4)} \end{aligned}$$

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

$$\begin{aligned} A_{0,i} &= p_0 - MA_{1,i} B_{0,i}, & \text{(A-6)} \\ A_{1,i} &= \frac{MB_{1,i}\rho\sigma_v^2}{MB_{1,i}^2\rho\sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2}. & \text{(A-7)} \end{aligned}$$

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

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

Equating Eq. (A-7) to Eq. (A-8) implies that $B_{1,i}^2 = \frac{\sigma_z^2}{M\rho\sigma_v^2}$, i.e., that $B_{1,i} = \frac{\sigma_z}{\sigma_v\sqrt{M\rho}}$. We then substitute this expression back into Eq. (A-8), yielding $A_{1,i} = \frac{\sigma_v\sqrt{M\rho}}{\sigma_z[2+(M-1)\rho]}$, and define $\lambda \equiv A_{1,i}$. Lastly, we follow Caballé and Krishnan (1994) to note that the equilibrium of Proposition 1 with

M speculators is equivalent to a symmetric n-firm Cournot equilibrium. As such, the "backward reaction mapping" technique in Novshek (1984) proves that, given a linear pricing rule (like the one of Eq. (1)), the symmetric linear strategies $x_i(m)$ of Eq. (2) represent the unique Bayesian-Nash equilibrium of the Bayesian game among speculators. ■

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

Proof of Corollary 2. Given the distributional assumptions in Section 2.1 (and $\sigma_{zz} \geq 0$), the statement stems from observing that under less-than-perfectly correlated noise trading ($\sigma_{zz} < \sigma_z^2$): $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial \rho} = \frac{\sigma_z^2 (M-1)\left(\sigma_z^2 - \sigma_{zz}\right)}{[2+(M-1)\rho]^2} > 0$, $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial \sigma_z^2} = -\frac{\sigma_{zz}}{\sigma_z^4 [2+(M-1)\rho]} \leq 0$, $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial M} = \frac{\sigma_z^2 \rho \left(\sigma_z^2 - \sigma_{zz}\right)}{[2+(M-1)\rho]^2} > 0$, and $\frac{\partial corr(p_{1,1}, p_{1,2})}{\partial \sigma_{zz}} = \frac{1}{\sigma_z^2 [2+(M-1)\rho]} > 0$. ■

Proof of Proposition 2. As noted above, the proof is by construction. Its outline is based on Pasquariello and Vega (2009) and Pasquariello et al. (2014). First, we conjecture linear functions for equilibrium prices and trading activity of speculators (in assets 1 and 2) and the stylized government of Eq. (4) (in asset 1 alone): $p_{1,i} = A_{0,i} + A_{1,i}\omega_i$, $x_i(m) = B_{0,i} + B_{1,i}\delta_v(m)$, where $A_{1,i} > 0$ and $i = \{1, 2\}$, and $x_1(gov) = C_{0,1} + C_{1,1}\delta_v(gov) + C_{2,1}\delta_T(gov)$. Since $E[\delta_v(gov)|\delta_v(m)] = \psi\delta_v(m)$ and $E[\delta_T(gov)|\delta_v(m)] = \delta_v(m)$ under the parametrization in Section 2.2, these conjectures imply that:

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

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

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

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

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

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

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

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

$$\begin{aligned}
0 \;=\;& 2\gamma A_{1,1}^2 x_1(gov) + 2\gamma A_{1,1}^2 M B_{0,1} + 2\gamma A_{1,1}^2 M B_{0,1}\rho\delta_v(gov) + 2\gamma A_{0,1}A_{1,1} - 2\gamma p_{1,1}^T A_{1,1} \\
&+(1-\gamma)A_{0,1} + 2(1-\gamma)A_{1,1}x_1(gov) + (1-\gamma)MA_{1,1}B_{0,1} \qquad \text{(A-19)} \\
&+(1-\gamma)MA_{1,1}B_{1,1}\rho\delta_v(gov) - (1-\gamma)p_0 - (1-\gamma)\delta_v(gov).
\end{aligned}$$

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 then correct iff

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

Eq. (A-22) implies that $C_{2,1} = \frac{d}{1+dA_{1,1}} > 0$. Our prior conjectures for $x_i(m)$ and $x_1(gov)$ also imply that the aggregate order flows ω_1 and ω_2 are normally distributed with means $E(\omega_1) =$

$MB_{0,1} + C_{0,1}$ and $E(\omega_2) = MB_{0,2}$, variances

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

$$var(\omega_2) = MB_{1,2}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2, \tag{A-24}$$

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

$$p_{1,1} = p_0 + \frac{(MB_{1,1}\rho + C_{1,1}\psi + C_{2,1})\sigma_v^2}{\sigma_z^2 + \sigma_v^2 \left\{MB_{1,1}^2 \rho [1 + (M-1)\rho] + D_1 + E_1\right\}} (\omega_1 - MB_{0,1} - C_{0,1}), \tag{A-25}$$

$$p_{1,2} = p_0 + \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2} (\omega_2 - MB_{0,2}). \tag{A-26}$$

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

$$A_{0,1} = p_0 - MA_{1,1}B_{0,1} - A_{1,1}C_{0,1}, \tag{A-27}$$

$$A_{1,1} = \frac{(MB_{1,1}\rho + C_{1,1}\psi + C_{2,1})\sigma_v^2}{\sigma_z^2 + \sigma_v^2 \left\{MB_{1,1}^2 \rho [1 + (M-1)\rho] + D_1 + E_1\right\}}, \tag{A-28}$$

$$A_{0,2} = p_0 - MA_{1,2}B_{0,2}, \tag{A-29}$$

$$A_{1,2} = \frac{MB_{1,2}\rho\sigma_v^2}{MB_{1,2}^2 \rho \sigma_v^2 [1 + (M-1)\rho] + \sigma_z^2}. \tag{A-30}$$

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 $A_{0,1} = p_0 + 2dA_{1,1}\left(p_0 - \overline{p}_{1,1}^T\right)$ and $C_{0,1} = 2d\left(\overline{p}_{1,1}^T - p_0\right)$. 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):

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

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 $A_{1,1}$,

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

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

$$\begin{aligned} g_{0,1} &= -\mu\psi\sigma_v^2\left[M\rho\left(2-\psi\right)^2 + \psi\left(2-\rho\right)^2\right] < 0, && \text{(A-34)} \\ g_{1,1} &= -2\mu\psi\sigma_v^2 d\left\{M\rho\left[2\left(2-\psi\right) - \psi^2\left(1-\rho\right) - \rho\psi\right] + 2\psi\left(2-\rho\right)^2\right\} < 0, && \text{(A-35)} \end{aligned}$$

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

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

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

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

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

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) under some mild restrictions on exogenous parameter values to ensure its convergence to a solution (e.g., such that the government is "reasonably committed" to a "reasonably uncertain" policy target p_T [i.e., γ is sufficiently lower than 1, while ψ and μ are sufficiently higher than 0]). ■

Proof of Corollary 3. As for the proof of Corollary 1, we start by observing that $corr\left(p_{1,1}^*, p_{1,2}^*\right) = \frac{covar\left(p_{1,1}^*, p_{1,2}^*\right)}{\sqrt{var\left(p_{1,1}^*\right) var\left(p_{1,2}^*\right)}}$, where Eqs. (5) and (6) imply that $var\left(p_{1,1}^*\right) = \lambda^{*2} var\left(\omega_1^*\right)$, $var\left(p_{1,2}^*\right) = \lambda^2 var\left(\omega_2^*\right)$, and $covar\left(p_{1,1}^*, p_{1,2}^*\right) = \lambda\lambda^* covar\left(\omega_1^*, \omega_2^*\right)$. Because of the distributional assumptions of Sections 2.1 and 2.2, it is straightforward to show that $var\left(\omega_1^*\right) = \sigma_z^2 + \sigma_v^2 \left\{M\rho B_{1,1}^{*2}\left[1 + \left(M-1\right)\rho\right] + D_1^* + E_1^*\right\}$, $var\left(\omega_2^*\right) = \sigma_z^2\left[2 + \left(M-1\right)\rho\right]$, and $covar\left(\omega_1^*, \omega_2^*\right) = \sigma_{zz} + \sigma_z\sigma_v\sqrt{M\rho}\left\{B_{1,1}^*\left[1 + \left(M-1\right)\rho\right] + \psi C_{1,1}^* + C_{2,1}^*\right\}$. 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 U.S. cross-listings by the country or most recent currency area of listing (i.e., most recent currency of denomination) of the underlying foreign stocks, as well as summary statistics on the country-level and marketwide measures of their mispricings and illiquidity used in the analysis. These measures are constructed by first obtaining all viable Level II and Level III ADRs and ordinaries ("ADRs") listed on the NYSE, AMEX, or NASDAQ from the entire Datastream sample of U.S. cross-listings between January 1, 1973 and December 31, 2009; N_i is their number in each grouping, where all ADRs issued in the 1970s are available afterwards. The "Other" grouping includes Colombia (COP), Denmark (DKK), Egypt (EGP), Hungary (HUF), Israel (ILS), New Zealand (NZD), Norway (NOK), Philippines (PHP), Singapore (SGD), Sweden (SEK), Taiwan (TWD), Thailand (THB), and Venezuela (VEF). $ADRP_m$ 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 experiences a zero return on day t ($P^{FOR}_{i,t} = P^{FOR}_{i,t-1}$, $P_{i,t} = P_{i,t-1}$, or $S_{t,USD/FOR} = S_{t-1,USD/FOR}$), respectively. 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 the foreign exchange ("forex") market between January 1, 1980 and December 31, 2009 used in the analysis. This database is compiled by the Federal Reserve Bank of St. Louis 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 earliest available historical distribution on month m since 1973; $\Delta N_m\left(gov\right) = N_m\left(gov\right) - N_{m-1}\left(gov\right)$ 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	1.402
$\Delta N_m^z\left(gov\right)$	n.a.	n.a.	360	-0.004	0.911

Table 3. Marketwide ADRP Violations and Forex Intervention

This table reports OLS estimates of interest (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 $LOP_m = ADRP^-_m$ or $ADRP^{-z}_m$, i.e., after removing ADRs from emerging countries where and when capital controls were introduced, as defined in Section 3.3.1) 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 $\{\beta_1, \beta_0, \beta_{-1}\}$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

	$I = N\,(gov)$						$I = N^z\,(gov)$						
	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)		
$\Delta ADRP^-_m$	1.329	3.484***	1.763**	4.812***	6.575***	4%	2.265*	5.281***	2.957**	7.546***	10.503***	4%	359
	(1.51)	(3.69)	(2.01)	(3.15)	(3.26)		(1.67)	(3.62)	(2.19)	(3.19)	(3.37)		
$\Delta ADRP^{-z}_m$	0.002	0.026***	0.009	0.028**	0.036**	4%	0.005	0.039***	0.014	0.043**	0.057**	4%	359
	(0.33)	(3.83)	(1.37)	(2.55)	(2.53)		(0.47)	(3.71)	(1.44)	(2.56)	(2.55)		
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 of interest (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.

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: $LOP_m = ADRP^z_m$												
	$I_m = N_m\,(gov)$						$I_m = N^z_m\,(gov)$						
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	-0.009	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 of interest (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.

	$I_m = N_m\,(gov)$							$I_m = N_m^z\,(gov)$						
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 of interest (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 $\{\beta_1, \beta_0, \beta_{-1}\}$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

	$I_m = N_m\,(gov)$						$I_m = N_m^z\,(gov)$						
$ILLIQ_m$ 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 of interest (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 $\{\beta_1, \beta_0, \beta_{-1}\}$. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

	$I_m = N_m\,(gov)$						$I_m = N_m^z\,(gov)$						
$ADRP_m$ 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 of interest (and bracketed t-statistics) of the regression model of Eq. (14):

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

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 fractions of ADRs in LOP_m whose underlying foreign stock, ADR, or exchange rate experiences zero returns; $\Delta DISP_m = \Delta DISP_q$ for each month m within quarter q; $DISP_q$ is a measure of information heterogeneity, defined in Section 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 Section 3.5) including U.S. and world stock market volatility, global exchange rate volatility, official NBER recession dummy, U.S. risk-free rate, U.S. equity market liquidity, U.S. funding liquidity, and U.S. investor sentiment. Eq. (14) is estimated over the sample period 1980-2009; each estimate is then multiplied by the standard deviation of the corresponding original regressor(s). N is the number of observations; R^2 is the coefficient of determination. A *, **, or *** indicates statistical significance at the 10%, 5%, or 1% level, respectively.

	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)			

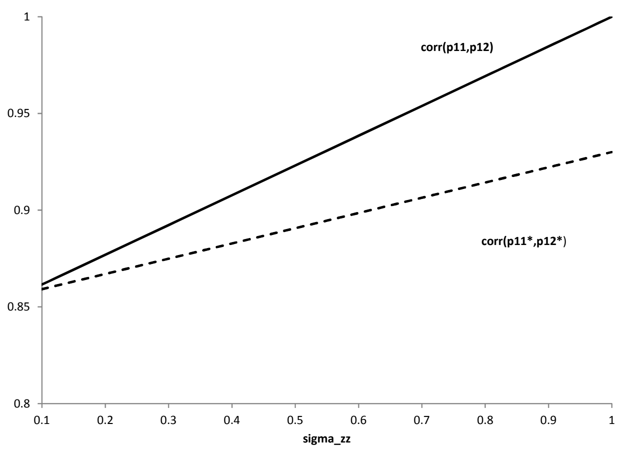
Table 8. (*Continued*)

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

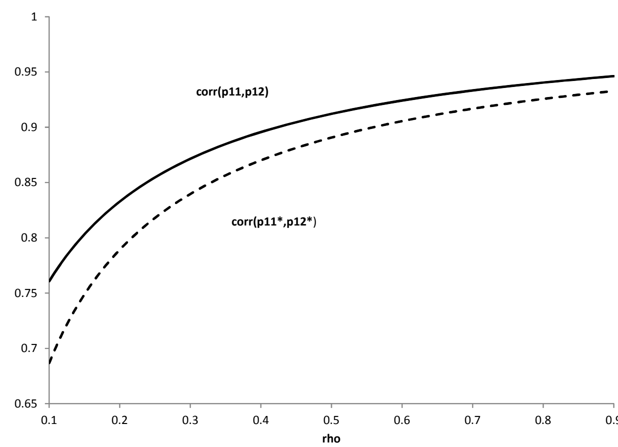
Figure 1. Law of One Price Violations

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 $S_v(m)$ 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 $L(gov)$ of Eq. (4)), μ (the correlation of the government's policy target $p^T_{1,1}$ with its private signal $S_v(gov)$ about the identical terminal payoff v of assets 1 and 2), ψ (the precision of the government's private signal of v, $S_v(gov)$), and σ^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 $M = 10$.

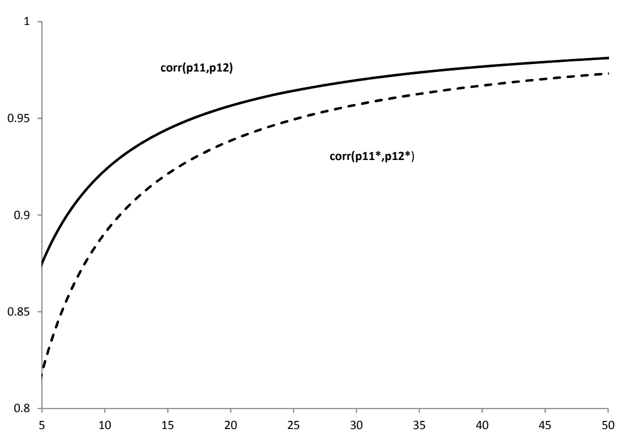
a) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus σ_{zz}



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

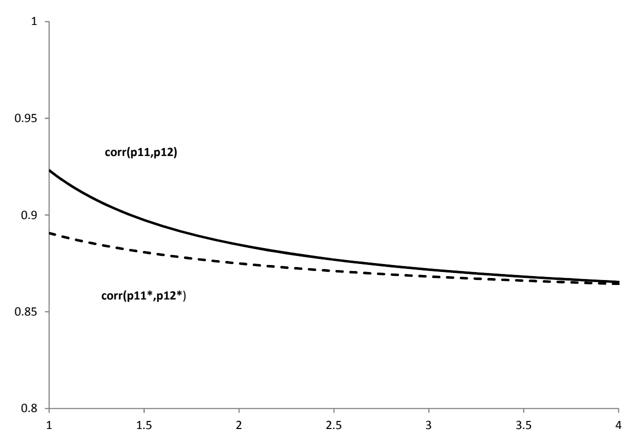
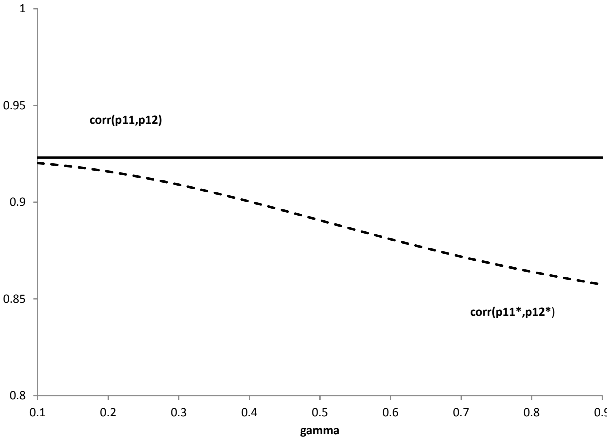
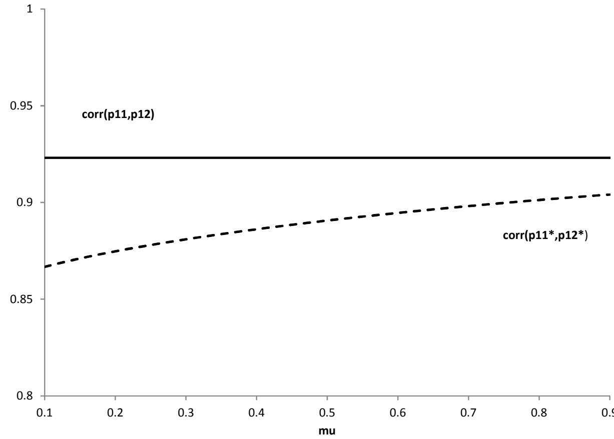


Figure 1 (*Continued*).

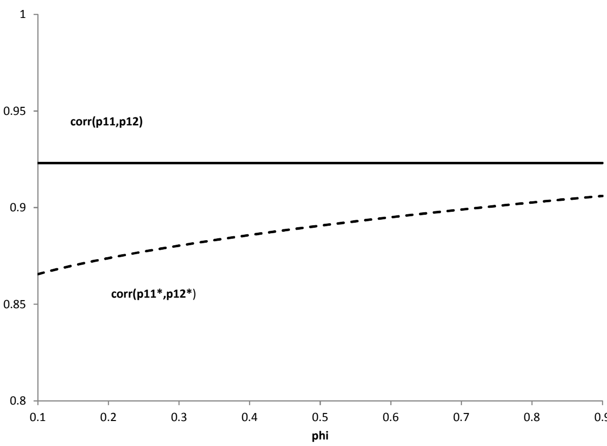
e) $corr\left(p_{1,1}, p_{1,2}\right), corr\left(p^*_{1,1}, p^*_{1,2}\right)$ versus γ



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_v^2

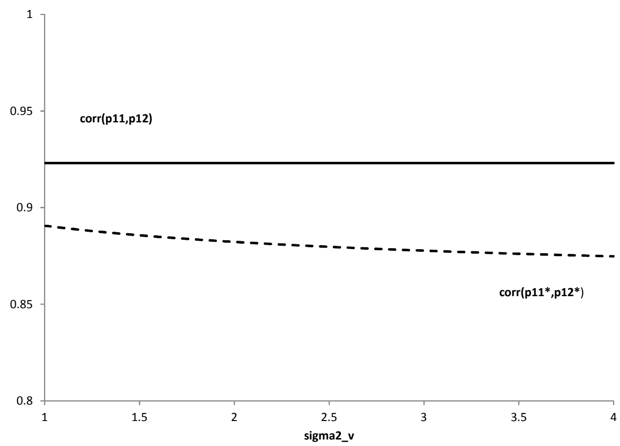
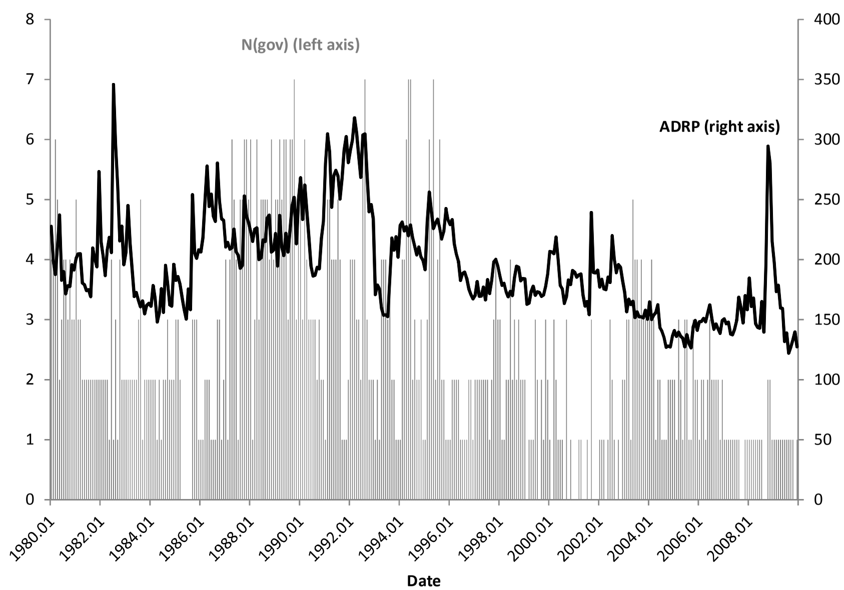


Figure 2. ADR Parity Violations and Forex Interventions

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

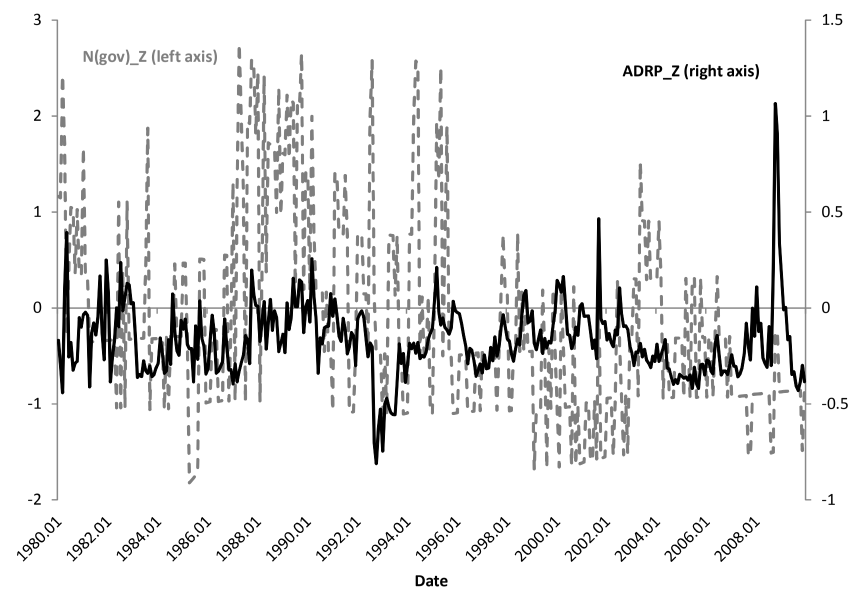
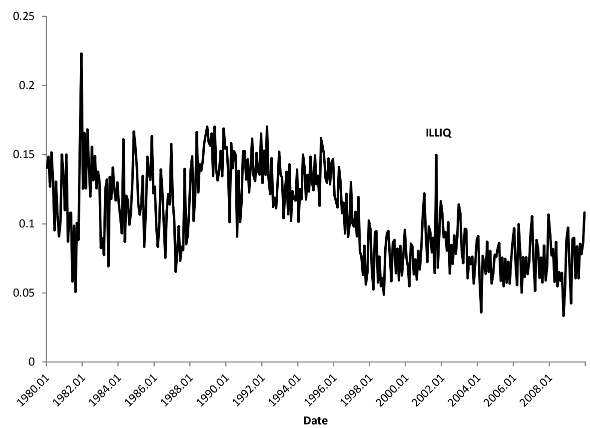


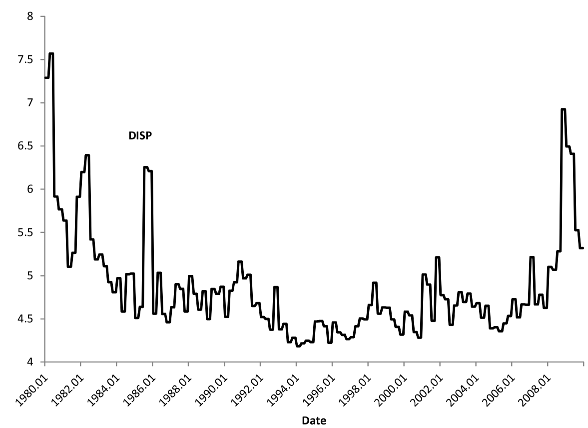
Figure 3. Proxies for Market Conditions

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