Strategic Investors and Exchange Rate Dynamics

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Abstract

We study how the exchange rate dynamics are influenced by the presence of heterogeneous investors with varying degrees of price impact. Leveraging data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions, we show that foreign exchange rate markets display a significant level of concentration, and investors' price impact is stronger in more concentrated markets. We develop a monetary model of exchange rate determination that incorporates heterogeneous investors with different degrees of price impact. We show that the presence of price impact amplifies the exchange rate's response to non-fundamental shocks while dampening its response to fundamental shocks. As a result, investors' price impact contributes to the disconnect of exchange rates from fundamentals and the excess volatility of exchange rates. We provide empirical evidence in line with our theoretical predictions, using data on trading volume concentration from the US CFTC foreign exchange rate market for 10 currencies spanning from 2006 to 2016. Additionally, we extend our framework to account for information heterogeneity among investors, which presents a competing dimension of heterogeneity with qualitatively similar implications for exchange rate dynamics. Both dimensions of heterogeneity are quantitatively relevant, with the heterogeneity in price impact accounting for 62% of the additional volatility and 35% of the additional disconnect attributed to investors' heterogeneity.

JEL Codes: F31, G11, G15

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1 Introduction

Two well-known puzzles in international economics are the limited explanatory power of macroeconomic fundamentals in accounting for exchange rate fluctuations (known as the exchange rate determination puzzle) and the excessive volatility of exchange rates relative to fundamentals (known as the excess volatility puzzle) (Meese and Rogoff, 1983; Obstfeld and Rogoff, 2000).[1] Recent evidence from the microstructure approach to exchange rates suggests that investor heterogeneity plays a crucial role in understanding exchange rate dynamics and determination. For example, both puzzles can be explained by the rational confusion arising from information heterogeneity (Bacchetta and Van Wincoop, 2006). Similarly, exchange rate behavior is linked to order flow, which, in turn, is associated with the heterogeneity among investors (Lyons et al., 2001; Evans and Lyons, 2006).

This paper investigates how the exchange rate dynamics are influenced by the presence of heterogeneous investors with varying degrees of price impact. We use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions to document that currency markets are highly concentrated, meaning that a relatively small number of entities have a substantial presence in the foreign exchange markets. Moreover, we document the presence of heterogeneity in price impact: trading activities in the foreign exchange rate market impact exchange rate prices, and these effects are stronger when markets are more concentrated. Existing models of exchange rate determination typically assume that investors perceive the equilibrium price as given, overlooking the influence of a small group of large investors who recognize the price impact of their decisions and have the ability to exert pressure on market prices.[2]

We embed the heterogeneity in price impact into a two-country, dynamic monetary model of exchange rate determination. Investors face an international portfolio choice model with noise shocks. Departing from the conventional assumption of price-taking investors, we introduce a continuum of investors who exhibit varying degrees of price impact. A fraction of

[1] Meese and Rogoff (1983) show that macroeconomic models have lower predictive power compared to a random walk model. Similarly, Obstfeld and Rogoff (2000) show that exchange rates exhibit significantly more fluctuations than their underlying fundamentals.

[2] Evidence of manipulation in the exchange rate market further support the assumption of non-zero price impact. In June 2013, Bloomberg News reported that "*traders at some of the world's biggest banks colluded to manipulate the benchmark foreign-exchange rates used to set the value of trillions of dollars of investments in Pensions Funds and money managers globally*". Subsequently, extensive investigations were conducted, resulting in banks pleading guilty and paying fines totaling more than \$10 billion. Despite significant institutional reforms implemented in 2015, there are indications that market manipulation may not have completely ceased (Osler, 2014; Osler et al., 2016; Cochrane, 2015).

investors are atomistic and competitive, operating as price takers. Conversely, the remaining fraction consists of a finite number of strategic investors with a non-zero mass, who act oligopolistically and internalize the effects of their trading decisions on equilibrium prices.

Our theory of exchange rate determination with heterogeneity in price impact highlights market structure as a crucial factor influencing exchange rate dynamics. According to our theory, the exchange rate is determined as a weighted average of fundamental factors, such as interest rate differentials, and noise components. Strategic investors, who recognize their price impact, adjust their trading behavior by trading less on any given information. Therefore, the presence of strategic investors amplifies the impact of noise shocks on the exchange rate while dampening the influence of fundamental shocks.

Heterogeneity in price impact contributes to understanding the exchange rate disconnect and the excess volatility puzzles. Firstly, the presence of strategic investors leads to a reduction in the information loading factor of the exchange rate (reduced informativeness), meaning that the exchange rate provides less information about underlying fundamentals. Consequently, strategic behavior helps accounting for the limited explanatory power of macroeconomic variables in predicting exchange rates. Secondly, as fundamental factors exhibit lower volatility compared to noise shocks, the strategic behavior of investors helps to rationalize the excess volatility observed in exchange rates relative to fundamentals. By increasing the relevance of the noise component in exchange rate dynamics, strategic behavior contributes to the heightened volatility of exchange rates relative to the underlying fundamentals factors.

We use a panel of 10 currencies spanning from 2006 to 2016 to empirically validate the main predictions of our model. We combine daily exchange rate data with currency-level concentration data obtained from U.S. Commodity Futures Trading Commission (CFTC). In line with the theoretical predictions, a currency traded in a market with a 10% higher market share of strategic investors exhibits an 18% lower predictive power compared to the average predictive power in the data. Similarly, a currency traded in a market with a 10% higher market share of strategic investors exhibits an excess volatility ratio that is 12% higher compared to the average ratio.

Lastly, we assess the impact of strategic behavior on exchange rate dynamics and compare it to the influence of another dimension of investors' heterogeneity previously explored in existing literature, specifically information heterogeneity (Bacchetta and Van Wincoop, 2006; Candian and De Leo, 2022; Stavrakeva and Tang, 2020). Information heterogeneity also contributes to the disconnect of exchange rates from fundamentals and the excess volatility of exchange rate. Due to rational confusion, investors are uncertain whether changes in the exchange rate stem from noise shocks or fundamental shocks. As a result, this leads to the amplification of the effects of noise shocks and the dampening of the effects of fundamental shocks.

We extend our theoretical framework to include information heterogeneity in the spirit of Nimark (2017) and Bacchetta and Van Wincoop (2006). We use the ECB Professional Forecasters survey data on analysts' forecasts for future exchange rates from 2002 to 2020 to calibrate information dispersion. We solve the dynamic infinite regress problem using the recursive algorithm developed by Nimark (2017). By filtering the underlying states, we construct counterfactual exchange rates by removing one dimension of heterogeneity and examining the resulting dynamics.

In our benchmark calibration, investors' heterogeneity significantly influences the dynamics of exchange rates, increasing the exchange rate disconnect by 24% and the excess volatility by 13%. Moreover, each dimension of heterogeneity is quantitatively relevant, with the heterogeneity in price impact accounting for 62% of the additional volatility and 35% of the additional disconnect attributed to investors' heterogeneity. Thus, heterogeneity in price impact appears to be more relevant in explaining exchange rate excess volatility, underscoring the importance of jointly considering both dimension in the analysis of exchange rate markets. Furthermore, the two dimensions of heterogeneity reinforce each other: as strategic investors trade less, strategic behavior reduces the informativeness of the exchange rate, making prices more dispersed for any level of information heterogeneity. Our decomposition analysis underscores the importance of incorporating investors' heterogeneity, particularly highlighting a crucial aspect of the exchange rate markets that has been overlooked until now.

1.1 Related literature

Our work contributes to the microstructure approach to exchange rates by focusing on the heterogeneity of investors' price impact. Recent evidence from this literature highlight the importance of investor heterogeneity in understanding exchange rate dynamics and determination. For instance, the exchange rate determination puzzle, the excess predictability puzzle and the excess volatility puzzle can be explained by the rational confusion resulting from information heterogeneity among investors (Bacchetta and Van Wincoop, 2006; Candian and De Leo, 2022; Stavrakeva and Tang, 2020). Furthermore, exchange rate behavior is linked to order flow, which, in turn, is associated with the heterogeneity among investors (Lyons et al., 2001; Evans and Lyons, 2006). However, despite extensive evidence that foreign exchange rate markets are highly concentrated and atomistic price-taking investors are hardly realistic, the literature has ignored the potential heterogeneity in price impact (Osler, 2014; Osler et al., 2016; Cochrane, 2015). A notable exception is the work in Corsetti et al. (2004) and Corsetti et al. (2002), which theoretically studies the role that large investors have in speculative attacks in the foreign exchange markets. Differently to them, we focus on exchange rate determination and puzzles by incorporating heterogeneity in price impact, drawing on the modeling approach of Kyle (1989) and Kacperczyk et al. (2018), which has not been previously applied in the context of exchange rate markets.

This paper contributes to the rich literature on the determination and dynamics of exchange rates in the presence of frictions. Prior work explores various types of frictions, including informational frictions (Evans and Lyons, 2002; Bacchetta and Van Wincoop, 2006), infrequent portfolio adjustment (Bacchetta and Van Wincoop, 2010, 2019), imperfect and frictional markets (Gabaix and Maggiori, 2015; He and Krishnamurthy, 2013). To the best of our knowledge, our work is the first to specifically focus on this aspect of the market structure – the presence of strategic investors and heterogeneity in price impact – for the determination of the exchange rate.

This paper also relates to the vast literature attempting to explain major puzzles in international economics, both theoretically and empirically. We contribute by providing a new rationale, based on strategic behavior and price impact, for the failure of macroeconomic fundamentals to predict exchange rates and the large volatility of the exchange rate relative to fundamentals (Meese and Rogoff, 1983; Obstfeld and Rogoff, 2000; Engel and Zhu, 2019).[3] Moreover, we empirically study cross-currency differences in exchange rate puzzles and dynamics, which have been relatively unexplored, and find that different levels of price impact can explain cross-currency differences in a panel of 10 currencies.

The rest of the paper is organized as follows. Section 2 documents a set of facts that are consistent with the presence of strategic behavior in currency market. Section 3 introduces the theoretical framework and explains the fundamental mechanism of strategic behavior. In Section 4, we discuss the main implications for the dynamics of the exchange rate and

[3] We also show that the presence of strategic behavior and excess predictability interact (Fama, 1984). Although we do not propose novel explanations for UIP deviations, the presence of strategic investors can account for currency level differences in UIP deviations.

provide empirical evidence that supports the theoretical predictions. Section 5 expands the basic framework to incorporate information heterogeneity and quantifies the respective contributions of each mechanism. Finally, Section 6 presents the conclusion. Any proofs, derivations, and robustness analyses that were omitted can be found in the Appendices.

2 Motivating Facts

As a first step, we use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions to show that currency markets are highly concentrated, and investors' price impact decreases in more competitive markets. The U.S. Commodity Futures Trading Commission (CFTC) data provides detailed information on currency futures positions held by asset managers, institutional investors, and leveraged funds in the currency futures market. The dataset encompasses 11 currency pairs, including both major and non-major USD currency pairs traded in the market. Data is reported on a weekly basis and spans the years 2006 to 2016.

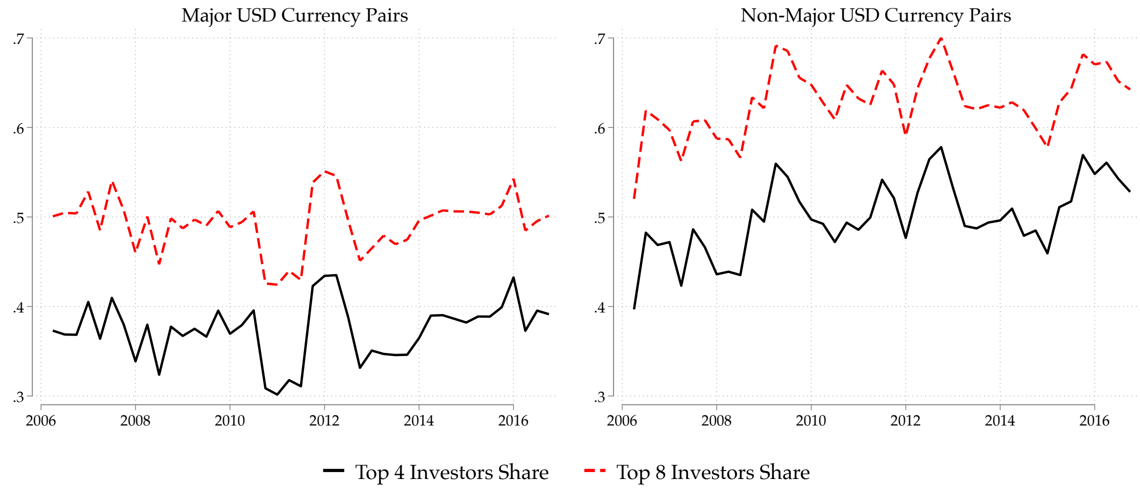
Our first fact show that a relatively small number of entities have a substantial presence in the foreign exchange markets. Figure 1 reports the average concentration ratios by currency groups (major and non-major currencies), computed as the share of net open interest positions held by the largest four and eight entities operating the foreign exchange market.[4] [5] Two noteworthy observations emerge. Firstly, the eight (four) largest entities collectively held approximately 50% to 70% (40% to 60%) of the open interest positions in the market, revealing a significant level of market concentration. Secondly, concentration is highly heterogeneous across currency pairs, with Non-Major USD currency pairs exhibiting a 20% higher degree of concentration compared to major currency pairs.[6] Figure 9 in Appendix A shows qualitatively similar patterns when concentration is measured using the number of entities trading each currency (on average, 10 to 25 entities actively trade, with

[4]Net positions are calculated by offsetting each trader's long and short positions. As a result, an entity with relatively large, balanced long and short positions in a single market may be counted among the four and eight largest traders in both the gross long and gross short categories, but it is unlikely to be counted among the four and eight largest traders on a net basis.

[5]As standard in this literature, we refer to Euro, Yen, Pound, and Swiss Franc as major currencies, while non-major currencies include Brazilian Real, Russian Rublo, Mexican Peso, Australian Dollar, New Zealand Dollar, and Canadian Dollar

[6]Figure 8 in Appendix A shows the concentration ratios for all individual currencies from 2006 to 2016. The Brazilian Real, Russian Rublo, and New Zealand Dollar are the currency pairs with the highest concentration, while the Euro and and Canadian Dollar exhibit the lowest.

Figure 1: Market Concentration – U.S. CFTC



Notes: The figure shows the average concentration ratio of net open interest positions help by asset managers, institutional investors, and leveraged funds across currencies, divided between major and non-major currency groups. We consider the share held by the eight and the four largest entities in each market. Concentration ratios are computed on 'Net Position', meaning that are calculated after offsetting each trader's long and short positions. Major currency pairs consist of the United States Dollar paired with the Euro, British Pound, Japanese Yen, and Swiss Franc. Non-Major currency pairs include the United States Dollar paired with the Australian Dollar, Canadian Dollar, New Zealand Dollar, Mexican Peso, Brazilian Real, and Russian Ruble. The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016, with quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

more traders being active in major currency markets).[7] The high concentration in the foreign exchange markets raises the question whether leading traders can significantly influence market dynamics.

Our second fact shows that trading activities in the foreign exchange rate market impact exchange rates, and the effects are stronger when markets are more concentrated. We aim to estimate how the trading activities of market participants influence exchange rate movements. To this end, we follow Evans and Lyons (2002) and Ready and Ready (2022) and regress the changes in exchange rates on the investors' net imbalances reported in our data,

[7]The high concentration measured in here aligns with other pieces of evidence, such as the BIS Triennial Survey of Foreign Exchange Markets or the NY FED OTC Foreign Exchange Market Survey. However, these surveys are limited in their scope, frequency of observation or coverage. The leading foreign exchange rate market survey, conducted by Euromoney and covering global markets, reveals that around 25 entities transact 70% of the total turnover. Additional information can be found here: https://www.euromoney.com/article/b1lp5n97k4v6j0/fx-survey-2020-press-release.

as follows:

$$\Delta s_{i,t} = \alpha_i + \gamma_t + \beta \text{ Imbalance}_{i,t} + \eta(i_t - i_t^\star) + \varepsilon_{i,t} \quad (1)$$

where $\Delta s_{i,t}$ represents the one-month percentage change in exchange rates, defined as domestic currency over foreign currency (i.e., an increase in exchange rate represents a depreciation of the foreign currency); α_i and γ_t are currency and time fixed effects, respectively, which controls for currency-specific characteristics and common temporal variations; $(i_t - i_t^\star)$ captures the one-month interest rate differential between US and the foreign country, common determinant in standard exchange rate models (Evans and Lyons, 2002). Lastly, $\text{Imbalance}_{i,t}$ represents the sum of net open interests positions of asset managers, institutional investors, and leveraged funds in a specific currency i within the month.[8] A value of β_1 different from zero suggests the presence of a price impact of traders' flow in the foreign exchange rate market. We then augment the baseline regression in Equation (6) by interacting $\text{Imbalance}_{i,t}$ with a proxy for the degree of concentration in the currency market. We measure concentration in each currency market using the market concentration measure as in Figure 1, the numbers of active traders (Figure 9 in Appendix A), or by distinguishing between major and non-major currencies. The coefficient of the interaction term is informative on how investors' price impact changes depending on the degree of market competition.

Table 1 reports the results of the estimates. Columns (1) and (2) indicate that increased trading flow within the future FX market exerts a downward pressure on foreign-to-domestic exchange rates (Evans and Lyons, 2002).[9] Specifically, a one-million-dollar increase in trading imbalances towards a foreign currency leads to approximately a 0.01% appreciation of the foreign currency. These effects are both statistically and economically significant, accounting for roughly 5% of the average monthly exchange rate variation.

The impact of tradings on the exchange rate is more pronounced in markets that are

[8] The CFTC distinguishes the market participants into the 'sell side' and 'buy side.' Sell-side participants include financial intermediaries that usually act as dealers in the market, while asset managers, institutional investors, and leveraged funds represent buy-side participants. We exclusively focus on buy-side participants as our primary focus is on active traders. Figure 7 in Appendix A presents the net open interest positions by market participants for each currency in our dataset.

[9] Episodes of market manipulation provide additional evidence of non-zero price impact in the exchange rate market. In June 2013, Bloomberg News reported that "*traders at some of the world's biggest banks colluded to manipulate the benchmark foreign-exchange rates used to set the value of trillions of dollars of investments in Pensions Funds and money managers globally*". Subsequently, extensive investigations were conducted, resulting in banks pleading guilty and paying fines totalling more than $10 billion. Despite significant institutional reforms implemented in 2015, there are indications that market manipulation may not have completely ceased (Osler, 2014; Osler et al., 2016; Cochrane, 2015).

Table 1: Price Impact Regressions

Dep. Variable: Δ Exchange Rate (%)	Average		Heterogeneity		
	(1)	(2)	(3)	(4)	(5)
Imbalances (Mil $)	-0.0118***	-0.0129***	0.0198	-0.0105***	-0.0288***
	(0.0020)	(0.0020)	(0.0142)	(0.0019)	(0.0069)
Interest Differential		2.2537*	2.2332*	2.2778*	2.2319*
		(1.1561)	(1.1330)	(1.1659)	(1.1556)
Imbalances (Mil $) × Conc. (Avg)			-0.0642**		
			(0.0278)		
Imbalances (Mil $) × Non-Major Pairs				-0.0080**	
				(0.0031)	
Imbalances (Mil $) × Number (in tens)					0.0044**
					(0.0019)
Time FE	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes
Cluster SE	Currency	Currency	Currency	Currency	Currency
Observations	1,160	1,160	1,160	1,160	1,160
Mean of Dep. Variable	0.2004	0.2004	0.2004	0.2004	0.2004

Notes: The table displays the results of a pooled regression in which the dependent variable is the monthly exchange rate change, and the independent variable is the contemporaneous one-month net trade imbalance. The net imbalance is the sum of net imbalances among asset managers, institutional investors, and leveraged funds. Exchange rate change is measured in percentages, and net imbalance is measured in millions of dollars (i.e., a coefficient of 0.01 represents a weekly exchange rate change of 0.01% per million dollars of trading imbalance). Interest differential measures the difference between the one-month US interest rate and the one-month foreign interest rate. Columns (1)-(2) present the results with currency and time fix effects, and controlling for the lagged one-month interest rate differential, respectively. Column (3)-(5) report the heterogeneous effect due to market concentration. Concentration is measured using the market share of the top eight entities (Column (4)), distinguishing between major and non-major currencies (Column (5)), and the number of active traders (Column (6)). Standard errors are clustered at the currency pair level and are displayed in parentheses. The sample period covers June 2006 through December 2016, except for the Brazilian Real-USD pair, which starts in May 2011. Additional information about the data used is provided in Appendix A

more concentrated. Columns (3)-(5) examine the relationship between net imbalances and exchange rates, depending on different measures of market concentration. In Column (3), an increase in trading imbalances has a more significant negative impact on exchange rates when the share of open interests held by the top 8 traders is larger. This result remains robust when measuring concentration by currency pairs group or by the number of active traders, as shown in Column (4) and Column (5), respectively.

Taken together, the two facts highlight that market concentration is a salient feature of the exchange rate markets, with key implications on investors' price impact and its heterogeneity across currencies. In the next section, we demonstrate the importance of incorporating strategic behavior into models of exchange rate determination to gain a deeper understanding exchange rate dynamics and puzzles.

3 A Monetary Model with Strategic Investors

We propose a framework that incorporates strategic behavior in the spirit of Kyle (1989) and Kacperczyk et al. (2018) into a standard two-country, discrete time, general equilibrium monetary model of exchange rate determination (Mussa, 1982; Jeanne and Rose, 2002). To provide the key insight on the main mechanism, we initially present a version of the model that assumes agents have rational expectations about the dynamics of the exchange rate. In Section 5, we extend the model to include dispersed information, following Bacchetta and Van Wincoop (2006), and conduct our quantitative decomposition.

3.1 Basic Set-up

There are two economies, Home and Foreign, both producing the same good. Variables referring to Foreign are indicated with a star. We assume that purchasing power parity holds, so that:

$$p_t = p_t^\star + s_t,$$

where s_t is the log nominal exchange rate, p_t ($p_t^\star$) the log price level in the Home (Foreign) country. The exchange rate is defined as the value of the foreign currency in term of domestic currency, and an increase in the exchange rate reflects an appreciation of the foreign currency. There are three assets: one-period nominal bonds issued by both Home and Foreign with interest rates i_t and $i_t^\star$, respectively, and a risk-free technology with fixed real return r. The latter is infinitely supplied while bonds are in fixed supply in their respective currency. We follow Bacchetta and Van Wincoop (2010) and assume asymmetric monetary rules between the two countries. The Home central bank commits to a constant price level, $p_t = 0$, which implies that the domestic interest rate is equal to the risk free technology, $i_t = r$. On the other hand, the monetary policy in Foreign is stochastic, $i_t^\star = -u_t$ where

$$u_t = \rho_u u_{t-1} + \sigma_u \epsilon_t^u \qquad \epsilon_t^u \sim N(0,1) \tag{2}$$

is the Foreign monetary policy shock. Thus, the interest rate differential is defined as

$$i_t - i_t^\star = u_t + r,$$

implying that the dynamics of the exchange rate are solely influenced by the monetary policy of the Foreign country.[10] In our model, we refer to a shock in the Foreign monetary policy as a fundamental shock.

There is a continuum of investors of mass one. We assume there are overlapping generations of investors that live for two periods and make only one investment decision. We abstract away from saving decisions by assuming that investors derive utility only from their end-of-life wealth (Bacchetta and Van Wincoop, 2006, 2010). Investors in both countries are born with an exogenous endowment, ω, and have the possibility to invest in nominal bonds and the risk free technology. We assume that Foreign country is infinitesimally small, implying that the market equilibrium is determined by the investors located in the Home country. There are two type of investors: strategic (S) and competitive (C). A mass $1-\lambda$ of investors consists of standard atomistic price-takers investors. The remaining segment, with size λ, consists of a finite number N of strategic investors. Each strategic investors has a positive mass, λ_i, with $\sum_i^N \lambda_i = \lambda$. Notably, strategic investors internalize their effect on asset prices, operating as an oligopoly.

Investor j maximizes mean-variance preferences over next period wealth, w_{t+1}^j, by allocating their initial endowment between domestic and foreign bonds:

$$\max_{b_t^j} \quad E_t^j(w_{t+1}^j|\Omega_t^j) - \frac{\rho}{2} Var_t^j(w_{t+1}^j|\Omega_t^j) \tag{3}$$

$$\text{s.t. } w_{t+1}^j = (\omega - b_t^j)i_t + (i_t^\star + s_{t+1} - s_t)b_t^j, \tag{4}$$

where b_t^j represents the foreign bond holdings, ρ the rate of risk aversion and Ω_t^j the information set of investor j at time t. i_t and $i_t^\star + s_{t+1} - s_t$ are the log-linearized returns of domestic and foreign bonds, respectively. Under PPP and the monetary policy assumptions above, we have that $p_t^\star = -s_t$, implying that both returns are expressed in real terms. The only difference between the two assets is that the return on foreign bonds is stochastic.[11] We assume that agents have symmetric rational expectations about the dynamics of the exchange rate, $\Omega_t^j = \Omega_t$, postponing dispersed information to Section 5.

Investors' demand schedule and portfolio allocation vary depending on their type. Strate-

[10] Bacchetta and Van Wincoop (2010) specify a simplified Wicksellian rule of the form $i_t^\star = \psi(p_t^\star - \bar{p^\star}) - u_t$ where ψ is set equal to zero, consistent with the low estimates of ψ reported by Engel and West (2005). Bacchetta and Van Wincoop (2010) show that an exogenous interest rate rule, as in our case, does not compromise the existence of a unique stochastic steady state for the exchange rate.

[11] $p_t = 0$ implies $i_t = r$. Similarly, $p_t^\star = -s_t$ implies that the return on foreign bonds, $i_t^\star + s_{t+1} - s_t$, is expressed in real terms as well.

gic investors internalize the effects that their demand has on equilibrium prices (more precisely, on the equilibrium exchange rate), while competitive investors do not. In Appendix B, we show that the optimal demand for foreign bonds by investor j is as follows:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2}, & \text{for } j = C \\ \\ \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}}, & \text{for } j = S \end{cases} \tag{5}$$

where σ_t^2 is the variance of the exchange rate change, $Var_t(s_{t+1} - s_t)$. We focus on a stochastic steady state where the variance σ_t^2 is time-invariant.

Investors' demand for foreign bonds depends positively on the expected excess return, $q_{t+1} \equiv E_t(s_{t+1}) - s_t + i_t^\star - i_t$. On the other hand, it depends negatively on the variance of the exchange rate, σ_t^2, and on investors' risk aversion, ρ. Note that strategic behavior, captured by investors' own price impact $\frac{\partial s_t}{\partial b_t^S}$, reduces investors' demand of foreign bonds for every level of excess return. Given a total supply of foreign bond B, the price impact of a strategic investor i is

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} > 0, \tag{6}$$

which is positive, increasing in the mass of the investor, λ_i, and decreasing in the fraction of atomistic investors $1 - \lambda$. The individual price impact becomes $\frac{1}{N}\frac{\lambda\rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)}$ in the case strategic investors are symmetric and have the same mass, $\lambda_i = \frac{\sum_i \lambda_i}{N} = \frac{\lambda}{N}$.[12] The structure of the market determines the magnitude of the price impact and, consequently, the relevance of strategic behavior: the magnitude of the individual price impact is negatively affected by the number of strategic traders, N, and positively related to the size of the strategic segment, λ. Therefore, the price impact is larger in more concentrated markets characterized by a lower N and/or higher λ.[13] Importantly, Table 1 in Section 2 provides empirical evidence

[12] In our analysis, we focus on the case of symmetric strategic investors due to the unavailability of comprehensive investor-level market share data. The U.S. CFTC data, used in Section 2 and in the rest of the paper analysis, provides information only on the aggregate market share of the top four or eight investors or the number of investors in total. Importantly, all qualitative predictions are not altered by the symmetry assumption. See Appendix B for the derivation of the analytic expression of the price impact.

[13] In our international portfolio model, strategic investors have a lower price impact on the equilibrium price of an asset compared to a closed-economy version. This is due to the presence of valuation effects on the supply of assets once denominated in domestic currency. By internalizing the effect that their demand has on the exchange rate, strategic investors also take into account how the value of the supply of foreign assets denominated in domestic currency varies when the exchange rate changes. This is reflected by the

on how the degree of market competition affects investors' price impact that are in line with the theoretical implications of Equation (6).

In addition to strategic and competitive investors, we introduce another group of investors referred to as noise traders. As is standard, their presence allows to match key empirical moments of exchange rates, such as exchange rate volatility, disconnect and deviations from UIP (Kyle, 1989; Bacchetta and Van Wincoop, 2006, 2010). Following Bacchetta and Van Wincoop (2010), we assume that the demand of noise traders for foreign bonds is exogenous and given by:

$$X_t = (\bar{x} + x_t)\bar{W},$$

where $\bar{W}$ is the steady state aggregate financial wealth in the Home economy, $\bar{x}$ is a constant and x_t follows the following exogenous process:

$$x_t = \rho_x x_{t-1} + \sigma_x \epsilon_t^x \qquad \epsilon_t^x \sim N(0, 1).$$

In the stochastic steady state, the demand for foreign assets absorbed by noise traders is equal to $\bar{x}\bar{W}$. Deviations from this steady state are driven by x_t, which is interpreted as a noise shock and is orthogonal to the fundamental shock u_t in Equation (2). Positive shocks to x_t increase the desire for foreign assets, leading the foreign currency to appreciate without movements in the interest rate differential.

Equilibrium and Basic Mechanism We derive an expression for the equilibrium exchange rate by combining the demand schedules of investors and the market clearing condition of the foreign bond market. The market clearing condition is given by:[14]

$$(1 - \lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i} + X_t = Be^{s_t}, \tag{7}$$

where the left hand side represents the total demand of foreign bonds from competitive investors, strategic investors and noise traders, and the right hand side represents the (con-

presence of B, the total supply of foreign assets, at the denominator of Equation (6). See Appendix B for additional details.

[14]The market clearing for the domestic bond is not explicitly considered because domestic bonds are perfectly substitutable with the risk free technology, which is infinitely supplied. Furthermore, in a monetary model, a market clearing condition for the money market would also be required. Bacchetta and Van Wincoop (2006) and Bacchetta and Van Wincoop (2010) assume that investors generate a money demand (independent of their portfolio decision) and that money supply accommodates it under the exogenous rule for interest rates. We do not explicitly model the money market in order to limit notation, leaving it in the background.

stant) supply of foreign bonds, B, denominated in domestic currency.

We define the concept of equilibrium in our model as follow: for a history of fundamental and noise shocks $\{\varepsilon_t^{\Delta i}, \varepsilon_t^x\}_{t=0}^{-\infty}$, an equilibrium path is a sequence of portfolio allocations, $\{b_t^C$, $\{b_t^{S,i}\}_{i=1}^N\}$, and foreign bond price (exchange rate), $\{s_t\}$, such that investors optimally choose their portfolio allocation and the market clearing condition holds.

The model allows us to derive an explicit solution for the exchange rate s_t from the market clearing condition in Equation (7):

$$s_t = \underbrace{(1-\mu)\left(\frac{\bar{x}}{b} - 1\right)}_{\text{constant}} + \underbrace{\mu\left(E_t s_{t+1} + i_t^\star - i_t\right)}_{\text{fundamental}} + \underbrace{(1-\mu)\frac{1}{b}x_t}_{\text{noise}}, \tag{8}$$

where $b = \frac{B}{W}$ and $\mu = \frac{1}{1+\Phi(\lambda,N)}$ with $\Phi(\lambda, N) = \frac{B\rho\,\mathrm{Var}_t(s_{t+1})\left(1+B\rho\,\mathrm{Var}_t(s_{t+1})-\lambda\frac{N-1}{N}\right)}{\left(1+B\rho\,\mathrm{Var}_t(s_{t+1})-\lambda\frac{N-1}{N}\right)-\frac{\lambda^2}{N}}$. The exchange rate follows a forward looking auto-regressive process with drift, where the constant term depends on a set of parameters and the stochastic component depends on future fundamental and noise shocks. By further manipulating Equation (8), it can be shown that the exchange rate s_t can be written as follows:

$$s_t = \mu\sum_{k=0}^{\infty}\mu^k\left(i_{t+k}^\star - i_{t+k}\right) + \frac{1-\mu}{b}\sum_{k=0}^{\infty}\mu^k\left(x_{t+k}\right). \tag{9}$$

The exchange rate is a weighted average of current and future fundamental shocks $(i_{t+k}^\star - i_{t+k})$ and noise shocks (x_{t+k}). The weight μ quantifies the amount of information about the fundamental conveyed by the exchange rate. Notably, the informativeness of the exchange rate decreases when strategic investors operate in the foreign bond market (higher λ or lower N imply higher Φ and, thus, lower μ). When there is a higher proportion of strategic investors (higher λ) or a lower number of strategic traders (lower N), investors' demand declines because of the stronger price impact. Therefore, the demand from noise traders becomes relatively more important in determining the exchange rate.[15] [16]

We calibrate and simulate the basic model to illustrate the mechanism discussed above. We use data on 18 exchange rates, all defined against the USD, from 1993 to 2019 at

[15]When traders recognize that the residual supply curve is upward-sloped, quantities are restricted and less elastic. Therefore, prices become less informative. This aligns with the key intuition from Kyle (1989).

[16]The informativeness parameter, μ, relates to the magnification factor in Bacchetta and Van Wincoop (2006). In their work, information dispersion among investors reduces the information content of exchange rates by amplifying the impact of noise traders. As in their work, the behavior of the parameter μ plays a crucial role in the amplification mechanism examined here.

Table 2: Benchmark Parametrization

Parameters	Value	Target
λ	0.6	Net concentration ratio (Top 8) – U.S. CFTC
N	8	Number of traders related to λ – U.S. CFTC
ρ_u	0.85	Average persistence AR(1) Δi_t
σ_u	0.005	Average StD innovation AR(1) Δi_t
σ_x	0.131	σ_t (StD ER change)
σ_t	0.028	Average StD ER change
ρ_x	0.9	ER Random Walk/Average Disconnect
b	0.333	Home Bias
ρ	50	Bacchetta and Van Wincoop (2019)

Notes: The table summarizes the parametrization used in the basic framework. For each parameters, we report the value used in the model, the corresponding moment and data used to calibrate, and, if applicable, the target moment used to estimate it. Appendix A provides additional information on the data used.

a monthly frequency.[17] Without loss of generality, we set $\bar{r} = 0$, so that the $i_t - i_t^\star = u_t$. Assuming covered interest rate parity holds, we compute the one-month interest rate differential as the difference between the one-month forward and the spot exchange rate. We assume that the fundamental, u_t, follows an AR(1) process. We estimate the volatility and the persistence of the fundamental process for each currency using interest rate differentials, and calibrate σ_u and ρ_u to match the average volatility and persistence across currencies. This yields $\sigma_u = 0.005$ and $\rho_u = 0.85$. The variance of the exchange rate change, σ_t, is assumed to be constant over time and calibrated to match the average standard deviation of the one-period exchange rate change across currencies, which is 0.028.

As standard in this literature, the process governing the demand of noise traders, x_t, is calibrated to match exchange rate dynamics. The persistence of the noise shock, ρ_x, is set high enough to ensure the exchange rate behavior is sufficiently close to a random walk. The volatility of the process is chosen to match the volatility of the one-period change in exchange rate. However, Equation (9) shows that exchange rate dynamics depend on the underlying market structure. Therefore, we first calibrate the parameters controlling the

[17]We consider the following currencies: Euro, Japanese Yen, Argentinian Peso, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Chilean Peso, Indian Rupee, Mexican Peso, British Pound, South African Rand, Russian Ruble, Swedish Krona, Turkish Lira, New Zeland Dollar, Singapore Dollar, Norwegian Krone. See Appendix A for additional details on data.

magnitude of the strategic behavior, λ and N, and then σ_x and ρ_x.[18] We use data from the U.S. Commodity Futures Trading Commission, and set $N = 8$ and $\lambda = 0.6$, which is the average concentration ratio of the top eight traders in the currency market (Figure 1). Given the benchmark values for λ and N, we set $\sigma_x = 0.131$ and $\rho_x = 0.9$.[19]

Lastly, we set b, the inverse home bias measure, equal to 0.33, indicating that foreign assets account for one third of the total domestic financial wealth. This value is an approximate average obtained from the IMF IIPS dataset (Bacchetta and Van Wincoop, 2019).[20] Moreover, we follow Bacchetta and Van Wincoop (2019) and set the rate of relative risk aversion, ρ, to 50.[21] The parametrization, summarized in Table 2, uses values in line with previous literature.

The main implication of heterogeneity in price impact is that the response of the exchange rate to fundamental and noise shocks depends on the presence of strategic behavior. Specifically, compared to a "competitive" exchange rate market without strategic investors ($\lambda = 0$ or $N \to \infty$), the presence of strategic investors amplifies the exchange rate's response to noise shocks and dampens its response to fundamental shocks. Appendix B shows that the result is independent of the parameterization of the model.

The bottom row of Figure 2 plots the impulse response functions to a noise shock in the presence of strategic investors compared to a scenario without strategic investors ("competitive" market). A positive noise shock, which can be interpreted either as a positive demand shock or a negative supply shock of foreign assets. Either way, the residual demand of foreign assets decreases, increasing the price of the foreign assets and the exchange rate without any

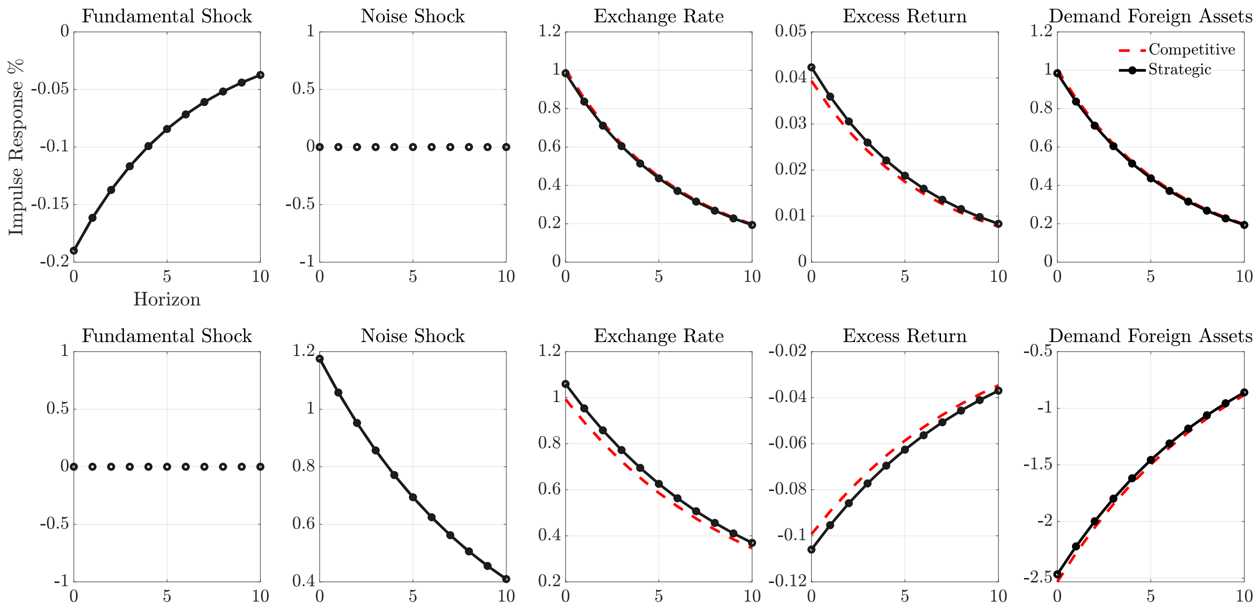
[18] $\bar{x}$ is calibrated such that the value of the exchange rate in the stochastic steady state is zero, excluding any trend in the dynamics of exchange rate. This assumption does not affect the results of our model.

[19] Taking into account the presence of strategic investors in the underlying market structure has the effect of reducing the implied volatility of noise traders required to match exchange rate dynamics. This is because strategic investors amplify the effects of noise traders. Figure 12 in Appendix D shows that there exists a negative relationship between the level of strategic behavior (N and λ) and σ_x, given a target value for the exchange rate volatility. In a competitive market, the volatility of the noise shock should be $\sigma_x = 0.14$ in order to match the same volatility of the exchange rate, which is almost 20% higher than in our benchmark calibration. This highlights the importance of considering the underlying market structure. Moreover, this represents a positive results for the determination of the exchange rate, as it suggests that noise traders are not as noisy as previously believed.

[20] Without loss of generality, the supply of foreign assets, B, is normalized to one. In order to ensure model consistency, we set ω, the initial endowment of each investor, equal to 3. This choice is derived from the relationship $b = \frac{B}{\bar{W}}$. By calibrating b and normalizing B, we determine that $\bar{W} = 3$. Total financial wealth in equilibrium is equal to the initial endowment.

[21] In the model, currency premia arise solely from investors' risk aversion, which would be relatively small for typical levels of risk aversion. However, our results are qualitatively robust when considering different levels of risk aversion.

Figure 2: Impulse Response to Exogenous Shocks



Notes: The top panel (bottom) shows the response to a fundamental (noise) shock. The size of the shocks is calibrated to produce a 1pp change in the exchange rate at impact in the competitive model. The first and second columns show the dynamics of the exogenous shocks in fundamentals and noise, respectively. The third column shows the dynamics of the exchange rate. Column four shows the response of the realized excess return, defined as $q_{t+1} = s_{t+1} - s_t + i_t^\star - i_t$. The last column shows the response of the total demand of foreign assets, defined as $(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i}$, where b_t^C and $b_t^{S,i}$ are defined according to Equation 5. The solid black line shows the response in the benchmark parametrization with strategic investors, $\lambda = 0.6$. The red dashed line shows the response in a competitive economy without strategic investors, $\lambda = 0$. Remaining parameters are common across scenarios, see Table 2.

change in fundamentals. As the exchange rate increases, the excess return falls below its steady state. The lower excess return prompts investors to purchase fewer foreign assets, rebalancing their portfolios in favor of domestic assets.

The presence of strategic investors amplifies the response of the exchange rate to a noise shock due to the lower sensitivity of the demand of foreign bonds. Strategic investors internalize the negative impact of their trades on prices. Therefore, in a world where investors are strategic (solid line), the decline in the demand for foreign assets is less pronounced compared to a competitive market scenario (dashed red line), making the total demand for foreign assets less sensitive to the noise shock. In order for the market to clear, the response of the excess return is dampened relative to a competitive market. In other words, the smaller decline in investors' demand due to strategic behavior exerts additional upward pressure on the price of the foreign bonds and the exchange rate, thereby amplifying the effect of noise shocks on the exchange rate.

The top row of Figure 2 shows the exchange rate's response to a fundamental shock and its dampening in the presence of strategic investors compared to a "competitive" market. A contraction in monetary policy in the foreign country leads to a drop in the interest differential, increasing the excess return, and thus, investors' demand for foreign assets. This results in the appreciation of the foreign currency. In a world where investors are strategic (solid black line), their holdings of foreign assets increase relatively less due to their price impact, which makes their demand less sensitive. As a consequence, the price of foreign assets increases relatively less compared to a competitive market, hereby dampening the effect of the fundamental shock on the exchange rate.

4 Implications for Exchange Rate Dynamics

We use the calibrated model to illustrate and discuss the implications of strategic behavior for exchange rate dynamics, focusing on exchange rate volatility and exchange rate disconnect. Specifically, we demonstrate that the presence of strategic investors amplifies the volatility of the exchange rate and contributes to an increased disconnect between the exchange rate and underlying fundamentals.[22]

Exchange Rate Disconnect One of the most robust empirical pieces of evidence on exchange rate dynamics is the disconnect between exchange rates and fundamentals (Meese and Rogoff, 1983; Cheung et al., 2005; Rossi, 2013). We show that heterogeneity in price impact and the presence of strategic behavior help explaining the limited explanatory power of standard theories of exchange rate determination.

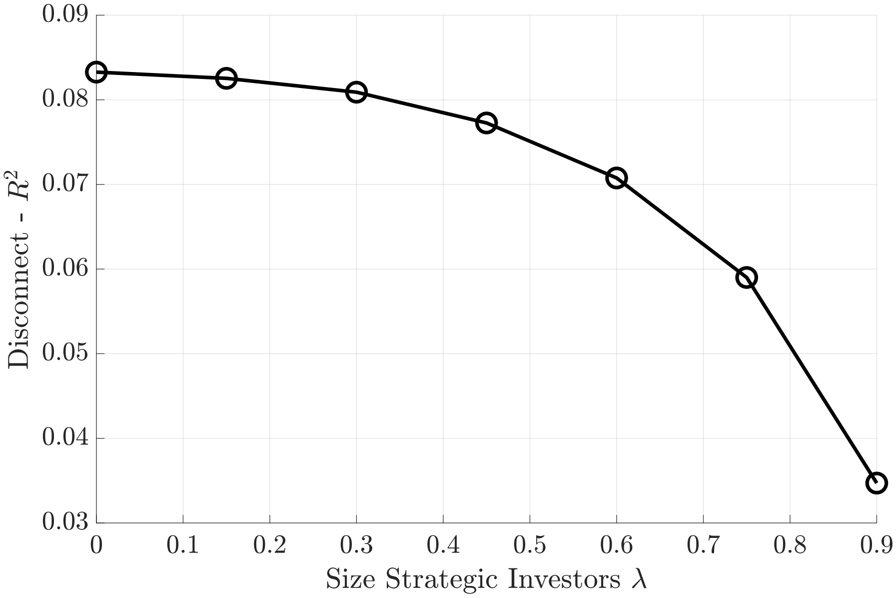
As is standard, we measure the disconnect of exchange rates by assessing the explanatory power of the following regression equation:

$$s_{t+1} - s_t = \alpha + \beta(i_t - i_t^\star) + \varepsilon_{t+1}, \tag{10}$$

where $i_t - i_t^\star$ represents the fundamental driver of the one-period exchange rate change $s_{t+1} - s_t$. We simulate the model, estimate Equation (10), and observe how the explanatory

[22] Appendix B demonstrates that the presence of strategic behavior also has implications for deviations from uncovered interest rate parity (UIP). Although strategic behavior does not inherently generate excess predictability, it does contribute to larger UIP deviations.

Figure 3: Exchange Rate Disconnect



Notes: The figure shows the estimated R^2 of the disconnect regression in Equation 10 using simulated data. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 2.

power – measured using the R^2 – of the disconnect regression changes as the economy becomes increasingly populated by strategic investors.[23]

Figure 3 illustrates the R^2 of the disconnect regression for different degrees of strategic behavior, represented by different levels of λ. On average, the R^2 is low, consistent with the notion that exchange rates are disconnected from fundamentals.[24] Importantly, the disconnect increases in the presence of strategic investors, with the R^2 in our benchmark calibration ($\lambda \approx 0.6$) being about 15% lower compared to a competitive market.[25] This can be explained by the behavior of the informativeness of the exchange rate μ. Less competitive markets reduce the information content of exchange rate, amplifying its response to noise shocks and increasing the share of total variance in the exchange rate explained by noise.

[23] We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in.

[24] The R^2 from simulated data is close to the average R^2 estimated from the data used for the calibration, approximately 0.07.

[25] Figure 13 in Appendix D shows that the same qualitative implications hold when the disconnect is measured using alternative measures used in the literature, such as the RMSE.

Exchange Rate Excess Volatility There is extensive evidence demonstrating that exchange rates exhibit higher volatility compared to fundamentals, which is commonly referred to as the "excess volatility puzzle" (Obstfeld and Rogoff, 2000; Engel and Zhu, 2019). We show how the presence of strategic behavior contributes to this excess volatility of the exchange rate relative to fundamentals by intensifying the influence of noise traders.

By manipulating Equation (9), we can derive an expression of the unconditional variance of the exchange rate as a combination of the variances of both fundamental and noise shocks:

$$\mathrm{Var}(s) = \frac{\mu^2}{(1-\mu\rho_u)^2}\left[\frac{1}{1-\mu^2}+\frac{\rho_u^2}{1-\rho_u^2}\right]\sigma_u^2 + \frac{(1-\mu)^2}{(1-\mu\rho_x)^2 b^2}\left[\frac{1}{1-\mu^2}+\frac{\rho_x^2}{1-\rho_x^2}\right]\sigma_x^2. \qquad (11)$$

The presence of strategic investors diminishes the informativeness of the exchange rate, placing relatively more emphasis on the noise component. Since the noise component is more volatile than the fundamental component, this contributes to the increasing the volatility observed in the exchange rate.[26]

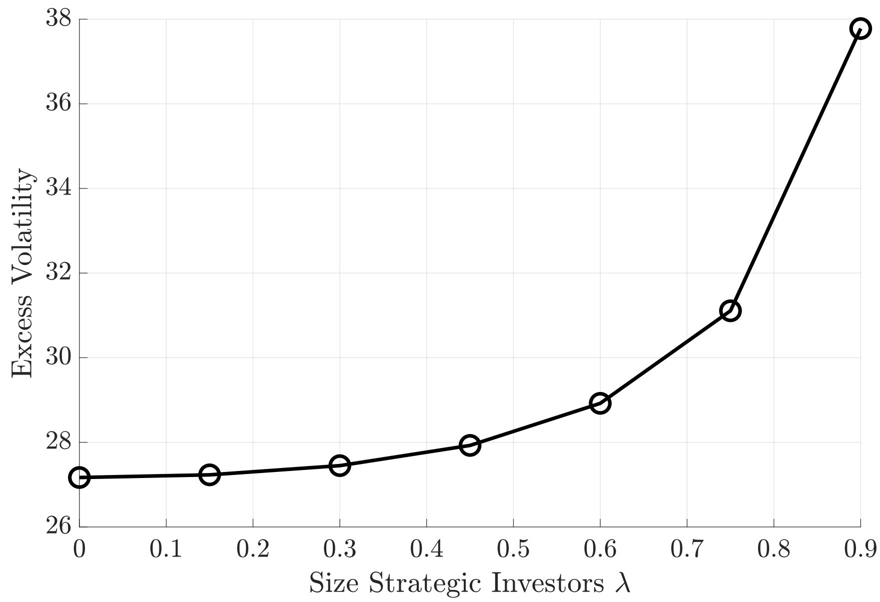
Figure 4 shows that the excess volatility of the exchange rate is increasing in the presence of strategic behavior, due to the higher volatility of the exchange rate induced by strategic behavior (Equation (11)). We compute the excess volatility of the exchange rate as the ratio between the volatility of the exchange rate in Equation (11) and the volatility of the fundamental, $\frac{\sigma_u}{\sqrt{1-\rho_u^2}}$ (Engel and Zhu, 2019). Using simulated data from our model, we show that the excess volatility rises with the presence of strategic investors, with the excess volatility ratio in our benchmark calibration ($\lambda \approx 0.6$) being around 8% higher compared to a competitive market.[27]

Testing predictions We leverage the heterogeneity in market concentration across currencies to test the implications provided by our theory. The model delivers two distinct testable relationships between exchange rate dynamics and the level of strategic behavior: (i) the disconnect of the exchange rate from fundamental increases in the level of strategic behavior (ii) higher the level of strategic behavior results in higher excess volatility of the

[26]Appendix B shows that the effect of strategic behavior is not necessarily monotonic from a theoretical perspective. However, it is important to note that under standard parameterizations, monotonicity is satisfied. On this regard, our calibration is very conservative, meaning that higher values of ρ_x and lower values ρ_u or b would all strengthen presence of monotonicity. Further details are available in Appendix B.

[27]Figure 14 in Appendix D shows that the same qualitative result holds when measuring the excess volatility of the exchange rate using the ratio between the volatility of the exchange rate change and the volatility of changes in the fundamental, $\frac{\mathrm{Var}(\Delta s)}{\mathrm{Var}(\Delta u_t)}$.

Figure 4: Excess Volatility



Notes: The figure shows the excess volatility ratio computed using simulated data from our model. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. The excess volatility ratio is computed using the ratio between the volatility of the exchange rate in Equation (11) and the volatility of the fundamental, $\frac{\sigma_u}{\sqrt{1-\rho_u^2}}$. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 2.

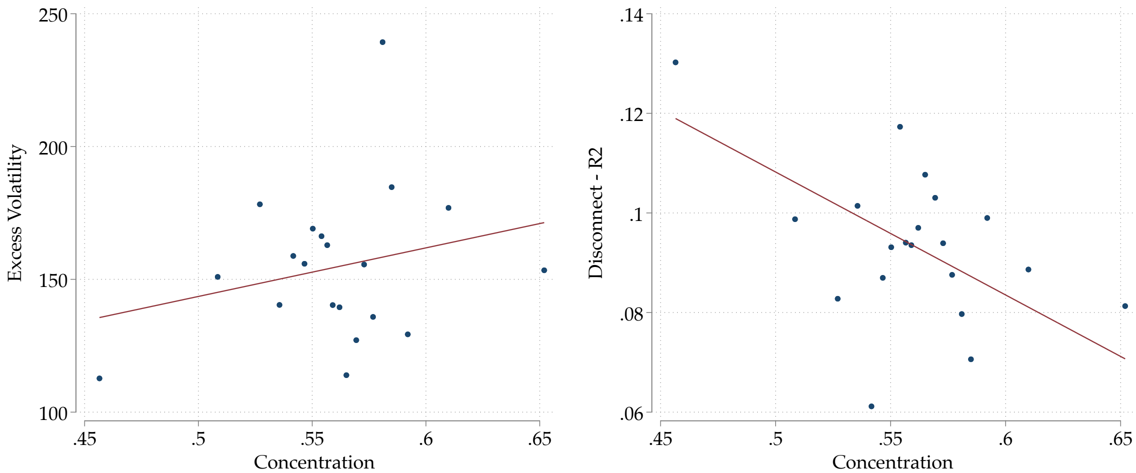
exchange rate. We test our predictions using a set of 10 currencies merged with the U.S. CFTC transaction data, available since June 2006 to December 2016.[28]

We use the concentration ratio of the top eight investors, as reported by the U.S. CFTC, as our proxy of strategic behavior in the foreign exchange market (λ). We correlate this information with time-varying metrics of exchange rate disconnect and excess volatility. We utilize a 2-year rolling window with monthly exchange rate data to create time-varying indexes for exchange rate disconnect and excess volatility. We measure the exchange rate disconnect using the R^2 of the regression in Equation (10), while excess volatility is calculated as the ratio between the volatility of the exchange rate in Equation (11) and the volatility of the interest rate differential. The panel nature of our dataset enable us to incorporate currency and year fixed effects, mitigating potential concerns regarding spurious correlation and strengthening the validity of the empirical evidence.[29]

[28]We exclude the South African Rand from our analysis due to a limited number of time observations in the CFTC dataset. To reduce noise in weekly transactions, we aggregate the data to a monthly level.

[29]The results remain unchanged when we increase the rolling window size to 3 and 4 years, and using

Figure 5: Testing Model Predictions



Notes: The figure plots the positive relationship between the level of strategic behavior and the excess volatility (left panel) and the disconnect (right panel) of the exchange rate in the actual data. Concentration is the share of open interest held by the top eight traders in the future FX market. Data is from the U.S. CFTC spanning from 2006 to 2016. The exchange rate disconnect is measured using the R^2 from the regression in Equation (10), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (11) to the volatility of the interest rate differential. To measure excess volatility and disconnect, we use a 2-years rolling window regression with average monthly exchange rate data. The resulting data are demeaned at the currency and year level, and values of the excess volatility ratio and disconnect are winsorized at 1%. We exclude the South African Rand from the set of 11 currencies. Table 6 in Appendix D reports the estimated coefficients. Appendix A provides additional information on the data used.

Figure 5 provides evidence that are consistent with the predictions of our theoretical framework. The left panel documents a strong, positive, and statistically significant relationship between our measure of strategic behavior in the exchange rate markets and the excess volatility of the exchange rate. Likewise, the right panel reveals that as the presence of strategic investors in the market increases, currencies become more disconnected to fundamentals, as evidenced by the decreasing estimated R^2.

Table 6 in Appendix D reports the estimated coefficients along with the corresponding standard errors clustered at the country level. We find that a currency traded in a market with a 10% higher concentration ratio exhibits an excess volatility ratio that is about 12% higher compared to the average excess volatility observed in the sample. Similarly, a currency traded in a market with a 10% higher concentration ratio exhibits an 18% lower predictive power compared to the average R^2 in the sample.

different proxies for strategic behavior, such as the number of active traders.

5 Strategic Behavior vs Dispersed Information: A Quantitative Assessment

We now compare the effects that heterogeneity in price impact have on excess volatility and disconnect to the effect of investors' information heterogeneity. Dispersed information arising from heterogeneous information sets leads to higher exchange rate disconnect and excess volatility (Bacchetta and Van Wincoop, 2006; Evans and Lyons, 2002), representing a competing mechanism with heterogeneity in price impact. To assess the relevance of these two competing dimensions of heterogeneity, we extend the basic framework presented in Section 3 by relaxing the full information assumption and including information heterogeneity based on Nimark (2017). Through the lens of our model, we quantitatively evaluate the relative importance of strategic behavior and information heterogeneity in driving the dynamics of exchange rates.

5.1 Relaxing the Full Information Assumption

The model incorporates all standard elements of an exchange rate monetary model, along with the strategic behavior described in Section 3. However, in contrast to the basic framework, we assume that investors possess imperfect knowledge of the shocks affecting the economy, resulting in dispersed information. The remaining structure of the economy remains the same.

The main implication of information heterogeneity is that the optimal demand for foreign bonds by investor j at time t now depends on their individual information set, $\Omega_t(j)$:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2} & \text{if } j = C \\[2ex] \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}} & \text{if } j = S \end{cases} \tag{12}$$

where the excess return, $q_{t+1} = E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t$, and the variance of the exchange rate change, σ_t^2, are now conditional to the information set at time t, $\Omega_t(j)$. In contrast to the basic framework, we assume that σ_t^2 is endogenous but common to all investors, implicitly assuming that investors have the same capacity to process information. Despite the presence of information heterogeneity, the main implication of strategic behavior still holds true. Specifically, the own price impact reduces the demand of strategic investors for any given level of excess return.

Information Structure The information structure in our model follows Nimark (2017), and generalize the case in Singleton (1987) and Bacchetta and Van Wincoop (2006). Investors form expectation regarding the future price of the foreign bond (exchange rate) by observing their private signal about the fundamental, as well as the history of the exchange rate. Formally, investors' information set is given by:

$$\Omega_t(j) = \{f_{t-T}(j), s_{t-T} : T \geq 0\},$$

where

$$f_t(j) = \Delta i_t + \eta_t(j) \text{ where } \eta_t(j) \sim N\left(0, \sigma_\eta^2\right)$$

represents the private signal about fundamentals. Therefore, investors have imperfect knowledge about the history of shocks that affect the economy because they observe an unbiased signal $f_t(j)$ regarding Δi_t, with an idiosyncratic measurement error $\eta_t(j)$. Investors are unable to perfectly observe the path of the foreign interest rate, and cannot deduce the fundamental component from observing the exchange rate due to the presence of unobserved transitory noise shock x_t (Admati, 1985). The private signal, $\eta_t(j)$, implies that investors have different expectations about foreign Central Bank's operating procedures. Consequently, the need to 'forecast the forecasts of others' (infinite regress problem) arises due to information dispersion.[30]

Equilibrium and Solution. We extend the definition of equilibrium of the basic framework discussed in Section 3 to incorporate the presence of dispersed information. In the extended framework, an equilibrium path is defined as a sequence of quantities $\{b_t(j)\}$ and foreign currency (asset) price $\{s_t\}$ that satisfy the following conditions: given an history of shocks $\{\varepsilon_t^x\}_{t=0}^{-\infty}$ and signals about fundamentals $\{f_t(j)\}_{t=0}^{-\infty}$, investors optimally choose their portfolios, and the market clearing condition is upheld.

[30] The key distinction with Singleton (1987) and Bacchetta and Van Wincoop (2006) lies in the nature of private signals, which are not short-lived. In other words, innovations to the fundamental process are not perfectly and publicly observed after a finite number of periods. Short-lived private information allows to derive a finite dimensional state representation, overcoming the infinite regress problem. The solution method proposed by Nimark (2017)and used here enables us to solve our model while relaxing the assumption made by Singleton (1987).

The effect of strategic behavior on the exchange rate, as well as its mechanism, extends to the model with dispersed information as in the basic framework. Combining the market clearing condition with investors' demand schedules, we can derive the following expression for the exchange rate:

$$s_t = (1-\mu)\left(\frac{\bar{x}}{b}-1\right) + \mu\left(\int E\left[s_{t+1} \mid \Omega_t(j)\right] dj\right) - \mu\left(i_t - i_t^{\star}\right) + (1-\mu)\frac{1}{b}x_t, \tag{13}$$

where μ and Φ are defined as in the basic framework, with the former decreasing in the presence of strategic investors (decreasing in λ and increasing in N).

In the presence of dispersed information, a closed-form solution for the exchange rate is not available since it depends on higher-order expectations regarding the fundamental:

$$s_t = \mu \sum_{k=0}^{\infty} \mu^k \left[i_{t+k} - i_{t+k}^{\star}\right]_t^{(k)} + \frac{1-\mu}{b} x_t, \tag{14}$$

where $\left[i_{t+k} - i_{t+k}^{\star}\right]_t^{(k)}$ denotes the average expectation in period t of the average expectation in period t+1, and so on, of the average expectation in period t+k-1 of k period ahead fundamentals, that is, $\left[i_{t+k} - i_{t+k}^{\star}\right]_t^{(k)} = \underbrace{\int \mathbb{E}_t \ldots \left[\int \mathbb{E}_{t+k-1}}_{k} \left(i_{t+k} - i_{t+k}^{\star}\right) dj\right] \ldots dj$ for any integer $k > 0$. In the case of dispersed information, the informativeness parameter μ represents the weight assigned to higher-order expectations regarding future fundamentals in influencing exchange rate dynamics.

We solve the model using the methodology outlined in Nimark (2017). To account for higher order expectations, we assume that agents have rational expectations about how other agents form their own expectations, and that this information is common knowledge. Using this assumption, we compute the dynamics of the exchange rate while accounting for expectations of arbitrarily high orders. Denoting the hierarchy of expectations about fundamentals with $\Delta i_t^{(0:k)}$, which is the vector of average expectations on Δi_t of any order from zero to k, we show in Appendix C that the exchange rate s_t can be expressed as:[31]

$$s_t = v_0 \Delta i_t^{(0:k)} + \frac{1-\mu}{b} x_t \tag{15}$$

[31] There exist other approaches that rely on the fact that average first-order expectations about the endogenous variables can be computed given the guessed laws of motion of the endogenous variables by using the assumption of rational expectations. We find the approach in Nimark (2017) more reliable and fast to implement.

where v_0 is a vector of k weights associated to higher order expectations. In contrast to the baseline model, an aggregate shock in this model affects the exchange rate not only directly, but also through higher order expectations $\Delta i_t^{(1:k)}$.

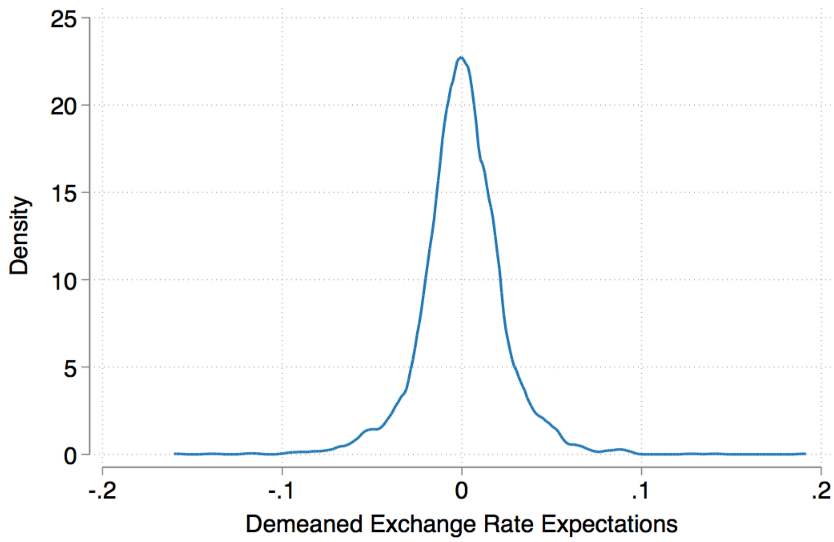
Parametrization and Mechanism. We extend the parametrization of the basic framework in Table 2 to account for the presence of dispersed information. We leverage the data on exchange rate expectations from the ECB Professional Forecasters survey to calibrate the volatility of the private signal, σ_η. The survey runs at quarterly frequency since 2002 and contains information on professional forecasters' expectations for the euro-dollar exchange rate at various horizons. The distribution of the demeaned, same-quarter exchange rate expectations in Figure 6 exhibits a significant dispersion, with a standard deviation of approximately 0.02, indicating the presence of information heterogeneity among investors.[32] To calibrate the precision of the private signal (σ_η) and the volatility of the noise component (σ_x), we use Simulated Method of Moments. We simulate the model for 8,000 periods with a burn-in of 3,000 periods, repeating it 25 times with different random number generators. We match the volatility of the exchange rate change and the median dispersion in the same-quarter exchange rate forecasts across quarters. This yields $\sigma_x = 0.024$ and $\sigma_\eta = 0.006$. Table 7 in Appendix D summarizes the parametrization.[33]

Similarly to the presence of strategic behavior in our basic framework, the presence of dispersed information also amplifies the effects of noise shocks on the exchange rate while dampening the effects of fundamental shocks. Information heterogeneity leads to rational confusion, which means that investors always revise their expectations whenever the exchange rate changes, independently of the underlying shock. This confusion arises because investors are uncertain whether the fluctuations in the exchange rate are driven by noise shocks or fundamental shocks. Consistent with previous literature (Bacchetta and Van Wincoop, 2006), Figure 16 in Appendix D shows that, after a negative fundamental shock, investors' expectation do not fully react because part of the response of exchange rates is attributed to the noise component. As a result, the response of exchange rate to a fundamental shock is dampened. Similarly, the response to a positive noise shock is amplified because the upward movements

[32] In the data, we consider the log of the expected exchange rate to be consistent with the log-linearized exchange rate s_t in our model. Table 5 in Appendix A provides additional measures of the dispersion of exchange rate expectation across horizon and time periods.

[33] Note that the dispersion in the exchange rate expectations generated by the model falls short relative to the target moment. One possible explanation is that the expectation data from the ECB Professional Forecasters survey are reported at the quarterly level, while our model is calibrated at a monthly horizon. Unfortunately, data on exchange rate expectations at higher frequencies are not available.

Figure 6: Distribution Exchange Rate Expectations



Notes: The figure shows the distribution of the same-quarter EUR/USD exchange rate expectations from the ECB Professional Forecasters survey. Data covers the period from 2002Q1 to 2020Q4 and is collected at a quarterly frequency Expectations are in log and demeaned at the quarterly frequency. Table 5 in Appendix A provides additional measures of the dispersion of exchange rate expectation across horizon and time periods.

in the exchange rate are mistakenly confused with a negative change in fundamentals. This rational confusion adds further upward pressure on the exchange rate.[34] This indicates that these two dimension of heterogeneity have similar qualitative implications for the dynamics of the exchange rate, albeit through different mechanisms. Strategic behavior reduces the sensitivity of investors' demand for foreign assets, while Information heterogeneity leads to rational confusion.

5.2 Quantitative Analysis

We leverage the model that incorporates the two dimensions of heterogeneity, and study whether investor heterogeneity matters for exchange rate puzzle and which dimension of heterogeneity is relatively more important.

We assume that the model embedding both strategic behavior and dispersed information

[34]As standard in this class of models, the model produces endogenous persistence due to the time it takes for rational confusion to be resolved. This means that average and higher-order expectations gradually converge to the rational expectation benchmark based on full information over time.

represents the actual data, and decompose the contributions of both elements to the dynamics of the exchange rate. Using our calibrated model, we filter the underlying states and conduct three different counterfactual scenarios:[35] Given our calibration, we use the model to filter the underlying states and perform three different counterfactuals: i) a competitive, full-information rational expectation benchmark economy without strategic investors and dispersed information ($\lambda = \sigma_\eta = 0$); ii) an economy where investors have dispersed information but are not strategic ($\lambda = 0$ and $\sigma_\eta > 0$); iii) an economy where investors are strategic and have full-information ($\lambda > 0$ and $\sigma_\eta = 0$). We perform the decomposition for different initial level of strategic behavior ($\lambda \in \{0, 0.2, 0.4, 0.6, 0.8\}$), given the measurement noise in our proxy for strategic behavior. We focus on the exchange rate disconnect, which is measured by the RMSE of the disconnect regression in Equation (10), and the exchange rate excess volatility, which is measured by the volatility of the exchange rate.[36]

Table 3 shows that investors' heterogeneity can have significant impact on exchange rate dynamics, and the relative importance of each dimension of heterogeneity greatly depends on the degree of strategic behavior in the market. Investors' heterogeneity increases exchange rate disconnect by 16% to 38% and volatility by 6% to 29%, playing a quantitatively significant role in shaping exchange rate dynamics, as highlighted in previous studies (Evans and Lyons, 2002; Bacchetta and Van Wincoop, 2006, 2010, 2019).[37]

By comparing the competitive rational expectation model to an economy with only one dimension of heterogeneity, we show that the specific contributions of each individual dimension to exchange rate dynamics depends on the degree of strategic behavior. As λ increases, the contribution of strategic behavior rises from 3% to 66% for disconnect and from 9% to 86% for excess volatility. It's worth noting that the marginal effect of λ on the additional disconnect is lower than on additional volatility, suggesting that dispersed information appears to be more relevant in explaining exchange rate disconnect, regardless of the size of strategic investors in the market. Meanwhile, heterogeneity in price impact has a relatively more

[35]See Appendix C for additional details on the filtering algorithm.

[36]To measure excess volatility, we directly examine the volatility of the exchange rate. This is without loss of generality because the denominator of the excess volatility ratio – the volatility of the fundamental – remains constant across all counterfactual scenarios.

[37]The economic relevance of the contribution of investors' heterogeneity extends beyond the changes in predictive power or in volatility, which may be relatively small in absolute terms. By influencing exchange rate dynamics, investors' heterogeneity has far-reaching implications fir carry trade return, invoicing choices, relative international prices, trade patterns, and other aggregate macro variables (Boz et al., 2020; Itskhoki and Mukhin, 2021; Lustig et al., 2019). Quantifying the macroeconomic effects resulting from investors' heterogeneity, alongside more granular documentation of this heterogeneity, offers promising venues for future work.

Table 3: Disconnect and Volatility Decomposition

Mass Strategic Investors (%)	Extra Disconnect (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
0.00	16.76	0.00	100.00	0.00
20.00	17.18	2.97	96.88	0.15
40.00	18.91	13.74	85.59	0.67
60.00	23.57	34.65	63.79	1.56
80.00	37.67	65.42	32.14	2.44

Mass Strategic Investors (%)	Extra Volatility (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
0.00	5.18	0.00	100.00	0.00
20.00	5.66	8.90	91.00	0.11
40.00	7.62	33.70	65.92	0.39
60.00	12.87	62.81	36.57	0.62
80.00	28.61	85.72	13.74	0.53

Notes: The table reports the contribution of strategic behavior and dispersed information to the exchange rate disconnect (top panel) and the excess volatility (bottom panel) for different value of λ (first column). Exchange rate disconnect is measured using the RMSE of a standard, one-period disconnect pooled regression, Equation (10). Excess volatility is measured using the standard deviation of the exchange rate. The second column reports the extra disconnect and volatility of the full model relative to a benchmark economy that abstract away from both dispersed information and strategic behavior ($\lambda = 0$ and $\sigma_\eta = 0$). The third and fourth columns report the share of the extra disconnect and volatility due to dispersed information and strategic behavior, respectively. The former (latter) is computed comparing RMSE/volatility in the benchmark economy to the RMSE/volatility from an economy without strategic behavior, $\lambda = 0$ and $\sigma_\eta > 0$ (without dispersed information, $\lambda > 0$ and $\sigma_\eta = 0$). The last column reports the discrepancy due to the non-linear interaction between dispersed information and strategic behavior. We exclude the Argentinian Peso from calculation. Appendix A provides additional information on the data. Appendix C provides additional information on the estimation and filtering procedure.

pronounced effect on excess volatility dynamics. These results underscore the importance of considering both dimensions in the analysis of exchange rate markets.

The final column in Table 3 shows that the response of the exchange rate in a model that incorporates both dispersed information and strategic behavior is not simply the sum of the individual mechanisms. Instead, there is a non-linear interaction between the two. For each value of λ, this non-linear interaction, accounting for approximately 0.1% to 2.5% of the overall effect, demonstrates that the two mechanisms reinforce each other. The idea is that strategic behavior leads to greater price dispersion regardless of the quality of the signal, σ_η. This, in turn, reduces the weight that investors assign to their signals and amplifies the impact of noise shocks while dampening the impact of fundamental shocks.[38]

[38] In Figure 15 in Appendix D, we show the simulated price dispersion for different levels of strategic

6 Conclusion

The heterogeneity in price impact and concentration in the foreign exchange rate markets may play a key role in understanding exchange rate dynamics. In this paper, we explore the implication of strategic behavior within a simple monetary model of exchange rate determination. We show that strategic behavior reduces the informativeness of the exchange rate by amplifying the response to non-fundamental shocks while dampening the response to fundamental shocks. As a result, heterogeneity in price impact helps to explain the weak empirical link between fundamentals and exchange rates, as well as the excess volatility observed in exchange rate movements.

Although our model is stylized to derive fundamental insights and analytic results, we provide empirical evidence supporting the theoretical predictions using a panel of 10 currencies. Furthermore, we extend the theoretical framework by including a competing dimension of investors' heterogeneity, namely information dispersion. We demonstrate that strategic behavior has a quantitative impact on influencing exchange rate dynamics similar to information dispersion.

This paper represents a step forward in incorporating microstructure institutions in the analysis of exchange rate dynamics. Our framework is tractable and can be integrated into macro models of exchange rate determination. As shown in previous literature, the introduction of investor heterogeneity qualitatively and quantitatively alters conclusions regarding optimal monetary and exchange rate policies. It also calls for additional efforts in documenting and studying investors' heterogeneity in foreign exchange rate markets.

behavior and signal quality. Note that when the quality of the signal is sufficiently low (high σ_η), the volatility of the exchange rate may no longer increase. As the signal quality deteriorates, less importance is given to the fundamental component. This leads to a situation where the exchange rate becomes less informative, resulting in a reduction in the amplification of the noise component (Bacchetta and Van Wincoop, 2006).

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Appendix

A Empirics

A.1 Data

We use three main sources of information:

- We use data on 18 currencies from December 1993 to December 2019. The currencies considered are: Euro, Japanese Yen, Argentinian Peso, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Chilean Peso, Indian Rupee, Mexican Peso, British Pound, South African Rand, Russian Ruble, Swedish Krona, Turkish Lira, New Zealand Dollar, Singapore Dollar, Norwegian Krone. The panel is not balanced.

  We obtain data for the spot and one-month forward exchange rates at a daily frequency from Datastream and Thompson Reuters. All exchange rates are defined against the US Dollar. To calculate the one-month interest rate, we took the difference between the logarithm of the one-month forward exchange rate and the logarithm of the spot exchange rate. We then computed monthly averages for the spot exchange rates and the one-month interest rate differentials.

- We use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions. The U.S. Commodity Futures Trading Commission (CFTC) data provides detailed information on several aspects within the currency futures market, including net open interest positions held by asset managers, institutional investors, and leveraged funds, as well as measures of concentration and the number of reportable traders. Data is reported on a weekly basis and spans the years 2006 to 2016 for 11 currency pairs. These pairs include both major and non-major USD currency pairs, reflecting the diversity of assets traded within the currency futures market. Major currency pairs typically involve the U.S. dollar and another major global currency, such as the Euro or Japanese Yen, while non-major pairs may involve currencies from emerging markets or smaller economies. Table 4 in Appendix A reports summary statistics on key variables. Figures 7, 8 and 9 in Appendix A respectively show the net open positions, the concentration ratio, and the number of reportable traders in the future FX market per currency and trader group.

- We use data on exchange rate expectations from the ECB Professional Forecasters survey. The survey runs at quarterly frequency since 2002Q1 until 2020Q4. It provides information on the expectations of professional forecasters regarding the euro-dollar exchange rate at different time horizons, including the current quarter and one to four quarters ahead. The dataset includes exchange rate forecasts from approximately forty professional forecasters.

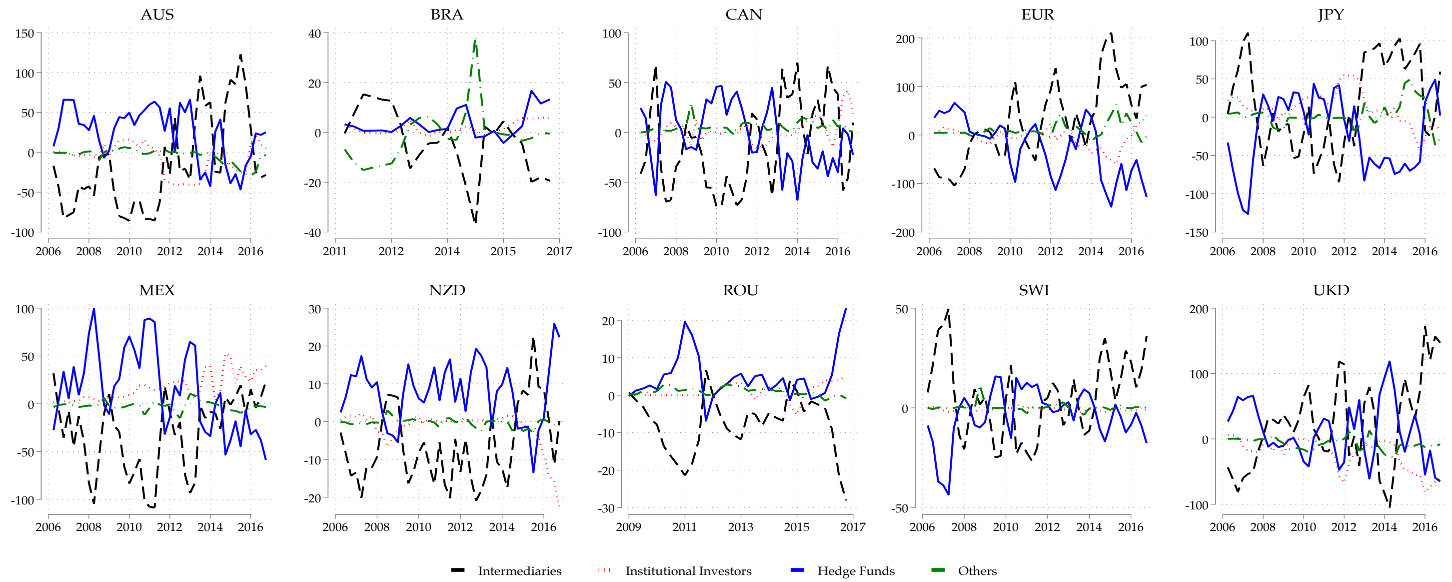
A.2 Additional Figures and Tables

Table 4: Summary Statistics

	Currency										
	AUS	BRA	CAN	EUR	JPY	MEX	NZD	ROU	SWI	UKD	Total
Imbalances (Mil $): Intermediaries	-16.187	-6.434	-12.622	28.306	18.102	-32.057	-6.518	-7.947	5.374	22.884	-0.135
Institutional Investors	-7.796	2.055	2.180	-5.056	11.952	17.415	-1.776	1.024	-0.638	-22.889	-0.541
Hedge Funds	24.308	3.976	-1.946	-26.019	-20.756	15.288	7.938	5.004	-3.836	10.268	1.153
Others	-4.226	0.307	5.804	9.966	2.195	-2.215	-0.282	0.969	0.263	-7.537	0.524
Concentration: Top 4 (Net)	0.433	0.700	0.368	0.295	0.392	0.537	0.553	0.566	0.411	0.396	0.448
Top 8 (Net)	0.564	0.795	0.484	0.399	0.513	0.680	0.704	0.676	0.537	0.523	0.572
Number: Intermediaries	7.795	4.693	7.442	13.417	8.921	7.069	6.761	6.327	6.180	7.289	7.832
Institutional Investors	6.117	0.084	5.430	15.686	7.775	6.196	2.744	0.000	1.983	7.331	6.444
Hedge Funds	15.600	6.129	13.881	25.064	19.689	16.121	9.867	4.883	8.896	16.649	14.734
Others	5.364	2.340	7.249	12.576	6.350	6.864	4.198	0.482	0.199	5.110	5.949

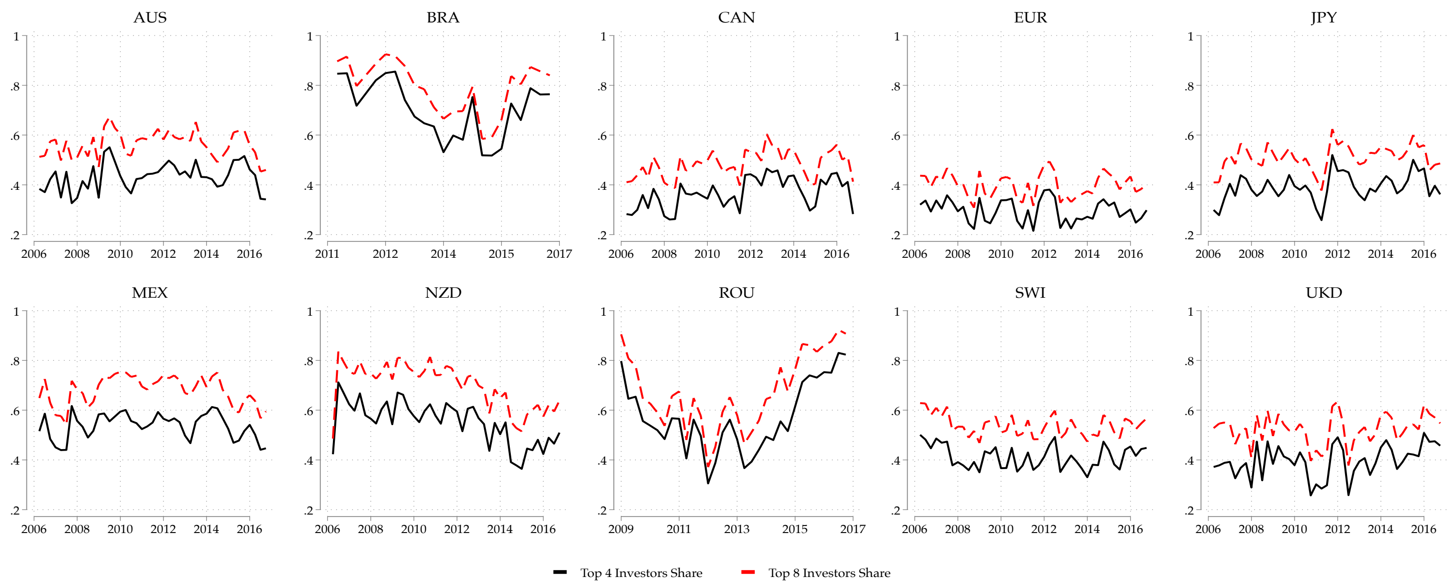
Notes: Report the means of the main variables in the CFTC dataset by currency pair. Net open interest positions are in millions of dollars ($), concentration ratios are expressed in percentages, and the number of traders is in count. The reported mean statistic is calculated based on a panel of weekly observations spanning from 2006 to 2018.

Figure 7: Net Open Interest Position by Currency Pairs



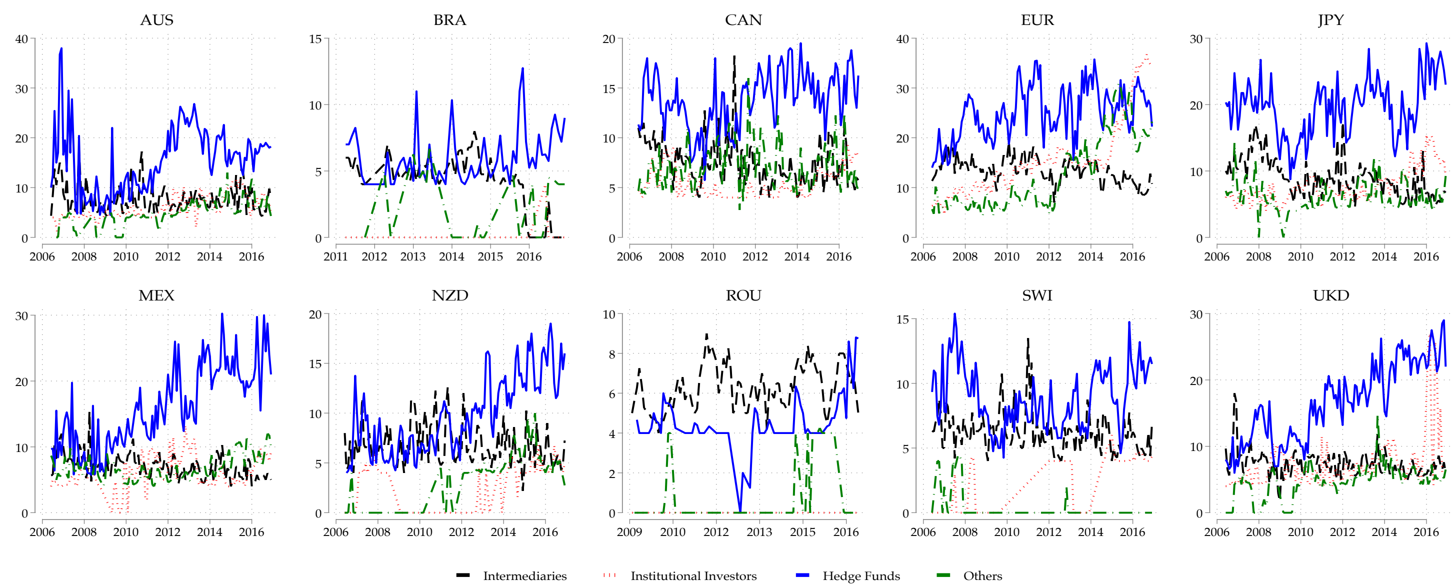
Notes: The figure shows the net positions for the reportable traders in the future FX market by currency pair. Net Positions are calculated after offsetting each trader's equal long and short positions. We report net positions for Dealers (black dashed line), Institutional Investors (red dotted line), Hedge Funds (blue line) and Other Reportable Traders (green dashed line). The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Figure 8: Concentration Ratios by Currency Pairs



Notes: The figure shows the average percentages of open interest held, referred to as Concentration Ratios, by the largest four (black line) and eight (red line) reportable traders in the future FX market by currency pair. These concentration ratios are based on 'Net Position' and are calculated after offsetting each trader's equal long and short positions. The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Figure 9: Number of Traders by Currency Pairs



Notes: The figure shows the numbers of reportable traders in the future FX market by currency pair. For each currency pair, we report the number of Dealers (black dashed line), Institutional Investors (red dotted line), Hedge Funds (blue line) and Other Reportable Traders (green dashed line). The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Table 5: Expectation Dispersion

	Whole Sample	Average across Quarters	Median across Quarters
Same Quarter	0.028	0.024	0.020
Across all Horizons	0.041	0.038	0.035

Notes: The table reports the standard deviation of EUR/USD exchange rate expectations from the ECB Professional Forecasters survey. Data covers the period from 2002Q1 to 2020Q4 and is collected at a quarterly frequency for various horizons ranging from the same quarter to one year ahead. The expectations are expressed in logarithmic form to maintain consistency with the log-linearized model. Expectations are demeaned at the quarterly-horizon level. The first row focuses on same-quarter expectations, while the second row considers all horizons pooled together. The first column reports the dispersion (standard deviation) in exchange rate expectations across the whole sample period. The second and third columns compute the dispersion for each quarter and report the average and median dispersion across all quarters, respectively.

B Derivations and Additional Results

B.1 Derivation Demand Functions - Rational Expectation Case

Each investor j solves the following problem:

$$\max_{b_t^j} E_t^j(w_{t+1}^j|\Omega_t^j) - \frac{\rho}{2} Var_t^j(w_{t+1}^j|\Omega_t^j)$$

$$\text{s.t. } w_{t+1}^j = (\omega - b_t^j)i_t + (i_t^\star + s_{t+1} - s_t)b_t^j$$

We assume that investors have symmetric rational expectation information sets, so that all j indexes on expectation and variance are dropped. We take the derivative of the objective function w.r.t. b_t^j. If the investor is strategic ($j = S$), they internalize the effect of their demand on the exchange rate. Thus, the demand schedule is:

$$b_t^{S,i} = \frac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho Var_t(s_{t+1}) + \frac{\partial s_t}{\partial b_t^{S,i}}},$$

where the $\frac{\partial s_t}{\partial b_t^j}$ represents the price impact. If the investor is competitive ($j = C$), the demand schedule follows a standard mean-variance specification:

$$b_t^C = \frac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho Var_t(s_{t+1})}.$$

We can now derive an expression for the price impact of a strategic investor. Assume there are N strategic investors, each with positive mass λ_i. Then, the market clearing condition for the foreign bond market is:

$$(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i} + (x_t + \bar{x})\bar{W} = B(1 + s_t).$$

Substituting the demand schedule and applying the Implicit function theorem, we can write:

$$(1-\lambda)\frac{\partial b_t^C}{\partial s_t}\frac{\partial s_t}{\partial b_t^{S,i}} + \lambda_i = B\frac{\partial s_t}{\partial b_t^{S,i}}$$

Thus:

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i}{B - (1-\lambda)\frac{\partial b_t^C}{\partial s_t}} \qquad \text{with } \frac{\partial b_t^C}{\partial s_t} \equiv -\frac{1}{\rho Var_t(s_{t+1})}$$

Therefore:

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho Var_t(s_{t+1})}{B\rho Var_t(s_{t+1}) + (1-\lambda)} \equiv \frac{1}{N}\frac{\lambda\rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} > 0$$

where the last equality holds in case of a symmetric oligopoly (i.e. $\lambda_i = \frac{\lambda}{N}\forall i$). The price impact is positive for $\forall(B, \lambda, N, \lambda_i, \rho, \sigma)$.

Lastly, in international portfolio choice models, the value of the supply of foreign assets in domestic currency (indirectly) depends on the value of the exchange rate when foreign assets are denominated in foreign currency. Differently from standard models of strategic trading (Kyle, 1989), strategic investors internalize not only their price effect on the quantity demanded but also on the quantity (value) supplied. Compared to closed economy models or cases in which foreign assets are denominated in domestic currency, the presence of this valuation effect on the supply implies a weakly lower price impact. Let pi^F and pi^D be the price impact on a foreign and a domestic asset, respectively.

$$pi^F \equiv \frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i\rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} \qquad pi^D \equiv \frac{\partial p_t}{\partial b_t^{S,i}} = \frac{\lambda_i\rho\sigma_t^2}{(1-\lambda)}$$

where p_t is the price of the domestic asset. It is easy to show that $pi^F \leq pi^D \quad \forall(B, \rho, \sigma_t^2, \lambda_i, \lambda)$. The intuition is fairly simple. The increase in the price of a currency (foreign currency appreciates) increases the nominal value of the supply of foreign assets when denominated in domestic currency. The supply shift dampens the initial rise in price, reducing the magnitude of the price impact. The overall effect of tradings on the exchange rate is lower due to the presence of a valuation effect. In other words, the residual net demand faced by strategic investors is more elastic than in a case with no valuation effects. The main implication is that strategic investors still reduce their exposure to foreign assets compared to competitive investors but not as much as in the case there was no valuation effect.

B.2 Effect of Strategic Behavior on Noise and Fundamental Shock

The presence of strategic investors amplifies (dampens) the response of the exchange rate to noise (fundamental) shocks.

Proof. Consider the law motion of the exchange rate in Equation (8). s_t can be rewritten as a forward looking sum of fundamentals and noises as follow:

$$s_t = -\mu \sum_{k=0}^{\infty} \mu^k \left(\Delta i_{t+k}\right) + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \mu^k \left(x_{t+k}\right),$$

where $\Delta i_{t+k} = i_{t+k} - i^{\star}_{t+k}$. Therefore, the response of the exchange rate to a unit shock in noise and fundamental at impact is:

$$\text{IRF}\left(s_{t+j}, j=0\right) = \begin{cases} \dfrac{\mu}{1-\mu\rho_u}, & \text{for } \varepsilon_u = -1 \\ \\ \dfrac{(1-\mu)}{(1-\mu\rho_x)b}, & \text{for } \varepsilon_x = 1 \end{cases}$$

Taking the derivative w.r.t. μ, we find:

$$\frac{\partial \text{IRF}(s_{t+j}, j=0)}{\partial \mu} = \begin{cases} \dfrac{1}{(1-\mu\rho_u)^2} > 0 \\ \\ -\dfrac{(1-\rho_x)}{(1-\mu\rho_x)^2 b^2} < 0 \end{cases}$$

Since μ is decreasing (increasing) function of λ (N), the response of the exchange rate to a unit shock in fundamental is dampened while noise shock are amplified as λ increases (N decreases). ■

B.3 Monotonicity of Unconditional Variance

The unconditional volatility of the exchange rate is non-monotonic in the presence of strategic investors.

Proof. Consider the law of motion of the exchange rate, Equation 8, and substitute the process for fundamental and noise:

$$s_t = -\mu \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \mu^k \rho^j \varepsilon^u_{t+k-j} + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \mu^k \rho_x^j \varepsilon^x_{t+k-j}.$$

After some algebra, s_t can be written as summation of its backward and forward components:

$$s_t = -\frac{\mu}{1-\mu\rho_u} \left[\sum_{k=0}^{\infty} \mu^k \varepsilon^u_{t+k} + \sum_{k=1}^{\infty} \rho_u^k \varepsilon^u_{t-k} \right] + \frac{1-\mu}{b(1-\mu\rho_u)} \left[\sum_{k=0}^{\infty} \mu^k \varepsilon^x_{t+k} + \sum_{k=1}^{\infty} \rho_x^k \varepsilon^x_{t-k} \right].$$

Thus, the unconditional variance of the exchange rate is:

$$\text{Var}(s) = \frac{\mu^2 \sigma_u^2}{(1-\mu\rho_u)^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2} \right] + \frac{(1-\mu)^2 \sigma_x^2}{(1-\mu\rho_x)^2 b^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2} \right],$$

which is a combination of the variances of fundamental and noise shocks. Taking the derivative of $\text{Var}(s)$ w.r.t. μ, we find:

$$\begin{aligned} \frac{\partial \text{Var}(s)}{\partial \mu} =& \frac{\mu \sigma_u^2}{(1-\mu\rho_u)^3} \left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2} \right] + \frac{\mu^3 \sigma_u^2}{(1-\mu\rho_u)^2 (1-\mu^2)^2} - \\ & \frac{(1-\mu)(1-\rho_x)\sigma_x^2}{(1-\mu\rho_x)^3 b^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2} \right] + \frac{\mu(1-\mu)^2 \sigma_x^2}{(1-\mu\rho_x)^2 (1-\mu^2)^2 b^2}. \end{aligned}$$

The unconditional volatility of the exchange rate is increasing in λ iff:

$$\begin{aligned} \frac{(1+\mu\rho_x)\sigma_x^2}{(1-\mu\rho_x)^2 (1+\mu)(1+\rho_x) b^2} - \frac{\mu \sigma_x^2}{(1-\mu\rho_x)^2 (1+\mu)^2 b^2} > \\ \frac{\mu \sigma_u^2}{(1-\mu\rho_u)^2} \frac{(1+\mu\rho_u)}{(1-\mu^2)(1-\rho_u^2)} + \frac{\mu^3 \sigma_u^2}{(1-\mu\rho_u)^2 (1-\mu^2)^2}, \end{aligned}$$

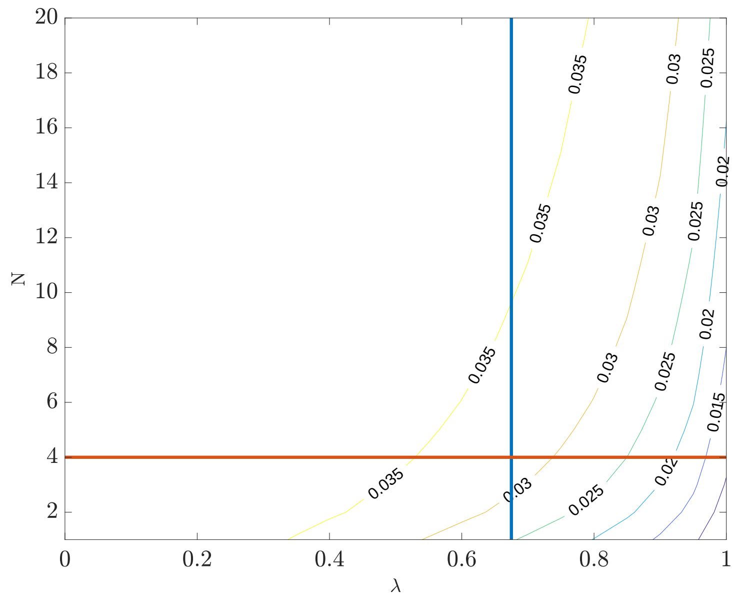
that can be rewritten as follows:

$$\frac{\text{Var}(x)}{\text{Var}(\Delta i)} \frac{1}{b^2} > \left[\frac{(1+\mu^2\rho_x)(1-\rho_x)}{\mu(1+\mu\rho_u)(1-\mu^2) + \mu^3(1-\rho_u^2)} \frac{(1-\mu\rho_u)^2(1-\mu)^2}{(1-\mu\rho_x)^2} \right]^{-1}. \qquad (16)$$

■

Equation (16) suggests that the unconditional variance of the exchange rate increases as λ increases when the variance of the noise shock is sufficiently high compared to the variance of the fundamental process.

Figure 10: $\underline{\sigma_x}$ for different combinations of N and λ.



Notes: The figure shows the minimum value of the volatility of the noise process, σ_x, that guarantees that the volatility of the exchange rate is monotonically increasing in the presence of strategic behavior (higher λ and/or lower N). The threshold is computed using Equation (16). We compute the minimum value of σ_x for different levels of λ and N. The horizontal and vertical lines pin down the combination of λ and N used in the parametrization of the basic framework. Remaining parameters are constant, see Table 2.

The non monotonic case is not relevant given standard parametrizations, including ours. Let define $\underline{\sigma_x}$ as the minimum value of the volatility of the noise process at which the relationship between the level of strategic behavior and exchange rate variance becomes non-monotonic. Figure 10 shows the value of $\underline{\sigma_x}$ for different combinations of N and λ. In our calibration, we find that the volatility of the noise shock should be at least 75% lower in order to break the monotonic relationship between strategic behavior (λ and/or N) and the unconditional variance of the exchange rate. In cases where λ or N take on other values, he minimum value of σ_x is at least 50% lower compared to the value implied by Figure 12 in Appendix D. For instance, in a market with a high level of strategic behavior (λ approximately 1), we find that σ_x is approximately 0.05. However, monotonicity in the relationship between strategic behavior and unconditional variance breaks if σ_x falls below 0.025.

Furthermore, it is important to note that the threshold value mentioned earlier is dependent on the parameters ρ_x, ρ_u and b. The robustness of the monotonic relationship between strategic behavior and unconditional variance is also guaranteed by the conservative nature of our calibration. In standard calibrations, only more persistent noise processes or less persistent fundamental processes would align with the observed data. Similarly, higher values of home bias (lower b) would be consistent with the data. Higher values of ρ_x, lower values of ρ_u and lower b all contribute to reducing the threshold, thereby relaxing the condition for monotonicity.

B.4 Excess Return Predictability - UIP

Another empirically robust evidence in exchange rate dynamics is the predictability of excess returns, commonly referred to as deviations from the Uncovered Interest Parity (UIP). Our model predicts systematic deviations from UIP due to a non-zero net supply of foreign assets, regardless of the presence of strategic investors. However, strategic behavior amplifies these UIP deviations compared to a competitive market.

Through the lens of our model, the one-period excess return, $q_{t+1} = s_{t+1} - s_t - (i_t - i_t^*)$, can be expressed as follow from Equation (8):

$$E_t q_{t+1} = \frac{\Phi}{B}\left(Be^{s_t} - X_t\right), \tag{17}$$

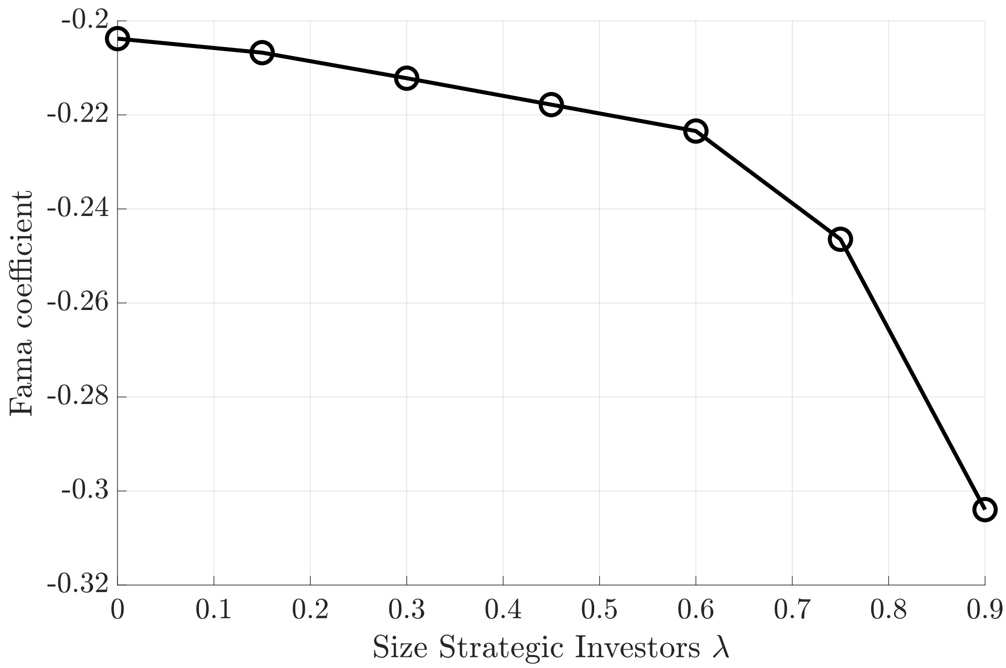
where the right-hand side represents the deviation from UIP. The deviations from UIP can be interpreted as the risk premium demanded by investors for holding foreign assets to clear the market. The risk premium consists of two main components: the net supply of foreign assets (adjusted for the demand of noise traders) and the market structure captured by Φ, which increases with λ or decreases with N. Our model predicts that UIP does not hold even in a fully competitive market when λ is zero. Moreover, as the market becomes more populated with strategic investors, UIP deviations become larger. The presence of strategic investors leads to a higher insensitivity in the total demand for foreign assets. Consequently, a larger risk premium is necessary to absorb the net supply of foreign assets compared to a competitive market. This results in a higher predictability of excess returns.

We use the calibrated model and simulated data to estimate a standard one-period Fama regression:

$$q_{t+1} = \alpha + \beta(i_t - i_t^\star) + \epsilon_t. \tag{18}$$

where q_{t+1} is the realized excess return. While UIP implies that the Fama coefficient, β, is zero, empirical evidence typically finds a negative number. Our model predicts that β is

Figure 11: Excess Return Predictability



Notes: The right panel shows the estimated one-period Fama coefficient using Equation 18 and simulated data from our model for different levels of strategic behavior. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 2.

given by:

$$\beta = -(1-\mu)\frac{1}{1-\mu\rho_u} < 0,$$

which is negative and decreasing in the level of strategic behavior.[39] Figure 11 plots the estimated excess return predictability coefficient β for different levels of λ. As anticipated, the coefficient is negative, consistent with the estimates found in the literature. Moreover, its magnitude is monotonically increasing in the level of strategic investors.

We now provide an analytic proof that the excess return is more predictable as λ increases.

[39] Interestingly, β is equal to zero if the supply of asset is constant when denominated in domestic currency, meaning that B is not multiplied by e^{s_t}. In this particular case, the excess return depends solely on the noise component X_t, which is orthogonal to fundamental shocks. Therefore, β is equal to zero even if there are systematic deviations in UIP. In other words, risk premium is still positive (UIP does not hold), but it is not predictable ($\beta = 0$).

Proof. Consider the law motion of the exchange rate, Equation 8:

$$s_t = \mu \left[E_t\left(s_{t+1}\right) + i_t^{\star} - i_t\right] + (1-\mu)\frac{\bar{x}}{b} + (1-\mu)\frac{1}{b}x_t,$$

where only the first term depends on fundamentals. Manipulating it, we can derive the j-period change in currency price as follows:

$$\Delta s_{t+j} = -\mu \sum_{k=0}^{\infty} \mu^k \left(\Delta i_{t+j+k} - \Delta i_{t+k}\right).$$

With Δs_{t+j} in hand, we can then calculate:

$$\begin{aligned}
\beta_1 = \frac{\text{Cov}\left(\Delta s_{t+1} - \Delta i_t; \Delta i_t\right)}{\text{Var}(\Delta i_t)} &= \left[\text{Cov}\left(-\mu \sum_{k=0}^{\infty} \mu^k \left(\Delta i_{t+k+1} - \Delta i_{t+k}\right); \Delta i_t\right) - \text{Var}\left(\Delta i_t\right)\right] / \text{Var}(\Delta i_t) \\
&= \left[-\mu \sum_{k=0}^{\infty} \mu^k \text{Cov}\left(\Delta i_{t+k+1} - \Delta i_{t+k}; \Delta i_t\right) - \text{Var}\left(\Delta i_t\right)\right] / \text{Var}(\Delta i_t) \\
&= \left[-\mu \sum_{k=0}^{\infty} \mu^k \rho_u^k (\rho_u - 1)\text{Var}(\Delta i_t) - \text{Var}(\Delta i_t)\right] / \text{Var}(\Delta i_t) \\
&= -(1-\mu)\frac{1}{1-\mu\rho_u} < 0,
\end{aligned}$$

which is negative for each value of μ and increasing (decreasing) in μ (in λ). ■

Notice that predictability reversal does not arise in our model, differently from Bacchetta and Van Wincoop (2010) and Engel (2016). Formally define the j-period ahead excess return as $q_{t+j} = s_{t+j+1} - s_{t+j} - (i_{t+j} - i^*_{t+j})$, and consider the following regression:

$$q_{t+j} = \alpha + \beta_j (i_t - i_t^*) + \epsilon_{t+j}. \tag{19}$$

The coefficient of interest, β_j, is:

$$
\begin{aligned}
\beta_j =& \frac{\text{Cov}(q_{t+j}, \Delta i_t)}{\text{Var}(\Delta i_t)} \\
& \frac{1}{\text{Var}(\Delta i_t 9} \left(\text{Cov}(\Delta s_{t+j}, \Delta i_t) - \text{Cov}(\Delta i_{t+j-1}, \Delta i_t)\right) \\
& \frac{1}{\text{Var}(\Delta i_t)} \left[\text{Cov}\left(-\mu \sum_{k=0}^{\infty} \mu^k \left(\Delta i_{t+k+j} - \Delta i_{t+k+j-1}\right); \Delta i_t\right) - \text{Cov}\left(\Delta i_{t+j-1}, \Delta i_t\right)\right] \\
& \frac{1}{\text{Var}(\Delta i_t)} \left[\left(-\mu \sum_{k=0}^{\infty} \mu^k \text{Cov}\left(\Delta i_{t+k+j} - \Delta i_{t+k+j-1}\right); \Delta i_t\right) - \text{Cov}\left(\Delta i_{t+j-1}, \Delta i_t\right)\right] \\
& - \mu \sum_{k=0}^{\infty} \mu^k (\rho_u^{k+j} - \rho_u^{k+j-1}) - \rho_u^{j-1} \\
& - \mu \rho_u^{j-1} (\rho_u - 1) \frac{1}{1 - \mu\rho_u} - \rho^{j-1} = -\rho^{j-1} \frac{1 - \mu}{1 - \mu\rho_u} \leq 0.
\end{aligned}
$$

Lastly, notice that $\frac{\partial \beta_j}{\partial j} = -(j-1)\rho_u^{j-1}\left(\frac{1-\mu}{1-\mu\rho_u}\right) < 0$. Therefore, for $j \to \infty$, the coefficient $\beta_j \to 0$ monotonically, excluding any reversal.[40]

[40]This is not surprising considering the absence of any friction, such as infrequent portfolio adjustment (Bacchetta and Van Wincoop, 2010, 2019).

C Solution Method of Dispersed Information Model

We solve the model with higher order expectations using the recursive solution algorithm in Nimark (2017). We approximate the equilibrium of the model to an arbitrary precision with finite number of higher order expectations $\bar{k} < \infty$.

We recursively computes the exchange rate process and the law of motion of the expectations hierarchy for arbitrarily high orders of expectations following these steps:

Step 1. Define the zero order process ($k = 0$) for the exchange rate s_t as a function of the current fundamentals $\Delta i_t^{(0)}$:

$$\begin{aligned} s_t &= G_k \Delta i_t^{(0)} + R_1 \mathbf{w_t} \\ \Delta i_t^{(0)} &= M_k \Delta i_{t-1}^{(0)} + N_k \mathbf{w_t} \end{aligned}$$

where $\mathbf{w_t}$ is the vector of aggregate shocks, including both fundamental and noise shocks; R_1 and N_k represent the variance matrices associated with the zero-order state space representation; the matrix $G_k \equiv G_0 = -\mu$, and $M_k \equiv M_0 = \rho$ are stored separately in the zero-iteration period.

Because investors learn from the exchange rate s_t, the measurement equation for investor j at time t includes a noisy signal about Δi_t as well as s_t:

$$\mathbf{s_{j,t}} = D_0 \Delta i_t^{(0:k)} + R_1 \mathbf{w_t} + R_2 w_{j,t} \quad w_{j,t} \sim N(0, I)$$

where $D_0 = [1, G_0]'$ and $w_{j,t}$ is the idiosyncratic noise shock.

Step 2. Using the measurement equation and the law of motion of hierarchy, compute the Kalman gain K_k for the k^{th} step, as well as the matrices M_{k+1} and N_{k+1}:

$$M_{k+1} = \begin{bmatrix} M_0 & \mathbf{0}_{q \times kq} \\ \mathbf{0}_{kq \times q} & \mathbf{0}_{kq \times kq} \end{bmatrix} + \begin{bmatrix} \mathbf{0}_{q \times kq} & \mathbf{0}_{q \times q} \\ K_k D_k M_k & \mathbf{0}_{kq \times q} \end{bmatrix} + \begin{bmatrix} \mathbf{0}_{q \times q} & \mathbf{0}_{q \times kq} \\ \mathbf{0}_{kq \times q} & (I - K_k D_k) M_k \end{bmatrix}$$

$$N_{k+1} = \begin{bmatrix} N_0 \\ (K_k D_k N_k + K_k R_1) \end{bmatrix}.$$

to get the k^{th} step law of motion

$$\Delta i_t^{(0:k)} = M_{k+1}\Delta i_{t-1}^{(0:k)} + N_{k+1}\mathbf{w}_t, \quad \mathbf{w}_t \sim N(0, I)$$

where the matrix D_k is defined as:

$$D_k = \begin{bmatrix} 1 & \mathbf{0}_{q\times kq} \\ G_k & \end{bmatrix}$$

Step 3. The k-order process for the exchange rate s_t^{k+1} is:

$$s_t^{k+1} = G_{k+1}\Delta i_t^{(0:k+1)} + R_1 w_t$$

where

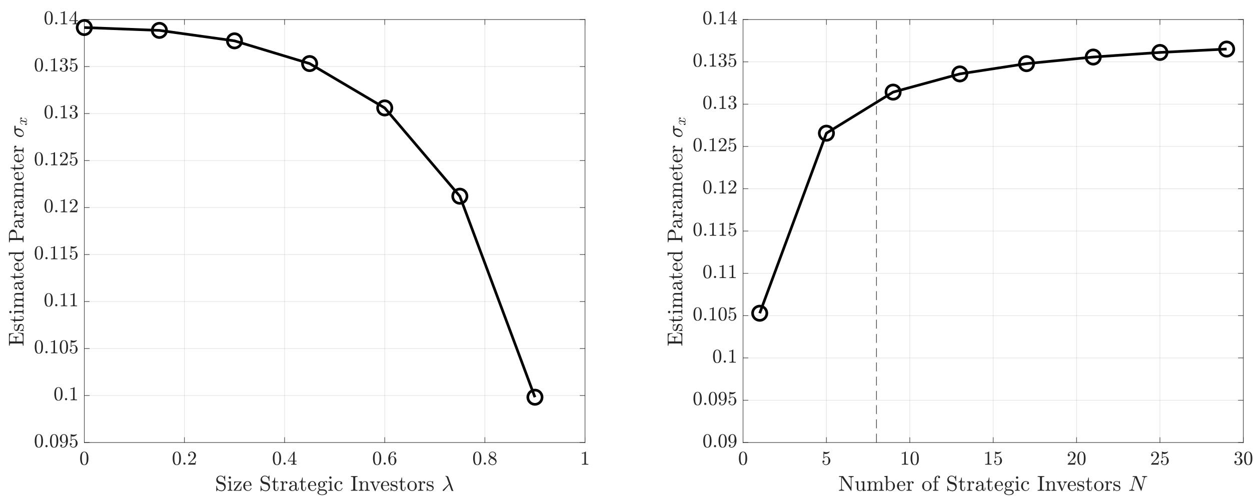
$$G_{k+1} = G_0 + \mu G_k M_k H_{k+1} \qquad \text{and} \qquad H_k \equiv \begin{bmatrix} \mathbf{0}_{(kq)\times q} & I_{kq} \end{bmatrix}$$

Step 4. Repeat Steps $2-3$ for $k = 1, 2, ..., \bar{k}$ where the number of iterations $\bar{k}$ can be chosen to achieve any desired degree of accuracy.

D Additional Tables and Figures

D.1 Strategic Behavior and Noise Volatility

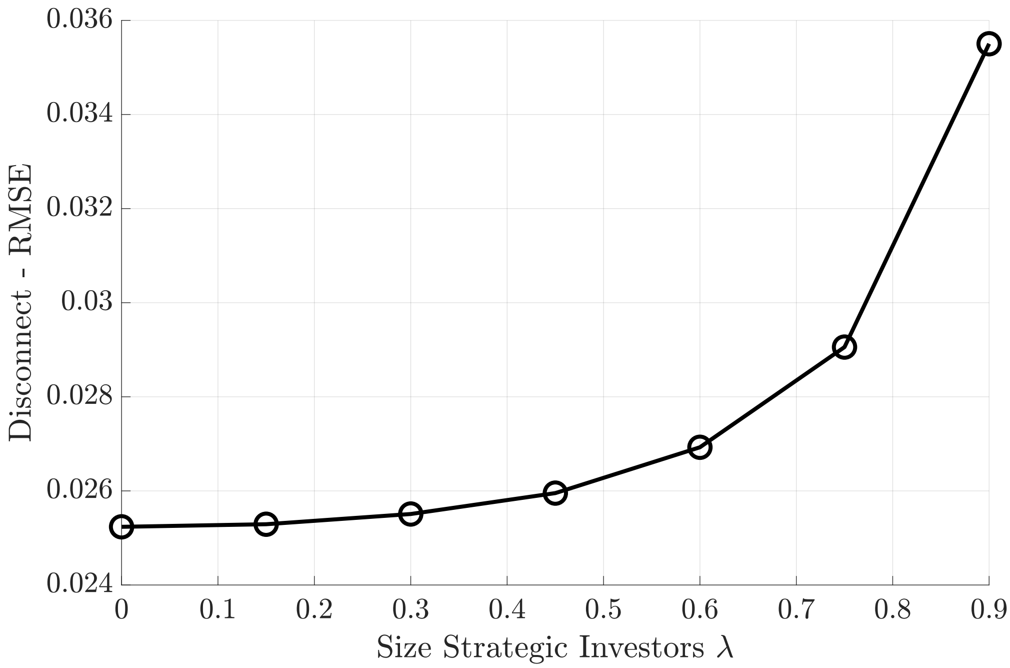
Figure 12: Relationship between Strategic Behavior and Noise Volatility



Notes: The figure shows the volatility of the noise component, σ_x, required to match the target volatility of the exchange rate change in the basic framework, for different levels of strategic behavior. The left panel considers different levels of strategic behavior in terms of λ for a number of strategic investors equal to $N = 4$. The left panel considers different levels of strategic behavior in terms of N for a total size of strategic investors equal to $\lambda = 0.675$. All other parameters are constant and summarized in Table 2.

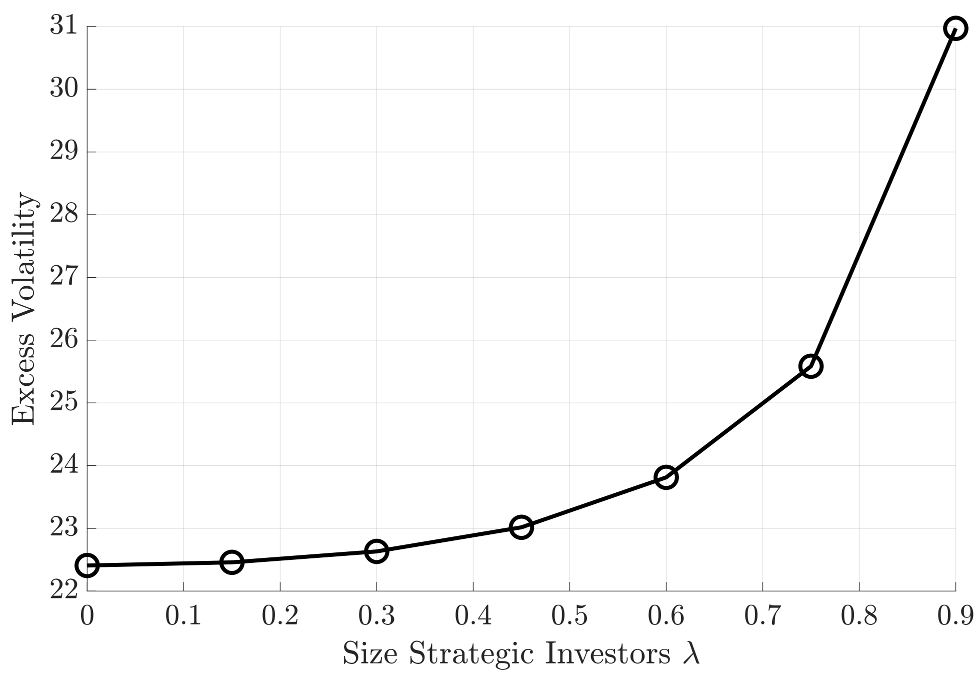
D.2 Strategic Behavior and Exchange Rate Dynamics

Figure 13: Exchange Rate Disconnect - RMSE



Notes: The figure shows the estimated Root-Mean Square Error (RMSE) of the disconnect regression in Equation 10 using simulated data. We run 3000 simulations and, for each iteration, the model runs for 8000 periods with 4000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 2.

Figure 14: Excess Volatility - Exchange Rate Change



Notes: The figure shows the excess volatility ratio computed using simulated data from our model. We run 3000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. The excess volatility ratio is computed using the ratio between the volatility of the exchange rate change and the volatility of changes in the fundamental, $\frac{\text{Var}(\Delta s)}{\text{Var}(\Delta u_t)}$. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 2.

D.3 Cross-Currency Model Predictions

Table 6: Testing Model Predictions

	(1) Excess Volatility	(2) Disconnect - R2
λ	182.898***	-0.247***
	(69.564)	(0.068)
Constant	52.115	0.232***
	(39.098)	(0.038)
Currency & Year FEs	Yes	Yes
Observations	900	900

Notes: The table reports the relationship between λ and the variables of interest. λ represents the net concentration ratio by the top eight reporting traders operating in the future FX market. Variable of interest are: exchange rate excess volatility (Columns (1)); exchange rate disconnect/R^2 (Column (2)). The exchange rate disconnect is measured using the Adjusted R^2 from the regression in Equation (10), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (11) to the volatility of the interest rate differential. λ is measured monthly from 2006 to 2016 using the U.S. CFTC data. To measure excess volatility and disconnect, we use a two-year periods rolling window and exchange rate data at monthly level. Values of the excess volatility ratio and disconnect are winsorized at 1%. All regressions include currency and year fixed effects. Standard errors in parenthesis are clustered at the currency level. Significance level:* p<0.10, ** p<0.05, *** p<0.01. Currencies considered are: Euro, Japanese Yen, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Mexican Peso, British Pound, Russian Ruble, and New Zeland Dollar. Appendix A provides additional information on the data used.

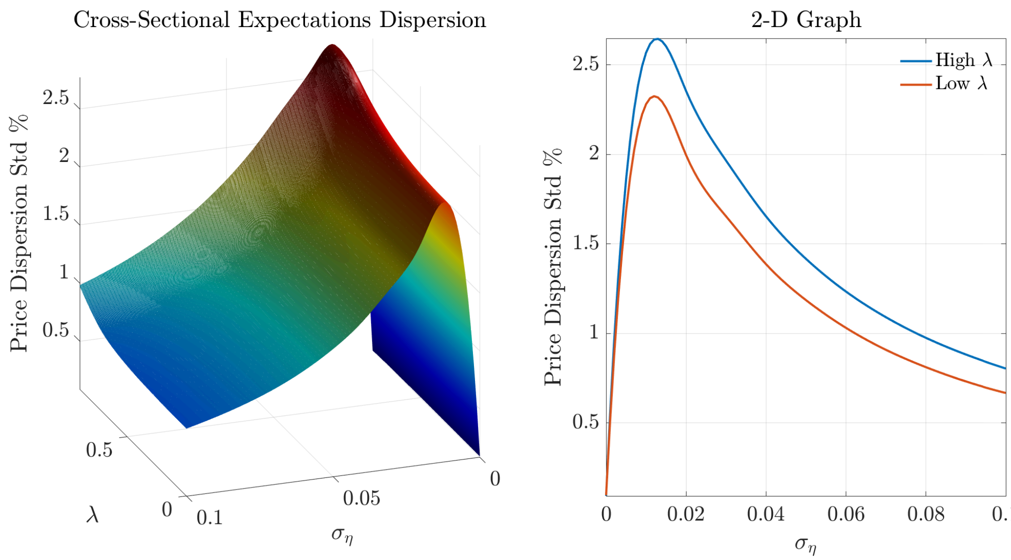
D.4 Parametrization Quantitative Model

Table 7: Parametrization Quantitative Model

	Value	Moment - Target	Data	Model
λ	0.675	Share transactions 1st quintile – NYFXC		
N	4	Number of investors 1st quintile – NYFXC		
ρ_u	0.85	Average persistence AR(1) Δi_t		
σ_u	0.005	Average StD innovation AR(1) Δi_t		
σ_t	0.028	Average StD ER change		
σ_η	0.006	Same Quarter Expectation Dispersion	0.02	0.01
σ_x	0.022	σ_t (Volatility ER change)	0.028	0.029
ρ_x	0.9	ER RW/Average Disconnect		
ρ	50	Average UIP level		
b	0.33	Home Bias		
$\bar{k}$	10			

Notes: The table summarizes the parametrization used in Section 5. For each parameters, we report the value used in the model, the corresponding moment and data used to calibrate, and, if applicable, the target moment used to estimate it. Appendix A provides additional information on the data used.

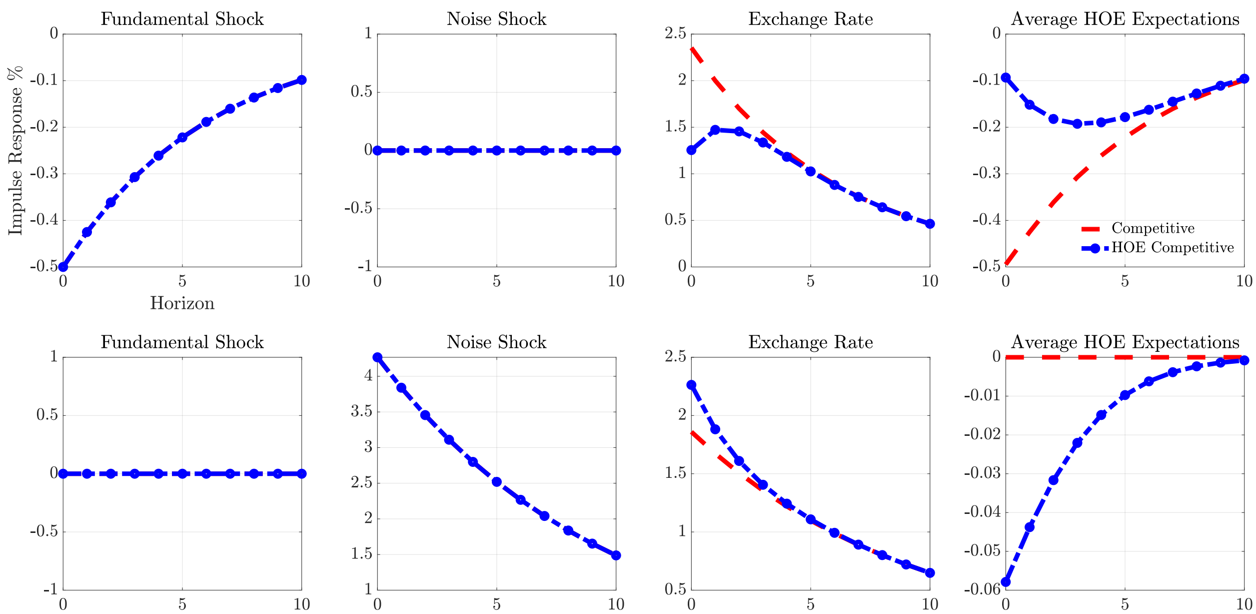
Figure 15: Exchange Rate Expectation - Dispersion



Notes: The figure shows the dispersion (standard deviation) across investors in the one-period exchange rate expectations for different level of strategic behavior (λ) and precision of the signal on fundamentals (σ_η) implied by the model in Section 5. The left panel shows the dispersion in expectations for values of $\lambda \in [0, 1]$, and $\sigma_\eta \in [0, 0.1]$. The right panel shows the dispersion in expectation for two levels of strategic behavior ("Low" with $\lambda = 0$, and "High" with $\lambda = 0.6$) and a precision of the signal σ_η between 0 and 0.1. The figure is generated for a representative calibration with $\sigma_u = 0.01$ and $\rho_x = 0$. All remaining parameters are reported in Table 7 in Appendix D.

D.5 Impulse Response under High Order Expectations (HOE)

Figure 16: Impulse Response to Exogenous Shocks



Notes: The top panel (bottom) shows the response to a fundamental (noise) shock. The first (second) column show the dynamics of a one standard deviation shock in fundamental (noise). The third column shows the dynamics of the exchange rate. The fourth column shows the response of the average first order ($k = 1$) expectation of future exchange rate defined in Equation (14). The blue dashed-dot line shows the response in an economy with dispersed information $\sigma_\eta > 0$. The red dashed line shows the response in an economy without dispersed information, $\sigma_\eta = 0$. In both scenario, markets are fully competitive ($\lambda = 0$). Remaining parameters are common across scenarios, see Table 7 in Appendix D.