Strategic Investors and Exchange Rate Dynamics

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First Draft: February 2020
This Draft: May 2023

Abstract

Foreign exchange rate markets exhibit a significant level of concentration. 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 foreign exchange rate market for 18 currencies spanning from 2005 to 2019. 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. We show that 80% of the disconnect and 66% of the excess volatility due to investors' heterogeneity can be attributed to heterogeneity in price impact.

JEL Codes: F31, G11, G15

Keywords: Exchange Rate, Investors' Heterogeneity, Price Impact, Strategic Investors, Dispersed Information, Exchange Rate Puzzles, Exchange Rate Disconnect, Excess Volatility.

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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 behavior of exchange rates is influenced by the presence of heterogeneous investors with varying degrees of price impact. The large turnover in the foreign exchange markets is highly concentrated among the a few large financial institutions. Figure 1 shows that the top quintile of financial institutions in the foreign exchange rate market in New York holds a market share of approximately 70% of the total turnover.[2] 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.[3]

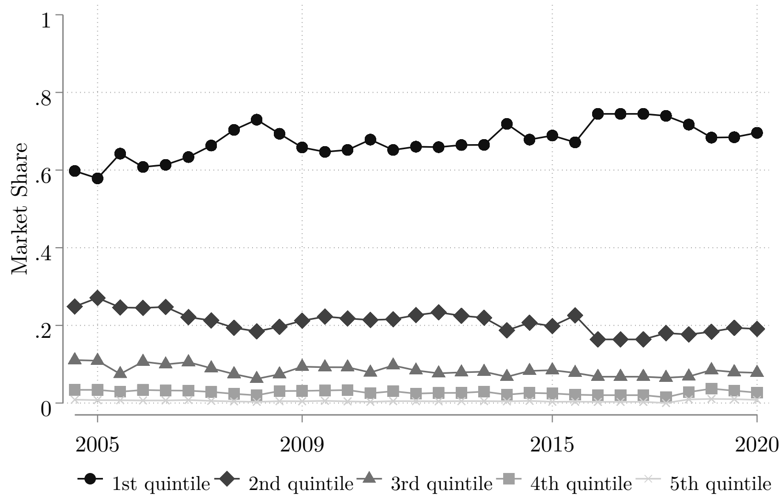
We embed the heterogeneity in price impact into a two-country, dynamic monetary model

[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]Using data from the BIS Triennial Survey of Foreign Exchange Markets spanning from 1995 to 2019, Tables 3 and 4 in Appendix A reveal the geographical concentration of foreign exchange rate markets, with a notable increase in concentration observed over the past few decades. Table 3 in Appendix A shows that the majority of foreign exchange global turnover takes place in six major markets, namely the UK, USA, Japan, Singapore, Switzerland, and Hong Kong. Furthermore, Table 4 in Appendix A shows that a small number of financial players intermediates 75% of the total turnover in each of these markets. This trend aligns with the broader consolidation patterns observed in the financial sectors,Corbae and D'Erasmo (2020).

[3]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).

Figure 1: Market Concentration – NY OTC Foreign Exchange Market



Notes: The figure shows the investors' market share in the New York foreign exchange market by quintile. Market share are computed in terms of total transactions across all currencies. Data are from the biannual NY Fed FXC report, spanning from 2005 to 2020. Appendix A provides additional information on the data used.

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 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 price 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 18 currencies spanning from 2005 to 2019 to empirically validate the main predictions of our model. We combine daily exchange rate data with currency-level concentration data obtained from the biannual reports of the New York Federal Reserve FXC. In line with the theoretical predictions, a currency traded in a market with a 10% higher market share of strategic investors exhibits an 8% 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 18% 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.

We show that investors' heterogeneity significantly influences the dynamics of exchange rates, with a primary role attributed to the heterogeneity in price impact. When considered jointly, both dimensions of heterogeneity contribute to an increase in the exchange rate disconnect and excess volatility by approximately 30%. Notably, the heterogeneity in price impact is the dominant factor: 80% of the disconnect and 66% of the excess volatility due to investors' heterogeneity can be attributed to heterogeneity in price impact.[4] Furthermore, the impact of each dimension of heterogeneity is qualitatively and quantitatively similar across various currencies. 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). In our framework, we address this gap 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.

[4]Notice that the two dimensions of heterogeneity interact. The effects of information heterogeneity are amplified by the heterogeneity in price impact: strategic investors trade less, reducing the informativeness of the exchange rate and making prices more dispersed for any level of information heterogeneity.

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).[5] 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 18 currencies.

The rest of the paper is organized as follows. Section 2 introduces the theoretical framework and explains the fundamental mechanism of strategic behavior. In Section 3, we discuss the main implications for the dynamics of the exchange rate and provide empirical evidence that supports the theoretical predictions. Section 4 expands the basic framework to incorporate information heterogeneity and quantifies the respective contributions of each mechanism. Finally, Section 5 presents the conclusion. Any proofs, derivations, and robustness analyses that were omitted can be found in the Appendices.

2 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 4, we extend the model to include dispersed information, following Bacchetta and Van Wincoop (2006), and conduct our quantitative decomposition.

[5] 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.

2.1 Basic Set-up

There are two economies, Home and Foreign, both producing the same good. 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.[6] 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

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

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.[7] 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

[6] Variables referring to Foreign are indicated with a star.

[7] 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.

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:

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

$$\text{s.t. } w_{t+1}^j = (\omega - b_t^j)i_t + (i_t^\star + s_{t+1} - s_t)b_t^j, \tag{3}$$

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.[8] 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 4.

Investors' demand schedule and portfolio allocation vary depending on their type. Strategic 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:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2}, & \text{for } j = C \\[2ex] \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}}, & \text{for } j = S \end{cases} \tag{4}$$

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.

[8] $p_t = 0$ 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.

Investors' demand for foreign bonds depends positively on the expected excess return, $q_{t+1} \equiv E_t(s_{t+1}) - s_t + i^\star_t - i_t$. On the other hand, it depends negatively on the variance of the exchange rate, σ^2_t, and on investors' risk aversion, ρ. Note that strategic behavior, captured by investors' own price impact $\frac{\partial s_t}{\partial b^S_t}$, 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

$$\frac{\partial s_t}{\partial b^{S,i}_t} = \frac{\lambda_i \rho \sigma^2_t}{B\rho\sigma^2_t + (1-\lambda)} > 0, \tag{5}$$

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 $\frac{1}{N}\frac{\lambda\rho\sigma^2_t}{B\rho\sigma^2_t+(1-\lambda)}$ in the case strategic investors are symmetric and have the same mass, $\lambda_i = \frac{\sum_i \lambda_i}{N} = \frac{\lambda}{N}$.[9] 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.[10]

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

[9] In our analysis, we focus on the case of symmetric strategic investors due to the unavailability of comprehensive investor-level market share data. The NY Fed FX reports, used in our calibration and empirical analysis, provide information only on the aggregate market share of each quintile and 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.

[10] 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 presence of B, the total supply of foreign assets, at the denominator of Equation (5). See Appendix B for additional details.

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 (1). 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:[11]

$$(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i} + X_t = Be^{s_t}, \tag{6}$$

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 (constant) 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 (6):

$$s_t = \underbrace{(1-\mu)\left(\frac{\bar{x}}{b} - 1\right)}_{\text{constant}} + \underbrace{\mu\left(E_t s_{t+1} + i_t^\star - i_t\right)}_{\text{fundamental}} + \underbrace{(1-\mu)\frac{1}{b}x_t}_{\text{noise}}, \tag{7}$$

[11]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.

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 (7), it can be shown that the exchange rate s_t can be written as follows:

$$s_t = \mu \sum_{k=0}^{\infty} \mu^k \left(i^\star_{t+k} - i_{t+k}\right) + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \mu^k \left(x_{t+k}\right). \tag{8}$$

The exchange rate is a weighted average of current and future fundamental shocks ($i^\star_{t+k} - i_{t+k}$) and noise shocks (x_{t+k}). The weight, μ, reflects the informativeness of the exchange rate and quantifies the amount of information about the fundamental conveyed by the exchange rate. Notably, the informativeness of 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.[12] [13]

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 a monthly frequency.[14] Without loss of generality, we set $\bar{r} = 0$, so that the $i_t - i^\star_t = u_t$. 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^2_t, is

[12]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).

[13]The price 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 informativeness index plays a crucial role in the amplification mechanism examined here.

[14]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.

Table 1: Benchmark Parametrization

Parameters	Value	Description
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_x	0.118	σ_t (Volatility 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	Average UIP Level / 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.

assumed to be constant over time and calibrated to match the average variance of the one-period exchange rate change across currencies, which is 0.029. The parameters controlling the magnitude of the strategic behavior, λ and N, are calibrated using data from the NY Fed Biannual FCX Reports from 2005 to 2019. We calibrate $\lambda = 0.675$ to match the market share of the top quintile of investors in the NY FX market, and $N = 4$ as the number of investors in the top quintile. 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. Given the benchmark values for λ and N, we set $\sigma_x = 0.118$ and $\rho_x = 0.9$.[15] [16] 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

[15] $\bar{x}$ 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.

[16] 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 – exchange rate volatility. This is because strategic investors amplify the effects of noise traders. Figure 10 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.

obtained from the IMF IIPS dataset (Bacchetta and Van Wincoop, 2019).[17] Lastly, the rate of relative risk aversion, ρ, is set to 50 following Bacchetta and Van Wincoop (2019).[18] The parametrization, summarized in Table 1, 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.[19]

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 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.

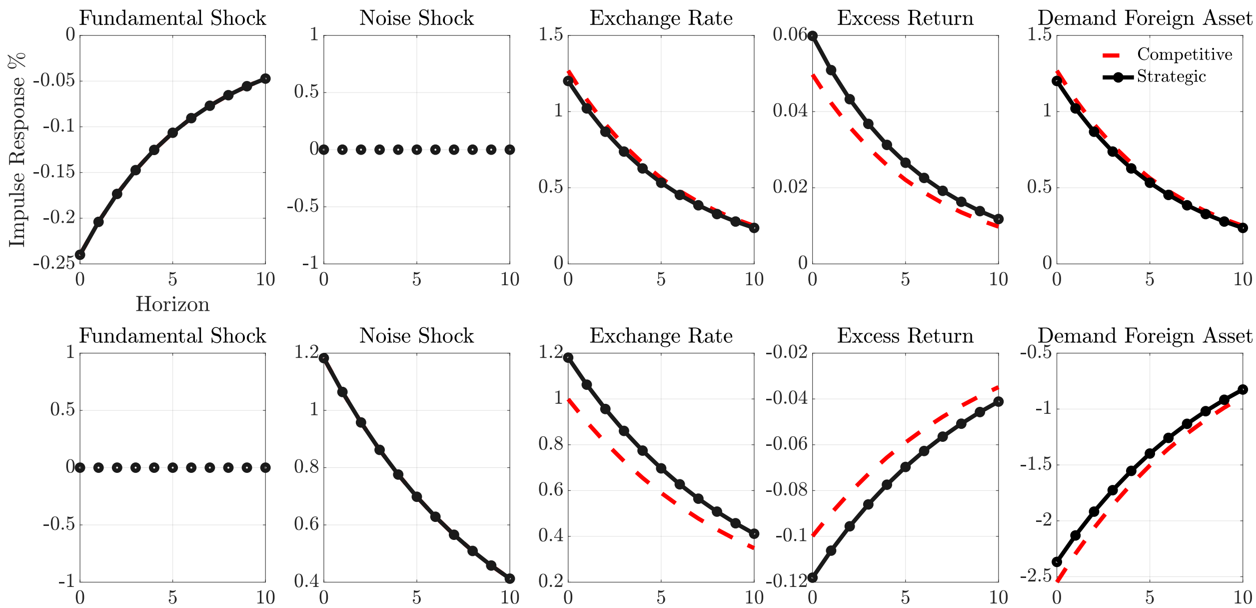
The top row of Figure 2 shows the exchange rate's response to a fundamental shock and its dampening in the presence of strategic investors compared to a "competitive" market.

[17] 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.

[18] 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.

[19] Appendix B shows that the result is independent of the parameterization of the model.

Figure 2: Impulse Response to Exogenous Shocks



Notes: The top panel (bottom) shows the response to a fundamental (noise) shock. The first and the second columns show the dynamics of a one standard deviation shock in fundamental 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 4. The solid black line shows the response in the benchmark parametrization with strategic investors, $\lambda = 0.675$. The red dashed line shows the response in a competitive economy without strategic investors, $\lambda = 0$. Remaining parameters are common across scenarios, see Table 1.

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.

3 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.[20]

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:

$$s_{t+1} - s_t = \alpha + \beta(i_t - i_t^\star) + \varepsilon_{t+1}, \tag{9}$$

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 (9), and observe how the explanatory power – measured using RMSE or R^2 – of the disconnect regression changes as the economy becomes increasingly populated by strategic investors.[21]

Figure 3 illustrates the RMSE of the disconnect regression for different degrees of strategic behavior, represented by different levels of λ. On average, the RMSE is low, consistent with the notion that exchange rates are disconnected from fundamentals.[22] Importantly, the disconnect increases in the presence of strategic investors, with the RMSE in our benchmark calibration ($\lambda = 0.675$) being 20% higher compared to a competitive market.[23] This can be explained by the behavior of the exchange rate informativeness. 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.

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

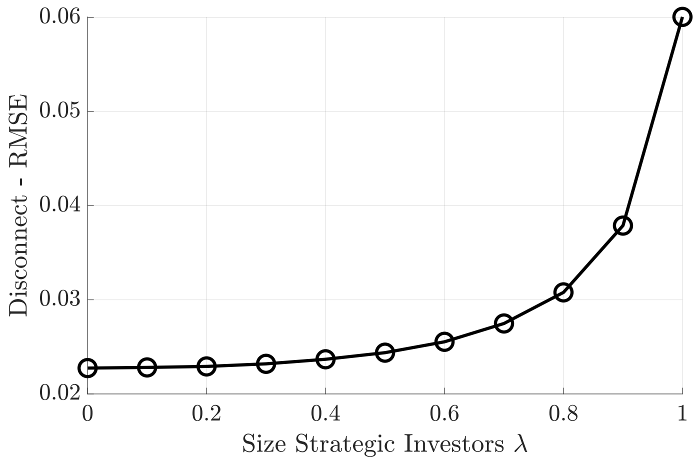
[20] Appendix B demonstrates that the presence of strategic behavior also has implications for deviations from uncovered interest rate parity (UIP). Although strategic behavior does not inherently generate excess predictability, it does contribute to larger UIP deviations.

[21] We run 3000 simulations and, for each iteration, the model runs for 1000 periods with 4000 burn-in.

[22] The RMSE from simulated data is close to the average RMSE estimated from the data used for the calibration, 0.025.

[23] Figure 11 in Appendix D shows that the same qualitative implications hold when the disconnect is measured using the R^2.

Figure 3: Exchange Rate Disconnect



Notes: The figure shows the estimated RMSE of the disconnect regression in Equation 9 using simulated data. We run 3000 simulations and, for each iteration, the model runs for 1000 periods with 4000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 1.

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 (8), 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:

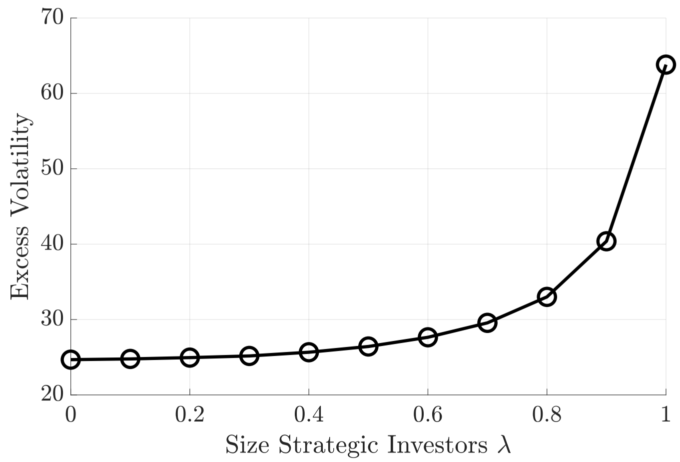
$$\operatorname{Var}(s) = \frac{\mu^2}{(1-\mu\rho_u)^2}\left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2}\right]\sigma_u^2 + \frac{(1-\mu)^2}{(1-\mu\rho_x)^2 b^2}\left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2}\right]\sigma_x^2. \tag{10}$$

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.[24]

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 (10)). We compute the excess volatility of the exchange rate as the ratio between the volatility of the exchange rate in Equation (10) and the volatility of the

[24] 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.

Figure 4: Excess Volatility



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 1000 periods with 4000 burn-in. The excess volatility ratio is computed using the ratio between the volatility of the exchange rate in Equation (10) 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 1.

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 ($\lambda = 0.675$) being 20% higher compared to a competitive market.[25]

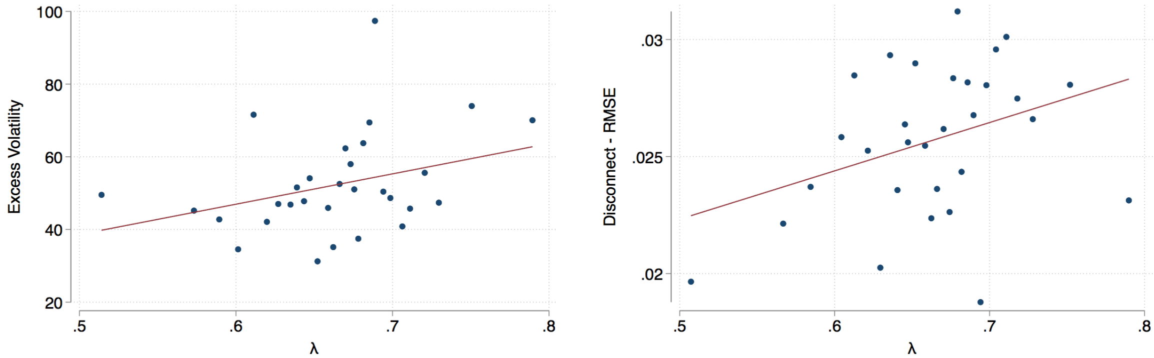
Testing predictions We test the implications provided by our theory using the data from the New York Fed Biannual FXC reports and leveraging the heterogeneity in λ across currencies. The model delivers two distinct testable relationships between exchange rate dynamics and the level of strategic behavior: (i) the disconnect of the exchange rate from fundamental increases in λ (ii) higher λ results in higher excess volatility of the exchange rate.

We consider the same of currencies used to calibrate the model from 2005 to 2019, as the FXC reports are available only since April 2005.[26] We use the share of total FX transactions intermediated by the top quintile of investors, as reported by the NY Fed FXC,

[25] Figure 12 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, $\frac{\mathrm{Var}(\Delta s)}{\mathrm{Var}(\Delta u_t)}$.

[26] We exclude the Argentinian Peso from our analysis due to the significant influence of default episodes on both exchange rate and interest rate dynamics during those years.

Figure 5: Testing Model Predictions



Notes: The figure plots the positive relationship between the level of strategic behavior (λ) and the excess volatility (left panel) and the disconnect (right panel) of the exchange rate. λ represents the share of transactions intermediated by the top quintile of investors operating in the New York FX market. The exchange rate disconnect is measured using the RMSE from the regression in Equation (9), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (10) to the volatility of the interest rate differential. λ is measured in April and October of each year from 2005 to 2019 using the New York Fed FX Market Report. To measure excess volatility and disconnect, we use daily exchange rate data within a six-month window surrounding April and October each year. The resulting data are demeaned at the currency and year level, and values of the excess volatility ratio exceeding 200 are excluded. We exclude the Argentinian Peso from the set of 18 currencies. Table 6 in Appendix D reports the estimated coefficients. Appendix A provides additional information on the data used.

as our measure of strategic behavior (λ) in the exchange rate market. The FXC report is published biannually, allowing us to measure λ in April and October of each year.[27] We match the information about λ with time-varying measures of exchange rate disconnect and excess volatility. To construct indexes of exchange rate disconnect and excess volatility, we use daily data on exchange rates within a six-month window around April and October of each year.[28] We measure the exchange rate disconnect using the RMSE of the regression in Equation (9), while excess volatility is measured with the ratio between the volatility of the exchange rate in Equation (10) 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.

Figure 5 provides empirical evidence consistent with the prediction of our theoretical framework. The left panel documents a strong positive and statistically significant rela-

[27]Figure 7 in Appendix A documents the rich heterogeneity in λ across currencies and over time.

[28]We use daily frequency data to increase the sample size within each window. However, we continue to use one-month interest rates and exchange rate changes.

tionship between our measure of strategic behavior in the financial markets and the excess volatility of the exchange rate. Likewise, the right panel reveals that as the presence of strategic investors investors in the market increases, currencies become more disconnected to fundamentals, as evidenced by the rising estimated RMSE. 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 market share of strategic investors exhibits an 8% lower predictive power compared to the average predictive power in the sample. Similarly, a currency traded in a market with a 10% higher market share of strategic investors exhibits an excess volatility ratio that is 18% higher compared to the average ratio observed in the sample.

4 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 2 by relaxing the symmetric rational expectation 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.

4.1 Relaxing the Rational Expectation Assumption

The model incorporates all standard elements of an exchange rate monetary model, along with the strategic behavior described in Section 2. 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, $\Omega_t(j)$:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2} & \text{if } j = C \\ \\ \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}} & \text{if } j = S \end{cases} \tag{11}$$

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.[29]

Equilibrium and Solution. We extend the definition of equilibrium of the basic framework discussed in Section 2 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.

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:

$$s_t = (1-\mu)\left(\frac{\bar{x}}{b} - 1\right) + \mu\left(\int E\left[s_{t+1} \mid \Omega_t(j)\right] dj\right) - \mu\left(i_t - i_t^\star\right) + (1-\mu)\frac{1}{b}x_t, \tag{12}$$

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:

$$s_t = \mu \sum_{k=0}^{\infty} \mu^k \left[i_{t+k} - i_{t+k}^\star\right]_t^{(k)} + \frac{1-\mu}{b}x_t, \tag{13}$$

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

[29]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).

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:[30]

$$s_t = v_0 \Delta i_t^{(0:k)} + \frac{1-\mu}{b} x_t \tag{14}$$

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 $\Delta i_t^{(1:k)}$.

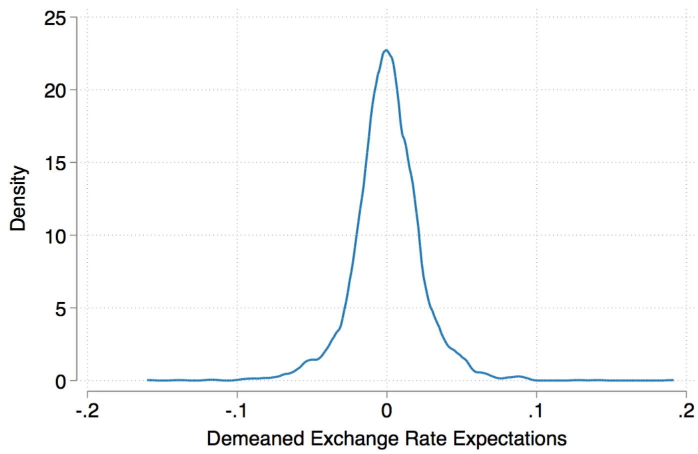
Parametrization and Mechanism. We extend the parametrization of the basic framework in Table 1 to account for the presence of dispersed information. We leverage the data on exchange rate expectations from the ECB Professional Forecasters survey to calibrate the volatility of the private signal, σ_η. 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.[31] 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 with 100 repetitions and 2000 periods each. We match the volatility of the exchange rate change and the median dispersion in the same-quarter exchange rate forecasts across quarters. This yields $\sigma_x = 0.022$ and $\sigma_\eta = 0.006$. Table 7 in Appendix D summarizes the parametrization.[32]

[30] 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.

[31] 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.

[32] 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.

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 13 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 in the exchange rate are mistakenly confused with a negative change in fundamentals. This rational confusion adds further upward pressure on the exchange rate.[33] 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

[33] 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.

sensitivity of investors' demand for foreign assets, while Information heterogeneity leads to rational confusion.

4.2 Quantitative Analysis

We leverage the model that incorporates the two dimensions of heterogeneity and show that strategic behavior plays a relatively larger role in driving the dynamics of the exchange rate, particularly in terms of exchange rate disconnect and excess volatility.

We assume that the model embedding both strategic behavior and dispersed information 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:[34] Given our calibration, we use the model to filter the underlying states and perform three different counterfactuals: i) a competitive, 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 rational expectations ($\lambda > 0$ and $\sigma_\eta = 0$). We focus on the exchange rate disconnect, which is measured by the RMSE of the disconnect regression in Equation (9), and the exchange rate excess volatility, which is measured by the volatility of the exchange rate.[35]

Table 2 show that, on average, exchange rates exhibit 24% higher volatility and 27% higher disconnect compared to a competitive, rational expectation benchmark.[36] To quantify the joint contribution of dispersed information and strategic behavior, we compare the exchange rates generated by the full model with both dimensions of heterogeneity to the counterfactual exchange rate series derived from the competitive, rational expectation model These findings suggest that investors' heterogeneity plays a quantitatively significant role in shaping the dynamics of exchange rates, as highlighted in previous studies (Evans and Lyons, 2002; Bacchetta and Van Wincoop, 2006, 2010, 2019).

Additionally, approximately 66% of the increased disconnect and 80% of the heightened volatility can be attributed to heterogeneity in price impact. By comparing the competitive, rational expectation model to an economy with only one dimension of heterogeneity, we

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

[35] To measure excess volatility, we directly examine the volatility of the exchange rate. This approach is taken because the denominator of the excess volatility ratio – the volatility of the fundamental – remains constant across all counterfactual scenarios.

[36] Although the increase in predictive power may be small in absolute terms, even small increments in predictive power can still be quantitatively relevant for carry trade strategies.

Table 2: Disconnect and Volatility Decomposition

	RMSE Full Model (Actual Data)	Extra Disconnect (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
Average	0.03	27.51	66.67	29.89	3.44

	Var(s_t) Full Model (Actual Data)	Extra Volatility (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
Average	0.29	23.92	82.58	15.20	2.22

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). Exchange rate disconnect is measured using the Root Mean-Square Error of a standard, one-period disconnect regression, Equation (9). Excess volatility is measured using the standard deviation of the exchange rate. The first column reports the estimated disconnect and volatility from the full model that includes both dispersed information and strategic behavior. 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. All values are the averaged across currencies; we exclude the Argentinian Peso. Tables 8 and 9 in Appendix D reports the currency-level decomposition. Appendix A provides additional information on the data. Appendix C provides additional information on the estimation and filtering procedure.

can determine the specific contribution of each individual dimension to the dynamics of the exchange rate. These findings indicate that heterogeneity in price impact is relatively more important for the dynamics of the exchange rate, suggesting the importance of taking into account this crucial aspect of exchange rate markets.[37]

The final column in Table 2 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. This non-linear interaction, accounting for approximately 3% 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]

[37]Tables 8 and 9 in Appendix D provide a breakdown of the decomposition at the currency level. While the decomposition results may vary across currencies, the qualitative findings remain consistent for most currencies (with the exception of the Turkish Lira, potentially due to recent turbulence in their exchange rate market). This suggests that the overall conclusions regarding the contributions of dispersed information and strategic behavior to the dynamics of the exchange rate hold true across various currencies.

[38]In Figure 14 in Appendix D, we show the simulated price dispersion for different levels of strategic

5 Conclusion

The high concentration in the foreign exchange market suggests that investors' heterogeneity in price impact 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 analytical results, we provide empirical evidence supporting the theoretical predictions using a panel of 18 currencies. Furthermore, we extend the theoretical framework by including a competing dimension of investors' heterogeneity, namely information dispersion. We show that strategic behavior is quantitatively more relevant in influencing the dynamics of the exchange rate compared 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.

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.

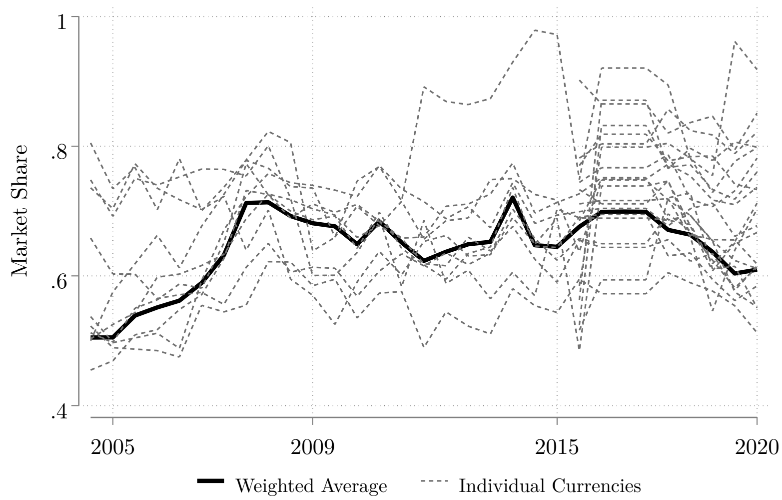
  We obtain data for the spot and one-month forward exchange rates at a daily frequency from Datastream and Thompson Reuters. All exchange rates are defined against the US Dollar. To calculate the one-month interest rate, we took the difference between the logarithm of the one-month forward exchange rate 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 on foreign exchange market concentration from the New York Fed FXC reports, which are available online. The data covers the same set of currencies from 2005 to 2019. This panel is also unbalanced. The FXC survey is conducted biannually, specifically in April and October.

- 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

Figure 7: Market Share of Top Quintile



Notes: The figure shows the market share of the top quintile of investors in the New York OTC foreign exchange market. Market share are computed in terms of total transactions. The thick black shows the weighted average across all currencies, weighted by turnover. All other dotted lines represent individual currencies. Data are from the NY Fed Biannual FXC report, from 2005 to 2020. Appendix A provides additional information on the data used.

Table 3: Geographic Concentration

Market	1995	1998	2001	2004	2007	2010	2013	2016	2019
Hong Kong	5,6	3,8	4,0	4,1	4,2	4,7	4,1	6,7	7,6
Japan	10,3	7,0	9,0	8,0	5,8	6,2	5,6	6,1	4,5
Singapore	6,6	6,9	6,1	5,1	5,6	5,3	5,7	7,9	7,7
Switzerland	5,4	4,4	4,5	3,3	5,9	4,9	3,2	2,4	3,3
UK	29,3	32,6	32,0	32,0	34,6	36,7	40,8	36,9	43,1
US	16,3	18,3	16,1	19,1	17,4	17,9	18,9	19,5	16,5
Others	26,6	27,1	28,2	28,4	26,3	24,2	21,7	20,4	17,2

Notes: The table reports the percentage share of turnover intermediated in each foreign exchange rate market. The values are expressed in percentage terms. The source of the data is the BIS Triennial Survey, covering the period from 1995 to 2019.

Table 4: Within Market Concentration

Market	1995	1998	2001	2004	2007	2010
Hong Kong	22	26	14	11	12	16
Japan	24	19	17	11	9	8
Singapore	25	23	18	11	11	10
Switzerland	5	7	6	5	3	2
United Kingdom	20	24	17	16	12	9
United States	20	20	13	11	10	7
Others		37	32	25	28	27

Notes: The table provides information on the number of investors accounting for 75% of the turnover in each foreign exchange rate market. The data is sourced from the BIS Triennial Survey, covering the period from 1995 to 2010.

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 (7). 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 7, 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:

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

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

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

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

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

that can be rewritten as follows:

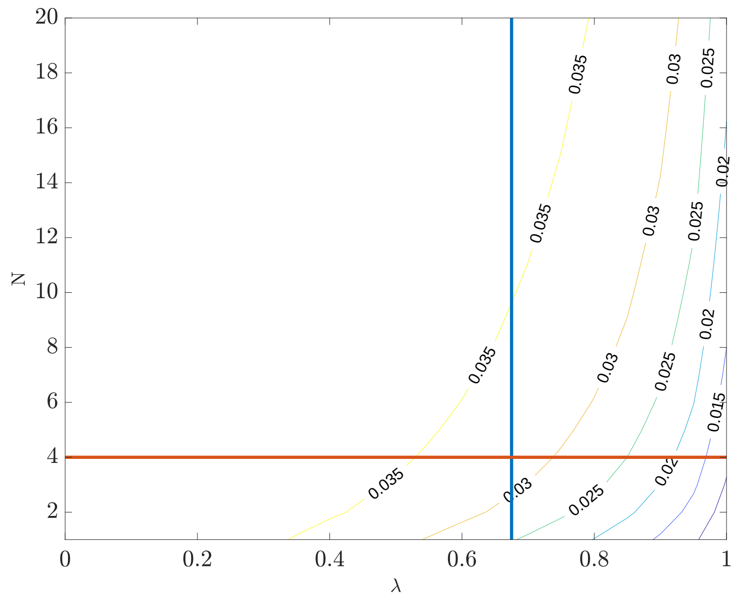
$$\frac{\mathrm{Var}(x)}{\mathrm{Var}(\Delta i)}\frac{1}{b^2} > \left[\frac{(1+\mu^2\rho_x)(1-\rho_x)}{\mu(1+\mu\rho_u)(1-\mu^2)+\mu^3(1-\rho_u^2)}\frac{(1-\mu\rho_u)^2(1-\mu)^2}{(1-\mu\rho_x)^2}\right]^{-1}. \tag{15}$$

■

Equation (15) 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.

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 8 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%

Figure 8: $\underline{\sigma_x}$ 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 (15). 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 1.

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 10 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 (7):

$$E_t q_{t+1} = \frac{\Phi}{B}\left(Be^{s_t} - X_t\right), \tag{16}$$

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:

$$q_{t+1} = \alpha + \beta(i_t - i_t^\star) + \epsilon_t. \tag{17}$$

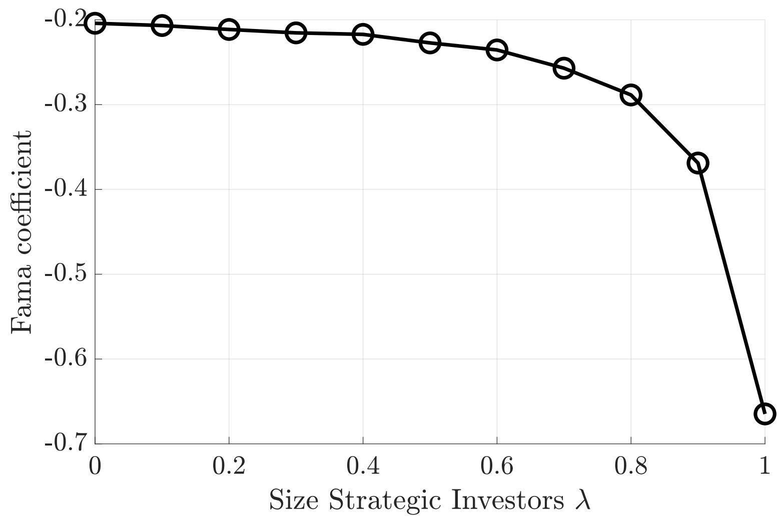
where q_{t+1} is the realized excess return. While UIP implies that the Fama coefficient, β, is zero, empirical evidence typically finds a negative number. Our model predicts that β is given by:

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

which is negative and decreasing in the level of strategic behavior.[39] Figure 9 plots the

[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

Figure 9: Excess Return Predictability



Notes: The right panel shows the estimated one-period Fama coefficient using Equation 17 and simulated data from our model for different levels of strategic behavior. We run 3000 simulations and, for each iteration, the model runs for 1000 periods with 4000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 1.

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.

Proof. Consider the law motion of the exchange rate, Equation 7:

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

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

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

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 ($\beta = 0$).

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:

$$q_{t+j} = \alpha + \beta_j (i_t - i^*_t) + \epsilon_{t+j}. \tag{18}$$

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

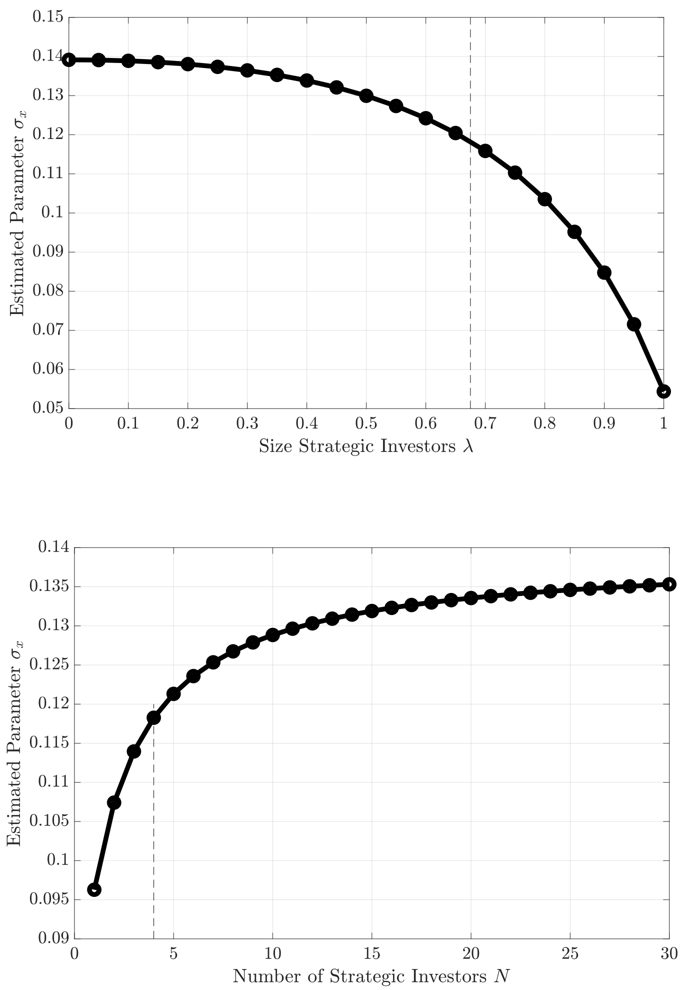
$$G_{k+1} = G_0 + \mu G_k M_k H_{k+1} \qquad \text{and} \qquad H_k \equiv \begin{bmatrix} \mathbf{0}_{(kq) \times q} & I_{kq} \end{bmatrix}$$

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

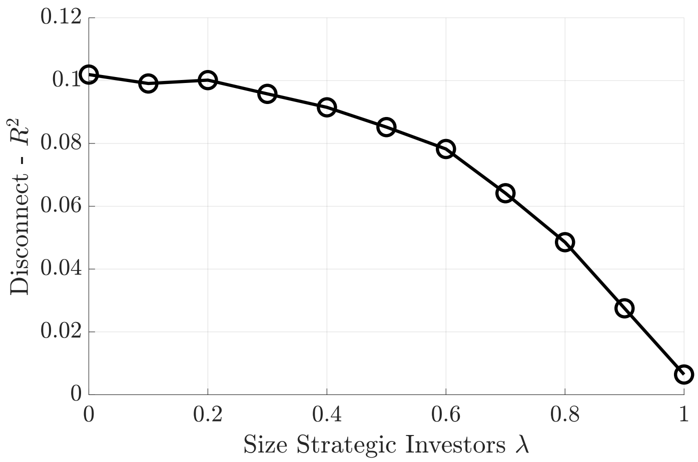
Figure 10: Relationship between Strategic Behavior and Noise Volatility



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 1.

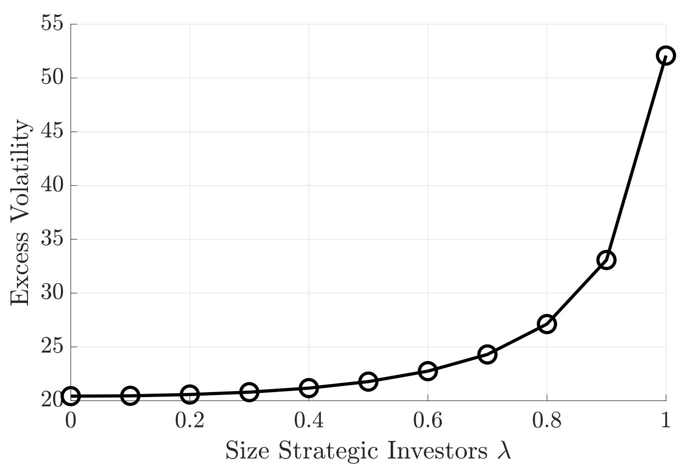
D.2 Strategic Behaviour and Exchange Rate Dynamics

Figure 11: Exchange Rate Disconnect - R^2



Notes: The figure shows the estimated R^2 of the disconnect regression in Equation 9 using simulated data. We run 3000 simulations and, for each iteration, the model runs for 1000 periods with 4000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 1.

Figure 12: Excess Volatility



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 1000 periods with 4000 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, $\frac{\mathrm{Var}(\Delta s)}{\mathrm{Var}(\Delta u_t)}$. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 1.

D.3 Cross-Currency Model Predictions

Table 6: Testing Model Predictions

	(1) Disconnect - RMSE	(2) Excess Volatility
λ	0.021**	83.455**
	(0.009)	(35.352)
Constant	0.012*	-3.117
	(0.006)	(23.425)
Currency & Year FEs	Yes	Yes
Observations	297	275

Notes: The table reports the relationship between λ and the variables of interest. λ epresents the share of transactions intermediated by the top quintile of investors operating in the New York FX market. Variable of interest are: exchange rate excess volatility (Columns (1)); exchange rate disconnect/RMSE (Column (2)). The exchange rate disconnect is measured using the RMSE from the regression in Equation (9), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (10) to the volatility of the interest rate differential. λ is measured in April and October of each year from 2005 to 2019 using New York FX Market Report. To measure excess volatility and disconnect, we use daily exchange rate data within a six-month window surrounding April and October each year. Values of the excess volatility ratio exceeding 200 are excluded. 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, Chilean Peso, Indian Rupee, Mexican Peso, British Pound, South African Rand, Russian Ruble, Swedish Krona, Turkish Lira, New Zeland Dollar, Singapore Dollar, Norwegian Krone. Appendix A provides additional information on the data used.

D.4 Parametrization Quantitative Model

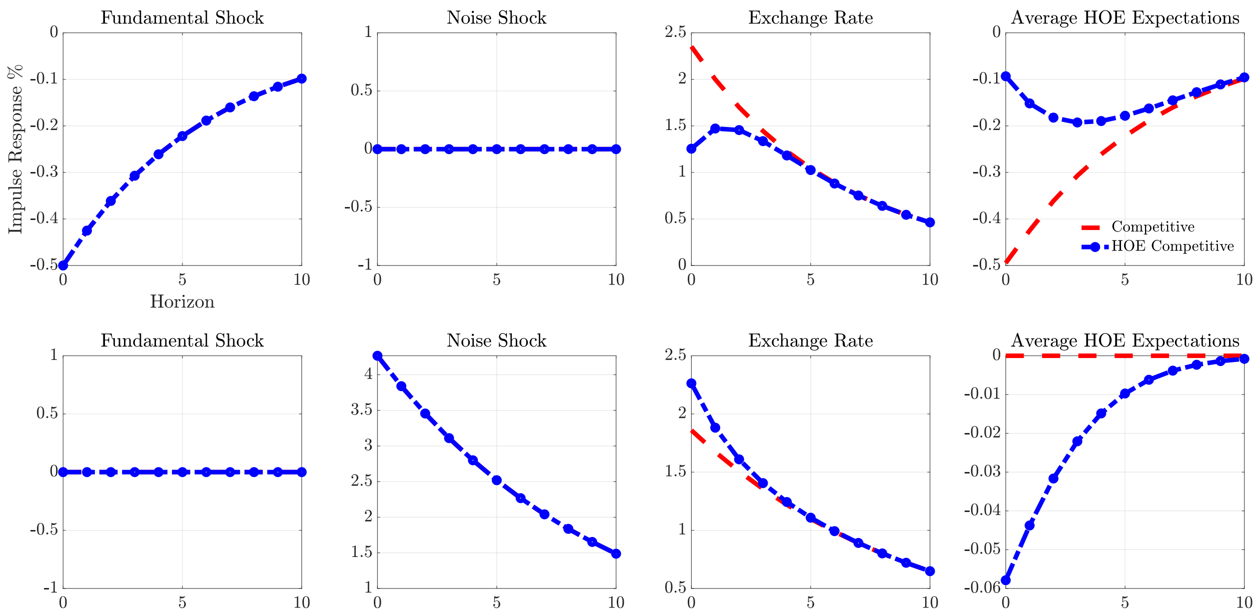
Table 7: Parametrization Quantitative Model

	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 4. 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.

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

Figure 13: 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 (13). 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.

D.6 Quantitative Results - Currency Level

Table 8: Disconnect Decomposition - Currency Level

	RMSE Full Model (Actual Data)	Extra Disconnect (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
Australia	0.03	32.92	57.02	44.76	-1.78
Brazil	0.05	4.96	219.62	-239.59	119.96
Canada	0.02	28.42	59.26	41.56	-0.82
Switzerland	0.03	31.76	59.07	41.70	-0.77
Chile	0.03	34.95	55.95	45.74	-1.68
Euro	0.02	33.03	56.53	45.50	-2.03
UK	0.02	32.48	56.16	46.08	-2.25
Japan	0.02	29.86	58.66	38.91	2.42
Mexico	0.03	45.11	54.32	45.47	0.21
Norway	0.02	27.67	61.82	38.75	-0.57
New Zealand	0.03	34.12	58.68	42.62	-1.31
South Africa	0.04	38.20	59.48	39.13	1.39
Russia	0.06	50.94	59.87	34.95	5.18
India	0.02	35.45	54.44	45.29	0.27
Singapore	0.01	40.91	50.05	49.72	0.23
Sweden	0.02	28.19	61.14	39.17	-0.31
Turkey	0.12	-61.29	51.34	108.39	-59.73

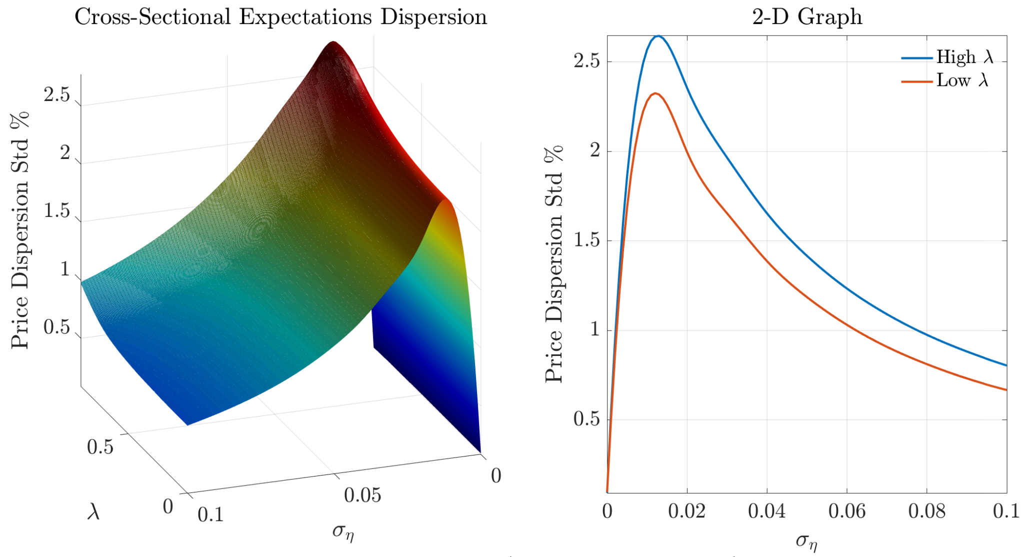
Notes: The table reports the contribution of strategic behavior and dispersed information to the exchange rate disconnect. Exchange rate disconnect is measured using the Root Mean-Square Error of a standard, one-period disconnect regression, Equation (9). The first column reports the estimated disconnect from the full model that includes both dispersed information and strategic behavior. The second column reports the extra disconnect 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 due to dispersed information and strategic behavior, respectively. The former (latter) is computed comparing RMSE in the benchmark economy to the RMSE 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. All values are the averaged across currencies; we exclude the Argentinian Peso. Appendix A provides additional information on the data. Appendix C provides additional information on the estimation and filtering procedure.

Table 9: Volatility Decomposition - Currency Level

	$\mathrm{Var}(s_t)$ Full Model (Actual Data)	Extra Volatility (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
Australia	0.20	22.25	83.38	17.13	-0.50
Brazil	0.35	26.97	82.01	17.03	0.96
Canada	0.14	21.33	83.77	17.05	-0.81
Switzerland	0.21	22.50	83.88	16.58	-0.46
Chile	0.14	23.16	81.74	18.66	-0.40
Euro	0.15	23.13	82.48	18.03	-0.51
UK	0.12	21.23	83.46	17.36	-0.81
Japan	0.13	19.88	84.31	16.40	-0.71
Mexico	0.31	25.01	84.13	15.47	0.40
Norway	0.16	22.45	82.41	18.25	-0.67
New Zealand	0.21	24.00	83.04	17.21	-0.25
South Africa	0.42	24.23	83.13	16.81	0.07
Russia	0.56	32.65	81.80	16.92	1.29
India	0.21	25.67	82.34	17.86	-0.20
Singapore	0.12	21.47	84.32	16.30	-0.62
Sweden	0.14	22.22	82.62	17.95	-0.57
Turkey	1.42	28.49	75.05	-16.59	41.54

Notes: The table reports the contribution of strategic behavior and dispersed information to the exchange rate excess volatility. Excess volatility is measured using the standard deviation of the exchange rate. The first column reports the estimated volatility from the full model that includes both dispersed information and strategic behavior. The second column reports the extra 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 volatility due to dispersed information and strategic behavior, respectively. The former (latter) is computed comparing volatility in the benchmark economy to the 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. All values are the averaged across currencies; we exclude the Argentinian Peso. Appendix A provides additional information on the data. Appendix C provides additional information on the estimation and filtering procedure.

Figure 14: 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 4. 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.