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ABSTRACT

International Equity Flows and Returns: A Quantitative Equilibrium Approach*

This paper reconsiders the role of foreign investors in developed country equity markets. It presents a quantitative model of trading that is built around two new assumptions about investor sophistication: (i) both the foreign and domestic populations contain investors with superior information sets; and (ii) these knowledgeable investors have access to both public equity markets and private investment opportunities. The model delivers a unified explanation for three stylized facts about US investors' international equity trades: (i) trading by US investors occurs in waves of simultaneous buying and selling; (ii) US investors build and unwind foreign equity positions gradually; and (iii) US investors increase their market share in a country when stock prices there have recently been rising. The results suggest that heterogeneity within the foreign investor population is much more important than heterogeneity of investors across countries.

JEL Classification: F30, G12, G14 and G15
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1 Introduction

The role of foreign investors in financial markets is an important unresolved issue in international finance. Existing empirical work has shown that foreigners behave differently than local investors. In particular, foreign investors tend to buy local stocks following high local stock returns. Foreign investors also tend to build positions slowly: their net purchases can be predicted from their own past purchases. Together these facts suggest systematic *cross-country* heterogeneity of investor populations. For example, foreign investors might know less about local stocks than do local investors. However, we document below that the foreign (i.e., U.S.) investor population simultaneously buys and sells large quantities of local equities within a quarter. This suggests a role for *within-country* heterogeneity: some U.S. investors buy, while others sell. This paper builds a quantitative model of asset trading to explain the above stylized facts and assess the link between investor heterogeneity and international equity flows.

We make two new assumptions. First, we allow for within-country differences in investor information sets. This is in contrast to the existing literature which focuses on cross-country heterogeneity: foreign investors are homogeneous and less informed. Our assumption is that while the average local investor may know more about the domestic market than the average foreign investor, *some* foreigners manage to obtain as much local knowledge as the smartest local investors. This assumption is particularly suitable for modern industrial country stock markets where the best foreign and local traders tend to have very similar backgrounds and skills and indeed may use the same asset manager. It is also supported by recent empirical studies on individual trading behavior and performance.

Our second assumption is that knowledgeable investors not only have better information about stocks, but also have a higher ability to locate off-market (private) investment opportunities. We label such investors as 'sophisticated'. In contrast, investors with inferior information and no private investment opportunities are labelled 'unsophisticated'. The assumption of differing investment opportunity sets is in the spirit of Merton's (1987) investor recognition hypothesis: some investors scan the economy more carefully for investment opportunities than do others. Sophisticated investors should thus not only be better at market research, but they should also be more likely to find profitable investment opportunities apart from the local stock market that are not recognized by unsophisticated investors. This second assumption also seems suitable in a world where private equity, real estate, foreign exchange, and derivatives markets are accessible to only a subset of investors.

Under these two assumptions, asking about the role of foreign investors is essentially asking whether the within-country difference or the cross-country difference in investor sophistication is more important. To provide a quantitative answer, we construct an asymmetric information model of the local stock market in a non-U.S. G7 economy. Market participants differ in sophistication, but they do not inherently differ by nationality. However, the populations of local and U.S.-based participants contain different shares of sophisticated and unsophisticated investors. We calibrate the model to quarterly data on dividends, returns, volume, and U.S. investors' aggregate gross and net trades in the G7 countries.

Our main result is that *within-country heterogeneity is much more important than cross-country heterogeneity*. We do find, in line with previous literature, that the *average* U.S.-based participant in a foreign market has less local knowledge than the *average* local participant. However, for all countries, the calibration implies that cross-country differences between average trades are much smaller than within-country differences between trades of sophisticated and unsophisticated investors. Otherwise, the model could not match the fact that the volatility of net cross-country flows is much smaller than average trading volume within a particular country.

Our model accounts for two regularities about U.S. investors' net purchases that are prominent in the empirical literature. One is *flow momentum*, or persistence in net purchases. In all non-U.S. G7 country stock markets, Americans build and unwind foreign positions gradually: a net purchase of foreign equity by U.S. investors in some quarter predicts additional net purchases over at least the following two quarters. In addition, the model generates *return chasing*–the fact that U.S. net purchases, normalized by foreign market capitalization, are positively correlated with both current and lagged local stock returns. U.S. investors thus chase returns: when they see foreign stock prices increase, they buy foreign shares from local investors.

The model not only speaks to the behavior of *net* flows, but also makes predictions for *gross* flows. If there is a lot of within-country heterogeneity and little cross-country heterogeneity, one should expect to observe positive contemporaneous correlation between U.S. investors' gross purchases and gross sales in a foreign market. Indeed, consider a shock that makes sophisticated investors buy shares from unsophisticated investors. Such a shock should generate a wave of *simultaneous* buying and selling by the population of Americans, which contains members of both groups. It should therefore induce positive co-movement of aggregate gross sales and purchases. We document this new stylized fact in the data for all the G7 countries.

To see how our model accounts for the above stylized facts, it is important to first clarify why investors trade. One motive for trade is *risk sharing*. Payoffs from private opportunities available only to sophisticated investors tend to be high in business cycle booms, when stock prices also rise. Sophisticated investors thus perceive stocks and private opportunities as substitutes: sophisticated investors who find good opportunities will try to sell stocks to share business cycle risk with unsophisticated investors. The second motive for trade is *disagreement* about expected stock returns. It occurs in equilibrium because stock prices do not reveal all of the sophisticated investors' information. While private opportunities are procyclical and thus provide information about the stock market, they may also be driven by factors orthogonal to the stock market. When unsophisticated investors see stock prices move, they cannot discern which type of information is inducing sophisticated investors to trade.

Now consider the beginning of a typical boom. As good news about the business cycle arrives, all investors update their assessment of future cash flows and stock prices begin to rise. At the same time, sophisticated investors increasingly locate profitable off-market opportunities. They begin to sell local stocks to exploit these private opportunities without unduly increasing their exposure to business cycle risk. This generates both volume and–when investor populations differ across countries–a wave of gross international equity flows. Moreover, since the average U.S. investor is less sophisticated than the average local investor, the U.S. population is buying foreign stocks as prices are rising.

The above risk-sharing trades are slowed down by disagreement: unsophisticated investors who have less information about the state of the business cycle are initially less optimistic and will only buy stocks at a discount. However, a string of favorable returns can help convince them that a boom is under way. This leads to more net purchases by unsophisticated investors and hence more net purchases by Americans. In contrast, sophisticated investors sell more and more stocks as the peak of the boom is approached. Only as the economy weakens and profitable private opportunities dry up do sophisticated investors return to the market. Again, the transition is slow as unsophisticated investors, who were overly optimistic at the peak, gradually revise their opinion.

The calibrated models do a good job of matching the autocorrelation functions of U.S. investors' net purchases in the different countries. Indeed, the models predict not only flow momentum (positive autocorrelation at short horizons of 1-3 quarters), but also *flow reversal*, that is, negative autocorrelation at longer horizons (5-7 quarters). This prediction derives from business cycle swings in trading – momentum and reversal are also features of the persistent component of dividends. In the data, there is strong evidence for flow reversal in Canada, France and Germany, and somewhat weaker evidence for Japan and Italy. By and large, the model does a decent job on the cross-correlogram of flows and returns.

Return chasing is often cited as an example of irrational behavior by foreign investors. However, Bohn and Tesar (1996) construct estimates of expected local returns based on public information. They show that U.S. investors tend to buy precisely when expected returns are high, suggesting rational "market timing" on the part of Americans. This finding begs the question of why foreigners behave the opposite way. In our model, the reason is that the average foreigner has more access to local private opportunities and information. We replicate the Bohn-Tesar exercise in our model economies, and obtain positive correlation between expected returns conditional on public information and net purchases by U.S. investors, in line with the data.

The paper is organized as follows. Section 2 discusses the related literature. Section 3 presents the model of equity trading. Section 4 discusses the properties of equilibrium stock flows and returns. Section 5 describes the data we use, and documents the stylized facts. Section 6 presents the calibration and shows how we infer the nature of heterogeneity. In Section 7, we show how the model accounts for the stylized facts and provide interpretation by comparing the role of different structural shocks. Section 8 concludes.

2 Related Literature

Empirical Work

We document a strong positive contemporaneous correlation of gross purchases and sales of U.S. investors. This new stylized fact is important, because it rules out a large class of models in international economics and finance in which representative agents live in different countries and trade country-stock indices with each other (or accumulate aggregate capital stocks).[1] The prevalence of waves of gross trading activity suggests that this highly aggregated view is not an appropriate way to think about capital flows. In our model, gross trading activity is instead explained by the heterogeneity of investor populations.

[1] The only way for such models to be consistent with the flow data would be a strong time aggregation effect. However, Albuquerque et al. (2003) document that positive correlation between gross purchases and sales also exists at the monthly frequency. In parallel work, Dvorak (2003) finds a positive correlation between gross purchases and sales of U.S. investors and links it to the role of within-country heterogeneity.

Two other stylized facts we emphasize–flow momentum and return chasing–are well known. Bohn and Tesar (1996) have documented persistence in aggregate data. Froot and Donohue (2002) have recently examined persistence in international trades by individual mutual funds. Bohn and Tesar (1996) also highlighted the return chasing phenomenon: positive contemporaneous correlation of flows and returns at the quarterly frequency. Later work by Choe et al. (1999) showed a strong correlation of flows with lagged returns, and Froot et al. (2001) showed that the contemporaneous correlation of flows and returns over longer periods is due in part to positive correlation of flows with lagged returns at higher frequencies. Our model captures both features: there is contemporaneous correlation between flows and returns, *and* returns predict flows. This suggests that the effects we identify could also be of interest for models calibrated to higher frequency data.

Evidence on investor heterogeneity is available in the literature on individual investor performance. There now exists a large number of studies that use data on individual trades to ask whether local investors outperform foreigners or vice versa. This literature has not been conclusive, with strong results in both directions, depending on the time period and the data set used.[2] This is what one would expect if there is indeed within-country investor heterogeneity. In addition, some studies have provided direct evidence on heterogeneity. In Finnish data, Grinblatt and Keloharju (2000) find differences in trading behavior and performance between domestic household investors and domestic institutions. Choe, Kho, and Stulz (2001) analyze the trading behavior of foreign investors (U.S. and others) and domestic institutions and individuals around days of significant abnormal returns and days of large buying or selling activity in Korea. They find that foreign investors trade at worse prices relative to domestic individuals, but not relative to domestic institutions.

Theoretical Work

The structure of our model is similar to that in Wang's (1994) seminal paper on trading volume. In both models, there is a group of agents who obtain private information and invest in a private asset. They perceive the private asset as a substitute to stocks, which leads to trading as well as disagreement in equilibrium. However, Wang's setup is geared to study trading volume – an absolute value – whereas we want to match data on signed trades – positive or negative flows – between identified investor groups. Wang's model generates negative serial correlation in signed trades and therefore cannot generate persistence or return chasing in flows. Moreover, Wang assumes that the persistent

[2] For a discussion of this literature see Stulz (2001) or Albuquerque et al. (2003).

component of dividends is: (i) an AR(1) process; (ii) directly observed by sophisticated investors; and (iii) orthogonal to private asset returns. These assumptions make his setup unsuitable for capturing equity flows driven by the business cycle.

We make different assumptions about the distribution of fundamentals and the information structure, motivated by the data we want to explain. First, we estimate a dividend process and show that the persistent component is not AR(1), but exhibits momentum and reversal. Second, there is no a priori reason to believe that investors can observe the persistent component. Instead, we assume that sophisticated investors observe public and private returns. The information revealed by these variables in equilibrium is inferred from the data through the calibration procedure. Third, to capture the possibility that S-investors have access to better private opportunities in booms, we allow expected private returns to be correlated with the business cycle. The strength and sign of the association is again inferred by calibration.

In terms of results, the momentum in dividends is critical in order to generate observed persistence of equity flows. In contrast, AR(1) fundamentals lead to AR(1) dynamics in equity holdings and therefore negative serial correlation in equity flows. In addition, imperfect information about the state of the business cycle and procyclical private opportunities are critical in our model to generate asset substitutability, and hence return chasing. Substitutability can also arise – as in Wang's model – if transitory shocks to private returns and dividends are positively correlated. To compare these sets of assumptions, we also calibrate a version of our model that allows for momentum and reversal in fundamentals, but otherwise adopts the information and correlation structure of Wang's setup. We show that this model cannot generate return chasing, and can produce persistence only if dividend and private return shocks are nearly perfectly correlated.

There are many models of foreign equity holdings, often motivated by data on equity home bias. However, the theoretical literature on *flows* is relatively recent. To our knowledge, there is no prior theoretical work on gross flows and their connection to volume and net flows. Brennan and Cao (1997) started the literature on *net flows*.[3] In their model, foreign investors are less informed than domestic investors. This implies that foreign investors react more to public information. If private information accumulates slowly, their model predicts positive contemporaneous correlation of foreigners' net purchases and returns. They do not calibrate their model and do not explain the other stylized facts we are interested in.

[3] See also Coval (1999), Hau and Rey (2002) and Griffin et al. (2004). These papers are not interested in the stylized facts we study, with the exception of the conteporaneous flow-return correlation.

As in Brennan and Cao, the average foreign investor in our model has less information than the average local investor. Moreover, a version of their overreaction effect is also present in our model: unsophisticated investors mistake a temporary shock to dividends (a public signal) for a persistent shock and become net buyers. However, overreaction plays a minor role in accounting for return chasing. Indeed, variance decompositions show that 96% of the contemporaneous covariance is contributed by business cycle shocks. These shocks affect trade primarily because sophisticated investors shift risk; unsophisticated investors actually underreact to them. The reason why our calibration procedure finds only a small role for overreaction is that trades due to temporary shocks are quickly reversed and contribute negatively to the autocovariance. Since flows are persistent, the contribution of these shocks must therefore be small.

3 The Model

Our model describes the stock market of a small, open economy. There are two types of investor – sophisticated (S) and unsophisticated (U). Investors also differ by nationality: there are U.S.-based investors and local investors. We assume that nationality does not lead to different behavior at the individual level: U.S. investors of type S (U) are identical to local investors of type S (U). However, the aggregate trades of U.S. investors will have distinctive properties if the composition of the U.S. investor population differs from that of the local population. Analysis of the model naturally proceeds in two steps. First, we describe the setup as one of trade between S and U-investors. Second, we introduce nationality and derive model statistics that involve U.S. investors' trades.

3.1 Setup

Preferences

There is a continuum of infinitely-lived investors. A fraction ν_U of investors is unsophisticated (indexed by U), while a fraction $1 - \nu_U$ is sophisticated (indexed by S). Investors have identical expected utility preferences that exhibit constant absolute risk aversion (CARA). At time t, an investor of type $i = U, S$ ranks contingent consumption plans $\{c_l^i\}_{l=t}^{\infty}$ according to

$$-E\left[\sum_{l=t}^{\infty} \beta^{(l-t)} \exp^{-\gamma c_l^i} |\mathcal{I}_t^i\right], \tag{1}$$

where $\beta < 1$ is the discount factor, $\gamma > 0$ is the coefficient of absolute risk aversion, and $\mathcal{I}_t^i$ is the information set at time t, to be specified below.

Investment Opportunities

Two assets are available to all investors. A risk-free bond pays a constant gross rate of return of $R_f = 1/\beta$. Moreover, all investors participate in the domestic stock market. The single asset traded in this market is a claim to the dividend stream $\{D_t\}$. At date t, shares trade at a per-share ex-dividend price of P_t, and hence deliver a per-share excess return of $R_t^D = P_t + D_t - R_f P_{t-1}$. A single share is traded every period. A third asset is accessible to S-investors alone; we refer to it as a private, or off-market, investment opportunity and denote its simple excess return by R_t^B.

Dividends and asset returns are subject to both persistent and transitory shocks. Let F_t^D denote the persistent component of dividends, which we also refer to as the *state of the business cycle*. Returns on off-market opportunities are predictable, and their conditional expected return is correlated with the business cycle. Other fluctuations in the expected return R_t^B are summarized by a state variable F_t^B, that is independent of F_t^D and labeled the *off-market factor*. Both F_t^D and F_t^B may depend on two lags of themselves. Letting $\mathbf{F}_t = \left(F_t^D, F_{t-1}^D, F_t^B, F_{t-1}^B\right)'$, the distribution of dividends and returns is:

$$
\begin{aligned}
D_t &= \bar{D} + F_t^D + \varepsilon_t^D & (2)\\
R_t^B &= \bar{R}^B + \eta_D F_{t-1}^D + \eta_B F_{t-1}^B + \varepsilon_t^B & (3)\\
\mathbf{F}_t &= \boldsymbol{\rho} \mathbf{F}_{t-1} + \boldsymbol{\varepsilon}_t^F. & (4)
\end{aligned}
$$

Bold-faced letters denote vectors and matrices, and variables with bars denote unconditional means. All shocks are components of the vector process $\boldsymbol{\varepsilon}_t := \left(\boldsymbol{\varepsilon}_t^{F\prime}, \varepsilon_t^D, \varepsilon_t^B\right)'$ that is serially uncorrelated and normally distributed with mean zero and diagonal covariance matrix $\mathbf{\Sigma}_{\varepsilon\varepsilon}$. The matrix $\boldsymbol{\rho}$ is block diagonal.

Information

At date t, all investors know past and present stock prices and dividends, as well as returns on the world asset. U-investors have no additional information, that is, $\mathcal{I}_t^U = \{P_{t-l}, D_{t-l}\}_{l=0}^{\infty}$. S-investors not only know $\mathcal{I}_t^U$, but they also observe the off-market factor F_t^B, as well as past and present returns on their private opportunities. All S-investors observe the same signals and thus share the information set $\mathcal{I}_t^S = \left\{P_{t-l}, D_{t-l}, R_{t-l}^B, F_{t-l}^B\right\}_{l=0}^{\infty}$.

Portfolio Choice

The budget constraint of investor i at date t is

$$w_{t+1}^i = R_f \left(w_t^i - c_t^i\right) + \boldsymbol{\psi}_t^{i\prime} \mathbf{R}_{t+1}^i, \tag{5}$$

where w_t^i is beginning-of-period wealth and the vectors $\boldsymbol{\psi}_t^i$ and $\mathbf{R}_t^i$ denote holdings and returns on assets that are available to investor i, respectively. In particular, for S-investors $\boldsymbol{\psi}_t^S = \left(\theta_t^S, \psi_t^{BS}\right)'$ and $\mathbf{R}_t^S = \left(R_t^D, R_t^B\right)'$, and for U-investors $\psi_t^U = \theta_t^U$ and $\mathbf{R}_t^U = R_t^D$. Here, θ_t^S and θ_t^U denote the number of local stocks held by S- and U-investors, respectively. Investor i chooses contingent plans for consumption $\{c_l^i\}_{l=t}^{\infty}$ and asset holdings $\{\boldsymbol{\psi}_l^i\}_{l=t}^{\infty}$ to maximize expected utility (1), conditional on the information set $\mathcal{I}_t^i$ and the budget constraint (5).

Equilibrium

A rational expectations equilibrium is a collection of stochastic processes $\{c_t^U, c_t^S, \boldsymbol{\psi}_t^U, \boldsymbol{\psi}_t^S, P_t\}$ for consumption, asset holdings and the domestic stock price such that: (i) both types of agents optimally choose consumption and portfolio plans given prices; and (ii) the domestic stock market clears:

$$\nu_U \theta_t^U + (1 - \nu_U)\,\theta_t^S = 1. \tag{6}$$

International Equity Flows

The U.S. and local populations both contain sophisticated and unsophisticated types. Let ν^* denote the fraction of U.S. investors in the total population and let ν_U^* denote the fraction of unsophisticated U.S. investors relative to all U.S. investors. Aggregate U.S. holdings of the local asset are given by

$$\theta_t^* = \nu^* \left[\nu_U^* \theta_t^U + (1 - \nu_U^*)\,\theta_t^S\right].$$

Since trade is due only to the heterogeneity between S- and U-investors, the market clearing condition (6) implies that we can write all relevant aggregate statistics in terms of the holdings or trades of just one investor type. We choose to express everything in terms of U-investors' holdings. In particular, U.S. holdings of local equities can be written as

$$\theta_t^* = \nu^* \left[\frac{1 - \nu_U^*}{1 - \nu_U} + \frac{\nu_U^* - \nu_U}{1 - \nu_U}\theta_t^U\right]. \tag{7}$$

This tight connection between U.S. and unsophisticated trades will be used extensively in our analysis below.

3.2 Stationary Equilibria

To compare model predictions to data, we focus on *stationary equilibria*, that is, stationary processes for consumption, portfolios and the stock price that satisfy the equilibrium conditions. A stationary equilibrium yields theoretical moments for trades and returns that are matched to the corresponding empirical moments. As in Wang (1994), the assumptions of normal shocks, exponential utility and hierarchical information sets imply that stationary equilibria can be represented using a low-dimensional state vector that contains only agents' conditional expectations. In particular, we focus on equilibria in which the stock price is a linear function of these expectations.

Let $\hat{\mathbf{F}}_t^i = E[\mathbf{F}_t|\mathcal{I}_t^i]$ denote investor i's conditional expectation of the vector $\mathbf{F}_t$ that drives persistent movements in fundamentals. Since $\mathcal{I}_t^U \subset \mathcal{I}_t^S$, the law of iterated expectations implies $\hat{\mathbf{F}}_t^U = E\left[\hat{\mathbf{F}}_t^S|\mathcal{I}_t^U\right]$. In other words, $\hat{\mathbf{F}}_t^U$ not only represents U-investors' expectation of $\mathbf{F}_t$ itself, but also their expectation of what S-investors expect $\mathbf{F}_t$ to be.

Theorem 1 *There exists a rational expectations equilibrium such that prices and stock holdings are stationary and take the form*

$$P_t = \bar{\pi} + \boldsymbol{\pi}'_S \hat{\mathbf{F}}_t^S + \boldsymbol{\pi}'_U \hat{\mathbf{F}}_t^U, \tag{8}$$

$$\theta_t^i = \bar{\theta}^i + \boldsymbol{\Theta}^i \hat{\mathbf{F}}_t^U \qquad ; i = S, U. \tag{9}$$

Investor i's decision problem at time t depends only on wealth w_t^i and his payoff-relevant information ϕ_t^i, where $\boldsymbol{\phi}_t^S = \left(\hat{\mathbf{F}}_t^{S\prime}, \hat{\mathbf{F}}_t^{U\prime}\right)'$ and $\boldsymbol{\phi}_t^U = \hat{\mathbf{F}}_t^U$. Continuation utility can be written as

$$V\left(w_t^i; \boldsymbol{\phi}_t^i\right) = -\exp\left[-\kappa^i - (1-\beta)\gamma w_t^i - \mathbf{u}_i' \boldsymbol{\phi}_t^i - \frac{1}{2} \boldsymbol{\phi}_t^{i\prime} \mathbf{U}_i \boldsymbol{\phi}_t^i\right]. \tag{10}$$

The proof of Theorem 1 is contained in appendix A.

The stationary equilibria have two important properties. First, equilibrium prices reveal neither the persistent components of dividends nor the expected return on private opportunities, but only investors' perceptions of these variables. This is because no investor has full information about the state of the business cycle F_t^D. Second, equilibrium holdings – and hence also trades – of both S and U-investors depend only on U-investors' estimates of the persistent factors $\hat{\mathbf{F}}_t^U$. Indeed, if the local asset demand of S-investors were to depend also on $\hat{\mathbf{F}}_t^S$, then U-investors could learn more about $\hat{\mathbf{F}}_t^S$ by comparing $\hat{\mathbf{F}}_t^U$ and their own demand, which would lead them to adjust $\hat{\mathbf{F}}_t^U$. Equilibrium expectations must therefore be such that holdings reflect only $\hat{\mathbf{F}}_t^U$. It follows that trading volume – captured by $|\theta_t^U - \theta_{t-1}^U|$ for example – does not provide information beyond what is already in $\mathcal{I}_t^S$ and $\mathcal{I}_t^U$. This distinguishes the present model from many noise trader models, where agents must be forced by assumption not to condition on trading volume.

3.3 Discussion of Assumptions

Information and Nationality

Our setup rules out any inherent advantage due to nationality *at the individual level:* the sophisticated U.S. investors know as much about the local economy as the sophisticated local investors. This assumption accommodates the fact that both U.S. and local investors can hire the best local portfolio managers and is especially suited in developed country markets where investors share similar backgrounds. Moreover, it makes the model parsimonious and easier to solve.

Small Open Economy

In our model the expected return on the domestic stock market is endogenous, while the riskless rate and the return on the off-market asset are taken as exogenous. In other words, we do not assume that there is one (exogenous) pricing kernel that can be used to price all assets. The simplest way to interpret our setup is that there is market segmentation. The domestic market is used by domestic investors as well as by a subset of U.S. investors who are themselves small relative to the U.S. market. The riskless rate is determined by the majority of investors in the rest of the world (including the U.S.) who do not participate in the country under consideration. Evidence in support of this assumption is provided by Albuquerque, Bris, and Schneider (2005) who document limited participation of U.S. investors in foreign markets.[4]

Private Investment Opportunities

We have referred to the fourth asset broadly as "private investment opportunities". These opportunities: (*i*) become available to a subset of market participants that is also well-informed about the market itself; and (*ii*) are too costly to observe and access by all other market participants. Examples of such opportunities are private equity, real estate, foreign exchange or derivatives markets. Importantly, our story does not require that the type of opportunity always be the same. All that matters is that, from time to time, the well-informed part of the population discover some new way to invest that is not known to everybody.

Lack of knowledge by U-investors can simply mean that the private opportunity is secret. More generally, one can think of U-investors as people who only concentrate on a

[4] We thus assume that equity home bias exists, and that it exists because of limited American participation in foreign markets. Our goal is not to explain the world distribution of asset holdings, or even the Americans' aggregate portfolio, but only trades made in the stock market under consideration, *conditional* on home bias.

subset of the available public information. Even though in principle there may be data on the latest investment opportunity that S-investors exploit, U-investors, who are not sure where to look, prefer to focus just on stock market information which they know how to process. In our model, they process this information optimally: they know the stochastic processes for prices and update their beliefs by Bayes' rule. The ability of S-investors to recognize investment opportunities that are not readily (or costlessly) available to U-investors is also present in Merton (1987) and Shapiro (2002).

Exchange Rates

Our focus on portfolio *equity* flows leads us to stress factors that are important for portfolio decisions of equity market participants, in particular time variation in expected excess returns on stocks and private investment opportunities. We abstract from other factors that are sometimes present in models of the current account. For example, a more general model might incorporate changes in the real exchange rate, so that foreign and domestic bonds are imperfect substitutes. Such a model would be of interest to study *bond* flows or total portfolio flows, but is left for future research.

While our results show that the factors we consider are sufficient to explain the moments of the joint distribution of equity flows and stock returns, we expect the behavior of equity flows in our model to carry over to more general setups. In Albuquerque et al. (2003), we find that U.S. investors' foreign portfolio equity flows are well explained by past flows and global variables, such as a world return, while real exchange rates do not add much explanatory power.[5] This suggests that, even if real exchange rate movements affect the conditional distribution of returns on all assets available to investors (including bonds), they are not important for portfolio decisions on equity. A potential reason is that excess returns are – to first order – the same whatever the currency they are measured in; changes in the unit of account affect both risky assets and the riskless rate and hence cancel out of the definition of an excess return.[6] The relative variability of expectations in these excess returns – the driver of equity flows in our model – is thus independent of

[5] Similarly, Portes and Rey (2001) find that the main determinant of the pattern of international equity flows is the geography of information proxied by variables that represent information transmission and information asymmetries between domestic and foreign investors.

[6] The argument is exact with instantaneous returns. Let S_t be the nominal exchange rate expressed as foreign/local currency units and B_t the bond price in local currency units, $dB_t/B_t = rdt$. The excess stock return in foreign currency units is

$$\frac{dP_tS_t}{P_tS_t} - \frac{dB_tS_t}{B_tS_t} = \frac{dP_t}{P_t} + \frac{dS_t}{S_t} - \left(rdt + \frac{dS_t}{S_t}\right) = \frac{dP_t}{P_t} - rdt.$$

the exchange rate.

Foreign Equity

We focus on only two risky assets, domestic stocks and domestic private opportunities. Trade derives from substitution between these assets over the course of the domestic business cycle. We thus isolate one mechanism that generates trade and show that it is qualitatively suitable and quantitatively important enough to generate observed patterns of equity flows. Of course, in reality investor wealth contains other assets, in particular foreign equity. It is thus useful to consider why the mechanism we emphasize is likely to be relevant also in a richer model.

Any model that successfully integrates a world (or U.S.) stock market as an additional asset will have to capture two pieces of evidence. The first is positive contemporaneous cross-country correlation of returns found by, among others, Dumas et al. (2002). The other is the weak relationship between U.S. returns and U.S. investors' net purchases in other countries, documented by Bohn and Tesar (1996). A successful model thus needs to incorporate a reason why shocks that affect both U.S. expected returns and domestic stock market prices are not accompanied by large trades.

The simplest model that generates this pattern has only one investor type so that no trading ever takes place. Instead, prices adjust to induce the homogeneous population to always hold the market. In a model with more than one investor type, one would expect similar effects provided that investors' access to the U.S. market is symmetric. To be more concrete, imagine a model with a world asset that both investor types can invest in without affecting its return, in line with our small, open economy assumption. Domestic dividends and opportunities can be hit by local shocks as well as by global shocks that also affect the expected world return.

Consider now a global shock that increases expected returns on U.S. stocks and domestic private opportunities as well as domestic expected dividends. With positive correlation between all returns, this shock would lead S-investors – who want to shift to private opportunities – to sell domestic stocks. The intuition is the same as in the present model, where a business cycle shock hits both payoffs on stocks and private opportunities. The new twist would be that both investor types would also try to sell more domestic stocks in order to shift to U.S. stocks. Since both investor types try to sell, the new effect would generated little additional trade between them. However, a larger correction in the price would be required to induce both to keep holding domestic stocks. With respect to global shocks, the economy would thus behave much like an economy with one investor type generating correlation of returns, but little trade. As a result, most trades would still be driven by local shocks as in the present model: an increase in local expected payoffs would lead S-investors to sell local stocks to shed tradable risk.

4 Equilibrium Flows and Returns

In this section, we characterize analytically S- and U- investors' motives for trade (Section 4.1) and link them to U.S. investors' aggregate equity flows (Section 4.2).

4.1 Motives for Trade

We need the following notation. Let $X_{t+1} = P_{t+1} + D_{t+1}$ denote the *payoff* on stocks, and define the conditional moments $\sigma_U^2 = var_t^U(X_{t+1})$, $\sigma_S^2 = var_t^S(X_{t+1})$, $\sigma_B^2 = var_t^S\left(R_{t+1}^B\right)$ and $\rho_S = corr_t^S\left(X_{t+1}, R_{t+1}^B\right)$.[7]

Individual Portfolio Choice and Asset Substitutability

As is common in portfolio choice problems, the optimal demand for stocks by U- and S-investors can be decomposed into myopic and hedging demands:

$$\theta_t^U = \frac{1}{\gamma\sigma_U^2}\left(\underbrace{E_t^U X_{t+1} - R_f P_t}_{\text{myopic demand}} + \underbrace{\bar{h}^U + \mathbf{H}^U \boldsymbol{\phi}_t^U}_{\text{hedging demand}}\right), \tag{11}$$

$$\theta_t^S = \frac{1}{\gamma\sigma_S^2\left(1-\rho_S^2\right)}\left(\underbrace{E_t^S X_{t+1} - R_f P_t - \rho_S\frac{\sigma_S}{\sigma_B}E_t^S R_{t+1}^B}_{\text{myopic demand}} + \underbrace{\bar{h}^S + \mathbf{H}^S \boldsymbol{\phi}_t^S}_{\text{hedging demand}}\right). \tag{12}$$

Investors' myopic demands depend on the distribution of returns *over the next period only*. For both types of investors, the myopic demand is higher when the expected excess return on stocks over bonds $E_t^i X_{t+1} - R_f P_t$ is high and when (subjective) risk σ_i^2 is low. Investors' intertemporal hedging demands depend on the conditional distribution of returns *beyond the next period*.[8] When investment opportunities are random, investors

[7] To simplify the formulas, these moments are computed under conditional distributions that are adjusted to capture agents' taste towards the variance in the state variables ϕ_t^i. This is spelled out in detail in the appendix.

[8] The hedging demand is zero for myopic investors who consume all wealth in the next period and do not reinvest. It is also zero in an equilibrium with i.i.d. returns, where investment opportunities are constant. In our model, changes in the conditional distribution of returns are captured by movements in the state variables $\boldsymbol{\phi}_t^i$. It can be verified from the shape of continuation utility that investor i behaves *as if* he was holding a portfolio of nontradable assets with return vector $\boldsymbol{\phi}_{t+1}^i$, where the vector of shares held in each "state variable asset" varies over time and is given by $\mathbf{u}_i + \mathbf{U}_i' E^i\left[\boldsymbol{\phi}_{t+1}^i | \boldsymbol{\phi}_t^i\right]$.

fear states that offer poor opportunities – for example, states where expected returns are low – and this concern affects portfolio choice today. In particular, it leads investors to favor assets that pay off primarily in states with poor opportunities and thus provide a hedge against such states.

For S-investors, the decomposition highlights two distinct reasons why stocks and off-market opportunities can be perceived as substitutes. The first is a positive correlation between *realized* stock and off-market returns ($\rho_S > 0$). This effect is apparent from the myopic demand in (12). Intuitively, a positive correlation of returns implies that holding stocks is only attractive to the extent that they pay an expected excess return larger than the off-market expected excess return $E_t^S R_{t+1}^B$.

A second, and more subtle, reason for substitutability is a positive correlation between *realized* stock returns R_{t+1}^D and *expected* off-market returns $E_{t+1}^S R_{t+2}^B$, coupled with persistence in $E_t^S R_{t+1}^B$. The key effect here is that the hedging motive makes investors reluctant to hold assets that pay off more when opportunities are good. In particular, if realized stock returns are higher in booms when $E_{t+1}^S R_{t+2}^B$ is also high, it makes sense for investors to hold less stocks than they would if they were myopic. With persistent off-market opportunities, this negative hedging demand becomes stronger whenever the *current* expected off-market return is high, making investors substitute out of stocks into private opportunities.

Indeed, persistence in off-market opportunities means that a high *current* expected return $E_t^S R_{t+1}^B$ implies that $E_{t+1}^S R_{t+2}^B$ is anticipated to be higher than the (unconditional) average off-market return. But higher $E_{t+1}^S R_{t+2}^B$ implies that more funds will be invested off-market in $t+1$, so that any shock to $E_{t+1}^S R_{t+2}^B$ will affect investor well-being more. Anticipation of a high average expected off-market return thus induces a greater need to hedge such shocks. The upshot is that an increase in the expected off-market return today lowers the demand for stocks, even if the contemporaneous correlation is $\rho_S = 0$.

Stock Prices, Predictability and the Information Revealed by Prices

To illustrate the impact of investor heterogeneity on the stock price, it is helpful to write the latter as a weighted average of individual investors' *valuations* P_t^U and P_t^S – hypothetical prices that would arise if stocks were held exclusively by U- or S-investors, respectively. Both valuations equal the subjective expected present discounted value of the payoff X_{t+1} minus a risk premium:[9]

$$\begin{aligned} P_t &= \tilde{\nu}_U P_t^U + (1-\tilde{\nu}_U) P_t^S, \\ P_t^U &= \beta E_t^U X_{t+1} - \beta \left[\gamma \sigma_U^2 - \left(\bar{h}^U + \mathbf{H}^U \boldsymbol{\phi}_t^U \right) \right], \\ P_t^S &= \beta E_t^S X_{t+1} - \beta \left[\gamma \sigma_S^2 \left(1 - \rho_S^2 \right) - \left(\bar{h}^S + \mathbf{H}^S \boldsymbol{\phi}_t^S \right) \right] - \beta \rho_S \frac{\sigma_S}{\sigma_B} E_t^S R_{t+1}^B. \end{aligned} \tag{13}$$

The valuation P_t^U moves when there is news about the payoff – a change in $E_t^U X_{t+1}$ – or when the risk premium changes with U-investors' hedging demand. The risk premium contained in S-investors' valuation P_t^S depends also on S investors' expected off-market return.

When stocks and off-market opportunities are substitutes, both the myopic and the hedging effects sketched above will be active: a drop in the expected off-market return increases S-investors demand for stocks and hence the stock price. There are two important implications. First, stock returns become predictable for S-investors; predictability of off-market returns "spills over" to the local stock market. Second, prices cannot fully reveal S-investors' information: given a price increase, U-investors cannot discern whether it is due to good news about payoff or whether it is triggered by bad off-market opportunities alone.[10]

Equilibrium Trades

Combining the portfolio choice and price equations, we obtain that trade occurs if individual valuations change in different ways. This can happen for two distinct reasons, disagreement and risk sharing:

$$\begin{aligned} \Delta\theta_t^U &= \frac{1-\tilde{\nu}}{\beta\gamma\sigma_U^2} \left(\Delta P_t^U - \Delta P_t^S \right) \\ &\propto \underbrace{\Delta E_t^U X_{t+1} - \Delta E_t^S X_{t+1}}_{\text{Disagreement}} + \underbrace{\rho_S \frac{\sigma_S}{\sigma_B} \Delta E_t^S R_{t+1}^B + \mathbf{H}^U \Delta \boldsymbol{\phi}_t^U - \mathbf{H}^S \Delta \boldsymbol{\phi}_t^S}_{\text{Risk Sharing}}. \end{aligned} \tag{14}$$

Naturally, U-investors buy stocks from S-investors if they are more optimistic about payoffs. But even if both investors agree on the distribution of payoffs, there may be

[9] The weight $\tilde{\nu}_U = \left(1 + \frac{1-\nu_U}{\nu_U} \frac{\sigma_U^2}{\sigma_S^2 \left(1-\rho_S^2\right)} \right)^{-1}$ measures U-investors' ability to "move the market". It is higher the larger the share of U-investors in the population and the lower their subjective risk σ_U^2 relative to that perceived by S-investors – which translates into a higher market share.

[10] More formally, substitutability of stocks and private opportunities implies that the price must depend on any variable that affects S investors' expected off-market return. It thus depends on both state variables $\hat{F}_t^{D,S}$ and $\hat{F}_t^{B,S}$, so that the price cannot be inverted to recover both of these variables.

gains from trade if the need for risk sharing has changed. In particular, when S-investors perceive stocks and off-market opportunities as substitutes, they will sell stocks in equilibrium when the expected off-market return increases. Again, both the myopic and the hedging demand effects contribute to trading in the same direction.

Comparing (13) and (14), we can assess price and quantity responses to shocks. It is helpful to distinguish the *payoff effect* – the change in prices and quantities that occurs because the shock moves the expected payoffs $E_t^U X_{t+1}$ and $E_t^S X_{t+1}$ from its *opportunity cost effect* – changes that occur because the shock moves S-investors' expected off-market return. As a general rule, payoff effects tend to move prices more than quantities, while opportunity costs move quantities more than prices.

Indeed, the payoff effect typically moves *both* investors' valuations in the same direction, which produces a price response, but not necessarily a trade. This is because the price depends on the average of the individual valuations, while a trade requires differences in those valuations. Consider the polar case of a shock that increases expected payoffs, but does not change off-market returns at all. Since both investors care about future payoffs, there is relatively little incentive for trade, but the stock price must still rise to prevent excess demand for stocks.

In contrast, the opportunity cost effect changes the valuation of S-investors alone, which generates a trade, but only a muted price response. The polar case here is a shock to off-market expected returns that is orthogonal to stock payoffs. The quantity response to such a shock is relatively large since the whole change in S-investors' valuation amounts to a difference in valuations across investors. At the same time, the price response is relatively small because the average valuation moves less than S-investors' valuations. Intuitively, as long as a shock only affects S-investors' opportunity cost of investing in stocks, U-investors are happy to absorb stocks even in the absence of a large price change.

4.2 International Equity Flows

U.S. investors' holdings are connected to U-investors' holdings by (7). As a measure of the relative importance of cross-country vs. within-country heterogeneity, we use a regression coefficient of nationality on type. Consider an investor chosen at random from the population. To find how well type predicts nationality, define

$$\begin{aligned}\delta &= \Pr(\text{nationality} = \text{U.S.} \mid \text{type=U}) - \Pr(\text{nationality} = \text{U.S.} \mid \text{type=S}) \\ &= \nu^* \frac{\nu_U^* - \nu_U}{\nu_U (1 - \nu_U)}.\end{aligned}$$

If $\delta = 0$, then $\nu_U^* = \nu_U$, that is, nationality and type are independent. In this case, the U.S. investor population is simply a scaled version (by a factor ν^*) of the total population. Both the U.S. and local populations contain the same proportions of U- and S-investors – there is no cross-country heterogeneity. In contrast, $\delta = 1$ implies both $\Pr(\text{nationality} = \text{U.S.} \mid \text{type=U}) = 1$ and $\Pr(\text{nationality} = \text{U.S.} \mid \text{type=S}) = 0$. Nationality and type are then effectively the same characteristic. This is the assumption of no within-country heterogeneity typically made in the literature. Our model allows for anything in between the two extremes.

Taking differences of (7), U.S. investors' net purchases can now be written as

$$\Delta\theta_t^* = \delta\nu_U \Delta\theta_t^U. \tag{15}$$

Here $\nu_U \Delta\theta_t^U$ is the total amount of stocks that is purchased by all U-investors and therefore changes hands in the model. If U.S. and U-investors are identical ($\delta = 1$), it also represents U.S. investors total net purchases. More generally, purchases by U.S.-based U-investors are given by $\nu_U \Pr(\text{nationality} = \text{U.S.} \mid \text{type=U})\, \Delta\theta_t^U$. At the same time, sales by U.S.-based U-investors are $\nu_U \Pr(\text{nationality} = \text{U.S.} \mid \text{type=S})\, \Delta\theta_t^U$. In the polar case $\delta = 0$, the two trades exactly wash out and U.S. investors' net purchases are zero.

Volume, Flow Volatility and Heterogeneity

Our calibration exercise identifies the parameter δ by comparing the volatility of U.S. investors' net flows, $\sigma(\Delta\theta_t^*) = \delta\nu_U \sigma\left(\Delta\theta_t^U\right)$, to mean aggregate trading volume in the local market. Consider the turnover of shares as a measure of volume. Since every trade is an exchange of shares between the two types of investors, turnover is given by

$$VOL_t = \nu_U \left|\Delta\theta_t^U\right|.$$

With normally distributed holdings, mean volume is $\mu(VOL_t) = \nu_U \sqrt{2/\pi}\sigma\left(\Delta\theta_t^U\right)$ and we have

$$\sigma(\Delta\theta_t^*) = \delta\sqrt{\pi/2}\mu(VOL_t). \tag{16}$$

If nationality and type amount to the same characteristic ($\delta = 1$), the volatility of net flows of U.S. investors should be roughly the same size as mean volume, since every trade is a cross-country trade. As within-country heterogeneity becomes more important (lower δ), less cross-country trades contribute to total volume. As a result, volatility of net flows will be much smaller relative to volume.

Waves of Gross Trading Activity

Gross purchases by U.S. investors in period t are determined by which investor type is a net buyer during the period. Let $\mathbf{1}_{\Delta\theta_t^U>0}$ denote the indicator function for the event that U-investors are net buyers, that is, $\Delta\theta_t^U > 0$. Mean gross purchases by U.S. investors are given by

$$\begin{aligned} \mu\left(GP_t^*\right) &= \nu^* E\left[\mathbf{1}_{\Delta\theta_t^U>0}\ \nu_U^*\ \Delta\theta_t^U + \mathbf{1}_{\Delta\theta_t^U<0}\ \left(1-\nu_U^*\right)\ \Delta\theta_t^S\right] \\ &= \left(\nu^* + \delta\ \left(1/2 - \nu_U\right)\right)\ \mu\left(VOL_t\right). \end{aligned}$$

Mean gross purchases are thus proportional to mean volume. Without cross-country heterogeneity ($\delta = 0$), the scaling factor is the population share ν^*. More generally, the factor depends on the relative importance of U-investors in the total vs the U.S. population.

Flow Momentum, Reversal, and Return Chasing

Several other statistics of interest can be read off directly from the properties of U-investors trades. The n-th autocorrelation of U.S. net purchases satisfies $\rho_n\left(\Delta\theta_t^*\right) = \rho_n\left(\Delta\theta_t^U\right) = \rho_n\left(\Delta\theta_t^S\right)$. The emergence of flow momentum and flow reversal in equilibrium is thus independent of the population parameters: it depends only on the properties of trade across investor types. To quantify return chasing, we also consider the cross-correlogram of U.S. investors' net purchases and local returns. By (15), correlation of flows and returns depends on population parameters only to the extent that they determine which group is tracked by U.S. investors:

$$\rho\left(\Delta\theta_t^*, R_{t-j}^D\right) = \text{sign}\left(\delta\right)\ \rho\left(\Delta\theta_t^U, R_{t-j}^D\right).$$

If $\delta > 0$, there are proportionately more U-investors in the population of U.S. international investors than in the local population. Holdings and net purchases of U.S. investors are then perfectly correlated with those of U-investors.

5 Data

This section describes the data and explains how it relates to the model output. We focus on quarterly data from the G7 countries – apart from the U.S., these are Germany, Japan, U.K., France, Canada, and Italy – over the period 1977:1 through 2000:3. We have selected these countries as they best fit the assumptions of our model. First, flows and returns in these countries are likely to be driven by stable economic relationships.

In contrast, the on-going process of liberalization of equity markets in developing countries may lead to capital flows that are driven by changing risk-sharing opportunities or declining transactions costs. Second, the absence of trading frictions in our model is more at odds with the institutional environment of emerging markets.

5.1 Data on Dividends

We use data on the dividend yield and the price index of Datastream's international stock market indices, with all variables converted to constant U.S. dollars. Not surprisingly, per-share dividends exhibit a trend. To obtain a stationary forcing process $\{D_t\}$ for our model, we follow Campbell and Kyle (1993) in removing an exponential trend. This procedure is described in detail in appendix B. We also show in appendix D that it is consistent with our normalization of holdings and flows by beginning-of-period market capitalization, discussed below.

Table 1 presents key first and second moments of detrended dividends. We choose units such that the price index in 1977:1 equals market capitalization. Thus, mean dividend reflects the size of the stock market. The true dividend process follows a truncated normal distribution which we approximate by modelling the dividend as normally distributed in levels. The table confirms that the approximation is sensible as mean dividends are more than 3.5 standard deviations above zero for all countries except Italy.

Preliminary specification analysis of the dynamic behavior of dividends reveals two features. First, the autocorrelation function switches from positive to negative values after three to four quarters. Second, while the first two partial autocorrelation coefficients are significant for all countries except Canada, all countries exhibit several significant partial autocorrelation coefficients beyond the first two. To accommodate both properties in a parsimonious way, we use a special case of the system (2)-(4) and decompose dividends into a persistent cyclical component, captured by an AR(2) process, and a transitory shock:

$$\begin{aligned} D_t &= \bar{D} + F_t^D + \varepsilon_t^D \\ F_t^D &= a_1 F_{t-1}^D + a_2 F_{t-2}^D + \varepsilon_t^{FD}, \end{aligned} \tag{17}$$

where ε_t^D and ε_t^{FD} are uncorrelated i.i.d. sequences of shocks with zero mean and standard deviations σ_{ε^D} and $\sigma_{\varepsilon^{FD}}$, respectively. Here F_t^D captures the oscillatory behavior of the correlogram that is typical of variables affected by the business cycle. The presence of transitory noise ε_t^D that cannot be distinguished from the underlying business cycle movement implies that lags longer than two are still helpful in forecasting dividends.

Table 2 presents the estimated moments for (17).[11] The persistent component F_t^D is stationary: the roots of the autoregressive polynomial are outside the unit circle. For most countries, the roots are complex, which accounts for oscillations in the correlogram. In addition, the persistent component has persistent differences. Indeed, the process of changes in F_t^D satisfies

$$\Delta F_t^D = (-a_2)\ \Delta F_{t-1}^D - (1 - a_1 - a_2)\ F_{t-1}^D + \varepsilon_t^{FD}.$$

For all countries, we have that $0 < (-a_2) < 1$ and that $(1 - a_1 - a_2)$ is a small positive number. After a shock hits, two counteracting effects are at work. First, any change in a certain direction leads to more changes in the same direction, although at a decreasing rate since $(-a_2) < 1$. If this was the only effect, the level F_t^D would be nonstationary. However, the second term causes mean reversion in the level by pulling F_t^D towards its mean of zero whenever it is positive, and by pulling it up when it is negative. For the impulse response of the level, the first effect dominates early on, before the second effect takes over. The result is a hump-shaped impulse response function.

The persistent component explains almost all the variation in dividends: its share of total variance is larger than 96% for all countries except Italy. For 3 of the 7 countries, the volatilities of the shocks hitting the persistent component in any given quarter is also higher than that of transitory shocks. Still, changes in dividends are typically less persistent than changes in the persistent component. Changes in dividends can be decomposed into changes in F_t^D, which are positively serially correlated, and changes in the temporary component, which are negatively serially correlated and thus reduce overall persistence.

5.2 Data on Equity Flows

Data on international equity flows of U.S. investors are from the Treasury International Capital (TIC) reporting system of the U.S. Treasury. Trading volume data are from Datastream's Global Equity Indices. Both flow and volume data record sums over all transactions in a given month or quarter. In contrast, our discrete time model makes predictions about holdings at a point in time. To match model-implied changes in holdings to flow data, we divide flows by total market capitalization at the beginning of the period. In appendix D, we describe why this procedure makes sense and how it interacts with our approach to detrending.

[11] The estimation method is explained in appendix C. The autoregressive parameters a_1 and a_2 are statistically significant for all countries at the 1% level except for Japan's a_2.

Table 3a presents summary statistics for net purchases of stocks abroad by U.S. investors as well as excess returns on domestic indices for the countries we consider. The mean excess returns in this table are based on detrended data, which means that the effects of dividend growth are already removed. This explains why excess returns are smaller than the mean equity premia usually reported from raw data and why Sharpe ratios implied by the table are unusually low. In our set of countries, changes in American investors' holdings are small relative to total market capitalization. Within a given quarter, it is rare to see a change in position of more than one percent of market capitalization.

Figure 2 displays serial correlograms of net purchases of U.S. investors (in the first column) and cross-correlograms of net purchases and local stock returns (in the second column). It documents three stylized facts about the joint distribution of net inflows and excess returns. First, net inflows are persistent. The first autocorrelation coefficient (also listed in Table 3a) ranges between 0.16 for Italy and 0.52 for Canada. The autocorrelation coefficient is statistically significant at the 5% level in all countries.[12] Second, the serial correlogram of flows further indicates a reversal of flows 5 to 6 quarters out for all countries except the U.K. The third fact is return chasing: U.S. investors' net purchases in a country are positively correlated with both current and lagged local stock returns.

Table 3b collects summary statistics for holdings, gross flows and volume. U.S. investors hold significant fractions of the market in all countries except Italy. Gross purchases and sales are of the same order of magnitude in all countries. The stylized fact that gross sales and purchases are highly positively correlated holds both in the time series for every countries and in the cross section of countries. Importantly, the time series results do not only reflect trend behavior. While there are trends in gross flows over the whole sample, behavior over a five year period is mostly driven by volatility that is common to both series. This is illustrated in the second column of Figure 1. Finally, volume varies widely across countries. However, holdings of U.S. investors turn over *less* frequently than holdings of other investors within the country, except for Canada and the U.K.

[12] The persistence of net inflows is not due to trends. The first column in Figure **??** plots the net inflow series for all our countries. It is apparent that the main feature is slow transitions from periods of high to low net inflows.

6 Calibration

Preferences

One period in the model corresponds to one quarter. The preference parameters are standard. We choose an annual, real discount rate of 4 percent, that is, $\beta = 1/R_f = 0.9901$. This value is within the range used in the real business cycle literature. Cooley and Prescott (1995) calibrate the annual real discount rate to 5.2% to match the U.S. capital-output ratio and King and Rebelo (2001) calibrate it to match the U.S. real return to capital of 6.5%. On the low side, Hansen and Singleton (1982) estimate an annual rate of time preference of 1%. The coefficient of absolute risk aversion is set to $\gamma = 10$. In our calibrations below this corresponds to an average coefficient of relative risk aversion of approximately five.

Investment Opportunities

The moments of local dividends and world asset returns are taken directly from the data. For dividends, we use the detrended process estimated in section 5.1. It is difficult to construct an observable counterpart of the returns to private investment opportunities. Our strategy is to first impose a number of a priori plausible restrictions that give rise to a two-parameter family of processes, with the free parameters η_D and η_B introduced in (3). We then fix the remaining parameters to match selected moments on stock market trading activity.

We postulate four specific features of private returns. First, private returns can be predictable. Predictability has been documented in many securities markets and it is certainly prevalent for non-traded assets, where returns need not be competed away quickly. Second, only the predictable component of returns is correlated with the local business cycle. Third, there may be persistent factors other than the local business cycle that affect expected private returns. This feature is of interest because some opportunities chased by S-investors active in the local markets may in fact be located in other countries. Finally, we assume that the unconditional mean and variance of private returns are the same as those of the return on the U.S. market (see Table 3a.)

According to (3), the first component of private expected returns is proportional to the persistent component of local dividends F_t^D. The second component is driven by a process F_t^B that is independent of F_t^D and also has an AR(2) structure. We impose that it captures oscillations at business-cycle frequencies by setting the AR(2) parameters equal to those of the persistent component in U.S. dividends. As a normalization, the variance of shocks to F_t^B is set equal to that of F_t^D. The overall volatility of expected returns and the relative importance of the local business cycle is then governed by the parameters η_D and η_B. Given values for η_D and η_B, the variance of unexpected returns $\sigma^2_{\varepsilon^B}$ must be chosen to ensure that the unconditional variance of private returns matches that of the world asset return. Our specification of investment opportunities thus leaves two degrees of freedom that can be used to match statistics of trading activity.

Matching Flow Moments

In total, we are left to choose five parameters: the fractions ν^*, ν_U and ν^*_U that govern the composition of the investor population and the numbers η_D and η_B that govern the volatility and business cycle correlation of private returns. We select these parameters in order to best match five moments of trading activity: mean local holdings and mean gross purchases by U.S. investors, the standard deviation and the first autocorrelation of net purchases by U.S. investors, and mean trading volume in the local stock market. In addition, we use the positive sign of the contemporaneous correlation of U.S. net purchases and returns to provide guidance on which type of investor is more prevalent in the U.S. investor population. The relevant model statistics are defined in section 4.2.

Table 4 lists the parameter values of the baseline calibration for all countries together with data and model values of the target moments. The first three moments–mean holdings, volatility of U.S. net purchases, and persistence of U.S. net purchases–are matched everywhere. In France and Canada we further match volume data and the calibration delivers a value for δ equal to that in the data. The model understates mean volume in Germany, U.K., Japan, and Italy and understates mean gross purchases in Canada, U.K., Japan, and Italy. This should not be viewed as a failure of the model as data compilation issues highlighted above indicate that too much volume is measured for the U.K. and perhaps also for Japan.

The model generates trade because of persistent changes in the expected off-market return: $\eta_D, \eta_B > 0$. As explained in Section 4, such changes matter for S-investors' stock demand when stocks and off-market opportunities are perceived as substitutes. In our calibrations, substitutability obtains because off-market returns are procyclical ($\eta_D > 0$). We return to this mechanism and the separate role of business cycle and off-market shocks in Section 7.2 below, where we present impulse responses for both shocks.

The top line of table 4 gives the loadings on the factors in the off-market expected return. Each loading has been scaled to represent the impact of a one standard deviation shock to the factor. For all countries the impact of the off-market factor dominates the impact of the local business cycle factor. Also, the dispersion of the scaled loadings across countries is small: $\eta_D \sigma_{\varepsilon^{FD}}$ ranges from 0.23% for the U.K. to 0.94% for France while $\eta_B \sigma_{\varepsilon^{FB}}$ ranges from 0.38% for Italy to 1.07% for Canada. As we will explain below, the greater impact of the off-market factor is due to its ability to generate both persistence and volume in the calibration.

Inferring the Nature of Investor Heterogeneity

Table 4 delivers estimates of the extent and nature of investor heterogeneity. With the exception of the U.K. and Japan, the average international U.S. investor is sophisticated: $\nu_U^* < 0.5$. However, the average U.S. international investor is less sophisticated than the average local investor for all countries: we have $\nu_U < \nu_U^*$ or, equivalently, $\delta > 0$. Aggregate net flows of U.S. investors are thus proportional to U-investors' net flows (cf. 15). As a result, the average U.S. investor looks less informed than the average local investors, as is usually assumed in the literature on home bias.

At the same time, the association of unsophisticated and U.S. investors is far from perfect. Indeed, the parameter δ that measures the strength of this association is close to zero. Table 4 shows that its value in the data varies from 0.22% in Germany and 0.29% in Italy to 2.2% in Japan and 4.9% in the U.K. The model matches these values quite well. In comparison, a standard setup where all U.S. investors are uninformed would imply $\delta = 100\%$. Our results thus suggest that within-country heterogeneity is much more important than cross-country heterogeneity in explaining observed trading behavior.

It is interesting to note that this result does not depend on the particular mechanism that generates trade in our model. Indeed, while our matching procedure determines all five free parameters simultaneously, the correlation coefficient δ is pinned down by the ratio of mean volume to the volatility of U.S. investors (cf (16) above). As long as the model is required to match both of these moments, it must feature small δ – within-country heterogeneity must be large relative to cross-country heterogeneity.

7 Quantitative Analysis

7.1 Flow Reversal, Gross Flows and Return Chasing

Out of the three stylized facts we set out to explain, only the persistence of net flows (as reflected in $\rho\left(\Delta\theta_t^U, \Delta\theta_{t-1}^U\right)$) was directly used to calibrate the model. Table 5 reports data and model statistics on the other stylized facts not used in the calibration. In addition, Figure 2 plots model-implied autocorrelograms of flows and cross-correlograms of returns and flows for all six countries together with the respective correlograms from the data. 90% confidence bands were computed using Newey-West standard errors.

The first column in Figure 2 presents the autocorrelogram of U.S. investors' net purchases. Both the model and the data display a J-curve pattern, with flow momentum up to 3 (and sometimes 4) lags and flow reversal at lags 5 and 6. In addition, flow correlations eventually increase again, although the rebound is quicker in the data than in the model. For France, Germany and Canada, the model produces high positive contemporaneous correlation between gross purchases and gross sales – gross trading activity occurs in waves of simultaneous buying and selling. The fact that it over-predicts the correlation could be due to transitory idiosyncratic shocks that are recorded as gross flows. For the U.K., Japan, and Italy the model cannot account for the positive contemporaneous correlation between purchases as the model predicts too much cross-country heterogeneity.

Return chasing behavior is apparent both from Table 5 and from the cross-correlograms in the second column of Figure 2. The model generates positive contemporaneous correlation between returns and net purchases ($\rho\left(NF_t^*, R_t^D\right) > 0$) for all countries. Moreover, it captures the tent-shape curve around the contemporaneous correlation displayed in the data. Qualitatively, it also captures cyclicality in the correlation of lagged returns and flows: low and negative at 2 and 3 lags, and increasing after lags 4 or 5. The model also generates positive correlation between net purchases by U.S. investors and expected returns based on public information: $\rho\left(\Delta\theta_t^*, E_t^U R_{t+1}^D\right) > 0$. This is consistent with evidence presented by Bohn and Tesar (1996) for our set of countries. These authors estimate expected returns using a comprehensive set of instruments that proxies the public information set. They then show that U.S. investors move into a market when their fitted expected returns are high.

7.2 Interpreting Structural Shocks

To provide intuition for our numerical results, we now discuss the role of three structural shocks in generating the stylized facts we are interested in. We consider the business cycle shock ε_t^{FD}, the transitory shock to dividends ε_t^D and the innovation to the off-market factor ε_t^{FB}. We omit the transitory shock to off-market returns, since its contribution to the moments of interest is negligible. We also focus on one country, France, as a representative example. The construction of variance decompositions and structural impulse response functions is explained in appendix E.

Variance Decompositions and Impulse Responses

Figure 3 provides variance decompositions that quantify the relative importance of the three shocks. Every panel plots the contribution of the three shocks to one key second moment. The top right panel shows the first autocovariance of U-investors' net purchases, a measure of persistence. The other panels illustrate three aspects of return chasing: the covariances of U-investors' net purchases with current, lagged, and expected future returns. As discussed above, U.S. investors' net purchases are proportional to those of U-investors, so that their properties can also be directly read off of the figure. From Tables 4 and 5, we have that all four moments are positive in the data.

Figure 4 provides impulse responses for the three shocks (in columns), where the size of a shock is normalized to one standard deviation. Every column displays: the reaction of the local stock price P_t; U-investors' forecast error of the business cycle, $F_t^D - \hat{F}_t^{DU}$; the local per-dollar stock return, R_t^D; U-investors' net purchases, $\Delta\theta_t^U$; and U-investors' conditional one-quarter-ahead forecast of the local stock return, $E_t^U\left(R_{t+1}^D\right)$.

Business Cycle Shocks, Persistence and Return Chasing

The business cycle shock ε^{FD} contributes positively and significantly to all four moments in Figure 3. It is especially important for the return chasing moments as well as for the oscillating correlograms of Figure 2. Using the terms introduced in Subsection 4.1, a positive realization of ε^{FD} has both an opportunity cost effect and a payoff effect. On the one hand, it increases S-investors' expected off-market return. With asset substitutability, this opportunity cost effect induces S-investors to sell stocks and tends to lower the stock price.

On the other hand, the shock raises both investors' dividend expectations. This payoff effect increases the stock price. It also leads S-investors to buy stocks, since they become relatively more optimistic. Indeed, both investors "underreact": since they cannot be sure that the observed signals – including dividends and prices movements – have not been caused by other shocks, their forecast moves by less than the true state of the business cycle. Moreover, S-investors receive more signals: with pro-cyclical opportunities, the off-market return also provides information about the business cycle. As a result, S-investors underreact by less, which makes them more optimistic.

The opportunity cost and payoff effects of a business cycle shock thus affect both trades and prices in opposite directions. Figure 4 shows that the overall outcome reflects the principle stated in Subsection 4.1: the opportunity cost effect dominates the quantity response (here U-investors buy on impact) while the payoff effect dominates the price response (the stock price rises on impact). The business cycle shock thus leads to a high realization of stock returns together with a net purchase by U-investors, and with $\delta > 0$, also by U.S. investors. In fact, Figure 3 shows that this shock is responsible for most of the contemporaneous correlation of flows and returns generated by our model.

This outcome is exactly what is needed for stocks and private opportunities to actually be perceived as substitutes in equilibrium. Indeed, it contributes to positive correlation of realized stock returns with both expected off-market returns and realized off-market returns – the two conditions for substitutability discussed in Section 4. On the one hand, if the price rises with a business cycle shock, realized stock returns are high when off-market opportunities are good. On the other hand, imperfect information about the true state of the business cycle, together with procyclicality of off-market opportunities $(\eta_D > 0)$, implies that a high realization of the off-market return R^B signals high F^D. It thus leads to an increase in S-investors' estimate $\hat{F}^{D,S}$. Through the payoff effect, off-market returns are then associated with high realized stock returns.

The high stock return realized on impact is followed by further net purchases by U-investors, before reversal sets in. In fact, for three quarters after the impact effect, disagreement and risk sharing trades go in the same direction, thus generating pronounced return chasing. While disagreement is reduced as U-investors learn the nature of the shock and become more inclined to buy, business cycle momentum creates more private opportunities. S-investors' incentive to sell shares thus also increases, at least in the short run. After about three quarters, reversal sets in. Disagreement has become weaker, while the return on private opportunities is now beginning to revert to the mean. As a result, S-investors return to the stock market. Both initial momentum and eventual reversal of flows are predictable given the high realized return caused by the initial shock. This explains the observed oscillations of the cross-correlogram in Figure 2.

Off-Market Shocks and Persistence

Figure 3 shows that the off-market shock ε^{FB} contributes significantly to the persistence of net purchases. However, it also makes it more difficult for the model to account for return chasing as it generates a negative correlation between net purchases and current and lagged returns. Consider a positive realization of ε^{FB}. There is an opportunity cost effect that increases S-investors' expected off-market return, depresses the stock price and makes S-investors sell. There is also a payoff effect. Indeed, as U-investors see the price fall, they believe that F^D may have moved and end up underestimating the state of the business cycle. A lower expectation of dividends induces them to sell and puts further downward pressure on the price.

The price response to an off-market shock is thus clearly negative. For trades, the large risk sharing trade generated by the opportunity cost effect overrides the disagreement trade generated by the payoff effect. The latter is small since the shock does not generate a lot of disagreement: Figure 4 shows that U-investors' forecast error is close to zero, while S-investors' forecast error is equal to zero since they observe the shock. Overall, the off-market shock leads S-investors to sell as prices fall, thus working against return chasing. As the shock persists and F_t^B increases, investors learn the nature of the shock and the forecast error is reduced. However, S-investors keep leaving the stock market to pursue private opportunities, thus generating persistent flows. This is an opportunity cost effect that affects trades much more than prices. As U-investors buy following low returns, the shock also generates negative covariance of lagged returns and flows.

Dividend Shocks, Public Signals and Overreaction

Transitory shock to dividends ε^D contribute positively only to contemporaneous correlation of flows and returns. They work against both persistence and positive correlation of flows and lagged returns. In response to a positive realization of ε^D, both investors see dividends increase. However, they cannot exclude the possibility that the business cycle factor F^D has moved and increase their forecast of F^D. This is a payoff effect that has a strong positive effect on the stock price. It is also stronger for U-investors because they have access to fewer signals. Disagreement thus induces U-investors to buy. The shock also has an opportunity cost effect: S-investors' believe that the expected off-market return has increased. As a result, they sell and put downward pressure on the price.

The quantity response is thus a purchase by U-investors. In addition, the price increases as the strong payoff effect overrides the small price impact from the opportunity cost effect. As in Brennan and Cao (1997), overreaction to a public signal – here dividends – induces positive correlation between U-investors' flows and local stock returns. However, trades driven by a transitory shock are quickly reversed as investors correct their forecast errors. Since transitory shocks generate negative serial correlation in flows, too large a contribution from these shocks would prevent the model from matching persistence. This is why our calibration procedure finds the other two shocks to be relatively more important. Reversal of trades also generates positive correlation of net purchases with lagged returns. While we do not target this moment directly in the calibration, the limited role of transitory shocks is important for the success of our model along this dimension.

7.3 Transitory Links

In the baseline model discussed so far, we have maintained the assumption that transitory shocks to off-market returns and dividends are uncorrelated, that is, there are no "transitory links". The results show that dependence of expected off-market returns on the business cycle, or $\eta_D > 0$, is sufficient for generating the stylized facts. However, the baseline model generates "too much" return chasing for France: the contemporaneous correlation is too high. In this section we show that the model performance can be improved further with transitory links, in particular, $\rho\left(\varepsilon^B, \varepsilon^D\right) > 0$. However, we also show that correlation of persistent shocks is necessary: a model with only transitory links cannot generate the stylized facts.

To assess the contribution of transitory links, we recalibrate the model for France, using the contemporaneous correlation of returns and net purchases as an additional target. We obtain population parameters $\nu_U = 0.44$, $\nu_U^* = 0.47$, and $\nu^* = 0.124$, and the return parameters satisfy $\eta_D \sigma_{\varepsilon^{FD}} = 0.85\%$, $\eta_B \sigma_{\varepsilon^{FB}} = 1\%$, and $\rho\left(\varepsilon^B, \varepsilon^D\right) = .675$. At these parameter values, the model replicates the results in Table 4, but also yields $\rho\left(NF_t^*, R_t^D\right) = 0.32$, a significant improvement.

The main qualitative difference to the baseline model is that transitory links induce more disagreement. This is because correlated noise makes it harder for U-investors to quickly infer the nature of shocks. The response to any shock thus become more persistent as learning only gradually resolves disagreement. This is the key to improved quantitative performance. Indeed, in the baseline calibration, persistence must be explained to a much greater extent by risk sharing trades following a business cycle shock. But such trades are accompanied by payoff effects that generate a lot of return chasing. With transitory links, the implied dependence of off-market expected returns on the business cycle is weaker – $\eta_D \sigma_{\varepsilon^{FD}}$ drops to 0.85% (from 0.92%) in the new calibration. Disagreement trades ensure that the model can still account for persistence, but return chasing is now much lower.

Are Transitory Links Enough?

To check whether transitory links are sufficient for generating the stylized facts, we again recalibrate the model for France. In addition to allowing $\rho\left(\varepsilon^B, \varepsilon^D\right) \neq 0$, we also shut down dependence of expected off-market returns on the business cycle: $\eta_D = 0$. We also assume that S-investors observe the local business cycle factor F^D. In terms of information and correlation of shocks, the setup now mimics that in Wang (1994). However, in contrast to Wang's model, we retain the distribution of fundamentals from our baseline model, so that the transitory links model can match observed persistence.[13]

[13] Wang's original model assumes AR(1) fundamentals, which imply AR(1) terms in equity holdings and hence negative serial correlation in trades. While it can generate persistence in trading volume – an absolute value – it cannot accomodate persistence in net purchases of a known investor class – a

The calibration procedure targets the same moments as in the baseline case. However, we no longer need to find η_D, but instead seek to determine the new free parameter $\rho\left(\varepsilon^B, \varepsilon^D\right)$.

The transitory links model can account for U.S. holdings in France, the volatility of U.S. investors net purchases, and flow persistence. However, it cannot match observed trading volume jointly with those three moments at any parameter values. We focus on the parameter vector that generates the highest mean volume, which is still only $\mu(VOL) = 12\%$; mean gross purchases are then $\mu(\text{GP}) = 1.47\%$. The population parameters are $\nu_U = 0.5$, $\nu^* = 0.119$, and $\nu_U^* = 0.538$, while the parameters of the off-market return process are $\eta_B \sigma_{\varepsilon^{FB}} = 0.33\%$ and $\rho\left(\varepsilon^B, \varepsilon^D\right) = 0.97$.

For the non-calibrated moments, we have $\rho\left(NF_t^*, R_t^D\right) = 0.24$, $\rho(R_{t-1}^D, NF_t^*) = -0.6$ and $\rho\left(GP_t^*, GS_t^*\right) = 0.97$. The transitory links model thus generates less contemporaneous correlation than the baseline model. However, it fails dramatically to generate the fact that high returns forecast high U.S. investors' net purchases. Finally, even though unexpected returns are highly correlated ($\rho\left(\varepsilon^B, \varepsilon^D\right) = 0.97$), the equilibrium correlation of *expected* returns as seen by an econometrician with the same information as U-investors is close to zero and negative ($\rho(E_t^U R_{t+1}^D, E_t^U R_{t+1}^B) - 0.02$).

As discussed above, transitory links induce disagreement and thereby persistence. However, with only transitory links, extremely high correlation of the shocks ε^B and ε^D is required. There are two reasons why the model with only transitory links fails to generate sufficient volume. One is the large amount of asymmetric information: given high uncertainty, U-investors are more reluctant to buy or sell in the absence of large price changes. In addition, S-investors now use stocks much less to hedge shocks to future expected off-market returns. With $\eta^D = 0$ the strong positive correlation between realized stock returns and expected future off-market returns has disappeared.

To see why the model with only transitory links cannot explain why high realized returns forecast U.S. investor net purchases, consider a shock to the business cycle factor F^D. On impact, S-investors sell stocks. This effect is as in the baseline model, and implies that the transitory links model also explains positive *contemporaneous* correlation of U.S. net purchases and returns. However, S-investors reverse their trades and start returning to the stock market immediately after the impact period. Indeed, it is profitable to buy for

sequence of "signed trades" that can be positive or negative. Explaining persistent volume is easier, since taking the absolute value of the first difference of a stationary process is itself a way of inducing persistence.This is seen most easily when the process itself is iid. The first difference of an iid process is an MA(1) process with negative serial correlation. Taking the absolute value makes the correlation positive and thus induces persistence.

four quarters, as long as U-investors' forecasts worsen. This sellout by U-investors after a period of large positive returns is inconsistent with the data. In contrast, the baseline model does not generate immediate reversal. If $\eta_D > 0$, business cycle momentum keeps off-market opportunities plentiful after an F^D shock and encourage further selling as S-investors shed risk.

8 Conclusion

This paper has used a calibrated dynamic model of asset trading to study the role of U.S. investors in foreign equity markets. The model rationalizes two well-known facts about U.S. net purchases – flow momentum and return chasing – as well as a new fact about gross purchases – waves of gross trading activity. Trade occurs in the model because sophisticated investors with access to off-market opportunities exhibit a need for risk sharing and an informational advantage that change systematically over the course of the business cycle.

Within-country heterogeneity between sophisticated and other investors turns out to be much more important for explaining trade than cross-country heterogeneity between investor populations. This conclusion is derived from the small ratio of the volatility of net flows to mean trading volume and mean gross purchases. It is thus independent of the particular nature of heterogeneity that generates trade in our model. We expect it to be a robust fact that will resurface in any model that aims to match key moments of trading.

There are a number of directions for future research. We have taken a rather parsimonious approach to modelling heterogeneity. While our setup does a reasonable job at capturing properties of aggregate flow data, it would be interesting to examine a richer structure with more types and assets. Such an exercise could be guided by more micro-level data on both equity flows as well as flows in and out of private opportunities. We have also retained the standard assumption that investors trade broad stock indices. An extension to multiple stocks would introduce portfolio rebalancing within a country portfolio as a separate source of gross flow correlation.

Finally, it would be interesting to apply our setup to emerging markets. The motives for trade we emphasize – risk sharing and disagreement – are often mentioned in policy discussions on the merits of financial liberalization or capital controls. A quantitative model that captures both motives could be useful to examine the welfare consequences of such policies.

Appendix

A Proof of Theorem 1

The proof of the theorem proceeds in four steps. First, we show that, if prices take the form (8), then the vector ϕ_t^i captures investor $i's$ payoff relevant information. In other words, $\boldsymbol{\phi}_t^U = \hat{\mathbf{F}}_t^U$ is a sufficient statistic for forecasting stock returns given U-investors' information set $\mathcal{I}_t^U$, while $\boldsymbol{\phi}_t^S = \left(\hat{\mathbf{F}}_t^{S\prime}, \hat{\mathbf{F}}_t^{U\prime}\right)'$ is a sufficient statistic for forecasting all future stock *and* private returns, given S-investors' information set $\mathcal{I}_t^S$. Second, we use the Kalman filter to obtain difference equations for the evolution of the individual state vectors ϕ_t^i and verify that these difference equations have a stationary solution. Third, we solve for optimal portfolio allocations as a function of ϕ_t^i and current price. Finally, we derive market clearing prices and verify that they indeed take the form (8). In the numerical exercises below, finding an equilibrium then reduces to solving a nonlinear system of equations in the price coefficients $(\bar{\pi}, \boldsymbol{\pi}_S, \boldsymbol{\pi}_U)$.

In equilibrium the local equity asset price depends on the beliefs of S-investors and U-investors of the underlying factors:

$$P_t = \bar{\pi} + \boldsymbol{\pi}_S' \hat{\mathbf{F}}_t^S + \boldsymbol{\pi}_U' \hat{\mathbf{F}}_t^U. \tag{18}$$

Consider first the agents' payoff-relevant information. Suppose the information sets $\mathcal{I}_t^i$ contain only normal random variables. This implies normality of the conditional expectations $\hat{\mathbf{F}}_t^i$, and, if the price satisfies (18), also of all per-share returns. It follows that $\boldsymbol{\phi}_t^S = \left(\hat{\mathbf{F}}_t^{S\prime}, \hat{\mathbf{F}}_t^{U\prime}\right)'$ is a sufficient statistic for forecasting all future returns, given the information set $\mathcal{I}_t^S$. Now, $\boldsymbol{\phi}_t^U = \hat{\mathbf{F}}_t^U$ is a sufficient statistic for forecasting returns given the information set $\mathcal{I}_t^U$. This includes one-step-ahead returns, since the current price can be written as a function of $\hat{\mathbf{F}}_t^U$. Indeed, U-investors know $\hat{\mathbf{F}}_t^U$, so that observing the price is the same as observing the signal

$$P_t - \bar{\pi} - \boldsymbol{\pi}_U' \hat{\mathbf{F}}_t^U = \boldsymbol{\pi}_S' \hat{\mathbf{F}}_t^S.$$

But then $\boldsymbol{\pi}_S' \hat{\mathbf{F}}_t^U = E\left[\boldsymbol{\pi}_S' \hat{\mathbf{F}}_t^S | \mathcal{I}_t^U\right] = \boldsymbol{\pi}_S' \hat{\mathbf{F}}_t^S$ and we can write the price as $P_t = \bar{\pi} + (\boldsymbol{\pi}_S' + \boldsymbol{\pi}_U') \hat{\mathbf{F}}_t^U$. It follows that the state vector $\boldsymbol{\phi}_t^U$ captures the payoff-relevant information of U-investor's consumption-savings and portfolio choice problem.

Since all state variables are normal and homoskedastic, the evolution of investors' beliefs can be described by tracking conditional expectations, using the Kalman filter. S-investors learn about the state of the business cycle by observing dividends and returns on their private opportunities. They do not learn from the price since they already know $\hat{\mathbf{F}}_t^S$ and hence $\hat{\mathbf{F}}_t^U$. We collect their relevant observables in a vector $\mathbf{y}_t^S = \left(D_t - \bar{D},\ R_t^B - \bar{R}^B - \eta_B F_{t-1}^B\right)'$ that can be represented as

$$\mathbf{y}_t^S = \mathbf{M}^{ySF}\mathbf{F}_{t-1} + \mathbf{M}^{yS\varepsilon}\varepsilon_t. \tag{19}$$

Equations (4) and (19) form a state-space system. S-investors' conditional expectation of the state vector, $\hat{\mathbf{F}}_t^S$, then takes the form

$$\begin{aligned} \hat{\mathbf{F}}_t^S &= \boldsymbol{\rho}\hat{\mathbf{F}}_{t-1}^S + \mathbf{K}^S\left(\mathbf{y}_t^S - \mathbf{M}^{ySF}\hat{\mathbf{F}}_{t-1}^S\right) \\ &= \boldsymbol{\rho}\hat{\mathbf{F}}_{t-1}^S + \hat{\boldsymbol{\varepsilon}}_t^S, \end{aligned} \tag{20}$$

where $\mathbf{K}^S$ is a steady-state Kalman gain matrix. The matrix $\mathbf{M}^{yS\varepsilon}$ allows errors in the observation equation (19) to be correlated with errors in the state equation (20).

U-investors obtain valuable information from dividends as well as from the signal contained in prices, so that $\mathbf{y}_t^U = \left(D_t - \bar{D},\ \boldsymbol{\pi}_S'\hat{\mathbf{F}}_t^S\right)$. These variables[14] can be represented using $\hat{\mathbf{F}}_t^S$:

$$\mathbf{y}_t^U = \mathbf{M}^{yUF}\hat{\mathbf{F}}_{t-1}^S + \mathbf{M}^{yU\varepsilon}\hat{\boldsymbol{\varepsilon}}_t^S. \tag{21}$$

Equations (20) and (21) form the state space system of U-investors. Their conditional expectation, and hence their state variable $\boldsymbol{\phi}_t^U$, can be written as

$$\begin{aligned} \hat{\mathbf{F}}_t^U &= \boldsymbol{\rho}\hat{\mathbf{F}}_{t-1}^U + \mathbf{K}^U\left(\mathbf{y}_t^U - \mathbf{M}_{t-1}^{yUF}\hat{\mathbf{F}}_{t-1}^U\right) \\ &= \left(\boldsymbol{\rho} - \mathbf{K}^U\mathbf{M}^{yUF}\right)\hat{\mathbf{F}}_{t-1}^U + \mathbf{K}^U\mathbf{M}^{yUF}\hat{\mathbf{F}}_{t-1}^S + \mathbf{K}^U\mathbf{M}^{yU\varepsilon}\hat{\boldsymbol{\varepsilon}}_t^S. \end{aligned} \tag{22}$$

Note that all that U-investors are doing is trying to forecast the forecast of the S-investors. Letting $\hat{\mathbf{u}}_t^U = \mathbf{y}_t^U - \mathbf{M}_{t-1}^{yUF}\hat{\mathbf{F}}_{t-1}^U$, the Kalman filter on U-investors' problem yields:

$$E_t\left[\hat{\mathbf{u}}_t'\hat{\mathbf{u}}_t\right] = \mathbf{M}^{yUF}E_t\left[\left(\mathbf{F}_{t-1} - \hat{\mathbf{F}}_{t-1}^U\right)\left(\mathbf{F}_{t-1} - \hat{\mathbf{F}}_{t-1}^U\right)'\right]\mathbf{M}^{yUF\prime} + \mathbf{M}^{yU\varepsilon}E\left[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right]\mathbf{M}^{yU\varepsilon\prime}. \tag{23}$$

The law of motion of $\boldsymbol{\phi}_t^U = \hat{\mathbf{F}}_t^U$ is then:

$$\boldsymbol{\phi}_{t+1}^U = \boldsymbol{\Phi}^U\boldsymbol{\phi}_t^U + \mathbf{M}^{\phi\varepsilon U}\boldsymbol{\varepsilon}_{t+1}^{\phi U}.$$

Repeating the same process for S-investors' conditional forecasts $\hat{\mathbf{F}}_t^S$ we have $\boldsymbol{\phi}_t^S = \left(\hat{\mathbf{F}}_t^{S\prime}, \hat{\mathbf{F}}_t^{U\prime}\right)'$:

$$\boldsymbol{\phi}_{t+1}^S = \boldsymbol{\Phi}^S\boldsymbol{\phi}_t^S + \mathbf{M}^{\phi\varepsilon S}\boldsymbol{\varepsilon}_{t+1}^{\phi S}. \tag{24}$$

[14] The matrices are $M^{yUF} = \begin{pmatrix} \boldsymbol{\pi}_S'\boldsymbol{\rho} \\ \mathbf{M}_{1\cdot}^{ySF} \end{pmatrix}$, where $\mathbf{M}_{1\cdot}^{ySF}$ is the first line of $\mathbf{M}^{ySF}$, and $M^{yU\varepsilon} = \begin{pmatrix} \boldsymbol{\pi}_S' \\ \mathbf{e}_1 \end{pmatrix}$, where $\mathbf{e}_1$ is the first unit vector.

Let us turn to the decision problem of both investors. Write returns as

$$\mathbf{R}_{t+1}^{i} = \bar{\mathbf{R}}^{i} + \mathbf{M}^{R\phi i}\boldsymbol{\phi}_{t}^{i} + \mathbf{M}^{R\varepsilon\phi i}\boldsymbol{\varepsilon}_{t+1}^{\phi i},$$

for each investor. Guess that investors' i value function is of the form

$$V\left(w_{t}^{i};\boldsymbol{\phi}_{t}^{i}\right) = -\exp\left[-\kappa^{i} - \tilde{\gamma}w_{t}^{i} - \mathbf{u}_{i}'\boldsymbol{\phi}_{t}^{i} - \frac{1}{2}\boldsymbol{\phi}_{t}^{i\prime}\mathbf{U}_{i}\boldsymbol{\phi}_{t}^{i}\right].$$

Define $\boldsymbol{\Omega}^{i} = \left(\mathbf{M}^{\phi\varepsilon i\prime}\mathbf{U}_{i}\mathbf{M}^{\phi\varepsilon i} + \left(\boldsymbol{\Sigma}_{\phi\phi}^{i}\right)^{-1}\right)^{-1}$ where $\boldsymbol{\Sigma}_{\phi\phi}^{i} = E\left[\boldsymbol{\varepsilon}_{t}^{\phi i}\boldsymbol{\varepsilon}_{t}^{\phi i\prime}\right]$. We have that (superscript i dropped for simplicity):

$$\begin{aligned} E_{t}V\left(w_{t+1},\boldsymbol{\phi}_{t+1}\right) &= -\frac{\left(\det\boldsymbol{\Sigma}_{\phi\phi}\right)^{-\frac{1}{2}}}{\left(\det\boldsymbol{\Omega}\right)^{-\frac{1}{2}}}\exp\left(-\kappa - \tilde{\gamma}\left(R_{f}\left(w_{t}-c_{t}\right) + \boldsymbol{\psi}_{t}'(\bar{\mathbf{R}} + \mathbf{M}^{R\phi}\boldsymbol{\phi}_{t})\right)\right) \\ &\quad \times\exp\left(-\frac{1}{2}\boldsymbol{\phi}_{t}'\boldsymbol{\Phi}'U\boldsymbol{\Phi}\boldsymbol{\phi}_{t} - \mathbf{u}'\boldsymbol{\Phi}\boldsymbol{\phi}_{t} + \frac{1}{2}\tilde{\omega}\boldsymbol{\Omega}\tilde{\omega}'\right), \end{aligned}$$

where $\tilde{\omega} = \tilde{\gamma}\boldsymbol{\psi}_{t}'\mathbf{M}^{R\varepsilon\phi} + \left(\boldsymbol{\phi}_{t}'\boldsymbol{\Phi}'\mathbf{U} + \mathbf{u}'\right)\mathbf{M}^{\phi\varepsilon}$. Solving for the optimal portfolio we obtain:

$$\begin{aligned} \boldsymbol{\psi}_{t} &= \tilde{\gamma}^{-1}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\left(\overline{\mathbf{M}}^{\psi} + \mathbf{M}^{\psi\phi}\boldsymbol{\phi}_{t}\right) \\ &= \overline{\boldsymbol{\psi}} + \boldsymbol{\Psi}\boldsymbol{\phi}_{t}, \end{aligned}$$

where the matrices are given by $\overline{\mathbf{M}}^{\psi\prime} = \bar{\mathbf{R}}' - \mathbf{u}'\mathbf{M}^{\phi\varepsilon}\boldsymbol{\Omega}\mathbf{M}^{R\varepsilon\phi\prime}$, $\mathbf{M}^{\psi\psi} = \mathbf{M}^{R\varepsilon\phi}\boldsymbol{\Omega}\mathbf{M}^{R\varepsilon\phi\prime}$, and $\mathbf{M}^{\phi\psi\prime} = \mathbf{M}^{R\phi\prime} - \boldsymbol{\Phi}'\mathbf{U}\mathbf{M}^{\phi\varepsilon}\boldsymbol{\Omega}\mathbf{M}^{R\varepsilon\phi\prime}$. The first term in matrix $\boldsymbol{\Psi}$ gives the myopic demand of the investor (i.e., $\tilde{\gamma}^{-1}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\mathbf{M}^{R\phi}$) and the second term gives the hedging demand of the investor (i.e., $-\tilde{\gamma}^{-1}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\mathbf{M}^{R\varepsilon\phi}\boldsymbol{\Omega}\mathbf{M}^{\phi\varepsilon\prime}\mathbf{U}\boldsymbol{\Phi}$).

From the value function $V\left(w_{t}^{i};\boldsymbol{\phi}_{t}^{i}\right)$ we see that risk averse investors not only care about fluctuations in wealth, but also about changes in beliefs, captured by the state vector $\boldsymbol{\phi}_{t}^{i}$. The quadratic term reflects investors' taste for 'unusual' investment opportunities. Intuition for this effect can be obtained by thinking about the case of one state variable. $\mathbf{U}_{i}$ is then a positive number and continuation utility is higher the further $\boldsymbol{\phi}_{t}^{i}$ is from its mean of zero. Since $\boldsymbol{\phi}_{t}^{i}$ is payoff-relevant, it drives expected returns at some time in the future. An unusual value signals that above average expected returns will be available, by either going long or short.

We can now describe in detail the coefficients of the optimal portfolio policy $\boldsymbol{\psi}_{t}^{i} = \overline{\boldsymbol{\psi}}^{i} + \boldsymbol{\Psi}^{i}\boldsymbol{\phi}_{t}^{i}$. We have

$$\begin{aligned} \boldsymbol{\psi}_{t}^{i} &= \tilde{\gamma}^{-1}\tilde{\boldsymbol{\Sigma}}_{R^{i}R^{i}}^{-1}E^{i}\left(\mathbf{R}_{t+1}^{i}|\boldsymbol{\phi}_{t}^{i}\right) \\ &\quad -\tilde{\gamma}^{-1}\tilde{\boldsymbol{\Sigma}}_{R^{i}R^{i}}^{-1}Cov\left(\left(\mathbf{u}_{i}' + E^{i}\left[\boldsymbol{\phi}_{t+1}^{i}|\boldsymbol{\phi}_{t}^{i}\right]'\mathbf{U}_{i}\right)\boldsymbol{\phi}_{t+1}^{i},\mathbf{R}_{t+1}^{i}|\boldsymbol{\phi}_{t}^{i}\right), \qquad (25) \\ &= \tilde{\gamma}^{-1}\tilde{\boldsymbol{\Sigma}}_{R^{i}R^{i}}^{-1}\left(E^{i}\left(\mathbf{R}_{t+1}^{i}|\boldsymbol{\phi}_{t}^{i}\right) + \left(\bar{\mathbf{h}}^{i} + H^{s}\boldsymbol{\phi}_{t}^{i}\right)\right) \end{aligned}$$

where the matrix $\tilde{\mathbf{\Sigma}}_{R^iR^i} = \mathbf{M}^{R\phi i}\left(Var\left(\boldsymbol{\phi}_{t+1}^i|\boldsymbol{\phi}_t^i\right)^{-1}+\mathbf{U}_i\right)^{-1}\mathbf{M}^{R\phi i\prime}$ is a transformation of the conditional covariance matrix of returns, and $\mathbf{M}^{R\phi i}$ is such that $\mathbf{R}_t^i = \mathbf{M}^{R\phi i}\boldsymbol{\phi}_t^i$. We use this decomposition in the main text.

Solving for the optimal consumption level and the value function we get that for given price function, optimality requires that the following constraints are met: $\tilde{\gamma} = \gamma\frac{R_f-1}{R_f}$, and

$$\begin{aligned}
\kappa &= -\log\left(\frac{R_f}{R_f-1}\right) \\
&\quad -\frac{1}{R_f-1}\frac{1}{2}\left(\log\left(\frac{\det\mathbf{\Omega}}{\det\mathbf{\Sigma}_{\phi\phi}}\right)+\mathbf{u}'\mathbf{M}^{\phi\varepsilon}\mathbf{\Omega}\mathbf{M}^{\phi\varepsilon\prime}\mathbf{u}-\overline{\mathbf{M}}^{\psi\prime}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\overline{\mathbf{M}}^{\psi}\right) \\
\mathbf{u} &= \frac{1}{R_f}\left(\overline{\mathbf{M}}^{\phi}+\mathbf{M}^{\psi\phi\prime}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\overline{\mathbf{M}}^{\psi}\right) \\
\mathbf{U} &= \frac{1}{R_f}\left(\mathbf{M}^{\phi\phi}+\mathbf{M}^{\psi\phi\prime}\left(\mathbf{M}^{\psi\psi}\right)^{-1}\mathbf{M}^{\psi\phi}\right),
\end{aligned}$$

with $\overline{\mathbf{M}}^{\phi\prime} = \mathbf{u}'\left(\mathbf{I}-\mathbf{M}^{\phi\varepsilon}\mathbf{\Omega}\mathbf{M}^{\phi\varepsilon\prime}\mathbf{U}\right)\mathbf{\Phi}$ and $\mathbf{M}^{\phi\phi} = \mathbf{\Phi}'\mathbf{U}\left(\mathbf{I}-\mathbf{M}^{\phi\varepsilon}\mathbf{\Omega}\mathbf{M}^{\phi\varepsilon\prime}\mathbf{U}\right)\mathbf{\Phi}$.

Finally, to solve for an equilibrium, let $\mathbf{\Theta}_{\hat{F}^S}^S$ be the part of the first row of $\mathbf{\Psi}^S$ that is associated with $\hat{\mathbf{F}}_t^S$, let $\mathbf{\Theta}^U$ be the first row of $\mathbf{\Psi}^U$ and let $\bar{\theta}^i$ be the mean local asset demand by investor i. The equilibrium requires

$$\begin{aligned}
\Delta\bar{\theta}^U+(1-\Delta)\,\bar{\theta}^S &= 1, \\
\Delta\mathbf{\Theta}^U+(1-\Delta)\,\mathbf{\Theta}_{\hat{F}}^S &= \mathbf{0}.
\end{aligned}$$

This is a system of nonlinear equations that can be solved for the price coefficients.

B Detrending

Data on dividends and flows exhibit trends, while our quantitative exercise explores a detrended economy. We now outline a consistent approach to detrending dividends and flows. To fix ideas, consider the following stylized view of the stock market. There are N firms, each with a single share, paying the same (per-share) dividend $\tilde{D}_t$ and having the same (per-share) price $\tilde{P}_t$. Dividends grow at an exponential rate η. The parameter η thus captures trend firm productivity growth, which benefits owners through dividends.

An observed aggregate price index records the change in the value of the average firm, $\tilde{P}_t/\tilde{P}_{t-1}$. This change in valuation has two components: capital gains that arise from fluctuations in the firm's *stationary* price P_t/P_{t-1} and the growth in prices built in from productivity growth:

$$\tilde{P}_t/\tilde{P}_{t-1} = e^{\eta} P_t/P_{t-1}.$$

The observed dividend yield is $y_t = \tilde{D}_t/\tilde{P}_t = D_t/P_t$. A natural way to remove the trend from dividends is to exponentially detrend the measure $y_t\tilde{P}_t$. The observed holdings of the domestic equity index by investor i are $\tilde{P}_t\tilde{\theta}^i_t$. The observed market capitalization at the end of period t is the combined value of all plants, $\tilde{M}_t = \tilde{P}_t N$. The normalization of holdings by beginning-of-period market capitalization is thus a natural way to remove the exponential trend in holdings. The normalized holdings are:

$$\theta^i_t = \frac{\tilde{\theta}^i_t \tilde{P}_t}{\tilde{M}_t} = \frac{\tilde{\theta}^i_t}{N}.$$

There is an explicit connection between dividends and equilibrium holdings before and after detrending. We can summarize an economy driven by trending exogenous variables by a tuple $\mathcal{E} = \left(\tilde{R}_f, N, \left(\tilde{D}_t, \tilde{R}^B_t\right)_{t=0}^{\infty}\right)$. Suppose that $\tilde{D}_t = e^{\eta t} D_t$ and that $\left(\tilde{P}_t, \tilde{\theta}_t, \tilde{\psi}^B_t, \tilde{c}_t\right)$ is an equilibrium of $\mathcal{E}$, where we suppress the indices for the different types of agent. It can be verified that the tuple

$$\left(P_t, \theta_t, e^{-\eta t}\tilde{\psi}^B_t, e^{-\eta t}\tilde{c}_t\right),$$

is an equilibrium of the detrended economy

$$\mathcal{E}_\eta = \left(\tilde{R}_f e^{-\eta}, 1, \left(D_t, e^{-\eta}\tilde{R}^B_t\right)_{t=0}^{\infty}\right).$$

In our quantitative exercise, we consider a detrended economy. We determine a stationary dividend process D_t as the residuals in a regression of average firm dividends on a time trend,

$$\log\left(y_t\tilde{P}_t\right) = E\left[\log D_t\right] + \eta t + \left(\log D_t - E\left[\log D_t\right]\right). \tag{26}$$

We then match the equilibrium flows to observed flows normalized by market capitalization. In the light of the above result, this ensures consistent detrending of dividends and flows.

We also need to select an interest rate R_f for the detrended economy. Here we use the observed average interest rate. In terms of the above notation, we are thus analyzing the economy $\mathcal{E}_0$. Given our data, this is preferable to considering the economy $\mathcal{E}_{\hat{\eta}}$ where $\hat{\eta}$ is the growth rate estimate from (26). The reason is that, in a small sample such as ours, $\hat{\eta}$ is driven by medium term developments and does not reflect the long run average growth rate. In particular, in our sample $\hat{\eta}$ exceeds the average real riskless interest rate. We are thus not likely to learn much by considering equilibrium flows from $\mathcal{E}_{\hat{\eta}}$. At the same time, the result of the previous paragraph shows that the only role of the trend growth rate η is to shift *all* returns. This suggests that the behavior of the correlations we are interested in will be similar across all economies $\mathcal{E}_\eta$ for η reasonably small.

C The Dividend Process

In this appendix we discuss the estimation of the dividend process. We derive conditions under which a general ARMA(2,2) process permits a representation of the type we assume for our dividend process:

$$\begin{aligned} F_t^D &= a_1 F_{t-1}^D + a_2 F_{t-2}^D + \varepsilon_t^{FD}, \\ D_t &= \bar{D} + F_{t-1}^D + \varepsilon_t^D, \end{aligned} \tag{27}$$

where ε_t^{FD} and ε_t^D are serially uncorrelated and independent random variables with zero mean and variances $\sigma^2_{\varepsilon^{FD}}$ and $\sigma^2_{\varepsilon^D}$, respectively. To prove our result we need to compare the correlogram of dividends under the two representations. Consider first the representation (27). The correlogram of the persistent component F_t^D is summarized by

$$\begin{aligned} \sigma^2\left(F_t^D\right) &= \left(1 - a_1^2 - a_2^2 - \frac{2a_2a_1^2}{1-a_2}\right)^{-1} \sigma^2_{\varepsilon^{FD}}, \\ \sigma\left(F_t^D, F_{t-1}^D\right) &= \frac{a_1}{1-a_2}\sigma^2\left(F_t^D\right), \\ \sigma\left(F_t^D, F_{t-2}^D\right) &= a_1\sigma\left(F_t^D, F_{t-1}^D\right) + a_2\sigma^2\left(F_t^D\right) \\ &= \left(\frac{a_1^2}{1-a_2} + a_2\right)\sigma^2\left(F_t^D\right), \\ \sigma\left(F_t^D, F_{t-s}^D\right) &= a_1\sigma\left(F_t^D, F_{t-s+1}^D\right) + a_2\sigma\left(F_t^D, F_{t-s+2}^D\right);\ s \geq 3. \end{aligned}$$

The correlogram of the dividend process is thus given by

$$\begin{aligned} \sigma^2\left(D_t - \bar{D}\right) &= \sigma^2\left(F_t^D\right) + \sigma^2_{\varepsilon^D}, \\ \sigma\left(D_t - \bar{D}, D_{t-1} - \bar{D}\right) &= \sigma\left(F_t^D, F_{t-1}^D\right) \\ &= \frac{a_1}{1-a_2}\left[\sigma^2\left(D_t - \bar{D}\right) - \sigma^2_{\varepsilon^D}\right], \\ \sigma\left(D_t - \bar{D}, D_{t-2} - \bar{D}\right) &= \sigma\left(F_t^D, F_{t-2}^D\right) \\ &= a_1\sigma\left(D_t - \bar{D}, D_{t-1} - \bar{D}\right) + a_2\left[\sigma^2\left(D_t - \bar{D}\right) - \sigma^2_{\varepsilon^D}\right], \end{aligned}$$

as well as, for every $s \geq 3$,

$$\begin{aligned}\sigma\left(D_t - \bar{D}, D_{t-s} - \bar{D}\right) &= \sigma\left(F_t^D, F_{t-s}^D\right) \\ &= a_1 \sigma\left(D_t - \bar{D}, D_{t-s+1} - \bar{D}\right) + a_2 \sigma\left(D_t - \bar{D}, D_{t-s+2} - \bar{D}\right).\end{aligned}$$

Now consider a general ARMA(2,2) process

$$D_t - \bar{D} = a_1\left(D_{t-1} - \bar{D}\right) + a_2\left(D_{t-2} - \bar{D}\right) + u_t + \lambda_1 u_{t-1} + \lambda_2 u_{t-2}, \tag{28}$$

where u_t is serially uncorrelated with mean zero and variance σ_u^2. Squaring both sides and taking expectations, we have

$$\begin{aligned}\sigma^2\left(D_t - \bar{D}\right) &= a_1^2 \sigma^2\left(D_{t-1} - \bar{D}\right) + a_2^2 \sigma^2\left(D_{t-2} - \bar{D}\right) + \sigma_u^2\left(1 + \lambda_1^2 + \lambda_2^2\right) \\ &\quad + 2a_1\lambda_1\sigma\left(D_{t-1} - \bar{D}, u_{t-1}\right) + 2a_1\lambda_2\sigma\left(D_{t-1} - \bar{D}, u_{t-2}\right) \\ &\quad + 2a_2\lambda_2\sigma\left(D_{t-2} - \bar{D}, u_{t-2}\right) + 2a_1a_2\sigma\left(D_t - \bar{D}, D_{t-1} - \bar{D}\right). \end{aligned} \tag{29}$$

In addition, multiplying both sides of (28) by $\left(D_{t-1} - \bar{D}\right)$ and taking expectations, we have

$$\sigma\left(D_t - \bar{D}, D_{t-1} - \bar{D}\right) = \frac{a_1}{1 - a_2}\sigma^2\left(D_t - \bar{D}\right) + \frac{\lambda_1 + \lambda_2\lambda_1 + \lambda_2 a_1}{1 - a_2}\sigma_u^2. \tag{30}$$

Finally, multiplying both sides of (28) by $\left(D_{t-2} - \bar{D}\right)$ and taking expectations, we obtain

$$\sigma\left(D_t - \bar{D}, D_{t-2} - \bar{D}\right) = a_1\sigma\left(D_t - \bar{D}, D_{t-1} - \bar{D}\right) + a_2\sigma^2\left(D_t - \bar{D}\right) + \lambda_2\sigma_u^2. \tag{31}$$

Using (29)-(31) above, the variance can be solved out in terms of parameters only:

$$\begin{aligned}\sigma^2\left(D_t - \bar{D}\right) &= \sigma_u^2\left(1 - a_1^2 - a_2^2 - \frac{2a_1^2 a_2}{1 - a_2}\right)^{-1}\left(1 + \lambda_1^2 + \lambda_2^2 + 2a_1\lambda_1\right. \\ &\quad \left. + 2a_1^2\lambda_2 + 2a_1\lambda_2\lambda_1 + 2a_2\lambda_2 + 2a_1a_2\frac{\lambda_1 + \lambda_2\lambda_1 + \lambda_2 a_1}{1 - a_2}\right).\end{aligned}$$

The first and second covariances are then given by (30) and (31) and all further covariances (for $s \geq 3$) follow the recursion

$$\sigma\left(D_t - \bar{D}, D_{t-s} - \bar{D}\right) = a_1\sigma\left(D_t - \bar{D}, D_{t-s+1} - \bar{D}\right) + a_2\sigma\left(D_t - \bar{D}, D_{t-s+2} - \bar{D}\right).$$

It is clear that if a given ARMA(2,2) process is to have the representation (27), the autoregressive coefficients must be the same in both representations. Moreover, since the recursions for all covariances beyond lag 2 are identical, a representation of the type (27) exists if there exist $\sigma^2_{\varepsilon^{FD}}, \sigma^2_{\varepsilon^D} > 0$ such that the variance and the first two covariances are matched, which require that:

$$
\begin{aligned}
& \sigma_u^2 \left(1+\lambda_1^2+\lambda_2^2+2a_1\lambda_1+2a_1^2\lambda_2+2a_1\lambda_2\lambda_1+2a_2\lambda_2+2a_1a_2\frac{\lambda_1+\lambda_2\lambda_1+\lambda_2 a_1}{1-a_2}\right) \\
= & \ \sigma^2_{\varepsilon^{FD}}+\sigma^2_{\varepsilon^D}\left(1-a_1^2-a_2^2-\frac{2a_2a_1^2}{1-a_2}\right),
\end{aligned}
$$

$$
(\lambda_1+\lambda_2\lambda_1+\lambda_2 a_1)\,\sigma_u^2 = -a_1\sigma^2_{\varepsilon^D},
$$

$$
\lambda_2\sigma_u^2 = -a_2\sigma^2_{\varepsilon^D}.
$$

The first and last equations can be used to calculate the implied values of $\sigma^2_{\varepsilon^D}$ and $\sigma^2_{\varepsilon^{FD}}$ and obtain two inequality constraints on the ARMA(2,2) parameters:

$$
\begin{aligned}
\sigma^2_{\varepsilon^D} &= -\frac{\lambda_2}{a_2}\sigma_u^2 > 0, \\
\sigma^2_{\varepsilon^{FD}} &= \sigma_u^2\left[1+\lambda_1^2+\lambda_2^2+2a_1\lambda_1+2a_1^2\lambda_2+2a_1\lambda_2\lambda_1+2a_2\lambda_2\right. \\
&\left. +2a_1a_2\frac{\lambda_1+\lambda_2\lambda_1+\lambda_2 a_1}{1-a_2}+\frac{\lambda_2}{a_2}\left(1-a_1^2-a_2^2-\frac{2a_2a_1^2}{1-a_2}\right)\right] > 0. \qquad (32)
\end{aligned}
$$

The second equation implies the additional constraint

$$
0 = a_2\lambda_1(1+\lambda_2)-a_1\lambda_2(1-a_2). \qquad (33)
$$

In a first estimation step, we impose (33), but do not impose the inequality constraint. The inequalities are not binding in all countries except for Japan and U.K. For these countries, we impose $\sigma^2_{\varepsilon^D} = 0.001$, and reestimate the restricted ARMA(2,2) process. Setting the variance of transient shocks to dividends equal to zero implies that there are no trades based on private information as the equilibrium is fully revealing.

Table 6 presents the estimates for the restricted ARMA(2,2) process. These estimates are then used to produce Table 2 in the main text according to the formulas in (32). The estimated ARMA(2,2) produces statistically significant estimates of the autoregressive parameters a_1 and a_2 most all countries (except for Japan's a_2) and of the moving average parameters λ_1 and λ_2 as well (except for France and Japan). Estimates of σ_u^2 are also significant in all cases except for Canada. Finally, the constraint (33) is not rejected in 3 out of 7 countries at the usual 5% significance level and is barely rejected in the case of the U.S.

D Matching Model and Data Flows

Both flow and volume data record sums over all transactions in a given month or quarter; the TIC database does not provide guidance on which days, and hence at what prices, the transactions took place. In contrast, our discrete time model makes predictions about holdings at a point in time. To match model-implied changes in holdings to flow data, we need to normalize the latter. One convenient way to do this is to divide flows by total market capitalization at the beginning of the period. To see why this makes sense, suppose that there are n dates between t and $t+1$ at which transactions are recorded. Let x_i denote the fraction of the net change $\theta_t^* - \theta_{t-1}^*$ in U.S. investors' holdings that takes place at date t_i (with θ_t^* measured as a fraction of outstanding shares). Then normalized net flows are given by

$$NF_t = \frac{1}{\tilde{P}_t} \left(\theta_t^* - \theta_{t-1}^*\right) \sum_{i=1}^{n} x_i \tilde{P}_{t_i} = \left(\theta_t^* - \theta_{t-1}^*\right) \sum_{i=1}^{n} x_i \frac{\tilde{P}_{t_i}}{\tilde{P}_t},$$

where $\tilde{P}_t$ is the undetrended local stock price. Appendix B above shows that this normalization is consistent with exponential detrending of dividend levels.

Normalized flows are thus equal to the change in holdings multiplied by a weighted average of within-month capital gains. In what follows, we match normalized net flows to the first term, $(\theta_t^* - \theta_{t-1}^*)$. This match is exact if all transactions take place on the first day of the month, that is, $t_1 = t$, $x_1 = 1$ and $x_i = 0$ for $i > 1$. Some evidence on the importance of the resulting bias can be obtained by comparing results to the polar opposite case, when flows are normalized by the end-of-period market capitalization (i.e. $t_n = t + 1$ and $x_n = 1$). In terms of our stylized facts, this change somewhat reduces both the contemporaneous correlation of flows and returns and the persistence of flows, but the effect is on the order of a few percentage points for all countries. We conclude that the normalization is reasonable.

E Impulse Response Functions and Variance Decompositions

The vector $\mathbf{x}_t = \left(F_t^D, F_{t-1}^D, \boldsymbol{\phi}_t^{s\prime}, D_t, R_t^B\right)'$ has a vector AR(1) representation

$$\mathbf{x}_t = \bar{\mathbf{x}} + \mathbf{M}_{xx}\mathbf{x}_{t-1} + \mathbf{M}_{x\varepsilon}\boldsymbol{\varepsilon}_t, \tag{34}$$

where $\boldsymbol{\varepsilon}_t$ is the vector of economy wide shocks and $\mathbf{M}_{xx}$ and $\mathbf{M}_{x\varepsilon}$ are matrices constructed using the equilibrium outcome including the matrices from the Kalman filtering problem.

These matrices are built using equations (4), (2), and (3) as describing the processes for F_t^D, F_{t-1}^D, D_t, and R_t^B, respectively. For $\boldsymbol{\phi}_t^{s\prime} = \left(\hat{\mathbf{F}}_t^{S\prime}, \hat{\mathbf{F}}_t^{U\prime}\right)'$ we need to convert the residuals $\hat{\boldsymbol{\varepsilon}}_t^S$ into $\boldsymbol{\varepsilon}_t$. Since $\hat{\varepsilon}_t^{FB,S} = \varepsilon_t^{FB}$, we need four equations to obtain the values of $\left(\hat{\varepsilon}_t^{FD,S}, \hat{\varepsilon}_{t-1}^{FD,S}, \hat{\varepsilon}_t^{D,S}, \hat{\varepsilon}_t^{B,S}\right)$. This is done using the first two equations in

$$\hat{\varepsilon}_t^S = \mathbf{K}^S \mathbf{M}^{yS\varepsilon} \varepsilon_t,$$

obtained from (20), and the two equations that arise from:

$$\begin{aligned} \mathbf{y}_t^S &= \mathbf{M}^{ySF} \mathbf{F}_{t-1} + \mathbf{M}^{yS\varepsilon} \varepsilon_t \\ &= \mathbf{M}^{ySF} \hat{\mathbf{F}}_{t-1}^S + \mathbf{M}^{yS\varepsilon} \hat{\varepsilon}_t^S. \end{aligned}$$

If $\mathbf{S}_t$ is a vector of stock variables like P_t, θ_t^i, $i = U, S$, we can write $\mathcal{S}_t = \bar{\mathbf{S}} + \bar{\mathbf{M}}^{Sx} \mathbf{x}_t$, and similarly for flow variables such as net purchases and returns, $\mathcal{F}_t = \bar{\mathbf{F}} + \mathbf{M}^{Fx1} \mathbf{x}_t + \mathbf{M}^{Fx} \mathbf{x}_{t-1}$.

Generating impulse response functions requires iteration of (34) and application of the formulas for $\mathcal{S}_t$ and $\mathcal{F}_t$. Calculating unconditional first and second moments of the relevant variables is also immediate given the simple linear process in (34). For example, noting that the unconditional mean of $\mathbf{x}_t$ is $E[\mathbf{x}_t] = [\mathbf{I} - \mathbf{M}_{xx}]^{-1} \bar{\mathbf{x}}$, we obtain the unconditional variance matrix of $\mathbf{x}_t$ solving the Ricatti equation

$$\begin{aligned} \Sigma_{xx} &= E\left[(\mathbf{x}_t - E[\mathbf{x}_t])(\mathbf{x}_t - E[\mathbf{x}_t])'\right] \\ &= \mathbf{M}_{xx} \Sigma_{xx} \mathbf{M}_{xx}' + \mathbf{M}_{x\varepsilon} \Sigma_{\varepsilon\varepsilon} \mathbf{M}_{x\varepsilon}'. \end{aligned}$$

For more details on impulse response functions and variance decompositions see Hamilton (1994, pp. 318-324).

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Table 1. Summary Statistics of Dividends.

Country	$\mu(D)$	$\sigma(D)$	$\rho_1(D)$
CAN	4.89	0.34	0.93
FRA	2.19	0.47	0.96
GER	5.50	1.41	0.97
ITA	0.57	0.27	0.98
JAP	14.81	2.87	0.98
U.K.	12.91	2.23	0.92
U.S.	91.51	3.61	0.90

NOTES: Mean μ, standard deviation σ and first autocorrelation ρ_1 of detrended, seasonally-adjusted dividends, deflated by U.S. CPI; 1977:1-2000:3.

Table 2. Estimated Dividend Process.

	a_1	t_{a_1}	a_2	t_{a_2}	$\sigma_{\varepsilon^{FD}}$	σ_{ε^D}	$\sigma(F^D)$	$\rho_1(\Delta F^D)$	*Roots*	$\rho_1(\Delta D)$
CAN	1.859	6.59	−0.896	−3.94	0.036	0.073	0.409	0.88	1.04±0.20i	−0.002
FRA	1.369	33.39	−0.420	−20.60	0.110	0.026	0.458	0.39	1.11;2.15	0.327
GER	1.734	19.47	−0.773	−8.99	0.143	0.183	1.095	0.75	1.12±0.19i	0.217
ITA	1.685	51.41	−0.708	−32.03	0.031	0.170	0.272	0.70	1.12;1.26	0.454
JAP	1.212	4.884	−0.275	−0.295	0.783	0.031	2.988	0.24	1.10;3.30	0.248
U.K.	1.223	16.408	−0.294	−5.464	0.572	0.031	2.403	0.26	1.12;3.04	0.252
U.S.	1.679	6.60	−0.747	−3.18	0.698	0.818	3.836	0.71	1.12±0.28i	0.088

NOTES: Roots are computed for the autoregressive polynomial of F_t^D. t_x is the Newey-West t-statistic of the statistic x.

Table 3a. Excess Returns and Net Purchases.

	Excess Returns (%)		Net Inflows (%)					
	$\mu(R^D)$	$\sigma(R^D)$	$\mu(NF^*)$	$\sigma(NF^*)$	$\rho_1(NF^*)$	$t_{\rho_1(NF^*)}$	$\rho(R^D, NF^*)$	$t_{\rho(R^D,NF^*)}$
CAN	1.4	8.1	0.17	0.37	0.52	11.68	0.27	3.98
FRA	1.5	11.7	0.15	0.28	0.46	5.23	0.17	1.61
GER	0.7	9.8	0.03	0.14	0.35	4.98	0.28	3.81
ITA	0.9	15.0	0.05	0.31	0.16	2.47	0.13	1.73
JAP	0.8	13.0	0.05	0.13	0.45	5.69	0.40	2.93
U.K.	0.8	9.3	0.12	0.24	0.51	4.43	0.16	2.25
U.S.	1.9	7.4	–	–	–	–	–	–

NOTES: Means μ, standard deviations σ and first autocorrelations ρ_1 for U.S.$ Excess Returns and Net Inflows. $\rho(R^D, NF^*)$ is the contemporaneous correlation of Excess Returns and Net Inflows. Quarterly data, 1977:2-2000:3. t_x is the Newey-West t-statistic of the statistic x.

Table 3b. Holdings, Turnover and Gross Flows.

	U.S. Holdings (%)	Volume (%)		Gross Flows (%)		
	h^*	$\mu(VOL)$	$\sigma(VOL)$	$\mu(GP^*)$	$\mu(GS^*)$	$\rho(GP^*, GS^*)$
CAN	14.3	14.1	2.7	3.2	3.0	0.97
FRA	12.7	16.0	3.4	0.9	0.9	0.62
GER	9.9	51.6	13.2	1.0	1.0	0.87
ITA	1.1	86.2	35.1	0.8	0.8	0.60
JAP	8.0	4.8	2.7	0.9	0.8	0.91
U.K.	12.4	3.9	2.1	4.5	4.5	0.95

NOTES: U.S. holdings are a fraction of local market capitalization, as of 12/31/1999. Volume is total value of shares traded divided by market capitalization. Gross purchases (GP) and gross sales (GS) are divided by market capitalization. Gross flow and volume statistics are averages over 1995:1-2000:3.

Table 4. Parameters and Calibrated Moments

	France		Canada		Germany		U.K.		Japan		Italy	
Parameters												
Private	η_D	η_B	η_D	η_B	η_D	η_B	η_D	η_B	η_D	η_B	η_D	η_B
Return, in %	0.94	1.02	0.25	1.07	0.66	0.79	0.23	0.92	0.47	0.63	0.37	0.38
# U-investors		ν_U		ν_U		ν_U		ν_U		ν_U		ν_U
		0.42		0.41		0.43		0.20		0.45		0.01
U.S.	ν^*	ν_U^*	ν^*	ν_U^*	ν^*	ν_U^*	ν^*	ν_U^*	ν^*	ν_U^*	ν^*	ν_U^*
Population	0.12	0.44	0.14	0.44	0.10	0.45	0.12	0.92	0.08	0.82	0.01	0.44
Moments	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
$\mu(\theta^*)$, %	12.7	12.7	14.3	14.3	9.9	9.9	12.4	12.4	8.0	8.0	1.1	1.1
$\sigma(\Delta\theta^*)$, %	0.28	0.28	0.37	0.37	0.14	0.14	0.24	0.24	0.13	0.13	0.31	0.31
$\rho_1(\Delta\theta^*)$	0.46	0.46	0.52	0.52	0.35	0.35	0.51	0.51	0.45	0.45	0.16	0.16
$\mu(VOL)$, %	16.9	16.9	14.1	14.1	51.6	15.1	3.9	0.4	4.8	0.9	86.2	0.9
$\mu(GP^*)$, %	0.9	2.1	3.2	2.0	1.0	1.5	4.5	0.1	0.9	0.1	0.8	0.13
δ, %	1.32	1.32	2.09	2.09	0.22	0.74	4.91	47.9	2.16	11.5	0.29	27.5

NOTES: The calibrated parameters for private returns η_D and η_B are expressed as the product of the original parameter with $\sigma_{\varepsilon^{FD}}$ obtained from Table 2b.

Table 5. Non-calibrated Moments

	France		Canada		Germany		U.K.		Japan		Italy	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
$\rho_{NF_t^*, R_t^D}$	0.17	0.50	0.27	0.14	0.28	0.28	0.16	0.10	0.40	0.33	0.13	0.56
$\rho_{NF_t^*, E^U R_{t+1}^D}$	+	0.16	+	0.17	+	0.20	+	0.16	+	0.19	+	0.20
σ_{Vol}, %	3.1	12.8	2.7	10.7	13.2	11.4	2.1	0.3	2.7	0.7	35.1	0.7
$\rho_{GP_t^*, GS_t^*}$	0.63	0.98	0.97	0.97	0.87	0.99	0.95	-0.43	0.91	-0.13	0.60	-0.45

NOTES: Data for $\rho_{NF_t^*, E_t^U(R_{t+1}^D)}$ was taken from Table 2 in Bohn and Tesar (1996).

Table 6. estimates of ARMA(2,2) process.

	a_1	a_2	λ_1	λ_2	σ_u^2	$\chi_{(1)}$/p-value
CAN	1.859	−0.896	−1.051	0.365	0.013	4.499
	6.59	−3.94	−4.23	2.91	0.78	0.033
FRA	1.369	−0.420	−0.092	0.020	0.014	5.327
	33.39	−20.60	−0.64	0.62	5.42	0.020
GER	1.734	−0.773	−0.803	0.253	0.101	2.608
	19.47	−8.99	−4.92	3.80	6.18	0.106
ITA	1.685	−0.708	−0.398	0.108	0.001	30.41
	51.41	−32.03	−4.94	4.47	8.28	0.000
JAP	1.212	−0.275	−0.002	0.0004	0.786	2.768
	4.884	−0.295	−0.815	0.272	3.141	0.096
U.K.	1.223	−0.294	−0.003	0.0005	0.575	2.089
	16.408	−5.464	−9.349	6.125	8.212	0.148
U.S.	1.679	−0.747	−0.754	0.237	2.100	3.846
	6.60	−3.18	−2.02	1.55	9.48	0.049

NOTES: For each country, the second row gives t-statistics on the corresponding estimates. $\chi_{(1)}$ and p-values are given for the non-linear constraint (33).

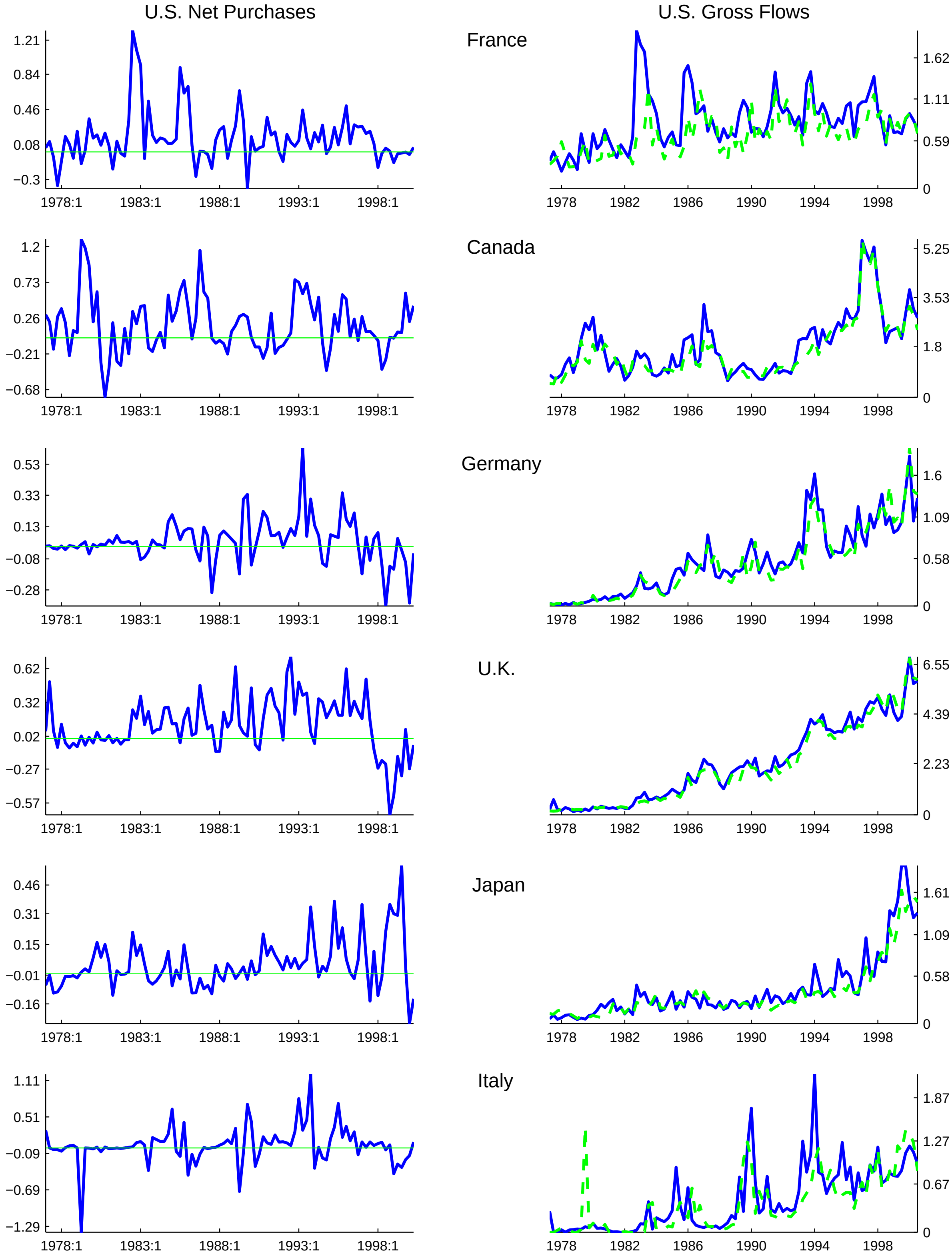

Figure 1: U.S. investors' net purchases (left column) as well as gross purchases (right column; solid black line) and gross sales (right column; dashed gray line) to the 6 non-U.S. G7 countries. All flows are quarterly 1977:1-2000:4 and stated as a percent of beginning-of-quarter market capitalization.

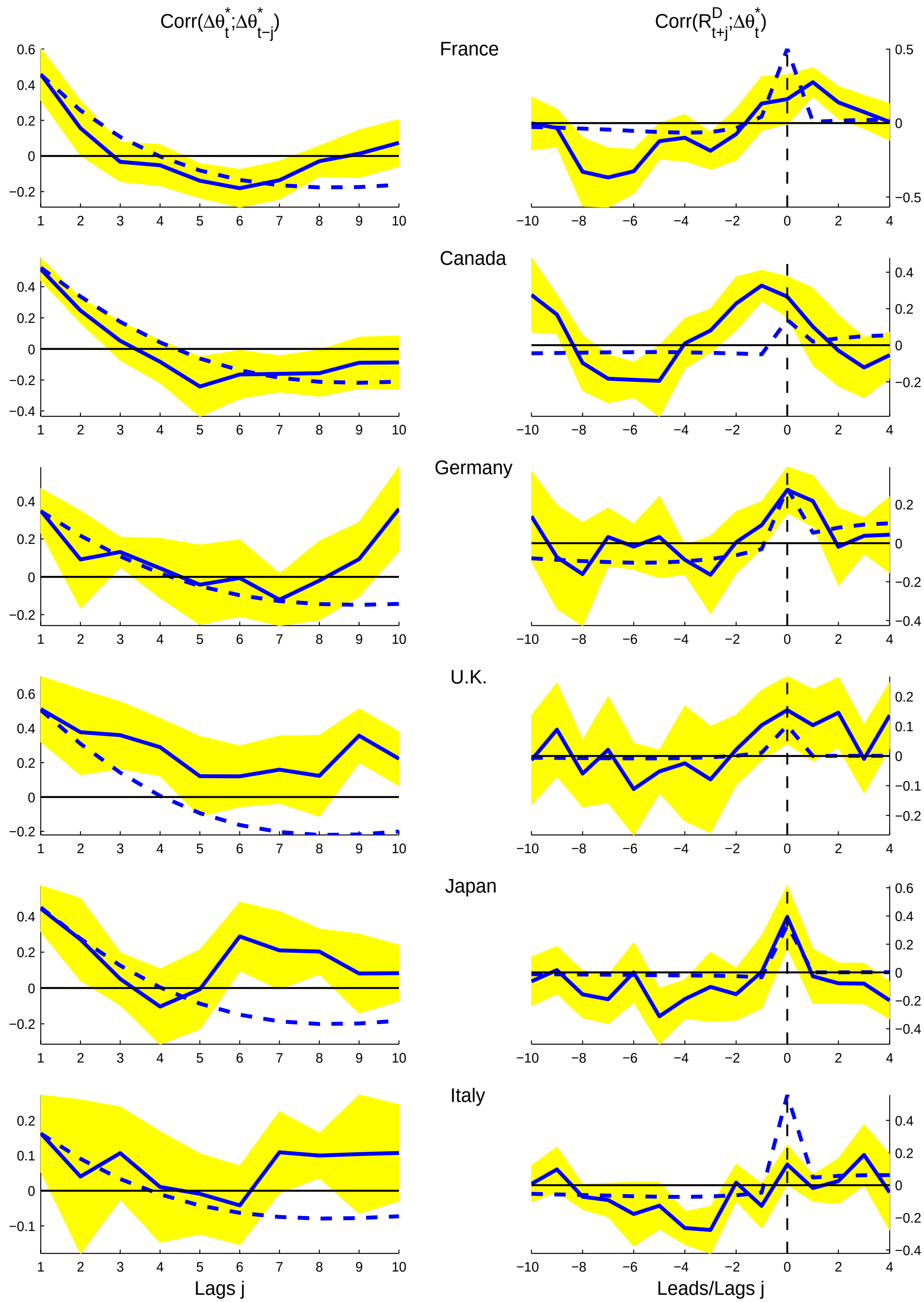

Figure 2: Autocorrelogram of flows (left column) and cross-correlogram of returns and flows (right column). $\Delta\theta_t^{D*}$ is net-purchases of the local asset by U.S. investors; R_t^D is the current return on the local asset. The shaded area is bounded by 90 percent confidence bands.

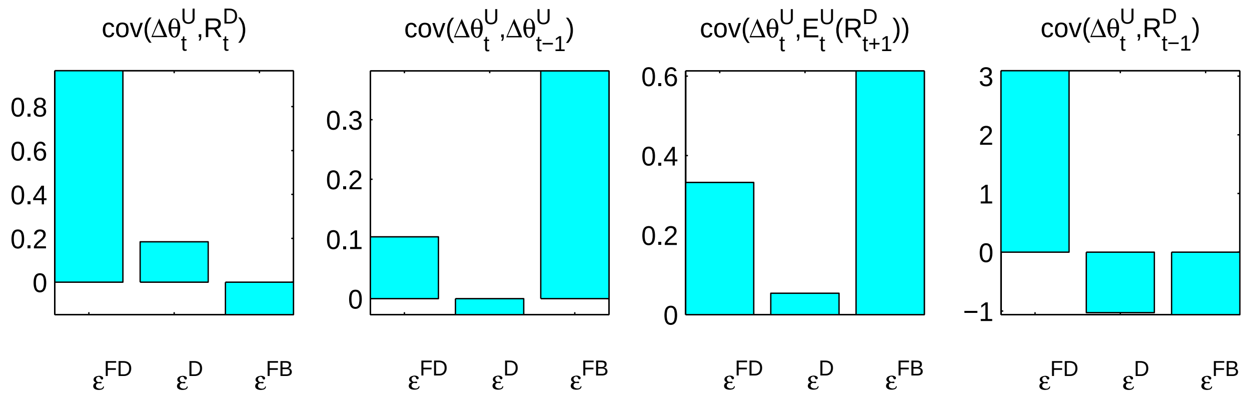

Figure 3: Variance decompositions for four key second moments. The contributions of the three shocks ε^{FD}, ε^{D} and ε^{FB} are stated as fractions of the total covariance. $\Delta\theta_t^U$ denotes net-purchases of local stocks by U-investors; R_t^D is the local stock return; $E_t^U R_{t+1}^D$ is U-investors' time t expectation of the time $t+1$ local stock return.

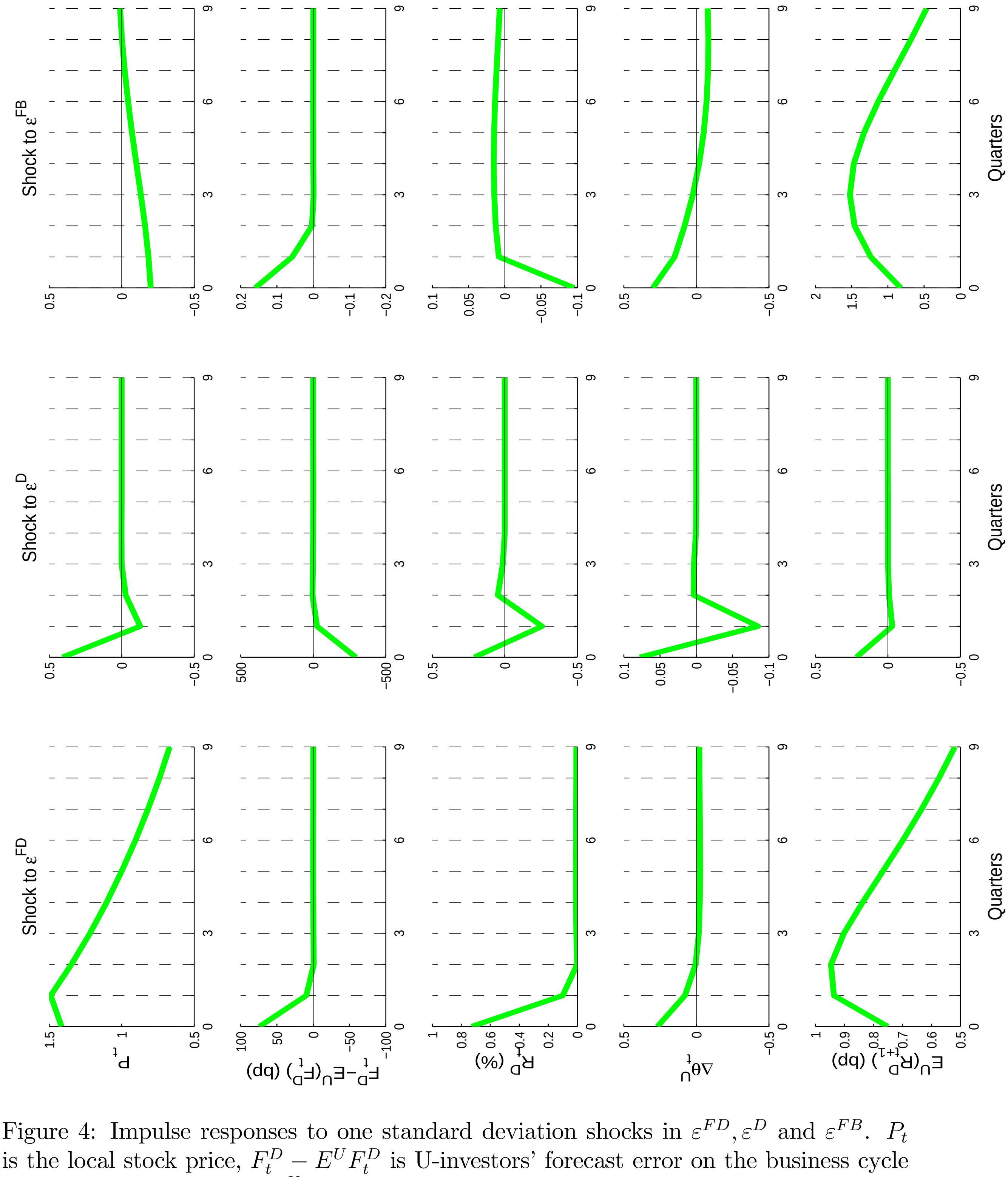

Figure 4: Impulse responses to one standard deviation shocks in $\varepsilon^{FD}, \varepsilon^{D}$ and ε^{FB}. P_t is the local stock price, $F_t^D - E^U F_t^D$ is U-investors' forecast error on the business cycle factor (in basis points), $\Delta\theta_t^U$ is net purchases of the local stocks by U-investors; R_t^D is the local stock return and $E_t^U R_{t+1}^D$ is U-investors' time t expectation of the time $t+1$ local stock return (in basis points).