Global private information in international equity markets

Rui Albuquerque, Gregory H. Bauer, Martin Schneider

ARTICLE INFO
Article history:
Received 2 December 2007
Received in revised form
15 April 2008
Accepted 20 June 2008
Available online 6 June 2009

JEL classification:
F36
G12
G14
G15

Keywords:
Private information
Global private information
Asymmetric information
Portfolio choice
International equity flows and returns
Home bias
Return chasing

ABSTRACT
This paper studies international equity markets when some investors have private information, which is valuable for trading in many countries simultaneously. We use a dynamic model of equity trading to show that global private information helps explain US investors' trading behavior and performance. In particular, the model predicts global return chasing (positive co-movement of US investors' net purchases with returns in many countries) which we show to be present in the data. Return chasing in our model can be due to superior performance of US investors, not inferior knowledge or naive trend-following. We also show that trades due to private information are strongly correlated across countries. A common (global) factor accounts for about half their variation.

1. Introduction

US investors' net purchases in a foreign equity market co-move positively with returns there. This co-movement has been labeled “return chasing”: US investors tend to be net buyers of equity in a foreign country when stock prices there are rising. A common explanation for return chasing is based on the assumption that US investors lack the private information of local investors in foreign markets. In the presence of local private information, less informed US investors react more strongly to public signals than better informed local investors, even if all investors have rational expectations. If public signals are sufficiently important drivers of returns, this mechanism generates both return chasing and underperformance of US investors in foreign markets.

While the private information view of international equity markets helps explain return chasing and equity home bias, it has been challenged by recent empirical findings on investor performance. If local private information were important, domestic investors should make higher trading profits than foreign investors. However, the
evidence on the performance of foreign and local investors is mixed, with a number of studies suggesting that foreign investors outperform their domestic counterparts. In light of models with local private information, it is puzzling why foreigners should sometimes have country-specific private information that is not available to local investors. This paper proposes to broaden the private information view of international equity markets by considering global private information that is relevant for trading in many foreign countries simultaneously. As a concrete example, consider market research about the technology sector. Insights about the future of this sector in the United States, a country that dominates growth in the sector, are likely to be important for the valuation of tech stocks in Europe as well. Experience gained in the US market thus could give sophisticated US investors an advantage in recognizing global trends in technology and lead them to outperform domestic investors in Europe. More generally, the presence of global factors in international equity returns is a robust stylized fact, and in many empirical studies global factors are captured by US-specific variables (e.g., Campbell and Hamao, 1992; Harvey, 1991). This suggests that US investors’ local private information could be valuable in foreign markets as well.

The presence of global private information reconciles the private information view with mixed evidence on investor performance and helps explain new evidence we present on the cross-country correlation of returns and flows. To show this, we first set out a theoretical model of international equity trading and derive its implications for returns and equity flows. Stock returns in our model are driven by both local and global factors. We view the world as a set of regions, a subset of which makes up the United States. In every region, local investors receive signals about local factors and some investors also receive signals about global factors. The key assumption is that the fraction of investors who receive global signals is larger in the US than in the rest of the world. With this information structure, local private information leads to home bias (in fact, to regional “home bias at home”). At the same time, global private information generates return chasing that reflects superior performance of US investors. This is because local investors abroad underreact to movements in global factors, about which they know less than US investors.

Analysis of the model leads to three new predictions. First, if global information is important, we should observe global return chasing: US investors’ net purchases in any given country should co-move positively not only with returns in that country, but also with returns in other countries. We show this new fact in a monthly data set of US investors’ equity purchases in eight developed countries. Second, the model suggests that it is natural to find mixed evidence on the performance of foreign investors relative to local investors. While local shocks (which are reflected in local private signals) favor local investors, global shocks (which are reflected in global private signals) favor US (i.e., foreign) investors. Empirical studies could thus uncover under- or overperformance of foreign investors depending on the particular time period and country studied.

The third prediction is that global private information induces positive correlation in US investors’ trades across countries. To assess it, we construct empirical measures of US investors’ trades due to private information. If most private information were local, then the correlation of such trades across countries should be low. For example, private information generated by market research about France that leads sophisticated US investors to purchase French equities should not help forecast returns in Germany and, therefore, should not entail purchases of German equities. In contrast, the more private information is global, the higher the cross-country correlation of trades due to private information. We find that a global factor accounts for slightly more than half of the variation in trades due to private information across the eight countries we study. At the same time, private information accounts for about one-half of the overall variation in trades. Global private information thus plays an important role in international equity markets; it explains approximately 30% of US investors’ trades abroad. To the best of our knowledge, this paper is the first to show global return chasing and global private information in international markets.

In our model, the key feature that allows both home bias and return chasing to obtain is the presence of asymmetric information. A benchmark symmetric information model cannot account for either fact. Under standard assumptions—all investors have identical hyperbolic absolute risk aversion (i.e., HARA) preferences and all assets are tradable—two fund separation obtains in equilibrium. Under two fund separation all investors hold all risky assets in the same proportions. As a result, there is no bias toward home assets, and there are no equity flows across borders that are systematically related to country returns.

A deviation from this benchmark that can lead to global return chasing is a gradual, simultaneous opening of equity markets in many countries to US investors. If markets become gradually more accessible, US investors increase their positions. At the same time, the marginal investor becomes more diversified and requires lower risk premia, which raises stock prices. Integration could thus lead to positive co-movement of US net purchases and returns at low frequencies. However, we show that most global return chasing occurs at high frequencies: The correlations between detrended flows and returns are similar to the raw correlations. This high frequency correlation is unlikely to be due to gradual market

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Integration. However, it is consistent with an asymmetric information setup.

The new feature of our model is that it allows for private and public information about both local and global factors in asset payoffs. We build on the static model of private and public information about both local and global information setup. However, their setup precludes global factors. Our closed form solution goes beyond theirs in that we show how different types of shocks contribute to return chasing, with individual contributions expressed as tractable functions of exogenous fundamentals. Our solution thus clarifies the role of local private information. More generally, it allows us to trace out how public and private signals are used by investors and then become observable in equity flows and returns.

In particular, our solution highlights that the relation among trades, returns, and information is different when information is global instead of local. With local private information, a natural tension exists between the presence of private information and observed return chasing. The arrival of local private signals induces negative correlation between US investors’ purchases and returns. This is because a private signal that brings good news and is partly reflected in a price increase leads local informed investors to buy from US investors. US investors underreact relative to a symmetric information benchmark and sell. In a model with local private information, return chasing can come only from local public signals, which must be important enough to outweigh the opposing effect from local private signals.

In contrast, both public and private global signals contribute to global return chasing. The arrival of a good global private signal is partly reflected in price increases in many countries and leads the US investors who receive the signal to buy in those countries, while local investors underreact and sell. The arrival of a good public signal has two effects. On the one hand, it reduces US investors’ information advantage with respect to the global factors. One might thus expect local investors in the other countries to overreact to the signal and become net buyers. On the other hand, the signal reduces local investors’ information advantage about payoffs. Our analysis shows that in a world where local private information is strong enough that home bias holds, as in the data, the second effect is always stronger, and both types of signals induce US investors to buy when prices rise.

The existing empirical literature on foreign investors’ trading behavior focuses on data sets from a specific country or short time period. In contrast, we use data on US investors’ monthly purchases and sales of equities in the eight major foreign markets between 1977 and 2003. This allows for a comparison of trades across markets, which is required to identify global return chasing and trades due to global private information. In particular, we can examine the factor structure of private information. Previous analyses of international expected return variation try to separate the influence of global and local risk factors. Here, we are interested in describing the extent to which measured private information also displays significant global components.

The paper proceeds as follows. In Section 2, we develop our model of international equity flows with global private information. In Section 3, we present our data and results on global return chasing. In Section 4, we introduce the empirical models of the expected components of international equity flows and returns and show a significant common variation in US private information trades. In Section 5, we show that our measures of private information can be used to forecast returns. Section 6 concludes. Appendix A contains proofs to the propositions in the main text, and Appendix B has details on the empirical estimable models.

2. The model

In this section we describe a general model of equity trading under asymmetric information that accommodates global factors. We allow for both local and global risk factors. In addition, public and private information can be either local or global in nature.

2.1. Setup

This section gives a description of the available assets, the existing investors and their information sets, and of the equilibrium.

2.1.1. Assets

Asset trade takes place over $T$ periods, $t = 1, \ldots, T$. Investors in the global equity market have access to $n$ regional stock indices as well as a riskless asset that pays a zero interest rate. Regions are identified by the subscript $j$. The $j$-th stock index is a claim to a terminal payoff $U_{t}^{j}$ that is received at date $T$. In what follows, we refer to the terminal payoff as a dividend, although it can also be interpreted as the initial price in a future round of trading. The dividend has mean $\mu_{d}$ and depends on a local factor $U_{t}^{l}$, as well as a global factor $U_{t}^{g}$ that is the same for all regions.

The vector of all dividends is written as

$$U = \mu + U^{l} + U^{g},$$

where $U^{l}$ is an $(n \times 1)$-vector of local factors and $i$ is an $(n \times 1)$-vector of ones. We assume that all factors are normally distributed with mean zero. Local factors are uncorrelated across regions and have identical variance $1/\pi_{l}$. The global factor is uncorrelated with the local factors and has variance $1/\pi_{g}$. It follows that the covariance matrix of dividends is

$$\Sigma = \pi_{l}^{-1}I + \pi_{g}^{-1}I',$$

where $I$ is an identity matrix of size $n$.

2.1.2. Investors

Each region $j$ is populated by informed investors and liquidity traders. The mass of informed traders and...
liquidity traders is the same in each region, namely, \(1/n\). Informed investors have preferences over terminal wealth represented by \(U(W_i) = -\exp(-(1/r)W_i)\); their coefficient of absolute risk aversion is thus \(1/r\). Informed investors are identified by the index \(i\). Any informed investor \(i\) starts out in period 0 with some initial vector of asset positions \(A_0(i)\).

At every date, the liquidity traders sell the same exogenous amount of every regional index.\(^4\) We assume that the vector \(x_t\) of liquidity traders’ sales at date \(t\) is normally distributed with mean zero and covariance matrix \(\Sigma_t\). Liquidity traders start out with a position \(-\mu_x\). The vector of liquidity traders’ total demand is thus \(-X_t = -\mu_x - \sum_{t=1}^{t} x_t\). The quantity of assets \(X_t\) must be held by informed investors in equilibrium.

### 2.1.3. Public information

All investors observe local and global public signals. The local signals are informative only about dividends in region \(j\), while the global signals provide information relevant to all regions. We assume

\[ \alpha_j(i) = \begin{cases} U_j + v_{ij}, & j = 1, \ldots, n \\ \end{cases} \]  

(2)

and

\[ \gamma^p_t = \frac{1}{n} \sum_{j=1}^{n} U_j + v^p_{ij}, \]  

(3)

where the shocks \(v_{ij}\) and \(v^p_{ij}\) are normally distributed and mutually as well as serially uncorrelated, with \(\text{var}(v_{ij}) = 1/q_j\), \(j = 1, \ldots, n\), and \(\text{var}(v^p_{ij}) = 1/q_p\). The cumulative errors in the public signals are denoted \(V_{ij} = \sum_{t=1}^{T} v_{ij}\).

### 2.1.4. Local private information

Investors in region \(j\) know more about the dividend in their home region than investors in other regions. At date 0, they start out with background information about the dividend in their home region. As trading progresses, they obtain further local signals about their home region dividend. The local signal received by informed investor \(i\) in region \(j\) at date \(t\) is

\[ z_{ij}(i) = U_j + e_{ij}(i), \quad j = 1, \ldots, n, \quad i \in [0, 1/n], \]  

(4)

where the shocks \(e_{ij}(i)\) are normally distributed and mutually as well as serially uncorrelated, with \(\text{var}(e_{ij}(i)) = 1/p_i\).

Following common practice in Bayesian statistics, we encode background information in investors’ prior beliefs at date 0. In particular, the prior is set equal to the posterior that obtains if investors have already seen \(f_0\) local signals. The precision matrix of the prior (the inverse of the covariance matrix) for any informed investor living in region \(j\) is therefore

\[ K_{0j} = \frac{\pi_{ij}}{\pi_{ij} + \pi_g \cdot t^j + t_0 p J_j}, \]  

(5)

where \(J_j\) is a matrix that has a one in the \(j\)-th diagonal element, while all other elements are zero. The matrix \(K_{0j}\) captures investors’ initial knowledge about the different asset markets. Without background information (\(t_0 = 0\)), investors would start off with identical beliefs about the indices in all regions. The background information that an investor has about his own region increases knowledge about the domestic index only, which is reflected in a higher precision.

### 2.1.5. Global private information

In region \(j\), there are \(z_j\) global investors who receive not only a local signal about their home region \(j\), but also global signals \(\gamma^g_{ij}(i)\) that are informative about the sum of the dividends:

\[ \gamma^g_{ij}(i) = \frac{1}{n} \sum_{j=1}^{n} U_j + \gamma^g_{ij}(i), \quad j = 1, \ldots, n, \quad i \in [0, z_j], \]  

(6)

where the noise \(\gamma^g_{ij}(i)\) is again normally distributed and uncorrelated with all other shocks, with \(\text{var}(\gamma^g_{ij}(i)) = 1/q_g\). Because the local factors \(U_j\) are uncorrelated, the \(\gamma^g_{ij}\)’s are effectively signals about the global factor in dividends \(U^g\).

Having a subset of investors receiving the signal on the global factor means that the off-diagonal terms in the precision matrix of the private signals of such investors differ from those of the remaining investors. Information endowments are thus not symmetric in our model, whereas Brennan and Cao (1997) assume symmetric information endowments.

### 2.1.6. Equilibrium

A rational expectations equilibrium is a sequence of random variables for prices \(P_t\) and a collection of individual asset demands \(A_i(i)\) for informed investors such that (1) at every date \(t\), informed investors’ asset demands maximize utility given equilibrium prices and information and (2) the \(n\) stock markets clear, that is,

\[ \int A_i(i) \, dl = X_i, \quad t = 0, 1, \ldots, T - 1. \]  

(7)

In equilibrium, informed investors must take the other side of all the liquidity trades.

### 2.1.7. The United States

A fraction \(a\) of the \(n\) regions form the United States. The key assumption for what follows is that the fraction of investors who receive a global signal in the US is larger than the fraction of such investors in the world at large. To simplify notation, and without loss of generality, we let the fraction of investors who receive a global signal be the same across all US regions (that is, \(z_j = z^{US}\) if \(j\) is a US region) and across all non-US regions. Let \(\alpha\) denote the fraction of investors in the world who receive a global signal; the fraction of investors who receive a global signal in a non-US region \(j\) must then be \(\alpha_j = (\alpha - \alpha^{US})/(1 - \alpha)\).

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\(^4\) As is common in the literature, the role of liquidity traders in our model is to allow for a nonrevealing rational expectations equilibrium. Our assumption that all liquidity traders are identical ensures that liquidity traders play no other role. In particular, their trades cannot be themselves generate home bias or return chasing, as becomes clear below.
The regions of the model can be interpreted either as individual countries with homogenous populations or as subregions of a country. Following Coval and Moskowitz (1999), a number of papers show regional home bias within countries. This literature suggests that superior local information is responsible for this phenomenon. Alternatively, one could think about the regional stock indices as individual stocks, where each individual stock has a clientele of investors who have better information than the public at large.

2.1.8. Interpreting global private information

Our interpretation of global private information received by US investors is that it originates in information about US economic variables. For example, US investors could have superior knowledge about US business cycle variation. Lumnsdale and Prasad (2003) estimate a common component in industrial production growth rates in 17 Organization for Economic Co-operation and Development (OECD) countries. The average weight of US industrial production in this common component is 38.92%, well above the weights for all of the other countries. This common component is shown to drive industrial production in all of the countries. Similarly, Kwark (1999) finds that shocks to US output are important in explaining shocks to foreign country output, and Glick and Rogoff (1995), analyzing productivity shocks in the manufacturing industries of seven major industrial countries, find that gross country investment responds to a global productivity shock. Superior knowledge of US industrial production or aggregate output would then be of benefit in many countries.

US investors could also have a superior ability to interpret US monetary or productivity shocks which would help in forecasting growth in foreign economies. Kim (2001) estimates several different identified vector autoregression models of the effects of US monetary policy shocks on the current account and foreign country growth. He finds that expansionary shocks to US money have a clientele of investors who have better information about the local factors through local signals. The direct contribution of local private signals to average knowledge is fairly general. In our model, both the local and global public information set of any particular investor. Nevertheless, it is useful for characterizing equilibria. The evolution of its local and global components are conveniently summarized by two sequences of numbers:

\[ K_t = K_0 t + \frac{1}{n} q t \sum_{j} K_j, \quad t = 1, \ldots, T, \]

\[ K_0 t = K_0 + \Delta K_t = K_0 + p (t_0 + t) / n + q_t + r^2 \pi_s p_t / n^2 t, \]

\[ K_0 t = K_0 + \Delta K_t = K_0 + \pi_s p_t + q_t + r^2 \pi_s \pi_g (\pi_s + 2 p_t / n) t. \]

The first sequence \( \{K_0 t\} \) represents the accumulation of knowledge about the local factors through local signals. The number \( K_0 = \pi_t \) captures the initial knowledge of foreign investors, and \( \Delta K_t \) captures the increase in knowledge through local signals, including the background information of local investors. The direct contribution of local private signals to average knowledge is \( p (t_0 + t) / n \), because the signals are received only in one of the \( n \) regions, namely, the home region. Moreover, local private signals contribute to average knowledge indirectly, as they are partly revealed by the price. The indirect contribution (the last component of \( K_0 t \)) is larger the smaller is the variance of the liquidity trades (\( \pi_t \) larger).

2.2. Model solution

We need to track investors’ information as it evolves over time. As for the initial period, we identify knowledge with the inverse of an investor’s posterior covariance matrix of dividends based on his own signals. Consider for example an individual investor \( i \) who lives in region \( j \). The knowledge of this investor, denoted \( K_i^j \), accumulates linearly:

\[ K_i^j = K_0 j + t \left( q_i l + \frac{1}{n} q_x l \right) + t \pi_d j, \]

if \( i \) does not get global signals

and

\[ K_i^j = K_0 j + t \left( q_i l + \frac{1}{n} q_x l \right) + t \pi_d j + \frac{1}{n} t \pi_g l, \]

if \( i \) gets global signals.

Individual knowledge can grow for three reasons. First, all investors learn by observing the public signal. Second, nonglobal investors learn only about home country dividends, so that the arrival of private signals changes their knowledge matrix only in one position. For global investors, the arrival of global private information changes the knowledge in all positions.

We define average knowledge \( K_t = \sum K_i^j, di \) as the population weighted average of the individual knowledge matrices. Average knowledge does not describe the information set of any particular investor. Nevertheless, it is useful for characterizing equilibria. The evolution of its local and global components are conveniently summarized by two sequences of numbers:

\[ K_t = K_0 t + \frac{1}{n} q t \sum_{j} K_j, \quad t = 1, \ldots, T, \]

\[ K_0 t = K_0 + \Delta K_t = K_0 + p (t_0 + t) / n + q_t + r^2 \pi_s p_t / n^2 t, \]

\[ K_0 t = K_0 + \Delta K_t = K_0 + \pi_s p_t + q_t + r^2 \pi_s \pi_g (\pi_s + 2 p_t / n) t. \]

The second sequence \( \{K_0 t\} \) represents the accumulation of knowledge about the local factors through local signals. The number \( K_0 = \pi_t \) captures the initial knowledge of foreign investors, and \( \Delta K_t \) captures the increase in knowledge through local signals, including the background information of local investors. The direct contribution of local private signals to average knowledge is \( p (t_0 + t) / n \), because the signals are received only in one of the \( n \) regions, namely, the home region. Moreover, local private signals contribute to average knowledge indirectly, as they are partly revealed by the price. The indirect contribution (the last component of \( K_t \)) is larger the smaller is the variance of the liquidity trades (\( \pi_t \) larger).

2.2.1. Asset demand and equilibrium prices and quantities

We now characterize equilibrium prices and equity holdings in terms of subjective expected dividends as well as individual and average knowledge. This characterization is fairly general. In our model, both the local and global signals are linear combinations of the factors \( U_i \) plus

\[ 5 \text{ Because dividends across countries are positively correlated } K_0 < 0. \]
At consist of the disagreement term in Eq. (15) plus a that increases with the risk aversion coefficient $j$ asset part of the return $U$ portfolio demand equation (13) in two ways: directly as information. This includes in particular any information from liquidity investors. If informed investors disagree, how the investor population learns about the dividend. expectation, the first term in Eq. (14). This term captures information through the knowledge-weighted average $Pt$ equity holdings of investor $i$ consist of three terms. The first term gives the share of liquidity trades absorbed by investor $i$ absent any information consideration. The second term depends on investors’ expectations about fundamentals or, more specifically, their disagreement about fundamentals: It is zero with symmetric information, that is, when $E_t[U]$ is independent of $i$ and $K' = K$. More generally, investor $i$ takes a long position in an asset if his own subjective expectation of the dividend is higher than the knowledge-weighted average of others’ expectations. The last term depends on liquidity shocks: It reflects the fact that in equilibrium informed investors must offset the sales of liquidity investors. Because the demand of the liquidity traders is simply $-X_t$, the equilibrium holdings of the informed investors consist of the disagreement term in Eq. (15) plus a component due to liquidity, $(K'_tK_t^{-1} - I)X_t$. Here the expression $K'_tK_t^{-1} - I$ could be thought of as investor $i$’s information advantage. If informed investors disagree, then better informed investors take larger positions and hence absorb more of the supply fluctuations. If informed investors agree and $K' = K$, then the supply by domestic liquidity traders is absorbed by domestic informed investors.

We now characterize equilibrium prices and holdings in terms of the shocks to fundamentals, errors in public signals, and liquidity trades. The proof is in Appendix A. There, we first establish a more general result that allows for arbitrary linear dependence of signals on dividends, as well as an arbitrary sequence of signal precisions. Proposition 1 builds on that general result, exploiting the symmetry assumptions on information imposed above to work out explicitly the contributions of different shocks in terms of the primitives of the model.

**Proposition 1.** (i) The stock price at date $t$ in a region $j$ outside the US is

$$P_{tj} = \mu + \frac{\Delta E_t'[U]}{K'_t} (U_{it} - \bar{U}_t) + \frac{\Delta E_t[U]}{K_t} (U_{it} - \bar{U}_t) + \frac{1}{K_t} \eta_{tj}^q + \frac{1}{K_t} \eta_{t}^r$$

$$- r^{-1} \left( \frac{1}{K_t} (X_{tj} - \bar{X}_t) + \frac{1}{K_t} \bar{X}_t \right),$$

where

$$\eta_{tj}^q = q (V_{tj} - \bar{V}_t) - r \pi_s(p_i/n)(X_{tj} - \bar{X}_t),$$

$$\eta_{t}^r = \frac{1}{n} \bar{q}_s \bar{V}_t^r + q (V_{t} - \bar{V}_t) - r \pi_s(x p_i/n)(\bar{X}_t - \mu_X).$$

and where $\bar{U}_t$, $\bar{V}_t$, and $\bar{X}_t$ are cross-sectional averages of the local factors, the cumulative local public signals, and the liquidity trades, respectively.

(ii) The equilibrium per capita position of informed US investors in stock $j$ at date $t$ is

$$A_{tj}^U = X_{tj} + r \frac{1}{K_t} p_i(t + t_0)(-\pi_t(U_{it} - \bar{U}_t)$$

$$+ q (V_{tj} - \bar{V}_t) - (1 + r^2 \pi_s(p_i/n)(X_{tj} - \bar{X}_t))$$

$$+ r \frac{1}{n} \bar{q}_s (\bar{U}_t - \bar{U}_t - \bar{V}_t) - \left( \frac{1}{n} \bar{q}_s \bar{V}_t^r + q \bar{V}_t \right)$$

$$+ r \pi_s(x p_i/n)(\bar{X}_t - \mu_X) + r^{-1} \mu_X),$$

where $\pi_t$, $\bar{q}_s$, $\bar{V}_t$, and $\bar{X}_t$ are cross-sectional averages of the public signals, the (subjective) posterior mean $\bar{X}_t$, and the (inverse of) the posterior variance $\pi_s(x p_i/n)$. (13)

**Proof.** See Appendix A.

The simple analytical formulae provided in Proposition 1 allow us to conduct comparative statics and trace out how public and private signals are used by investors and become observable in equity flows and returns. Our solution thus goes beyond that in Brennan and Cao (1997) even for the case in which there are no global signals. We use it below to clarify the role of local private information.

### 2.2.2. Price formation

In every trading round, the stock price depends on the true payoff factors $U$, the (cumulative) aggregate errors in public signals, collected in the terms $\eta_{tj}^q$ and $\eta_{t}^r$, as well as the liquidity trades $X$. The first line of Eq. (16) represents
the knowledge-weighted average expectation introduced in Eq. (14). It depends on the unobservable payoff factors $U$ because the latter are reflected in public and private signals. It also depends on aggregate errors in public signals, which affect trades by all investors. In contrast, errors in private signals do not affect the average expectation because they cancel out across investors by the law of large numbers. Aggregate errors contain not only the errors $V$ in the (nonprice) public signals $Y$, but also a term driven by liquidity trades. This is because prices are public signals and liquidity trades create noise in prices. By Eq. (14), liquidity trades matter beyond their effect on the average expectation: The second line of Eq. (16) represents the additional risk adjustment $r^{-1}K_tX_t$.

Because all factors have mean zero, the mean price of stock $j$ is

$$E[p_{t,j}] = \mu_j - \mu_x/rK_t.$$  \hspace{1cm} (18)

The mean price is thus the mean dividend less a risk premium that is inversely related to $k_t = k_t^l + k_t^U$, the parameter that captures the accumulation of average public and private knowledge. The more knowledgeable the average investor is, the less he has to be compensated for risk and the higher is the price.

The price of stock $j$ is higher than its mean if asset $j$ is perceived to be attractive relative to other assets. Eq. (16) shows that this can happen either for fundamental reasons or because of aggregate errors. On the one hand, when the local factor $U^l$ is higher than the average local factor $U^l$, both public and private signals suggest to investors that asset $j$ is valuable, and the price is bid up. Because signals are imperfect, the price does not fully reflect the unobservable payoff; Instead, there is a sequence of positive price changes as average knowledge accumulates ($\Delta k_t^l/k_t^l$ is increasing over time). On the other hand, errors in public signals $V_t^l$ (which enter $\eta_t^l$) induce investors to trade asset $j$. This effect becomes less important over time as an increase in knowledge $k_t^l$ reduces the weight on the error.

The price of stock $j$ is also affected by global shocks. The second line of Eq. (16) shows that the price is high if either the global factor is high or if there is a high realization of the global public signal. Because $\Delta k_t^U/k_t^U$ is increasing over time, a high realization of the global factor gives rise to global momentum: All prices tend to move up together in positively correlated steps. The mechanism is analogous to the case of local shocks: The price moves further away from the mean and closer to the dividend realization, as more signals arrive and beliefs move away from the prior.

The averages of the local factor and errors have similar effects on price as their global counterpart. This is natural because a simultaneous high realization of all local factors, say, has the same effect on signals as an increase in the global factor. However, the mean $\bar{U}$ has variance $1/\tau_l n_l$. With a large number of countries, its volatility is thus an order of magnitude smaller than that of the global factor, which has variance $1/\tau_g$. In what follows, we mostly ignore terms involving $\bar{U}$ in the analysis. Finally, the risk adjustment of stock $j$ is larger than the average premium if the liquidity trades in stock $j$ are high relative to the average liquidity trade. Intuitively, investors require a price discount if they have to incur a higher than average exposure to the local factor $U^l$ in equilibrium. The risk premium decreases over time as average knowledge about the local factor increases.

2.3. Home bias and global return chasing

In this subsection, we derive the main theoretical result of the paper: The model can jointly explain home bias and global return chasing.

2.3.1. US investors’ positions and home bias

US investors’ equilibrium holdings Eq. (17) depend on the same factors as do prices. In the absence of any signals, and hence any disagreement, all investors simply absorb a proportional amount of the liquidity trades $X_t$. Because all liquidity traders are identical, all country portfolios are identical. On average, every informed investor would then hold $\mu_x$ units of every stock; There would be no equity home bias. More generally, the per capita mean demand for stock $j$ by informed investors in the US is given by

$$E[x_{t,j}^{US}] = \mu_j + \frac{1}{nk_t}((\sigma^{US}_l - 2\sigma p_t - p_l(t + t_0))\mu_x).$$  \hspace{1cm} (19)

Home bias emerges in equilibrium if the second term is negative, that is, if

$$p_l(t + t_0) > (\sigma^{US}_l - 2\sigma p_t).$$  \hspace{1cm} (20)

If this condition holds, US investors’ per capita average holdings of foreign stock $j$ are below the per capita mean amount of stock outstanding $\mu_x$. The condition says that local investors’ knowledge, measured by the total precision of all local signals that have arrived up to date $t$, is larger than the knowledge advantage derived by US investors from global signals. Naturally, there must be enough local private information to generate home bias.

Consider next how US positions vary with the different shocks. The first line of Eq. (17) shows the impact of local factors. The higher is the local factor $U^l$ relative to the cross-sectional mean, the less of the equity from region $j$ is held by US investors. This is because local factors are better understood by local investors who buy up local stocks when the local factor promises high payoffs. In contrast, positive errors $V_t^l$ in local public signals increase investment by US investors who overreact to such errors, mistaking them for good news about the local factor.

The second and third lines of Eq. (17) show the effect of global factors on holdings. We focus on the case in which there is home bias. US investors’ positions in foreign countries at any point in time decrease with the global factor $U^F$. Intuitively, a high global factor affects dividends and is therefore reflected not only in global signals, but also in local signals around the world. Because the sum of these signals is more precise than the global signals (this is precisely the condition for home bias above), US home bias is more pronounced when a global boom occurs. At the same time, US investors’ access to global private information reduces home bias over time.
2.3.2. Global shocks and return chasing

The main fact we are interested in is return chasing, or positive co-movement of local returns in a market with US investors’ net purchases in that market. In the context of our model, returns from one trading period to the next are simply changes in the price, while changes in US investors’ market share in region $j$ correspond to changes in the position $x_{ij}^{US}$. It is helpful to think of an econometrician who observes a large number of trades and price changes generated by the model, possibly based on different realizations of the fundamentals $U$. Formulas (16) and (17) reveal the extent to which various shocks induce positive co-movement of local returns and US net purchases in the eyes of the econometrician.

Consider first the effect of the global factor $U^g$ on changes in prices and US positions. The coefficient on $U^g$ in Eq. (16) is increasing over time: As investors learn, the price function places more and more weight on the true realization of the global factor. It follows that a shock to $U^g$ induces return chasing if, and only if, the coefficient on $U^g$ in Eq. (17) also increases with time. Suppose this is true and that the realization of $U^g$ is, say, high. US investors’ positions then gradually increase over time, an increase that must be achieved by a sequence of stock purchases in foreign markets. At the same time, prices (in all countries) increase as they move closer to reflecting the true high dividend component $U^g$. Similarly, when $U^g$ is low, US investors’ positions in all foreign countries decrease as prices there decrease toward lower dividend realizations.

In sum, if the coefficient on $U^g$ in Eq. (17) is increasing in time, the time series of returns and US net purchases contain a component, proportional to $U^g$, that must be achieved by a sequence of stock purchases in foreign markets. At the same time, prices (in all countries) increase as they move closer to reflecting the true high dividend component $U^g$. On the other hand, if $U^g$ is low, US investors’ positions in all foreign countries decrease as prices there decrease toward lower dividend realizations.

In this subsection, we further characterize the joint dynamics of returns and equity flows implied by our model. First, we show that private information leads to return chasing. The coefficient on $U^g$ in Eq. (17) is increasing in time if, and only if,

$$\left(\alpha_{U^g} - \alpha\right)p_{g} > p_i - \frac{p_{i0}}{k_0} \left(q_l + q_g + p_k \frac{1}{n} + \alpha \frac{n-1}{n} \right) + \pi_t \left(\alpha p_{g} + p_i/n\right)^2. \tag{21}$$

Intuitively, this condition says that US investors become more informed about the global factor over time, relative to local investors. As US investors learn more about the true realization of the global factor, their position reflects that realization more closely; i.e., the weight on $U^g$ increases.

Two features of the information structure matter for return chasing. First, US investors become relatively more informed over time if their global private signals are sufficiently precise, that is, other things equal, inequality (21) holds as long as $p_{g}$ is large enough. Second, US investors tend to learn more if they know relatively little to begin with, that is, if the initial advantage of local investors is large (high $t_0$). This is because there are always public signals that gradually reveal any information that makes up local investors’ initial advantage. Even if there is no exogenous public signal ($q_l = q_g = 0$), prices partially reveal the content of local private signals, especially if there is not much noise from liquidity trades ($\pi_t$ large). Whenever some initial information advantage of local investors ($t_0 > 0$) exists, US investors thus become relatively more informed about the global factor over time as long as the available public signals, including prices, are sufficiently precise.

It remains to show that conditions (20) and (21) are mutually compatible, so that the model jointly predicts home bias and return chasing by US investors. Proposition 2 says that both facts emerge in equilibrium as long as local investors’ initial information advantage (measured by the number of initial local signals $t_0$) is sufficiently large.

**Proposition 2.** Assume $\alpha_{U^g} > \alpha$. For any set of signal precisions, a threshold exists for local investors’ initial information advantage, captured by the number of initial signals $t_0$, such that if $t_0$ is above the threshold then (i) US investors’ portfolios are on average biased against foreign stocks and (ii) there is a common factor in US investors’ international equity trades that induces global return chasing.

**Proof.** See Appendix A.

We draw two main lessons from this analysis. First, if global information, either private or public, is important, there should be global return chasing: positive correlation of US net purchases in one country with returns in another country. This fact is shown in Section 3. Second, if global private information is important, then trades based on private information should be correlated across target countries. This is examined in Sections 4 and 5.

Another lesson is that return chasing could reflect superior performance of US investors, because it could be driven by global private information. A high realization of the global factors induces a period in which prices increase as US investors buy. Moreover, subsequent global returns are high as the price reveals more and more of the true global factor. To an observer, it thus looks as if US investors bought at precisely the right time, on average. This result shows that studies in the literature concluding superior performance by foreigners are not incompatible with an asymmetric information explanation of home bias and return chasing.

2.4. Price volatility and changes in risk premia

In this subsection, we further characterize the joint dynamics of returns and equity flows implied by our model. First, we show that private information leads to price changes that an observer, such as an econometrician performing an empirical asset pricing study, attributes to changes in risk premia, not changes in cash flows. In particular, we show that the shocks that induce return chasing also induce changes in risk premia. This result is reassuring, because empirical work has shown that most stock price volatility in the data is due to changes in risk premia, not changes in expected cash flows.

In the empirical asset pricing literature, it is common to decompose price movements into changes in expected future dividends (cash flow news), and other movements, often labeled changes in discount rates. The latter make
up the bulk of price movements at the aggregate level and are hard to generate in standard asset pricing models. In our model, investor learning contributes to measured changes in discount rates when investors have private information. Consider an econometrician who performs a price decomposition based on data from our model. His starting point is a forecast of cash flow that is necessarily based on public information. For simplicity, assume a perfect model of cash flow, that is, the econometrician’s forecast is the theoretical expectation based on public information, $E[U]$. We can then write the price Eq. (14) as

$$P_t = E_t[U] - r^{-1}K_t^{-1}X_t + K_t^{-1} \int K_t(E_t[U] - E_t[U]) di. \quad (22)$$

If there is no private information, then $K_t = K_t$ and $E_t[U] = E_t[U]$; The price equals the expected dividend given public information, $E_t[U]$, less a vector $r^{-1}K_t^{-1}X_t$ of risk premia commanded by a representative investor. Except for (temporary) shocks due to liquidity traders, movements in the price are then due to movements in expected cash flows. More generally, investors have private information that makes their individual forecasts $E_t[U]$ different from the econometrician’s forecast $E_t[U]$. This introduces a new source of price movements: changes in the knowledge-weighted difference between private and public (or econometricians’) forecasts. The econometrician interprets these movements as changes in risk premia, relative to his public information benchmark.

To further characterize time variation in measured risk premia, define the ratio of private to public information in the market, for both local and total information:

$$\rho_t^i = \frac{p_t(t_0 + t)/n}{(K_t^- - p_t(t_0 + t)/n)}, \quad \rho_t = \frac{2p_tI_t + p_t(t_0 + t)/n}{K_t - 2p_tI_t - p_t(t_0 + t)/n}. \quad (23)$$

Both ratios are positive as long as there is some local private information. Appendix A shows that the price of stock $j$ can be written as

$$P_t = E_t[U] - r^{-1} \left( \frac{1}{K_t} (X_t - X_t) + \frac{1}{K_t} X_t \right)$$

$$+ \rho_t (k_0(U_t - O_t') - \eta_t^j) + \rho_t (k_0(U^t - O^t') - \eta_t^j). \quad (24)$$

Here, the first line is the price implied by a representative agent model when agents share only the public information. The second line represents the knowledge-weighted difference between private and public forecasts, expressed in terms of the various shocks.

It follows that time-varying risk premia in our model are correlated with the payoff factors $U$. In particular, from the perspective of the econometrician, prices appear to overreact to changes in fundamentals. For example, when $U^g$ is high, the econometrician observes jointly a high price and a low expected excess return $E_t[U] - P_t$. This drop in the (measured) expected excess returns is not due to changes in risk or risk aversion; Instead, it occurs because investors receive favorable private information that drives up the stock price. We conclude that the same shocks that induce global return chasing in our model also contribute to time variation in risk premia.$^6$

2.5. The role of local private information

In this subsection, we show that local private information can contribute to return chasing in a single country, but only if local public information is sufficiently important in the market. In contrast, global private information generates global return chasing and does so even in the absence of public information.

The explicit formulas for prices and positions in Proposition 1 clarify the contribution of local shocks to return chasing. Suppose, for instance, that the local factor $U^l$ is higher than the cross-sectional mean $\bar{U}$. The local shock induces return chasing if the first component of the price Eq. (16) is increasing over time. Return chasing in country $j$ thus obtains when the corresponding component of US investors’ positions also increase over time, so that the sequence of positive price changes is accompanied by a sequence of US purchases. The coefficient on $U^l_j$ in Eq. (17), is increasing over time if, and only if,

$$\pi_t < t_0 (r^2 p_t^2/n^2 + q_t). \quad (25)$$

Local fundamental shocks in country $j$ induce return chasing in that country only if there is some initial information advantage of local investors ($t_0 > 0$) and local shocks become public to a sufficient extent (the bracketed term on the right-hand side is large enough). The intuition is analogous to the above discussion of global return chasing: A shock to $U^l_j$ leads US investors to chase returns in country $j$ if the arrival of more local signals over time makes US investors more informed about the local factor. The latter tends to be true if there are more precise public signals (high $q_t$), if a significant amount of the information contained in local private signals is revealed by prices, and if local investors’ initial information advantage is larger (which makes the reaction to any signal stronger).

It follows that, if information is local, a natural tension exists between information asymmetry and return chasing: The latter occurs only if local public information is sufficiently important. If, instead, local private information is important and not revealed by prices, for example, if there are no public signals and liquidity trades are very volatile (small $\pi_t$), then local investors’ information advantage grows over time and the local factor does not contribute to return chasing. This tension does not arise, however, when information is global because both private and public global signals serve to make US investors relatively more informed about the global factor.$^7$

$^6$ At the same time, an econometrician who views data from the model would find that prices underreact to public signals. The effect of $q_t$ and $q_t^2$, which contain the errors in public signals, on the price is positive, whereas the effect on the second line of Eq. (24) is negative. It follows that the expectation $E_t[U]$ responds more to public signals than the price. The reason is that investors have access to both public and private information and hence put a smaller weight on the former than an econometrician.

$^7$ For public signals, this follows because the coefficients on the cumulative errors in both Eqs. (16) and (17) are positive.
particular, the presence of public signals is not needed for the global factor to induce global return chasing.

The presence of public signals contributes to return chasing in a second way. Because the coefficients on the cumulative errors $\delta_{it}$ in both Eqs. (16) and (17) are positive, the arrival of such an error makes local returns and US net purchases move together. For example, a positive error misleads all investors to believe that dividends are high, thus driving up the stock price. At the same time, the initially less informed US investors put more weight on the signal. They are therefore misled more and purchase stocks from local investors. This mechanism, emphasized by Brennan and Cao (1997), implies that return chasing can reflect underperformance of US investors. After a positive error has occurred, subsequent returns are low on average, because the true dividend is not related to the error and the price must thus come down from its temporarily inflated value. From the point of view of an observer, US investors have thus purchased local stocks at exactly the wrong time, on average.

3. US international equity flows

This section describes the data used in the empirical analysis.

3.1. Data

Data on gross purchases, gross sales, and net purchases of foreign equities by US residents are obtained from the Treasury International Capital (TIC) reporting system of the US Treasury. The TIC data have one important advantage for our study. The data contain the equity flows across a large cross-section of countries with long, coincident time spans. This is typically not available in other data sets and is necessary to measure common components in unexpected flows and their effects on asset prices. The TIC data have two main weaknesses. First, the Treasury does not collect data on transactions in equity derivative securities, which have grown in importance in recent years. To the best of our knowledge, this criticism applies to all data sets used in this literature. Second, the Treasury collects data by geographic center and not by the security’s country of origin. This means that the data could be unrepresentative of countries such as the UK and Switzerland that host large international financial centers. The typical example of this problem is a European company that issues securities in the euro-equity market, selling them through banks in London to US investors. This transaction is recorded as a sale of UK equity (Warnock and Cleaver, 2002).

In this paper, we examine transactions by US investors in the equity markets of eight large, developed countries (Canada, France, Germany, Italy, Japan, Netherlands, Switzerland, and UK) which account for approximately 68% of the market value of non-US markets at the end of our sample period. We restrict the analysis to a group of relatively homogeneous, developed countries to correctly measure the public and private components of US net purchases; Flows in and out of the equity markets in these countries are likely to be driven by stable economic relations. In contrast, the ongoing process of liberalization of equity markets in developing countries leads to capital flows that are mostly driven by changing risk-sharing opportunities or declining transactions costs (e.g., Stulz, 1999; Bekaert and Harvey, 2003). Distinguishing these effects from the asymmetric information effect in flows is difficult. Moreover, empirical models of portfolio flows into emerging markets suffer from nonstationarity due to structural breaks from changing foreign ownership restrictions that make them difficult to estimate. This is perhaps one of the reasons that researchers have focused on aggregate or regional data for these countries (e.g., Froot, O’Connell, and Seasholes, 2001; Bekaert, Harvey, and Lumsdaine, 2002).

Table 1 details our data set, which ranges from January 1977 (the start of the monthly TIC data) to April 2007. We normalize the flows data by dividing by Datastream’s beginning-of-period index of foreign equity market capitalization. The table reveals three properties of US international equity flows: (1) gross flows are much larger than net flows, with numbers for the UK likely overstated because London is an international financial center; (2) gross flows have higher volatilities, but lower coefficients of variation, than net flows; and (3) flows display considerable serial correlation, with net flows reversing after one year, though they all appear stationary. Persistence of US equity flows is consistent with persistence of order flow of individual stocks (Hasbrouck, 1991) and persistence of mutual fund flows (Warther, 1995).

Table 2 presents the summary statistics of data on excess returns. We use the end-of-month equity return index from Datastream translated into US dollars and subtract from it the US risk-free interest rate. Table 2 shows that the volatility of excess returns is much larger than that of equity flows. This has implications when we try to model the expected portions of flows and returns. The indexes are based on the firms with the largest equity values in each country. Because evidence exists that US investors tilt their portfolios toward the largest companies in each market, we assume, as is usual in the literature, that the returns on these indexes track closely the returns actually obtained by US investors in foreign markets.

3.2. Local versus global return chasing

Table 3 presents the correlations of excess returns with US investors’ net purchases of foreign equities. The main diagonal of the table illustrates the well-known fact of local return chasing by US investors: In each country, US net purchases of equities correlates positively with excess returns. With the exception of Switzerland and the UK, these correlations are statistically significant at the 5% level.
One would then expect a gradual trend movement. In contrast, the global private information story we introduce is relevant at frequencies in which private information is likely to be relevant, which includes business cycle or higher frequencies. To gauge the importance of low frequency movements for global return chasing, we remove a linear trend from all our flow series. We redo Table 3 with the detrended series. The results are shown in Table 4 and suggest significant global return chasing at high frequencies as measured by the correlation of detrended flows and returns. Most correlations remain positive and significant, and all of the nine negative correlations are insignificant.

Recall how global return chasing arises in our model. After a positive shock to a global factor, prices rise in all countries at the same time that US investors increase their positions in all countries. While this could appear to be an irrational response, it is optimal for US investors because they are better informed about the global factor than any other investor in the world. Following the lead of the model, in the rest of the paper we study the phenomenon of global return chasing as it relates to US investors’ global private information. We first extract a measure of co-movement in unexpected US net purchases of foreign stocks and call it the global private information of US investors. We show that global private information is a nontrivial component of US trading. Second, we show that foreign stock market returns also respond positively to shocks to global private information. The combination of the two facts implies that global private information is an important driver of global return chasing.

### 4. Measuring trades based on private information

In this section, we estimate empirical models of international equity flows and present measures of private information. If private information is to be valuable, equilibrium prices must not be fully revealing. In our model this is true due to the presence of noise traders, but prices are also nonrevealing if there is private information about nontraded labor income or the number of market participants. With nonrevealing prices, investors’ trades contain private information that we can measure.

To obtain a measure of trades based on private information, we need to provide an empirical framework that accounts for trades due to public information. With high frequency microstructure data, as in Hasbrouck (1991), this is easily achieved by regressing trades on lagged trades and lagged prices, because at this frequency the public news can be assumed to impact trades only indirectly via the price. The residual of this regression is a
measure of private information. (It is a noisy measure of private information as it contains transient liquidity shocks.) With our data sampled with a monthly frequency, we generalize Hasbrouck’s approach by allowing the public information contained in variables other than prices to also drive flows directly.
4.1. Expected international equity flows

To measure expected equity flows we use four different comprehensive sets of public information variables. In the first public information set (A), we use an autoregressive model to capture the expected portion of the flows. This is motivated by two reasons. First, our model suggests that the diffusion over time of private information generates persistence in flows (from changes in the terms $k_1^t$ and $k_2^t$). Second, as noted in Table 1, US flows are persistent.

In the second and third information sets (B and C), we choose public information variables that have been shown to predict the cross-section of international equity returns. These account for trades driven by myopic demand changes or hedging demand changes, which are correlated with the variables that drive expected returns. It is common to separate these variables into two groups, global and local, where the use of local variables is justified by the existence of incomplete international risk sharing (e.g., Harvey, 1991; Ferson and Harvey, 1993, 1994). From this literature we select the US short-term interest rate, the US credit spread, the dividend yield on the global stock market, the slope of the US term structure, and the US equity return to act as global variables. The global variables, along with lagged flow variables, are used as our second data set (B). Table 2 provides the summary statistics of the global instruments, which resemble those in many other papers.

The inclusion of the US stock market return, the US short-term interest rate and slope of the term structure, and the US credit spread is important for two additional reasons. First, they reflect public information about the US that might lead US investors to trade abroad. Second, the inclusion of these variables accounts for trading that is much more predictable than net purchases.

Table 4

Local and global return chasing: correlations of linearly detrended US investors' net purchases of foreign equities with foreign excess stock returns.

The table shows correlation coefficients of linearly detrended US investors' net purchases of foreign equities with foreign excess returns. The net purchases data are presented in Table 1, and the excess returns are given in Table 2. Below each correlation estimate is the $p$-value of the null hypothesis that the correlation is zero. The numbers in bold represent significance at the 10% cent level or better.

<table>
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<tr>
<th>US investors' net purchases of foreign equities in</th>
<th>Canada</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>Japan</th>
<th>Netherlands</th>
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[footnote continued]

directly in modeling gross purchases and sales, which turn out to be much more predictable than net purchases.

11 Most of the data are from Datastream. We use the 30-day euro-currency rate on the last business day of each month as the risk-free interest rate for each country. We use the Datastream equity return index and dividend yield on the index available at the end of each month. The dividend yield series is deseasonalized in the usual manner (we take the average dividend over the last 12 months and divide by the current price). The exchange rate is reported daily by Datastream in UK pounds, and we translate the end-of-month values into US dollar equivalents. The US credit spread is the difference between the AAA and BBB bond yields available at the US Federal Reserve website. The term structure slope is the long bond yield from the OECD database less the 30-day euro-dollar interest rate.

See Albuquerque, Bauer, and Schneider (2007) for an alternative theoretical justification.

Bohn and Tesar (1996a, b) also separate their instruments into local and global groups and find that net purchases are related to the cross-section of expected equity returns using a similar list of instruments. Our approach differs from theirs by using the variables available at the US Federal Reserve website. The term structure slope is the long bond yield from the OECD database less the 30-day euro-dollar interest rate.
motivated by changes in US stockholders’ wealth (as captured by the returns on the stock, government, and corporate bond markets). We include these variables for completeness but are aware that Bohn and Tesar (1996a) show that portfolio rebalancing is not an important determinant of US investors’ net trades abroad.

The information set (C) adds local variables for each foreign country to information set (B). These local variables are the country’s stock return (to capture any local return chasing activities by investors), the country’s dividend yield and interest rate differential to the US, and the change in the spot exchange rate of the country’s currency against the US dollar.

To construct our fourth information set (D), we rely on the literature that examines the links between trading activity and market volatility. This literature shows a positive contemporaneous correlation between conditional volatility and trading volume (e.g., Lamoureux and Lastrapes, 1990; Gallant, Rossi, and Tauchen, 1992). As our international equity flows represent the trading activity of a specific group of investors, it could be that they are correlated with conditional volatility and that instruments forecasting time-varying second moments can also forecast the flows. We thus use a very simple autoregressive conditional heteroskedasticity (ARCH) type representation to capture these potential effects. We form a small vector autoregression (VAR of order 1) composed of the US excess equity return, the foreign country excess equity return, and the change in the spot exchange rate between the two countries. The squared estimated residuals from this VAR act as instruments to forecast future flows. Again we include lagged flows in information set (D) to capture any additional missing variation.

The long list of variables we consider is designed to avoid the concern that our measure of private information-based trading is picking up idiosyncratic shocks that are orthogonal to private information about future asset returns. Possible examples include hedging demand trades triggered by news about individual human capital or trades due to individual liquidity shocks. On the one hand, the impact of such shocks on our measure of private information is mitigated by the averaging of individual trades; in any given month, some investors typically receive positive liquidity shocks, while others receive negative shocks. To the extent that these idiosyncratic trades survive aggregation, it should be possible to explain them through changes in observable aggregate public information variables. We do this via the long list of variables discussed above.

On the other hand, liquidity shocks could be correlated across investors and be hard to explain with public information variables, e.g., aggregate noise trades. These trades naturally contaminate our measure of trades due to private information and bias our results toward not finding anything. We demonstrate below that this measurement error is not serious because (1) we find that our measure of trades based on private information is correlated across countries, while it is not clear why noise trades should be correlated across countries, and (2) that the global factor extracted from our measure of private information helps predict future returns (see Section 5).

The latter finding is inconsistent with an i.i.d. sequence of noise trades that only exert temporary price pressure.

A final criticism of our approach is that the model of expected equity flows does not impose enough structure to separate private information from portfolio inventory shocks or other microstructure type shocks (e.g., smoothing of the price process by the specialist, stale quotes). However, these microstructure effects are important at very short horizons of one day or less, whereas our data are monthly.

4.2. Private information based trades

Define the econometrician’s information set as

\[ \tilde{\Omega}_t = \{Z_t, (Z_{t-h}, NF_{t-h}^{US})_{h=1} \}. \] (26)

\( \tilde{\Omega}_t \) describes the information used by the econometrician to predict net flows in month \( t \). The vector \( Z_t \) contains public information variables as described above, which we separate from lagged US net flows, \( NF_{t-h}^{US} \) (information set A). All time \( t \) variables are measured at the end of the month, including returns realized during the month, both in the target country and in the US market. This implies that all publicly relevant information is reflected in \( \tilde{\Omega}_t \) at least through its effect on current stock prices. The measured residuals from a linear projection of the net flows \( NF_t^{US} \) on the information set \( \tilde{\Omega}_t \) are given by

\[ \hat{\nu}_t = NF_t^{US} - E(NF_t^{US} | \tilde{\Omega}_t). \] (27)

Given our discussion above on the motivations for trading and our long list of variables in the information set \( \tilde{\Omega}_t \), it follows that the residuals \( \hat{\nu}_t \) reflect trades due to private information.

Unfortunately, the residual \( \hat{\nu}_t \) is likely to underestimate the average trade due to private information in a given month. This happens when private information that drives trades within the month is later incorporated into prices and hence in the information set \( \tilde{\Omega}_t \). We thus label \( \hat{\nu}_t \) our conservative measure of private information and view it as a lower bound on the contribution of private information to unexpected flows. For comparison, we provide a measure that acts as an upper bound on the contribution of private information. This broad measure is constructed using beginning-of-period values of the public information variables. Let \( \Omega_t = \{Z_t, (NF_{t-h}^{US})_{h=1} \} \), so that no end-of-period variables are included. Using this information set the econometrician recovers the residuals

\[ \nu_t = NF_t^{US} - E(NF_t^{US} | \Omega_t). \] (28)

The broad measure is likely to overstate the effects of private information if investors trade on unexpected public information released during the month. Nevertheless, it is reassuring that our main results below are similar for the two measures.

A potential concern with using residuals as a measure of private information is that we could be picking up the effect of public information that is observed by investors, but not by the econometrician, that is, \( \hat{\Omega}_t \) or \( \nu_t \) might not contain the full public information vector. This is a concern with the broad measure; Here the best we can
do is include in $\Omega$, as many good predictors of flows as we can. However, this concern does not apply to the conservative measure. By including returns over the month when the flow is measured in the information set $\Omega$, we ensure that the conservative measure is orthogonal to any public information that is released during the month and is relevant for future returns. This is because any relevant public information is quickly incorporated into prices.\footnote{Andersen, Bollerslev, Diebold, and Vega (2007) show that news about a number of public information variables are incorporated into stock prices within a five minute period.}

### 4.3. Regression results

Summary statistics for ordinary least squares (OLS) regressions of gross purchases and gross sales on the four different information sets are presented in Tables 5 and 6, respectively.\footnote{The regressions are part of a system of just-identified equations that is estimated by generalized method of moments as described in Appendix B.} These regressions use beginning-of-month values of the variables (i.e., information set $\Omega_t$). The regressions using end-of-month values (i.e., information set $\Omega_{t-1}$) produce similar results and are available on request. A simple auto-regressive specification (information set A) is able to capture a large part of the expected flow variation with $R^2$ measures (adjusted for degrees of freedom) ranging from 0.335 for France up to 0.958 for the UK for gross purchases by US residents. A similar range is recorded for gross sales by US residents.\footnote{The optimal lag lengths for information set A are chosen by the BIC criterion. Our tests are robust to the choice of lag length (results available on request).}

With information set B, most of the regressions show slightly higher $R^2$ and joint significance of the global variables (excluding lagged flows). Thus, the global instruments that are typically used to explain the cross-section of international equity returns also explain the cross-section of international equity flows. It is clear, however, that most of the predictability comes from including the lagged values of the flows as the $R^2$ statistics increase only marginally.

We test for the predictability of the local instruments using information set C. The $R^2$ statistics increase slightly from adding the local variables to the regressions, except for those explaining gross purchases of Italian equities and gross sales of French and Italian equities. However, the local variables as a group are jointly significant at the 10% level for equity flows in and out of only a small number of countries.

The fourth information set (D) uses lagged values of squared residuals to capture any time variation in flows related to time-varying volatility. The statistics show that, while these instruments are significant in some of the regressions, they do not help to explain time variation in expected flows much beyond that captured by the lagged flow itself.

Table 7 provides the $R^2$ and Wald test statistics for the OLS regressions of the net equity flows on the four information sets. The striking fact is that net flows are much less predictable than either of the gross flows. This is even more striking as most of the existing literature has focused on explaining the expected component of net portfolio equity flows. Using instrument set A, the $R^2$ statistics for the net flow regressions range from 0.023 for Italy to 0.419 for Japan. The global, local, and heteroskedastic variables appear to generate a small amount of extra predictability in the net flows regressions.

In summary, we find that much of the predictability of flows derives from lagged flows and that gross flows are more predictable than net flows.

Our results also have interest for more general international asset pricing applications using similar forecasting variables. One potential criticism of most asset pricing applications is that many of these variables have been chosen by an on going implicit process of data snooping, i.e., choosing the variables based on ex post statistical criteria of return predictability. To the extent that the flows data represent a new source of information, the (limited) predictability shown here could alleviate some of these concerns.

### 4.4. Residuals as measures of private information

The regressions detailed in Section 4.3 offer a way of estimating the expected portion of the gross and net portfolio equity flows. Following our derivations in Section 4.2, the private information of US residents can be estimated by the unexpected portion of the net equity flows.\footnote{Kaufmann, Mehrrez, and Schmukler (2005) proceed in a similar fashion to obtain a measure of private information. They use survey data on firm managers’ assessments of how the economy will perform. The advantage of using flow data is that investors actually put their money where their mouth is.} In this subsection, we discuss only the construction of our broad measure of private information and note that the exact same steps apply for our conservative measure.

Recall from Eq. (28) that the vector of broad measures of private information is obtained from the unexpected net portfolio flows into the equity markets of the eight foreign countries and is denoted by $v_t = (v_{1,t}, \ldots, v_{8,t})$. Our regression results allow two possible routes to estimating $v_t$. One is to use net purchases of equities by US investors in each foreign country as the dependent variable (Table 7). The residual from that regression is $v_t$ as desired. An alternative route is to estimate the regressions for gross sales and gross purchases separately and let

$$v_{nt} = v_{nt}^p - v_{nt}^s,$$

where $v_{nt}^p$ and $v_{nt}^s$ are the residuals from the gross purchases and gross sales regressions (Tables 5 and 6), respectively.

Although the gross flow regressions show substantially greater explanatory power than their net flow counterparts, it is uncertain as to whether the expected portion of the net flows are modeled better by using the difference between the expected gross flows or by using the net flows directly in a regression. To answer this, we construct...
an expected net flow variance ratio. The numerator is the variance of the expected net flow from the net flow regressions (Table 7). The denominator is the variance of the implied expected net flow constructed using the difference between the expected gross purchases and expected gross sales (Tables 5 and 6). A ratio below 1.0 indicates that the approach using the gross flow regressions is to be preferred. We also test whether this difference is statistically significantly different from 1.0.16

Table 8 presents the estimated variance ratios and the small-sample marginal significance levels (p-values) of the Wald test statistics. For all countries and information sets, the ratios are below 1.0, often by a substantial amount. The p-values indicate that all of the ratios are significantly different from 1.0 at the 5% level, except those from France, which are significantly different at the 10% level. It appears that this result is primarily driven by the different time-series properties of the gross purchases.

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16 As described in Appendix B, the variance ratio and its standard error are estimated using GMM on the same system of just-identified equations that produces the linear regressions shown in Tables 5, 6 and 7. In this way the standard error on the variance ratio reflects the estimation uncertainty in the regression parameters.

**Table 5**

Summary statistics from ordinary least squares (OLS) regressions of US investors’ gross purchases of foreign equities on different information sets.

The table presents summary statistics from OLS regressions of gross purchases of foreign equities by US investors on four information sets: (A) lagged gross purchases, (B) lagged gross purchases plus the global instruments, (C) lagged gross purchases plus global and local instruments, and (D) lagged gross purchases plus lagged squared residuals from a vector autoregression of the US excess stock return, the foreign country excess stock return, and the change in the exchange rate. The global instruments are detailed in Table 2. The local instruments (all lagged three periods) are the foreign country’s stock return, the foreign country’s dividend yield, the difference in interest rates between the foreign country and the US, and the change in the spot exchange rate of the country’s currency against the US dollar. The regressions are part of a system of just-identified equations that are estimated by generalized method of moments as described in Appendix B. The $R^2$ statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2$) along with its small-sample marginal significance level (p-value). The small-sample adjustment follows the procedure outlined in Ferson and Foerster (1994).

<table>
<thead>
<tr>
<th>Country</th>
<th>Instrument set</th>
<th>(A) lagged gross purchases</th>
<th>(B) lagged gross purchases + global instruments</th>
<th>(C) lagged gross purchases + global + local instruments</th>
<th>(D) lagged gross purchases + squared residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\bar{R}^2$</td>
<td>$\chi^2$ for lagged gross purchases, p-value</td>
<td>$\bar{R}^2$</td>
<td>$\chi^2$ for global variables, p-value</td>
<td>$\bar{R}^2$</td>
</tr>
<tr>
<td>Canada</td>
<td>0.744</td>
<td>950.99 &lt; 0.001</td>
<td>0.750</td>
<td>11.21 0.047</td>
<td>0.754</td>
</tr>
<tr>
<td>France</td>
<td>0.335</td>
<td>191.64 &lt; 0.001</td>
<td>0.356</td>
<td>13.64 0.018</td>
<td>0.363</td>
</tr>
<tr>
<td>Germany</td>
<td>0.775</td>
<td>1404.72 &lt; 0.001</td>
<td>0.780</td>
<td>12.03 0.034</td>
<td>0.781</td>
</tr>
<tr>
<td>Italy</td>
<td>0.487</td>
<td>286.36 &lt; 0.001</td>
<td>0.497</td>
<td>11.13 0.049</td>
<td>0.491</td>
</tr>
<tr>
<td>Japan</td>
<td>0.927</td>
<td>4042.65 &lt; 0.001</td>
<td>0.929</td>
<td>9.64 0.086</td>
<td>0.930</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.624</td>
<td>360.84 &lt; 0.001</td>
<td>0.633</td>
<td>19.87 0.001</td>
<td>0.639</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.452</td>
<td>220.40 &lt; 0.001</td>
<td>0.464</td>
<td>5.71 0.336</td>
<td>0.468</td>
</tr>
<tr>
<td>UK</td>
<td>0.958</td>
<td>7819.17 &lt; 0.001</td>
<td>0.958</td>
<td>13.8 0.927</td>
<td>0.959</td>
</tr>
</tbody>
</table>
and sales that are obscured when one models net flows directly. This is shown in the first column of the table, which compares the variances of the estimates using the AR models for the flows. Adding on other information variables to the basic AR specification raises the variance ratios in all cases. In the following, therefore, we use the gross flow residuals to construct our measures of private information according to Eq. (29).

### 4.5. Global factors in private information

Our model hypothesizes that US investors use global private information signals that help them forecast international returns and make investment decisions across international stock markets. Therefore, to measure global private information, we construct a linear combination of unexpected net flows

\[ I_t = \phi I_t, \]

which explains a large fraction of the variance of \( \nu_t \). We also define \( I_t = \phi I_t \) as the global factor in private information using the conservative measure. In either case, a global factor in private information is consistent with traders having private information about the global variables driving factor returns.

We perform a factor analysis on the residuals from the gross purchases and sales regressions separately (\( \nu_{P,t} \) and \( \nu_{S,t} \), \( n = 1, \ldots, N \)). The factor analysis is done by both the method of iterated principal factors and by maximum-

### Table 6

Summary statistics from ordinary least squares (OLS) regressions of US investors’ gross sales of foreign equities on different information sets.

The table presents summary statistics from OLS regressions of gross sales of foreign equities by US investors on four information sets: (A) lagged gross sales, (B) lagged gross sales plus the global instruments, (C) lagged gross sales plus global and local instruments, and (D) lagged gross sales plus lagged squared residuals from a vector autoregression of the US excess stock return, the foreign country excess stock return, and the change in the exchange rate. The global instruments are detailed in Table 2, and the local instruments are detailed in Table 5. The regressions are part of a system of just-identified equations that are estimated by generalized method of moments as described in Appendix B. \( \hat{R}^2 \) The statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column (\( \chi^2 \)) along with its small-sample marginal significance level (\( p \)-value). The small-sample adjustment follows the procedure outlined in Ferson and Foerster (1994).

<table>
<thead>
<tr>
<th>Country</th>
<th>Instrument set</th>
<th>(A) lagged gross sales</th>
<th>(B) lagged gross sales + global instruments</th>
<th>(C) lagged gross sales + global + local instruments</th>
<th>(D) lagged gross sales + squared residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \hat{R}^2 )</td>
<td>( \chi^2 ) for lagged gross sales, p-value</td>
<td>( \hat{R}^2 )</td>
<td>( \chi^2 ) for global variables, p-value</td>
<td>( \hat{R}^2 )</td>
</tr>
<tr>
<td>Canada</td>
<td>0.792</td>
<td>0.384</td>
<td>0.792</td>
<td>0.738</td>
<td>0.798</td>
</tr>
<tr>
<td>France</td>
<td>0.370</td>
<td>0.181</td>
<td>0.394</td>
<td>0.145</td>
<td>0.391</td>
</tr>
<tr>
<td>Germany</td>
<td>0.820</td>
<td>0.442</td>
<td>0.824</td>
<td>0.145</td>
<td>0.828</td>
</tr>
<tr>
<td>Italy</td>
<td>0.422</td>
<td>0.147</td>
<td>0.440</td>
<td>0.683</td>
<td>0.438</td>
</tr>
<tr>
<td>Japan</td>
<td>0.947</td>
<td>4.024</td>
<td>0.946</td>
<td>0.724</td>
<td>0.948</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.707</td>
<td>0.541</td>
<td>0.712</td>
<td>0.603</td>
<td>0.723</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.277</td>
<td>0.738</td>
<td>0.291</td>
<td>0.548</td>
<td>0.295</td>
</tr>
<tr>
<td>UK</td>
<td>0.958</td>
<td>9.017</td>
<td>0.958</td>
<td>3.99</td>
<td>0.959</td>
</tr>
</tbody>
</table>
Table 7
Summary statistics from ordinary least squares (OLS) regressions of US investor’s net purchases of foreign equities on different information sets.

The table presents summary statistics from OLS regressions of net purchases of foreign equities by US investors on four information sets: (A) lagged net purchases, (B) lagged net purchases plus the global instruments, (C) lagged net purchases plus global and local instruments, and (D) lagged net purchases plus lagged squared residuals from a vector autoregression of the US excess stock return, the foreign country excess stock return, and the change in the exchange rate. The global instruments are detailed in Table 2, and the local instruments are detailed in Table 5. The regressions are part of a system of just-identified equations that are estimated by generalized method of moments as described in Appendix B. \( R^2 \) The statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column \( (\chi^2) \) along with its small-sample marginal significance level \( (p\text{-value}) \). The small-sample adjustment follows the procedure outlined in Ferson and Foerster (1994).

<table>
<thead>
<tr>
<th>Country</th>
<th>Instrument set</th>
<th>( R^2 )</th>
<th>( \chi^2 ) for lagged net purchases, p-value</th>
<th>( R^2 )</th>
<th>( \chi^2 ) for global variables, p-value</th>
<th>( R^2 )</th>
<th>( \chi^2 ) for local variables, p-value</th>
<th>( R^2 )</th>
<th>( \chi^2 ) for squared residuals, p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>(A) lagged net purchases</td>
<td>0.200</td>
<td>89.73 &lt; 0.001</td>
<td>0.220</td>
<td>6.62 0.251</td>
<td>0.240</td>
<td>4.45 0.974</td>
<td>0.194</td>
<td>4.93 0.841</td>
</tr>
<tr>
<td>France</td>
<td>(B) lagged net purchases + global instruments</td>
<td>0.138</td>
<td>18.23 0.003</td>
<td>0.174</td>
<td>14.91 0.011</td>
<td>0.169</td>
<td>3.97 0.959</td>
<td>0.144</td>
<td>12.83 0.170</td>
</tr>
<tr>
<td>Germany</td>
<td>(C) lagged net purchases + global + local instruments</td>
<td>0.117</td>
<td>31.14 &lt; 0.001</td>
<td>0.120</td>
<td>8.09 0.151</td>
<td>0.128</td>
<td>9.18 0.688</td>
<td>0.121</td>
<td>15.53 0.077</td>
</tr>
<tr>
<td>Italy</td>
<td>(D) lagged net purchases + squared residuals</td>
<td>0.023</td>
<td>8.33 0.402</td>
<td>0.019</td>
<td>3.52 0.620</td>
<td>0.018</td>
<td>5.86 0.923</td>
<td>0.009</td>
<td>7.00 0.637</td>
</tr>
<tr>
<td>Japan</td>
<td>(A) lagged net purchases</td>
<td>0.419</td>
<td>80.25 &lt; 0.001</td>
<td>0.440</td>
<td>14.71 0.012</td>
<td>0.440</td>
<td>14.45 0.273</td>
<td>0.413</td>
<td>4.98 0.837</td>
</tr>
<tr>
<td>Netherlands</td>
<td>(B) lagged net purchases + global instruments</td>
<td>0.156</td>
<td>50.39 &lt; 0.001</td>
<td>0.174</td>
<td>8.71 0.121</td>
<td>0.218</td>
<td>19.31 0.081</td>
<td>0.150</td>
<td>16.24 0.062</td>
</tr>
<tr>
<td>Switzerland</td>
<td>(C) lagged net purchases + global + local instruments</td>
<td>0.094</td>
<td>23.90 0.008</td>
<td>0.106</td>
<td>8.27 0.142</td>
<td>0.116</td>
<td>7.49 0.823</td>
<td>0.096</td>
<td>13.16 0.156</td>
</tr>
<tr>
<td>UK</td>
<td>(D) lagged net purchases + squared residuals</td>
<td>0.153</td>
<td>22.76 0.030</td>
<td>0.164</td>
<td>6.49 0.261</td>
<td>0.169</td>
<td>10.87 0.540</td>
<td>0.155</td>
<td>21.31 0.011</td>
</tr>
</tbody>
</table>

Table 9 presents the results of the factor analysis on the residuals from the gross flow regressions using instrument set C, for the broad measure of private information. The results for the conservative measure are similar and available on request. The first factor captures 55% of the unanticipated purchases and 54% of the unanticipated sales. Adding in the next two factors raises the total variation captured to approximately 85% of gross purchases and sales. Hence, global private information is an important determinant of US investors’ total private information. Moreover, because estimated net flows explain an average of 47% of total variation in net flows, global private information is also an important determinant of co-movement in US investors’ net flows, accounting for an average 29% of US investors’ net flows.17

We perform likelihood-ratio tests for the number of factors using the results of the maximum-likelihood factor method. The tests reject the hypothesis that no factors are present in the residuals. The tests also reject a one-factor representation in favor of two factors. Additional tests (not reported) reject more than two factors for both sets of residuals. Clearly, then, the covariance matrices of the

17 Using expected gross purchases and gross sales results in an approximate \( R^2 \) ratio of 47% for net purchases (using the results of Tables 5 and 6). The product of the percent of variation in unexplained flows explained by the first component times the percent of total variation in net flows that is unexplained is equal to 0.29 = 0.55 × (1 – 0.47).
Gross flow residuals show reduced rank structures associated with a common factor representation in total private information. In the sequel, we concentrate on the first, predominate factor.\textsuperscript{18}

To measure global private information in net flows, we use the factors estimated on the gross purchases and sales residuals, $U_p^t$ and $U_s^t$, respectively. As the scale of the factors is arbitrary, we normalize each to have a standard deviation equal to the simple average standard deviation of its constituent residuals. We then obtain a measure of the global factor in net flows as

$$U^t = \frac{U_p^t}{C_0 U_s^t}.$$

5. Private information and aggregate equity returns

In this section, we explore whether US investors' global private information helps investors allocate assets across broad stock market indices. We specify an estimable model of aggregate returns and confirm that our measures of global private information ($U_t^t$ and $e_U^t$) help predict aggregate returns. This demonstrates that global private

<table>
<thead>
<tr>
<th>Country</th>
<th>Instrument set</th>
<th>(A) lagged net purchases</th>
<th>(B) lagged net purchases + global instruments</th>
<th>(C) lagged net purchases + global + local instruments</th>
<th>(D) lagged net purchases + squared residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>Variance ratio</td>
<td>0.482</td>
<td>0.544</td>
<td>0.687</td>
<td>0.516</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>&lt;0.001</td>
<td>0.001</td>
<td>0.015</td>
<td>0.002</td>
</tr>
<tr>
<td>France</td>
<td>Variance ratio</td>
<td>0.730</td>
<td>0.838</td>
<td>0.926</td>
<td>0.790</td>
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<tr>
<td></td>
<td>p-value</td>
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<td>0.036</td>
<td>0.070</td>
<td>0.081</td>
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<tr>
<td>Germany</td>
<td>Variance ratio</td>
<td>0.312</td>
<td>0.417</td>
<td>0.525</td>
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<td></td>
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<td>0.467</td>
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<tr>
<td></td>
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<td>&lt;0.001</td>
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</tr>
<tr>
<td>Japan</td>
<td>Variance ratio</td>
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<tr>
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<td>Variance ratio</td>
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<tr>
<td>Switzerland</td>
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<td>UK</td>
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</table>

\textsuperscript{18} Froot, O’Connell, and Seasholes (2001) show in the earlier versions of their paper that there is an important regional factor in expected flows. We remove the expected portion of the flows using the global and local instrument sets and our factor analysis is thus concerned with unexpected flows.
information is an important determinant of global return chasing.

5.1. A model of international equity returns

As a benchmark, we adopt the latent-factor model of Hansen and Hodrick (1983) and Gibbons and Ferson (1985). In a K-factor model, the market price of risk of the k-th factor can be written as a linear combination of the set of L instruments $Z_t = (Z_{t1}, \ldots, Z_{tL})$ that are in the information set of the econometrician. Thus, the process for one-period returns conditional on the econometrician’s information is described by

$$R_t = \beta Z_{t-1} + \beta f_t + \epsilon_t,$$

(32)

where $f$ is a $K \times 1$ vector of factor realizations with $Ef_t | Z_{t-1} = 0$. $\beta = \text{cov}(R_t, f_t | Z_{t-1})$ is a constant $N \times K$ matrix, $\alpha$ is a $K \times L$ matrix, and $f$ and $\epsilon$ are uncorrelated. In this model, the linear combination $\alpha Z_{t-1}$ represents the expected returns on the latent factors, while the $\beta$ matrix is the loading of the assets on the factors. The latent-factor model of returns summarizes the public information relevant for forecasting returns in a parsimonious way. For example, under a one-factor model, the estimated combination $\alpha Z_{t-1}$ is often interpreted as the return on the global factor which is relevant for all stock markets if world equity markets are integrated (e.g., Campbell and Hamou, 1992).

Having properly identified trades due to global private information means that this estimated variable can be used to forecast returns. Let $R^G_t$ be the cumulative equity return from the beginning of period $t$ to the end of period $t + H$. For the broad measure $Y_t$, we use the fact that $Z_{t-1}$ and $Y_t$ are uncorrelated and require for each holding period $H \geq 0$,

$$E[R^G_t | Z_{t-1}, Y_t] = \beta_H Z_{t-1} + \gamma_H Y_t,$$

(33)

where the $N \times 1$ vector $\gamma_H$ measures the impact of unexpected net flows on the cross-section of expected returns. The conservative measure $\tilde{Y}_t$ is uncorrelated with $R_t$. As a result, the $\gamma_H$ coefficients from a projection similar to Eq. (33) are not significant for $H = 0$ by construction. However, if private information does have long lived effects, then future months’ returns reflect the impact of private information released at time $t$. Therefore, our tests of the effects of the global factor in the conservative measures of private information follow the same form as Eq. (33) for holding periods $H = 1$ to 3 with $\gamma_t$ replacing $\gamma_t$.

5.2. Impact of global private information

The model is estimated by generalized method of moments (GMM) separately for each holding period $H$. We relegate the details of the estimation as well as results for the coefficients $\alpha$ and $\beta$ to Appendix B. Here we focus on the coefficients $\gamma_H$ and $\tilde{\gamma}_H$ that capture whether the global factor of private information contains information about future stock returns. The top panel of Table 10 presents the value of the chi-squared statistics associated with the Wald test of the null hypothesis that all of the $\gamma_H$ coefficients in Eq. (33) are jointly equal to zero. The low $p$-values indicate that the global factor is jointly significant across all of the foreign countries and holding periods regardless of the instrument set used to construct the expected equity flows.

The bottom panel of the table shows the corresponding tests for the coefficients $\tilde{\gamma}_H$ derived under the conservative measure of private information. The test statistics tend to be lower as they are orthogonal to contemporaneous information. Nevertheless, the global factor is clearly significant for all instrument sets also under the conservative measure. To summarize, tests using both measures show that the unexpected component of US residents’ net purchases of foreign securities leads to a long-run increase in stock prices. As these measures provide lower and upper bounds on the private information set of the US investors, we conclude that, on aggregate, US investors have significant private information about international equity markets.

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19 Some authors (e.g., Harvey and Zhou, 1993) note potential problems with Wald tests in systems with instrumental variables and advocate calculating the Gallant and Jorgenson (1979) test statistic as well. We calculate the G-J test statistic and find that all of the G-J statistics are larger in value than our reported Wald statistics. Both test statistics are $\chi^2$ distributed with eight degrees of freedom.

20 No conservative measure of private information uses instrument set A as it contains only lagged values of the flow series.
5.3. Discussion

Mechanically, joint significance implies that there exists a linear combination of the coefficients $g_H$, $H$, say $w^r H$, that is significantly different from zero. In the present context, the coefficients $w$ have an economic interpretation: Up to normalization, they define a vector of portfolio weights. Therefore, the return on the time-invariant portfolio strategy described by $w$, $w^r H$, is well predicted by the global factor. The ability to predict this portfolio return and co-movement in US net flows is what makes the global factor an important determinant of global return chasing. There exist dynamic trading strategies that use information contained in the global factor to time international markets. For example, suppose a riskless asset is available and consider a zero cost strategy that goes long in the portfolio $w$ (and short in the riskless asset) whenever the expected return $w^r (\beta^H) \Sigma_z z_t + \gamma^H \gamma^T) / \sum w_t$ is higher than the riskless rate and goes short in the portfolio $w$ (and long in the riskless asset) otherwise. Such a trading strategy would use both public information and the global factor to generate positive excess returns on average. 21

A potential alternative explanation of the results in this section is price pressure. Unanticipated net inflows into a country’s equity market cause prices to rise even if they are devoid of information content as the market absorbs the extra demand. However, there are two primary reasons that the price pressure explanation is unlikely using our monthly data. First, the net flows shown in Tables 1, 2, and 3 are a very small portion of the total market value and the unanticipated net flows are an even smaller portion. The markets that we examine are all in developed countries where there should be adequate liquidity for absorbing such small amounts. Second, if there were temporary price pressure impacts from

21 Our setup does not imply that all US investors should be following the same strategy. The global factor is derived from average trades based on private information, whereas the theoretical framework allows for the possibility that only informed investors receive signals about the global factor in real time.
6. Conclusion

This paper hypothesizes and shows the existence of global private information in the portfolio equity trades of US investors abroad. We build a model to show that global private information is consistent with one of the main features of international trading: US investors chase foreign returns by increasing their positions in months of high foreign returns. Provided that local investors have an accumulated initial information advantage, we show that in our model return chasing obtains together with home bias. Finally, because of its nature, global private information shows up in the trades of US investors across all foreign countries. We take this lead from the model to conduct our empirical analysis.

This paper obtains measures of US investors’ trades based on private information by estimating empirical models of international gross equity flows. We show that modeling gross flows results in a better model of expected net flows than modeling net flows directly. We then show that residuals from our models provide bounds on the amount of trading based on private information.

To identify a global factor in private information, we test for a factor structure in our measures of trading based on private information. We find that the first factor, which we call the global factor, accounts for over half of the variation in total private information. We also show that this global factor has a significant impact on the cross-section of international equity returns. Although the trades of US investors constitute a very small amount of the total market capitalization of the foreign country, the unexpected flows are able to predict returns.

Our results suggest that US investors play a special role in international markets. Instead of suffering from an absolute information disadvantage because of insufficient local information, they could enjoy at times an information advantage because of superior global information. This information advantage appears to be long lived and suggests trading strategies where (sophisticated) US investors outperform the average non-US investor participating in the foreign equity market. Further analysis of such strategies is an interesting issue for future research.

Appendix A. Proof of propositions

A.1. Proof of Proposition 1

To derive formulas for the price vector and equilibrium portfolios, it is helpful to write the problem first in more general notation, before exploiting the particular information structure assumed in the text. We consider a general model with \( T + t_0 \) trading periods \(-t_0, \ldots, 0, \ldots, T\), where the variances of all shocks are allowed to depend on calendar time. Below, we specify the variances in the first \( t_0 \) periods in a way to capture investors’ background information. However, the solution of the general model does not depend on this and could just as well be used to characterize a setup without background information.

Consider an investor \( i \) living in a region \( j \). Because it is convenient to work with matrices, we stack the public signals, and we define a whole vector of private signals for investor \( i \), one for each region. All signals are linear functions of the dividends and shocks:

\[
Y_i^t = (y_{i,1}, y_{i,2}, \ldots, y_{i,n}, y_{i,n})^T = U'C + (v_{i,1}, v_{i,2}, \ldots, v_{i,n}, v_{i,n})^T
\]

and

\[
Z_i(t) = (z_{i,1}(t), z_{i,2}(t), \ldots, z_{i,n}(t), z_{i,n}(t))^T
\]

The variances of the shocks are denoted \( \text{var}(v_i) = N_i^{-1} \) and \( \text{var}(z_i(t)) = (S_i)^{-1} \).

We now derive equilibrium prices for this general setup. To specialize to the assumptions below, we set \( C = (I - n^{-1}) \), an \( n \times (n + 1) \) matrix. We make the matrices \( S' \) diagonal, with nonzero elements in the row corresponding to the investor’s home region, as well as possibly in the last row (if the agent receives a global signal). By introducing the heterogeneity via the \( S' \) matrices, a constant \( C \) matrix is sufficient to accommodate the information structure in the text.

In the general notation, the individual and aggregate knowledge matrices are

\[
K_t = K_{-t_0} + \sum_{\tau=-t_0+1}^{T} [C'N_tC + C'S_tC + r^2C'S_tC\Phi_tC'S_tC]
\]

and

\[
K_t^i = K_{-t_0} + \sum_{\tau=-t_0+1}^{T} [\sum_{\tau=-t_0+1}^{T} C'N_tC + \sum_{\tau=-t_0+1}^{T} C'S_tC + r^2C'S_tC\Phi_tC'S_tC].
\]

We conjecture the following solution for the equilibrium price:

\[
P_t = K_t^{-1}K_{-t_0}\mu_u - r^{-1}K_t^{-1}\mu_x
\]

\[
+ K_t^{-1} \sum_{\tau=-t_0+1}^{T} [C'N_tY_t + (r^2C'S_tC\Phi_t + I) \\
\times C'S_tC(U - r^{-1}(C'S_tC)^{-1}x_t)].
\]

To verify the conjecture, we proceed in three steps. First, we compute an individual investor’s belief given his private signals as well as the public signals including the price. Second, we compute the investor’s optimal portfolio demand if he expects prices to follow Eq. (38). In particular, we show that the optimal demand is given by Eq. (13). The market clearing price is then given by Eq. (14). Finally, we verify that this market clearing price is the same as the conjecture Eq. (38).

If the price takes the form Eq. (38), the information contained in \( P_t \) over and above the public signals \( Y \) and past prices can be represented by the signal

\[
Q_t := U - r^{-1}(C'S_tC)^{-1}x_t.
\]
which is independent of the other public and private signals conditional on $U$. Consider an investor who starts from a normal prior over $U$ and mean $\mu_u$ and variance $K_{-t_0}$. He updates his beliefs given the signals $(Y_t, Z_t, P_t, Q_t)_{t\leq t}$ or equivalently $(Y_t, Z_t, Q_t)_{t\leq t}$. All signals as well as the dividend $U$ are jointly normal. Using standard formulas for the conditionals of a multivariate normal distribution (see, for example, Greene, 1993, p. 258), we obtain a posterior that is normal with variance $(K_t^{-1})$ and mean

$$E_t[U] = (K_t^{-1})^{-1}\left\{K_{-t_0}\mu_u + \frac{1}{t} \sum_{t=t_0+1}^t \left[C'S_tZ_t + C'N_tY_t + r^2(C'S_tC)\Phi_t(C'S_tC)Q_t\right]\right\}. \tag{40}$$

The supplementary appendix to this paper (available upon request) solves the investor's optimal portfolio choice problem, assuming that price expectations are upon request) solves the investor's optimal portfolio demand is given by Eq. (13). In particular, we show that for all $t \leq T$, the optimal portfolio demand is given by Eq. (13). In other words, the optimal portfolio depends only on the expected excess return $b_t = E_t(U) - P_t$ over the remaining $T - t$ periods, as well as on the conditional variance of that excess return (that is, $(K_t^{-1})$). Moreover, utility at the optimum for an investor with wealth $W_t$ is

$$A_t = -\exp\left(-\frac{1}{\bar{r}} W_t - \frac{1}{2} b_t'K_t^{-1}b_t\right) \bar{A}_t, \tag{41}$$

where $\bar{A}_t$ depends only on calendar time (and not on wealth or any past or current signals). The derivation is standard but involves a significant amount of tedious algebra.

The market clearing price now follows from combining Eq. (13) and the market clearing condition:

$$P_t = K_t^{-1} \int K_t' E_t[U] \, dU - r^{-1} K_t^{-1} X_t. \tag{42}$$

Using our formula for $E_t[U]$, the knowledge-weighted integral of individual expectations is

$$\int K_t'E_t[U] \, dU = K_{-t_0}\mu_u + \sum_{t=t_0+1}^t \left[ C' \int S_t Z_t U \, dU + C'N_t Y_t + r^2(C'S_tC)\Phi_t(C'S_tC)Q_t \right]$$

where the second equality uses the fact that many investors share any given distribution of signals, so that the cross-sectional mean of the idiosyncratic shocks $\epsilon_t(i)$ is zero by the law of large numbers for i.i.d. random variables and that by definition $S_t = \int S_t \, dU$.

Substituting for $\int K_t'E_t[U] \, dU$ in Eq. (42) and using the definition of $Q_t$, we obtain the market clearing price

$$P_t = K_t^{-1} \int K_t'E_t[U] \, dU - r^{-1} K_t^{-1} X_t$$

$$= K_t^{-1} K_{-t_0}\mu_u + K_t^{-1} \sum_{t=t_0+1}^t \left[ C'S_tC + r^2(C'S_tC)\Phi_t(C'S_tC)U \right]$$

$$+ K_t^{-1} \sum_{t=t_0+1}^t \left[ C'N_t Y_t - r(C'S_tC)\Phi_t X_t \right]$$

$$- r^{-1} K_t^{-1} \left[ \mu_x + \sum_{t=t_0+1}^t x_t \right]. \tag{44}$$

Rearranging terms, we arrive back at Eq. (38), thus verifying the conjecture for the equilibrium price.

Because we are interested in US investors’ per capita position, not individual positions, we need to integrate over individuals. It is convenient to define $A_t^i$ as the average position of all investors who have the same signal distribution as agent $i$. For example, if $i$ is an investor in region $j$ who obtains a global signal, then $A_t^i$ is the average demand of all investors who also live in region $j$ and who also obtain a global signal. The difference between $A_t(i)$ and $A_t^i$ is that the former depends on investor $i$’s idiosyncratic shocks $\epsilon_t(i)$. In contrast, because there exist many investors who share any given signal distribution, the law of large numbers implies that the shocks $\epsilon_t(i)$ do not affect the average position:

$$A_t^i = K_{-t_0}\mu_u + \sum_{t=t_0+1}^t \left[ C'N_t Y_t + C'S_tC\Phi_t C'S_tC Q_t \right]$$

$$+ r^2(C'S_tC)\Phi_t(C'S_tC)Q_t - K_t^i P_t. \tag{45}$$

Substituting for the equilibrium price $P_t$ and expressing the signals $Y_t$ and $Q_t$ as $U$ plus shocks, we obtain

$$A_t^i = K_{-t_0}\mu_u + (K_t^i-K_{-t_0})U$$

$$+ \sum_{t=t_0+1}^t \left[ C'N_t v_t - r(C'S_tC)\Phi_t X_t \right] - K_t^i P_t. \tag{46}$$

Similarly, the price can be simplified to

$$P_t = K_t^{-1} (K_{-t_0}\mu_u + (K_t-K_{-t_0})U)$$

$$+ K_t^{-1} \sum_{t=t_0+1}^t \left[ C'N_t v_t - r^{-1}(I + r^2(C'S_tC)\Phi_t X_t) \right]$$

$$- r^{-1} K_t^{-1} \mu_x. \tag{47}$$

Finally, using the fact that $K_t' - K_t = \sum_{t=0}^t C(S_t' - S_t)C$, we have

$$A_t^i = r \sum_{t=t_0+1}^t C(S_t' - S_t)C K_t^{-1} \left\{ K_{-t_0}(U - \mu_u) - \sum_{t=t_0+1}^t C'N_t v_t \right\}$$

$$+ \left[ I + \sum_{t=0}^t C(S_t' - S_t)C K_t^{-1} \right] \left( \mu_x + \sum_{t=t_0+1}^t x_t \right)$$

$$+ r^2 \sum_{t=t_0+1}^t C(S_t' - S_t)C K_t^{-1} \left( \sum_{t=t_0+1}^t C'S_tC \Phi_t X_t \right). \tag{48}$$
A.1.1. Simplifying the information structure

We now specialize to the information structure of our model. Investors’ background information consists only of local private signals. We thus assume that for the first $t_0$ periods, that is, dates $-t_0 + 1, \ldots, 0$, \( \var{\epsilon_t(i)} = (S_0)_{-1} \) and we define $S_0 = fS_{t_0}$. To capture the fact that there are no public signals, we assume that $N_t = 0$ for $t \leq t_0$. We restrict attention to realizations in which $x_t = 0$ for $t \leq 0.25$ For the trading periods $t = 1, \ldots, T$, we assume $\var{\epsilon_t(i)} = (S^t)_{-1}$ as well as $\var{\epsilon_t(i)} = (S^t)_{-1}$, and we define $S = fS dt$. The matrix $C$ mapping dividends into signals is the same for all periods.

An important term in the solution Eq. (38) is an individual investor's information advantage $K_iK_{t}^{-1} - I$. Given our specific assumption on the time dependence of the precision matrices, it simplifies to

\[
K_iK_{t}^{-1} - I = \sum_{t=-t_0+1}^{T} C(S^t_i - S^t)CK_{t}^{-1} = (t_0C(S_0 - S_0^n) + C + C(S^t - S)C)K_{t}^{-1}.
\]

(49)

We can then rewrite $A^n_i$, the per capita holdings of informed investors with the same signal distribution as investor $i$, together with the price Eq. (38) as

\[
A^n_i = r[K_iK_{t}^{-1} - I][K_{t} - (U - \mu_u) - C'\Sigma_i V_t] + [r[K_iK_{t} - I]X_t + [K_iK_{t}I - I] rCSC\Phi X_t - \mu_X {
\mathbf{50}}
\]

and

\[
P_t = K_{t}^{-1}[(K_{t} - (U - \mu_u) - C'\Sigma_i V_t \] 
\[
- r^{-1}(r^2\pi S'CSC\Phi X_t - \mu_X) - r^{-1}\mu_X].
\]

(51)

Further simplification is possible by exploiting the symmetry of investors’ information. Under the assumptions in the text, the matrices $\Phi, S_q$, and $C$ are

\[
\Phi = \pi_x I, \quad S_q = \begin{pmatrix} q_l & 1 & 0 \\ 0 & q_o \\ 0 & q_g & 1 \end{pmatrix}, \quad C = \begin{pmatrix} I \\ n' \end{pmatrix}.
\]

(52)

Moreover, the precision matrices for an individual investor $i$ from region $j$ who receives a global signal is

\[
S'_{i} = \begin{pmatrix} p_{d_j} & 0 \\ 0 & p_{g_{j}} \end{pmatrix}, \quad S_{0} = \begin{pmatrix} p_{d_j} & 0 \\ 0 & 0 \end{pmatrix}.
\]

(53)

If the individual investor does not receive a global signal, the precision matrices are the same, except that $p_{g_{j}}$ in the bottom right corner of $S'$ is replaced by zero. Finally, set $K_{-t_0} = \pi_x l - \pi_{x}'(n_{x} + \pi_{x})_{-1} I'$. For an investor $i$ living in region $j$, we thus have $K_{0} = K_{0_{j}}$ as defined in Eq. (5).

We now simplify various terms that appear in the solution equation (50) for US investors’ position. The holdings of any informed investor $i$ depend on the realized signals only through the term

\[
K_{-t_0}(U - \bar{U}) - C\Sigma_i V_t 
\]

\[
= K_{-t_0}(U^i + U^g) - C\Sigma_i V_t 
\]

\[
= \pi_i(U^i - \bar{U}) + \frac{\pi_i \pi_g}{\pi_{x} + \pi_{x}'}(U^g + \bar{U}) - q_i V_t - \frac{1}{n} q_{g} V_{g}^i,
\]

(54)

where $\bar{U} = n^{-1} \sum_{j=1}^{J} U^j$ is the cross-sectional average of the dividends.

Let $z$ denote the number of investors who receive a global signal and let $z'$ denote the number of investors who have information about every local factor. The precision of background information is the same across investors, so that, for every investor $i$ in region $j$,

\[
C_0 S_{q_i} C_0 = p_{d_j},
\]

(55)

Summing up across investors, we have $C_0 S_{q_i} C_0 = z' p_{d_j}$. In contrast, the precision of information investor $i$ obtains during trading depends on whether he receives a global signal. Let $G(i)$ denote an indicator variable that is equal to one if $i$ receives a global signal and zero otherwise. We then have

\[
C S'C = p_{d_j} + G(i) \frac{1}{n} p_{g_{j}} 1' i',
\]

(56)

and summing up across investors now yields

\[
CSC = z' p_{d_j} (1 + (1/n) p_{g_{j}} i').
\]

The aggregate knowledge matrix for $t = 1, \ldots, T$ can now be rewritten as

\[
K_{t} = (z + z' p_{d_j} (t + t_0) + r^{2} \pi_x z'^{2} p_{d_j}^2 t + q_i t)l 
\]

\[
+ \frac{1}{n} \left( -\frac{\pi_x}{\pi_{x} + \pi_{x}'} + zp_{g} t + r^{2} \pi_x zp_{g} (zp_{g} + 2z' p_{d_j}) t + q_i t \right) i' 
\]

\[
= k_{t} l + \frac{1}{n} k_{i} i'.
\]

(57)

This defines the coefficients $k_{t}$ and $k_{l}$ used in the text. It is also helpful to introduce notation for their sum:

\[
k_i := k_{t} + k_{l} = \frac{\pi_x}{\pi_{x} + \pi_{x}'} + zp_{d_j} (t + t_0) + zp_{g} t 
\]

\[
+ r^{2} \pi_x zp_{d_j} (zp_{g} + 2z' p_{d_j}) t + (q_i + q_{g} t).
\]

(58)

We can then write the inverse of the aggregate knowledge matrix as

\[
K_{t}^{-1} = \frac{1}{k_{t}^i} \left[ I - \frac{k_{l} l}{k_{t}^i} i' \right].
\]

(59)

Now consider an individual investor $i$. Substituting the preceding expressions into Eq. (49), his information advantage is

\[
k_i k_{t}^{-1} - I = \left[ K_{t} - z' p_{d_j} (t + t_0)l 
\right.
\]

\[
+ \frac{1}{n} \left( (G(i) - z) p_{g} i' l + p_{d_j} l \right)] K_{t}^{-1} - I 
\]

\[
= -z' p_{d_j} (t + t_0) K_{t}^{-1} 
\]

\[
+ \frac{1}{n} \left( (G(i) - z) p_{g} i' K_{t}^{-1} + p_{d_j} K_{t}^{-1} \right).
\]

(60)

The information advantage is relevant for computing the full vector of investors’ optimal portfolio holdings, for both domestic and foreign assets. Because we are interested only in US investors’ positions in foreign assets,
we can ignore the matrices $J_jK_i^{-1}$, which has all zero elements in rows that correspond to foreign assets. We thus focus on the matrix

$$
\Pi_t := K_i^t K_i^{-1} - \Pi_t^{(i)} K_i^{-1}
$$

$$
= - \kappa' \Pi_t^{(i)}(t + t_0) K_i^{-1} + G(i) \left( \frac{1}{n} \Pi_t \frac{\kappa'}{K_i} K_i^{-1} \right)
$$

$$
= - \kappa' \Pi_t^{(i)}(t + t_0) I + \left\{ \frac{(G(i) - \kappa') \kappa_t + \kappa' \Pi_t^{(i)}(t + t_0)}{n K_i K_i^{-1}} \right\} I
$$

$$
= - \kappa' \Pi_t^{(i)}(t + t_0) I + \left\{ \frac{(G(i) - \kappa') \kappa_t + \kappa' \Pi_t^{(i)}(t + t_0)}{n K_i K_i^{-1}} \right\} I
$$

$$
= \beta_t I + (\delta(i) \Pi_t^{(i)} I)
$$

A row of $\Pi_t^{(i)}$ that corresponds to a foreign asset accurately captures the information advantage of any US investor.

For an arbitrary vector $x$ we have

$$\Pi_t x = \beta_t (x - \bar{x}) + (\delta(i) \Pi_t^{(i)} I) x \tag{62}$$

$$K_i^{-1} x = \frac{1}{K_i} (x - \bar{x}) \tag{63}$$

and

$$C' SCx = \kappa' \Pi_t^{(i)}(t + t_0) + (\kappa' \Pi_t^{(i)}(t + t_0) \bar{x}) \tag{64}$$

A.1.2. Solution for equilibrium prices and holdings

For an individual US investor $i$, consider again $A_i$, the per capita portfolio holdings of the group of US investors who have the same signal distribution as $i$. Applying the above formulas to the specific $x$ given by Eq. (54), and using our assumption $\kappa' = 1/n$, the demand for foreign asset $j$ can be read from the corresponding rows of $A_i$

$$A_i^j = r \Pi_t^{(i)}(K_i U^j + U^j t) - C' S N V_i$$

$$+ U - \Pi_t^{(i)}(t + t_0) \bar{x} + \Pi_t^{(i)}(t + t_0) \bar{x} - \Pi_t^{(i)}(t + t_0) \bar{x}$$

$$= X_t - \Pi_t^{(i)}(t + t_0)$$

$$\times \left\{ (\kappa(i) \kappa' - \bar{x}) - \Pi_t^{(i)}(t + t_0) \bar{x} + \Pi_t^{(i)}(t + t_0) \bar{x} \right\}$$

$$+ G(i) \left( \frac{1}{n} \Pi_t \frac{\kappa'}{K_i} K_i^{-1} \right) \left\{ \frac{(G(i) - \kappa') \kappa_t + \kappa' \Pi_t^{(i)}(t + t_0)}{n K_i K_i^{-1}} \right\} I
$$

To compute the per capita position of all US investors, it remains to integrate across US investors with different signal distributions. The group position $A_i^j$ depends on $i$ only via the global signal indicator $G(i)$, which enters linearly. Because a fraction $x^{US}$ of US investors receive global signals, the per capita position is obtained by replacing $G(i)$ by $x^{US}$, which delivers the expression Eq. (17) in the text.

Substituting the expressions derived above into the price formula equation (51) yields

$$P_t = K_i^{-1} [K_0 \mu_t + (K_i - K_0) U + C_S q V_t + r^{-1}(1 + r^2 \pi_g C' S C X_t)]$$

$$= U - K_i^{-1} K_0 U^j + U^j t + K_i^{-1} C_S q V_t$$

$$+ r^{-1} K_i^{-1}(1 + r^2 \pi_g C' S C X_t)$$

$$= U - \frac{1}{K_i} (\kappa(i) \kappa' - \bar{x}) - q(i) V_t - V_t'$$

$$+ r^{-1}(1 + r^2 \pi_g p_i / n)(X_t - \bar{x})$$

$$+ \frac{1}{K_i} \left\{ \frac{\pi_g}{\pi_g + \pi_n} \left( U^j + V^j \right) - \left\{ \frac{1}{n} \pi_g q g + q(i) V_t \right\} - r \pi_g (2 p_i \kappa' + p_i / n)(X_t - \bar{x} - \kappa_{LX}) + r^{-1} \mu_X \right\}$$

Rearranging of terms delivers expression Eq. (16) in the text.

A.2. Proof of Proposition 2

For part (i), the condition for home bias follows the argument in the text. We first take unconditional expectations of US per capita aggregate asset demand for foreign asset $j$, Eq. (17). Net of mean per capita US noise trades, US average aggregate holdings are

$$E[\kappa_{ij}^{US} - X_t] = \frac{1}{n K_i} [(x^{US} - \bar{x}) \Pi_t^{(i)} + r^{-1}(1 + r^2 \pi_g C') \mu_x] \tag{67}$$

Home bias means that US investors hold less than their cumulative average noise supply. This happens when the term in square brackets is negative:

$$x^{US} - \bar{x} \Pi_t^{(i)} < r^{-1}(1 + t_0 / t). \tag{68}$$

To guarantee that the condition holds for all trading periods, we require that it holds for $t = T$:

$$x^{US} - \bar{x} \Pi_t^{(i)} < r^{-1}(1 + t_0 / T). \tag{69}$$

This condition is satisfied if $t_0$ is large enough.

For part (ii) we show that the terms associated with $U^j$ in the price and demand equations both increase with $t$. In the price function it is easy to see that $\Delta \kappa_{LX}$ is increasing in $t$. In the demand function, the relevant term is

$$\frac{1}{K_i} (1 - \kappa') \Pi_t^{(i)}(t + t_0). \tag{70}$$

This term is increasing if, and only if, condition (21) in the text holds or, equivalently, if

$$1 - \kappa' \Pi_t^{(i)}(t + t_0) > q(i) + q(i) \left( \frac{1}{n} + \frac{n - 1}{n} \right)$$

$$+ r^2 \pi_g (2 \kappa' + \kappa' / n)^2. \tag{71}$$

This condition is also satisfied if $t_0$ is large enough. The threshold in the statement of the proposition is defined as the smaller of the thresholds implied by inequalities (69) and (71).
A.3. Proof of decomposition (24)

We first derive the expected payoff given only public information. From Eq. (13) and Eq. (51), the expected payoff of an individual investor is

\[ E_t^p(U) = (K_t^p)^{-1}(K_{t-1}u_t + (K_t - K_0)u_t + C_{t}S_{t}V_{t} + rC_{t}C_{t}S_{t}C_{t}S_{t}C_{t}S_{t}C_{t}) \]

(72)

We obtain the expected payoff given public information by setting the precision of private signals in \( K_t \) to zero. It follows that

\[ E_t^p(U) = (K_t^p)^{-1}(K_{t-1}u_t + (K_t - K_0)u_t + C_{t}S_{t}V_{t} + rC_{t}C_{t}S_{t}C_{t}S_{t}C_{t}) \]

(73)

where public knowledge is defined by

\[ K_t^p = K_{t-1} + \sum_{i=t-1}^{T} [C_{N_{t}}C + r^{2}C_{S_{t}}C_{t}S_{t}C_{t}S_{t}C_{t}S_{t}C_{t}] \]

(74)

It follows that the formula for \( E_t^p(U) \) has the same structure as that for \( P_t + \frac{1}{rT}K_{t-1}X_{t} \), except that in the former \( K_t \) is replaced everywhere by \( K_t^p \). Moreover, formulas (55) and (56) imply that the public knowledge matrix \( K_t^p \) has the same structure as the average knowledge matrix \( K_t \):

\[ K_t^p = (k_t^p - p_t(t_0 + t)/n)I + \frac{1}{T}((k_t^p - 2p_t^2)I)^{l} \]

(75)

It remains to simplify the difference between the average and public expectations:

\[ P_t + \frac{1}{rT}K_{t-1}X_{t} - E_t^p(U) = (K_t^p)^{-1}(K_{t-1}u_t + (K_t - K_0)u_t + C_{t}S_{t}V_{t} + rC_{t}C_{t}S_{t}C_{t}S_{t}C_{t}) \]

(76)

Here the second equality uses the same simplifications that led to the price equation (16), applying them once to the terms in the first line involving \( K_t \) and then again to those in the second line involving \( K_t^p \). Rearranging terms now delivers Eq. (24) in the text.

Appendix B. Empirical models

B.1. Empirical models of flows and returns

This appendix contains details of the empirical models of flows and returns used in Sections 4 and 5.

B.1.1. GMM estimation of expected gross purchases, gross sales and net purchases

To determine the effect of the public information variables on gross purchases, gross sales, and net purchases, we estimate a system of just-identified regressions via generalized method of moments. The moment conditions for the system are

\[ g_t(\theta) = \sum_{t=1}^{T} \begin{pmatrix} GP_t - \beta_{GP}X_{GP}^t \n GS_t - \beta_{GS}X_{GS}^t \n NF_t - \beta_{NF}X_{NF}^t \n \end{pmatrix} \]

(77)

The first three moment conditions in the system model the gross purchases (\( GP_t \)), gross sales (\( GS_t \)), and net purchases (\( NF_t \)) as linear functions of the regressors \( X_{GP}^t, X_{GS}^t, \) and \( X_{NF}^t \), respectively. We use different notation for each set of regressors as the lag length in each is chosen optimally using the Bayesian information criterion (BIC). The last two moment conditions follow Richardson and Smith (1991) and Ronen (1997) and are used to estimate the variance ratio (VR). The variance ratio measures the variability of the expected net flows modeled using a linear projection of the net flows (the third moment condition) relative to the variability of a model for the net flows that uses the expected gross purchases and gross sales separately as in the first two moment conditions, \( V_{GP - GS} \).

The variance ratios should also be adjusted for the number of parameters used in their construction: As the number of regressors in the gross purchase and gross sales regressions could be much larger than that of the net purchases regression, the variance ratio could be naturally biased downward (i.e., away from 1.00). We therefore multiply the estimated variance ratio by a correction factor \( (T - K(n))/\sqrt{T - K(g)} \), where \( T \) is the number of observations, \( K(n) \) is the number of parameters in the net purchases regression, and \( K(g) \) is the number of combined parameters in the gross purchases and gross sales regressions.

The moment conditions are multiplied by a set of instruments to yield the GMM system. The instruments for each of the first three moment conditions are the regressors used in that moment. The instruments for the last two moment conditions are constants. We use the Newey-West form of the optimal weighting matrix. Maximization of this just-identified system thus yields parameter estimates \( (\beta_{GP}^*, \beta_{GS}^*, \text{ and } \beta_{NF}^*) \) that are the same as those from OLS regressions, in addition to an estimate of the variance ratio VR. The standard errors on the variance ratios account for the errors in estimating the coefficients in all of the regressions, thus avoiding an errors-in-variables problem. We correct all of the standard errors using the small-sample method of Ferson and Foerster (1994).

B.1.2. GMM estimation of Eq. (33)

Consider projecting the cross-section of the returns onto the instrument set \( Z_{t-1} \) and the private
information $Y_t$:

$$R_{t+1}^i = \Phi_{Hi}Z_{t-1} + \gamma_H Y_t + \epsilon_{Hi}. \quad (78)$$

The model imposes a number of cross-equation restrictions on the $N \times L$ coefficient matrix $\Phi_{Hi}$. Under a $K$-factor model, the typical element of the matrix $\Phi_{Hi} = \beta_{Hi}Z_t$ is $\Phi_{Hi}Z_{t-i} = \sum_{i=1}^{K} \beta_{Hi}Z_{t-i}$. However, the model is not identified, and we follow the broad measures of private information.

These proxies would contain return variation due to the release of private information revealed by the trades variables for the factor returns. These proxies would have a reduced rank structure with rank $(\Phi_{Hi}) = K$. These restrictions can be used as a test of the model using the GMM J-statistic, which is distributed as $\chi^2$ with $(N - K(L - K))$ degrees of freedom.23

Imposing the over-identifying restrictions of the latent-factor model results in more precise estimates of return variation due to the public and private information variables. This latter effect is important due to the noisiness of monthly return data.24

Latent-variable models of international stock returns have been used by Harvey (1991), Campbell and Hamao (1992), and Harvey, Solnik, and Zhou (2002) among others. The results of these studies are mixed. Campbell and Hamao (1992) examine the integration of the US and Japanese equity markets and find that a single latent-variable model is rejected during the 1970s but not during the 1980s. Harvey (1991) finds that the data reject a single source of risk across all of the world’s equity markets, implying that the world market portfolio is not conditionally mean-variance efficient. However, the rejection is strongest for Japan; the model holds for the other countries examined in the paper. Harvey Solnik, and Zhou (2002) find that a one to three latent-factor model is rejected by the cross-section of 18 country index returns. However, when they examine the models’ pricing errors and variance ratios, they find that a two or three latent-variable model captures the cross-section of country returns.25

23 We use the Newey-West form of the asymptotic covariance matrix to capture any autocorrelation in $\epsilon_{Hi}$. Ferson and Foerster (1994) examine the small-sample properties of latent-variable models estimated by GMM. They find that an iterated GMM procedure results in coefficient estimates with small biases but that the standard errors are underestimated. They propose a correction factor that results in appropriate sized standard errors. We use the iterated GMM approach and apply their small-sample correction factor to our standard errors.

24 Alternative models for the cross-section of expected international equity returns (e.g., the international version of the three-factor model presented in Fama and French, 1998) would use realized returns on subportfolios (e.g., international book-to-market portfolios) as proxy variables for the factor returns. These proxies would contain return variation due to the release of private information revealed by the trades of US investors during the month, thus invalidating the tests using our broad measures of private information.

25 One key assumption in the latent-variable model is that the betas are constant. This is not a strong assumption at the country level. Ferson and Harvey (1993) test an asset pricing model in which the risk factors are global, but the conditional betas depend on country-specific attributes. They find that, although time variation in the betas is statistically significant, it contributes little to the variation in expected returns. Ferson and Harvey (1994) examine whether country-specific fundamental attributes can be used to help motivate time-varying beta models. Again, the risk premia are global while the betas are functions of specific country attributes, which they label fundamental determinants. They find some limited support for their model. However, the estimation

### Table B1

<table>
<thead>
<tr>
<th>Holding period</th>
<th>$z_H$ coefficient in latent-variable model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant, $r_{H0}^{us}$, $crsp_{H0}^{us}$, $div_{H0}^{us}$, $sl_{H0}^{us}$, $rs_{H0}^{us}$, p-value</td>
</tr>
<tr>
<td>$H = 0$</td>
<td>1.214 (0.402), 0.813 (0.515), -16.804 (4.647), 1.504 (1.704), -1.073 (0.741), 0.028 (0.026)</td>
</tr>
<tr>
<td></td>
<td>0.003 &lt; 0.001, 0.378 (0.148), 0.148 (0.005)</td>
</tr>
<tr>
<td>$H = 1$</td>
<td>0.985 (0.638), -2.388 (1.205), -12.423 (6.554), 13.922 (3.920), -6.691 (1.593), 0.106 (0.036)</td>
</tr>
<tr>
<td></td>
<td>0.124 &lt; 0.001, 0.048 (0.059)</td>
</tr>
<tr>
<td>$H = 2$</td>
<td>0.554 (0.954), -3.776 (1.440), 5.301 (3.831), 16.221 (4.221), -9.646 (2.327), 0.225 (0.040)</td>
</tr>
<tr>
<td></td>
<td>0.562 &lt; 0.001, 0.009 (0.324)</td>
</tr>
<tr>
<td>$H = 3$</td>
<td>-1.671 (1.057), -1.939 (1.495), 21.098 (9.834), 14.865 (4.271), -6.620 (2.334), 0.260 (0.044)</td>
</tr>
<tr>
<td></td>
<td>0.115 &lt; 0.001, 0.016 (0.033), 0.001 (0.005) &lt; 0.001</td>
</tr>
</tbody>
</table>

### B.1.3. Impact of public information

We estimate a one-factor version of the latent-factor model equation (33) without any private information to examine how it captures expected return variation. Imposing the restrictions of the latent-variable model leads to precise estimates of the coefficients on the global information variables. Table B1 presents the estimated $z_H$ coefficients for holding periods ranging from the current month ($H = 0$) to three months forward ($H = 3$). The coefficients are statistically significant on most of the variables (except the intercept) at most forecast horizons. The coefficient on the short-term US interest rate is negative as has been shown in other studies. The coefficient of the credit spread is significant and negative at short horizons. The global dividend yield is shown to have a positive and significant effect on international

(footnote continued)
returns over longer horizons. The slope of the US term structure and the lagged US equity market return are significant at most forecast horizons.

The estimated $\beta_H$ coefficients are presented in Table B2. The coefficient on the US equity returns is normalized to 1.00 for identification. The coefficients are precisely estimated for most of the foreign country returns. For the current month ($H = 0$), the coefficients range from 0.294 for Japanese returns to 1.6 for Swiss returns. Most of the coefficients are significant at the 5% level indicating that the single global factor forecasts the cross-section of international returns.

The model is able to capture return variation due to public information. To show this, we construct a variance-ratio statistic similar to the ones presented by Campbell and Hamaro (1992) and Harvey (1991). The numerator is the variance of the fitted values from Eq. (33), denoted $\text{var}(\hat{\beta}_H z_{t-1})$, where $\hat{\beta}_H$ and $\hat{\beta}_H$ are the GMM coefficients for holding period $H$ given in Tables B1 and B2, respectively. The denominator is the variance of the fitted values from an OLS regression of the excess return on the global instruments $\text{var}(\hat{o} z_{t-1})$. The variance ratio thus shows how imposing the baseline model’s over-identifying restrictions leads to a degradation of the data’s ability to forecast expected returns.

The results are presented in Table B3. As can be seen, the latent-variable model does a good job at capturing expected return variation. The ratios range from 0.028 for Japanese returns up to 1.107 for Dutch returns during the current month ($H = 0$). As the holding period lengthens, the impact of the model’s restrictions increases for some countries and the ratios occasionally fall. However, all of the ratios are higher at the three month holding period. In Table B3, we also present the $J$-statistics that evaluate the over-identifying restrictions of the latent-variable model. The $J$-statistics show that the model is not rejected at any forecast horizon. Given the performance of the one-factor latent-variable model according to all of these metrics, we use it as our model of public information in the subsequent tests.