ESSAYS IN INTERNATIONAL CAPITAL MARKETS

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ESSAYS IN INTERNATIONAL CAPITAL MARKETS

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To My Family.

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SUMMARY

My dissertation consists of three essays in international capital markets.

In Chapter I, we examine the herd behavior of U.S. institutional investors trading around the world. Do investors herd across countries? What are the impacts of their herding behavior, if any, on local stock market performances? Do countries' information environments affect the herding behavior? In this chapter, we address these questions by using a new transaction-level trades database of 531 U.S. institutional investors trading across 37 countries during the period 2002-2009. We find robust evidence of intra-period herding (correlated trading) by employing the Lakonishok, Shleifer, and Vishny (1992) measure and evidence of inter-period herding by employing the Sias (2004) measure at the monthly frequency. We also find evidence of return continuations following intra-period buy herding and no evidence of return reversals following intra-period sell herding. Hence, there is no evidence that trades by institutions in our sample drive prices away from the fundamental values; rather, they help to speed the price-adjustment process. Further analysis shows that: (i) in the buy side, both intra- and inter-period herdings are more pronounced in countries with weaker information environments; and (ii) in the sell side, intra-period herding is more pronounced in countries with stronger information environments, whereas inter-period herding is not significantly related to information environments. The overall results of the paper suggest that information environments have asymmetric effects on the buy- and sell-side herdings and are consistent with the view that, in the buy side, institutions herd as a result of 'intentionally' inferring information from each other's trades, whereas, in the sell side, correlated signals primarily drive institutions' 'unintentional' herding across countries.

In Chapter II, we (i) document that the degree of co-movement between bilateral USD exchange rates has increased substantially since the introduction of the euro in 1999 and (ii) investigate what drives the increased co-movement. For each of our 33 sampled bilateral USD exchange rates, we measure the degree of co-movement using the R-square from regressing weekly exchange rate changes on the weekly world exchange rate factor. Our results show that, for the majority of sample exchange rates, the R-square has increased substantially over the period 1999-2010. Specifically, the average R-square was 0.15 in 1999, but it increased to 0.47 by more than 200% in 2010. Further analysis reveals that the rising influence of the euro relative to USD over a third currency can explain most of the increase in the measured co-movement over time. Our cross-sectional regression analysis indicates that trade propensity, financial integration, and inflation have some additional power in explaining the cross-sectional variation in the measured co-movement. However, our cross-sectional and time-series regression analysis reveals that once the effect of the influence of the euro relative to USD over a third currency is controlled for, the other explanatory variables lose most of their power in explaining the time-series variation in the measured co-movement.

In Chapter III, we examine the level and trend of U.S. domestic market integration. Investors are known to exhibit home (local) bias even when they invest in their domestic markets. Since home bias is symptomatic of market segmentation, the 'home bias at home' phenomenon raises an important question: How well integrated are domestic financial markets? The answer for this question will have implications for a wide range of financial decision makings, including the cost of capital estimation, asset allocation, and performance evaluation. In this chapter, we address this question by estimating the level and trend of integration of U.S. domestic stock markets. Specifically, for each of our sample states, we construct the state (market) portfolio comprising public firms headquartered within the state and compute R-square, our measure of integration, from regressing state portfolio returns on national stock

market factors. Using weekly returns, we estimate the regression for each year of our sample period 1963-2008. The key findings are: (i) For the majority of sample states, the R-square exhibits a statistically significant upward trend, implying that U.S. domestic stock markets were not fully integrated and have been integrating during the sample period; (ii) consistent with the previous result, the explanatory power of the state factor over individual stock returns has been decreasing for the majority of states; and (iii) the increasing integration of U.S. domestic stock markets is associated with the decreasing home state bias, suggesting that investors' pursuit of nation-wide investment opportunities may be a significant driver of domestic financial integration.

CHAPTER I

HERDING ACROSS COUNTRIES: THE EFFECT OF INFORMATION ENVIRONMENTS

Do investors herd across countries? What are the impacts of their herding behavior, if any, on local stock market performances? Do countries' information environments affect the herding behavior? In the current paper, we address these questions by using a new transaction-level trades database of 531 U.S. institutional investors trading across 37 countries during the period 2002-2009. We find robust evidence of intra-period herding (correlated trading) by employing the Lakonishok, Shleifer, and Vishny (1992) measure and evidence of inter-period herding by employing the Sias (2004) measure at the monthly frequency. We also find evidence of return continuations following intra-period buy herding and no evidence of return reversals following intra-period sell herding. Hence, there is no evidence that trades by institutions in our sample drive prices away from the fundamental values; rather, they help to speed the price-adjustment process. Further analysis shows that: (i) in the buy side, both intra- and inter-period herdings are more pronounced in countries with weaker information environments; and (ii) in the sell side, intra-period herding is more pronounced in countries with stronger information environments, whereas inter-period herding is not significantly related to information environments. The overall results of the paper suggest that information environments have asymmetric effects on the buy- and sell-side herdings and are consistent with the view that, in the buy side, institutions herd as a result of 'intentionally' inferring information from each other's trades, whereas, in the sell side, correlated signals primarily drive institutions' 'unintentional' herding across countries.

1.1 Introduction

The role of institutional investors in the world equity markets has grown steadily during the past couple of decades. The reduction of explicit barriers to cross-border capital flows together with the decreasing level of investors' home bias have helped such an increasing role of institutional investors (Ahearne, Griever, and Warnock, 2004; Stulz, 2005). According to 2010 Investment Company Fact Book, U.S.-registered investment companies managed \$12.2 trillion as of the end of 2009; and, including funds offered in foreign countries, worldwide mutual fund assets are estimated to be \$23.0 trillion. Considering that the world stock market capitalization is estimated to be \$47.8 trillion at the same year-end, the mutual fund industry managed nearly 50% of the world equity shares. Thus, institutional investors' trading behavior across the world equity markets and its impacts on local stock market performances deserve a close look. Although the existing literature on institutional investors' herding behavior and its impacts on stock prices is extensive, most extant studies have focused on institutional investors trading within a single country, predominantly the United States (see, e.g., Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Nofsinger and Sias, 1997; Wermers, 1999; Sias, 2004; Puckett and Yan, 2008; Choi and Sias, 2009; Christoffersen and Tang, 2010). To our knowledge, no prior studies have yet investigated the existence and impacts of institutional investors' herding behavior across countries.[1]

Do institutional investors herd across countries? What are the impacts of their herding behavior, if any, on local stock market performances? This paper addresses these important questions using a new proprietary transaction-level trading database of 531 U.S. institutional investors trading across 37 countries around the world during

[1] This may be due to the difficulty of obtaining appropriate data to use. Froot, O'Connell, and Seasholes (2001) and Froot and Ramadorai (2008) investigate the relation between international portfolio flows into and out of a country and local stock market performances, but their studies are conducted only at the aggregate flow level.

the period January 2002 to December 2009, which we purchased from Ancerno Ltd. (formerly the Abel Noser Corporation).[2]

Apart from examining whether institutional investors herd across countries, we address another important question: whether and how do cross-country differences in information environments affect their herding behavior? In the literature on herding theories, the primary cause of herding behavior is information asymmetry among a group of decision makers and their sequential decision making process. In theory, herding results from an intent by some decision makers to copy or mimic the behavior of other decision makers when they have imperfect, differential information.[3] Consistent with the prediction of herding theories, many studies, including Wermers (1999), find evidence of a higher level of institutional herding in smaller stocks than in larger stocks and tend to attribute their findings to the fact that information asymmetry among institutions is generally larger in smaller stocks than in larger stocks.[4] Information asymmetry among institutions, however, is likely to be much larger in stocks of foreign countries than in domestic stocks. Intuitively, this is so because the degree of information disclosure requirements, the quality and comprehensiveness of disclosed information, and the timeliness of information disclosures, etc. vary widely across countries (see, e.g., La Porta, Lopez de-Silanes, Shileifer, and Vishny, 1998; Bushman, Piotroski, and Smith, 2004; Lakonishok, Shileifer, and Vishny, 2006; Frost, Gordon, and Hayes, 2006). The cost of collecting information should also vary to a great extent across countries. Hence, chances are high that some

[2]Ancerno collects transaction-level trade data from a large sample of U.S. institutional traders and conducts and provides transaction cost analysis for them.

[3]Popular theories of herding proposed in the literature include: theory based on decision makers' reputational concerns of acting differently from others (Scharfstein and Stein, 1990; Trueman, 1994); theory based on decision makers inferring information from others' previous decisions (Benerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Welch, 1992); theory based on decision makers following fads or preferring certain characteristics (Friedman, 1984; Falkenstein, 1996); and theory based on correlated signals (Froot, Scharfstein, and Stein, 1992).

[4]Throughout this paper, we use the terms "institutional investors" and simply "institutions" interchangeably.

institutions may be better in accessing and analyzing information about a particular stock or stocks from a particular country than other institutions. Thus, the effect of information environments on institutional herding behavior, if it exists, may manifest itself more clearly in an international setting. Examining herding behavior using data from institutional investors' trading across a wide cross-section of countries can add to our understanding of the relation between information environments and herding behavior.

To address our research questions, we measure institutional herding at a monthly horizon and define an institutional investor as a buyer (seller) of a given country during a given month if the total dollar value of the institution's position in the country increased (decreased) over the month (Lakonishok, Shleifer, and Vishny, 1992; Choi and Sias, 2009). We consider the monthly horizon to be a reasonable time horizon to measure institutional herding, especially in an international investment context.[5] Next, as measures of herding, we employ two measures: one proposed by Lakonishok, Shleifer, and Vishny (1992; LSV henceforth), which we refer to as the LSV measure, and the other proposed by Sias (2004), which we refer to as the Sias measure. These are the two most popular measures of herding in the literature. The two herding measures capture different characteristics of trading patterns. The LSV measure measures cross-sectional herding (correlated trading) over one period, and the Sias measure measures inter-temporal herding over two adjacent periods.[6] To

[5]Measuring herding at a longer time horizon, a quarterly horizon for example, would not capture intra-period round-trip transactions and may not identify institutional herding behavior adequately (LSV, 1992; Puckett and Yan, 2008). Also, measuring herding at a shorter time horizon, a daily or weekly horizon for example, may not allow institutions to infer information from other institutions' trades adequately, especially in an international setting. In addition, influential fund rating agencies such as Morningstar and Barron's/Lipper report the rating of funds based on funds' performance regularly, and one-month horizon is the shortest time horizon they consider. Hence, if any kind of market disciplinary mechanism affects institutional investors' trading behavior, we expect that institutional trading behavior is likely to manifest itself clearly at a monthly horizon.

[6]As Lakonishok, Shleifer, and Vishny (1992) themselves have put it, the LSV measure cannot disentangle 'intentional' (or 'true') herding from 'unintentional' (or 'spurious') herding. Unintentional herding results when institutions move in the same direction simply because they get similar signals and follow similar trading strategies (momentum strategy, for example). According to Bikhchandani

put it simply, for a stock and a period of interest, LSV measure herding as the *excess* tendency of a group of investors to buy (sell) the stock at the same time over the period, relative to what could be expected if they traded independently. On the other hand, Sias measures herding as the portion of the inter-temporal correlation between contemporaneous and lag investor demands over two adjacent periods that is due to investors' following the lag demand of other investors. Throughout this study, we also refer to the LSV herding as 'intra-period' herding and the Sias herding as 'inter-period' herding for obvious reason. Examining both intra- and inter-period herdings together would give us a better understanding of how differently institutions behave in different information environments.

We begin with examining intra-period herding across countries using the LSV herding measure. We find a mean intra-period herding of 2.2% when we consider country-month pairs with at least five active institutions.[7] At a first glance, the size of intra-period herding may look small. However, the LSV measure is computed by subtracting the so-called adjustment factor term, and the mean value of this adjustment term amounts to 6.5%. During our sample period, the time-series mean of the average institutional demand across all countries was 50.4%. Hence, the mean intra-period herding value of 2.2% can be interpreted as implying that 59.1% (=50.4+2.2+6.5) of institutions were moving in the same direction in an average country-month pair and 40.9% in the opposite direction.[8] The measured intra-period herding is also strongly significant with a t-statistic value of 17.23. Excluding a few

and Sharma (2000), what the LSV measure really measures is the correlation in trading patterns for a particular group of traders. For this reason, Feng and Saesholes (2004) use the term "correlated trading" rather than "herding" while they employ the LSV measure.

[7]The measured level of intra-period herding of 2.2% is smaller than that found by Wermers (1999), 3.4% for U.S. individual stocks, and larger than that by Choi and Sias (2009), 1.4% for 49 U.S. industries, although these values are not directly comparable to each other.

[8]Previous studies do not consider the effect of the adjustment term for this kind of argument (Lakonishok et al., 1992; Wermers, 1999). However, the adjustment term is usually sizable as can be seen from Figure 1.

smallest market capitalization countries from the sample does not change the measured herding level significantly. Importantly, we find that the measured intra-period herding varies greatly across countries. In terms of the time-series average over the sample period, the measured intra-period herding ranges from the lowest -0.7% for Thailand to the highest 4.0% for Korea.

Next, using the Sias herding measure, we find strong evidence of inter-period herding. Specifically, the inter-temporal correlation between the fraction of institutional investors buying a country this month and the fraction buying last month amounts to about 0.3, and more than 60% of the correlation is accounted for by institutional investors' following other institutional investors' previous trades, which represents inter-period herding in Sias (2004). The portion of the inter-temporal correlation due to inter-period herding increases monotonically as we require more number of active institutions in country-month pairs. The results of inter-period herding are also robust from the influence of a few small market capitalization countries. Again, we find that the measured inter-period herding varies a great deal across countries. In terms of the standardized time-series average over the sample period, the measured inter-period herding ranges from the lowest -1.85 for Brazil to the highest 3.13 for Russia.

Given the evidence of widely varying intra- and inter-period herdings across countries, we then investigate whether the cross-country differences in information environments can explain such variations in the measured herding levels across countries. For this purpose, we employ nine proxies for a country's information environments, which are drawn from the finance and accounting literature. They are: (1) the average idiosyncratic volatility across all stocks of a country divided by the average systematic volatility (Morck, Yeung, and Yu, 2000); (2) a dummy variable indicating whether a country is classified as a developed market; (3) a dummy variable indicating whether English is the official language; (4) a dummy variable indicating whether the legal origin is the English common law; (5) the level of corporate information disclosure requirements; (6) the level of accounting standards; (7) the frequency of information disclosures; (8) the percentage of firms audited by big five auditing companies; and (9) the number of analysts following the largest 30 companies in a country. Considering that each of the nine proxies above is an imperfect proxy for information environments, we also consider a composite proxy for information environments constructed based on the first principal component of the correlation matrix of these nine proxy variables (Baker and Wurgler, 2006; Brown and Cliff, 2004). To examine the effect of information environments on herding, we employ the Fama-MacBeth regression procedure with controlling for previous-period local stock market performances.

With regard to intra-period herding, we find that buy herding is inversely related to the quality of information environments, meaning that buy herding is larger in countries with weaker information environments.[9] On the other hand, sell herding is positively related to the quality of information environments, meaning that intra-period sell herding is larger in countries with stronger information environments. We find that previous-month local market returns have no significant relation with intra-period herding this month. Next, with regard to inter-period herding, we find that buy herding is inversely related to the quality of information environments, meaning that inter-period buy herding is larger in countries with weaker information environments.[10] On the other hand, inter-period sell herding has no significant relation with the quality of information environments. We also find that inter-period buy herding is significantly larger when previous market returns are larger, but that inter-period

[9]Following Wermers (1999), we define a country-month pair as a buy herding pair if the fraction of institutions buying the country relative to active institutions is greater than its expected value under the null hypothesis of no herding.

[10]Following Choi and Sias (2009), we define a country-month pair this month as a buy herding pair if the fraction of institutions buying the country relative to active institutions *last month* is greater than its expected value under the null of no herding. In addition, we decompose the inter-temporal correlation between contemporaneous and lag investor demands over two adjacent periods into its country-wise components, which is detailed in Section 2. This way, we can compute inter-period herding at the country level, which is straight-forward when we use the LSV measure.

sell herding has no significant relation with previous market returns. Both results of intra- and inter-period herdings taken together suggest that information environments have asymmetric effects on the buy- and sell-side herdings, and are consistent with the view that, in the buy side, institutions herd as a result of 'intentionally' inferring information from each other's trades, whereas, in the sell side, correlated signals primarily drive their 'unintentional' herding across countries.

Last, but not the least, we find that institutional demand impacts local stock market performances. In an average month over the sample period, top five countries most heavily demanded by institutions outperform bottom five countries least demanded by 1.52% per month (18.2% per annum). We also find that institutions in our sample tend to demand countries that performed poorly more than those that performed well over the previous six to twelve months. Hence, institutions as a group tend to act as contrarians at six- to twelve-month horizons. Also, countries demanded most this month exhibit return continuation over the next 6-month period and there is no return reversal phenomenon for countries demanded least this month. The long-short portfolio constructed by longing countries demanded more than average and shorting countries demanded less than average generates positive returns over the next 1- to 3-month periods. Taken together, these results show no evidence that trades by institutions in our sample drive prices away from the fundamental values; rather, they help to speed the price-adjustment process.

Our findings in this paper contribute to the herding literature in at least two ways. First, we provide the first evidence of institutional herding across countries and its impacts on local stock market performances. As mentioned earlier, most prior studies examining institutional herding behavior have focused only on a single country. Second, our study is also the first to explicitly examine the link between institutional herding across countries and countries' information environments. Despite that information asymmetry among decision makers plays a critical role in the theoretical literature of herding, few prior studies have explicitly examined the link between the two.[11]

The rest of the paper is organized as follows. The next section introduces the two herding measures we employ. It also introduces some notations used throughout this study. Section 3 describes our data. Section 4 presents evidence of both intra- and inter-period herdings. Section 5 investigates the relation between institutional demands and local stock market performances. Section 6 addresses the question of whether and how information environments affect the herding behavior. Section 7 concludes.

1.2 Measurement of Herding

In this section, we introduce two herding measures we use: one proposed by Lakonishok, Shleifer, and Vishny (1992), which we refer to as the LSV measure, and the other proposed by Sias (2004), which we refer to as the Sias measure. For ease of our discussion and readers' understanding, we first present several notations that we use throughout this study.

1.2.1 Notations

To enumerate countries, months, and institutional investors, we use k for a country, t for a month, and n (or m) for an institutional investor. We define $N_{k,t}$ as the number (or index set) of institutions active in country k during month t and $I_{n,k,t}$ as the number (or index set) of country k's stocks actively traded by institution n during month t.[12] Following LSV (1992), Grinblatt, Titman, and Wermers (1995),

[11] One notable exception is Christoffersen and Tang (2010), who examine the relation between institutional herding and information environments in the U.S. stock markets by constructing various proxies for information environments at the individual stock level.

[12] The reason why we define $N_{k,t}$, for example, as either the number or the index set of institutions is as follows. Suppose there are 100 institutions and a unique identification number (ID) ranging from 1 to 100 is assigned to each institution. Suppose that, during month t, only three institutions with IDs 11, 40, and 89 were active in country k. Then, a notation such as $\sum_{n=1}^{N_{k,t}}$ does not make sense whereas $\sum_{n\in N_{k,t}}$ makes sense since $N_{k,t}$ also means the index set $\{11, 40, 89\}$.

and Sias (2009), we define institution n as a buyer of country k during month t if the dollar value of the institution's position in the country increased over the month.[13] Specifically, institution n is classified as a buyer of country k during month t if

$$\sum_{i \in I_{n,k,t}} P_{i,t-}(\text{Shares}_{n,i,t+} - \text{Shares}_{n,i,t-}) > 0 \tag{1.1}$$

and as a seller if this value is negative. Here, $P_{i,t-}$ represents the price of stock i of country k at the beginning of month t, and $\text{Shares}_{n,i,t-}$ ($\text{Shares}_{n,i,t+}$) represents the number of shares of stock i held by institution n at the beginning (end) of month t. The number of shares are adjusted for both stock splits and stock dividends. Finally, we use the following notations:

- $D_{n,k,t} = 1$ (0) if institution n is a buyer (seller) of country k during month t;
- $B_{k,t} =$ the number of institutions that are buyers of country k during month t;
- $S_{k,t} =$ the number of institutions that are sellers of country k during month t; and
- $\Delta_{k,t} = B_{k,t}/(B_{k,t}+S_{k,t}) = B_{k,t}/N_{k,t} =$ the fraction of buyers of country k relative to active institutions during month t.

1.2.2 LSV herding measure

In their abstract, LSV (1992) define herding as "buying (selling) simultaneously the same stocks as other managers buy (sell)." For country k during month t, the LSV herding measure is defined as follows:

$$H_{k,t} = |\Delta_{k,t} - \overline{\Delta_t^*}| - E_0[|\Delta_{k,t} - \overline{\Delta_t^*}|] = |\Delta_{k,t} - \overline{\Delta_t^*}| - AF_{k,t} \tag{1.2}$$

where

$$\overline{\Delta_t^*} = \frac{\sum_k B_{k,t}}{\sum_k B_{k,t} + S_{k,t}} = \sum_k \frac{N_{k,t}}{\sum_k N_{k,t}} \Delta_{k,t}. \tag{1.3}$$

[13] Although the focus of the LSV (1992) study is on institutional herding at the individual stock level, they also examine institutional herding at the industry level (p.34).

The term $AF_{k,t} = E_0[|\Delta_{k,t} - \overline{\Delta_t^*}|]$ is called the adjustment factor. It is calculated under the null hypothesis of no herding, the reason why we add subscript '0' to the expectation operator. More specifically, during month t, under the null hypothesis of no herding the probability of a randomly-chosen institutional investor being a buyer of country k is simply $\overline{\Delta_t^*}$.[14] For example, suppose that we have $\overline{\Delta_t^*} = 0.55$, $B_{k,t} = 6$, and $S_{k,t} = 4$. Then, under the null hypothesis of no herding, $B_{k,t}$ follows a binomial distribution $BN(10, 0.55)$ and $AF_{k,t}$ is computed as follows:

$$AF_{k,t} = \sum_{j=0}^{10} |\frac{j}{10} - 0.55| \binom{10}{j} 0.55^j 0.45^{10-j}. \tag{1.4}$$

Note that, given $\overline{\Delta_t^*}$, $AF_{k,t}$ depends only on $N_{k,t}$ and $\overline{\Delta_t^*}$, although both $B_{k,t}$ and $S_{k,t}$ affect $\overline{\Delta_t^*}$ in the beginning. Figure 1 shows the size of the adjustment factor when the number of active institutions varies from 1 to 100. For the figure, we use $\overline{\Delta_t^*} = 0.504$. Note from the figure that the adjustment factor can be very large for a wide range of $N_{k,t}$ values.[15] When the number of active institutions is 1, 10, 50, and 100, the adjustment factor is equal to 0.5, 0.123, 0.056, and 0.040, respectively.

Since its introduction, the LSV herding measure has been widely used in empirical studies examining the herding behavior in financial markets. Since the measure is computed at each security level (at each country level in our study), it is easy to compute the herding level for any particular group of securities. On the other hand, however, as LSV themselves have put it, the LSV measure cannot disentangle 'intentional' herding from 'unintentional' herding. Unintentional herding results when institutions move in the same direction simply because they get similar signals and follow similar trading strategies (momentum strategy for example). According to Bikhchandani and Sharma (2000), "while it (the LSV measure) is called a herding

[14] Some studies, such as Grinblatt et al. (1995), use $\overline{\Delta_t} = (1/K)\sum_{k=1}^{K} \Delta_{k,t}$ instead of $\overline{\Delta_t^*}$.

[15] When N goes to infinity, $AF(N,p)$ converges to zero. But, it does so very slowly with the order of $1/\sqrt{N}$ since $AF(N,p) = E|(X/N) - p| \sim \sqrt{2/\pi}\sqrt{p(1-p)}/\sqrt{N}$. Here, $a_N \sim b_N$ means $\lim_{N\to\infty} a_N/b_N = 1$. If $p = 0.5$, then we have $AF(N,p) \sim 0.3989/\sqrt{N}$ and hence $AF(100, 0.5)$ is close to 0.04.

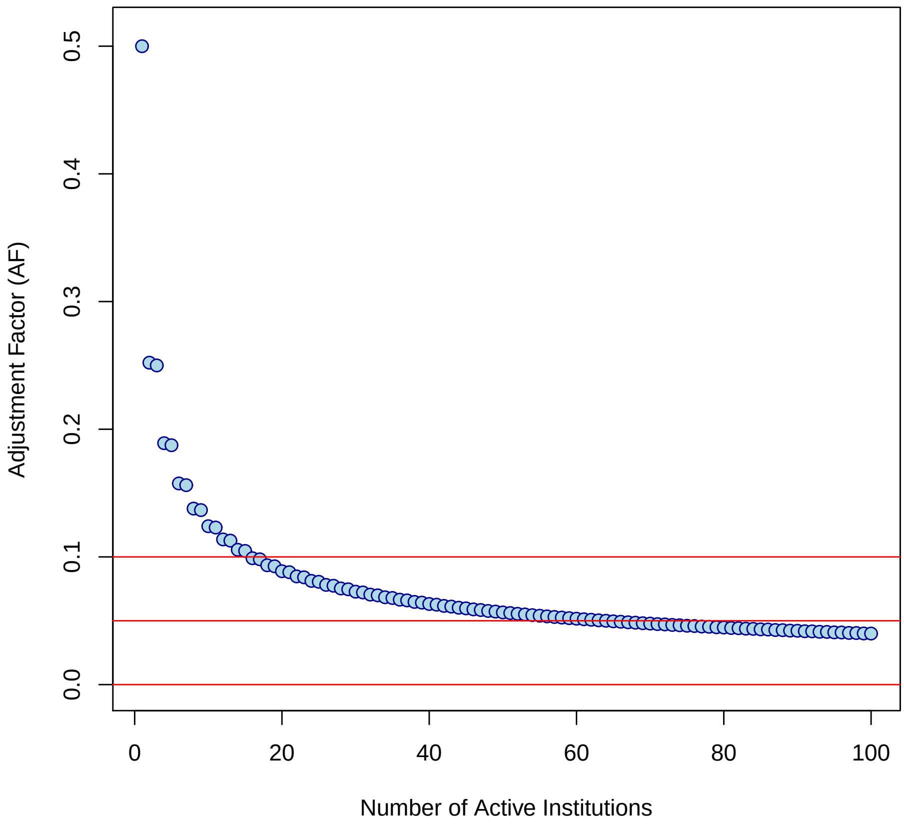

Figure 1.1: Adjustment Factor

This figure shows the size of the adjustment factor when the number of active institutions varies from 1 to 100. Let N be the number of active institutions and p be the fraction of buyers under the null hypothesis of no herding. Then, the adjustment factor (AF) is equal to

$$AF = \sum_{j=0}^{N} |\frac{j}{N} - p| \binom{N}{j} p^j (1-p)^{N-j}.$$

To compute adjustment factor, we use the average of $\overline{\Delta_t^*}$s over 96 months, i.e., $(1/96)\sum_{t=1}^{96} \overline{\Delta_t^*}$ as p, which is 0.504. The three horizontal lines inserted represent $y = 0$, $y = 0.05$, and $y = 0.1$. For example, when the number of active institutions is one (a hundred), the adjustment factor is equal to 0.500 (0.040).

measure, it really assesses the correlation in trading patterns for a particular group of traders and their tendency to buy and sell the same set of stocks. (Intentional)

Herding clearly leads to correlated trading, but the converse need not be true." In addition, the LSV measure does not allow researchers to identify inter-temporal trading patterns (Sias, 2004; Puckett and Yan, 2008; Choi and Sias, 2009).

Throughout this study, we refer to the LSV herding as 'intra-period' herding to distinguish it from the Sias herding introduced in the following subsection, which we refer to as 'inter-period' herding.

1.2.3 Sias herding measure

The Sias (2004) herding measure, the second measure of herding we use, implements the idea that herding should occur sequentially in principle (see, e.g., Banerjee, 1992; Scharfstein and Stein, 1990; Bikhchandani, Hirshleifer, and Welch, 1992; Welch, 1992; Devenow and Welch, 1996; Bikhchandani and Sharma, 2000). The Sias measure is defined as the term ρ_t^H in the decomposition of the inter-temporal cross-sectional correlation between institutional demand this month $\Delta_t = (\Delta_{1,t}, ..., \Delta_{K,t})$ and demand last month $\Delta_{t-1} = (\Delta_{1,t-1}, ..., \Delta_{K,t-1})$ into two parts as shown in the following:

$$\begin{aligned}
\rho_t = \ & \mathrm{corr}(\Delta_t, \Delta_{t-1}) = \frac{1}{(K_t-1)\sigma_t\sigma_{t-1}} \sum_{k=1}^{K} (\Delta_{k,t} - \overline{\Delta_t})(\Delta_{k,t-1} - \overline{\Delta_{t-1}}) \\
= \ & \frac{1}{(K_t-1)\sigma_t\sigma_{t-1}} \sum_{k=1}^{K} \left(\sum_{n \in N_{k,t}} \frac{D_{n,k,t}}{N_{k,t}} - \overline{\Delta_t} \right) \left(\sum_{m \in N_{k,t-1}} \frac{D_{m,k,t-1}}{N_{k,t-1}} - \overline{\Delta_{t-1}} \right) \\
= \ & \frac{1}{(K_t-1)\sigma_t\sigma_{t-1}} \sum_{k=1}^{K} \left[\sum_{n \in N_{k,t} \cap N_{k,t-1}} \left(\frac{D_{n,k,t} - \overline{\Delta_t}}{N_{k,t}} \right) \left(\frac{D_{n,k,t-1} - \overline{\Delta_{t-1}}}{N_{k,t-1}} \right) \right] \\
& + \frac{1}{(K_t-1)\sigma_t\sigma_{t-1}} \sum_{k=1}^{K} \left[\sum_{n \in N_{k,t}, m \in N_{k,t-1}, n \neq m} \left(\frac{D_{n,k,t} - \overline{\Delta_t}}{N_{k,t}} \right) \left(\frac{D_{m,k,t-1} - \overline{\Delta_{t-1}}}{N_{k,t-1}} \right) \right] \\
:= \ & \sum_{k=1}^{K} \rho_{k,t}^{SR} + \sum_{k=1}^{K} \rho_{k,t}^{H} := \rho_t^{SR} \text{ (self-reinforcing) } + \rho_t^{H} \text{ (herding) }. \qquad (1.5)
\end{aligned}$$

Here, $\overline{\Delta_t} = \frac{1}{K_t} \sum_{k=1}^{K} \Delta_{k,t}$, $\sigma_t = \frac{1}{K_t-1} \sum_{k=1}^{K} (\Delta_{k,t} - \overline{\Delta_t})^2$, and $\overline{\Delta_{t-1}}$ and σ_{t-1} are defined similarly; K_t represents the number of countries for which both $\Delta_{k,t}$ and $\Delta_{k,t-1}$ are defined;[16] and we use the convention that $\sum_{k=1}^{K} \Delta_{k,t}\Delta_{k,t-1}$, for example, is equal to the sum of $\Delta_{k,t}\Delta_{k,t-1}$s for which $\Delta_{k,t}$ and $\Delta_{k,t-1}$ both are defined.

Note that the Sias measure ρ_t^H in Equation (1.5) represents the portion of the correlation accounted for by individual investors following the lag demand of other investors, i.e, herding. On the other hand, the term ρ_t^{SR} represents the portion of the correlation accounted for by individual investors following their own lag demand. A positive ρ_t^{SR} implies that investors tend to increase (decrease) their investments this month in countries that they increased (decreased) their investments last month. That is, ρ_t^{SR} can be interpreted as the extent to which investors engage in inter-period 'self-reinforcing' trading. Finally, as shown in the defining equation, we can decompose ρ_t^H, inter-period herding, into its country-wise components $\rho_{k,t}^H$s. Later, when we examine the relation between inter-period herding and information environments at the country level, we will use these country-wise components. For example, inter-period herding in country k during month t refers to $\rho_{k,t}^H$.

1.3 Data

The key dataset for the current study is the transaction-level trading data of a large sample of U.S. institutional investors trading around the world from January 1, 2002 to December 31, 2009, which we purchased from Ancerno Ltd. (formerly the Abel/Noser Corporation).[17] During our 8-year sample period, the Ancerno Non-US Equity Trade database contains more than 30 million transaction records of more than 530 institutional investors trading around the world outside the U.S.[18] Although

[16]Although $K = 37$ in our sample, K_t can be less than 37, especially in the earlier part of the sample period.

[17]Ancerno collects transaction-level trade data from a large sample of U.S. institutional traders and conducts and provides transaction cost analysis for them.

[18]The Ancerno US Equity Trading database has been utilized by many researchers to examine trading activities of institutional investors within the U.S. (Goldstein, Irvine, Kandel, and Wiener, 2009; Lipson and Puckett, 2007; Puckett and Yan, 2008, 2011; Hu, McLean, Pontiff, and Wang, 2010). However, the Ancerno Non-US Equity Trading database has been provided to academics only recently, so few prior studies have utilized the database to date. As far as we know, Pagano (2009a) and Pagano (2009b) are only studies that use the database to examine the time-trend of

the database does not capture trading by all institutional investors registered in the U.S., it does represent a significant portion of institutional investors' trading activities around the world. Later, we show that the Ancerno Non-US Equity Trading database represents about 5% of the worldwide equity trading volume outside the U.S., a substantial portion of the world equity trading volume.

Among several data files of the Ancerno Non-US Equity Trade database, we combine three data files: (i) Equity Trade Data File, which contains the date of transaction, client code (institutional investor identification code), stock identifier, country code of stock origin, market code, buy/sell indicator, amount of shares transacted, currency code, exchange rate applied, etc.; (ii) Stock Reference File, which contains the stock identifier, company name, ticker symbol, 8-character alphanumeric CUSIP, 7-character SEDOL[19]; and (iii) Country Reference File, which contains the country code and country name. After carefully checking and screening erroneous transaction data, we merge the transaction data with the data of daily stock prices and number of shares outstanding from the COMPUSTAT Global and North America databases. We exclude transaction data of preferred stocks, units, trusts, income funds, real estate investment trusts, exchange-traded funds, etc. from the sample and include transaction data of only common stocks and depository receipts, mostly American Depository Receipts (ADRs), in our analysis.[20] For each transaction, we require the stock involved to have data on previous month-end stock price and the number of shares outstanding from the COMPUSTAT databases. Stocks for which the total number of transactions during the entire sample period is less than 30 are also excluded from the sample. In addition, to maintain the integrity of the data and

trading costs and trading volume in global equity markets.

[19]SEDOL stands for the Stock Exchange Daily Official List, a list of security identifiers used in the United Kingdom and Ireland for clearing purposes. It is assigned by the London Stock Exchange, on request by the security issuer.

[20]For a company that has multiple share classes, we include only its primary class in our sample. The COMPUSTAT database provides the unique company identifier GVKEY (6 digits) and issue identifier IID (2 digits plus 1 character) to identify a company and its share classes.

filter out possible errors, we eliminate transaction data where the order quantities are greater than 5% of the total number of shares outstanding of the involved stock.

Table 1.1 reports the summary characteristics of the data. Panel A of the table reports the number of stocks traded by institutions and the number of active institutions by year. The reported mean value shows that in an average year 4747 stocks were traded by institutions in our sample. The reported total value shows that, during the 8-year sample period 2002-2008, a total of 7759 stocks were traded by a total of 531 institutional investors. Panel A also shows that both the number of stocks traded and the number of active institutions increased steadily over the period from 2002 to 2008. However, in the aftermath of global financial crises in late 2008, the number of active institutions decreased by about 27% from 278 in 2008 to 202 in 2009, and the number of stocks traded also decreased by about 14% from 6254 in 2008 to 5391 in 2009.

Next, Panel B of Table 1.1 reports the descriptive statistics for the number of stocks traded by institutions and the number of active institutions in a randomly selected country-month pair. For each month, we calculate the cross-sectional mean, standard deviation, minimum, median, and maximum of the number of stocks traded and the number of active institutions across 37 countries. Panel B reports the monthly time-series average of these five statistics. It shows that, for a randomly selected country-month pair, 91 different stocks were traded by 52 institutions on average.

Table 1.1: Sample Characteristics

This table presents the sample characteristics of our trading data of 531 U.S. institutional investors trading across 37 countries during the period from January 2002 to December 2009 (96 months), which is from Ancerno Ltd. (formerly the Abel/Noser Corporation). Panel A presents the number of stocks traded by institutions and the number of institutions active by year. The last column *Total* represents the total number of different stocks traded and the total number of different institutions active during the entire sample period. Panel B presents descriptive statistics for the number of stocks traded by institutions and the number of institutions active measured at the monthly frequency. For each month during the sample period, we calculate the mean, standard deviation, minimum, median, and maximum of the number of stocks traded and the number of institutions active across 37 countries. Then, we compute the time-series average over 96 months of these five statistics. Lastly, Panel C presents the time-series average over 96 months of the number of stocks traded (*N stock*) and the number of institutions active (*N inst*) measured at the monthly frequency, together with stock market capitalization and turnover information by country. The *N tran* and *T val* represent the average number of transactions (in thousands) and the average value of transactions (in billion dollars) measured at the yearly frequency, respectively. The *MktCap* and *Turn* represent the average stock market capitalization (in billion dollars) and the average turnover ratio (in percent terms) measured at the yearly frequency, respectively. The annual turnover ratio we use represents the total value, not volume, of shares traded during a given year divided by the average market capitalization for the year. Stock market capitalization and turnover ratio data are obtained from the World Development Indicators (WDI) database of the World Bank for all countries except for Taiwan. For Taiwan, we collect data from various annual issues of the Taiwan Stock Exchange Fact Book.

Table 1.1: Sample Characteristics (Continued)

Panel A: Number of stocks and institutions by year

	2002	2003	2004	2005	2006	2007	2008	2009	Mean	Total
N stocks traded	2864	3451	3744	4591	5530	6147	6254	5391	4747	7759
N institutions active	102	131	140	131	157	244	278	202	173	531

Panel B: Number of stocks and institutions per month

	Mean	SD	Min	Med	Max
N stocks traded in a country	91	145	9	47	804
N institutions active in a country	52	26	12	48	99

Panel C: Number of stocks and institutional investors by country

	N stock	N inst	N tran	T val (a)	(%)	MktCap (b)	(%)	Turn (c)	wTurn a/(b*c)
Australia	133	74	118.7	33.9	(2.8)	950.0	(3.8)	86.8	4.1
Austria	22	43	18.2	6.5	(0.5)	105.7	(0.4)	43.0	14.4
Belgium	32	44	26.7	9.3	(0.8)	260.2	(1.0)	71.2	5.0
Brazil	26	27	16.7	5.3	(0.4)	631.4	(2.5)	44.9	1.9
Canada	202	70	94.0	39.5	(3.3)	1336.2	(5.3)	78.3	3.8
China	76	50	58.4	20.2	(1.7)	2425.8	(9.6)	109.7	0.8
Denmark	27	52	22.3	8.4	(0.7)	169.5	(0.7)	82.8	6.0
Finland	35	61	36.3	17.3	(1.5)	197.7	(0.8)	137.6	6.4
France	141	92	249.6	112.2	(9.4)	1791.6	(7.1)	106.0	5.9
Germany	115	88	167.0	95.9	(8.1)	1295.4	(5.1)	155.1	4.8
Greece	30	44	23.4	6.9	(0.6)	132.4	(0.5)	48.5	10.7
Hong Kong	150	79	125.5	31.8	(2.7)	1006.4	(4.0)	62.2	5.1
India	83	25	24.4	10.0	(0.8)	712.3	(2.8)	119.5	1.2
Indonesia	29	29	15.8	4.0	(0.3)	108.4	(0.4)	50.6	7.4
Ireland	23	58	39.3	12.8	(1.1)	95.0	(0.4)	63.4	21.2
Israel	18	23	8.4	3.0	(0.3)	133.1	(0.5)	57.7	3.9
Italy	96	73	80.6	37.8	(3.2)	703.9	(2.8)	162.9	3.3
Japan	803	96	652.0	186.6	(15.7)	3667.7	(14.5)	115.5	4.4
Korea	128	52	67.7	31.0	(2.6)	627.1	(2.5)	210.5	2.3
Malaysia	53	30	17.5	3.8	(0.3)	208.7	(0.8)	33.0	5.5
Mexico	28	38	19.3	5.2	(0.4)	246.0	(1.0)	28.6	7.4
Netherlands	70	84	107.5	49.3	(4.1)	588.6	(2.3)	146.1	5.7
New Zealand	14	21	6.3	0.9	(0.1)	39.6	(0.2)	42.3	5.5
Norway	39	58	39.4	15.6	(1.3)	185.2	(0.7)	119.3	7.0
Philippines	14	16	3.6	0.6	(0.1)	54.5	(0.2)	19.2	6.1
Poland	17	20	5.0	1.5	(0.1)	101.7	(0.4)	37.6	3.8
Portugal	14	30	8.2	2.4	(0.2)	82.7	(0.3)	69.8	4.1
Russia	11	27	13.2	7.0	(0.6)	624.1	(2.5)	53.3	2.1
Singapore	60	58	34.1	8.4	(0.7)	264.8	(1.0)	72.9	4.4
South Africa	54	40	43.7	11.5	(1.0)	532.4	(2.1)	53.5	4.0
Spain	56	71	60.9	36.4	(3.1)	1060.1	(4.2)	173.2	2.0
Sweden	73	71	67.1	25.3	(2.1)	395.2	(1.6)	127.9	5.0
Switzerland	93	85	259.4	92.0	(7.7)	939.4	(3.7)	113.2	8.7
Taiwan	121	36	49.0	19.3	(1.6)	488.8	(1.9)	168.0	2.3
Thailand	22	24	5.8	1.3	(0.1)	123.4	(0.5)	85.5	1.3
Turkey	36	28	13.2	5.1	(0.4)	144.2	(0.6)	155.3	2.3
United Kingdom	442	98	560.1	231.9	(19.5)	2819.4	(11.2)	162.7	5.1
Average	91	52	85.4	32.2	(2.7)	682.4	(2.7)	93.7	5.3

Lastly, Panel C of Table 1.1 reports transaction information by country, together with stock market capitalization and turnover information. The first two columns report the monthly time-series average over 96 months of the number of stocks traded and number of active institutions by country. In an average month, institutions in our sample traded the largest number of stocks of Japan (803 stocks). They traded more than 100 stocks in another 8 countries: the United Kingdom (442), Canada (202), Hong Kong (150), France (141), Australia (133), Korea (128), Taiwan (121), and Germany (115). On average, they traded 91 stocks of one country during one month, which is the same as the mean value reported in Panel B. Next, in an average month, the largest number of institutions traded actively in the United Kingdom (98 institutions), followed by Japan (96), France (92), Germany (88), Switzerland (85), Netherlands (84), Hong Kong (79), Australia (74), Spain (71), Sweden (71), and Canada (70). On average, 52 institutions traded actively in one country during one month, which is also the same as the mean value reported in Panel B.

The next two columns report the yearly time-series average over 8 years of the number and value of transactions by country. The number of transactions is represented in a multiple of thousand and the value of transactions in U.S. billion dollars. In an average year, institutions in our sample made transactions most frequently in Japan (652 thousands). They made more than 100 thousand transactions in another 7 countries: the United Kingdom (560), Switzerland (259), France (250), Germany (167), Hong Kong (126), Australia (188), and Netherlands (107). On average, they made 85.4 thousand transactions in one country during one year. Next, in terms of the total value of shares traded, in an average year, institutions in our sample made transactions worth more than 231 billion dollars in the United Kingdom. They made transactions worth more than 100 billion dollars in another 2 countries: Japan (186) and France (112). On average, they made transactions worth more than 32 billion dollars in one country during one year.

The fifth and sixth columns report the yearly time-series average over 8 years of the country stock market capitalization, *MktCap*, and turnover ratio, *Turn*, by country.[21] The turnover ratio represents the total value, not volume, of shares traded in an average year divided by the average market capitalization for the year. In terms of the market capitalization, the three largest countries outside the U.S. was Japan, the United Kingdom, and China. During the sample period, they represented 14.5%, 11.2%, and 9.6% of the total market capitalization of the sampled countries, respectively. Not surprisingly, the correlation between column (a) and column (b) is very high with 0.85. During our sample period, the average turnover ratio was the highest for Korea (211%), followed by Spain (173%), Taiwan (168%), Italy (163%), and the United Kingdom (163%).

The last column, *wTurn*, represents the total value of shares traded by institutions in our sample divided by the product of market capitalization and turnover ratio, i.e., a/(b*c). Hence, 4.1% for Australia, for example, can be interpreted as meaning that the total value of shares traded by institutions in our sample accounts for 4.1% of the total value of shares traded in Australia during an average year. The average of the *wTurn* values across 37 countries amounts to 5.3%, confirming that our data represent a substantial portion of the world equity trading value. At the country level, trades by institutions in our sample account for more than 10% of the total value of shares traded for Ireland (21.2%), Austria (14.4%), and Greece (10.7%). On the other hand, they account for less than 2% of the total value of shares traded for China (0.8%), India (1.2%), Thailand (1.3%), and Brazil (1.9%).

[21] We obtain stock market capitalization and turnover ratio data from the World Bank World Development Indicators (WDI) for all countries except for Taiwan. For Taiwan, we collect data from various issues of the Taiwan Stock Exchange Fact Book.

Table 1.2: Intra-period Herding

This table presents the results of intra-period herding measured by using the LSV herding measure (Lakonishok, Shleifer, and Vishny, 1992). For each country and a given month, an institutional investor is defined as a buyer (seller) of the country if the total net dollar purchases during the month is greater (less) than zero. The LSV herding measure $H_{k,t}$ for a given country-month is then calculated as $|\Delta_{k,t} - \overline{\Delta_t^*}| - E_0[|\Delta_{k,t} - \overline{\Delta_t^*}|]$, where $\Delta_{k,t}$ equals the proportion of institutions that are buyers of country k during month t relative to the total number of institutions active and $\overline{\Delta_t^*}$ the proportion of institutions that are buyers of any country during month t relative to the total number of institutions active. The second term $E_0[|\Delta_{k,t} - \overline{\Delta_t^*}|]$ is called the adjustment factor. This adjustment factor is calculated under the null hypothesis of no herding, which is the reason subscript '0' added in the expectation operator. The numbers in parentheses are t-statistics calculated under the assumption that all $H_{k,t}$s available are independent and identically distributed. The bottom row reports the number of country-month pairs used to calculate the mean herding value. Note that the maximum number of country-month pairs possible is 3552 (=37 countries*96 months).

	Number of active institutions			
	≥ 1	≥ 5	≥ 10	≥ 20
Mean herding	0.022	0.022	0.023	0.024
T statistic	(16.76)	(17.23)	(16.26)	(15.51)
Mean adjustment factor	0.067	0.065	0.062	0.057
Number of country-months	3548	3499	3374	3020

1.4 Institutional Herding across Countries

In this section, we examine whether institutional investors do herd across countries. We begin with examining intra-period herding by employing the LSV measure, and then move on to examine inter-period herding by employing the Sias measure. Lastly, we show that there exists substantial cross-country and inter-temporal variations in the measured intra- and inter-period herding levels.

1.4.1 Intra-period herding

Table 1.2 presents the results of intra-period herding measured by using the LSV measure. The reported mean herding values are the average of $H_{k,t}$s defined through Equation (1.2) across all country-month pairs with at least 1, 5, 10, or 20 active institutions. The numbers in parentheses are associated t-statistics calculated under the assumption that all $H_{k,t}$s are independent and identically distributed. The mean adjustment factor represents the average of the adjustment factor $AF_{k,t}$ in Equation (1.2). The bottom row reports the number of country-month pairs used to calculate the mean herding value. Note that the maximum number of country-month pairs possible is 3552 (=37 countries*96 months).

When country-months with at least five active institutions are considered, the measured intra-period herding value is equal to 2.2%, which is strongly significant with a t-statistic value of 17.23. The measured level of intra-period herding of 2.2% is smaller than 3.4% for U.S. individual stocks in Wermers (1999), and 2.5% for U.K. individual stocks in Wylie (2005), but larger than 1.4% for U.S. industries in Choi and Sias (2009), although these values are not directly comparable to each other. At a first glance, the size of intra-period herding may look small. However, the LSV measure is computed by subtracting the so-called adjustment factor term, and the mean value of this adjustment term amounts to 6.5%. During our sample period, the time-series average of average institutional demand across all country-month pairs was 50.4%. Hence, the mean intra-period herding value of 2.2% can be interpreted as that 59.1% (=50.4+2.2+6.5) of institutions were moving in the same direction in an average country-month pair and 40.9% in the opposite direction. The same analysis with restricting sample to those country-months with at least 10 or 20 active institutions produces almost identical results, suggesting that the results of intra-period herding are not driven by country-months with only a few number of active institutions.

1.4.2 Intra-period herding: Further results

The results of intra-period herding reported in Table 1.2 show that institutional investors do tend to increase (or decrease) their investments in the same countries at the same time. In this subsection, as further analyses, we first examine whether

Table 1.3: Further Results of Intra-period Herding

This table presents the results of several further tests for intra-period herding. All results reported in this table are calculated using relevant statistics for country-month pairs with at least five active institutions. In Panel A, the mean LSV herding measure, the average of $H_{k,t}$s, is calculated separately conditioned on $\Delta_{k,t} > \overline{\Delta_t^*}$ (labeled as buy herding) and $\Delta_{k,t} < \overline{\Delta_t^*}$ (labeled as sell herding). Panel A also reports the result of the test for the difference between buy and sell herdings. Panel B reports the mean intra-period herding after excluding countries with the monthly average number of stocks traded less than 20 from the sample. Specifically, we exclude six countries–Israel, New Zealand, Philippines, Poland, Portugal, and Russia–from the sample (refer to Table 1) and use only 31 countries remaining. Lastly, Panel C reports the mean intra-period herding separately for two sub-periods along with the result of the test for the difference between two sub-periods. Numbers in parentheses are t-statistics.

	Mean herding
Panel A: Buy herding vs. sell herding	
Buy	0.023
	(13.29)
Sell	0.021
	(12.72)
Difference	0.002
	(0.82)
Panel B: Excluding countries with the average number of stocks per month < 20	
	0.023
	(15.30)
Panel C: Sub-period results	
2002-2005	0.028
	(13.59)
2006-2009	0.017
	(12.48)
Difference	0.011
	(4.75)

there is any difference between the buy and sell intra-period herdings. Studies like Wylie (2005) and Brown, Wei, and Wermers (2009) point out the possibility that short-selling constraints imposed on institutional investors may prevent them from herding on the sell-side, suggesting that institutional sell herding might be more limited than buy herding. In addition, short-selling a stock would be much more difficult for stocks of foreign countries than for domestic stocks. Following Grinblatt et al.

(1995) and Wermers (1999), we partition all country-month pairs into those country-month pairs with $\Delta_{k,t} > \overline{\Delta_t^*}$ and those country-month pairs with $\Delta_{k,t} < \overline{\Delta_t^*}$, where $\Delta_{k,t}$ and $\overline{\Delta_t^*}$ are defined in Section 2. We interpret $H_{k,t}$ as representing buy herding when $\Delta_{k,t} > \overline{\Delta_t^*}$ and as representing sell herding when $\Delta_{k,t} < \overline{\Delta_t^*}$. Panel A of Table 1.3 reports the results of buy and sell intra-period herdings separately along with the test for the difference between the two. Note that all the results reported in Table 1.3 are calculated using relevant statistics for country-month pairs with at least five active institutions. The results of Panel A show that there is no significant difference between the measured buy and sell intra-period herding values, although sell herding is slightly smaller than buy herding.

Next, as robustness checks of the results reported in Table 1.2, we repeat the same analysis in Table 1.2 (i) by using only a sub-sample of countries and (ii) by dividing the sample into two equally-divided 48-month periods, i.e., 2002-2005 and 2006-2009. Panel B of Table 1.3 reports the mean intra-period herding after excluding countries with the monthly average number of stocks traded less than 20 from the sample. Specifically, we exclude six countries–Israel, New Zealand, Philippines, Poland, Portugal, and Russia–from the sample (refer to Table 1.1) and use only 31 countries remaining. The results show that excluding these six countries from the sample does not produce any noticeable difference in the measured mean intra-period herding values. Next, Panel C of Table 1.3 reports the results of intra-period herding for two equally-divided 48-month periods. The results show that the intra-period herding has decreased from 2.8% in earlier sub-period to 1.7% in later sub-period over the two sub-periods. The test for the difference shows that the decrease is statistically significant at the 1% level.

In summary, the results of Table 1.3 confirm that the evidence of institutional intra-period herding across countries documented in Table 1.2 remains robust to various specifications, although the level of intra-period herding has decreased somewhat

Table 1.4: Inter-period Herding

This table presents the results of inter-period herding measured by using the Sias herding measure (Sias, 2004). The Sias herding measure, denoted by ρ^H, is derived from decomposing the inter-temporal correlation ρ between institutional demands this month $\Delta_t = (\Delta_{1,t}, ..., \Delta_{K,t})$ and last month $\Delta_{t-1} = (\Delta_{1,t-1}, ..., \Delta_{K,t-1})$ into two parts, where $\Delta_{k,t}$ equals the proportion of institutions that are buyers of country k during month t relative to the total number of institutions active (refer to Equation (1.5) in Section 2). The column labeled as ρ^{SR} represents the portion of the correlation ρ due to institutions following their own lag demand. If ρ^{SR} is positive, then it means that investors tend to increase (decrease) their investments this month in countries that they increased (decreased) their investments last month. That is, ρ^{SR} can be interpreted as the extent to which investors engage in inter-period self-reinforcing trades. The column labeled as ρ^H represents the portion of the correlation ρ due to institutions following others' lag demands, which represents the Sias herding measure. Numbers in parentheses are t-statistics computed using the standard errors adjusted for hetero-skedasticities and autocorrelations by using the Newey and West (1986) procedure. Specifically, to determine the lag length when applying the Newey and West procedure, we use the automatic lag selection procedure suggested by Newey and West (1994). Numbers in brackets represent the contribution of ρ^{SR} and ρ^H to ρ.

	Partitioned correlation				
	Institutions following	Institutions following	Number of countries		
Correlation (ρ)	their own trades (ρ^{SR})	others' trades (ρ^H)	Min	Med	Max
Panel A: Countries with ≥ 1 *active institutions in both this month and last month*					
0.295	0.109 [37.0%]	0.186 [63.0%]	36	37	37
(13.40)	(25.09)	(9.63)			
Panel B: Countries with ≥ 5 *active institutions in both this month and last month*					
0.301	0.107 [35.6%]	0.194 [64.4%]	31	37	37
(14.96)	(28.98)	(9.40)			
Panel C: Countries with ≥ 10 *active institutions in both this month and last month*					
0.305	0.099 [32.3%]	0.206 [67.7%]	23	36	37
(14.46)	(18.93)	(11.12)			
Panel D: Countries with ≥ 20 *active institutions in both this month and last month*					
0.308	0.088 [28.7%]	0.219 [71.3%]	16	32	37
(16.39)	(16.14)	(11.27)			

over the sample period.

1.4.3 Inter-period herding

Table 1.4 presents the results of inter-period herding measured by using the Sias measure. The first column of the table reports the time-series average of 95 inter-temporal cross-sectional correlations between institutional demands this month and last month, i.e., $(1/95)\sum_{t=2}^{96}\rho_t$, where ρ_t is defined in Equation (1.5) in Section 2. Here, $t = 2$ represents the second month in our sample period, February 2002, and $t = 96$ the last month, December 2009. The numbers in parentheses are associated t-statistics computed using the Newey-West hetero-skedasticity and autocorrelation consistent standard errors (Newey and West, 1986).[22] The results of Table 1.4 show strong evidence that institutional demands this month and last month are significantly correlated across countries. When country-months with at least one active institution are considered (Panel A), the correlation amounts to 0.295, which is strongly significant with a t-statistic value of 13.40. As we require more number of active institutions in country-month pairs, the correlation increases monotonically from 0.295 (Panel A) to 0.308 (Panel D), although the increment appears to be not substantial. In previous studies examining institutional inter-period herding, Sias (2004) reports correlations ranging from 0.120 to 0.176 in his study of institutional herding across U.S. individual stocks, and Choi and Sias (2009) report correlations ranging from 0.247 to 0.414 in their study of institutional herding across U.S. industries. Although any direct comparison between these numbers is not fully meaningful, the correlation coefficient of 0.295 in our study is almost two times larger than that of Sias (2004) for individual stocks and comparable to that of Choi and Sias (2009) for U.S. industries.

The second and third columns of Table 1.4 report the time-series average of the 95 partitioned correlations ρ_t^{SR}s and ρ_t^{H}s defined in Equation (1.5) with their associated t-statistics in parentheses. Recall that ρ_t^{SR} is due to institutions following their own previous trades and ρ_t^{H} due to institutions following others' previous trades and that ρ_t^{H} measures the extent of inter-period herding. When country-months with at least one active institution are considered (Panel A), the time-series average of the 95 correlations due to institutions following their own previous trades amounts to 0.109,

[22]Specifically, to determine the lag length when applying the Newey and West procedure, we use the automatic lag selection procedure suggested by Newey and West (1994).

which is strongly significant with a t-statistic value of 25.09. On the other hand, the time-series average of the 95 correlations due to institutions following others' previous trades amounts to 0.186. Hence, the herding component explains 63.0% (=0.186/0.295) of the inter-temporal correlation of institutional demands between this month and last month, and the remaining 37.0% (=0.109/0.295) is explained by institutions following their own previous trades.[23] As we require more number of active institutions, the correlation due to inter-period herding increases monotonically from 0.186 (Panel A) to 0.219 (Panel D). Note also that the percentage of contribution due to herding also increases monotonically from 63.0% (Panel A) to 71.3% (Panel D).

The last three columns of Table 1.4 report the time-series minimum, median, and maximum of the number of countries for which both $\Delta_{k,t}$ and $\Delta_{k,t-1}$ are defined, i.e., K_t in Equation (1.5) in Section 2. By definition, K_t is decreasing in the number of active institutions required. For example, the value of 16 for the minimum in Panel D means that if we require at least 20 active institutions, both $\Delta_{k,t}$ and $\Delta_{k,t-1}$ are defined only for 16 countries for some adjacent months t and $t-1$.

1.4.4 Inter-period herding: Further results

As further tests of institutional inter-period herding, we first examine whether the extent to which institutions follow others' previous trades in country-month kt depends on the previous month demand $\Delta_{k,t-1}$. Following Choi and Sias (2009), for each month t, we partition all countries into those countries with the proportion of buyers last month greater than $\overline{\Delta^*_{t-1}}$ (i.e., $\Delta_{k,t-1} > \overline{\Delta^*_{t-1}}$) and those countries with the proportion of buyers last month smaller than $\overline{\Delta^*_{t-1}}$ (i.e., $\Delta_{k,t-1} < \overline{\Delta^*_{t-1}}$). We interpret $\rho^H_{k,t}$ as representing buy herding when $\Delta_{k,t-1} > \overline{\Delta^*_{t-1}}$ and as representing

[23]One reason why institutions follow their own previous trades could be due to the fact that institutions execute their trading over time through multiple orders to minimize both price impacts and transaction costs of their trading (Keim and Madhavan, 1995; Chan and Lakonishok, 1995).

Table 1.5: Further Results of Inter-period Herding

This table presents the results of several further tests for inter-period herding. All results reported in this table are calculated using relevant statistics for country-month pairs with at least five active institutions. In Panel A, following Sias (2004) and Choi and Sias (2009) the inter-temporal correlation ρ between institutional demands this month $\Delta_t = (\Delta_{1,t}, ..., \Delta_{K,t})$ and last month $\Delta_{t-1} = (\Delta_{1,t-1}, ..., \Delta_{K,t-1})$ is decomposed into two parts ρ^{SR} and ρ^{H} conditioned on $\Delta_{k,t-1} > \overline{\Delta^*_{t-1}}$ (labeled as buy herding) and $\Delta_{k,t-1} > \overline{\Delta^*_{t-1}}$ (labeled as sell herding). Panel A also reports the result of the test for the difference between buy and sell herdings. Panel B reports the mean inter-period herding after excluding countries with the monthly average number of stocks traded less than 20 from the sample. Specifically, we exclude six countries–Israel, New Zealand, Philippines, Poland, Portugal, and Russia–from the sample (refer to Table 1) and use only 31 countries remaining. Lastly, Panel C reports the mean inter-period herding separately for two sub-periods along with the result of the test for the difference between two sub-periods. In all results, the numbers in parentheses are t-statistics computed using the standard errors adjusted for hetero-skedasticities and autocorrelations by using the Newey and West (1986) procedure. Specifically, to determine the lag length when applying the Newey and West procedure, we use the automatic lag selection procedure suggested by Newey and West (1994). Numbers in brackets represent the contribution of ρ^{SR} and ρ^{H} to ρ.

		Partitioned correlation		Number of countries		
	Correlation (ρ)	Institutions following their own trades (ρ^{SR})	Institutions following others' trades (ρ^{H})	Min	Med	Max
Panel A: Buy herding vs. sell herding						
Buy	0.159	0.062 [39.3%]	0.096 [60.7%]			
	(12.11)	(17.93)	(7.23)			
Sell	0.143	0.045 [31.4%]	0.098 [68.6%]			
	(14.57)	(14.60)	(10.10)			
Difference	0.016	0.018	-0.002			
	(1.35)	(3.26)	(-0.18)			
Panel B: Excluding countries with the average number of stocks per month < 20						
	0.285	0.095 [33.2%]	0.190 [66.8%]	29	31	31
	(14.99)	(22.41)	(10.20)			
Panel C: Sub-period results						
2002-2005	0.289	0.106 [36.5%]	0.184 [63.5%]	31	37	37
	(9.92)	(21.57)	(6.20)			
2006-2009	0.316	0.108 [34.2%]	0.208 [65.8%]	36	37	37
	(13.17)	(23.04)	(8.30)			
Difference	0.027	0.003	0.024			
	(0.75)	(0.39)	(0.65)			

sell herding when $\Delta_{k,t-1} < \overline{\Delta^*_{t-1}}$.[24] Panel A of Table 1.5 reports the results. Note

[24]We also examined the results using $\overline{\Delta_{t-1}}$ or 0.5 instead of $\overline{\Delta^*_{t-1}}$ as a cutoff value, but obtained the nearly same results as those reported in Panel A of Table 1.5.

that all the results reported in Table 1.5 are calculated using relevant statistics for country-month pairs with at least five active institutions. Hence, the sum of the average correlations for buy and sell herdings is equal to 0.301 from Panel B of Table 1.4. The results show that there is no significant difference between buy and sell inter-period herdings, although the portion of the correlation due to institutions following own previous trades is statistically larger for the buy herding than for the sell herding.

Next, as robustness checks of the results reported in Table 1.4, we repeat the same analysis in Table 1.4 (i) by using only a sub-sample of countries and (ii) by dividing the sample period into two equally-divided 48-month periods, i.e., 2002-2005 and 2006-2009. Panel B of Table 1.5 reports the results when we exclude from the sample countries with the monthly time-series average of the number of stocks traded less than 20. Specifically, we exclude six countries–Israel, New Zealand, Philippines, Poland, Portugal, and Russia–from the sample (refer to Table 1.1) and use only 31 countries remaining. The average correlation coefficient decreases slightly to 0.2848 from 0.3014 (Panel B of Table 1.4). However, the contribution of the herding component increases slightly to 66.8% from 64.4% (Panel B of Table 1.4). Panel C of Table 1.5 reports the results of inter-period herding for two equally divided sub-sample periods. The results show that the average correlation has increased from 0.2894 to 0.3162 by 0.0268 over the two sub-periods. The contribution of the herding component has also increased slightly from 63.5% to 65.8%. But, the tests for the differences in average correlations and in average partitioned correlations between these two sub-periods show no evidence that the inter-period herding behavior of the sampled institutional investors has changed over time.

In summary, results from Table 1.5 confirm that the institutional inter-period herding across countries documented in Table 1.4 remains robust to various specifications.

1.4.5 Cross-country and inter-temporal variations in intra- and inter-period herdings

Table 1.6 presents the mean and standard deviation for the LSV herding value, $H_{k,t}$ and Sias herding value, $\rho_{k,t}^{H}$, by country. The LSV herding values are presented in percent terms. Also, for ease of presentation, we multiplied the Sias herding values by one hundred. The results at the bottom row tell us that for a randomly selected country k the time-series standard deviation of the intra-period herding (6.82%) is more than three times larger than its time-series mean (2.23%) and that the time-series standard deviation of the inter-period herding (2.80) is more than five times larger than its time-series mean (0.54). This observation implies that, for each country, both intra- and inter-period herding varies widely over time.

More importantly, Table 1.6 also shows that both intra- and inter-period herdings vary widely across countries. In terms of the time-series average over the sample period, the measured intra-period herding is the highest for Korea (4.04%), followed by Russia (3.99%) and Turkey (3.72%), and is the lowest for Thailand (-0.66%), followed by Brazil (0.14%) and India (0.26%). The measured mean inter-period herding is the highest for Russia (2.03), followed by Portugal (1.30) and Taiwan (1.29), and the lowest for Brazil (-0.35), followed by Thailand (-0.28) and India (-0.22).

Figure 2 shows the relation between intra- and inter-period herdings measured at the country level. Interestingly, it shows that the two herding measures–LSV and Sias measures–are significantly positively related. The correlation between the LSV herding (H) and the Sias herding (ρ^{H}) measures amounts to 0.72, which is strongly significant. This observation suggests that the two herding measures are closely related although they are intended to capture different patterns of herding behavior, i.e., intra-period herding vs. inter-period herding.

Table 1.6: Summary Statistics for Intra- and Inter-period Herdings by Country

This table presents the time-series means and standard deviations by country for the intra-period herding (H) and the inter-period herding (ρ^H). The LSV herding values are presented in percent terms. Also, for ease of presentation, we multiplied the Sias herding values by a hundred and then computed its time-series mean and standard deviation for each country k.

	LSV herding (H)		Sias herding (ρ^H)	
Country	Mean	SD	Mean	SD
Australia	2.46	5.63	0.37	2.40
Austria	2.53	7.72	1.08	3.34
Belgium	0.59	6.13	-0.16	2.18
Brazil	0.14	7.47	-0.35	4.05
Canada	1.91	5.28	0.29	1.61
China	3.22	6.94	0.55	2.94
Denmark	2.17	6.23	0.40	1.72
Finland	2.60	6.06	0.59	2.25
France	1.74	4.67	0.35	1.64
Germany	3.68	5.55	0.36	2.14
Greece	2.04	7.20	0.41	2.55
Hong Kong	3.13	5.70	0.68	2.06
India	0.26	7.94	-0.22	2.66
Indonesia	3.23	8.08	0.49	3.53
Ireland	1.46	5.29	0.38	1.63
Israel	1.70	9.60	0.64	4.73
Italy	3.36	5.77	0.75	2.09
Japan	3.80	6.29	0.61	2.14
Korea	4.04	7.07	1.26	3.18
Malaysia	2.63	7.26	1.13	3.65
Mexico	1.81	5.53	0.27	2.16
Netherlands	1.76	4.97	0.19	1.46
New Zealand	1.50	9.25	0.26	4.10
Norway	1.47	5.66	0.28	1.72
Philippines	0.60	9.96	0.36	5.13
Poland	0.38	7.54	0.50	3.53
Portugal	2.97	9.35	1.30	3.82
Russia	3.88	8.39	2.03	6.21
Singapore	2.48	6.54	0.67	1.98
South Africa	1.58	6.89	0.47	2.95
Spain	2.94	6.05	0.98	3.18
Sweden	1.71	5.93	0.32	1.42
Switzerland	3.03	5.77	0.31	1.82
Taiwan	3.40	7.68	1.29	2.93
Thailand	-0.66	5.76	-0.28	2.16
Turkey	3.72	9.74	0.86	4.67
United Kingdom	3.24	5.51	0.42	1.82
Average	2.23	6.82	0.54	2.80

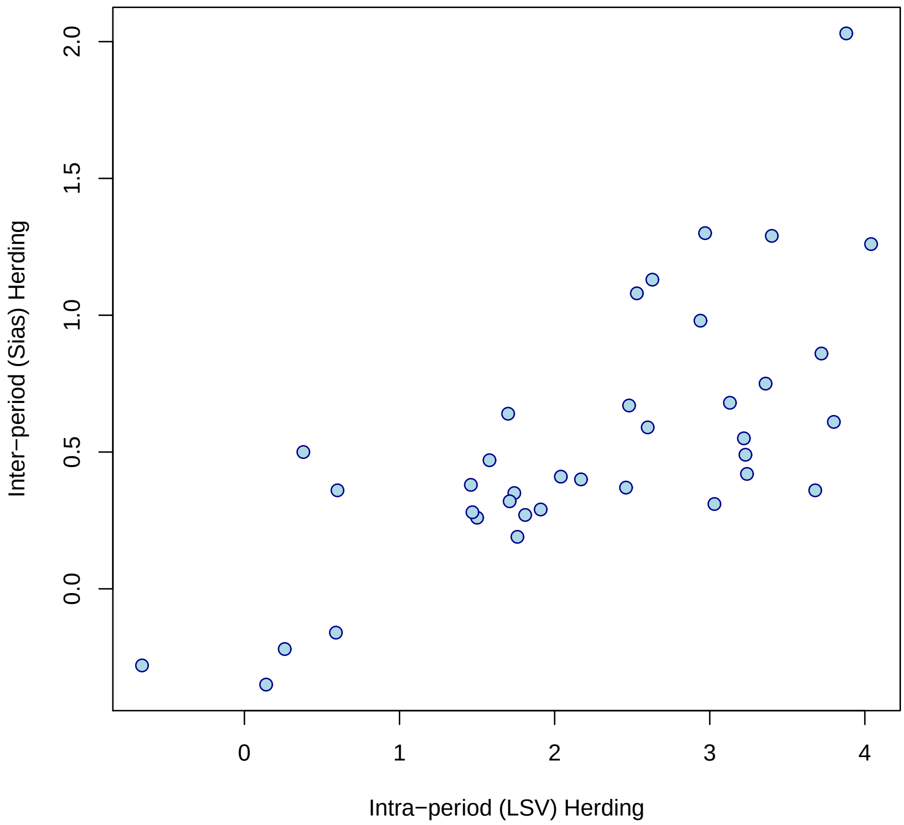

Figure 1.2: Relation between the LSV and Sias Herding Measures

This figure shows the relationship between the LSV and Sias herding measures computed at the country level and reported in Table 9.

1.5 Institutional Demands and Stock Market Performances

In the previous section, we have documented evidence of intra-period herding across countries by employing the LSV measure and evidence of inter-period herding by employing the Sias measure. In this section, we examine (i) whether such a herding behavior simply reflects their return-chasing strategies and (ii) what are the impacts of their herding behavior on contemporaneous and subsequent stock market performances. The answers to these two questions has long been of particular interest to

Table 1.7: Prior Market Performances and Institutional Demands

This table presents institutional demands this month by prior market performance. For example, in the last column of the table (titled as '-1'), for each month t we partition countries into five quintiles based on their previous month local market returns, and then calculate the average of current institutional demands $\Delta_{k,t}$s this month across countries within each group of those five quintiles. In the columns labeled as '-12 to -1', '-6 to -1', and '-3 to -1', countries are grouped into five quintiles based on their previous 12-month, 6-month, and 3-month local market returns, respectively. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Prior market return	-12 to -1	-6 to -1	-3 to -1	-1
R1 (Highest)	50.13	50.29	51.24	51.25
R2	49.96	50.88	50.49	50.41
R3	50.65	50.12	50.43	50.48
R4	50.57	50.66	50.08	50.24
R5 (Lowest)	51.47	50.90	50.71	50.59
R1 - R5	-1.35**	-0.62	0.53	0.66
	(-2.25)	(-0.75)	(0.72)	(0.99)

academics, practitioners, and policy makers with regard to whether institutional investors destabilize stock markets or not (see, e.g., Cutler, Poterba, and Summers, 1990; DeLong, Shleifer, Summers, and Waldman, 1990; Lakonishok, Shleifer, and Vishny, 1992; Choe, Kho, and Stulz, 1999; Wermers, 1999).

We begin with examining the relation between prior market performance and current institutional demand. Table 1.7 presents the results. The last column of the table (titled as '-1') reports the fraction of buyers this month conditioned on the previous one-month local market returns. Specifically, each month we partition countries into five quintile groups based on their previous month local market returns and then calculate the average of institutional demands $\Delta_{k,t}$s this month across countries within each of five quintile groups. The results show that institutions in our sample do not exhibit the return-chasing behavior at the one-month horizon. The institutional demand for countries performed well last month (51.25%) is slightly larger than that for countries performed poorly last month (50.29%), but the difference between the two has no statistical significance. Also, across the five quintile groups, institutional demands display rather a U-shaped pattern. That is, they demand both countries that performed well and countries that performed poorly in the previous month more than countries that performed in the middle. A similar demand pattern is observed when we partition countries into quintiles based on their local market returns over the previous three months. However, when we partition countries into quintiles based on their local market returns over the previous six or twelve months, a different demand pattern emerges. Institutions in our sample demand countries that performed poorly more than those that performed well over the previous six to twelve months. Hence, they as a group tend to act as contrarians conditioned on the six- to twelve-month local market returns.

Next, we examine the relation between institutional demand and contemporaneous and subsequent market performances. Table 1.8 presents the results. The first column of the table (titled as '0') reports the contemporaneous one-month local market returns conditioned on the fraction of buyers this month. Specifically, each month we partition countries into six groups based on the intensity of institutional demand and then calculate the equal-weighted average abnormal returns across countries within each group. In the table, the intense buy (sell) group represents the top (bottom) five countries based on the faction of buyers this month. The medium buy (sell) group represents the next top (bottom) five countries, and the light buy (sell) group represents the remaining countries in the buy (sell) group. Following Kaniel, Saar, and Titman (2008), we calculate abnormal returns by subtracting the equal-weighted average return across all countries in the sample. Not surprisingly, we find that the demand intensity is positively related to the contemporaneous local stock market performances. The average abnormal return for the group of countries demanded most is positive (1.02% per month) and statistically significant at the 1% level. On the other

Table 1.8: Institutional Demands and Contemporaneous and Subsequent Market Performances

This table presents contemporaneous and subsequent market performances by institutional demand this month. For example, in the first column of the table (titled as '0'), for each month t we partition countries into six groups based on their current month institutional demands, and then calculate the average of current month local market returns across countries within each of six groups. The intense buy (sell) group represents the top (bottom) five countries based on the faction of buyers this month. The medium buy (sell) group represents the next top (bottom) five countries, and the light buy (sell) group represents the remaining countries in the buy (sell) group. The columns labeled as '1', '1 to 3', '1 to 6', and '1 to 12' reports subsequent 1-month, 3-month, 6-month, and 12-month holding period returns for each of six groups, respectively. In each column, we calculate abnormal returns by subtracting the equal-weighted average return across all countries in the sample (Kaniel, Saar, and Titman, 2008). *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Current demand	0	1	1 to 3	1 to 6	1 to 12
B1 (Intense buy)	1.02***	0.30*	1.16***	1.64**	1.08
	(4.39)	(1.71)	(2.65)	(2.45)	(1.08)
B2 (Medium buy)	0.33	0.09	-0.07	-0.51	-0.24
	(1.37)	(0.38)	(-0.19)	(-1.00)	(-0.26)
B3 (Light buy)	-0.11	-0.06	-0.24	-0.52	-1.10*
	(-1.07)	(-0.35)	(-0.88)	(-1.41)	(-1.95)
S3 (Light sell)	-0.21	0.05	-0.39*	-0.35	-1.32***
	(-1.41)	(0.31)	(-1.74)	(-1.08)	(-2.99)
S2 (Medium sell)	-0.34**	-0.27	-0.60	-0.38	-0.60
	(-2.11)	(-1.28)	(-1.60)	(-0.72)	(-0.52)
S1 (Intense sell)	-0.50**	-0.10	0.26	0.26	1.10
	(-1.99)	(-0.64)	(0.68)	(0.43)	(1.07)
B1 - S1	1.52***	0.39*	0.91	1.39	-0.02
	(3.73)	(1.80)	(1.51)	(1.32)	(-0.01)
(B1 to B3) - (S1 to S3)	0.68***	0.14	0.45*	0.20	0.09
	(3.76)	(1.16)	(1.74)	(0.40)	(0.14)

hand, the average abnormal return for the group of countries demanded least is negative (-0.50% per month) and statistically significant at the 5% level. The difference of the abnormal returns between these two extreme groups (1.52% per month) is also significant at the 1% level. The bottom row of the table also shows that the abnormal return of countries demanded more than the cross-country average demand is higher by 0.68% per month than that of countries demanded less than the cross-country average demand, with the difference being also significant at the 1% level. The next four columns of the table report subsequent stock market performances at the 1-, 3-, 6-, and 12-month horizons. The results show that countries demanded most exhibit return continuation over the next 6-month period. On the contrary, there is no evidence of return reversal phenomenon for countries demanded least. The long-short portfolio constructed by longing countries demanded more than average and shorting countries demanded less than average generates significantly positive returns over the next 1- to 3-month horizons.

In summary, our findings in this section suggest that institutional investors in our sample do not engage in potentially destabilizing practices. Rather, they tend to help to speed the price-adjustment process.

1.6 Institutional Herding and Information Environments

In Section 4, we have documented evidence of both intra- and inter-period herdings. Importantly, we have also documented evidence that institutional herding varies widely across countries and over time. In this section, we examine whether the cross-country differences in information environments can explain such variations in the measured herding levels across countries and over time. In the following subsection, we first introduce our proxies of a country's information environments. Then, we move on to examine the effect of information environments on intra-period herding and on inter-period herding one by one.

1.6.1 Proxies for a country's information environments

As proxies for a country's information environments, we consider a total of nine variables, which are drawn from the finance and accounting literature. As somewhat indirect proxies for information environments, we consider the following four variables:

1. *Idio/Sys*: The average idiosyncratic volatility across all stocks of a country divided by the average systematic volatility, which equals minus one times the stock return co-movement measure from Morck, Yeung, and Yu (2000);[25]

2. *English*: A dummy variable which takes one if the official language of a country is English and zero otherwise;

3. *Develop*: A dummy variable which takes one if a country is classified as developed and zero otherwise; and

4. *ComLaw*: A dummy variable which takes one if the legal origin of a country is the English common law and zero otherwise.

The extent of idiosyncratic volatility relative to systematic volatility of a stock has long been regarded as a proxy for the degree of private information impounded into the stock's prices (see, e.g., French and Roll, 1986; Roll, 1988; Morck, Yeung, and Yu, 2000; Campbell, Lettau, Malkiel, and Xu, 2001; Durnev, Morck, Yeung, and Zarowin, 2003; Jin and Meyers, 2006; Fernandes and Ferreira, 2008). Hence, it is likely that the higher the *Idio/Sys* value of a country, the stronger the country's information environments. Next, we hypothesize that, from the perspective of U.S. investors, information environments would be stronger in countries whose official language is English than in countries otherwise the same. Also, it is conceivable that developed countries have more stronger information environments than emerging or developing countries. Lastly, a long literature of law and finance has documented evidence that common-law countries tend to provide stronger information environments than civil-law countries (see, e.g., La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998, 2000, 2002; La Porta, Lopez-de-Silanes, and Shleifer, 2006).

[25]Specifically, for country k, the *Idio/Sys* variable represents $-\log(R_k^2/(1-R_k^2))$, where R_k^2 is the weighted average of $R_{i,k}^2$ of stock i across all stocks of country k. Following Morck, Yeung, and Yu (2000), we calculate $R_{i,k}^2$ as the regression R-square from the regression of weekly returns of stock i on weekly returns of local market index and weekly returns (converted in local currency terms) of U.S. market index. Refer to Morck et al. for a more detailed explanation.

In addition to these four proxies, we consider the following five more variables as proxies for a country's information environments, which measure corporate reporting- and disclosure-specific information environments more directly:

5. *DiscReq*: The corporate information disclosure requirement index drawn from La Porta, Lopez-de-Silanes, and Shleifer (2006), which is the average of six sub-category scores regarding the quality of disclosure requirements on: (1) prospectus; (2) insider compensations; (3) large shareholder ownership; (4) insider ownership; (5) irregular contracts; and (6) related parties transactions;

6. *AcctgStd*: The accounting standard index drawn from Bushman, Piotroski, and Smith (2004), which examines and rates companies' annual reports on their inclusion or omission of 90 items. This index is an updated version by using more recent data of the 'Accounting Standards' variable from La Porta et al. (1998);

7. *RepFreq*: The average ranking of the answers to the following interim reporting questions drawn from Bushman et al. (2004): frequency of reports; count of disclosed items; and consolidation of interim reports;

8. *PctgAudit*: The percentage of the share of total value of firms in a country audited by the Big 5 accounting firms, which is drawn from Bushman et al. (2004);

9. *NAnalyst*: The number of analysts following the largest 30 companies, which is drawn from Chang, Khanna, and Palepu (2000) and Frost, Gordon, and Hayes (2006).

By the very definition of these variables, we interpret a higher value of each one of these five variables as indicating stronger information environments of a country.

Table 1.9: Regression Variables

This table presents the summary of the regression variables used. All values reported are time-series averages over the entire sample period 2002-2009. The first two columns labeled as *LSV H* and *Sias* ρ^H represent the intra-period herding and the intra-period herding, respectively, measured at the monthly frequency. The LSV herding values are presented in percent terms. For ease of presentation, we multiplied the Sias herding values by a hundred and then computed its time-series mean and standard deviation for each country k. The other regression variables are detailed in Section 6. Briefly, *Idio/Sys* represents the average idiosyncratic volatility across all stocks of a country divided by the average systematic volatility, which equals minus one times the stock return co-movement measure from Morck, Yeung, and Yu (2000); *English* takes one if the official language of a country is English and zero otherwise; *Develop* takes one if a country is classified as developed by IMF and zero otherwise; *ComLaw* takes one if the legal origin of a country is the English common law and zero otherwise; *DiscReq* represents the information disclosure requirements index from La Porta et al. (2006); *AcctgStd* is the index created by examining and rating companies' annual reports on their inclusion or omission of 90 items taken from Bushman et al. (2004); *RepFreq* represents the timeliness and frequency of information disclosures, which is drawn from Bushman et al. (2004); *PctgAudit* represents the percentage of the total value of firms in a country audited by the Big 5 accounting firms, which is drawn from Bushman et al. (2004); and *NAnalyst* represents the number of analysts following the largest 30 companies of a country, which is drawn from Chang et al. (2000). Lastly, *InfoEnv* represents the first principal component, rescaled to have unit variance, of the correlation matrix of nine proxies for information environments.

Table 1.9: Regression Variables (Continued)

Country	LSV H	Sias ρ^H	Idio/Sys	English	Develop	ComLaw
Australia	2.46	0.37	2.41	1	1	1
Austria	2.53	1.08	1.98	0	1	0
Belgium	0.59	-0.16	2.11	0	1	0
Brazil	0.14	-0.35	1.58	0	0	0
Canada	1.91	0.29	2.63	1	1	1
China	3.22	0.55	0.83	0	0	0
Denmark	2.17	0.40	1.92	0	1	0
Finland	2.60	0.59	1.70	0	1	0
France	1.74	0.35	1.99	0	1	0
Germany	3.68	0.36	2.36	0	1	0
Greece	2.04	0.41	1.31	0	1	0
Hong Kong	3.13	0.68	1.97	1	1	1
India	0.26	-0.22	1.72	1	0	0
Indonesia	3.23	0.49	1.68	0	0	0
Ireland	1.46	0.38	1.88	1	1	1
Israel	1.70	0.64	2.47	0	0	1
Italy	3.36	0.75	1.57	0	1	0
Japan	3.80	0.61	1.73	0	1	0
Korea	4.04	1.26	1.83	0	0	0
Malaysia	2.63	1.13	1.46	1	0	1
Mexico	1.81	0.27	1.49	0	0	0
Netherlands	1.76	0.19	1.85	0	1	0
New Zealand	1.50	0.26	2.29	1	1	1
Norway	1.47	0.28	1.74	0	1	0
Philippines	0.60	0.36	1.41	1	0	0
Poland	0.38	0.50	1.76	0	0	0
Portugal	2.97	1.30	1.56	0	1	0
Russia	3.88	2.03	1.02	0	0	0
Singapore	2.48	0.67	1.48	1	1	1
South Africa	1.58	0.47	2.16	1	0	1
Spain	2.94	0.98	1.91	0	1	0
Sweden	1.71	0.32	1.71	0	1	0
Switzerland	3.03	0.31	1.78	0	1	0
Taiwan	3.40	1.29	1.11	0	0	0
Thailand	-0.66	-0.28	1.38	0	0	1
Turkey	3.72	0.86	1.08	0	0	0
United Kingdom	3.24	0.42	2.15	1	1	1

Table 1.9: Regression Variables (Continued)

Country	DiscReq	AcctgStd	RepFreq	PctgAudit	NAnalyst	InfoEnv
Australia	0.75	80	89.13	4	12.30	1.49
Austria	0.25	62	68.12	3	8.63	-0.72
Belgium	0.42	68	63.04	3	15.33	-0.31
Brazil	0.25	56	86.96	3	16.10	-1.14
Canada	0.92	75	99.28	4	16.90	1.71
China	.	.	.	.	.	
Denmark	0.58	75	73.91	4	12.87	0.17
Finland	0.50	83	78.99	4	14.90	0.29
France	0.75	78	78.26	3	23.20	0.36
Germany	0.42	67	68.12	4	32.40	0.31
Greece	0.33	61	17.39	1	6.10	-1.90
Hong Kong	0.92	73	69.57	4	25.00	1.22
India	0.92	61	45.65	1	11.90	-0.97
Indonesia	0.50	.	.	.	.	
Ireland	0.67	81	69.57	4	5.43	0.94
Israel	0.67	74	66.67	2	3.19	-0.07
Italy	0.67	66	86.96	4	21.57	0.02
Japan	0.75	71	86.23	4	14.87	0.19
Korea	0.75	68	17.39	3	9.90	-0.94
Malaysia	0.92	79	65.22	3	19.90	0.50
Mexico	0.58	71	84.78	3	18.53	-0.52
Netherlands	0.50	74	78.26	4	29.53	0.33
New Zealand	0.67	80	17.39	3	0.00	0.43
Norway	0.58	75	94.20	4	12.83	0.22
Philippines	0.83	64	75.36	1	10.87	-0.90
Poland	.	.	.	.	.	
Portugal	0.42	56	62.32	3	5.33	-1.09
Russia	.	.	.	.	.	
Singapore	1.00	79	63.77	4	20.90	1.09
South Africa	0.83	79	86.96	4	7.40	1.00
Spain	0.50	72	89.13	4	22.73	0.28
Sweden	0.58	83	86.23	4	20.60	0.49
Switzerland	0.67	80	73.91	3	19.97	0.18
Taiwan	0.75	58	17.39	2	6.80	-1.87
Thailand	0.92	66	89.13	3	9.77	-0.20
Turkey	0.50	58	17.39	1	7.97	-2.25
United Kingdom	0.83	85	86.96	4	20.10	1.65

Table 1.9 presents the summary of these regression variables by country. The *Idio/Sys* column shows that the influence of market-wide systematic factors on individual stock returns is highest for China (Idio/Sys=0.83), followed by Russia (1.02) and Turkey (1.08). On the contrary, stocks of Canada (Idio/Sys=2.63), Israel (2.47), and Australia (2.41) are less influenced by market-wide systematic factors. For the other variables, we reserve comments to save space.

1.6.2 Intra-period herding and information environments

To examine the effect of a country's information environments on intra-period herding, we employ the Fama-MacBeth regression procedure (Fama and MacBeth, 1973). Specifically, for each month t, we run the cross-sectional regression of the following form:

$$H_{k,t} = \alpha_t + \beta_t R_{k,t-1} + \gamma_t X_{k,t} + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37, \tag{1.6}$$

where $H_{k,t}$ represents the intra-period herding measured by using the LSV measure for country k during month t when country months with at least five active institutions are considered, $R_{k,t-1}$ represents the local market return of country k during month $t-1$, and $X_{k,t}$ represents a proxy for information environments of country k.[26] Note that, except for the *Idio/Sys* variable, all proxies for information environments are not time-varying by construction. The *Idio/Sys* variable is updated annually. After obtaining estimates of β_t and γ_t for each month t, we calculate their time-series averages and associated time-series standard errors. Noting that buy-side and sell-side intra-period herdings can depend on prior market performances in a different fashion, we run the above regression (1.6) separately for a sup-sample of those country-month pairs with $\Delta_{k,t} > \overline{\Delta_t^*}$ and for a sub-sample of those country-month pairs with $\Delta_{k,t} < \overline{\Delta_t^*}$, where $\Delta_{k,t}$ and $\overline{\Delta_t^*}$ are defined in Section 2.

[26]Note that replacing $R_{k,t-1}$ with $(R_{k,t-1} - \overline{R_{t-1}})$, for example, does not change the estimates of β_t and γ_t and their significances.

Table 1.10: Information Environments and Intra-period Herding

This table presents the results of the following regressions

$$H_{k,t} = \alpha_t + \beta_t R_{k,t-1} + \gamma_t X_{k,t} + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37,$$

where $H_{k,t}$ represents the intra-period herding for country k during month t, $R_{k,t-1}$ the local market return of country k during month $t-1$, and $X_{k,t}$ a proxy for information environments of country k. Except for the *Idio/Sys* variable, all proxies for information environments are not time-varying. The *Idio/Sys* variable is updated annually. After obtaining estimates of β_t and γ_t for each month t, we calculate their time-series averages and associated time-series standard errors. Following Wermers (1999), we interpret $H_{k,t}$ as representing buy herding when $\Delta_{k,t} > \overline{\Delta_t^*}$ and as representing sell herding when $\Delta_{k,t} < \overline{\Delta_t^*}$. Numbers in parentheses are t-statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm-specific Return Volatility, Language, Development Stage, and Legal Origin

		$X_{k,t}$			
		Idio/Sys	English	Develop	ComLaw
Buy	$R_{k,t-1}$	0.024	0.024	0.020	0.028
		(0.55)	(0.53)	(0.43)	(0.59)
	$X_{k,t}$	-1.049***	-1.474***	-0.330	-1.292***
		(-2.83)	(-4.01)	(-0.77)	(-3.53)
Sell	$R_{k,t-1}$	-0.050	-0.077	-0.028	-0.069
		(-0.93)	(-1.46)	(-0.57)	(-1.37)
	$X_{k,t}$	-0.442	0.380	1.206***	0.098
		(-1.02)	(0.96)	(2.74)	(0.26)

Panel B: Disclosure Requirement, Accounting Standard, Reporting Frequency, and Credibility

		$X_{k,t}$				
		DiscReq	AcctgStd	RepFreq	PctgAudit	NAnalyst
Buy	$R_{k,t-1}$	-0.032	-0.027	0.025	0.001	-0.015
		(-0.66)	(-0.52)	(0.49)	(0.02)	(-0.31)
	$X_{k,t}$	-2.689***	-0.031	-0.035***	-0.415*	-0.005
		(-2.69)	(-1.20)	(-3.53)	(-1.73)	(-0.23)
Sell	$R_{k,t-1}$	-0.052	-0.086	-0.025	-0.064	-0.079
		(-0.85)	(-1.56)	(-0.43)	(-1.10)	(-1.37)
	$X_{k,t}$	1.606	0.039*	0.020**	1.058***	0.081**
		(1.31)	(1.71)	(2.28)	(4.16)	(2.48)

Table 1.10 reports the results using each of nine proxies for information environments of a country. The buy-side regression results show that information environments is generally negatively related to the cross-sectional intra-period herding. That

is, intra-period buy herding is larger in countries with weaker information environments. All coefficients on our nine proxies are estimated as being negative, and those on six proxies—*Idio/Sys*, *English*, *ComLaw*, *DiscReq*, *RepFreq*, and *PctgAudit*—are statistically significant at least at the 10% level. Judging from the estimated significance, institutions in our sample tend to intra-period-herd more in countries where stock markets are more driven by systematic or market-wide shocks (*Idio/Sys*), where the official language is not English (*English*), where the legal origin is not English common law (*ComLaw*), where corporate disclosure requirements are lower (*DiscReq*), where the timeliness of financial information dissemination is worse (*RepFreq*), and where the credibility of disclosed accounting information is lower (*PctgAudit*). In short, in the buy side, they tend to intra-period-herd more in countries that have weaker information environments.

In contrast to the buy-side regression results, the sell-side regressions deliver opposite results. The results show that information environments is generally positively related to the intra-period herding, meaning that intra-period sell herding is larger in countries with stronger information environments. Coefficients on eight proxies are estimated as being positive, and those on five proxies are statistically significant at least at the 10% level. Except for one proxy variable *Develop*, all proxy variables that are significantly positively related to intra-period herding are variables directly related to corporate information disclosure environments. Again, judging from the estimated significance, institutions in our sample tend to intra-period-herd more in more developed countries (*Develop*), in countries where accounting standards are higher (*AcctgStd*), in countries where the timeliness of financial information dissemination is better (*RepFreq*), and in countries where more analysts follow and produce information on companies (*NAnalyst*). In short, in the sell side, they tend to intra-period-herd more in countries that have stronger information environments.

Lastly, we find that previous-month market returns have no significant relation to intra-period herding this month, which is consistent with the results from Table 1.7.

In summary, our results for intra-period herding show that information environments of a country have asymmetric effects on the buy- and sell-side herding. In the buy-side, institutions tend to intra-period-herd more in countries with weaker information environments; on the other hand, in the sell-side, they tend to intra-period-herd more in countries with stronger information environments.

1.6.3 Inter-period herding and information environments

To examine the effect of information environments of a country on inter-period herding, we run the cross-sectional regression of the following form

$$\rho^H_{k,t} = \alpha_t + \beta_t R_{k,t-1} + \gamma_t X_{k,t} + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37 \tag{1.7}$$

for each month t, and then calculate the time-series averages of β_t and γ_t and associated time-series standard errors. Here, $\rho^H_{k,t}$ represents the inter-period herding measured by using the Sias measure when country months with at least five active institutions are considered. Similarly as in the previous subsection, we run the above regression (1.7) separately for a sup-sample of those country-month pairs with $\Delta_{k,t-1} > \overline{\Delta^*_{t-1}}$ and for a sub-sample of those country-month pairs with $\Delta_{k,t-1} < \overline{\Delta^*_{t-1}}$, which is consistent with Choi and Sias (2009).

Table 1.11 reports the results using each of nine proxies for information environments of a country. Compared with the results of intra-period herding in the previous subsection, three points are noteworthy. First, information environments of a country are significantly related to only buy-side inter-period herding. In the sell-side, the inter-period herding has no significant relation with information environments. Second, like the buy-side intra-period herding in Table 1.11, the buy-side inter-period herding is also larger in countries with weaker information environments. Third, the buy-side inter-period herding is larger in countries that performed well in the previous month. The estimated coefficients on the previous-month market return are all

Table 1.11: Information Environments and Inter-period Herding

This table presents the results of the following regressions

$$\rho_{k,t}^{H} = \alpha_t + \beta_t R_{k,t-1} + \gamma_t X_{k,t} + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37,$$

where $\rho_{k,t}^{H}$ represents the inter-period herding for country k over this month t and last month $t-1$, $R_{k,t-1}$ the local market return of country k during month $t-1$, and $X_{k,t}$ a proxy for information environments of country k. Except for the *Idio/Sys* variable, all proxies for information environments are not time-varying. The *Idio/Sys* variable is updated annually. After obtaining estimates of β_t and γ_t for each month t, we calculate their time-series averages and associated time-series standard errors. Following Choi and Sias (2009), we interpret $\rho_{k,t}^{H}$ as representing buy herding when $\Delta_{k,t-1} > \overline{\Delta_{t-1}^{*}}$ and as representing sell herding when $\Delta_{k,t-1} < \overline{\Delta_{t-1}^{*}}$. Numbers in parentheses are t-statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm-specific Return Volatility, Language, Development Stage, and Legal Origin

		$X_{k,t}$			
		Idio/Sys	English	Develop	ComLaw
Buy	$R_{k,t-1}$	0.073***	0.076***	0.062**	0.070***
		(3.07)	(2.85)	(2.51)	(2.87)
	$X_{k,t}$	-0.665***	-0.644***	-0.250	-0.305*
		(-3.18)	(-3.69)	(-1.38)	(-1.71)
Sell	$R_{k,t-1}$	0.013	0.014	0.011	0.015
		(0.63)	(0.67)	(0.52)	(0.69)
	$X_{k,t}$	-0.244	0.140	0.055	-0.032
		(-1.47)	(0.88)	(0.29)	(-0.20)

Panel B: Disclosure Requirement, Accounting Standard, Reporting Frequency, and Credibility

		$X_{k,t}$				
		DiscReq	AcctgStd	RepFreq	PctgAudit	NAnalyst
Buy	$R_{k,t-1}$	0.042**	0.027	0.040*	0.032	0.041*
		(2.14)	(1.08)	(1.77)	(1.37)	(1.67)
	$X_{k,t}$	-0.998**	-0.018*	-0.012**	-0.103	-0.029**
		(-2.30)	(-1.68)	(-2.58)	(-1.05)	(-2.60)
Sell	$R_{k,t-1}$	0.023	0.003	0.022	0.025	0.003
		(0.98)	(0.12)	(0.80)	(1.18)	(0.14)
	$X_{k,t}$	0.230	-0.006	0.005	0.152	0.016
		(0.53)	(-0.45)	(1.26)	(1.41)	(1.39)

positive, and they are statistically significant in seven out of nine regression models.

In summary, our results for inter-period herding show that, in the buy-side, institutions in our sample tend to inter-period-herd more in countries with weaker information environments. However, in the sell-side, information environments have no significant relation to their inter-period herding.

1.6.4 Herding and a composite information proxy

In this subsection, we construct a composite information index that captures the common component in the nine proxies for information environments and then examine the relation between information environments and intra- and inter-period herdings by using this composite proxy for information environments. Following Baker and Wurgler (2006) and Brown and Clifford (2004), we compute the first principal component of the correlation matrix of our nine proxy variables. The first principal component thus computed, which we denote as *InfoEnv*, is equal to

$$\begin{aligned} InfoEnv_k =& 0.195 * Idio/Sys_k + 0.155 * English_k + 0.139 * Develop_k \\ &+0.185 * ComLaw_k + 0.135 * DiscReq_k + 0.242 * AcctgStd_k \\ &+0.181 * RepFreq_k + 0.227 * PctgAudit_k + 0.115 * NAnalyst_k, \quad (1.8) \end{aligned}$$

where each proxy has first been standardized. The loading coefficients on individual proxies in *InfoEnv* are rescaled so that *InfoEnv* has unit variance. We use the numbers presented in Table 1.9 to compute the first principal component. Here, all proxy variables, including the *Idio/Sys* variable which we updated annually in the previous two subsections, are assumed to be constant over the sample period. Hence, *InfoEnv* has no argument for time.

Although four countries–China, Indonesia, Poland, and Russia–are removed from the sample due to missing values for some individual proxies, the *InfoEnv* index has some nice properties. First, each individual proxy enters with the expected sign and with roughly similar magnitude. Second, *InfoEnv* explains 39% of the sample variance, so we conclude that it captures substantial portion of the common variation.

Table 1.12: A Composite Proxy for Information Environments and Herdings: Bivariate Relationship

This table shows bivariate relations between information environments and intra- and inter-period herdings. For the LSV herding measure, a country-month pair (k, t) is classified as a buy-side pair if $\Delta_{k,t} > \overline{\Delta_t^*}$ and as a sell-side pair if $\Delta_{k,t} < \overline{\Delta_t^*}$. For the Sias herding measure, a country-month pair (k, t) is classified as a buy-side pair if $\Delta_{k,t-1} > \overline{\Delta_{t-1}^*}$ and as a sell-side pair if $\Delta_{k,t-1} > \overline{\Delta_{t-1}^*}$. The information environment of a country is classified as "Strong" if the *InfoEnv* value in Table 9 is above the median and as "Weak" if the value is below the median. The LSV herding values are presented in percent terms and, for ease of presentation, the Sias herding values are multiplied by a hundred. Numbers reported are the average herding values for each category. The correlation represents the correlation between *InfoEnv* and herding for each column. Numbers in parentheses are t-statistics, and *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Intra-period (LSV) herding, H		Inter-period (Sias) herding, ρ^H	
Information Environments	Buy	Sell	Buy	Sell
Strong	1.81%	2.68%	0.27	0.67
Weak	2.50%	1.46%	0.63	0.37
Correlation	-0.085***	0.093***	-0.084***	0.026
	(-3.36)	(12.17)	(-3.29)	(1.03)

The last column labeled as *InfoEnv* in Table 1.9 shows this composite proxy for information environments by country. Turkey has the weakest information environments (*InfoEnv*=-2.25), followed by Greece (-1.90) and Taiwan (-1.87). On the other hand, Canada has the strongest information environments (*InfoEnv*=1.71), followed by the United Kingdom (1.65) and Australia (1.49).

As a preliminary analysis, we first examine the bivariate relationship between herding and information environments of a country proxied by *InfoEnv*. Table 1.12 and Figure 1.3 present the results. The information environment of a country is classified as "Strong" if the *InfoEnv* value of the country is above the median and as "Weak" if the value is below the median. Numbers reported in both Table 1.12

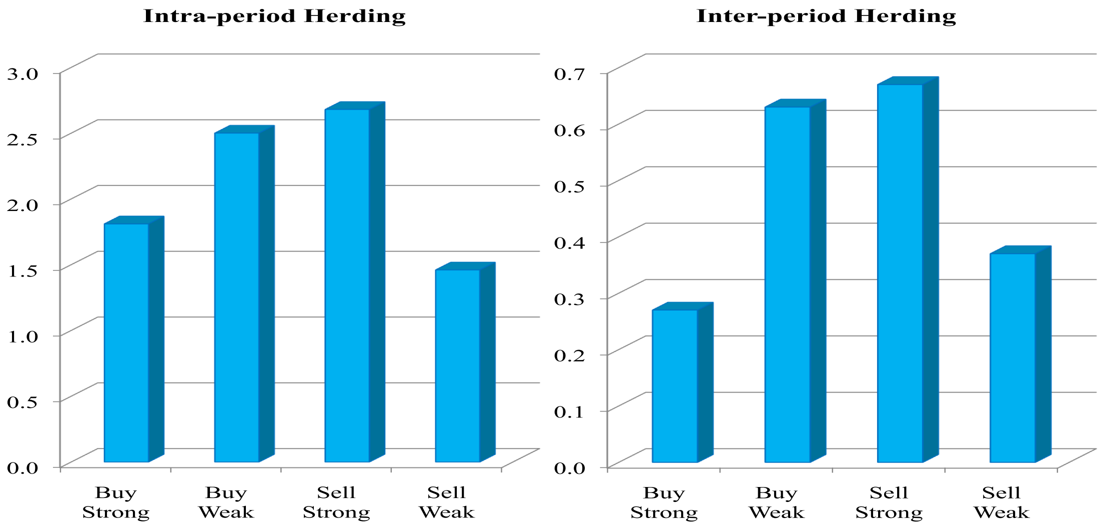

Figure 1.3: Information Environments and Herding

This figure shows the bivariate relationship between information environments and intra- and inter-period herdings. For the intra-period LSV herding measure, a country-month pair (k, t) is classified as a buy-side pair if $\Delta_{k,t} > \overline{\Delta_t^*}$ and as a sell-side pair if $\Delta_{k,t} < \overline{\Delta_t^*}$. For the inter-period Sias herding measure, a country-month pair (k, t) is classified as a buy-side pair if $\Delta_{k,t-1} > \overline{\Delta_{t-1}^*}$ and as a sell-side pair if $\Delta_{k,t-1} > \overline{\Delta_{t-1}^*}$. The information environment of a country is classified as "Strong" if the *InfoEnv* value in Table 9 is above the median and as "Weak" if the value is below the median. The LSV herding values are presented in percent terms and, for ease of presentation, the Sias herding values are multiplied by a hundred. Numbers reported are the average herding values for each category.

and Figure 1.3 represent the average herding values for each category.[27] Consistent with the results in the previous two subsections, the results of Table 1.12 and Figure 1.3 clearly show that, in the buy side, both intra- and inter-period herdings are more pronounced in countries with weak information environments and that, in the sell-side, inter-period herding is more pronounced in countries with stronger information environments, whereas the relation between inter-period sell herding and information environments is not significant. Note that inter-period sell herding is also larger in countries with stronger information environments, however.

[27]The LSV herding values are presented in percent terms, and, for ease of presentation, we multiplied the Sias herding values by a hundred.

Next, using this composite proxy for information environments, we run the cross-sectional regression of the following form

$$H_{k,t} \text{ (or } \rho^H_{k,t}) = \alpha_t + \beta_t R_{k,t-m\to t-1} + \gamma_t InfoEnv_k + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37 \qquad (1.9)$$

for each month t, and then calculate the time-series averages of β_t and γ_t and associated time-series standard errors. Here, $H_{k,t}$ ($\rho^H_{k,t}$) represents the intra-period (inter-period) herding for country k this month t (over this month t and last month $t-1$) when country months with at least five active institutions are considered, and $R_{k,t-m\to t-1}$ the local market return of country k during previous m months.

Table 1.13 presents the results of the regression (1.9) for $m = 1, 3, 6, 12$. Again, it shows that, irrespective of which prior market returns we use, the effect of information environments on intra- and inter-period buy and sell herdings remains the qualitatively same as the results from the previous two subsections. That is, (i) in the buy side, both intra- and inter-period herdings are more pronounced in countries with weaker information environments, but (ii) in the sell side, intra-period herding is more pronounced in countries with stronger information environments, whereas inter-period herding is not significantly related to information environments.

In terms of the effect of the previous market returns on herding, the results of Table 1.13 show that, for intra-period herding, the sell-side herding exhibits a return-chasing behavior conditioned on the previous 1-, 3-, or 6-month market returns, whereas the buy-side herding exhibits no return-chasing behaviors conditioned on the short-term market returns but a contrarian behavior conditioned on the previous 12-month market returns. For inter-period herding, only the buy-side herding exhibits a contrarian behavior conditioned on the previous 6- or 12-month market returns.

Table 1.13: A Composite Proxy for Information Environments and Herdings

This table presents the results of the following regressions

$$H_{k,t} \text{ (or } \rho^H_{k,t}) = \alpha_t + \beta_t R_{k,t-m\to t-1} + \gamma_t InfoEnv_k + \epsilon_{k,t}, \qquad k = 1, 2, ..., 37,$$

where $H_{k,t}$ ($\rho^H_{k,t}$) represents the intra-period (inter-period) herding for country k this month t (over this month t and last month $t-1$), $R_{k,t-m\to t-1}$ the local market return of country k during previous m months, and $InfoEnv_k$ the first principal component, rescaled to have unit variance, of the correlation matrix of nine proxies for information environments of country k. After obtaining estimates of β_t and γ_t for each month t, we calculate their time-series averages and associated time-series standard errors. For the definition of buy and sell herdings, refer to annotations in Tables 10 and 11. Numbers in parentheses are t-statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Variable = $H_{k,t}$					
		Market Return over the Previous m Months			
		$m=1$	3	6	12
Buy	$R_{k,t-m\to t-1}$	-0.016	-0.026	-0.039	-0.045***
		(-0.33)	(-0.90)	(-1.66)	(-2.74)
	$InfoEnv_k$	-0.512**	-0.538**	-0.476**	-0.505**
		(-2.47)	(-2.49)	(-2.18)	(-2.23)
Sell	$R_{k,t-m\to t-1}$	-0.089*	-0.071**	-0.052**	0.004
		(-1.73)	(-2.12)	(-2.01)	(0.23)
	$InfoEnv_k$	0.634***	0.547***	0.452*	0.480**
		(3.01)	(2.65)	(1.93)	(2.05)
Panel B: Dependent Variable = $\rho^H_{k,t}$					
		Market Return over the Previous m Months			
		$m=1$	3	6	12
Buy	$R_{k,t-m\to t-1}$	0.031	0.002	-0.022**	-0.019***
		(1.25)	(0.12)	(-2.02)	(-2.81)
	$InfoEnv_k$	-0.192**	-0.178*	-0.236**	-0.239***
		(-2.21)	(-1.87)	(-2.40)	(-2.72)
Sell	$R_{k,t-m\to t-1}$	0.012	-0.004	-0.014	0.007
		(0.54)	(-0.30)	(-1.19)	(1.01)
	$InfoEnv_k$	0.040	-0.000	0.006	-0.034
		(0.39)	(-0.00)	(0.05)	(-0.28)

1.6.5 Discussion of the regression results

Taken together, our regression results in this section show: (i) in the buy side, both intra- and inter-period herdings are more pronounced in countries with weaker infor-

mation environments; but (ii) in the sell side, intra-period herding is more pronounced in countries with stronger information environments, whereas inter-period herding is not significantly related to information environments.

At a first glance, the results obtained may seem to be not easily reconcilable. However, note that the intra-period herding measured by employing the LSV measure cannot distinguish 'intentional' herding from 'unintentional' herding (LSV, 1992). Intentional herding is likely to be larger when information asymmetry is larger among investors and thus investors tend to mimic or copy other investors' trading. On the other hand, unintentional herding is likely to be larger when information asymmetry is smaller among investors because in such environments investors would receive correlated signals and may react to them in a similar fashion. This is also the case for inter-period herding.

Hence, our regression results in the buy-side is consistent with the intentional herding story, which predicts that both intra- and inter-period buy herdings would be more pronounced in countries with weaker information environments. This is what we have found in the buy side. On the other hand, our regression results in the sell-side is consistent with the unintentional herding story or herding story based on correlated signals. We have found that intra-period sell herding is more pronounced in countries with stronger information environments. Although we have found that inter-period sell herding is not significantly related to information environments, this finding is also not unexpected. In psychology, it is well known that bad news is stronger or more influential than good news (see, e.g., Baumeister et al., 2001; Peeters and Czapinski, 1990; Skowronski and Carlston, 1989). This suggests that, when institutions receive bad signals, they tend to react quickly to them and may do so independently without paying attention to what others are doing. Thus, they tend to "unintentionally" herd to sell quickly within a period, and would do so more in countries with stronger information environments than in countries with weaker information environments.

Hence, it is likely that inter-period sell herding is not significantly related to information environments, although we still observe a higher level of mean inter-period sell herding in countries with stronger information environments (Table 1.12). This story is consistent with what we have found for the intra- and inter-period herdings in the sell side.

1.7 Summary and Concluding Remarks

In the current paper, we document evidence of institutional herding across a wide cross-section of countries, examine its impacts on local stock market performances, and investigate whether information environments of a country affect their herding behavior. Using a new transaction-level trading data of 531 U.S. institutional investors trading across 37 countries around the world for the period January 2002 to December 2009, we find: (i) institutions in our sample engage in a significant level of intra- and inter-period herdings across countries; (ii) their herding behavior, however, does not destabilize local stock markets; rather, they help to speed the price-adjustment process; and (iii) information environments of a country have asymmetric influences on their buy- and sell-side herding behavior. We find that both intra- and inter-period buy herdings are larger in countries with weaker information environments, but that intra-period sell herding is larger in countries with stronger information environments whereas inter-period sell herding is not significantly related to information environments.

The overall results of the current study suggests that information environments have asymmetric effects on the buy- and sell-side herdings and are consistent with the view that, in the buy side, institutions herd as a result of "intentionally" inferring information from each other's trades, whereas, in the sell side, correlated signals primarily drive their "unintentional" herding across countries.

CHAPTER II

EXCHANGE RATE SYNCHRONICITY

In the current paper, we (i) document that the degree of co-movement between bilateral USD exchange rates has increased substantially since the introduction of the euro in 1999 and (ii) investigate what drives the increased co-movement. For each of our 33 sampled bilateral USD exchange rates, we measure the degree of co-movement using the R-square from regressing weekly exchange rate changes on the weekly world exchange rate factor. Our results show that, for the majority of sample exchange rates, the R-square has increased substantially over the period 1999-2010. Specifically, the average R-square was 0.15 in 1999, but it increased to 0.47 by more than 200% in 2010. Further analysis reveals that the rising influence of the euro relative to USD over a third currency can explain most of the increase in the measured co-movement over time. Our cross-sectional regression analysis indicates that trade propensity, financial integration, and inflation have some additional power in explaining the cross-sectional variation in the measured co-movement. However, our cross-sectional and time-series regression analysis reveals that once the effect of the influence of the euro relative to USD over a third currency is controlled for, the other explanatory variables lose most of their power in explaining the time-series variation in the measured co-movement.

2.1 *Introduction*

Reducing risk by investing in a variety of assets, i.e., diversification, is at the heart of finance. Diversification does not work, of course, if assets move in lock-step with each other. As such, practitioners and academics have long been interested in the degree of co-movement between given assets and its inter-temporal dynamics. For international stock markets, for example, earlier studies like Grubel (1968), Levy and Sarnat (1970), and Solnik (1974) report that international stock markets during the 1950s and 1960s were relatively weakly correlated and thus the gains from international diversification were substantial. However, a number of more recent studies report that international stock markets have been becoming more integrated over the past two to three decades, suggesting the decreasing benefits from international diversification (see , e.g., Bekaert, Harvey, Lundblad, and Siegel, 2009; Brooks and Del Negro, 2004; Carrieri, Errunza, and Hogan, 2007; Eun and Lee, 2010; Goetzman, Li, and Rouwenhorst, 2005; Hardouvelis, Malliaropulos, and Priestley, 2006; Korajczyk, 1996; Levine and Zervos, 1998; Longin and Solnik, 1995; and Pukthuanthong and Roll, 2009). For example, Pukthuanthong and Roll (2009) report that international stock markets have been becoming more integrated over the period 1973-2006 in the sense that the influence of common global factors on local stock markets has been becoming more important.

There is, however, little empirical research on the degree of co-movement between foreign exchange rates and its inter-temporal dynamics. This is surprising considering that the foreign exchange market is by far the largest financial market as a single asset market.[1] According to a recent survey report by Bank for International Settlements (BIS), the average daily turnover value of global foreign exchange markets is about

[1]The popular press such as Wall Street Journal and New York Times reports frequently that currency has emerged as an independent asset class in the sense that currency exposure is a way to diversify portfolio risk and introduce new sources of return.

\$4.0 trillion during April 2010, which is more than 8 times larger than the average daily turnover value of global equity markets during 2010 (BIS, 2010).[2]

To be precise, there exist a few number of studies under the title of 'comovement among exchange rates' (Baffes, 1994) or 'comovements of exchange rates' (Kuhl, 2008). However, the interest of these studies is in the existence of cointegration between sample exchanges rates and its implications for market efficiency, like that of many other studies including Hakkio and Rush (1989), MacDonald and Taylor (1989), Coleman (1990), Alexander and Johnson (1992), Ballie and Bollerslev (1989, 1994), Norrbin (1996), Ferre and Hall (2002), and Kuhl (2007). Simply speaking, this strand of literature is based on the Granger's (1986) argument that different asset prices coming from jointly efficient markets cannot be cointegrated, since if they were one would help predict the other and hence profit opportunities would arise.[3] However, documenting evidence of the cointegration relation between sampled exchange rates by using data for a certain period of time does not tell us much about the degree of co-movement between them and its change over time, on which the current paper is focused.

The purpose of this paper is (i) to document the degree of co-movement between

[2]According to the 2010 World Federation of Exchanges (WFE) Market Highlights, the average daily turnover value of gloabl equity markets is about \$497 billion (WFE, 2010).

[3]Consider two bilateral exchange rates S^a and S^b against a same base currency and suppose there exists an error correction representation of the following form (Engle and Granger, 1987):

$$\Delta S_t^a = -\rho_1(S_{t-1}^a - \beta S_{t-1}^b) + \text{lagged } (\Delta S_t^a, \Delta S_t^b) + \varepsilon_{1,t},$$
$$\Delta S_t^b = -\rho_2(S_{t-1}^a - \beta S_{t-1}^b) + \text{lagged } (\Delta S_t^a, \Delta S_t^b) + \varepsilon_{2,t}.$$

Then, as long as $|\rho_1| + |\rho_2| \neq 0$, knowing S_{t-1}^a and S_{t-1}^b helps predict S_t^a or S_t^b. Hence, tests for the existence of cointegration between S^a and S^b have implications for market efficiency. However, such test results are not helpful in quantifying the degree of co-movement between S^a and S^b and its change over time. For example, using 10 bilateral USD exchange rates for the period 1973-1985, MacDonald and Taylor (1989) find no strong evidence of cointegration. However, even if they found some evidence of cointegration for the period, it would not tell us what the degree of co-movement between their sample exchange rates was in 1983, for example, and how it evolved over their sample period.

foreign exchange rates and its inter-temporal dynamics over the 12-year period 1999-2010 after the introduction of the euro in 1999 and (ii) to investigate what drives the degree of co-movement and its change over time. For this purpose, we consider 33 bilateral USD exchange rates, i.e., 34 currencies that have been relatively independently floating during the sample period 1999-2010. We measure the degree of co-movement of a currency x's bilateral USD exchange rate with the other bilateral USD exchange rates by the regression R-square from regressing the weekly change in log \$/X exchange rates on the weekly world exchange rate factor. The weekly world exchange rate factor is constructed as either the GDP-weighted, trade-weighted, or equally-weighted average of the weekly changes in log \$/X exchange rates across all currencies, although most results are presented using the GDP-weighted world exchange rate factor. Throughout this paper, we refer to the regression R-square computed in this manner as the 'currency R-square.' Our first key finding is that the degree of co-movement between 33 bilateral USD exchange rates in our sample has increased substantially over the sample period 1999-2010. Specifically, in 1999 the average currency R-square across all currencies was 0.15, but it increased to 0.47 in 2010 by more than 200%.

Next, to investigate what drives such a marked increase in the measured co-movement between sample exchange rates, we begin with examining how many currencies play a dominant role among sample exchange rates. Answering this question first is critical in our subsequent analysis because the behavior of many currencies, especially currencies of relatively small economies may be influenced by a few major currencies of large economies such as the U.S., euro area, Japan, and the U.K. Employing statistical clustering analysis, we find that there are essentially two large currency clusters: one cluster centered around the U.S. dollar and the other cluster centered around the euro.

The results of our cluster analysis, though informal, suggests that two currencies—the U.S. dollar and euro—would play an important role in explaining co-movement between sampled exchange rates.[4] Thus, we consider the influence of the euro relative to the U.S. dollar on a currency x to be a key variable that could explain our finding, i.e., the increased co-movement between sample exchange rates. Specifically, following Eun and Lai (2003), we compute the so-called 'currency beta' to measure the influence of the euro relative to the U.S. dollar on a third currency x. For other factors that might drive the increased co-movement between sample exchange rates, we also consider trade propensity, degree of financial integration, and inflation. We expect that, other things being equal, currencies of countries with lower trade propensity, countries less financially integrated with the rest of the world, and countries with higher inflation are likely to behave more independently against other foreign currencies.

We find that, cross-sectionally, the currency beta together with the other three explanatory variables that we consider can explain about 90% of the cross-currency variation in the measured currency R-square values. In terms of statistical significance, the explanatory power of the currency beta variable is by far the largest. The currency beta variable alone can explain more than 80% of the cross-currency variation in the measured currency R-square values. Although the other explanatory variables also retain some statistically significant explanatory power, they, all combined, can increase the explanatory power only by 7% to 9% once the effect of the currency beta variable is controlled for. Next, from the cross-sectional and time-series regression analysis, we also find that the explanatory power of the currency beta variable is by far the largest. The change in the currency beta values alone can explain the change in the currency R-square values as much as about 70% to 80%. Of the other explanatory variables, only the financial integration variable survives to explain

[4]The discussion in Subsection 4.1 further suggests that the extent to which a currency tracks the euro or the dollar would play an important role in explaining the level of the currency R-square and its change over time

the change in the currency R-square values over time, but its explanatory power is much smaller than that of the currency beta variable.

Our findings of the markedly increased degree of co-movement between bilateral USD exchange rates over the recent decade have implications for a wide range of financial decision makings such as asset allocation, currency hedging, as well as economic policies. Our findings indicate that currency risk is becoming more systematic and its main driver is the increasing alignment of many currencies with the euro. Hence, for USD-based investors, our findings imply that investing in international financial markets is more exposed to currency risk. This is also the case for multinational companies headquartered in the U.S. As such, our findings suggest that when hedging international investments through currency forward and/or derivatives markets, investors or multinational companies need to pay more attention to the dynamics of the dollar-euro exchange rate. Policymakers might as well be concerned that an increasing co-movement between exchange rates will lead to a rising susceptibility of the economy's current and capital account balances to currency risk.

The rest of the paper is organized as follows. The next section describes our sample currencies and exchange rates data. Section 3 introduces the notion of the world exchange rate factor and the currency R-square, and then document evidence of the increasing degree of co-movement between bilateral USD exchange rates. In Section 4, we explore possible factors that might drive the degree of co-movement and its change over time. Section 5 presents the results of the cross-sectional and time-series regression analysis. Section 6 concludes.

2.2 Data

2.2.1 Sample Currencies

In this study, we use 33 bilateral USD exchange rates (34 currencies) for the sample period from January 1999 to December 2010. Our sample period starts from January

1, 1999, when the euro was introduced to the world financial markets as an accounting currency.

We select our sample currencies according to the following procedure. We first start with 74 currencies that are classified as independently floating or managed floating according to the classification of exchange rate arrangements and monetary policy frameworks by International Monetary Fund (IMF) as of April 2010.[5] According to IMF, "the classification system is based on the members' actual, *de facto* arrangements, as identified by IMF staff, which may differ from their officially announced, *de jure* arrangements [italics added]." We then exclude currencies of 27 small-economy countries that may have negligible effects on the foreign exchange rate markets. Specifically, we exclude currencies of countries whose gross domestic products (GDP) account for less than 0.05% of the world GDP as of 2010. This step excludes currencies of such countries as Albania, D.R. Congo, Ghana, Paraguay, Uganda, and Zambia from the sample. In addition, due to the lack of available daily exchange rates data against the U.S. dollar, U.K. pound, or euro for the substantial sub-period of our sample period, we exclude currencies of 7 countries from the sample: Costa Rica, Dominican Republic, Guatemala, I.R Iran, Myanmar, Serbia, and Sudan. As a final screening, for the remaining 40 currencies we have investigated both the history of exchange rate arrangements and their actual exchange rate behaviors against the U.S. dollar, UK pound, or euro to identify currencies that can be considered to be *de facto* floating during our sample period. From this investigation, we exclude currencies of 6 more countries from the sample: Argentina, Egypt, Kuwait, Malaysia, Ukraine, and Vietnam. This leaves us with 34 (=74-27-7-6) currencies.

Table 2.1 presents the 34 sampled currencies, along with the GDP and foreign

[5] In terms of the number of countries, currencies of 89 countries are identified as free floating, floating, or managed floating by IMF as of April 2010. The 89 countries, however, contain 16 eurozone countries. Hence, in terms of the number of distinct currencies, only 74 currencies, including the euro, are identified as either floating or managed floating. [Estonia joined the eurozone in January 2011.]

Table 2.1: Sample Currencies

Our sample consists of 34 currencies that are identified as floating or managed floating according to the exchange rate regime classification by IMF (2010). The currency ISO code represents the three-letter currency code by the International Organization for Standardization. GDP represents the gross domestic products and Trade the sum of imports and exports. Both GDP and trade amount are 2010 data, obtained from the International Financial Statistics (IFS) database. The numbers in (%) columns are computed relative to the sample.

Country	Currency (ISO Code)	GDP ($ bil)	(%)	Trade ($ bil)	(%)
Algeria	Dinar (DZD)	159	(0.3)	98	(0.5)
Australia	Dollar (AUD)	1,220	(2.4)	414	(2.3)
Brazil	Real (BRL)	2,024	(4.0)	393	(2.2)
Canada	Dollar (CAD)	1,564	(3.1)	777	(4.3)
Chile	Peso (CLP)	199	(0.4)	127	(0.7)
Colombia	Peso (COP)	283	(0.6)	80	(0.4)
Czech Rep.	Koruna (CZK)	195	(0.4)	255	(1.4)
Euro Area	Euro (EUR)	12,067	(23.9)	3,844	(21.1)
Hungary	Forint (HUF)	132	(0.3)	189	(1.0)
India	Rupee (INR)	1,430	(2.8)	584	(3.2)
Indonesia	Rupiah (IDR)	695	(1.4)	290	(1.6)
Israel	Shekel (ILS)	201	(0.4)	117	(0.6)
Japan	Yen (JPY)	5,391	(10.7)	1,462	(8.0)
Kenya	Shilling (KES)	32	(0.1)	15	(0.1)
Korea	Won (KRW)	986	(2.0)	892	(4.9)
Mexico	Peso (MXN)	1,004	(2.0)	600	(3.3)
New Zealand	Dollar (NZD)	138	(0.3)	63	(0.3)
Nigeria	Naira (NGN)	207	(0.4)	125	(0.7)
Norway	Krone (NOK)	414	(0.8)	206	(1.1)
Pakistan	Rupee (PKR)	175	(0.3)	57	(0.3)
Peru	Nuevo sol (PEN)	154	(0.3)	63	(0.3)
Philippines	Peso (PHP)	189	(0.4)	113	(0.6)
Poland	Zloty (PLN)	439	(0.9)	326	(1.8)
Romania	Leu (RON)	158	(0.3)	111	(0.6)
Russia	Rouble (RUB)	1,477	(2.9)	613	(3.4)
Singapore	Dollar (SGD)	217	(0.4)	663	(3.6)
South Africa	Rand (ZAR)	354	(0.7)	162	(0.9)
Sweden	Krona (SEK)	445	(0.9)	306	(1.7)
Switzerland	Franc (CHF)	522	(1.0)	353	(1.9)
Thailand	Baht (THB)	313	(0.6)	380	(2.1)
Turkey	Lira (TRY)	729	(1.4)	299	(1.6)
U.K.	Pound sterling (GBP)	2,259	(4.5)	971	(5.3)
U.S.	Dollar (USD)	14,624	(29.0)	3,246	(17.8)
Uruguay	Peso (UYU)	41	(0.1)	16	(0.1)
SUM		50,436	(100.0)	18,210	(100.0)

trade amount information as of year 2010.[6] The foreign trade amount, the Trade variable in the table, is defined as the sum of exports and imports. In terms of both GDP and foreign trade amount, the United States, euro area, Japan, and the United Kingdom come first, second, third, and fourth, respectively.[7] The United States and euro area together account for 53 percent of the total GDP and 39 percent of the total trade amount of the sampled countries.

2.2.2 Exchange Rates Data

In this study, we use daily exchange rates sampled at the weekly frequency on every Wednesday during our sample period 1999-2010 (626 weeks). The data are obtained from Datastream. Specifically, we use exchange rates supplied by WM/Reuters, if possible, which provides exchange rates recorded at 4:00 p.m. in London time.

Table 2.2 presents the descriptive statistics for our exchange rates data. The bilateral exchange rate between USD and a given currency x is expressed in \$/X, and weekly exchange rate changes are computed as the first difference of log spot exchange rates. A few points are noteworthy from the table. First, the mean exchange rate change is negative for 17 currencies and positive for 16 currencies. Since the exchange rate between USD and a currency x is expressed in \$/X, the positive (negative) mean represents the appreciation (depreciation) of the currency x against USD during the sample period. For example, the euro appreciated 0.018 percent per week against USD, which is translated to about 11.3 percent during the 1999-2010 period (626 weeks). Among the sample currencies, the Australian dollar appreciated most against USD. The Canadian dollar, Japanese yen, and Swiss franc also appreciated strongly against USD. On the other hand, the Turkish lira depreciated most against USD, followed by Romanian leu and Uruguayan peso. Second, the standard deviation

[6] The euro area represents 16 countries. Unless there could be some confusion, however, we regard the euro area as representing one country.

[7] Among countries not included in our sample, China is the largest economy country with the GDP amount of \$5,745 billion and the foreign trade amount of \$2,972 billion as of 2010.

Table 2.2: Weekly Exchange Rate Changes: Summary Statistics

This table reports the descriptive statistics for the weekly changes in the log bilateral USD exchange rates during the sample period 1999-2010. The bilateral exchange rate between USD and a given currency x is expressed in $/X, obtained from Datastream. SD, Min, Max, Skew, and Kurt represent the standard deviation, minimum, maximum, skewness, and excess kurtosis, respectively. JB represents the Jarque-Bera statistic which tests for normality. The JB statistic follows asymptotically the chi-square distribution with two degrees of freedom, $\chi^2(2)$. The upper critical value of $\chi^2(2)$ at the one-sided 1% significance level is 9.2. Serial Corr represents the autocorrelation at lag one. Mean, SD, Min, and Max are expressed in percent terms. The star symbols *, **, and *** represent the statistical significance at the %10, %5, and %1 levels, respectively.

Currency	Mean	SD	Min	Max	Skew	Kurt	JB	Serial Corr
Algeria	-0.035	1.05	-6.53	4.09	-0.70	5.56	859.0	-0.13***
Australia	0.076	1.82	-17.05	6.36	-1.74	13.54	5100.9	0.01
Brazil	-0.053	2.82	-20.72	16.10	-1.63	16.90	7724.7	-0.05
Canada	0.066	1.33	-6.03	6.07	-0.24	3.03	245.1	-0.03
Chile	0.000	1.46	-10.44	5.74	-0.58	4.67	603.6	0.10**
Colombia	-0.038	1.58	-7.39	6.47	-0.19	3.64	349.2	0.03
Czech Rep.	0.069	1.82	-8.62	8.14	-0.31	2.35	154.5	0.02
Euro Area	0.018	1.47	-5.09	9.81	0.30	3.00	244.6	0.01
Hungary	0.001	2.08	-9.20	9.18	-0.41	2.13	136.1	-0.06
India	-0.009	0.76	-3.83	4.58	0.29	7.66	1539.0	0.07*
Indonesia	-0.020	2.08	-13.76	11.50	-0.19	10.73	3005.2	-0.02
Israel	0.021	1.09	-5.26	5.36	-0.18	3.17	265.7	0.02
Japan	0.051	1.39	-4.11	6.18	0.37	0.97	39.1	0.00
Kenya	-0.042	1.17	-8.64	8.01	0.05	12.41	4016.4	-0.12***
Korea	0.002	1.69	-16.11	12.03	-0.88	23.64	14655.2	-0.10
Mexico	-0.038	1.45	-11.81	6.29	-1.14	9.02	2258.0	-0.02
New Zealand	0.056	1.91	-11.60	7.27	-0.84	3.86	460.8	-0.02
Nigeria	-0.081	1.54	-11.21	11.22	-0.55	18.76	9215.8	-0.13***
Norway	0.036	1.66	-9.55	5.99	-0.57	2.64	215.8	-0.06
Pakistan	-0.086***	0.64	-5.83	2.77	-2.16	17.93	8868.7	0.05
Peru	0.020	0.71	-5.31	4.94	-0.92	14.16	5315.2	-0.03
Philippines	-0.022	1.00	-6.12	11.70	2.32	32.47	28054.6	-0.09**
Poland	0.020	2.00	-12.31	5.99	-1.31	5.44	950.7	-0.06
Romania	-0.171**	1.79	-18.24	11.43	-1.41	21.70	12492.1	-0.08*
Russia	-0.042	1.14	-10.41	4.67	-2.64	20.50	11685.9	-0.09**
Singapore	0.041	0.67	-2.23	3.66	0.04	2.01	105.2	0.06
South Africa	-0.025	2.39	-16.77	10.79	-1.01	6.21	1112.4	-0.04
Sweden	0.023	1.66	-8.25	5.75	-0.25	1.62	75.1	-0.01
Switzerland	0.060	1.45	-4.26	9.99	0.49	3.03	264.9	0.05
Thailand	0.030	0.87	-8.95	4.91	-1.45	20.45	11126.3	-0.03
Turkey	-0.255**	2.58	-33.90	8.35	-5.04	55.18	82076.7	0.02
U.K.	-0.011	1.37	-7.17	5.30	-0.55	3.07	278.0	-0.01
Uruguay	-0.098	1.71	-14.82	16.51	-1.09	31.81	26511.3	0.09**
MEAN	-0.013	1.52	-10.35	7.79	-0.73	11.61	3573.8	-0.02

ranges from 0.76 for Peru to 2.82 for Brazil, with a mean of 1.52. Assuming no serial correlations in the weekly exchange rate changes, the mean standard deviation of 1.52 percent per week is translated to about 11.0 percent per year ($11.0=1.52*\sqrt{52}$). Note also that the standard deviation is much larger than the mean by one or two order of magnitude, indicating that exchange rate changes are very volatile. Third, the minimum, maximum, skewness, kurtosis, and Jarque-Bera statistics, combined together, suggest that exchange rate changes can be characterized by highly skewed and heavy-tailed non-normal distributions. Lastly, for 9 currencies, the autocorrelation coefficient at lag one is significant at least at the 10% level. The associated countries are relatively poor countries among the sample.

2.3 Measurement of Co-movement

2.3.1 The World Exchange Rate Factor

We construct a so-called 'world exchange rate factor' at time t, $f_{W,t}$, of the following form

$$f_{W,t} = \sum_{j=1}^{N(t)} w_{j,t}(\ln S_{j,t} - \ln S_{j,t-1}) + w_{\$,t}(\ln S_{\$,t} - \ln S_{\$,t-1}), \tag{2.1}$$

with a restriction

$$\sum_{j=1}^{N(t)} w_{j,t} + w_{\$,t} = 1. \tag{2.2}$$

Here, $S_{j,t}$ represents the spot exchange rate between USD and currency j expressed in \$/J, $w_{j,t}$ an weight assigned to $S_{j,t}$, and $N(t)$ the number of bilateral USD exchange rates.[8] In this study, we consider three alternative definitions of the world exchange rate factor of this form, namely, GDP-weighted, trade-weighted, and equally-weighted world exchange rate factors. As the names imply, the weight $w_{j,t}$ is proportional to

[8]Let's consider a dollar exchange rate index at time t, I_t, defined as

$$I_t = I_{t-1} \times \prod_{j=1}^{N(t)} (S_{j,t}/S_{j,t-1})^{w_{j,t}}$$

the country j's GDP at time t for the GDP-weighed world exchange rate factor; it is proportional to the country j's foreign trade amount at time t for the trade-weighted world exchange rate factor; and it is simply $1/(N(t)+1)$ for the equally-weighted world exchange rate factor. Although we consider three alternative definitions of the world exchange rate factor, the most results presented in this study are obtained by using the GDP-weighted world exchange rate factor. Using the other two definitions of the world exchange rate factor produces qualitatively similar results, however.

Note that the last term in Equation (2.1) is zero since $S_{\$,t} = 1$ by definition. Still, the last term affects $f_{W,t}$ through its effect on the weights. Though the inclusion of this last term might look strange at a first glance, there are several reasons for us to do so. To begin with, suppose a USD-based agent invests \$1 in $N(t)+1$ currencies, including the U.S. dollar, with the weight $w_{j,t}$ to currency j at time $t-1$. Then the log return to this investment over the interval $[t-1, t]$ can be expressed as

$$\sum_{j=1}^{N(t)} w_{j,t}(\ln S_{j,t} - \ln S_{j,t-1} + i_{j,t-1}) + w_{\$,t}(\ln S_{\$,t} - \ln S_{\$,t-1} + i_{\$,t-1}), \tag{2.3}$$

where $i_{j,t-1}$ represents the interest rate on currency j over the interval $[t-1,t]$. Here, the last term represents the return to investing in the home currency. Since $i_{j,t-1}$ is extremely small over the one-week interval and exchange rate changes are much more volatile as evidenced by Table 2.2, Equations (2.1) and (2.3) are essentially the same. Therefore, if one views currencies as an independent asset class, defining the world exchange rate factor with including the last term in Equation (2.1) is more consistent

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with $N(t)$ being the number of foreign currencies at time t. Then we have

$$\ln(I_t) - \ln(I_{t-1}) = \sum_{j=1}^{N(t)} w_{j,t}(\ln S_{j,t} - \ln S_{j,t-1}).$$

Hence, without the last term in Equation (1), the world exchange rate factor $f_{W,t}$ is simply the log return of the dollar exchange rate index I_t. When the weight $w_{j,t}$ is proportional to the bilateral trade amount between the U.S. and country of currency j, the dollar exchange rate index I_t thus constructed is usually referred to as the nominal effective exchange rate. The U.S. Federal Reserve Board has been publishing an index of the foreign exchange value of the dollar of this form since 1977 (Hooper and Morton, 1978; Pauls, 1987; Leahy, 1998, 2005).

with the convention in the asset pricing literature than defining the world exchange rate factor without the last term in Equation (2.1).

To explain another reason for including the last term in Equation (2.1), consider the GDP-weighted world exchange rate factor for example. If we use the GDP data reported in Table 2.1, then the weight assigned to the dollar-euro exchange rate is 0.336 (=0.239/[1-0.290]) without the last term in Equation (2.1) whereas it is 0.239 with the last term. In general, the weight $w_{j,t}$ is $GDP_{j,t}/[\sum_j GDP_{j,t} - GDP_{US,t}]$ without the last term whereas it is $GDP_{j,t}/\sum_j GDP_{j,t}$ with the last term, where $\sum_j GDP_{j,t}$ includes the U.S. GDP. Hence, if we let $f^*_{W,t}$ be the world exchange rate factor without the last term in Equation (2.1), then we have the following relation

$$f^*_{W,t} = f_{W,t} * \sum_j GDP_{j,t}/(\sum_j GDP_{j,t} - GDP_{US,t}). \tag{2.4}$$

If we update the weight $w_{j,t}$ only annually, $f^*_{W,t}$ is just a constant multiple of $f_{W,t}$ except for only 11 weeks during the 12-year sample period 1999-2010. In this study, $f_{W,t}$ is used only for the purpose of computing the regression R-square from the regression of $(\ln S_{j,t} - \ln S_{j,t-1})$ on $f_{W,t}$. Therefore, the effects of the last term in Equation (2.1) on the empirical results obtained in this study would be minimal, if not zero.

One additional reason for the inclusion of the last term in Equation (2.1) is that with this definition it is easier to construct the world exchange rate factor when we change the base currency. For example, if one wants to construct the world exchange rate factor by using the U.K. pound as the base currency, this can be easily done by using the following relation:

$$f^{£}_{W,t} = f_{W,t} - (\ln S_{£,t} - \ln S_{£,t-1}), \tag{2.5}$$

where $f^{£}_{W,t}$ and $f_{W,t}$ represent the world exchange rate factors constructed by using the U.K. pound and U.S. dollar as the base currency, respectively.

2.3.2 The Exchange Rate Market Model and Currency R-square

In this study, we measure the extent to which bilateral exchange rates between USD and currency j move together with the other bilateral USD exchange rates by the explanatory power of the following time-series regression model

$$f_{j,t} = a_j + b_j f_{W,t} + \varepsilon_{j,t}, \tag{2.6}$$

where

$$f_{j,t} = (\ln S_{j,t} - \ln S_{j,t-1}). \tag{2.7}$$

Throughout this paper, we refer to this regression model as the 'exchange rate market model,' borrowing a terminology from the asset pricing literature, and the explanatory power of this regression model as the 'currency R-square' to differentiate it from regression R-squares obtained from any other regression models.

Table 2.3 presents the estimation results of the regression model Equation (2.6) for each of 33 bilateral USD exchange rates for the entire sample period 1999-2010. The results are reported separately for three alternative choices of weighting schemes—GDP-weighted, trade-weighted, and equally-weighted approaches. In the table, the currency R-square is denoted by CR^2 for clarity. Note first that the estimation results across three alternative choices of weighting schemes are roughly comparable to each other. Indeed, the correlation between currency R-squares obtained from using the GDP-weighted world factor and from using the trade-weighted world factor amounts to 0.989, for example.[9] On the other hand, there exists a wide variation in the estimated beta coefficients and currency R-square values across currencies. Specifically, currencies of European countries and those of Australia and New Zealand have relatively large beta coefficients and large currency R-square values. By contrast,

[9]The correlation between currency R-squares obtained from using the GDP-weighted world factor and from using the equally-weighted world factor amounts to 0.900; and the correlation between currency R-squares obtained from using the trade-weighted world factor and from using the equally-weighted world factor amounts to 0.924.

Table 2.3: Estimation of the Exchange Rate Market Model

This table reports the estimation results from the regression of weekly changes in the log bilateral USD exchange rates on the world exchange rate factor for the sample period 1999-2010 (a total of 625 weekly changes). The bilateral exchange rate between USD and a given currency x is expressed in \$/X. The weekly world exchange rate factor is computed as the GDP-weighted, trade-weighted, or equally-weighted average of weekly changes in the log bilateral USD exchange rates. For the euro, GDP is computed as the sum of 16 eurozone countries' GDPs. α, β, and CR^2 represent the intercept, slope, and R-square, respectively, from the estimated regression results.

	GDP-weighted World Factor			Trade-weighted World Factor			Equally-weighted World Factor		
Currency	α	β	CR^2	α	β	CR^2	α	β	CR^2
Algeria	-0.0004	0.57	13.7	0.0004	0.44	12.5	0.0003	0.45	12.1
Australia	0.0006	1.84	47.8	-0.0007	1.63	58.3	-0.0010	1.77	62.2
Brazil	-0.0007	1.56	14.3	0.0005	1.43	18.4	0.0003	1.74	24.9
Canada	0.0005	1.16	36.0	-0.0006	1.02	42.7	-0.0008	1.09	44.2
Chile	-0.0001	0.71	11.3	0.0000	0.75	18.9	-0.0001	0.84	22.0
Colombia	-0.0004	0.75	10.5	0.0004	0.75	16.4	0.0003	0.88	20.2
Czech Rep.	0.0005	2.21	69.2	-0.0007	1.74	66.9	-0.0009	1.75	60.9
Euro Area	0.0000	1.96	83.4	-0.0002	1.40	66.5	-0.0004	1.41	61.1
Hungary	-0.0002	2.50	67.5	0.0000	2.10	73.7	-0.0003	2.12	68.4
India	-0.0001	0.54	23.5	0.0001	0.49	30.3	0.0000	0.53	31.8
Indonesia	-0.0003	0.67	4.9	0.0002	0.77	9.7	0.0001	0.82	10.0
Israel	0.0001	0.70	19.5	-0.0002	0.63	24.0	-0.0003	0.65	23.6
Japan	0.0004	0.77	14.2	-0.0005	0.24	2.1	-0.0005	0.23	1.6
Kenya	-0.0005	0.38	4.9	0.0004	0.41	8.7	0.0004	0.44	9.0
Korea	-0.0001	1.16	22.0	0.0000	1.11	31.0	-0.0002	1.17	31.5
Mexico	-0.0004	0.75	12.5	0.0004	0.83	23.4	0.0003	0.92	25.9
New Zealand	0.0004	1.88	45.3	-0.0005	1.67	55.5	-0.0008	1.79	57.6
Nigeria	-0.0008	0.04	0.0	0.0008	0.13	0.4	0.0008	0.14	0.4
Norway	0.0002	2.01	68.4	-0.0004	1.56	64.0	-0.0006	1.62	61.9
Pakistan	-0.0009	0.05	0.3	0.0009	0.07	0.6	0.0009	0.08	1.0
Peru	0.0002	0.26	6.3	-0.0002	0.29	11.9	-0.0002	0.33	13.9
Philippines	-0.0003	0.46	9.9	0.0002	0.49	17.6	0.0002	0.51	17.1
Poland	0.0000	2.21	57.5	-0.0002	1.95	69.5	-0.0005	2.02	67.4
Romania	-0.0019	1.52	33.9	0.0017	1.31	39.2	0.0015	1.36	38.3
Russia	-0.0005	0.77	21.4	0.0004	0.67	24.9	0.0003	0.71	24.8
Singapore	0.0003	0.73	55.7	-0.0004	0.61	60.8	-0.0005	0.60	54.2
South Africa	-0.0004	1.78	26.0	0.0003	1.70	36.6	0.0000	1.83	38.5
Sweden	0.0000	2.01	68.8	-0.0002	1.60	67.6	-0.0004	1.65	64.6
Switzerland	0.0004	1.70	64.5	-0.0006	1.14	45.3	-0.0007	1.13	39.8
Thailand	0.0003	0.48	14.0	-0.0003	0.44	18.1	-0.0004	0.43	15.7
Turkey	-0.0027	1.40	13.8	0.0025	1.45	22.9	0.0023	1.67	27.4
U.K.	-0.0003	1.48	55.0	0.0001	1.13	49.6	0.0000	1.15	46.8
Uruguay	-0.0010	-0.05	0.0	0.0010	1.28	17.5	0.0010	0.15	0.4
MEAN	-0.0002	1.12	30.2	0.0001	1.01	33.5	0.0000	1.03	32.7

currencies of African, Asian (except for Singapore), and South American countries have relatively small beta coefficients and small currency R-square values. If we focus on the results obtained using the GDP-weighted world exchange rate factor, of 33 currencies, currencies of seven European countries and Singapore have currency R-square values larger than 0.50. Also, currencies of Australia and New Zealand have relatively large currency R-square values of 0.48 and 0.45, respectively. For the remaining currencies, the currency R-square value is less than 0.30, except for currencies of two countries Canada (currency R-square=0.36) and Romania (currency R-square=0.34).

To examine whether the degree of co-movement among the bilateral USD exchange rates has changed over time, we next estimate the exchange rate market model, Equation (2.6), separately for two equally-divided six-year sub-periods: 1999-2004 and 2005-2006. Table 2.4 presents the estimation results by currency. The last column of the table reports the difference in the currency R-square values between two sub-periods, ΔCR^2. Again, we denote the currency R-square by CR^2 in the table for clarity. The results show that the currency R-square value has decreased only for 7 currencies and increased for the remaining 26 currencies. Of the 7 currencies whose currency R-square values have decreased, the Japanese yen appears to be the only currency with a substantial decrease. On the other hand, of the 26 currencies whose currency R-square values have increased, 8 currencies exhibit an increase of the currency R-square value by more than 0.3, 7 currencies by more than 0.2, and 9 currencies by more than 0.1. For currencies of most European countries, the currency R-square value in the earlier sub-period 1999-2004 was already fairly large. Even with this, however, the increase of the currency R-square values between two sub-periods is also very large for several currencies. For example, the currency R-square value has increased by 0.146 for Czech Republic, by 0.145 for the euro area, by 0.212 for Hungary, and by 0.118 for Switzerland.

Table 2.4: Estimation of the Exchange Rate Market Model: Sub-period Results

This table reports the regression statistics presented in Table 3 separately for two six-year subperiods: 1999-2004 and 2005-2010. Here, the world exchange rate factor is computed as the GDP-weighted average of the weekly changes in the log bilateral USD exchange rates. In the last two columns, $\Delta\beta$ (ΔCR^2) represents the difference of β (CR^2) between later and earlier sub-periods.

	1999-2004			2005-2010				
Currency	α	β	CR^2	α	β	CR^2	$\Delta\beta$	ΔCR^2
Algeria	-0.0007	0.85	15.7	-0.0001	0.43	14.7	-0.42	-1.1
Australia	0.0005	1.39	28.2	0.0007	2.07	59.4	0.69	31.2
Brazil	-0.0027	1.23	4.7	0.0014	1.73	32.0	0.50	27.3
Canada	0.0006	0.67	16.8	0.0005	1.41	46.3	0.74	29.5
Chile	-0.0006	0.31	2.1	0.0005	0.92	19.0	0.61	17.0
Colombia	-0.0015	0.15	0.5	0.0006	1.05	19.1	0.90	18.6
Czech Rep.	0.0006	2.20	60.2	0.0003	2.21	74.9	0.01	14.6
Euro Area	0.0002	2.24	76.8	-0.0002	1.81	91.2	-0.43	14.5
Hungary	0.0003	2.19	53.7	-0.0007	2.65	74.9	0.46	21.2
India	-0.0001	0.14	4.4	-0.0001	0.74	33.5	0.60	29.2
Indonesia	-0.0006	0.73	2.5	0.0001	0.64	14.1	-0.08	11.7
Israel	-0.0002	0.20	2.0	0.0006	0.95	33.0	0.75	30.9
Japan	0.0001	1.46	36.1	0.0007	0.42	5.3	-1.04	-30.8
Kenya	-0.0007	0.22	1.6	-0.0002	0.46	7.4	0.24	5.8
Korea	0.0003	0.62	12.0	-0.0004	1.43	27.1	0.81	15.1
Mexico	-0.0005	0.14	0.5	-0.0004	1.06	25.0	0.92	24.5
New Zealand	0.0007	1.54	29.8	0.0001	2.05	54.4	0.52	24.6
Nigeria	-0.0012	0.11	0.1	-0.0005	0.01	0.0	-0.11	-0.1
Norway	0.0004	1.92	61.1	-0.0001	2.05	72.3	0.13	11.2
Pakistan	-0.0006	0.10	0.6	-0.0012	0.03	0.2	-0.06	-0.4
Peru	-0.0001	0.05	0.3	0.0005	0.37	10.7	0.32	10.4
Philippines	-0.0013	0.17	0.8	0.0008	0.61	27.0	0.44	26.2
Poland	0.0003	1.38	27.7	-0.0002	2.63	74.4	1.25	46.7
Romania	-0.0031	0.65	5.2	-0.0005	1.96	62.9	1.31	57.7
Russia	-0.0006	0.07	0.2	-0.0004	1.13	47.0	1.07	46.8
Singapore	0.0000	0.64	37.0	0.0007	0.77	68.9	0.13	32.0
South Africa	-0.0002	1.19	9.5	-0.0006	2.08	39.9	0.89	30.4
Sweden	0.0003	2.02	61.5	-0.0003	2.01	73.3	-0.02	11.8
Switzerland	0.0004	2.13	69.4	0.0005	1.48	63.9	-0.65	-5.6
Thailand	-0.0003	0.56	15.3	0.0008	0.44	13.6	-0.12	-1.7
Turkey	-0.0048	0.94	3.3	-0.0006	1.63	36.1	0.69	32.9
U.K.	0.0003	1.35	49.4	-0.0008	1.55	58.0	0.19	8.6
Uruguay	-0.0028	-0.15	0.2	0.0009	0.01	0.0	0.15	-0.1
MEAN	-0.0005	0.89	20.9	0.0001	1.24	38.8	0.34	17.9

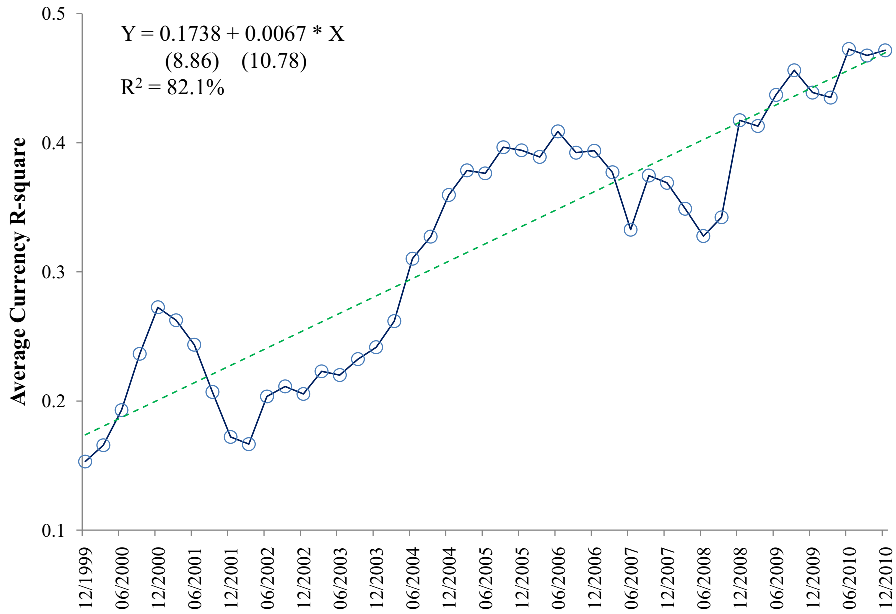

Figure 2.1: Time-trend of the Average Currency R-square

This figure shows the time-trend of the average of the currency R-square values across 33 currencies. A three-month moving window approach is employed. For each quarter end and a given currency, past one-year weekly observations are used in computing the currency R-square. The estimated linear time-trend equation with t-statistics in parentheses are overlaid. The t-statistics are computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 4 (Newey and West, 1987).

We next estimate the exchange rate market model using a three-month moving one-year-window approach to examine the time-varying degree of co-movement between bilateral USD exchange rates more closely. The first currency R-square values of individual currencies are computed using the one-year weekly observations between 01/01/1999 and 12/31/1999. The second currency R-square values are computed using the one-year weekly observations between 04/01/1999 and 03/31/2000. Proceeding this way, the last currency R-square values are computed using the one-year weekly observations between 01/01/2010 and 12/31/2010. We then compute the cross-currency average of the currency R-square values at each quarter end. Figure 2.1 shows the time-trend of the cross-currency average of the currency R-square values across 33 currencies. The fitted linear time-trend regression model is inserted within the figure. The t-statistics in parentheses are computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 4. The figure strongly indicates that the degree of co-movement between bilateral USD exchange rates has steadily increased over the past 12-year period since the euro was adopted. According to the estimated slope coefficient, the cross-currency average of the currency R-square values has increased about 0.027 (=0.0067*4) per year, i.e., about 0.32 during the past 12-year period. Indeed, the cross-currency average of the currency R-square values was 0.15 for year 1999 and it increased to 0.47 for year 2010. Hence, over the 12-year period since the introduction of the euro, the degree of co-movement between bilateral USD exchange rates has increased substantially by more than 200%.

Figure 2.2 shows the effect of the increased co-movement between bilateral USD exchange rates on the diversification benefits from a USD-based investor's viewpoint. The figure plots the relation between the number of currencies in a currency portfolio and the risk of the portfolio for the period 1999-2004 and for the period 2005-2010 separately. Similarly as in Solnik (1974), for a given N ($2 \leq N \leq 31$), we choose N bilateral USD exchange rates (expressed in US dollars per foreign currency unit) randomly out of our 33 sample exchange rates. Then, we compute the variance of a currency portfolio constructed by equally-weighting the N sampled weekly log exchange-rate changes. We repeat this procedure 300 times and compute the average of the 300 variances computed in this manner and denote it by $Var(P_N)$. For $N = 1$, $Var(P_1)$ is computed as the average of the 33 individual variances of weekly log exchange-rate changes. For $N = 33$, $Var(P_{33})$ is computed as the variance of the equally-weighted portfolio of all 33 weekly exchange-rate changes. For $N = 32$, the number of different combinations of choosing 32 out of 33 is only 33, so we compute $Var(P_{32})$ as the average of all possible 33 equally-weighted portfolio variances, where

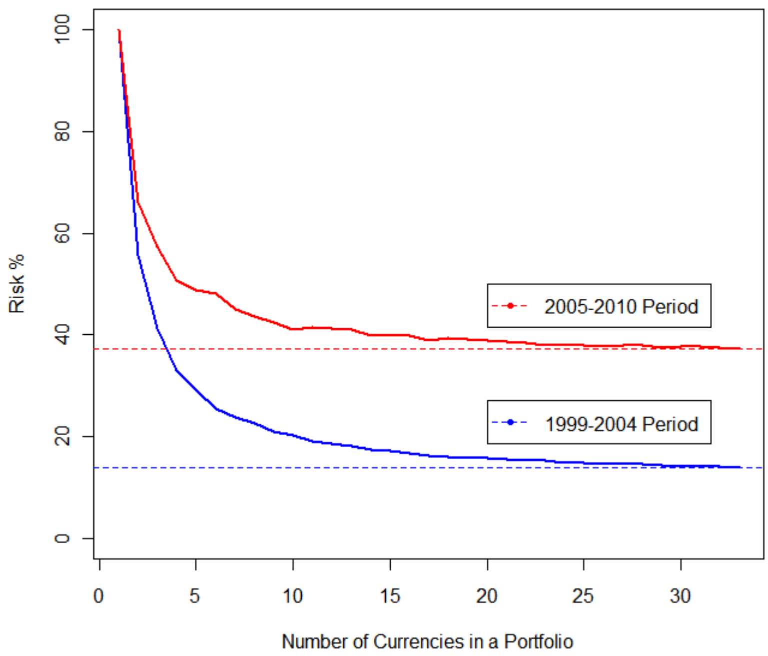

Figure 2.2: The Effect of Diversification on Risk Reduction: 1999-2004 vs. 2005-2010

This figure plots the relation between the number of currencies in a currency portfolio and the risk of the portfolio for the period 1999-2004 and for the period 2005-2010 separately. For a given N ($2 \leq N \leq 31$), we choose N bilateral USD exchange rates (expressed in US dollars per foreign currency unit) randomly out of 33 exchange rates. Then, we compute the variance of a currency portfolio constructed by equally-weighting the N sampled weekly log exchange-rate changes. We repeat this procedure 300 times and compute the average of the 300 variances computed in this manner and denote it by $Var(P_N)$. For $N = 1$, $Var(P_1)$ is computed as the average of the 33 individual variances of weekly log exchange-rate changes. For $N = 33$, $Var(P_{33})$ is computed as the variance of the equally-weighted portfolio of all 33 weekly exchange-rate changes. For $N = 32$, the number of different combinations of choosing 32 out of 33 is only 33, so we compute $Var(P_{32})$ as the average of all possible 33 equally-weighted portfolio variances, where each portfolio contains only 32 exchange-rate changes. The y axis labeled as "Risk %" represents

$$\text{Risk \%} = \frac{Var(P_N)}{Var(P_1)} \times 100.$$

The two dotted horizontal lines represent y=13.9% for the 1999-2004 period and y=37.3% for the 2005-2010 period.

each portfolio contains only 32 exchange-rate changes. The y axis labeled as "Risk

%" represents

$$\text{Risk \%} = \frac{Var(P_N)}{Var(P_1)} \times 100.$$

The two dotted horizontal lines represent y=13.9% for the 1999-2004 period and y=37.3% for the 2005-2010 period. The figure shows that an American investor in foreign exchange markets can enjoy most of the diversification benefits by holding about 15 to 20 different currencies. Importantly, the figure also shows that the systematic risk of a well-diversified currency portfolio is substantially higher for the 2005-2010 period than that for the 1999-2004 period. The ratio of the return variance of a well-diversified currency portfolio relative to that of a portfolio containing only one currency increased from 13.9% for the earlier sub-period to 37.3% for the later sub-period by about 200%.

2.4 What Can Explain the Currency R-square and Its Change Over Time?

2.4.1 A Close Look at the World Exchange Rate Factor

In the previous section, we have seen that there exists a wide variation in the measured currency R-square values across the sample currencies (Table 2.3). We have also seen that the degree of co-movement between bilateral USD exchange rates has steadily increased over time since the euro was adopted (Table 2.4 and Figures 2.1 and 2.2). The next question arising naturally is, then, what drives these findings. To address this question, we need to better understand the exchange rate market model, Equation (2.6). Suppose that there are essentially only two currencies in the world, the U.S. dollar and euro, and that the currency of any third country is pegged to either the dollar or the euro. Then, the world exchange rate factor

$$f_{W,t} = \sum_{j=1}^{N(t)} w_{j,t}(\ln S_{j,t} - \ln S_{j,t-1}) + w_{\$,t}(\ln S_{\$,t} - \ln S_{\$,t-1})$$

reduces to a constant multiple of the dollar-euro exchange rate change. Recall that $S_{j,t}$ represents the spot exchange rate between USD and currency j expressed in

$/J. Therefore, for the currency pegged to the euro, the currency R-square is simply one, and for currency pegged to the dollar, the currency R-square is simply zero. Under this situation, then, the only way that we can observe an increase of the cross-currency average of the currency R-square values over time is that more countries should change its exchange rate regime from the pegged-to-the-dollar regime to the pegged-to-the-euro regime than countries do the other way around.

Extending this extreme case one step further, suppose next that there are essentially three currencies in the world, the U.S. dollar, euro, and U.K. pound, and that the currency of any third country is pegged to one of these three currencies. This time, then, the world exchange rate factor reduces to a weighted sum of the dollar-euro and dollar-pound exchange rate changes. Still, for the currency pegged to the dollar, the currency R-square is simply zero. However, for the currency pegged to the euro, the currency R-square will take some value A between 0 and 1, and for currency pegged to the pound, it will take another value B between 0 and 1. Under this situation, there are several ways in which we can observe an increase of the cross-currency average of the currency R-square values over time. Clearly, however, if some countries change its exchange rate regime from the pegged-to-the-dollar regime to either the pegged-to-the-euro or pegged-to-the-pound regime, then we will observe an increase of the cross-currency average of the currency R-square values with assuming that currencies pegged to either the euro or pound at first remain the same.[10]

In general, the discussion here suggests that if the influence of other major currencies over a third currency increases over time than that of the U.S. dollar over the currency does, then we will observe an increase of the cross-currency average of the currency R-square values over time as seen in Figure 2.1.

[10]To explain there exists a more complicated way, suppose $A > B$ and $(A - B) > B$. Under this situation, if one country changes its exchange rate regime from the pegged-to-the-pound to the pegged-to-the-euro, then we will also observe an increase of the cross-currency average of the currency R-square values over time, even if one other country changes its exchange rate regime from the pegged-to-the-pound to the pegged-to-the-dollar.

2.4.2 Currency Clusters

According to the preceding discussion, it would be helpful to investigate the following questions: how many currencies play dominant roles in the foreign exchange rate markets?; and which countries belong to which currency cluster? These questions are also worthwhile to investigate by themselves (Mundell, 2000). In this subsection, we use the cluster analysis to explore this issue empirically.

Simply speaking, given a collection of items, the cluster analysis is a statistical method of finding a good cluster solution in which each cluster is very different from other clusters (between-cluster heterogeneity) and items within each cluster are as similar as possible (within-cluster homogeneity). To apply the cluster analysis in our situation, we first need to define a measure of the similarity or dissimilarity between two currencies. For this, here we treat currency j as identical with the 625-dimensional vector $f_j = (f_{j,1}, f_{j,2}, ..., f_{j,625})$, where $f_{j,t} = (\ln S_{j,t} - \ln S_{j,t-1})$, and measure the dissimilarity between two currencies j and j* as the Euclidean distance between two vectors f_j and f_{j*}. Note that $f_{\$}$ represents the origin of the 625-dimensional Euclidean space. Note also that the Euclidean distance between two vectors f_j and f_{j*} does not depend on the choice of a base currency (refer to Appendix 2.7.1 for explanation). Accordingly, the results of the clustering analysis presented here remain the same whichever currency we use as the base currency when expressing bilateral exchange rates.

There are many alternative ways of doing the cluster analysis, but we choose to use the Ward's method (Ward, 1963), the most widely used clustering method. Basically, the Ward's method regards the cluster analysis as an analysis of variance problem. The homogeneity or similarity of each cluster is measured by the within-cluster sum of the squared deviations of individual items in the cluster from the cluster center, which is known as the *error sum of squares* (ESS). To explain the Ward's method, suppose we have N items in the beginning and x_j, $j = 1, 2, ..., N$, represents the multivariate measurement associated with the jth item. If there are currently K clusters, define ESS as

$$ESS = ESS_1 + ESS_2 + \cdots + ESS_K, \tag{2.8}$$

where ESS_k, $k = 1, 2, ..., K$, is the sum of the squared deviations of individual items in cluster k from the cluster mean. At each step of the analysis, the union of every possible pair of clusters obtained from the previous step is considered, and the two clusters whose combination results in the smallest increase in ESS are merged into one. Initially, each cluster consists of a single item. Hence, $ESS_k = 0$ for all $k = 1, 2, ..., N$, and thus we have $ESS = ESS_1 + ESS_2 + \cdots + ESS_N = 0$. At the end of the cluster analysis, all N items will be combined into one single cluster of N items, and the value of ESS is equal to the *total sum of squares* (TSS) defined by

$$TSS = \sum_{j=1}^{N} (x_k - \bar{x})'(x_k - \bar{x}), \tag{2.9}$$

where $\bar{x} = \frac{1}{N}\sum_{j=1}^{N} x_j$.

To measure the goodness of fit of the current cluster solution at each step of the analysis, we define the following quantity

$$R^2 = \frac{TSS - ESS}{TSS} = \frac{TSS - (ESS_1 + ESS_2 + ... + ESS_K)}{TSS}. \tag{2.10}$$

Here, we assumed that the current cluster solution consists of K clusters. This R^2 value can be interpreted as the proportion of variation explained by the current cluster solution, which is similar to the R^2 value in the regression analysis. The difference of the R^2 values between two successive steps is equal to $\Delta ESS/TSS$, and referred to as the *semi-partial R-square*. The semi-partial R-square value measures the loss of homogeneity due to merging two clusters to form a new cluster at each step of the cluster analysis. If the value obtained is small, then it suggests that the cluster solution obtained at the current step is formed by merging two very homogeneous clusters from the previous step. On the other hand, if the value obtained is large, then it suggests that the cluster solution obtained at the current step is formed by merging two relatively heterogeneous clusters from the previous step. Appendix 2.7.2 contains a simple numerical example explaining the Ward's clustering procedure.

Figure 2.3 displays the results of the cluster analysis graphically. Such a tree diagram is called the dendrogram. It clearly shows the currency groupings and the distance levels at which they occur. The x-axis represents the semi-partial R-square that measures the loss of homogeneity due to merging two clusters to form a new cluster at each step of the cluster analysis. From the dendrogram, we can see that there are two large currency groups, one containing the U.S. dollar and the other containing the euro. Note also that the currencies of three countries, Brazil, Turkey, and South Africa, are separated from these two large currency groups and that they can be grouped into one group or two groups.

Next, Figure 2.4 presents the plot of the semi-partial R-square against the number of clusters. It shows that there is a large loss of within-cluster homogeneity when we try to merge the last three or four clusters.

Lastly, Table 2.5 presents the distances of a currency from the cluster center, the U.S. dollar, and the euro. In the table, we assumed the three-cluster solution from the cluster analysis, which seems acceptable as evidenced by Figures 2.3 and 2.4. The results show that the euro is located closest to the center of the cluster it belongs to and that, except for the Singapore dollar, the U.S. dollar is also located closest to the center of the cluster it belongs to.

To summarize, our cluster analysis in this section suggests that there are essentially two large currency clusters–one cluster centered around the U.S. dollar and the other cluster centered around the euro–and that the U.S. dollar plays a 'central' role within one cluster group and the euro within the other cluster group.

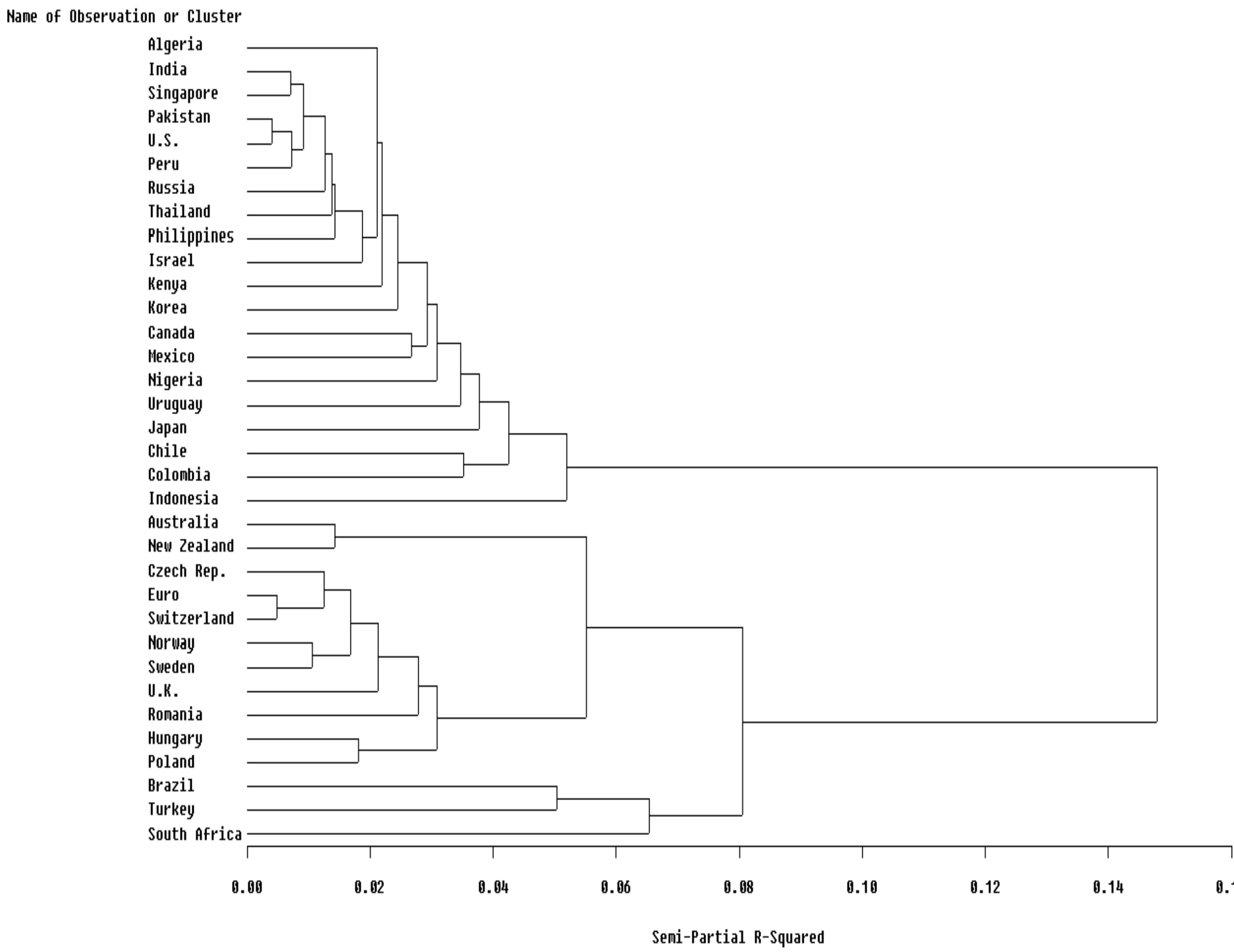

Figure 2.3: Currency Dendrogram

This figure shows the clustering patterns among 34 currencies. In performing cluster analysis, a currency x is treated as identical with the 625-dimensional vector of the weekly changes in the log bilateral USD exchange rates during the sample period, denoted by $f_x = (f_{x,1}, ..., f_{x,625})$, where $f_{x,t} = (\ln S_{x,t} - \ln S_{x,t-1})$ with S the spot exchange rate between USD and currency x expressed in $\$/X$. We employed the Ward's hierarchical clustering procedure (Ward, 1963), which is detailed in Section 4.2. The clustering patterns presented in this figure are independent of the choice of a base currency (here USD).

2.4.3 Currency Beta

The cluster analysis in the previous subsection, though informal, suggests that the U.S. dollar and euro play a central role in the foreign exchange markets. The discussion in Subsection 4.1 then further suggests that the extent to which a currency

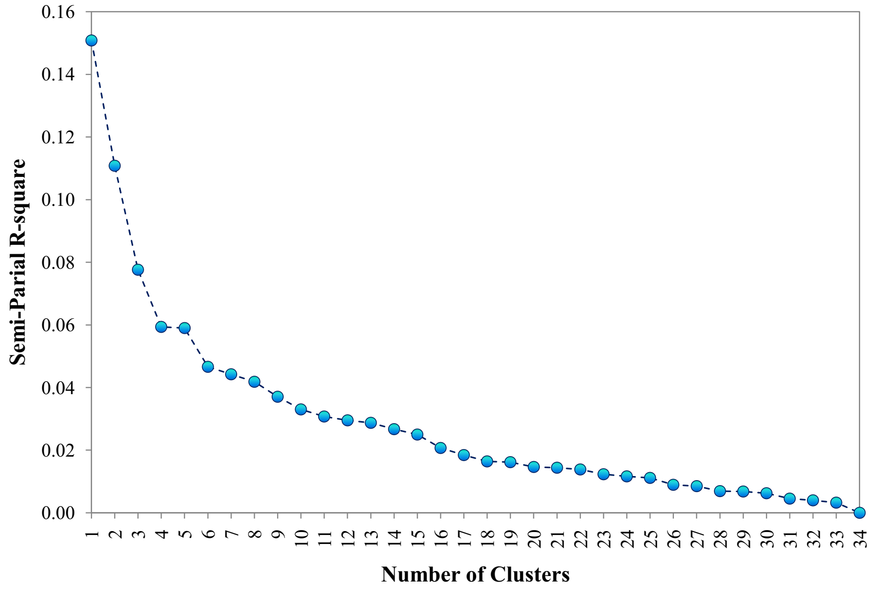

Figure 2.4: Plot of the Number of Clusters vs. the Semi-partial R-square

This figure shows the relation between the number of clusters and the semi-partial R-square. For example, the figure tells us that when the number of clusters changes from two to one, the loss of within-cluster homogeneity amounts to a semi-partial R-square of about 0.15.

tracks the euro or the dollar would play an important role in explaining the level of the currency R-square and its change over time.

To formally measure the extent to which a certain currency tracks either the U.S. dollar or euro, we use the concept of the 'currency beta' proposed by Eun and Lai (2003). Following Eun and Lai, we define the euro beta, $\beta_{€}$, and dollar beta, $\beta_{\$}$, of a currency x using the estimated slope coefficients from the following regressions

$$\Delta \ln S_{X/\$} = \alpha_1 + \beta_{€} \Delta \ln S_{€/\$} + \varepsilon_1 \tag{2.11}$$

$$\Delta \ln S_{€/X} = \alpha_2 + \beta_{\$} \Delta \ln S_{€/\$} + \varepsilon_2, \tag{2.12}$$

where S denotes the spot exchange rate and Δ the first difference operator. The euro beta $\beta_{€}$ (dollar beta $\beta_{\$}$) measures the sensitivity of the movements of the x-dollar

Table 2.5: Currency Clusters

This table reports the distances of each individual currency from the cluster center, US dollar, and euro with assuming that there exist three cluster groups. In performing cluster analysis, a currency x is treated as identical with the 625-dimensional vector $f_x = (f_{x,1}, ..., f_{x,625})$, where $f_{x,t} = (\ln S_{x,t} - \ln S_{x,t-1})$ with S the spot exchange rate between currency x and USD expressed in $\$/X$. We employed the Ward's hierarchical clustering procedure (Ward, 1963). The cluster center is computed as the average of f_x across all currencies belonging to each cluster, and the distance represents the Euclidean distance. The results presented are independent of the choice of a base currency (here USD). For ease of interpretation, within each cluster, currencies are sorted in ascending order based on their distances from the cluster center.

Cluster	Currency	Distance from Cluster Center	Distance from USD	Distance from Euro
Cluster 1	Singapore	0.120	0.167	0.297
	U.S.	0.128	0.000	0.366
	India	0.150	0.189	0.347
	Peru	0.167	0.177	0.382
	Pakistan	0.190	0.160	0.394
	Thailand	0.193	0.217	0.368
	Philippines	0.214	0.250	0.397
	Israel	0.239	0.272	0.367
	Russia	0.252	0.286	0.370
	Algeria	0.259	0.263	0.347
	Canada	0.272	0.332	0.363
	Kenya	0.273	0.292	0.422
	Mexico	0.311	0.363	0.462
	Chile	0.316	0.364	0.452
	Colombia	0.341	0.395	0.477
	Japan	0.350	0.347	0.446
	Korea	0.355	0.422	0.468
	Nigeria	0.387	0.386	0.534
	Uruguay	0.420	0.427	0.570
	Indonesia	0.470	0.519	0.606
Cluster 2	Euro	0.155	0.366	0.000
	Sweden	0.193	0.415	0.230
	Norway	0.207	0.416	0.239
	Czech Rep.	0.225	0.454	0.240
	Switzerland	0.237	0.362	0.177
	U.K.	0.241	0.341	0.283
	Hungary	0.262	0.520	0.310
	Poland	0.282	0.499	0.363
	Australia	0.294	0.455	0.390
	New Zealand	0.312	0.478	0.402
	Romania	0.340	0.448	0.400
Cluster 3	Turkey	0.417	0.647	0.661
	South Africa	0.422	0.597	0.566
	Brazil	0.470	0.706	0.729

(euro-x) exchange rate to the movements of the euro-dollar exchange rate. As long as the triangular parity holds among the dollar, euro, and currency x, we have the following relationships:

$$\alpha_1 + \alpha_2 = 0, \quad \beta_{€} + \beta_{\$} = 1, \quad \text{and} \quad \varepsilon_1 + \varepsilon_2 = 0. \tag{2.13}$$

That is, the euro and dollar betas sum to unity. At extreme, if a currency x is pegged to the U.S. dollar, we have $\beta_{€} = 0$ and $\beta_{\$} = 1$, whereas if a currency x is pegged to the euro, we have $\beta_{€} = 1$ and $\beta_{\$} = 0$. In general, the more closely a currency tracks the dollar, the closer $\beta_{\$}$ is to unity, whereas the more closely a currency tracks the euro, the closer $\beta_{€}$ is to unity.

Table 2.6 presents the euro and dollar betas of the 34 sampled currencies, estimated using data for the entire sample period 1999-2010. For the computation of the euro betas, bilateral exchange rates against the U.S. dollar are used, and for the computation of the dollar betas, bilateral exchange rates against the euro are used. Hence, empirically $\beta_{€} + \beta_{\$}$ don't have to be exactly equal to one because the triangular parity among the dollar, euro, and currency x does not hold strictly in the real world. The t-statistics are computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 4 (Newey and West, 1987). The reported t-statistics for the estimated euro and dollar beta coefficients are strongly significant for all cases except only four: euro betas for Nigeria and Pakistan and dollar betas for Norway and Sweden. The estimated euro beta $\beta_{€}$ is larger than 0.5 for 11 currencies, excluding the euro itself, and the estimated dollar beta $\beta_{\$}$ is larger than 0.5 for 21 currencies, excluding the U.S. dollar itself. Not surprisingly, the euro exerts a dominant influence over the currencies of several European countries such as Czech Republic ($\beta_{€}$=1.01), Hungary ($\beta_{€}$=1.10), Norway ($\beta_{€}$=0.88), Poland ($\beta_{€}$=0.91), Sweden ($\beta_{€}$=0.94), and Switzerland ($\beta_{€}$=0.87). The euro also exhibits a significant influence over the currencies of such non-European countries as Australia ($\beta_{€}$=0.69), New Zealand ($\beta_{€}$=0.72), and

Table 2.6: The Euro Beta and Dollar Beta

This table reports the euro and dollar betas estimated for the period 1999-2010. The euro and dollar betas of a currency x are estimated from the following regressions:

$$\Delta \ln(X/\$) = \alpha_1 + \beta_{€}\Delta \ln(€/\$) + \epsilon_1; \quad \Delta \ln(€/X) = \alpha_2 + \beta_{\$}\Delta \ln(€/\$) + \epsilon_2.$$

For the euro betas, weekly changes in bilateral exchange rates against USD are used; and for the dollar betas, weekly changes in bilateral exchange rates against the euro are used. The t-statistics are computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 4.

Currency	$\beta_{€}$	t(β)	R^2	$\beta_{\$}$	t(β)	R^2	$\beta_{€} + \beta_{\$}$
Algeria	0.28	8.32	15.3	0.74	34.74	35.0	1.02
Australia	0.69	12.49	31.7	0.26	6.98	4.9	0.95
Brazil	0.40	4.74	4.9	0.70	16.65	13.9	1.10
Canada	0.38	7.85	17.3	0.59	21.45	32.8	0.97
Chile	0.22	4.72	5.1	0.78	29.26	38.5	1.00
Colombia	0.24	4.02	5.1	0.79	31.73	35.3	1.04
Czech Rep.	1.01	23.85	66.9	-0.03	-2.08	0.3	0.98
Euro Area	1.00	n.a.	100.0	0.00	0.00	0.0	1.00
Hungary	1.10	20.66	60.1	-0.11	-4.94	1.6	0.99
India	0.18	6.63	12.0	0.87	69.87	76.3	1.05
Indonesia	0.12	2.13	0.7	0.92	32.30	32.4	1.04
Israel	0.28	5.91	14.5	0.81	42.49	55.1	1.09
Japan	0.21	3.35	4.1	0.72	21.72	33.7	0.93
Kenya	0.12	3.33	2.2	0.92	59.39	58.0	1.04
Korea	0.32	4.98	7.7	0.80	27.61	34.3	1.12
Mexico	0.18	2.90	3.4	0.87	30.42	44.3	1.05
New Zealand	0.72	14.23	31.9	0.26	7.56	4.6	0.98
Nigeria	-0.01	-0.16	0.0	1.01	48.76	50.5	1.00
Norway	0.88	20.12	60.8	0.03	1.39	0.1	0.91
Pakistan	0.01	0.63	0.1	0.99	97.96	80.0	1.01
Peru	0.07	2.59	2.0	0.97	90.51	82.1	1.03
Philippines	0.13	3.67	3.5	0.91	59.18	63.8	1.04
Poland	0.91	11.74	44.5	0.11	3.18	1.2	1.02
Romania	0.61	9.68	25.4	0.31	8.92	8.8	0.92
Russia	0.29	7.10	14.0	0.72	34.07	48.4	1.01
Singapore	0.26	12.99	33.7	0.75	63.67	76.8	1.01
South Africa	0.61	6.21	14.0	0.36	9.20	5.2	0.97
Sweden	0.94	23.35	63.6	-0.01	-0.28	0.0	0.94
Switzerland	0.87	26.57	67.8	0.06	3.38	1.3	0.93
Thailand	0.17	8.02	8.2	0.88	72.65	66.3	1.05
Turkey	0.41	4.16	5.6	0.55	13.23	7.5	0.97
U.K.	0.57	14.66	38.4	0.37	19.07	22.3	0.95
U.S.	0.00	0.00	0.0	1.00	n.a.	100.0	1.00
Uruguay	-0.02	-0.56	0.0	1.03	41.49	44.4	1.01
MEAN	0.42	8.51	22.5	0.59	30.05	34.1	1.01

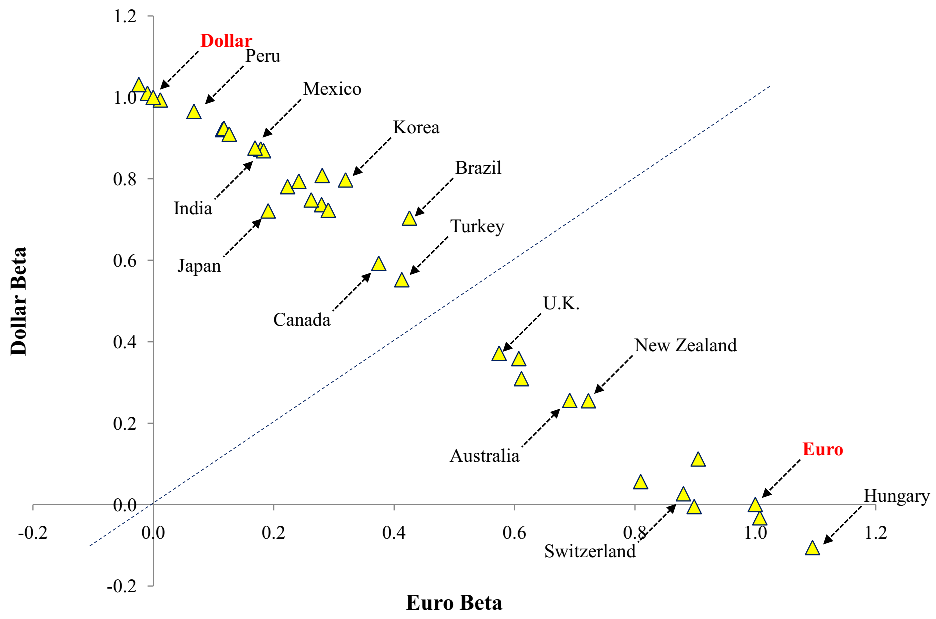

Figure 2.5: The Euro Beta vs. the Dollar Beta

This figure shows the relation between the euro and dollar betas. The inserted dotted line is the straight 45-degree line.

South Africa ($\beta_{€}$=0.61). On the other hand, the U.S. dollar exerts a dominant influence over the currencies of most American, Asian, and African countries.

Figure 2.5 displays the results of Table 2.6 graphically. It shows clearly that the euro beta is larger than 0.5 for 11 currencies, excluding the euro, and smaller than 0.5 for 21 currencies, excluding the U.S. dollar.

Next, to examine whether the influence of the euro relative to USD over a third currency has changed over time, we also estimated the euro beta separately for two equally-divided six-year sub-periods: 1999–2004 and 2005–2010. Table 2.7 presents the estimation results by currency. The column labeled as $\Delta\beta_{€}$ reports the change in the euro beta estimates between two sub-periods. The euro beta estimate increased for 29 currencies and decreased only for 4 currencies. Of the 4 currencies whose

Table 2.7: The Euro Beta: Sub-period Results

This table reports the euro beta estimates separately for two six-year sub-periods: 1999-2004 and 2005-2010. The euro beta of a currency x is estimated from the following regression

$$\Delta \ln(X/\$) = \alpha + \beta_{€} \Delta \ln(€/\$) + \epsilon$$

For the computation of the euro betas, weekly changes in bilateral exchange rates against USD are used. The t-statistics are computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 4. $\Delta\beta_{€}$ (ΔR^2) represents the difference of $\beta_{€}$ (R^2) between later and earlier sub-periods.

	1999-2004			2005-2010				
Currency	$\beta_{€}$	$t(\beta)$	R^2	$\beta_{€}$	$t(\beta)$	R^2	$\Delta\beta_{€}$	ΔR^2
Algeria	0.37	7.98	19.1	0.20	5.78	12.4	-0.17	-6.7
Australia	0.44	6.55	17.4	0.91	12.13	44.6	0.47	27.3
Brazil	0.20	1.95	0.8	0.62	4.57	15.5	0.42	14.7
Canada	0.16	4.38	5.9	0.56	7.94	27.4	0.40	21.4
Chile	0.07	1.41	0.7	0.36	5.84	10.7	0.29	10.1
Colombia	0.00	-0.02	0.0	0.45	5.97	13.2	0.45	13.2
Czech Rep.	0.93	27.48	67.6	1.08	14.59	67.1	0.15	-0.5
Euro Area	1.00	n.a.	100.0	1.00	n.a.	100.0	0.00	0.0
Hungary	0.88	22.20	54.8	1.28	13.73	65.6	0.40	10.8
India	0.03	1.83	1.6	0.30	9.44	21.2	0.27	19.6
Indonesia	-0.02	-0.15	0.0	0.23	4.90	6.6	0.24	6.6
Israel	0.07	2.38	1.6	0.46	8.48	28.8	0.39	27.2
Japan	0.17	2.36	3.0	0.21	2.50	5.3	0.05	2.3
Kenya	0.05	1.33	0.5	0.17	3.27	4.1	0.12	3.5
Korea	0.06	1.14	0.7	0.54	6.22	14.6	0.48	13.9
Mexico	-0.07	-1.56	0.8	0.40	4.36	12.9	0.48	12.1
New Zealand	0.50	7.14	19.9	0.91	16.69	42.5	0.41	22.6
Nigeria	0.00	0.05	0.0	-0.02	-0.27	0.1	-0.02	0.1
Norway	0.79	24.82	64.5	0.96	12.01	59.7	0.18	-4.8
Pakistan	0.02	0.81	0.1	0.01	0.21	0.0	-0.01	-0.1
Peru	0.00	-0.19	0.0	0.13	3.33	5.0	0.13	5.0
Philippines	0.00	-0.09	0.0	0.24	7.75	15.9	0.25	15.9
Poland	0.55	10.97	27.8	1.21	8.70	58.7	0.65	30.9
Romania	0.21	3.40	3.6	0.95	14.42	55.9	0.74	52.3
Russia	0.04	1.42	0.3	0.51	7.46	35.6	0.47	35.3
Singapore	0.17	6.62	15.5	0.35	18.72	52.7	0.18	37.1
South Africa	0.31	3.64	4.0	0.86	5.17	26.0	0.56	22.0
Sweden	0.82	23.96	64.3	0.96	13.68	63.7	0.14	-0.7
Switzerland	0.89	28.29	75.7	0.75	15.25	61.1	-0.14	-14.7
Thailand	0.13	3.66	5.5	0.20	8.63	11.0	0.07	5.6
Turkey	0.15	1.25	0.5	0.64	4.20	21.0	0.49	20.4
U.K.	0.47	14.75	37.5	0.66	9.81	40.3	0.20	2.8
U.S.	0.00	n.a.	0.0	0.00	n.a..	0.0	0.00	0.0
Uruguay	-0.04	-0.59	0.1	-0.01	-0.12	0.0	0.03	-0.1
MEAN	0.27	6.54	17.47	0.53	7.98	29.39	0.26	11.92

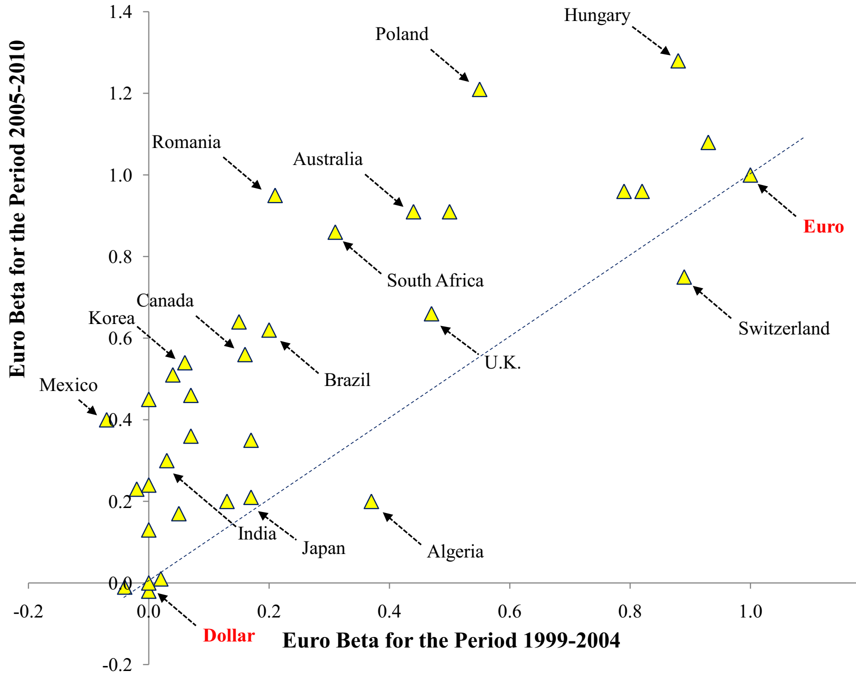

Figure 2.6: The Euro Beta: 1999-2004 vs. 2005-2010

This figure shows the relation between the euro beta for the period 1999-2004 and the euro beta for the 2005-2010. The inserted dotted line is the straight 45-degree line.

euro beta estimates decreased, the Algerian dinar and Swiss franc appear to be only currencies with a substantial decrease. On average, the euro beta estimate increased by as much as 0.26 from 0.27 in the earlier sub-period to 0.53 in the later sub-period. Of the 29 currencies whose euro beta estimates increased, 2 currencies exhibit an increase of more than 0.6 (Polish zloty and Romanian leu), 12 currencies an increase of between 0.3 and 0.6, 11 currencies an increase of between 0.1 and 0.3, and 4 currencies an increase of between 0.0 and 0.1. Not surprisingly, for currencies of all European countries, except for Switzerland, the euro beta value increased over the two sub-periods. However, it is surprising that the euro beta value increased substantially for almost all currencies across the world.

Figure 2.6 displays the results of Table 2.7 graphically. It shows clearly that the euro beta value has increased over the two sub-periods for almost all currencies.

2.4.4 Other Explanatory Variables

In addition to the currency beta, as other factors that could explain the level of the currency R-square and its change over time, we consider the following three: (i) the trade propensity of a country, (ii) the degree of financial integration of a country with the rest of the world, and (iii) inflation.

Since the exchange rate between currencies of two countries is by definition the relative price of two currencies, it should be affected by trade and capital flows between two countries. Hence, we consider the degree of a country's trade propensity one of the explanatory variables in our regression analysis. We expect that if a country trades less with the rest of the world, its currency may behave more independently against foreign currencies, other things being equal. Specifically, we measure the trade propensity of a country as the sum of imports and exports divided by GDP of the country. Similarly, if a country is less financially integrated with the rest of the world, its currency may behave more independently against foreign currencies, other things being equal. Thus, we consider the degree of a country's financial integration with the rest of the world another explanatory variable in our regression analysis. Specifically, we measure the degree of financial integration using the stock market integration measure proposed by Puthuanthong and Roll (2009).[11] Simply speaking, Pukthuanthong and Roll measures a country's financial integration with the rest of the world using the explanatory power of a globally-defined multi-factor model in explaining the country's stock market returns. In Appendix 2.7.3, we detail how we computed the stock market integration measure proposed by Puthuanthong and Roll.

[11]There is no firm consensus on which measure is the most appropriate proxy for the degree of a country's financial integration with the rest of the world, however. For example, we may consider the ratio of the sum of capital investment flows into and out of a country to GDP to be a proxy for the degree of the country's financial integration with the rest of the world. Unfortunately, however, the investment flow data were not available for the majority of our sample countries.

Lastly, we include inflation as another control variable in our regression analysis. We expect that currencies of countries with higher inflation rates would be traded less in the foreign exchange markets and thus may behave more independently against foreign currencies, other things being equal. In addition, inflation is a key variable in many economic models of exchange rates, so it will be worthwhile to examine its effect on the currency R-square without any directional prediction.

2.4.5 Descriptive Statistics for the Regression Variables

Table 2.8 presents the descriptive statistics for all the variables used in our regression analysis. The currency R-square and euro beta values are estimated from the regression models Equation (2.6) and Equation (2.11), respectively, by using data for the entire sample period 1999-2010. Hence, the currency R-square values reported here are the same as the currency R-square values obtained from using the GDP-weighted world exchange rate factor reported in Table 2.3. The euro beta values are also the same as the euro beta values reported in Table 2.6. The other three variables—trade propensity, financial integration , and inflation—are computed annually first and then taken the time-series average. The table shows that there exists a substantial cross-sectional variation in each of the regression variables. The currency R-square, expressed in percent terms, ranges from the minimum 0.0 for Uruguay to the maximum 83.4 for the euro area. The mean and standard deviation of the currency R-square values are 30.2 and 25.1, respectively. The euro beta ranges from the minimum -0.06 for Uruguay to the maximum 1.10 for Hungary. The trade propensity ranges from the minimum 0.21 for Brazil to the maximum 3.03 for Singapore. Singapore is the most trade-intensive country in our sample, followed by Czech Republic, Hungary, and Thailand. The financial integration variable, which measures the degree of stock market integration, ranges from the minimum 2.1% for Nigeria to the maximum 80.4% for the U.K.

Table 2.8: The Regression Variables

This table reports the summary of the variables used in our regression analyses by country. The currency R-square is computed by using the GDP-weighted world exchange rate factor. The currency R-square and euro beta variables are estimated by using data for the entire sample period 1999-2010. The financial integration variable represents the stock market integration measure proposed by Pukthuanthong and Roll (2010). It is computed annually first and then taken the time-series average. The trade propensity and inflation variables are the time-series average of annual values over the 12-year sample period 1999-2010. The trade propensity variable is defined as imports plus exports divided by GDP. The currency R-square and financial integration variables are expressed in percent terms.

	Currency R^2	Euro Beta	Trade Propensity	Financial Integration	Inflation
Algeria	13.7	0.28	0.57	n.a.	3.0
Australia	47.8	0.69	0.32	64.6	3.0
Brazil	14.3	0.40	0.21	50.8	6.6
Canada	36.0	0.38	0.61	66.7	2.1
Chile	11.3	0.22	0.59	33.4	3.3
Colombia	10.5	0.24	0.28	17.8	6.3
Czech Rep.	69.2	1.01	1.19	40.2	2.6
Euro Area	83.4	1.00	0.31	71.5	2.0
Hungary	67.5	1.10	1.21	49.4	6.3
India	23.5	0.18	0.27	35.5	6.0
Indonesia	4.9	0.12	0.52	34.7	9.2
Israel	19.5	0.28	0.59	39.5	2.3
Japan	14.2	0.21	0.23	39.7	-0.3
Kenya	4.9	0.12	0.45	6.3	9.9
Korea	22.0	0.32	0.66	53.7	2.9
Mexico	12.5	0.18	0.53	53.6	6.1
New Zealand	45.3	0.72	0.47	54.1	2.5
Nigeria	0.0	-0.01	0.57	2.1	11.9
Norway	68.4	0.88	0.53	64.0	2.1
Pakistan	0.3	0.01	0.32	6.6	8.1
Peru	6.3	0.07	0.36	27.5	2.6
Philippines	9.9	0.13	0.85	26.5	5.2
Poland	57.5	0.91	0.58	50.4	3.8
Romania	33.9	0.61	0.65	25.0	18.0
Russia	21.4	0.29	0.51	39.7	19.4
Singapore	55.7	0.26	3.03	59.4	1.5
South Africa	26.0	0.61	0.50	52.6	5.9
Sweden	68.8	0.94	0.64	78.9	1.4
Switzerland	64.5	0.87	0.64	79.6	0.9
Thailand	14.0	0.17	1.14	37.6	2.3
Turkey	13.8	0.41	0.38	34.9	25.8
U.K.	55.0	0.57	0.39	80.4	2.7
Uruguay	0.0	-0.02	0.36	n.a.	8.2
MEAN	30.2	0.43	0.62	44.4	5.9

Table 2.9: Correlations between the Regression Variables

This table reports the correlations between the regression variables presented in Table 8. The numbers in parentheses here represent p-values. The star symbols *, **, and *** represent the statistical significance at the %10, %5, and %1 levels, respectively.

	Currency R^2	Euro Beta	Trade Propensity	Financial Integration
Euro Beta	0.92***			
	(0.00)			
Trade Propensity	0.31*	0.09		
	(0.08)	(0.61)		
Financial Integration	0.76***	0.65***	0.13	
	(0.00)	(0.00)	(0.48)	
Inflation	-0.37**	-0.22	-0.18	-0.47***
	(0.03)	(0.23)	(0.32)	(0.01)

Table 2.9 presents the correlations among the regression variables reported in Table 2.8. Several interesting points emerge from the results. Most notably, the correlation between the currency R-square and euro beta amounts to 0.92, indicating that about 85 percent of the variation in the currency R-square values across currencies are explained by the cross-currency variation in the euro beta values alone. The correlation between the currency R-square and financial integration (0.76) is also very large and strongly significant at the 1% level. The correlation between the currency R-square and trade propensity (0.31) is also positive, but significant only at the 10% level. By contrast, the correlation between the currency R-square and inflation (-0.37) is negative and significant at the 5% level. Overall, the bivariate relationships between the currency R-square and the other regression variables are consistent with our expectation. Note, however, that the correlations among the euro beta, financial integration, and inflation, are very large. Hence, it is an empirical question which

variables retain their power in explaining the cross-sectional and time-series variations in the currency R-square values when they are forced to compete with each other in the multivariate regression models.

2.5 Regression Analysis

Our primary interest in this section is in the estimation of the cross-sectional regression models of the following form and their time-series versions:

$$\begin{aligned}\text{Currency } R_k^2 = \gamma_0 + \gamma_1 * \text{Euro Beta}_k + \gamma_2 * \text{Trade Propensity}_k \\ + \gamma_3 * \text{Financial Integration}_k + \gamma_4 * \text{Inflation}_k + \varepsilon_k, \qquad (2.14)\end{aligned}$$

where k represents a currency or country.

2.5.1 Cross-sectional Analysis

Panels A, B, and C of Table 2.10 present the results of the cross-sectional regression model Equation (2.14) for the 1999-2010, 1999-2004, and 2005-2010 periods, respectively. In Panel A, the currency R-square and euro beta values are computed by using data for the entire sample period 1999-2010; for the other variables, we compute the time-series average of 12 corresponding annual values for the 1999-2010 period. Similarly, in Panel B, the currency R-square and euro beta values are computed by using data for the earlier sub-period 1999-2004; for the other variables, however, we compute the time-series average of 6 corresponding annual values for the 1999-2005 period. This is also the case for the cross-sectional analysis for the later sub-period 2005-2010 reported in Panel C. The t-statistics reported in the table are based on the White heteroscedasticity consistent robust standard errors (White, 1980).

First, the estimated regression R-square values in the bottom row of all three panels convey us a striking message. Even though the sample size is so small, the three explanatory variables we consider explain about 90 percent of the cross-sectional variation in the currency R-square values across all three alternative sample periods.

Table 2.10: Cross-sectional Regression Results

This table reports the results of the cross-sectional regressions of the following form for the period 1999-2010, 1999-2004, and 2005-2010

$$\text{Currency } R_k^2 = \gamma_0 + \gamma_1 * \text{Euro Beta}_k + \gamma_2 * \text{Trade Propensity}_k + \gamma_3 * \text{Financial Integration}_k + \gamma_4 * \text{Inflation}_k + \varepsilon_k,$$

where k represents a currency or country. The dependent variable is the currency R-square computed by using the GDP-weighted world exchange rate factor. The numbers in parentheses are t-statistics, which are based on the White heteroskedasticity consistent standard errors (White, 1980). All variables are expressed in percent terms. The star symbols *, **, and *** represent the statistical significance at the %10, %5, and %1 levels, respectively.

	Model 1	Model 2	Model 3
Panel A: Cross-Sectional Regression for the Period 1999-2010			
Euro Beta	0.69***		0.56***
	(16.80)		(11.72)
Trade Propensity		0.10	0.10***
		(1.64)	(3.86)
Financial Integration		0.87***	0.24***
		(7.46)	(3.33)
Inflation		-0.01	-0.37**
		(-0.01)	(-2.21)
Number of Observations	33	31	31
R-square	0.84	0.61	0.93
Panel B: Cross-Sectional Regression for the Period 1999-2004			
Euro Beta	0.69***		0.57***
	(20.02)		(15.24)
Trade Propensity		0.06	0.06*
		(1.14)	(1.97)
Financial Integration		0.78***	0.21***
		(5.70)	(3.71)
Inflation		-0.16	-0.25*
		(-0.79)	(-2.04)
Number of Observations	33	31	31
R-square	0.86	0.57	0.93
Panel C: Cross-Sectional Regression for the Period 2005-2010			
Euro Beta	0.65***		0.51***
	(13.65)		(8.76)
Trade Propensity		0.10*	0.11***
		(1.76)	(4.13)
Financial Integration		0.98***	0.37***
		(6.11)	(3.24)
Inflation		0.86	0.57
		(0.80)	(0.87)
Number of Observations	33	31	31
R-square	0.80	0.61	0.88

Next, in terms of the explanatory power, the euro beta variable emerges as the most important explanatory variable across all three alternative sample periods. This is consistent with our discussion in Subsection 4.1 and the results from the clustering analysis in Subsection 4.2. The coefficient estimate for the euro beta variable (0.55) from Model 3 of Panel A, for example, indicates that if a country's currency value is more sensitive by 0.01 to the euro's movement than to the dollar's movement, then its currency R-square value is higher by 0.0055 than a currency of the country otherwise the same. The trade propensity of a country is also positively associated with the country's currency R-square value, and the variable has become more significant in the later sub-period. The degree of financial integration of a country with the rest of the world is also positively associated with the country's currency R-square value, and it is significant at the 1% level in both the earlier and later sub-periods. Lastly, the inflation variable is negatively associated with the currency R-square values, but it is significant only in the earlier sub-period.

To summarize, the euro beta variable plays the most important role in explaining the cross-currency variation in the currency R-square values. The euro beta variable alone can explain more than 80% of the cross-currency variation in the measured currency R-square values. Although the other explanatory variables also retain statistically significant explanatory power, they, combined together, can increase the explanatory power only by 7% to 9% once the effect of the currency beta is controlled for.

2.5.2 Cross-sectional and Time-series Analysis

The results of Table 2.4 and Figure 2.1 indicate that the currency R-square values have increased over time for the majority of our sample currencies. The cross-sectional regression analysis in the previous subsection, however, do not tell us much about what drives such an increase in the measured currency R-square values over time. To investigate the dynamic relation between the currency R-square values and explanatory variables, we first employ a simple regression model of the following form

$$\begin{aligned}\Delta\text{Currency } R_k^2 = \gamma_0 + \gamma_1 * \Delta\text{Euro Beta}_k + \gamma_2 * \Delta\text{Trade Propensity}_k \\ + \gamma_3 * \Delta\text{Financial Integration}_k + \gamma_4 * \Delta\text{Inflation}_k + \varepsilon_k. \qquad (2.15)\end{aligned}$$

where k represents a currency or country and Δx the difference of x values computed for the 1999-2004 and 2005-2010 periods. Though very simple, this model is powerful in the sense that the estimated results are free from the endogeneity biases that can arise from the omission of any country-specific variables as long as they are not time-varying. Panel A of Table 2.11 presents the estimation results. The t-statistics reported in Panel A are based on the White heteroscedasticity consistent robust standard errors (White, 1980). If we focus on the result of Model 3, only the change in the euro beta values, i.e., the change of a currency's sensitivity to the euro relative to the U.S. dollar, is statistically significant. Also, from the result of Model 1, the euro beta variable alone can explain as much as 68 percent of the time-series variation in the currency R-square values. Changes in the other variables have no additional explanatory power once the change in the euro beta values is controlled for.

Next, we employ more general cross-sectional and time-series regression models of the following form

$$\begin{aligned}\text{Currency } R_{k,t}^2 = \gamma_0 + \gamma_1 * \text{Euro Beta}_{k,t} + \gamma_2 * \text{Trade Propensity}_{k,t} \\ + \gamma_3 * \text{Financial Integration}_{k,t} + \gamma_4 * \text{Inflation}_{k,t} \\ + \text{Currency and Year Fixed Effects} + \varepsilon_{k,t}, \qquad (2.16)\end{aligned}$$

where k represents a currency or country and t a year. Panel B of Table 2.11 presents the estimation results. We try three regression models: pooled regression model (labeled as Pooled), panel regression model with currency fixed effects only (labeled

Table 2.11: Cross-sectional and Time-series Regression Results

This table reports the results of the cross-sectional regression of the following form (Panel A)

$$\Delta\text{Currency } R^2_k = \gamma_0 + \gamma_1 * \Delta\text{Euro Beta}_k + \gamma_2 * \Delta\text{Trade Propensity}_k + \gamma_3 * \Delta\text{Financial Integration}_k + \gamma_4 * \Delta\text{Inflation}_k + \varepsilon_k$$

and results of the panel regression models of the following form (Panel B)

$$\text{Currency } R^2_{k,t} = \gamma_0 + \gamma_1 * \text{Euro Beta}_{k,t} + \gamma_2 * \text{Trade Propensity}_{k,t} + \gamma_3 * \text{Financial Integration}_{k,t} + \gamma_4 * \text{Inflation}_{k,t} + \text{Fixed Effects} + \varepsilon_{k,t},$$

where k represents a currency or country and t a year. The dependent variable is the currency R-square computed by using the GDP-weighted world exchange rate factor. The numbers in parentheses are t-statistics. In Panel A, t-statistics are based on the White heteroscedasticity consistent standard errors (White, 1980). In the pooled regression model of Panel B, t-statistics are based on the clustered standard errors clustered at each currency level (Rogers, 1993). In the other two fixed effect models of Panel B, t-statistics are based on the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 2 within each country (Newey and West, 1987; Petersen, 2009). All variables are expressed in percent terms. The star symbols *, **, and *** represent the statistical significance at the %10, %5, and %1 levels, respectively.

Panel A: Cross-Sectional Regression Using Time-Differenced Variables			
	Model 1	Model 2	Model 3
ΔEuro Beta	0.64***		0.57***
	(8.26)		(4.05)
ΔTrade Propensity		-0.13	-0.02
		(-0.63)	(-0.08)
ΔFinancial Integration		0.72***	0.14
		(3.70)	(0.73)
ΔInflation		-0.47	-0.20
		(-1.24)	(-0.88)
Number of Observations	33	31	31
R-square	0.68	0.43	0.68
Panel B: Panel Regression for the Period 1999-2010			
	Pooled	One-way Fixed	Two-way Fixed
Euro Beta	0.47***	0.42***	0.42***
	(14.33)	(11.30)	(10.03)
Trade Propensity	0.08***	0.06	-0.03
	(3.58)	(0.69)	(-0.35)
Financial Integration	0.20***	0.14***	0.11**
	(4.57)	(2.74)	(2.15)
Inflation	0.13	0.21	0.28
	(0.63)	(1.20)	(1.61)
Country Fixed Effect	No	Yes	Yes
Year Fixed Effect	No	No	Yes
Number of Observations	372	372	372
R-square	0.77	0.84	0.87

as One-way Fixed), and panel regression model with both currency and year fixed effects (labeled as Two-way Fixed). For the pooled regression model, t-statistics are computed using the clustered standard errors clustered at each country level (Rogers, 1993). For both the one-way and two-way fixed effect models, the t-statistics are computed using the standard errors adjusted for heteroscedasticities and autocorrelations with allowing for autocorrelations up to lag 2 within each country (Newey and West, 1987; Petersen, 2009). Most notably, judging from the magnitude of the estimated t-statistics across three alternative regression models, we can tell that the euro beta variable is the most important driver of the inter-temporal change in the currency R-square values. For the pooled regression model, all explanatory variables, except for inflation, are statistically significant at the 1% level. However, once we control for currency fixed effects, the trade propensity variable loses its statistical significance, and only the euro beta and financial integration variables remain statistically significant. Lastly, the results of the two-way fixed effect model is comparable to those of the one-way fixed effect model except that now the financial integration variable is significant only at the 5% level.

Lastly, Table 2.12 presents the results of the panel regression model (2.16) with both country and time fixed effects by using the currency R-square values computed from using GDP-weighted, trade-weighted, and equally-weighted world exchange rate factors, respectively. The results confirm that, irrespective of which currency R-square values we use, the euro beta variable is the most important driver of the inter-temporal change in the currency R-square values. The financial integration variable retains some explanatory power; however, it together with other explanatory variables adds only 1% power to the regression R-square value once the euro beta variable is controlled for.

Overall, the results of the cross-sectional and time-series regression analyses in this subsection convey us one message. The most important driver of the inter-temporal

Table 2.12: Cross-sectional and Time-series Regression Results: Robustness Check

This table reports the results of the panel regression models of the following form

$$\text{Currency } R^2_{k,t} = \gamma_0 + \gamma_1 * \text{Euro Beta}_{k,t} + \gamma_2 * \text{Trade Propensity}_{k,t} \\ + \gamma_3 * \text{Financial Integration}_{k,t} + \gamma_4 * \text{Inflation}_{k,t} + \text{Fixed Effects} + \varepsilon_{k,t},$$

where k represents a currency or country and t a year. The dependent variable is the currency R-square computed by using the GDP-weighted, trade-weighted, or equally-weighted world exchange rate factor. The numbers in parentheses are t-statistics based on the Newey-West heteroscedasticity and autocorrelation consistent standard errors with allowing for autocorrelations up to lag 2 within each country (Newey and West, 1987; Petersen, 2009). All variables are expressed in percent terms. The star symbols *, **, and *** represent the statistical significance at the %10, %5, and %1 levels, respectively.

	GDP-weighted		Trade-weighted		Equally-weighted	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Euro Beta	0.41***	0.42***	0.42***	0.42***	0.36***	0.33***
	(10.59)	(10.03)	(12.07)	(11.18)	(9.39)	(9.17)
Trade Propensity		-0.03		-0.04		-0.05
		(-0.35)		(-0.51)		(-0.57)
Financial Integration		0.11**		0.10**		0.19***
		(2.15)		(2.05)		(3.71)
Inflation		0.28		0.27		0.08
		(1.61)		(1.63)		(0.67)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	372	372	372	372	372	372
R-square	0.86	0.87	0.87	0.88	0.81	0.82

change in the currency R-square values is the change in the euro beta values over time. Once the effect of the influence of the euro relative to USD over a given currency is controlled for, the other explanatory variables have at best marginal explanatory power in explaining time-series change in the currency's co-movement with other currencies.

2.6 Summary and Concluding Remarks

During the recent decade, the foreign exchange market expanded rapidly. According to the triennial survey report by the Bank for International Settlements (BIS), over the 2001–2010 period the foreign exchange market turnover increased by more than 220% to $3.98 trillion a day as of April 2010 from $1.24 trillion a day as of April 2001 (BIS 2010). Investors' interest in currency trading has also soared together. The increasing number of currency exchange-traded funds (ETFs) and retail foreign-exchange trading sites reflects the increasing investors' interest and also makes easier for investors to trade currencies than ever.[12] Market experts often state that more investors are now looking at currencies as another asset class, like stocks and bonds, than they were ever.

Against this backdrop, this study have (i) examined the degree of co-movement between bilateral USD exchange rates and its change over time since the introduction of the euro in 1999 and (ii) investigated what drives the co-movement and its change over time. We first document that the degree of co-movement between foreign exchange rates has increased substantially during the period of 1999–2010. Specifically, we show that, for each of our 33 sampled bilateral USD exchange rates, its co-movement with the other bilateral USD exchange rates has increased, on average, by more than 200% over the period 1999–2010. This study also reveals that the euro beta variable alone, our measure of the influence of the euro relative to the U.S. dollar over a third currency, can explain about 90% of the cross-sectional variation in the measured co-movement and that the change in the euro beta variables over time can explain about 70 to 80% of the time-series variation in the measured co-movement.

As any other integration research, our findings of the markedly increased degree of co-movement between bilateral USD exchange rates over the recent decade have

[12]There was only one currency ETF in December 2005, but the number increased to 44 as of October 2010, and many financial-services firms keep launching their own currency-related products.

implications for a wide range of financial decision makings such as asset allocation, currency hedging, as well as economic policies. Our findings indicate that currency risk is becoming more systematic and its main driver is the increasing alignment of many currencies with the euro. Hence, for USD-based investors, our findings imply that investing in international financial markets is more exposed to currency risk. This is also the case for multinational companies headquartered in the U.S. Our findings also suggest that when hedging international investments through currency forward and/or derivatives markets, investors or multinational companies need to pay more attention to the dynamics of the dollar-euro exchange rate. Policymakers might as well be concerned that an increasing co-movement between exchange rates will lead to a rising susceptibility of the economy's current and capital account balances to currency risk.

2.7 *Appendix*

2.7.1 The Effect of Changing a Base Currency on the Currency Distance

Assume that the exchange rate between currency j and USD at time t, denoted by S_t^j, is quoted as units of \$ per one unit of currency j, i.e., $\$/J$. Let us set $s_t^j = \log(S_t^j)$ and $r_{t+1}^j = s_{t+1}^j - s_t^j$ for $t = 1, ..., T$. Define the distance between currency i and currency j, denoted by $d(i,j)$, as

$$d^2(i,j) = \sum_{t=2}^{T} \left(r_t^i - r_t^j\right)^2. \tag{2.17}$$

Note that $d(i,j)$ represents the Euclidean distance between two $(T-1)$-dimensional vectors $\mathbf{r}^i = (r_2^i, r_3^i, ..., r_T^i)'$ and $\mathbf{r}^j = (r_2^j, r_3^j, ..., r_T^j)'$. Of course, we have

$$d^2(i,\mathrm{USD}) = \sum_{t=2}^{T} \left(r_t^i - r_t^{\mathrm{USD}}\right)^2. \tag{2.18}$$

and

$$d^2(i,\mathrm{euro}) = \sum_{t=2}^{T} \left(r_t^i - r_t^{\mathrm{euro}}\right)^2. \tag{2.19}$$

Here, $r_t^{\mathrm{USD}} = 0$ by construction.

Suppose now that we used the Japanese yen (JPY), for example, as a numeraire currency in the beginning and that $S_t^j(¥)$ represents units of JPY per one unit of currency j, i.e., $¥/J$. If we set $s_t^j(¥) = \log S_t^j(¥)$ and $r_{t+1}^j(¥) = s_{t+1}^j(¥) - s_t^j(¥)$, then we have the following relation

$$r_t^j(¥) = r_t^j - r_t^{¥} \tag{2.20}$$

because we have $S_t^j(¥) = S_t^j / S_t^{¥}$. Hence, if we denote the distance between any two currencies with JPY as a numeraire currency by $d(i,j,¥)$, we have

$$\begin{aligned} d^2(i,j,¥) &= \sum_{t=2}^{T} \left(r_t^i(¥) - r_t^j(¥)\right)^2 \\ &= \sum_{t=2}^{T} \left([r_t^i - r_t^{¥}] - [r_t^j - r_t^{¥}]\right)^2 = d^2(i,j). \end{aligned} \tag{2.21}$$

That is, the distance between any two currencies with JPY as a numeraire currency, $d(i, j, ¥)$, is equal to $d(i, j)$ with USD as a numeraire currency. Note that the change of a numeraire currency from USD to JPY has an equivalent effect of changing the origin of the $(T - 1)$-dimensional Euclidean space from $\mathbf{r}^{\mathrm{USD}} = (0, 0, ..., 0)'$ to $\mathbf{r}^{\mathrm{JPY}} = (r_2^i(¥), r_3^i(¥), ..., r_T^i(¥))'$. Hence, the distance of any two currencies measured this way remains the same after the change of a numeraire currency.

2.7.2 Ward's Clustering Procedure

Suppose there are four items that are associated with two-dimensional vectors:

Item	(x_1, x_2)
A	(0, 0)
B	(2, 0)
C	(0, 4)
D	(6, 4)

Simply speaking, the Ward's clustering procedure regards the cluster analysis as an analysis of variance problem. The homogeneity or similarity of each cluster is measured by the within-cluster sum of the squared deviations of individual items in the cluster from the cluster center, which is known as the *error sum of squares* (ESS). Initially, we have 4 clusters each of which consists of a single item, so $ESS = 0$. At the first step, a total of 6 different three-cluster solutions are possible:

Cluster Solution	ESS
(AB), C, D	2
(AC), B, D	8
(AD), B, C	26
(BC), A, D	10
(BD), A, C	16
(CD), A, B	18

To see how the ESSs are calculated in this table, suppose A and B are combined in a single cluster at the first step. Then, the cluster center of A and B is (1,0) and $ESS_{AB} = [(0-1)^2 + (0-0)^2] + [(2-0)^2 + (0-0)^2] = 2$. Since $ESS_C = ESS_D = 0$, we have $ESS = ESS_{AB} + ESS_C + ESS_D = 2$. As another example, suppose A and D are combined in a single cluster at the first step. Then, the cluster center of A and D is (3,2) and $ESS_{AD} = [(0-3)^2 + (0-2)^2] + [(6-3)^2 + (4-2)^2] = 26$. Since $ESS_B = ESS_C = 0$, we have $ESS = ESS_{AD} + ESS_B + ESS_C = 26$. This way, we can compute ESSs for other solutions. Hence, the best cluster solution at the first step is

(AB), C, D

and we now have three clusters. The next step in the Ward's method is to evaluate all possible 3 different two-cluster solutions:

Cluster Solution	ESS
(ABC), D	40/3
(ABD), C	24
(AB), (CD)	20

Hence, the best solution at the second step is

(ABC), D.

At the third and final step, we have only one big cluster (ABCD), so $ESS = TSS = 40$.

2.7.3 Pukthuanthong and Roll's Global Market Integration Measure

Pukthuanthong and Roll (2009) argue that if the true return generating process is governed by more than one factor, the correlation across markets is a poor measure of integration. Assuming that multiple global sources of risks affect stock markets across the world, they propose a new measure of integration based on the explanatory power of a multi-factor model, i.e., R-square. We detail their procedure below, which are largely taken from the Section 7 of their article. It should be noted, however, that we use weekly returns while they use daily returns.

Following the Pukthuanthong and Roll's procedure, we estimate global factors using the principal component analysis. For each calendar year, we extract ten eigenvectors from the covariance matrix computed using dollar-denominated stock market index returns of the 17 countries, which they call the *pre-1974 cohort*. The ten eigenvectors are, of course, vectors associated with ten largest eigenvalues of the 17×17 covariance matrix. The 17 countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, Singapore, South Africa, Switzerland, the United Kingdom, and the United States. Then, the ten eigenvectors thus extracted are applied to the returns of the same 17 countries during the *next* year, to compute so-called *out-of-sample* principal components. These ten out-of-sample principal components serve as the proxies for global stock market factors.

In addition, following one of their two precautionary actions taken, for each member of the 17 pre-1974 cohort countries separate principal components were estimated after the country was excluded from the calculation. For example, when the subject country is Japan, Japan is excluded from the computation of the covariance matrix and the out-of-sample principal components. Excluding countries in this manner is intended to avoid any suspicion that a country's return regressed on global factors is biased by that same country being heavily weighted in the principal components. The other precautionary action Pukthuanthong and Roll take into account is related to the time zone differences. Since we use weekly returns, not daily returns, however, we do not consider this issue.

We then compute the regression R-square from the regression of each country's market returns on the ten global factors constructed this way for each calendar year from year 1999 to 2010. For the euro area, we use the average of the regression R-squares of twelve largest-economy member countries of the eurozone as the degree of financial integration.

CHAPTER III

HOW INTEGRATED ARE DOMESTIC STOCK MARKETS? EVIDENCE FROM U.S. STATE-SORTED PORTFOLIOS

Investors are known to exhibit home (local) bias even when they invest in their domestic markets. Since home bias is symptomatic of market segmentation, the 'home bias at home' phenomenon raises an important question: How well integrated are domestic financial markets? The answer for this question will have implications for a wide range of financial decision makings, including the cost of capital estimation, asset allocation, and performance evaluation. In the current paper, we address this question by estimating the level and trend of integration of U.S. domestic stock markets. Specifically, for each of our sample states, we construct the state (market) portfolio comprising public firms headquartered within the state and compute R-square, our measure of integration, from regressing state portfolio returns on national stock market factors. Using weekly returns, we estimate the regression for each year of our sample period 1963-2008. The key findings are: (i) For the majority of sample states, the R-square exhibits a statistically significant upward trend, implying that U.S. domestic stock markets were not fully integrated and have been integrating during the sample period; (ii) consistent with the previous result, the explanatory power of the state factor over individual stock returns has been decreasing for the majority of states; and (iii) the increasing integration of U.S. domestic stock markets is associated with the decreasing home state bias, suggesting that investors' pursuit of nation-wide investment opportunities may be a significant driver of domestic financial integration.

3.1 Introduction

Are the United States domestic stock markets fully integrated geographically? Standard economic and finance theories suggest the answer to this question should be yes. The U.S. financial market is national in scope, characterized by free capital flow across states. U.S. states or regions are subject to relatively few, if any, restrictions on movements of production, capital, and labor.[1] However, recent studies on international financial integration indicate that explicit or formal barriers to cross-border economic activities and capital flows cannot adequately account for the level of market segmentation observed in the data and that investor portfolio decisions play an important role in determining financial market integration.

In this paper, we study the process of integration within U.S. domestic stock markets. We view the U.S. stock markets primarily as a collection of 50 state markets and examine whether and how state stock markets have been integrating into the national market during the period 1963-2008. We utilize state portfolio returns computed by value-weighting the returns of all stocks within each state. Following the lead of Pukthuanthong and Roll (2009) and other previous studies, we examine the levels and changes of market integration based on the regression R-squares from various model specifications that capture the degree to which common national stock market factors drive state portfolio returns.

Our study builds on the two distinct strands of finance literature—the international financial integration and the local bias within the U.S market. The questions of whether and how international financial markets have been integrating over time have long attracted interests from academia, policy makers, as well as practitioners because answers for the questions have important implications for financial decisions such as the cost of capital estimation, international asset allocation, and performance

[1]See Barro and Sala-i-Martin (1990, 1991) for related discussions.

evaluation. For this reason, numerous studies have examined these questions and documented evidence of greater international market integration over time (Bekaert and Harvey, 1995; Longin and Solnik, 1995; Korajczyk, 1996; Levine and Zervos, 1998; Brooks and Del Negro, 2004; Bekaert, Harvey, Lundblad, and Siegel, 2008; Pukthuanthong and Roll, 2009).

Studying market integration within the U.S. offers important insights into the understanding of the level and determinants of international market integration. Considering that U.S. domestic markets are largely free from cross-border barriers and subject to similar national regulations, taxation, and accounting standards, the level of market integration within the U.S. can provide a 'benchmark' for evaluating global financial integration. Such a benchmark is useful for both evaluating the potential benefits of global market integration and understanding the impacts of economic barriers on the degree of market integration.

The second strand of literature centers on the role of investor behavior in market integration. Studies of international market integration document that home bias in portfolio holdings, strong investor preference for domestic stocks in international financial markets, is likely to be both a result of and a contributing factor to market segmentation (French and Poterba, 1991; Gehrig, 1993; Lewis, 1999; Van Nieuwerburgh and Veldkamp, 2009). Coval and Moskowitz (1999) show that investors' preference for investing close to home also applies to the U.S. domestic stock market. Recent studies further show that investor local bias has significant impacts on stock returns and stock valuations across geographic regions (Zhu, 2002; Hong, Kubik, and Stein, 2005, 2008; Ivkovic and Weisbenner, 2005; Pirinsky and Wang, 2006; Korniotis and Kumar, 2008). If investors prefer to invest close to home, such investment behavior can contribute directly to geographical segmentation within the U.S. domestic market. Our study of domestic market integration would help us to assess the extent of geographical segmentation of U.S. domestic financial markets and how investor behavior may contribute to market segmentation.

We find that state portfolios in our sample exhibit considerable variations in market integration over the sample period. For the majority of the states, national stock market factors now explain a greater portion of the state portfolio returns than they did a half century ago. The average R-square from the Fama-French three factor model increases from 0.50 in 1963 to 0.68 in 2008. The increase in market integration is particularly strong for smaller states and states with low level of integration at the beginning of the sample period. The results are robust to two alternative specifications for the underlying return generating process: the Fama-French three-factor model and a statistical factor model. Over the same time period, state portfolio returns exhibit a strong downward trend in explaining individual stock returns in the state, suggesting a declining local influence on stock returns. Taken together, the evidence indicates that U.S. domestic stock markets were unlikely to be fully integrated in the sample period and indeed have been integrating over the most recent time period.

What explains the variations of market integration within the U.S. domestic market and the increasing integration over time? U.S. states have enjoyed a high level of economic integration for a considerable period of time. Because there are few explicit barriers to economic activities and capital flows across states to begin with, changes in such restrictions are unlikely to be the explanations for the observed increasing market integration. While there is little evidence that overall economic integration at the state level has changed noticeably in the U.S. over the past half century, integration of economic fundamentals across states could have increased because of structural changes in the national and local economy and regulation or policy changes that affect cross-state market activities. For example, banking deregulation related to inter-state banking in the 1990s could help integrate credit market across states. We investigate whether changes in state level industry structure and overall economic linkages contribute to the increasing stock market integration during the sample period.

Greater industrial diversification at the state level could lead to higher market integration measured by the regression R-square. We find that changes in industrial structure at the state level have significant impact on the observed increase in domestic stock market integration. However, after controlling for the state level industry concentration in the time trend regression, we still obtain rather robust results of greater market integration for the majority of sample states over the sample period.

We next examine whether and how investor behavior, particularly local bias, contributes to the geographic segmentation of the U.S. domestic stock market and the increasing integration over time. To establish a direct link between investor home bias and market segmentation, we first compute a measure of local bias at the state level based on the degree of comovement between the growth of dividends paid by corporations in the state and the growth of dividends received by residents in the state. The degree of comovement proxies the propensity of investors to invest in companies located in the home states, i.e., the extent of local bias. We then examine whether changes (decline) in local bias over the sample period at the state level help to explain the increases in market integration during the same period.

In the cross-sectional regression, we find that declines in the measured home bias at the state level are significantly related to the increases in stock market integration. The results remain strong even after controlling for the impact of changes in industry concentration and various economic variables in the state. The empirical results based on home bias suggest that investor behavior and particularly home bias in domestic market contribute to geographic segmentation of the U.S. domestic stock market.

The paper is organized as follows. Section 2 describes the data and our measures of market integration. Section 3 presents the evidence on U.S. domestic market integration, while Section 4 examines the explanations of U.S. market integration based on the changes of economic activities and linkages at the state level. Section 5 studies the impact of local bias in investor behavior on the levels and changes of U.S. domestic stock market integration. Section 6 concludes.

3.2 Data, State Portfolio, and Measurement of Financial Integration

3.2.1 Data and State Portfolio

To examine the level of financial integration between U.S. states and its change over time, for each of our sample states, we construct the so-called state market portfolio by value-weighting stock returns of all companies headquartered within the state at the weekly frequency, which we refer to simply as the state portfolio.[2] We use weekly stock returns to mitigate the potential problems caused by the presence of nonsynchronous trading effects, and use only common stocks with CRSP share code 10 or 11 when constructing the state portfolios. We obtain stock return data from Center for Research in Security Prices (CRSP) and company headquarters location data from COMPUSTAT. However, COMPUSTAT provides only current headquarters information. For historical headquarters information after 1987, we collect data from CompactDisc. For companies that existed before 1987 and for which CRSP provides stock return data, we manually collect headquarters information, if available, from various annual issues of Standard and Poor's Stock Reports.

Our sample period spans from July 1963 to December 2008. It starts from 1963 mainly because the number of companies for which CRSP provides stock returns and COMPUSTAT provides headquarter information sharply increases in 1963. In our sample, the number was 955 in 1962 but increased sharply to 1,581 in 1963. We exclude seven states with the average number of stocks less than ten during the sample

[2]We use company headquarters location as a proxy for firm location following the local bias literature (Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2004; Korniotis and Kumar, 2008; Pirinsky and Wang, 2006).

period from our analysis. The excluded states are Alaska, Montana, New Mexico, North Dakota, South Dakota, Vermont, and Wyoming. Our final sample consists of 43 states and District of Columbia, which we refer to as 44 states henceforth for convenience. Of the 44 states, Hawaii is included in the sample from 1965, whereas Mississippi and Nebraska are included from 1970.

Table 3.1 presents the summary statistics for our data. The number of firms and market capitalization share represent the time-series average of annual values. The other statistics are computed by using weekly state portfolio returns for the entire sample period. The mean and standard deviation are reported in annualized terms for convenience. A few points are noteworthy from the table. First, California, New York, and Texas are three largest states in terms of both the number of firms listed and market capitalization share. These three states account for about 40 percent of the total U.S. stock market capitalization. Second, the mean and standard deviation of state portfolio returns vary widely across states. The mean return ranges from the highest 18.88% for Arkansas to the lowest 6.60% for Colorado. The standard deviation ranges from the highest 28.80% for Nevada to the lowest 14.93% for Ohio. Third, the Sharpe ratio (labeled as SHP) also varies widely across states. It ranges from the highest 0.493 for Arkansas to the lowest 0.028 for Colorado. The wide cross-sectional variation in the Sharpe ratios across states partly suggests that U.S. domestic stock markets may not be fully integrated since if they were we may observe similar levels of reward-to-risk ratios across states. Lastly, California and Massachusetts have the largest beta coefficients of 1.21 and 1.20, respectively, whereas Hawaii and Mississippi have the smallest beta coefficients of 0.64 and 0.65, respectively. Considering that California and Massachusetts host many technology-oriented companies, the relatively large beta coefficients for these two states are not surprising.

Table 3.1: Summary Statistics

This table reports summary statistics of our sample. Sample period spans from July 1963 to December 2008. U.S. states with fewer than ten stocks on average during the sample period are excluded from the sample. Of our 44 sample states, the Hawaii sample starts from 1965 and those of Mississippi and Nebraska start from 1970. We construct weekly state portfolio returns by value-weighting the returns of all stocks within each state. The mean, standard deviation, and Sharpe ratio (SHP) are reported in annualized terms. During the sample period, the average risk-free rate was 5.97% in annualized terms. The market beta reports the slope coefficient estimated from regressing weekly state portfolio returns on the weekly U.S. market returns. The market capitalization share is computed relative to the sample.

Table 3.1: Summary Statistics (Continued)

State	Code	MktCap	No. of Firms	Mean	Std. Dev.	Sharpe Ratio	Market Beta
Alabama	AL	0.38	29	12.56	20.91	0.315	0.921
Arizona	AZ	0.54	51	10.86	21.10	0.232	1.093
Arkansas	AR	1.62	17	18.88	26.18	0.493	1.042
California	CA	14.22	598	12.06	21.45	0.284	1.214
Colorado	CO	0.98	103	6.60	22.16	0.028	1.039
Connecticut	CT	4.26	129	12.14	19.98	0.309	1.098
D.C.	DC	0.79	17	12.47	29.02	0.224	1.020
Delaware	DE	0.82	22	10.20	22.35	0.189	1.015
Florida	FL	1.41	183	10.02	18.98	0.213	1.073
Georgia	GA	3.49	102	13.18	17.61	0.409	0.922
Hawaii	HI	0.07	10	12.22	18.99	0.329	0.641
Idaho	ID	0.19	10	10.69	27.02	0.175	1.030
Illinois	IL	6.81	250	11.33	15.80	0.339	0.942
Indiana	IN	1.20	60	11.56	19.51	0.287	0.863
Iowa	IA	0.26	29	11.94	18.43	0.324	0.847
Kansas	KS	0.36	27	8.75	24.25	0.115	0.968
Kentucky	KY	0.34	26	12.45	18.67	0.347	0.886
Louisiana	LA	0.34	26	10.25	19.46	0.220	0.883
Maine	ME	0.08	10	9.27	18.79	0.176	0.636
Maryland	MD	0.98	81	10.24	19.26	0.222	1.028
Massachusetts	MA	3.39	248	10.36	21.68	0.203	1.196
Michigan	MI	1.69	99	10.14	18.41	0.227	0.982
Minnesota	MN	2.68	121	12.18	18.10	0.343	0.994
Mississippi	MS	0.07	13	10.28	22.94	0.188	0.650
Missouri	MO	1.60	72	12.48	16.15	0.403	0.900
North Carolina	NC	2.31	78	10.65	18.74	0.250	0.956
New Hampshire	NH	0.12	19	13.16	25.95	0.277	1.118
New Jersey	NJ	6.88	238	10.78	15.62	0.308	0.821
New York	NY	15.00	512	10.60	17.79	0.261	1.064
Nebraska	NE	0.98	13	17.03	23.72	0.466	0.884
Nevada	NV	0.35	28	11.58	28.80	0.195	1.159
Ohio	OH	3.60	161	11.42	14.93	0.365	0.819
Oklahoma	OK	0.41	37	12.49	25.45	0.256	0.956
Oregon	OR	0.36	37	14.79	22.75	0.388	1.006
Pennsylvania	PA	2.92	201	9.72	17.14	0.219	1.003
Rhode Island	RI	0.30	13	14.92	23.33	0.384	0.939
South Carolina	SC	0.17	27	9.20	18.08	0.179	0.850
Tennessee	TN	0.98	55	11.49	20.04	0.276	1.037
Texas	TX	10.02	346	11.33	17.45	0.308	0.970
Utah	UT	0.19	28	11.54	19.34	0.288	0.878
Virginia	VA	3.05	99	13.78	18.49	0.423	0.955
West Virginia	WV	0.03	10	11.54	25.76	0.216	0.720
Washington	WA	2.98	59	14.63	22.74	0.381	1.050
Wisconsin	WI	0.80	58	13.24	17.81	0.408	0.947
Average		2.27	99	11.75	20.71	0.283	0.955

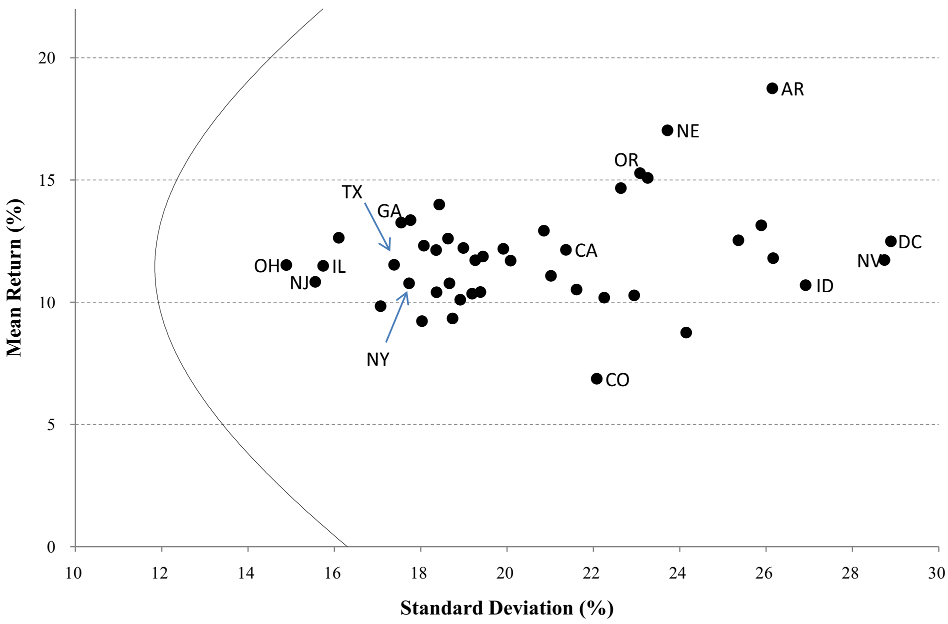

Figure 3.1: Scatter Plot of Risk and Return of State Portfolios

This figure plots the mean state portfolio return and its standard deviation for the 44 U.S. states in our sample. The mean returns and standard deviations are from Table 1. The solid line represents the mean-variance frontier. For the two-letter state code, please refer to Table 1.

Figure 3.1 plots the mean state portfolio return and its standard deviation for the 44 U.S. states in our sample. The mean returns and standard deviations are from Table 3.1. The solid line represents the mean-variance frontier.

3.2.2 Measurement of Market Integration

In this study, to examine the level and trend of integration of U.S. domestic stock markets, we use a measure of market integration based on the explanatory power of a multi-factor model.[3] Specifically, for each year t and state S, we compute the

[3]In international finance literature, Pukthuanthong and Roll (2009) argue that if the true return generating process is governed by more than one factor, then the correlation across markets is a poor measure of integration and one should use a measure of integration based on the explanatory power of a multi-factor model. Bekaert and Harvey (1995) also state: “Some have suggested that the correlation of the local market return with the world return is a measure of integration. However, this is flawed because a country could be perfectly integrated into world markets but have a low or

regression R-square, denoted by RSQ_t^S, from the following regression:

$$r_{t,w}^S - r_{t,w}^f = \alpha + \beta' \mathbf{X}_{t,w} + \varepsilon_{t,w}, \quad w = 1, ..., 52, \tag{3.1}$$

where w represents the w-th week of year t, $r_{t,w}^S$ the weekly return of state market portfolio, $r_{t,w}^f$ the weekly risk-free return, and $\mathbf{X}_{t,w}$ the national stock market factors. The RSQ_t^S calculated in this manner is our measure of the level of integration of state S's stock market with the national stock markets for year t. We then run the following linear time-trend regression to investigate whether there is any trend in the level of integration over time:

$$RSQ_t^S = \alpha^S + \beta^S (t - t_0) + \varepsilon_t, \quad t = t_0, .., 2008, \tag{3.2}$$

where t_0 represents the starting year of each state sample, which is 1963 for all sample states except for Hawaii, Mississippi, and Nebraska. The estimate of α^S can be interpreted as the state S's initial level of financial integration and β^S as the speed of financial integration.

We consider two multi-factor models for the return-generating process: the Fama-French three-factor model and a statistical factor model. For a statistical factor model, we estimate national stock market factors using principal component analysis. Specifically, for each calendar year and given state, we extract five eigenvectors associated with largest five eigenvalues from the covariance matrix computed using state portfolio returns of all sample states other than the subject state. Then, the five eigenvectors thus extracted are applied to the returns of the same sample states that are used in extracting eigenvectors to compute the so-called *in-sample* principal components. Note that, for each sample state, separate principal components are estimated after the subject state is excluded from the calculation. For example, when the subject state is California, California is excluded from the computation of the

negative correlation because its industry mix is much different from the average world mix."

covariance matrix and the in-sample principal components. Excluding the subject state in this manner is intended to avoid any suspicion that the regression R-square calculated from regressing the subject state's state portfolio return on national factors is biased by that same state being heavily weighted in the principal components (Pukthuanthong and Roll, 2009).[4]

Table 3.2 presents the estimated alpha, factor exposure, and regression R-square for two multi-factor models by state. For this table, the regression equation (3.1) is estimated with using all weekly return data for the entire sample period. A few points are noteworthy from the table. First, our five-factor statistical factor model is fairly comparable to the Fama-French three-factor model in terms of the (adjusted) regression R-squares; the average R-square across states is 0.584 for the Fama-French three-factor model and 0.583 for our statistical factor model. Second, from the estimated alphas from the Fama-French model, we can tell that stocks of Arkansas, Nebraska, and Washington performed fairly well, whereas stocks of Colorado performed very poorly during our sample period.[5] Third, from the estimated R-squares from the Fama-French model, we can tell that stock markets of California, Florida, Illinois, New York, and Pennsylvania are highly integrated with the national stock markets, whereas stock markets of Mississippi and West Virginia are less integrated with the national stock markets. Lastly, from the estimated HML factor exposure from the Fama-French model, California and Massachusetts have the lowest and negative HML factor exposures. This is expected because many technology-oriented, growth firms are headquartered in these states.

[4]We tried statistical factor models with five to ten different factors, but the results were qualitatively the same.

[5]In our statistical factor model, the five statistical factors have zero sample means by construction, so α^{SFM} simply represents the average excess state portfolio returns over the risk-free rate during the sample period. Hence, α^{SFM} should not be interpreted as abnormal returns as it should be in the Fama-French model. For this reason, statistical significance for α^{SFM} are not reported in the table.

Table 3.2: Summary Statistics for Two Alternative Models

This table reports alphas, factor exposures, and adjusted R-squares from the regression of weekly excess state portfolio returns on weekly factor returns over the entire sample period from July 1963 to December 2008. U.S. states with fewer than ten stocks on average during the sample period are excluded from the sample. Of the 44 sample states, the Hawaii sample starts from 1965 and those of Mississippi and Nebraska start from 1970. We construct weekly state portfolio returns by value-weighting the returns of all stocks within each state. For the statistical factor model, each year five factors are extracted from the covariance matrix of excess state portfolio returns over the risk-free rates. Five statistical factors have zero sample means, by construction, so α^{SFM} simply represents the average excess state portfolio returns over the risk-free return during the sample period. It should not be interpreted as abnormal returns, and statistical significance for α^{SFM} are not reported for this reason. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.2: Summary Statistics for Two Alternative Models (Continued)

	Fama-French Three-Factor Model						SFM	
State	α^{FF}		β^{MRF}	β^{SMB}	β^{HML}	R^2	α^{SFM}	R^2
Alabama	0.002		1.039	0.230	0.530	0.510	0.127	0.544
Arizona	-0.034		1.173	0.514	0.371	0.703	0.094	0.714
Arkansas	0.201	***	1.019	-0.165	-0.108	0.386	0.248	0.386
California	0.073	***	1.130	0.231	-0.362	0.804	0.117	0.747
Colorado	-0.078	*	1.047	0.514	0.058	0.570	0.012	0.588
Connecticut	0.053	*	1.102	-0.141	0.012	0.734	0.119	0.690
D.C.	-0.012		1.179	-0.139	0.696	0.336	0.125	0.389
Delaware	-0.021		1.118	-0.301	0.437	0.540	0.081	0.514
Florida	-0.034		1.129	0.426	0.264	0.816	0.078	0.821
Georgia	0.075	***	0.954	-0.246	0.129	0.683	0.139	0.648
Hawaii	0.001		0.773	0.391	0.593	0.360	0.119	0.383
Idaho	-0.017		1.089	0.362	0.278	0.367	0.091	0.419
Illinois	0.031	*	0.980	-0.117	0.158	0.872	0.103	0.838
Indiana	0.059		0.859	-0.094	-0.024	0.475	0.107	0.471
Iowa	-0.012		0.973	0.285	0.567	0.575	0.115	0.596
Kansas	-0.063		1.069	0.146	0.449	0.406	0.053	0.438
Kentucky	0.037		0.933	0.224	0.216	0.560	0.124	0.590
Louisiana	-0.012		0.958	0.063	0.330	0.515	0.082	0.535
Maine	-0.033		0.732	0.228	0.438	0.314	0.063	0.347
Maryland	0.002		1.031	0.357	0.029	0.713	0.082	0.727
Massachusetts	0.034		1.113	0.400	-0.348	0.782	0.084	0.728
Michigan	-0.034		1.091	-0.020	0.478	0.729	0.080	0.709
Minnesota	0.055	**	1.004	-0.072	0.038	0.731	0.119	0.719
Mississippi	-0.016		0.736	0.660	0.354	0.282	0.079	0.271
Missouri	0.050	**	0.933	0.058	0.151	0.756	0.125	0.773
North Carolina	-0.039		1.091	0.070	0.598	0.688	0.090	0.702
New Hampshire	0.031		1.132	0.756	0.092	0.510	0.138	0.502
New Jersey	0.053	**	0.821	-0.300	-0.013	0.695	0.092	0.615
New York	0.020		1.079	-0.124	0.062	0.870	0.089	0.837
Nebraska	0.129	**	0.939	-0.244	0.236	0.383	0.209	0.386
Nevada	-0.057		1.285	0.761	0.588	0.456	0.108	0.500
Ohio	0.028		0.878	-0.084	0.253	0.750	0.105	0.747
Oklahoma	0.027		1.022	0.173	0.294	0.351	0.125	0.410
Oregon	0.077		1.034	0.410	0.137	0.497	0.170	0.549
Pennsylvania	-0.018		1.047	0.145	0.200	0.841	0.072	0.830
Rhode Island	0.075		0.994	0.295	0.250	0.408	0.172	0.421
South Carolina	-0.043		0.917	0.471	0.317	0.594	0.062	0.589
Tennessee	-0.011		1.129	0.187	0.412	0.675	0.106	0.689
Texas	0.026		1.010	-0.082	0.169	0.756	0.103	0.711
Utah	0.001		0.960	0.267	0.370	0.529	0.107	0.557
Virginia	0.074	***	0.998	-0.116	0.185	0.655	0.150	0.633
West Virginia	-0.022		0.839	0.650	0.542	0.252	0.107	0.252
Washington	0.131	***	0.987	0.013	-0.278	0.524	0.166	0.487
Wisconsin	0.027		1.033	0.281	0.390	0.724	0.140	0.746
Average	0.019		1.008	0.166	0.240	0.584	0.111	0.583

3.3 *Evidence on the U.S. Domestic Stock Market Integration*

3.3.1 Evidence from State Portfolio Returns

In this section, we examine the level and trend of domestic market integration at the state portfolio level. Table 3.3 presents the estimation results from the regression model (3.2)

$$RSQ_t^S = \alpha^S + \beta^S(t - t_0) + \varepsilon_t, \quad t = t_0, .., 2008,$$

for each of our 44 sample states. When the hypothesized return-generating model is the Fama-French three-factor model, 38 states exhibit an increasing stock market integration and 27 of them a significantly increasing integration at least at the 10% level. In the beginning year of the sample period, the average R-square was about 0.50, but it increased to 0.68 at the end of the sample period, which represents a 36% increase in the explanatory power of the national factors over the state portfolio returns. Six states exhibit a decreasing stock market integration, but only one state—Connecticut—exhibits a significantly decreasing integration. When the hypothesized return-generating model is the statistical factor model, a stronger time trend of market integration emerges. Out of the 44 sample states, 37 states exhibit an increasing stock market integration and 30 of them a significantly increasing integration at least at the 10% level. Seven states exhibit a decreasing stock market integration, but only two states—Nebraska and New Hampshire—exhibit a significantly decreasing integration.

Table 3.3: Market Integration over Time at the State Level

For each state S and year t, we compute the regression R-square, RSQ_t^S, from the regression of weekly excess state portfolio returns on the weekly national market factors. Then, we run the following linear time-trend regression:

$$RSQ_t^S = \alpha^S + \beta^S(t - t_0) + \varepsilon_t,$$

where, t_0 represents the starting year of the state sample, which equals 1963 for all states except for Hawaii, Mississippi, and Nebraska. For Hawaii, t_0 equals 1965, and for Mississippi and Nebraska it equals 1970. Estimates of α^S and β^S are reported for each state S. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.3: Market Integration over Time at the State Level (Continued)

	Fama-French Model			SFM		
State	α^S	β^S		α^S	β^S	
Alabama	0.2417	0.0120	***	0.4009	0.0100	***
Arizona	0.5794	0.0039	**	0.6659	0.0038	***
Arkansas	0.3594	0.0022		0.8036	-0.0033	
California	0.8397	0.0006		0.8465	0.0012	
Colorado	0.5302	0.0011		0.5725	0.0049	***
Connecticut	0.8152	-0.0031	**	0.7917	-0.0015	
D.C.	0.3074	0.0046	***	0.3913	0.0098	***
Delaware	0.4099	0.0049	***	0.4938	0.0074	***
Florida	0.6496	0.0058	***	0.6949	0.0054	***
Georgia	0.5761	0.0037	*	0.6340	0.0037	**
Hawaii	0.1663	0.0096	***	0.4662	0.0035	
Idaho	0.2552	0.0052	**	0.3162	0.0144	***
Illinois	0.8338	0.0011		0.8147	0.0022	***
Indiana	0.4536	0.0011		0.5241	0.0029	
Iowa	0.4250	0.0063	***	0.4956	0.0054	***
Kansas	0.4969	-0.0032		0.4942	0.0072	***
Kentucky	0.4482	0.0039	*	0.5417	0.0038	***
Louisiana	0.3208	0.0083	***	0.5036	0.0065	***
Maine	0.1164	0.0077	***	0.2831	0.0091	***
Maryland	0.6353	0.0037	***	0.6648	0.0049	***
Massachusetts	0.6393	0.0059	***	0.6690	0.0059	***
Michigan	0.7145	-0.0001		0.6957	0.0019	
Minnesota	0.6328	0.0040	***	0.6478	0.0051	***
Mississippi	0.1671	0.0107	***	0.4460	0.0066	*
Missouri	0.6875	0.0026	**	0.7113	0.0033	***
North Carolina	0.5810	0.0045	***	0.6291	0.0047	***
New Hampshire	0.4216	0.0021		0.8565	-0.0060	***
New Jersey	0.6472	0.0014		0.6274	0.0031	*
New York	0.8609	0.0005		0.8120	0.0020	**
Nebraska	0.4889	-0.0041		0.8410	-0.0114	***
Nevada	0.3175	0.0057	***	0.6673	0.0016	
Ohio	0.7803	-0.0003		0.7839	0.0013	
Oklahoma	0.4566	0.0001		0.5333	0.0046	**
Oregon	0.4253	0.0077	***	0.7391	-0.0008	
Pennsylvania	0.7813	0.0025	***	0.7759	0.0039	***
Rhode Island	0.4417	0.0010		0.7234	-0.0035	*
South Carolina	0.3329	0.0101	***	0.4693	0.0076	***
Tennessee	0.5595	0.0055	***	0.6198	0.0059	***
Texas	0.7481	-0.0003		0.7226	0.0028	*
Utah	0.4326	0.0040	*	0.5220	0.0041	**
Virginia	0.5848	0.0020		0.5881	0.0039	**
West Virginia	0.0459	0.0102	***	0.7452	-0.0053	
Washington	0.3362	0.0080	***	0.5037	0.0060	***
Wisconsin	0.5490	0.0068	***	0.5734	0.0077	***
Average	0.5021	0.0039		0.6205	0.0036	

There exist some notable differences between the results from the statistical factor model and those from the Fama-French three-factor model, aside from the number of states that exhibit a significant time trend of integration. For such large states as Illinois, New York, and Texas, the time-trend coefficient β^S in equation (2) is not significant when the hypothesized return-generating model is the Fama-French three-factor model, whereas it is significantly positive when the hypothesized return-generating model is the statistical factor model. This difference derives from the difference in the construction of national factors between two models. The national factors in the statistical factor model are extracted from the covariance matrix of state portfolio returns, with each state weighted equally in the construction of statistical factors. In contrast, the market, size, and value factors in the Fama-French three-factor model are basically value-weighted stock returns, so they are influenced heavily by states with a larger number of public firms. Thus, when the hypothesized return-generating model is the Fama-French three-factor model, a large state is likely to exhibit a high level of integration throughout the sample period, so the intercept α^S, measuring the initial level of integration, is likely to be high, and the time-trend coefficient β^S, measuring the speed of integration, is likely to be small and insignificant. Consistent with this expectation, the five largest states in terms of market capitalization—New York, California, Texas, New Jersey, and Illinois—have large intercepts and insignificant time-trend coefficients when the hypothesized return-generating model is the Fama-French three-factor model. By identifying a different underlying return generating process and equally weighting the state portfolio returns, our statistical factor model offers an alternative insight into the level and trend of market integration across states. The results based on the statistical factor model show that four out of the five largest states also exhibits a significantly increasing integration.

Figure 3.2 displays the relation between α^S, a measure of initial level of integration,

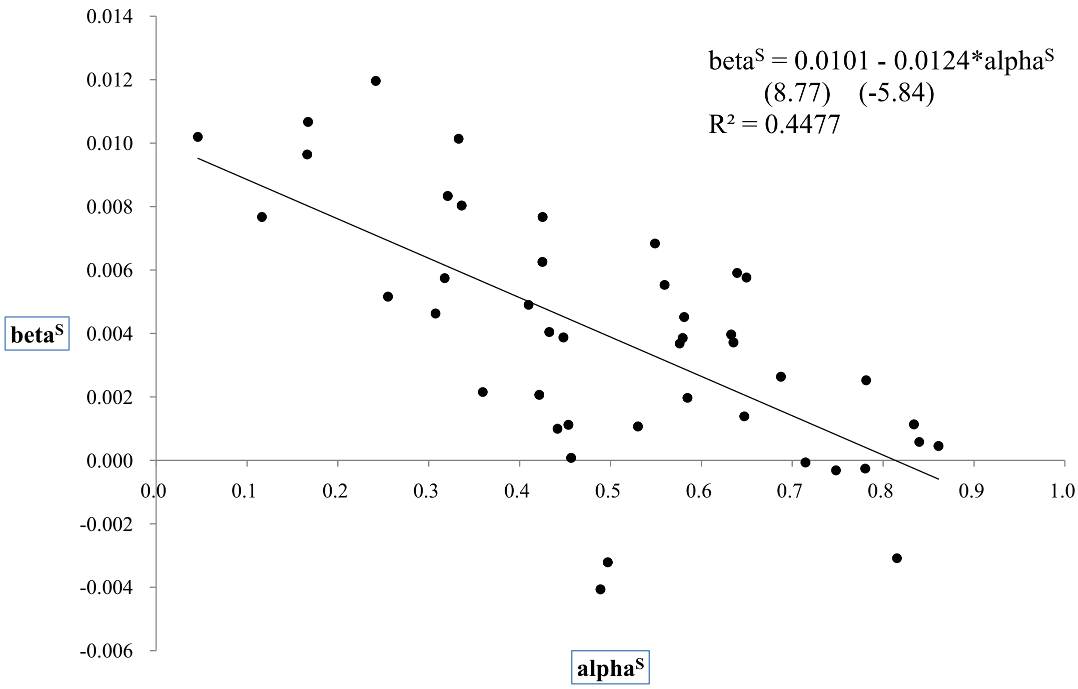

Figure 3.2: Relation between the Initial Level of Integration and Speed of Integration

This figure plots the relation between $\alpha^S$and β^S using estimates from the Fama-French three-factor model reported in Table 3. For each state S and year t, we compute the regression R-square, RSQ_t^S, from the regression of weekly state portfolio returns on the weekly Fama-French three factors. Then, we run the following linear time-trend regression:

$$RSQ_t^S = \alpha^S + \beta^S(t - t_0) + \varepsilon_t.$$

Here, t_0 represents the starting year of the state sample, which equals 1963 for all states except for Hawaii, Mississippi, and Nebraska. The fitted linear regression model is inserted within the figure. Numbers in parentheses are t-statistics.

and β^S, a measure of speed of integration. For the figure, we use estimates from the Fama-French three-factor model reported in Table 3.3.[6] The figure shows that the speed of integration is inversely related with the initial level of integration, meaning that a state that was initially less integrated with the national stock markets exhibits

[6]The results remain qualitatively the same when we use estimates from the statistical factor model.

a faster speed of integration over the sample period. The regression results, reported within the figure, show that the inverse relation is strongly significant. The R-square from the regression of β^S on α^S amounts to 44.8 percent.

To summarize, the results based on state portfolios tell us that, for the majority of our sample states, the R-square, our measure of integration, exhibits a statistically significant upward trend, implying that U.S. domestic stock markets were not fully integrated and have been integrating during the sample period. The speed of integration is faster for smaller states and those states with lower levels of integration at the beginning of the sample period. When the hypothesized return-generating model is the statistical factor model, we find a stronger trend of integration for more number of states, even for several large states.

3.3.2 Evidence from Individual Stock Returns

In the previous subsection, we have examined the domestic market integration at the state portfolio level. In this subsection, we examine the same issue but at the individual stock level. If U.S. domestic stock markets were not fully integrated and have been integrating over time, then we expect that the incremental power of the state portfolio returns over the national market factors in explaining individual stock returns exhibits a downward trend over time.

To explain our test procedure, let $\mathbf{X}$ be the national stock market factors as in equation (3.1). For the Fama-French three factor models, for example, $\mathbf{X}$ represents the three-dimensional vector of the market, size, and value factors. For each year t and state S, we first compute the state portfolio returns orthogonalized with respect to the national market factors. For this, we run the same regression as equation (3.1), i.e.,

$$r_{t,w}^S - r_{t,w}^f = \alpha + \beta' \mathbf{X}_{t,w} + \varepsilon_{t,w}, \quad w = 1, ..., 52. \tag{3.3}$$

The residual from this regression, which we denote by $r_{t,w}^{OS}$, represents the component in the state portfolio returns that is unique to the state and not explained by the national market factors. Next, for firm j headquartered in state S, we run the following two regressions

$$r_{t,w}^{j,S} - r_{t,w}^{f} = \alpha + \beta' \mathbf{X}_{t,w} + \varepsilon_{t,w}, \tag{3.4}$$

$$r_{t,w}^{j,S} - r_{t,w}^{f} = \alpha + \beta' \mathbf{X}_{t,w} + \gamma r_{t,w}^{OS} + \eta_{t,w}. \tag{3.5}$$

We denote the regression R-square from the first model (the base model) by $RSQ_t^{j,S,BM}$ and the regression R-square from the second model (the augmented model) by $RSQ_t^{j,S,AM}$. Then, compute the difference between the two and denote it by $RSQ_t^{j,S,LOC}$, i.e.,

$$RSQ_t^{j,S,LOC} = RSQ_t^{j,S,AM} - RSQ_t^{j,S,BM} \tag{3.6}$$

We refer to $RSQ_t^{j,S,LOC}$ as the local R-square since it measures the incremental explanatory power of the orthogonalized state portfolio returns over the national market factors in explaining the stock returns of firm j headquartered in state S. Then, compute the average of $RSQ_t^{j,S,BM}$ ($RSQ_t^{j,S,LOC}$) across all firms js headquartered in state S and denote it by $RSQ_t^{S,BM}$ ($RSQ_t^{S,LOC}$). Finally, to examine the time-varying influence of the national market factors and orthogonalized state portfolio returns in explaining individual stock returns, we run the following two linear time-trend regressions:

$$RSQ_t^{S,BM} = \alpha^{S,BM} + \beta^{S,BM}(t - t_0) + \varepsilon_t, \quad t = t_0, .., 2008 \tag{3.7}$$

and

$$RSQ_t^{S,LOC} = \alpha^{S,LOC} + \beta^{S,LOC}(t - t_0) + \varepsilon_t, \quad t = t_0, .., 2008. \tag{3.8}$$

Again, t_0 represents the starting year of the state sample, which is 1963 for all states except for Hawaii, Mississippi, and Nebraska.

Table 3.4: Market Integration over Time: Evidence from Individual Stock Returns

For each state S, we first regress weekly excess state portfolio returns on the weekly excess national market factors. We regard the residual from the regression as the component in the state portfolio returns that is unique to the state and not explained by the national market factors. We call the residual the orthogonalized state portfolio return. Then, for each firm j within state S, we compute the regression R-square $RSQ_t^{j,S,BM}$ from the regression of weekly excess stock returns on the base model and incremental regression R-square $RSQ_t^{j,S,LOC}$ resulting from the addition of the orthogonalized state portfolio returns to the base model. We then compute the average of $RSQ_t^{j,S,BM}$ ($RSQ_t^{j,S,LOC}$) across all firms js within state S and denote the average by $RSQ_t^{S,BM}$ ($RSQ_t^{S,LOC}$). Finally, we run the following two linear time-trend regressions:

$$RSQ_t^{S,BM} = \alpha^{S,BM} + \beta^{S,BM}(t - t_0) + \varepsilon_t$$

and

$$RSQ_t^{S,LOC} = \alpha^{S,LOC} + \beta^{S,LOC}(t - t_0) + \varepsilon_t.$$

Here, t_0 represents the starting year of the state sample, which is 1963 for all states except for Hawaii, Mississippi, and Nebraska. For Hawaii, t_0 equals 1965, and for Mississippi and Nebraska it equals 1970. Estimates of $\beta^{S,BM}$ and $\beta^{S,LOC}$ are reported for each state S and for each of two base models. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. respectively.

Table 3.4: Market Integration over Time: Evidence from Individual Stock Returns (Continued)

	Fama-French Model				SFM			
State	$\beta^{S,FF}$		$\beta^{S,LOC}$		$\beta^{S,SFM}$		$\beta^{S,LOC}$	
Alabama	0.0004		-0.0041	***	0.0003		-0.0032	***
Arizona	-0.0014	*	-0.0014	***	-0.0013		-0.0011	***
Arkansas	-0.0003		-0.0056	***	-0.0040	***	-0.0011	***
California	-0.0007		0.0001		0.0000		-0.0001	
Colorado	-0.0006		-0.0011	***	0.0003		-0.0010	***
Connecticut	-0.0005		-0.0001	*	0.0001		-0.0002	***
D.C.	0.0026	***	-0.0035	***	0.0030	***	-0.0032	***
Delaware	0.0001		-0.0018	***	0.0012		-0.0015	***
Florida	-0.0006		-0.0004	***	-0.0001		-0.0004	***
Georgia	-0.0005		-0.0006	***	0.0000		-0.0005	***
Hawaii	0.0008		-0.0067	***	-0.0011		-0.0039	***
Idaho	0.0001		-0.0045	***	0.0009		-0.0045	***
Illinois	-0.0004		0.0000		0.0003		-0.0002	**
Indiana	-0.0006		-0.0013	***	0.0001		-0.0011	***
Iowa	0.0007		-0.0015	***	0.0008		-0.0013	***
Kansas	-0.0006		-0.0022	***	-0.0006		-0.0021	***
Kentucky	-0.0002		-0.0017	***	0.0006		-0.0015	***
Louisiana	0.0012		-0.0016	***	0.0019	*	-0.0012	***
Maine	0.0011		-0.0054	***	0.0004		-0.0040	***
Maryland	0.0005		-0.0008	***	0.0009		-0.0008	***
Massachusetts	0.0008		-0.0003	***	0.0013		-0.0003	***
Michigan	0.0002		0.0000		0.0007		-0.0002	**
Minnesota	-0.0007		-0.0005	***	-0.0001		-0.0006	***
Mississippi	0.0024	**	-0.0092	***	-0.0054	*	-0.0009	*
Missouri	0.0005		-0.0004	***	0.0013		-0.0004	***
North Carolina	-0.0004		-0.0009	***	0.0003		-0.0009	***
New Hampshire	-0.0010		-0.0029	***	-0.0038	***	0.0000	
New Jersey	-0.0009		-0.0001		-0.0001		-0.0001	
New York	-0.0001		0.0001		0.0005		0.0000	
Nebraska	-0.0017		-0.0032	***	-0.0022		-0.0013	**
Nevada	-0.0007		-0.0056	***	-0.0035	***	-0.0023	***
Ohio	0.0001		0.0000		0.0008		-0.0001	
Oklahoma	0.0000		-0.0001		0.0015		-0.0007	***
Oregon	-0.0005		-0.0071	***	-0.0061	***	-0.0008	**
Pennsylvania	0.0002		-0.0001		0.0010		-0.0002	**
Rhode Island	-0.0013		-0.0015	***	-0.0019	***	-0.0004	
South Carolina	0.0002		-0.0024	***	0.0003		-0.0018	***
Tennessee	0.0002		-0.0010	***	0.0008		-0.0010	***
Texas	-0.0004		0.0006	***	0.0007		0.0000	
Utah	-0.0002		-0.0014	***	-0.0005		-0.0014	***
Virginia	-0.0013		-0.0005	***	-0.0008		-0.0005	***
West Virginia	0.0008		-0.0140	***	-0.0080	***	-0.0050	***
Washington	0.0005		-0.0019	***	0.0006		-0.0015	***
Wisconsin	0.0019	*	-0.0010	***	0.0027	***	-0.0010	***
Average	0.0000		-0.0022		-0.0004		-0.0012	

Table 3.4 presents the results from the regression equations (3.7) and (3.8). When the base model is the Fama-French three-factor model, 34 out of the 44 sample states have a significantly negative slope estimate of $\beta^{S,LOC}$ at the 1% level and one state at the 10% level. However, Texas has a significantly positive slope estimate of $\beta^{S,LOC}$ at the 1% level. When the base model is our statistical factor model, 36 out of 44 sample states have a significantly negative slope estimate of $\beta^{S,LOC}$ at the 5% level and one state at the 10% level. Not a single state has a significantly positive slope estimate when the base model is our statistical factor model.

The results based on individual stock returns corroborate the earlier results based on state portfolio returns in Section 3. For the majority of our sample states, once the influence of national market factors is controlled for, the role of state portfolio returns in explaining the individual stock returns has declined over time, indicating an increasing U.S. stock market integration over time.

3.4 Local Economic Fundamentals and Domestic Stock Market Integration

The evidence thus far shows that there is a significant trend of greater integration within the U.S. stock market over the past half century. For the majority of our sample states, national stock market factors now explain a greater portion of the state portfolio returns. Over the same time period, state portfolio returns exhibit a strong downward trend in its ability to explain individual stock returns within the state, indicating the declining influence of home state factor on individual stock returns. In this section, we explore possible explanations for the increasing integration of the U.S. stock market.

Increasing economic linkage across states and changes in state level economic structure could be the driving force behind the increasing market integration at the state level. In this section, we first examine whether the increase in market integration is a result of changing industrial structure at the state level. We then examine whether the state level results are largely 'state' specific, driven by regulation changes and policy changes at the state level. To this end, we re-examine the market integration results at the census regional level. Lastly, we examine whether increase in economic linkages across the states and between the state and the national market helps to explain the increase in market integration.

3.4.1 Industrial Structure and Market Integration

Industries tend to cluster geographically, at both state and local levels. The clustering of industries at the state level could have direct impact on the explanatory power of the national market index on the state portfolios (Kumar, Page, and Spalt, 2009). Changes of industrial structure over time at the state level, and to a lesser extent, at the national level may induce changes in the measured market integration. For example, increasing industrial diversification at the state level, as measured by both overall economic activity and the presence of public firms across industries, could alter the return structure of the state portfolio and its correlation with the national market portfolio. To examine whether changes in local industry structure helps to explain the increasing integration of the U.S. stock market during the sample period, we introduce a measure of industrial concentration at the state level in our analysis of time trend of market integration.

We use the Herfindahl-Hirschman index (HHI) of the market capitalizations of the public firms in a state as a measure of industry concentration in the state. For industry classification, we use the 30 industry classification from the Kenneth French's data library. We construct the Herfindahl-Hirschman index for each state and each year to capture changes in industrial concentration at the state level over time. To assess the impact of industrial structure on the market integration and examine the robustness of the documented market integration results, we add the Herfindahl-Hirschman index to the base model (2):

$$RSQ_t^S = \alpha^S + \beta^S(t - t_0) + \gamma^S HHI_t^S + \varepsilon_t. \tag{3.9}$$

Table 3.5 presents the regression results for the above model. The changes of industry structure at the state level has a noticeably negative effect on the level of market integration. In the above regression, HHI is significantly negatively related to the measured R-squares for many states. The results suggest that for those states that experience greater industrial diversification (i.e., a declining HHI), the state portfolios exhibit greater integration with the national market.

Nevertheless, changes of industrial structure are not the driving force behind the increase in the U.S. stock market integration. We can compare the results here with the HHI in the regression with the results in Table 3.3. As can be seen readily from the two tables, the inclusion of the HHI variable in the regression has relatively little impact on the significance of the time trend variable in the regression. Based on the Fama and French three-factor model, 27 states show a significantly increasing market integration without controlling for changes in the industry concentration, and 20 states exhibit a significantly increasing market integration with controlling for the effect of industry concentration.

Table 3.5: The Effect of Industrial Structure on Market Integration

Foe each state S and year t, we compute the regression R-square, RSQ_t^S, from the regression of weekly excess state portfolio returns on the weekly national market factors. Then, we run the following linear time-trend regression:

$$RSQ_t^S = \alpha^S + \beta^S(t - t_0) + \gamma^S HHI_t^S + \varepsilon_t,$$

where t_0 represents the starting year of the state sample, which equals 1963 for all states except for Hawaii, Mississippi, and Nebraska. For Hawaii, t_0 equals 1965, and for Mississippi and Nebraska it equals 1970. HHI_t^S represents the Herfindahl-Hirschman index of the market capitalizations of the public firms headquartered in state S as a measure of industry concentration in the state. For industry classification, we use the 30 industry classification from the Kenneth French's data library. Estimates of α^S, β^S, and γ^S are reported for each state S. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.5: The Effect of Industrial Structure on Market Integration (Continued)

	Fama-French Model					SFM				
State	α^S	β^S		γ^S		α^S	β^S		γ^S	
Alabama	0.4423	0.0093	***	-0.4695	***	0.4329	0.0096	***	-0.0750	
Arizona	0.6382	0.0033	*	-0.2375		0.7175	0.0033	**	-0.2084	
Arkansas	0.5876	0.0056	***	-0.5308	***	0.6885	-0.0051	***	0.2676	*
California	0.8705	0.0005		-0.1745		0.8355	0.0013		0.0624	
Colorado	0.8300	-0.0011		-1.1407	***	0.7142	0.0039	*	-0.5393	
Connecticut	0.8884	0.0013		-0.5687	***	0.8821	0.0039	**	-0.7022	***
D.C.	0.6788	0.0042	***	-0.8904	***	0.7780	0.0094	***	-0.9270	***
Delaware	0.3893	0.0051		0.0227		0.2135	0.0103	***	0.3101	
Florida	0.9963	-0.0001		-1.3093	***	1.0486	-0.0006		-1.3359	***
Georgia	0.9057	-0.0003		-1.1954	*	0.9736	-0.0003		-1.2316	***
Hawaii	0.3243	0.0078	***	-0.3215	***	0.4612	0.0036		0.0102	
Idaho	0.5796	0.0046	***	-0.8760	***	0.3240	0.0144	***	-0.0209	
Illinois	0.9672	0.0010		-1.4082	***	0.9442	0.0021	***	-1.3680	***
Indiana	0.5829	0.0021		-0.4255		0.5690	0.0033		-0.1480	
Iowa	0.5855	0.0046	**	-0.6376	*	0.5975	0.0043	**	-0.4050	
Kansas	0.7915	0.0035	*	-1.3745	***	0.5654	0.0088	***	-0.3320	
Kentucky	0.7838	0.0005		-0.9874	***	0.7029	0.0022		-0.4744	
Louisiana	-0.0946	0.0124	***	1.1316	**	0.0940	0.0105	***	1.1156	*
Maine	0.2117	0.0064	***	-0.1439		0.2313	0.0097	***	0.0782	
Maryland	0.7154	0.0044	***	-0.4674		0.8269	0.0063	***	-0.9454	*
Massachusetts	0.6151	0.0059	***	0.1244		0.6351	0.0060	***	0.1743	
Michigan	1.0848	-0.0040		-1.4064	*	1.2047	-0.0036		-1.9333	***
Minnesota	0.8734	0.0002		-0.6082	**	0.9712	0.0000		-0.8175	***
Mississippi	0.1413	0.0110	***	0.0415		-0.1116	0.0146	***	0.8968	***
Missouri	0.7782	0.0026	**	-0.8086		0.8852	0.0032	***	-1.5495	
North Carolina	0.7060	0.0093	***	-0.9652	***	0.7230	0.0082	***	-0.7248	***
New Hampshire	0.3907	0.0020		0.0810		0.7846	-0.0060	***	0.1886	
New Jersey	0.9543	-0.0002		-0.8692	*	0.8987	0.0017		-0.7677	*
New York	0.7718	-0.0002		0.7091	*	0.7620	0.0016		0.3977	
Nebraska	0.7534	-0.0070	***	-0.3598	**	0.9537	-0.0127	***	-0.1534	
Nevada	0.6637	0.0046	***	-0.9023	***	0.5769	0.0019		0.2356	
Ohio	0.9549	0.0004		-1.3863	***	0.9368	0.0019	*	-1.2138	***
Oklahoma	0.4768	-0.0001		-0.0417		0.6851	0.0034		-0.3139	
Oregon	0.7054	0.0021		-0.5184	***	0.5157	0.0037	*	0.4134	***
Pennsylvania	0.9587	0.0034	***	-1.5081	***	0.9630	0.0048	***	-1.5909	***
Rhode Island	0.7162	-0.0019		-0.5735	*	0.6356	-0.0025		0.1832	
South Carolina	0.6171	0.0058	***	-0.7506	***	0.6068	0.0055	***	-0.3631	**
Tennessee	0.8398	0.0007		-0.7150	***	0.8274	0.0023		-0.5295	***
Texas	0.7474	-0.0003		0.0027		0.7947	0.0030	***	-0.2770	
Utah	0.9314	-0.0001		-1.5511	***	0.7986	0.0019		-0.8601	
Virginia	0.9313	0.0020		-1.2335	***	0.8689	0.0039	***	-0.9995	***
West Virginia	0.1722	0.0092	***	-0.1766		1.3313	-0.0098	***	-0.8195	***
Washington	0.6699	0.0046	***	-0.6590	***	0.6693	0.0043	**	-0.3269	**
Wisconsin	0.8691	0.0015		-1.2630	***	0.9257	0.0018		-1.3903	***
Average	0.6818	0.0029		-0.6214		0.7146	0.0032		-0.4320	

3.4.2 Regional Stock Market Integration

Our evidence of increasing market integration within the U.S. is based on stock returns at the state level. Since many of the regulations of financial and economic activity in the U.S. are mandated at the state level (for example, banking regulations and corporate governance regulations), the increasing stock market integration we observe could be related to changes of regulation (particularly de-regulation) at the state level over the sample period. We now examine the time trend in the regional stock market integration with the national stock market. The regional level results can help to assess this explanation and further serve as a robustness check for the state level results.

We divide the U.S. into nine regions based on the U.S. Census region and division classification. The nine regions and the constituent states of each region are listed in the Appendix. Each of the regions is not only comprised of geographically proximate areas or states but also exhibits a high degree of social, cultural, and economic integration within the region. For the regional analysis, we first construct value-weighted regional portfolios, and then use the same multi-factor models used in the state level analysis to obtain the R-square for each region and year. Table 3.6 presents the time trend results for the nine regions.

As can be seen in Table 3.6, the time trend coefficient is positive for all nine regions, with three of them significant at the 10% level for the Fama-French three-factor models. With the statistical factor model, seven regions show significantly positive time trend at the 10% level. The somewhat weaker results at the regional level are not unexpected. These regions encompass large socio-economic areas and are diversified at the stock market level. Evidence at the regional level suggests that the state level results are robust, and the increasing integration at the state level is unlikely to be driven by overall changes in state regulations and policies.

Table 3.6: Market Integration at the Regional Level

This table reports the results of Table 3 by census region. The regional portfolio returns are constructed by value-weighting the returns of state portfolios within each region. In our sample, Pacific region includes CA, HI, OR, and WA; Mountain includes AZ, CO, ID, NV, and UT; West North Central includes IA, KS, MN, MO, and NE; East North Central includes IN, IL, MI, OH, and WI; Middle Atlantic includes NJ, NY, and PA; New England includes CT, ME, MA, NH, and RI; South Atlantic includes DC, DE, FL, GA, MD, NC, SC, VA, and WV; East South Central includes AL, KY, MS, and TN; and West South Central includes AR, LA, OK, and TX. For the two-letter state code, please refer to Table 1. For each region Reg and year t, we compute the regression R-square, RSQ_t^{Reg}, from the regression of weekly national market factors. Then, we run the following linear time-trend regression:

$$RSQ_t^{Reg} = \alpha^{Reg} + \beta^{Reg}(t - t_0) + \varepsilon_t.$$

Here, t_0 represents the starting year of the regional sample and equals 1963 for all nine census regions. Estimates of $\alpha^{Reg}$and β^{Reg} are reported for each census region Reg. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	Fama-French Model			SFM		
Region	α^{Reg}	β^{Reg}		α^{Reg}	β^{Reg}	
Pacific	0.6075	0.0026		0.5846	0.0038	**
Mountain	0.5086	0.0031	*	0.5077	0.0058	***
West North Central	0.5638	0.0014		0.5488	0.0027	
East North Central	0.6070	0.0011		0.5561	0.0032	*
Middle Atlantic	0.5953	0.0023		0.5371	0.0038	*
New England	0.6095	0.0018		0.5886	0.0029	
South Atlantic	0.5469	0.0038	**	0.5360	0.0050	***
East South Central	0.4863	0.0044	***	0.4977	0.0052	***
West South Central	0.5251	0.0020		0.4876	0.0045	***

3.4.3 Stock Market Integration and Economic Integration

U.S. states have enjoyed a high level of economic integration for a considerable period of time. Traditionally, the U.S. states have been subject to few restrictions on cross-state movements of production, capital, and labor. For example, by the late 1950s, there was no correlation between state investment rates and state saving rates, indicating free capital flow across state borders (Sinn, 1992). While there was substantial increasing economic integration and convergence in the early period of the U.S economic development, there is little evidence suggesting that overall economic integration at the state level has changed noticeably over the past half century (Barro and Sala-i-Martin, 1991, 1992; Kenworthy, 1999).

It is difficult to fully evaluate whether and how much the increasing stock market integration at the state level could be related to the increasing economic integration in the overall U.S. economy. The lack of evidence on the changing economic integration in our sample period and our evidence based on home bias in the next section leads us to believe that the observed increasing market integration is unlikely to be solely driven by increasing economic linkage across states within the U.S.

3.5 Local Bias and Domestic Market Integration

Extant studies on local bias provide robust evidence that both institutional investors and individual investors exhibit such bias: they prefer to invest in stocks that are located nearby (Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2005; Zhu, 2002). Recent studies further show that local bias can induce local and regional differences in the cost of capital of the firms, the comovement of stock prices, and the risk and return trade-off and that it could also contribute directly to geographical segmentation within the U.S. market (Grinblatt and Keloharju, 2001; Hong, Kubik, and Stein, 2005, 2008; Pirinsky and Wang, 2006; Korniotis and Kumar, 2008). While the documented impacts of local bias on the financial markets are far-reaching, there is little evidence on the cross-state differences in local bias and whether there are changes in the extent of local bias over time. We now turn to examine whether and how investor behavior, particularly local bias, contributes to the geographic segmentation of the U.S. domestic stock market and the increasing integration over time.

To establish a direct link between home bias and market integration, we compute a measure of home bias at the state level based on the degree of comovement between the growth of dividends paid by corporations in the state and the growth of dividends received by residents in the state.[7] Mathematically, our measure of home bias at the

[7]See Agronin (2003) for an earlier application of this method and related discussions. We obtain the state-level dividend income data from Bureau of Economic Analysis and construct the state-level

state level is calculated as follows:

$$HB^S = \frac{Cov(\Delta DR_t^S - \Delta DR_t, \Delta DC_t^S - \Delta DC_t)}{Var(\Delta DC_t^S - \Delta DC_t)}, \quad (3.10)$$

where DR_t^S and DC_t^S represent dividends received by residents of state S in year t and dividends paid by companies headquartered in state S in year t, respectively. ΔDR_t^S and ΔDC_t^S represent the growth rate of dividends received by residents and the growth rate of dividends paid by companies headquartered in state S. Note that HB^S measures indirectly the propensity of investors to invest in local companies, i.e., the degree of home bias.

As a preliminary analysis, we first examine the bivariate relationship between ΔHB^S and ΔRSQ^S. Here, Δx represents the change in x values over two sub-periods: 1963-1985 and 1986-2008. Figure 3.3 shows that ΔHB^S and ΔRSQ^S are significantly negatively related, suggesting that the decreased home state bias could be a contributing factor to the increased market integration over the two sub-periods. The figure also shows that the home state bias proxied by HB decreased for 26 out of our 44 sample states over two sub-periods and that, in general, states where the home state bias increased over the two sub-periods do not exhibit market integration, either.

Next, to examine the effect of home bias on the trend of integration more closely, we run the following cross-sectional regression

$$\Delta RSQ^S = a + b_1 \Delta HB^S + b_2 \Delta HHI^S + b_3 \Delta DI^S + b_4 \Delta PcPI^S + \varepsilon, \quad (3.11)$$

where ΔRSQ^S represents the change in the R-square between two sub-periods from the regression of state portfolio returns on the Fama-French three-factor model or our statistical factor model; ΔHB^S represents the change in the measured home bias between two sub-periods; ΔHHI^S represents the change in the degree of industry concentration measured by Herfindahl-Hirschman index (HHI) between two sub-periods;

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dividend payment by using dividend data from COMPUSTAT.

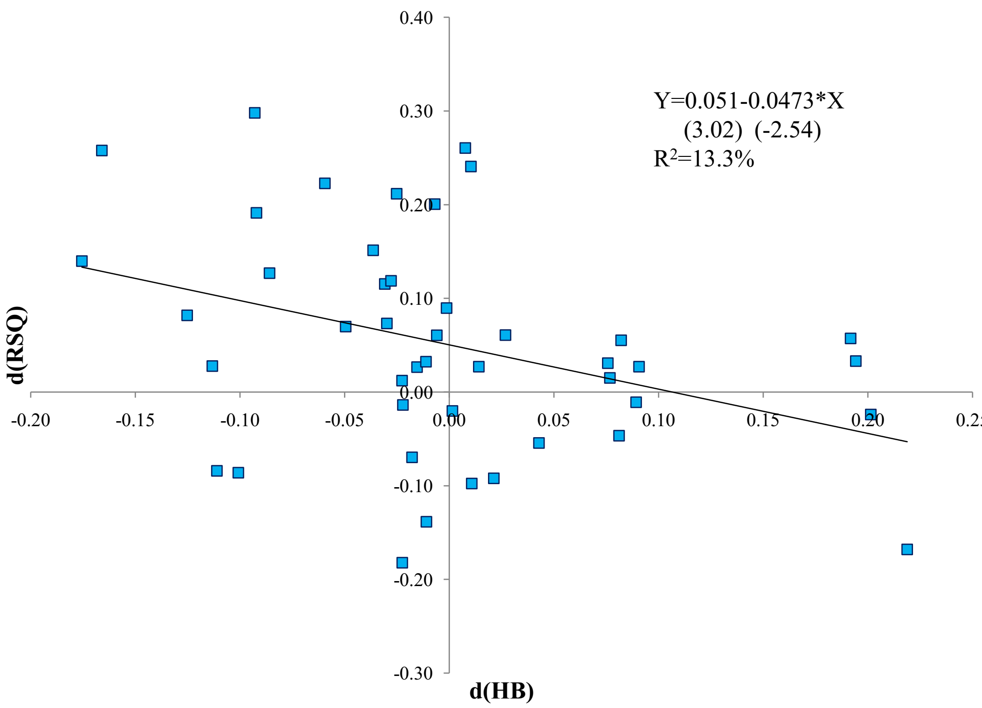

Figure 3.3: Relationship between Δ(Home Bias) and Δ(RSQ)

This figure plots the relation between ΔHB^S and ΔRSQ^S. Here, Δx represents the change in x values over two sub-periods: 1963-1985 and 1986-2008. For each sub-period and each state S, we compute a measure of home bias, HB^S, using the following formula:

$$HB^S = \frac{Cov(\Delta DR_t^S - \Delta DR_t, \Delta DC_t^S - \Delta DC_t)}{Var(\Delta DC_t^S - \Delta DC_t)}.$$

Here, DR_t^S and DC_t^S represent dividends that are received by residents of state S in year t and dividends that are paid by companies headquartered in state S in year t, respectively. ΔDR and ΔDC represent the growth rates of dividends received by residents and paid by companies, respectively. RSQ^S are estimated by using the Fama-French three-factor model for each sub-period. The fitted linear regression model is inserted within the figure. Numbers in parentheses are t-statistics.

ΔDI^S represents the change in the ratio of dividend income to dividend income plus interest income between two sub-periods; and $\Delta PcPI^S$ represents the change in the ratio of per-capita personal income of state S to national per-capita personal income between two sub-periods. The two variables, ΔDI^S and $\Delta PcPI^S$, are included to control for the effect of economic integration across states (Barro and Sala-i-Martin,

Table 3.7: Home Bias and Market Integration

We divide our sample period into two sub-periods: 1963-1985 and 1986-2008. For each sub-period and each state S, we compute a measure of home bias:

$$HB^S = \frac{Cov(\Delta DR_t^S - \Delta DR_t, \Delta DC_t^S - \Delta DC_t)}{Var(\Delta DC_t^S - \Delta DC_t)}.$$

Here, DR_t^S and DC_t^S represent dividends that are received by residents of state S in year t and dividends that are paid by companies headquartered in state S in year t, respectively. ΔDR and ΔDC represent the growth rate of dividends received by residents and paid by companies, respectively. In the table, the 'dividends common' does not include stock dividends and preferred stock dividends whereas 'dividends total' include all dividends paid. After obtaining the measure of home bias, we run the following cross-sectional regression:

$$\Delta RSQ^S = a + b_1 \Delta HB^S + b_2 \Delta HHI^S + b_3 \Delta DI^S + b_4 \Delta PcPI^S + \varepsilon,$$

where ΔRSQ^S represents the change in R-square between two sub-periods from the regression of state portfolio returns on the national market factors; ΔHB^S represents the change in the measured home bias between two sub-periods; ΔHHI^S represents the change in the degree of industry concentration measured by Herfindahl-Hirschman index (HHI) of the market capitalizations of the public firms in state S between two sub-periods; ΔDI^S represents the change in the ratio of dividend income to dividend income plus interest income between two sub-periods; and $\Delta PcPI^S$ represents the change in the ratio of per-capita personal income of state S to national per-capita personal income between two sub-periods. The star symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	Fama-French Model			SFM		
Variable	Estimate	t-stat		Estimate	t-stat	
Panel A: Dividends= Dividends Total						
Intercept	0.01379	0.68		0.03145	1.66	
ΔHB^S	-0.56707	-3.01	***	-0.53025	-3.01	***
ΔHHI	-0.57214	-3.69	***	-0.58870	-4.07	***
ΔDI	-0.14003	-0.44		-0.21489	-0.72	
$\Delta PcPI$	0.25469	0.99		0.18492	0.77	
Panel B: Dividends= Dividends Common						
Intercept	0.00706	0.33		0.02509	1.25	
ΔHB^S	-0.36911	-2.11	**	-0.35108	-2.15	**
ΔHHI	-0.56981	-3.50	***	-0.58661	-3.86	***
ΔDI	0.01800	0.05		-0.06786	-0.22	
$\Delta PcPI$	0.19060	0.70		0.12730	0.51	

1991, 1992; Sinn, 1999).

Table 3.7 presents the regression results. It shows that the change in the measured home bias is significantly negatively related to the change in the regression

R-square, our measure of integration, regardless of the underlying return-generating models, even after controlling for the change of industry concentration, the change of dividend income relative to total investment income (dividend plus interest income), and the change of personal income. The results indicate that investors' pursuit of nation-wide investment opportunities could be a significant driver of domestic financial integration.

3.6 Summary and Concluding Remarks

We document a significant variation in the level of stock market integration across U.S. states and trends toward greater integration at the state level during the period of 1963-2008. For the majority of the states, national stock market factors now explain a much greater portion of the state portfolio returns than they did a half century ago. Over the same time period, state portfolio returns exhibit a strong downward trend in its ability to explain individual stock returns within the state. The strong time trend of greater integration in the U.S. domestic market is surprising in a way because U.S. economic activities were already well integrated at the national level and there were few explicit barriers to cross-state economic activities and capital flows at the beginning of our sample period. Our analyses suggest that changes in the state economic structure and economic linkage across states are unlikely to explain the time trend of market integration within the U.S. domestic market.

We argue that investor behavior, and particularly local bias, helps to explain the cross-state differences in market integration and the time trend of market integration. We show that changes in home bias measured at the state level are significantly negatively related to changes in market integration over the sample period. While it is difficult to attribute the decline in local bias to a single source, the growth of professional investment industries and the development of information technology that facilitates trading and information transmission across states and regions are likely to be such candidates that can explain both the decline of local bias and the increase of market integration over time.

Our results on market integration within the U.S. offer insights into important questions arising from the studies of international market integration. The level of integration in the U.S. market provides an upper limit to the level of global integration. Reductions of explicit barriers to cross-border economic activities and international investment alone are unlikely to lead to full global market integration. The changes of market integration within the U.S. also suggest that social as well as political integration across the globe may have contributed substantially to the observed increasing global integration over the past few decades (Pukthuanthong and Roll, 2009).

We provide new evidence that highlights the importance of investor behavior in determining the market outcome. The results show that, in the absence of significant barriers to economic activities and investments, investors' portfolio choices could matter significantly for asset pricing. The evidence of geographical segmentation in the U.S. stock market implies that investors could benefit considerably by diversifying their portfolios across states and regions. Interestingly, investor local bias, the tendency to invest in stocks that are located nearby, may have contributed directly to the geographical segmentation of the U.S. stock market.

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