Commonality in ETF Mispricing and Contagion

Markus S. Broman[1]

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Abstract

A common component in the mispricing of ETFs can arise from limits to arbitrage. I find strong evidence of commonality among of international country ETFs. Differences in systematic risk between an ETF and its underlying index can explain some of this effect. While non-synchronicity alone cannot explain it, it does amplify the effect. I then investigate whether this commonality can be a channel of *contagion* between ETFs. Consistent with this hypothesis I find that extreme shocks to financial markets are followed by large changes in the systematic risks of ETFs. Extreme shocks to U.S. market returns or volatility generally amplify the over- and under-exposure to subsequent U.S. and regional market movements that already exists in normal times. These findings imply not only that ETF returns are *excessively* volatile in comparison to their underlying index, but also that *local risk* matters for the pricing of these ETFs, particularly in adverse markets.

Keywords: **C**ontagion, ETF, mispricing, market efficiency, arbitrage, international finance.

[1] Finance Department, Schulich School of Business, York University, 4700 Keele St., Toronto, Ontario M3J 1P3, Tel: (416) 736-2100 ext. 44655, e-mail: mbroman10@schulich.yorku.ca

1 Introduction

ETF mispricing can arise from limits to arbitrage when the "in-kind" share creation/redemption process does not operate smoothly. For instance, in the case of international ETFs an arbitrageur is exposed to several types of risks, namely the timing risk due to the non-simultaneous trading of ETF shares and the underlying portfolio, the unpredictable transaction costs associated with less liquid assets and other trading restrictions. The extent of ETF mispricing is often analyzed from the perspective of *idiosyncratic* risk. For instance, Petajisto (2011) design a methodology to correct for the staleness in NAVs that arises for funds investing internationally. Despite the simplicity and intuitive appeal of the proposed method, the author admits that "it does not capture a possible *systematic* mispricing for an entire fund group".

Anecdotal evidence does, however, suggest that systematic mispricing of ETFs can occur, particularly in distressed markets. For instance, during the Flash Crash in May 2010 the prices of ETFs declined dramatically across the board. ETFs as an asset class accounted for roughly 70 % of all the transaction that were subsequently cancelled, i.e. where prices dropped by more than 60 %. Even the largest and most liquid ETF, the SPDR tracking the S&P 500, declined by 8-9 %. Another example occurred in the week after President Bush signed into law the $700 billion Troubled Asset Relief Program (TARP); the mispricing on SPDR increased by 1.29 % (or 2.5 standard deviations), while mispricing increased on average by 5.80 % (or 4.0 standard deviations) for a group of international country ETFs. In fact, *every* country ETF became even more *underpriced* w.r.t. the NAV indicating that a common force was driving the mispricing's for all ETFs in the same direction.

In this paper I investigate whether there is a *common* component in the mispricing of ETFs and if so, whether it has any effect on the *systematic riskiness* of an ETF compared to its underlying benchmark, especially in periods of distress in financial markets. I begin by documenting the existence of commonality in the tracking performance of a group of international country ETFs and find significant evidence in support of this hypothesis. I find that some of this commonality indeed comes from differences in the systematic risk exposure of the ETF vis-à-vis its underlying portfolio of assets, but much of it remains intact even after controlling for some commonly used systematic risk factors.

A similar phenomenon has previously been documented by Bodurtha *et al.* (1995), who find that changes in country Closed-End Fund premiums move together mainly because CEF returns are affected by U.S. market movements, while the other leg of mispricing (the NAV) is not. In contrast to their study, I find that differences in returns between NAV and the underlying index are also correlated across ETFs, possibly due to the use of a common replication strategy across funds or periodic changes in the composition of the underlying index, but it only captures a relatively small portion of the overall degree of commonality.

My results highlight the importance of *trading location* in the pricing of these ETFs as commonality. The first piece of evidence to suggest this is that commonality is greatest for the Asian country funds. Non-synchronicity does not fully explain this phenomenon as commonality is strong not only for the European funds where there is some overlap in trading hours with the U.S. market, but also for the country funds of Canada, Brazil and Mexico where trading hours are aligned with the U.S. Even more convincingly of the trading location hypothesis, all country funds are significantly *over-exposed* to U.S. market movements (by 32.56 % on average) and most are significantly *under-exposed* to regional markets (by 21.00 % on average). A direct implication of this is that these ETFs are *excessively volatile* in comparison to their underlying benchmark. Several previous studies have also found evidence to suggest that trading location matters in the sense that local risk (or investor sentiment) affects the prices of securities traded in these markets (Bodurtha *et al.* 1995; Chan *et al.*, 2003 and Feng and Seasholes, 2004). The local pricing of risk hypothesis is further reinforced by the findings in Shum (2010) who documents that the iShares East Asian country ETFs behave more like large cap U.S. stocks in that their daily price movements are better explained by the return on S&P500 rather than the overnight returns of the underlying benchmark index.

In the second part of the paper I investigate whether the *degree of commonality* in mispricing changes in adverse market conditions, an indication of *contagion* between ETFs. I begin by documenting the extent to which limits to arbitrage can explain the time-series variation in commonality and find some evidence to support this notion; commonality is *greater* following large negative shocks to U.S. markets or to the financial sector, but somewhat surprisingly, also when overall level of ETF market liquidity is high. Using the financial crisis in 2007-2009 as a "natural" experiment, I show that while the overall level of commonality does not change in this time-period, that part which is attributed to differences in systematic risk exposure is significantly stronger for the European country funds. More specifically, I find that the European country funds become even *more under-exposed* to the regional market during the financial crisis with the average exposure decreasing from -0.229 to -0.380. In comparison, the average European MSCI country index has a regional factor loading of about 1.004, which indicates a large difference in systematic risk exposures.

A problem with any crisis dating procedure is that it may not be accurate enough to pinpoint episodes of distress in financial markets, particularly when the impact of such episodes is short-lived. In order to circumvent this problem I develop a methodology to *identify contagion* from extreme shocks to financial markets. In a factor pricing model contagion can be identified from changes in factor loadings following an unexpected shock (Bekeart *et al.*, 2012). The key insight in my model is that I allow the factor loadings to be affected by a shock to financial markets via a transition function, with the degree of *non-linearity* to be determined from the data. This functional form can, for instance, capture a discontinuous change in the degree of commonality following large negative shocks. I quantify the unexpected shocks as coming from U.S. market returns or volatility (VIX), regional market returns or the mispricing of SPDR (a proxy for ETF market liquidity).

The strongest evidence for contagion comes from that part commonality in mispricing attributed to *differences* in systematic risk exposure between the ETF and the underlying portfolio. More specifically, I find that extreme shocks to U.S. market returns and volatility are followed by a further *decrease* in the exposure to the regional factor in almost 90 % of cases, while the exposure to the U.S. factor *increases* in about 60 % of cases. Since all country ETFs are under-exposed to the regional market and vice-versa for the U.S. market, this finding implies an *increase* in co-movements. European country funds once again show the strongest results with the average fund experiencing a decline in regional factor loadings by as much as 256 % following a 99th percentile adverse shock to U.S. volatility. Similarly, a 90th percentile adverse shock to regional markets is followed by a decline in the regional factor loading by 74 % for Europe, 153 % for Asia and 121 % for the Americas. These effects are significant at least at the 10 % level for almost seven out of ten cases.

This approach of using extreme returns to analyze contagion is closely related to several prior studies that use non-linear models to predict future stock market crashes (Longin and Solnik, 2001; Bae *et al.*, 2003; Markwat *et al.*, 2009). The advantages of using extreme returns are that the identification of crisis periods is endogenized and the effect is modeled to last for only one period. In contrast, the crisis-dating approach for identifying contagion requires making the assumption that co-movements remain elevated throughout the entire crisis-period, which may not be reasonable when the length of the crisis-period is long. This is particularly true for the ETF market since the "in-kind" redemption/creation process would be expected to restore pricing efficiency in a relatively timely manner. Petajisto (2011) argues that the sheer magnitude of the average creation/redemption transaction (1556 % of average daily volume) may delay the time it takes for pricing efficiency to be restored. Consistent with this idea he finds that mispricing predicts share creations up to a period of 10 days in the future. Although these problems are expected to be more severe for funds with higher limits to arbitrage, such as the international funds, and during periods of market distress, mispricing should be restored in a number of days, possibly weeks, but not years.

ETF contagion has previously only been analyzed from the point of view of shock propagation *from the ETF market* to the underlying assets. Itzhak *et al.* (2012) pick up on this question and find that liquidity shocks to ETF prices are transmitted to the underlying securities via the arbitrage mechanism. This effect was particularly pronounced during the Flash Crash in 2010, when the SPDR acted as a conduit for the propagation of a negative demand shock from the S&P 500 E-mini futures market into the S&P 500 constituent stocks. In contrast, I analyze whether the degree of shock propagation *between* ETFs is greater than that implied by economic fundamentals, the underlying assets held by the ETF manager.

This study should also be of particular interest to regulators. Following the Flash Crash the SEC are considering the linkages between ETF price declines and the fall in the broader equity markets as a singular research item (Borkovec *et al.* 2010). Aside from this, regulatory concerns have mainly focused on issues such as systemic risk, transparency, lack of liquidity, complexity and counterparty risk in ETFs (Aggarwal, 2012). My paper highlights the potential for systemic risk because of the commonality in mispricing and how it can be one potential channel of contagion between ETFs. In the U.S., FINRA has also highlighted its focus on ETFs in its 2011 Annual Regulatory and Examination Priorities Letter. One of the concerns is the related to the overall sales practice of ETF providers, namely that marketing materials appear to omit the material risk involved in ETFs. In this paper I emphasize that ETFs may be differently exposed to systematic risk in comparison to their underlying benchmark, and investors should be aware of these risks.

2 Background on ETFs and Arbitrage

Exchange Traded Funds (ETFs) are investment companies that typically focus on tracking the performance of a pre-specified asset class, industry or geographical area. ETFs were initially introduced in the late 1980s, but they became popular only after the introduction of the SPDR, an ETF designed to track the S&P 500. ETF growth has since then been spectacular; in the U.S. there were 81 funds with $65.6 billion in assets in 2000, while in September of 2012 the number of funds had increased to 1188 with $1158.8 billion in AUM. This asset class is also capturing a large fraction of the transaction taking place in financial markets. In the U.S., ETFs and other exchange traded products have been reported to account for roughly 40 % of all trading volume (Blackrock, 2011).

Before the proliferation of ETF most individual investors were limited to open- or closed-ended mutual funds or individual stocks. In comparison to open-ended mutual funds, ETFs can be traded throughout the day, they can be sold short or bought on margin. Other advertised advantages of ETFs are their low expense ratio and tax efficiency. Unlike ETFs, open-ended funds typically suffer from a cash drag as these fund needs to keep some cash in hand for investor redemptions. Closed-end funds avoid this cash-drag by having their shares listed on an exchange. However, as the number of shares is fixed, excess demand or supply for a CEF may result in a significant premiums w.r.t. the NAV. Similar to CEFs, ETFs also have a secondary market for trading and because of the unique arbitrage mechanism by which the number of outstanding shares can change over time, no excess demand or supply can accumulate, at least in frictionless markets.

2.1 The Arbitrage Mechanism

Excess demand or supply may cause the share price of an ETF to deviate temporarily from the value of the underlying securities (NAV). In order to clear this excess demand or supply some large investors (called Authorized Participants) can purchase or redeem ETFs shares in bundles ("creation units") with the ETF sponsor. To illustrate how the process works. consider a situation where the ETF price is *below* the NAV. An AP can then purchase the ETF shares on the secondary market, redeem them for the underlying assets held by ETF and sell the underlying assets at the prevailing market price (the NAV). Similarly, when the NAV is below the ETF price the AP can submit a portfolio that matches the composition of the underlying benchmark and get new ETF shares in return and sell the ETF shares on the secondary market.

These “in-kind” transactions will change the number of outstanding shares available for trading in the secondary market. A typical creation unit consists of 50 000 or 100 000 shares with dollar values typically ranging from 300 000 $ to 10 m€. Every creation entails a fixed fee, usually $500 to $3000, which amounts to a few basis points of the creation value. These transaction costs along with the trading costs of the underlying securities would be expected to set boundaries on how much ETF prices can deviate from its NAV.

2.2 Limits of Arbitrage

The efficiency of ETF prices should depend on the transaction costs associated with the ETF and those for the underlying assets as well any other limits to arbitrage that may hinder arbitrageurs from trying to profit from an existing mispricing. The large amount of capital devoted to arbitrage trading strategies does not necessarily improve the efficiency of prices when arbitrage is limited (see e.g. Shleifer and Vishny, 1997 and Gromb and Vayanos, 2010).

The “in-kind” share creation/redemption process exposes an arbitrageur to two risks, namely the uncertain *transaction costs* associated with the transacting of illiquid assets as well as the *timing risk* due to the non-simultaneous purchase or sale of ETF shares and the underlying portfolio. The timing risk can be a concern for securities traded in international markets such as the East Asian markets where there is no overlap in trading hours with the U.S.. In this case it may not even be possible to simultaneously enter into an offsetting transaction involving ETF shares and the underlying securities. Uncertain *transaction costs* can be a problem in markets with low liquidity. For instance, in the case of the iShares Brazil country fund (TIC: EWZ), the ETF is itself highly liquid with an average spread of only 1 bp, but the underlying portfolio is relatively illiquid with an average spread of 80 basis points (Blackrock - iShares Institutional Trading Report, September 2010). One example of where the price improvement is not restricted to an illiquid asset class is MSCI Japan; the underlying securities have a value-weighted average spread of around 16 bps, while the spread of iShares Japan (TIC: EWJ) is even tighter at around 8 bp (Credit-Suisse Trading Strategy Report, December 2012). Such price improvements may, however, prove to be a double-edged sword. On the one hand, it arguably makes the ETF more attractive to short-term investors, and it may also attract smaller investors that have insufficient capital to transact directly and efficiently in the underlying assets. On the other hand, mispricing may become greater and last for longer as a result of the large liquidity differential between the ETF and the underlying portfolio.

ETFs may also be *exposed* to *liquidity shocks* to a greater extent than the underlying securities. Consistent with this conjecture, Itzhak *et al.* (2012) finds that ETFs are a catalyst for high turnover investors, who are arguably an important source of liquidity shocks. This finding is in line with Amihud and Mendelson's (1986) clientele effect theory, as the high liquidity of ETFs may attract investors with shorter trading horizons. This is particularly relevant for less liquid asset classes (such as fixed income), as well as in international markets where transaction costs are uncertain.

During the Flash Crash in May 2010 even the most liquid ETFs decoupled from fundamentals, with the SPDR declining by about 8-9 % within a period of a few minutes. The crisis affected less liquid ETFs to a much greater extent consistent with notion of limits to arbitrage. In fact, ETFs as an asset class accounted for roughly 70 % of all the transaction that were subsequently cancelled, i.e. where prices dropped by more than 60 %. Although the Flash Crash was an extreme example of when the arbitrage mechanism can fail, it raises the question of whether this mechanism can severely weaken during less extreme episodes of distress in the financial markets.

Previous studies have also found evidence to suggest that ETF mispricing is exploitable (see e.g. Engle and Sarkar, 2006; Marshall, Nguyen, and Visaltanachoti, 2010 and Petajisto, 2011). For instance, Petajisto (2011) proposes a methodology to control for some of the measurement issues in NAVs and he finds that a trading strategy designed to exploit these cross-sectional differences in ETF premiums generates a Carhart alpha of 11 % per year. The alpha rises to as much as 26 % year if only the fund categories most prone to mispricing are used, particularly international funds.

3 Hypothesis Development

My conjecture is that there is *commonality* in the *tracking performance* of ETFs. This common component can arise because of differences in the systematic risk exposure of the ETFs vis-a-vis its underlying portfolio of securities. For example, since ETFs have been shown to attract high turnover investors who are more prone to liquidity shocks (see Itzhak *et al.*, 2012), the prices of ETFs may be affected more by such shocks in comparison to the underlying portfolio. Whether these liquidity shocks come from fundamental or non-fundamental sources, the implication is the same; the tracking performance of the affected ETFs will share a common component. This effect may be particularly strong in adverse market conditions where overall market liquidity is already low, or when arbitrage capital is scarce so that mispricing can last for longer. Previous studies have found evidence consistent with a link between the overall efficiency of the ETF market and the scarcity of arbitrage capital: Itzhak *et al.* (2012) finds that the aggregate mispricing is greater following periods of low U.S. market returns, low financial sector returns, high VIX and TED spreads. The results are particularly strong during the fall of 2008.

If the degree of commonality in tracking performance *changes* in adverse market conditions, then it may be an indication of *contagion* between ETFs. Contagion is defined by Bekeart, Harvey and Ng (2005), among others, as the co-movement between markets in *excess* of that implied by economic fundamentals. In the current context contagion arise when ETF prices co-move excessively with each other. Since the tracking performance of an ETF is already benchmarked against the underlying portfolio of assets, any remaining co-movement *between* ETF tracking deviations is an indication of contagion, particularly when such co-movements change in adverse market conditions. I conjecture that there is *contagion between ETFs* in the sense that ETF returns co-move excessively with each other following large shocks to financial markets, such as those to U.S. market returns or volatility, regional returns or shocks to ETF specific variables (such as liquidity or overall mispricing.

Commonality in tracking performance can also arise when ETF prices are affected by their *trading location* and/or the pricing of *local risk* (or country-specific investor sentiment). Such commonality in tracking performance has previously been documented in the context of closed-end funds; Bodurtha, Kim and Lee (1995) find that the premiums of international country funds move together, primarily because of their shared exposure to U.S. market movements where they are traded. The authors argue that this co-movement reflects the pricing of local risk, which they interpret as market sentiment that is not solely due to non-synchronous trading. In a similar vein, Chan *et al.* (2003) investigate the pricing of Jardine stocks for which the trading activity moved from Hong Kong to Singapore, but where the core business remained in Hong Kong and mainland China. Their main finding is that the stock prices co-move more strongly with the Singapore market, and less with Hong Kong following the delisting consistent with the pricing of local risk. Feng and Seasholes (2004) find evidence suggesting that the trading activity of retail investors in China is correlated geographically. I also conjecture that ETF returns are over-exposed to U.S. market movements and possibly under-exposed to regional market movements as a result of the pricing of local (U.S.) risk. Furthermore, ETF returns may also co-move excessively with each through their shared exposure to these two systematic risk factors. More specifically, excess co-movements can arise when the degree of systematic risk of an ETF *changes* following large negative shocks to financial markets.

4 Data

In this study I focus on a group of 20 international country ETFs by iShares[2]. These ETFs have been around for long time, most of them since December of 1996. The only exceptions are the ETFs on South Korea, Taiwan and Brazil, which started trading in May, June and July of 2000 respectively. These 20 country ETFs cover three different regions; 10 European, 7 Asian and 3 funds in the Americas. These three regions allow for an interesting comparison of the effects of non-synchronicity on mispricing. Non-synchronicity is not an issue for the 3 American ETFs as the trading hours for Canada and Mexico overlap perfectly with the U.S., while for Brazil there is a one hour lag with the US. There is partial overlap in the trading hours between Europe and the U.S., in most cases this overlap is between 1.5 and 2 hours. For the Asian markets there is no overlap in the trading hours making it impossible to transact simultaneously in the ETFs and the underlying securities.

The sample period starts on 31 May 2002 and ends on 31 December 2011. I chose this starting particular starting date to correspond with the date of a major index revision whereby all MSCI equity indices were adjusted to account for free float and the market coverage was extended from 60 % to 85 %. Tracking was more complicated before this index revision because the index was not fully investable, many of the outstanding shares are privately held and not accessible for trading.

International Country ETFs provide an interesting setting to investigate commonality in mispricing and contagion. The reason is that we can easily compare differences in systematic risk exposures of these ETFs with their underlying benchmarks' and also to contrast whether these differences exist during adverse market conditions. This is particularly relevant for U.S. investors concerned about the *actual* downside risks in their portfolio. Moreover, the econometric framework that I develop to analyze impact of extreme shocks on commonality in mispricing is highly non-linear, and focusing on a relatively small, but representative group of international equity ETFs ensures that the dimensionality of the simultaneous estimation is not too severe. While the number of international ETFs used in this study represents only a small fraction of the total number of international equity funds (206), their AUM is relatively large at about 17 % of the total. If we compare these 20 ETFs with the entire universe of U.S. based ETFs, they accounted for about 5.15 % on average with the highest fraction in 2007 (7.44 %) and the lowest in 2008 (3.62 %).

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[2] I have only excluded two country ETFs from the sample, Indonesia and South Africa. The former was has a very short history from 05/2010. The latter has a longer history from 02/2003, but it is relatively small with about 500 m$ in AUM.

A *necessary* condition for the existence of commonality in tracking performance is that limits to arbitrage exist. Petajisto (2011) finds evidence to support the existence of these limits, particularly for international equity funds. He finds that the fund categories most affected by infrequent creations and redemptions are the ones with the most difficult-to-trade underlying assets, including international equities. Given that the average creation/redemption transaction accounts for 1556 % of the average daily volume, this finding suggests that it may take some time for mispricing to be corrected. Consistent with this idea, Petajisto (2011) also finds that mispricing predicts share creations up to a period of 10 days in the future. Further evidence consistent with the limits to arbitrage is that the securities with the highest transaction costs (and most stale) NAVs also have the most volatile premiums. The premiums of international equity ETFs exhibit annual volatilities of around 50-130 bp:s, whereas diversified U.S. equity ETFs have volatilities of only 11-20 bps. International equity ETFs have also been shown to suffer from volatile and predictable premiums in earlier time-periods (Engle and Sarkar, 2006; Ackert and Tian, 2008).

4.1 Measuring the Tracking Performance

The main measure of tracking performance used in this study is the difference between the ETF return and that of its underlying benchmark, named the Tracking Deviation (*TD*). In the current context this measure of tracking performance has several advantages over the more widely used measure of mispricing, the ETF premium[3].

First, investors are mainly concerned about the actual tracking performance of the ETF vis-à-vis the underlying index, which is what the tracking deviation captures. In contrast, the premium only reflects the mispricing of the ETF w.r.t. the assets held. Second, even if the ETF is not mispriced, it may still not properly track the underlying index. This may occur for a variety of reasons including; treatment of dividends, changes in index composition, securities lending and the purchase of only a subset of securities included in the underlying index. Changes in index composition due to additions or deletions, or because of supply & demand shocks (e.g. IPOs, SEOs, M&A:s) will force the ETF manager to trade in order to rebalance their portfolio. These amounts are not trivial; Petajisto (2011) documents that the median ETF generated an annual turnover of 29 % in 2010 by its *own* trading alone. Furthermore, Gastineau (2004) finds that some of the popular small-cap U.S. equity ETFs have historically underperformed against their corresponding mutual fund counterparts and they

[3] defined as the price differential between the ETF price and its NAV

attribute this underperformance to the *passiveness* on the part of ETF managers when faced with changes in index composition. In contrast, mutual fund managers typically anticipate upcoming events in an effort to reduce the transaction costs involved in the index modification process. Imperfect replication is also a concern for investors as a passive fund managers does not need to invest in all of the securities to replicate an index, but can rather use a sampling technique to select a subset of securities that have the highest degree of co-movement with the index. In contrast, arbitrageurs investing in ETFs through the "in-kind" creation/redemption process must transact the entire stock portfolio (Petajisto, 2011). It is possible to disentangle these effects by decomposing the total tracking deviation into a part attributed to mispricing, and another due to imperfect replication. I replicate all of the results for the NAV based tracking deviation (that excludes the mispricing component) to isolate the part of the total tracking deviation that is driving the results.

Third, in order to investigate ETF commonality we need to calculate the tracking deviations at a common point in time. This is problematic at the daily level because of differences in trading hours between the U.S. and international equity markets. This is reinforced by the findings in Shum (2010) who documents that the iShares East Asian country ETFs behave more like large cap U.S. stocks in that their daily price movements are better explained by the return on S&P500 rather than the overnight returns of the underlying benchmark index. In order to address this problem of non-synchronicity, I conduct the analysis at the weekly level. For the tracking deviation this corresponds to comparing two weekly returns which overlap at least 80 % in terms of trading hours. Using weekly data does not solve the problem if the premium is used, as it corresponds to a difference between two prices recorded at different points in time. In order to separate the impact of stale pricing from differential exposure to *systematic risk* factors, these factors also need to be time-aligned. Such an analysis would not be possible at the daily frequency.

4.2 Descirptive Statistics

In Table 1 I provide some summary statistics for the main dependent variables used in this study, the tracking deviation based on either the total or the NAV component. The average *TD* is economically small at a few bp:s, but the standard deviation is large at 1.51 % per week (or 10.6 % per year). The magnitude is considerable considering that the weekly s.d. of S&P 500 is about 2.61 %. The most volatilie *TD*:s are observed for Asia, followed by Europe and the Americas. This is not surpsing since the ordering corresponds exactly with the degree of non-synchronicity between the U.S. and these markets. Many ETFs also exhibit significant (negative) skewness and kurtosis highlighting that these ETFs occasionally suffer large price declines far greater than those observed for the underlying index. As for Tracking Deviations based on NAV returns, the volatility of *TD* is much smaller (average 0.49 % per week). These numbers are generally larger for less liquid stock markets consistent with the idea that the ETF manager purchases only a subset of securities to track the index in order to avoid securities with low liquidity (and high transaction costs). A further examination of fund characteristics related to ETF liquidity reveals some useful insights. Whether ETFs are ranked by AUM or quoted spreads, the most liquid ones are iShares Japan and Brazil. Asian ETFs generally have above median liquidity, while European ones (except Germany) have below median liquidity with Belgium and Italy at the bottom. ETFs investing in the Americas are generally among the most liquid.

The correlation between the different shocks is generally high. It should be noted that in this study I focus on extreme movements in this shocks as indication of adverse market conditions and hence a linear measure of dependence may not fully reveal the extent (or lack of) co-movement between these variables. Generally the three stock market shocks are highly correlated at about 0.75, whereas shocks to common mispricing have a much lower correlation with the aforementioned shocks (between 0.1 to 0.4). Shocks to ETF liquidity have a very low correlation of less than 0.10 with any of the other shocks.

5 Commonality in ETF Tracking Performance

I start by documenting the existence of commonality in tracking performance. A simple metric for the degree of commonality is the coefficient from a regression of the tracking deviation (TD_i) on the equally-weighted tracking deviation for the other 19 ETFs (*EWTD*):

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_r^{EW} EWTD_t + e_{TD,i,t}, \quad r \in \{EU, ASIA, AMERICAS\} \tag{2.1}$$

here the coefficients on *EWTD* are restricted to be equal across regions. The purpose of this is to document some overall patterns across regions grouped by their degree non-synchronicity with the U.S. Later I relax this restriction and allow for country specific estimates. I also control for four lags of the dependent variable to account for the high degree of persistence in *TD* for some ETFs.

The results for model (1) shows that the tracking deviations are to a large extent explained by the common tracking factor (*EWTD*), see Table 3 for further details. Even this simple model has an adjusted R2 of 62.6 %[4]. It is not surprising to find that the degree of commonality is related to non-synchronicity; commonality is greatest for the Asian country ETFs followed by Europe and the Americas. This finding is in line with Shum (2010), who shows that the East Asian country ETFs behave very much like large-cap U.S. stocks in that their intra-day behavior can to a large extent be explained by U.S. market movement. Stale pricing is, however, not the only reason for this commonality in tracking performance as indicated by the highly significant coefficients on *EWTD* for the European ($t = 27.16$) and American ETFs ($t = 8.01$) as well.

I also find evidence of a common component in the tracking deviations based on NAV, that is, between the return on NAV and that of the underlying index. Commonality between the NAV based tracking deviations can arise for several reasons. First, changes in index composition will force the ETF manager to rebalance the portfolio and this may induce correlated trading across ETFs. After each Quarterly and Semi-Annual Index Review, MSCI announces the index changes that will take place on the rebalancing date. The timing for these events is known in advance as MSCI provides the dates for the next four regular index reviews in advance. Even if some part of index changes is anticipated; ETFs are, unlike their mutual fund counterparts, unable to transact in anticipation of such changes (see Gastineau, 2004). Second, it is possible that there are similarities in the replication techniques used by these ETFs to track the performance of their respective underlying index. This is possible because these ETFs are all managed by iShares and none of them are fully replicated. Second, the underlying indices pay dividends on a continuous basis whereas iShares only pays them out at a maximum frequency of once every quarter. Finally, although the commonality in NAV based TD is statistically significant, it accounts for less than 25 % of the return variation compared with more than 60 % for *TD*.

Next I investigate whether the previously documented commonality is coming from differences in *systematic risk exposures* between the ETF and its underlying index. Similar to Bekeart, Harvey and Ng (2005), I consider two systematic risk factors, one based on the global market (*WRLD*) and the other on a regional market (*REG*)[5]. In order to avoid adding up constraints and spurious co-movements between markets, the regional factor for market i is constructed from the markets other

[4] Controlling only for 4 lags of the dependent variables yields an Adj. R2 of 34.3 %.

[5] Such a two-factor model has been shown to significantly outperform the one-factor global market model in modeling cross-country and industry correlations, while more sophisticated APT models only provide a slight improvement (see Bekaert *et al.*, 2009). Moreover, Brooks and Del Negro (2005) have shown that country factors within a region can to a great extent be explained by regional factors.

than *i*. MSCI already provides such indices for the European markets, but for the Asia markets I construct the regional factor as:

$$REG_{i,t} = \sum_{k \neq i} w_{k,t} R_{k,t} \Big/ \sum_{k \neq i} w_{k,t} \tag{2.2}$$

with *k* indexing an Asian market except market *i*. Returns and market values are provided by Datastream. I use the S&P 500 as a proxy for the global factor for Europe and Asia. As for the Americas, I use the S&P 500 as the regional factor and MSCI Europe, Asia and Far East (EAFE) as the global factor. In order to obtain an intuitive interpretation of the coefficients, the *REG* factor is orthogonalized w.r.t. the *WRLD* factor by regressing the former on the latter and then using the residual as the *REG* factor. Similar to Bekaert, Hodring and Zhang (2009) and Bekaert *et al.* (2012) this procedure is repeated every year to capture any possible changes in the integration between the *REG* and *WRLD* markets.

I run a regression of the Tracking Deviation on the two systematic risk factors, the *WRLD* and *REG* returns (Model 2):

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_r^{REG} REG_t + \beta_r^{US} WRLD_t + e_{TD,i,t} \tag{2.3}$$

Such a model has another interesting interpretation, the factor loadings measure the degree by which the ETF is *over- or underexposed* to the same systematic risk factors that drive the prices of the underlying portfolio of securities[6].

Model 2 shows that Asian ETFs (followed by EU and the Americas) are the most over-exposed to the *WRLD* factor, while European ETFs are the most under-exposed to the *REG* factor followed by Asia and the Americas. This finding, that even the European and American ETFs have differences in their risk exposure to the *WRLD* and *REG* factors, supports the trading location hypothesis, whereby local risk matters for the pricing of securities. Further evidence to support the importance of trading location is that the results are so strong despite the fact that I use weekly returns where non-synchronicity is less of a problem. Conducting the same regression at the daily level where non-synchronicity is even more of a concern shows that the over- (under-) exposure to

[6] Assume that the underlying country returns can be satisfactorily described by these two factors. Then we can decompose *TD* into its two components, plug in the expression for $r_{UND,i,t}$ and move it to the right hand side in equation (2.3) to yield:

$$r_{ETFi,t} = E_{t-1}\left(r_{ETFi,t} + r_{UNDi,t}\right) + \left(\beta_{i,t}^{WRLD} + \beta_{TDi,t}^{WRLD}\right) WRLD_t + \left(\beta_{i,t}^{REG} + \beta_{TDi,t}^{REG}\right) REG_t + e_{ETFi,t}$$

the *WRLD (REG)* is stronger by a factor of 4 to 5 (1 to 1.5). As for the tracking deviations based on NAV, these two systematic risk factors are statistically significant for the European (*WRLD* and REG factors) and Asian (*WRLD* factor) ETFs, but the coefficient estimates are economically not very meaningful and the explanatory power is low (at 2.5 %).

Model (3) combines the two previous models together and the results show that the common tracking factor (*EWTD*) remains the strongest explanatory variable both economically and statistically. However, controlling for *EWTD* renders the U.S. return insignificant for Americas and reduces the coefficient estimates for EU and Asia by more than half. The results remain virtually unchanged if the common tracking deviation factor is weighted by AUM. Other systematic risk factors such as changes in VIX and ETF liquidity only have some marginal explanatory power and the inclusion of these does not change any of the main conclusions. Turning the attention to tracking deviations based on NAV, we can see that the exposure to the common tracking component remains virtually unchanged from model (1), while the two systematic risk factors generally become even weaker.

Overall the results in this section highlight that there is indeed a common component in the tracking performance of country ETFs. While regional differences do exist, possibly because of non-synchronicity and the pricing of local (U.S.) risk, all country funds are significantly exposed to the common tracking factor. The results also indicate that these ETFs have large differences in their exposure to *systematic risk*, when compared against those for the underlying assets, with the Asian funds being the most over-exposed to the U.S., and the European funds the most under-exposed to the regional market. Some of this commonality is also evident in the NAV based tracking deviation, possibly as a result of correlated trading following index revisions, or from similarities in the replication techniques used.

6 Commonality and Limits to Arbitrage

If the degree of commonality in tracking performance *changes* in adverse market conditions, then it is an indication of *contagion* between ETFs. In this section I investigate whether there is any link between the degree of commonality and several proxies for the scarcity of arbitrage capital.

Previous studies by Petajisto (2011) and Itzhak *et al.* (2012) have found a link between the overall *efficiency* of the ETF market, as measured by the cross-sectional dispersion in ETF mispricing, and various proxies for limits to arbitrage. As depicted by Figure 3 in Petajisto (2011), the dispersion in mispricing generally increases in periods of market stress, which is particularly evident during 2008. Dispersion in ETF mispricing and commonality are not mirror-images of each other. A high degree of commonality may occur in periods of high dispersion in ETF mispricing if the two phenomena are driven by similar forces. Alternatively, the degree of commonality may change with the overall efficiency of the ETF market if it is driven by the pricing of local risk (location of trading hypothesis). More specifically, when the compensation for local risk is high, commonality in tracking will be greater for international ETFs where the limits to arbitrage are not sufficient to (completely) eliminate this risk.

I use five different measures for the limits to arbitrage. Similar to Hameed, Kang, and Viswanthan (2010), I use the value-weighted return on a portfolio of investment banks and securities brokers and dealears[7]. A severe negative return for these firms is likely to reflect a weak aggregate balance sheet of the funding sector. Extreme movements in the S&P 500 and its volatility might also serve as proxies for the scarcity of arbitrage capital (Petajisto, 2011). Based on the finding by Nagel (2002) that times of high VIX are related to a decrease in the supply of liquidity, I use the average level of VIX measured over the prior week. I also use the TED spread, measured as the difference between three-month LIBOR and T-bill rates, as another proxy for the scarcity of arbitrage capital. TED can be viewed as the premium that large financial institutions would pay for unsecured lending in excess of the risk-free rate to finance its trading activities (see Brunnermeier, Nagel, and Pedersen, 2009).

Finally, I use the absolute value of mispricing for SPDR (TIC: SPY), the largest equity ETF in the world with 91 b$ in AUM and daily trading volume of $24 billion per day, as a proxy for the overall liquidity of the ETF market. Itzhak *et al.* (2012) document that the average mispricing of *SPY* has declined over time, possibly because the ETF market has become more liquid over time. SPY mispricing is also found to increase in periods of market stress such as the summer of 2007 and the fall of 2008. The authors argue that this variable has a two-fold interpretation. First, low market liquidity will reduce the profitability of ETF arbitrage because of high transaction costs. Second, low market liquidity can be a manifestation of low funding liquidity, as in Brunnermeier and Pedersen (2009). In this case a decline in funding liquidity reduces the amount of capital committed to arbitrage and hence mispricing can last for longer periods of time.

[7] defined by standard industrial classification (SIC) code 6211. I orthogonalize this factor with the US market return.

6.1 Time-varying Commonality

Based on these five proxies for limits to arbitrage I estimate the following regression with time-varying factor loadings on the common tracking component (*EWTD*):

$$\begin{aligned} TD_{i,t} &= \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_r^{REG} REG_t + \beta_r^{WRLD} WRLD_t + \beta_{i,t}^{EW} EWTD_t + e_{TD,i,t} \\ \beta_{i,t}^{EWTD} &= \beta_{0,i} + \beta_1 TED_{t-1} + \beta_2 VIX_{t-1} + \beta_3 SP500_{t-1} + \beta_4 FIN + \beta_5 SPY \end{aligned} \quad (2.4)$$

where the factor loadings on *EWTD* is a linear function of the lagged values of these five information variables[8]. I also include the two systematic risk-factors as a parsimonious way to control for non-synchronicity & location of trade hypothesis (with r indexing the three regions).

The results in Table 4 provide some support for the notion that commonality is higher when the limits to arbitrage are more likely to be binding; negative movements in the S&P 500 are associated with a higher sensitivity to the common tracking factor (t-statistic of -2.7). However, commonality in tracking tends to *decrease* in periods of *low* ETF liquidity. As for the remaining proxies for limits of arbitrage, the coefficient on the financial sector return is insignificant, but it is of the same sign as the S&P 500. Neither the TED spread nor VIX appear to have any incremental explanatory power. This finding is not entirely surprising as Itzhak *et al.* (2012) already documented that the cross-sectional dispersion in ETF mispricing is only weakly related to VIX and TED in the sample of equity ETFs and the signs on the two variables even flip sign when a different measure of cross-sectional dispersion is used as the dependent variable.

Next I examine the time-variation in the exposures to the two systematic risk-factors, *WRLD* and *REG*. I estimate the following regression with time-varying factor loadings:

$$\begin{aligned} TD_{i,t} &= \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_t^{REG} REG_t + \beta_t^{WRLD} WRLD_t + e_{TD,i,t} \\ \beta_{i,t}^{REG} &= \beta_{0,i}^{REG} + \beta_{1,r}^{REG} TED_{t-1} + \beta_{2,r}^{REG} VIX_{t-1} + \beta_{3,r}^{REG} SP500_{t-1} + \beta_{4,r}^{REG} FIN + \beta_{5,r}^{REG} SPY \\ \beta_{i,t}^{US} &= \beta_{0,i}^{US} + \beta_1^{US} TED_{t-1} + \beta_2^{US} VIX_{t-1} + \beta_3^{US} SP500_{t-1} + \beta_4^{US} FIN + \beta_5^{US} SPY \end{aligned} \quad (2.5)$$

where *r* indexes the three regions. I include region specific coefficients for the *REG* factor since each region has its own factor. Here I exclude the *EWTD* factor since it may be endogenous and I

[8] Many existing studies model the conditional factor loadings as linear functions of information variables (see e.g. BHN 1997, 2005; Baele, 2005). This (linear) functional form can be justified from a Taylor expansion by ignoring higher-order terms (see e.g. Shanken, 1990).

want to focus on the differential risk-exposure of ETFs vis-à-vis the underlying stocks. The results are robust to whether this is done or not.

The results confirm that *every* European and Asian fund is on average over-exposed to the *WRLD* factor; this is particularly true for South Korea, Taiwan, Hong Kong and Japan (see Figure 3). In terms of the time-variation in factor loadings, these 20 ETFs become increasingly over-exposed to the *WRLD* factor following large negative shocks to either U.S. market returns, or to the financial sector (*FIN*). The latter finding is even more convincing of the limits to arbitrage channel as the impact is even greater, both statistically and economically, than that for the U.S. market and also because *FIN* only captures the component that is orthogonal to the U.S. market. The overall level of ETF market liquidity also has the same sign as in Table 4, that is, increases in ETF liquidity lead to stronger commonality, in this case via an *increase* in the U.S. factor loading. The effect is strong both statistically (t-statistic = 9.1), and economically; a two-standard deviation *increase* in ETF liquidity leads to an increase in *WRLD* factor loadings by almost 60 % in the following week. The TED spread also has the right sign and it is highly significant in all specifications, but VIX has surprisingly a negative sign. Economically these two coefficient estimates are of the same order of magnitude so it is not entirely clear which one dominates. The degree of multicollinearity between these two variables is not too severe, as the correlation is no more than 0.53.

Most country funds are on average *under-exposed* to the *REG* factor (see Figure 3). This under-exposure is strongest for the European funds, but they are equally strong for many Asian funds such as South Korea, Taiwan and Hong Kong. ETF liquidity has a very strong and *negative* effect on the Asian ETFs: the impact of a 2 standard deviation positive shock to ETF market liquidity is to *decrease* the REG factor loading by almost 80 %. Since all country funds are already under-exposed to the *REG* factor, this indicates a further deviation in the systematic risk exposure of these ETFs. Analyzing the impact of VIX on the regional factor loadings reveals that the relationship is *negative* and highly significant for Europe and Asia, and to a lesser extent also for Americas. This indicates that periods of high VIX are followed by a further reduction in *REG* factor loadings, that is, the ETF becomes *even more* under-exposed to this risk factor. In contrast, the TED spread has no impact on either Asian or American markets. For the European funds the effect of TED is positive and significant, particularly in some specifications that exclude the financial crisis dummy. Combined with the negative sign on VIX, these two effects offset each other economically. Regarding the impact of U.S. market returns and the financial sector, the results are weak and inconclusive at best.

In summary, the results in this section show that commonality in tracking tends to increase strongly in periods when the overall ETF market liquidity is *high*. This effect can be seen both through an increased exposure to the common tracking factor (*EWTD*), as well as from an increased (decreased) exposure to the *WRLD* (*REG*) factor. Since the average fund is over-exposed to the *WRLD* factor and under-exposed to the *REG* factor, this finding indicates an increase in commonality. There is also some limited evidence to suggest that large negative returns to the U.S. markets (or to the financial sector) are associated with an increase in commonality. Increases in VIX also tend to increase commonality via a reduction in the regional factor even further away from its mean.

7 ETF Contagion

Contagion is usually defined as the excess co-movement between markets in response to an unexpected shock (see e.g. Forbes and Rigobon, 2002; Bekeart, Harvey and Ng, 2005). In order to determine whether co-movements are *excessive* the first step is to establish a proper benchmark. In most applications we would have to take a stand on what constitutes fundamentals, that is, to first determine the systematic risk factors that are driving asset prices. ETFs on the other hand provide a unique setting to analyze contagion because the fundamentals are known by the investor in advance – ETFs have a mandate to track the underlying index. A more stringent definition of fundamentals involves only the value of the assets under management, the NAV. Hence we can use the Tracking Deviation as a measure of price changes filtered by fundamentals.

Rather than focus on a particular type of shock to financial markets, Bekeart *et al.* (2012) use the recent financial crisis as a "natural" experiment to examine whether the factor exposures change during this time-period. I replicate their analysis in my context by adding country-specific dummy variables for the financial crisis in 2007-2009 into the *EWTD* factor loadings in equation (2.1) and to the *WRLD* & *REG* factor loadings in eq. (2.3). Table 3 contrasts the previously documented findings for time-variation in commonality both with and without the financial crisis dummies. Overall the previously documented relationship between the degree of commonality and limits to arbitrage is unaffected by the inclusion or exclusion of the crisis dummies. Next, Table 6 provides the coefficient estimates on the financial crisis dummies country-by-country: the results are not suggestive of contagion through the common tracking factor *EWTD*, only two country funds (Brazil and Singapore) have a statically significant coefficient on the crisis dummy.

However, once we include crisis dummies in the *systematic* risk exposures to *WRLD* and *REG* factors, there is significant evidence of contagion. The results reveal that most European country funds suffer from contagion in the sense that they become even *more under-exposed* to the *REG* factor during the financial crisis (average t-statistic is -2.17). The effect is economically also strong; the *REG* factor loadings decreases by more than 65 % during the crisis period. For the remaining markets the signs are all negative, but I only find evidence of a significant decrease for Hong Kong, South Korea and Brazil. The impact of the financial crisis seems to be weaker for the *WRLD* factor loading. Of the European funds only Switzerland, and for the Asian funds only South Korea and Singapore show a significant *increase* in *WRLD* factor loadings during the crisis. Economically the WRLD factor loading increases by as much as 80 % for these three countries.

Overall the results in Table 6 are already indicative of contagion between ETFs. A crisis dating mechanism may, however, not be accurate enough to pinpoint episodes of distress in financial markets. Billion and Pelizzon (2003) have shown that contagion tests that rely on a crisis dating mechanism are sensitive to (1) the strength of idiosyncratic variances of returns, (2) the pre-specified crisis window, (4) the presence of omitted variables and (5) time-zone differences. Even when financial markets are not fully and equally efficient, one would expect that shocks to financial markets occur suddenly and die out quickly. The problem with any crisis dating mechanism is that it assumes that co-movements remain elevated throughout the entire period, which may not be a reasonable when the length of the crisis-period is long. This is particularly true for the ETF market since the “in-kind” redemption/creation process would be expected to restore pricing efficiency in a relatively timely manner. Petajisto (2011) argues that the sheer magnitude of the average creation/redemption transaction (1556 % of average daily volume) may delay the time it takes for pricing efficiency to be restored. Consistent with this idea he finds that mispricing predicts share creations up to a period of 10 days in the future. Although these problems are expected to be more severe for funds with higher limits to arbitrage, such as the international funds, and during periods of market distress, mispricing should be restored in a number of days, possibly weeks, but not years. In order to circumvent these problems I now turn to a different approach for identifying contagion that involves changes in co-movement following extreme returns to financial markets.

7.1 Identifying Contagion from Extreme Return

Several studies have found evidence of contagion in extreme returns by using non-linear models to predict future stock market crashes (Longin and Solnik, 2001; Bae *et al.*, 2003; Markwat *et al.*, 2009). For instance, Markwat *et al.* (2009) find strong evidence in favor of a “domino effect” in stock market crashes: in the wake of a regional stock market crash, the probability of subsequent regional and world crashes increase by more than 50 %. For a global crash the corresponding probabilities more than double from their unconditional values. The findings in these studies would seem to suggest that there is something different about *extreme* returns that can trigger contagion.

We can contrast these findings with the preliminary evidence in Table 5, where I already showed that the *WRLD* factor loadings generally *increase* following negative shocks to *U.S.* markets. Although this result can also be viewed as indicative of contagion, as the U.S. market return is unpredictable and hence can be considered an unexpected shock, the problem with this is that it implies a *linear* relationship between U.S. market returns and factor loadings. More specifically it implies that large negative shocks increase co-movements, while large positive shocks have the *opposite* effect.

Motivated by the previous findings that there is something special about extreme returns that can trigger contagion, I now allow shocks to affect factor loadings via a transition function where the degree of non-linearity is determined from the data. Consider the following form for the conditional factor loading:

$$\beta_{i,t}^{k} = \beta_{i,0}^{k} + \boldsymbol{\beta}^{k}\mathbf{Z}_{t-1} + \eta_{i}^{k} G\left(s_{t-1}\right), \quad k \in \left\{REG, US, EWTD\right\} \tag{2.6}$$

where $\boldsymbol{Z}$ is a vector that includes the five previously used proxies for the scarcity of arbitrage capital and $G(s_{t-1})$ is the transition function that control the degree of non-linearity between the unexpected shock (s_{t-1}) and the factor loading. Similar to Bekeart *et al.* (2012), I view *changes* in factor exposures after a shock has occurred to financial markets as indicative of contagion. In the current context this is captured by the contagion coefficient (η).

The transition function is modeled a first-order logistic function as follows:

$$G\left(s_{t-1};\gamma,c\right) = \left(1+\exp\left\{-\gamma\left(s_{t-1}-c\right)\right\}\right)^{-1}, \gamma > 0 \tag{2.7}$$

where s_{t-1} is the transition variable, or the lagged unexpected shock, to be discussed in greater detail in the following section. This logistic function increases monotonically from 0 to 1 as a function of s_{t-1}. This function has two important parameters that can be estimated from the data; the parameter c captures the location of the transition, whereas γ determines the smoothness of the transition from one regime to another. In order to illustrate the role of these two coefficients let us consider two special cases. First, when the smoothness parameter γ becomes increasingly large, the transition function $G(s_{t-1};\ \gamma,\ c)$ approaches the indicator function $I[s_{t-1} > c]$. It can then be interpreted as a dummy variable for a shock beyond the location parameter c. This implies that factor loadings change discontinuously at time t after the unexpected shock has exceeded the pre-estimated threshold c in t-1. Second, as γ becomes very small the transition function becomes linear in the unexpected shock s_{t-1}. In summary, the parameters c and γ combined determine the region of the distribution where shocks have the biggest impact on factor loadings (see Figure 1 for additional examples).

Combining the factor loadings specified in eq. (2.6-2.7) with the 1-Factor model (*EWTD*) in eq. (2.4) gives the following regression:

$$
\begin{aligned}
TD_{i,t} &= \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_{i,t}^{EWTD} EWTD_t + \beta_r^{REG} REG_t + \beta_r^{WRLD} WRLD_t + e_{TD,i,t} \\
\beta_{i,t}^{EWTD} &= \beta_{i,0}^{EWTD} + \mathbf{\beta}^{EWTD} \mathbf{Z}_{t-1} + \eta_i^{EWTD} \left(1 + \exp\left\{-\gamma\left(s_{t-1} - c\right)\right\}\right)^{-1}, \gamma > 0
\end{aligned}
\tag{2.8}
$$

Similarly for the 2-Factor model (WRLD & REG) in eq. (2.5) we get the following regression:

$$
\begin{aligned}
TD_{i,t} &= \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_t^{REG} REG_t + \beta_t^{WRLD} WRLD_t + e_{TD,i,t} \\
\beta_{i,t}^{REG} &= \beta_{0,i}^{REG} + \mathbf{\beta}^{REG} \mathbf{Z}_{t-1} + \eta_i^{REG} \left(1 + \exp\left\{-\gamma\left(s_{t-1} - c\right)\right\}\right)^{-1} \\
\beta_{i,t}^{WRLD} &= \beta_{0,i}^{US} + \mathbf{\beta}^{WRLD} \mathbf{Z}_{t-1} + \eta_i^{WRLD} \left(1 + \exp\left\{-\gamma\left(s_{t-1} - c\right)\right\}\right)^{-1}, \gamma > 0
\end{aligned}
\tag{2.9}
$$

In order to keep the model as parsimonious as possible I *restrict* the coefficients in the transition function to be equal across all 20 funds. This forces any cross-sectional differences to come from the contagion coefficients η_i making the interpretation of the results much easier. If contagion is more likely to occur in the tails of the distribution, then by pooling the coefficients we can effectively increase the sample size 20-fold and increase the power of the contagion test.

In a factor pricing model the co-movement between two assets is implicitly given by product of their factor sensitivities with the factor variance. For eq. (2.8) and (2.9) these are given by:

$$
\mathrm{COV}_{t-1}\left(TD_{i,t}, TD_{j,t}\right) = \beta_{i,t}^{EWTD} \beta_{j,t}^{EWTD} VAR_{t-1}\left(EWTD_t\right) \tag{2.10}
$$

$$\mathrm{COV}_{t-1}\left(TD_{i,t},TD_{j,t}\right)=\beta_{i,t}^{REG}\beta_{j,t}^{REG}VAR_{t-1}\left(REG_t\right)+\beta_{i,t}^{WRLD}\beta_{j,t}^{WRLD}VAR_{t-1}\left(WRLD_t\right) \qquad (2.11)$$

In summary, excess co-movements can arise *between* ETFs when the factor loadings *change* as a result of an unexpected shock (s_{t-1}) to financial markets. This effect is captured by the contagion coefficient η_i. The 2-Factor model in eq. (2.8) has another interesting interpretation. Excess co-movements can also be expressed between ETF *returns*:

$$\mathrm{COV}_{t-1}\left(r_{i,t}^{ETF},r_{j,t}^{ETF}\right)=\left(\beta_{i,t}^{REG}+\beta_{UND,t}^{REG}\right)\left(\beta_{j,t}^{REG}+\beta_{UND,t}^{REG}\right)VAR_{t-1}\left(REG_t\right)+$$
$$\left(\beta_{i,t}^{WRLD}+\beta_{UND,t}^{WRLD}\right)\left(\beta_{j,t}^{WRLD}+\beta_{UND,t}^{WRLD}\right)VAR_{t-1}\left(WRLD_t\right)$$

where *UND* refers to the underlying index. The contagion coefficient η can now also be interpreted as the contagion for ETFs in excess of that for the underlying benchmark.

The above regressions belong to a general class of non-linear time-series models usually referred to as Smooth Transition Regressions[9]. As is standard in the literature, I assume that the regression residuals are uncorrelated both across time (t) and funds (i). Generalizing the covariance structure would seriously complicate the parameter estimation (see Folk, Dick van Dijk and Franses, 2005). Estimation is carried out via Non-Linear least squares.

7.2 Specifying the Unexpected Shocks

The contagion model in eq. (2.10 and 2.11) also requires me to specify the unexpected shock that can be a source of contagion. First, I analyze whether *shocks* to *REG* or *WRLD* returns are a source of contagion between ETFs. These shocks are obtained from a simple time-series model as follows:

$$r_{k,t}=\mu_{k,t}+e_{k,t}, \quad k\in\left\{REG,WRLD\right\} \qquad (2.12)$$

where the expected return is modeled as a linear function of lagged dividend yields and an ARMA(1,1), and conditional variances are modeled with a GJR-GARCH(1,1). These market shocks are not only a proxy for aggregate shocks to these economies, but they are also related to liquidity crashes. For instance, in Brunnermeier and Pedersen (2009) a large market shock can trigger a liquidity crisis, i.e. a switch from a high- to a low liquidity regime. Hameed, Kang and

[9] For a survey see e.g. Granger and Teräsvirta (1993), Teräsvirta (1998) and Teräsvirta, Tjøstheim and Granger (2010).

Viswanathan (2010) further show that the cost of providing liquidity is highest in periods with large market declines.

Second, I use shocks to ETF market liquidity. As described earlier, the absolute value of mispricing for the SPDR, the largest equity ETF in the world, can be viewed as a measure of the overall efficiency of the ETF market (see also Itzhak *et al.*, 2012). This variable is highly autocorrelated, which is not surprising since the (absolute level of) mispricing is expected to be mean-reverting. In order to filter out the expected component, I use the residual from an ARMA(1,1) for abs($PREM_{SPY}$) to proxy for an unexpected liquidity shock.

Third, I also analyze the role of *volatility shocks*. Shocks to volatility and market liquidity are closely related, as illustrated in Brunnermeier and Pedersen (2009). Their model also predicts that when markets are already illiquid, liquidity is fragile in the sense that small shocks to speculators funding conditions can cause disproportionately large price effects. Empirically Polson (2010) finds that controlling for volatility shocks is important in explaining the co-movements between European countries during the financial crisis in 2007-2009. Following Ang *et al.* (2006), I use the volatility index VIX as a proxy for aggregate market volatility. The downside of using VIX is that IV may be a biased estimate of aggregate volatility because it contains both stochastic volatility and a separate risk-premium (Ang *et al.* 2006). As is expected from any volatility series, the time-series behavior of IV exhibits strong autocorrelation and positive skewness. Shocks to VIX are extracted by the residual for an ARIMA(1,1) on the natural logarithm of VIX.

7.3 Results: 1-Factor (EWTD) model

My findings suggest that there is indeed something different about extreme shocks to financial markets that can trigger contagion between ETFs. This can be seen by inspecting the estimated smoothness (γ) and location parameters (c): all of the transitions occur discontinuously in the negative tail of the distribution, beyond the 99th percentile (see Table 8). Although there are only a few observations beyond this threshold, the number of observations is effectively multiplied by 20 because of the pooling of coefficient estimates. The results in Table 8 clearly indicate that the degree of *commonality increases* for 17/20 countries following extreme negative shocks to either *U.S.* or regional markets and for 15/20 ETFs following large increases in VIX. While the timing of extreme *U.S.* and *REG* shocks is the same in four out of five cases, the overlap between VIX and U.S./REG is only one out of five. The country funds of Mexico, Brazil, Canada, Japan and Hong

Kong show a particularly strong increase in commonality following large adverse shocks to U.S. market returns or volatility, or to regional market return (see Figure 3). As an illustration of the economic impact consider a 99th percentile shock to VIX: the *EWTD* factor loadings increase on average by 178 % for these five country funds.

Next I analyze the impact of shocks to either common tracking or ETF liquidity. The results clearly indicate that the degree of *commonality decreases* following extremely adverse movements to ETF market *illiquidity* or to the average tracking deviation. The only exceptions are the country funds of Austria and Belgium, both of which are among the least liquid ETFs in the sample. When either of the ETF specific shocks is used, the *level* of ETF market liquidity loses its significance. This suggests that it is not the overall level of ETF illiquidity that drives the degree of commonality, but large shocks to illiquidity. Despite the similarity in results between these two ETF specific shocks, their correlations is only about -0.07 and the timing of extreme shocks overlap only in one out of five cases.

Since the estimated transition occurs below 5 standard deviations from the mean, we have essentially identified two weeks of extreme price movements. The first of these is the week from the 9-15 October, during which U.S. Treasury announced a revision of the Troubled Asset Relief Program (TARP). The second extreme event occurred in the week starting on the 20th and ending on the 26th of November 2008. This week was also eventful: on the 23rd the U.S. Treasury announcement an agreement to provide guarantees, liquidity and capital to Citigroup, on the 25th the U.S Treasury announced the creation of Term Asset-Backed Securities Lending Facility (TALF), the purpose of which was to lend up to $200 billion to holders of AAA-rated asset backed securities and recently originated consumer and small business loans. Finally, the Federal Reserve announced a program to purchase direct obligations ($100 billion) and MBS ($500 billion) from Fannie Mae, Freddie Mac and Federal Home Loan Banks.

The impact on ETF tracking was substantial following these two weeks. The country funds most strongly affected were South Korea, Mexico, Australia and Switzerland for which the *EWTD* factor loadings decreased on average by 289 %. During these two weeks the mispricing of SPY was at a historical high of -1.82 % and -2.56 %, but the recovery was fast and one week later the mispricing was reduced to -0.32 % and -0.096 % respectively. Similarly, average tracking deviation was at an all-time low of -5.26 %, but in the week after it had reversed to a positive deviation of 2.37 %. In this week commonality was driven by a common “recovery” in pricing efficiency, but the effect was highly uneven.

7.4 Results: 2-Factor model (REG & WRLD)

Finally, I analyze contagion through the 2-Factor model (see Table 9). Shocks to U.S. market returns and volatility are generally in agreement: the majority of country funds become under-exposed to the *REG* factor and over-exposed to the *WRLD* factor following such shock. The results are particularly strong for the European funds with all 10 of them becoming under-exposed to the regional market by a further 0.56 (a 256 % reduction from the mean) following a 99^{th} percentile adverse shock to U.S. volatility. Most European country funds also show an increase in the *WRLD* factor, but the results are not as strong or consistent. For the Asian funds the results are generally similar regarding the change in the *REG* factor loading: Australia, Hong Kong, Japan and Singapore show a decrease of 0.56 (or 311 %) in *REG* factor loadings following a 99^{th} percentile shock to VIX. The results are less consistent for the change in the *WRLD* factor.

For shocks to *regional markets* the results also show a clear pattern: all but one country fund shows a *decrease* in *REG* exposures, and all funds show a *decline* in the *WRLD* factor following large negative shocks to regional markets. A 90^{th} percentile adverse to REG market returns causes a decline in *REG* factor loadings by 0.17 (or -74 %) for Europe, 0.29 (or -153 %) for Asia and 0.09 (or -121 %) for the Americas. Similarly, the *WRLD* factor loadings decrease by 0.08 (or -67 %) for Europe, 0.15 (or 68 %) for Asia, and 0.13 (or -186 %) for the Americas. These effects are significant at least at the 10 % level for almost seven out of ten cases.

For shocks to ETF specific variables the results consistently show an increase in *REG* factor loadings following adverse movements in either ETF liquidity (SPY) or average tracking performance (EWTD). Following a 99^{th} percentile shock to *EWTD* the regional factor loadings increase by 0.20, which is enough to eliminate the under-exposure for the average fund (at -0.19). However, the two ETF shocks have a distinct effect on the *WRLD* factor loadings. Adverse shocks to the average tracking performance of international country ETFs is followed by a large increase in WRLD factor loadings, while the opposite is generally true for shocks overall ETF liquidity. These differences are not that surprising given the low correlation between these two shocks and the fact that SPY mispricing is an absolute measure of mispricing, whereas for shocks to *EWTD* the sign matters.

8 Summary and Conclusions

In this paper I analyze the degree of *commonality* in ETF mispricing and its implications for the *systematic* riskiness of an ETF vis-à-vis its underlying benchmark index. I emphasize how the degree of commonality can change in adverse market conditions, an indication of *contagion* between ETFs. I find strong evidence in favor of a common component in the tracking performance of a group of international country ETFs. The results are strongest for the Asian country ETFs, possibly because of the non-synchronicity between U.S. and these markets. However, commonality is strong not only for the European funds where non-synchronicity is less severe, but also for the country funds of Canada, Brazil and Mexico where non-synchronicity is non-existent. Instead, I make the argument that commonality is driven by the pricing of local (U.S.) risk consistent with a growing literature on the importance of trading location (see e.g. Bodurtha *et al.*, 1995; Chan *et al.*, 2003). More importantly, I find that these ETFs have large differences in their exposure to *systematic risk* when compared against those for the underlying assets; all country funds are significantly over-exposed to U.S. market movements and most are significantly under-exposed to regional markets. Asian country funds are the most over-exposed to U.S. market movements, while European funds are the most under-exposed to regional market movements.

In the second part of the paper I investigate whether the *degree of commonality* in mispricing is different between normal and crisis periods, an indication of *contagion* between ETFs. I begin by documenting the extent to which limits to arbitrage can explain the time-variation in commonality and find some evidence to support this notion; commonality is *greater* following large negative shocks to U.S. markets or to the financial sector, but somewhat surprisingly, also when overall level of ETF market liquidity is high. Using the financial crisis in 2007-2009 as a “natural” experiment, I show that while the overall level of commonality does not change in this time-period, that part which is attributed to differences in systematic risk exposure is significantly stronger for the European country funds. More specifically, I find that European country funds become even *more under-exposed* to the regional market during the financial crisis with the exposure decreasing from -0.229 to -0.380 for the average fund.

A crisis dating mechanism may, however, not be accurate enough to pinpoint episodes of distress in financial markets. In order to circumvent these problems I develop a methodology to identify contagion from *changes* in the degree of commonality following *extreme* returns to financial markets. My findings indicate that extreme shocks to U.S. or regional markets are followed by large changes in the degree of commonality, particularly the part that is attributed to differences in systematic risk. For instance, a 99th percentile shock to VIX causes the European country funds to become under-exposed to the regional market even further, by -256 % on average. Similar results hold for many Asian country funds: Australia, Hong Kong, Japan and Singapore show a decrease of 311 % in the regional factor loadings. As another illustration, a 90th percentile adverse return shock to regional stock market causes a decline in regional factor loadings by 74 % for Europe, 153 % for Asia and 121 % for the Americas. Overall my findings suggest that there are large differences in the systematic risks of an ETF and those for its underlying portfolio of assets, particularly following large negative shocks to financial markets.

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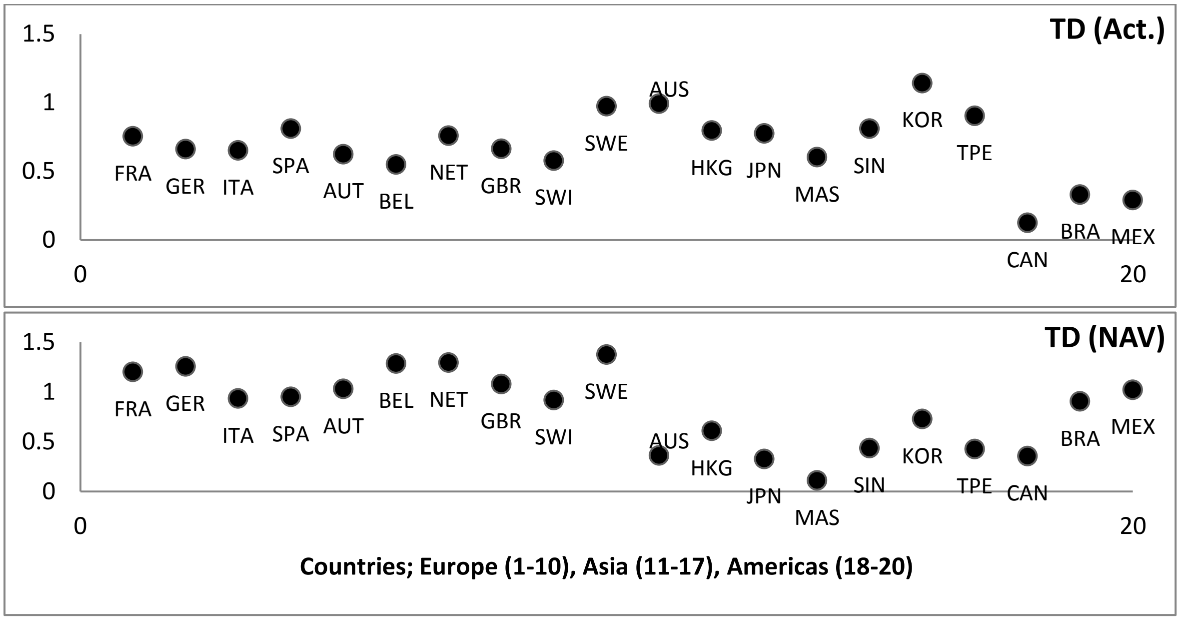

Figure 2: Average Factor Sensitivity to the Common Tracking Factor

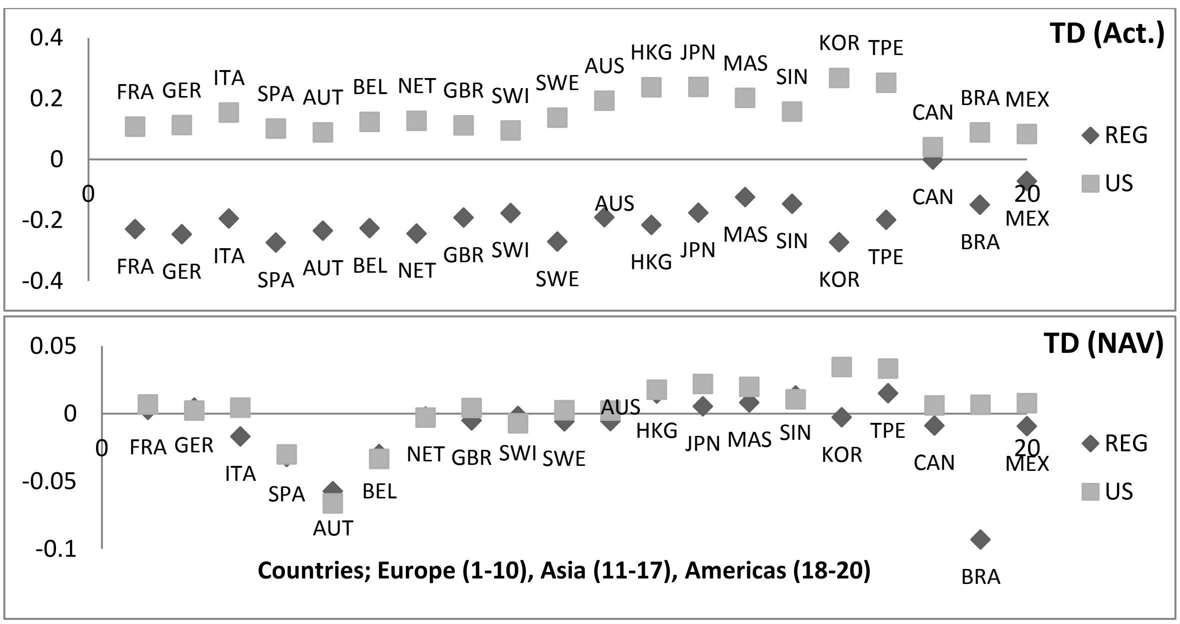

Figure 3: Average Factor Sensitivity to the US and REG Factors (Act. Tracking deviation up, NAV down)

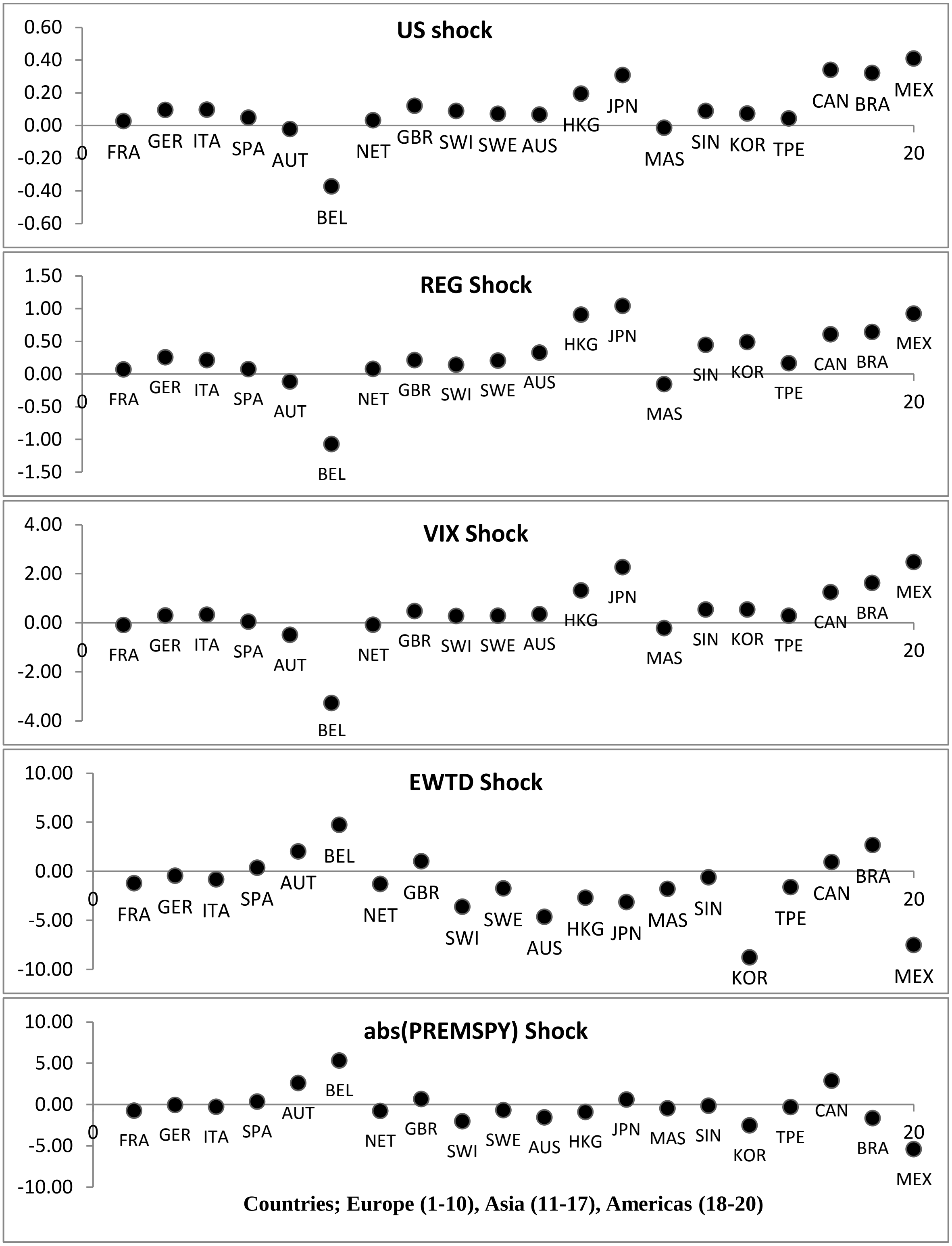

Figure 3: Impact of extreme shock on the factor loading (y-axis: % change in factor loading)

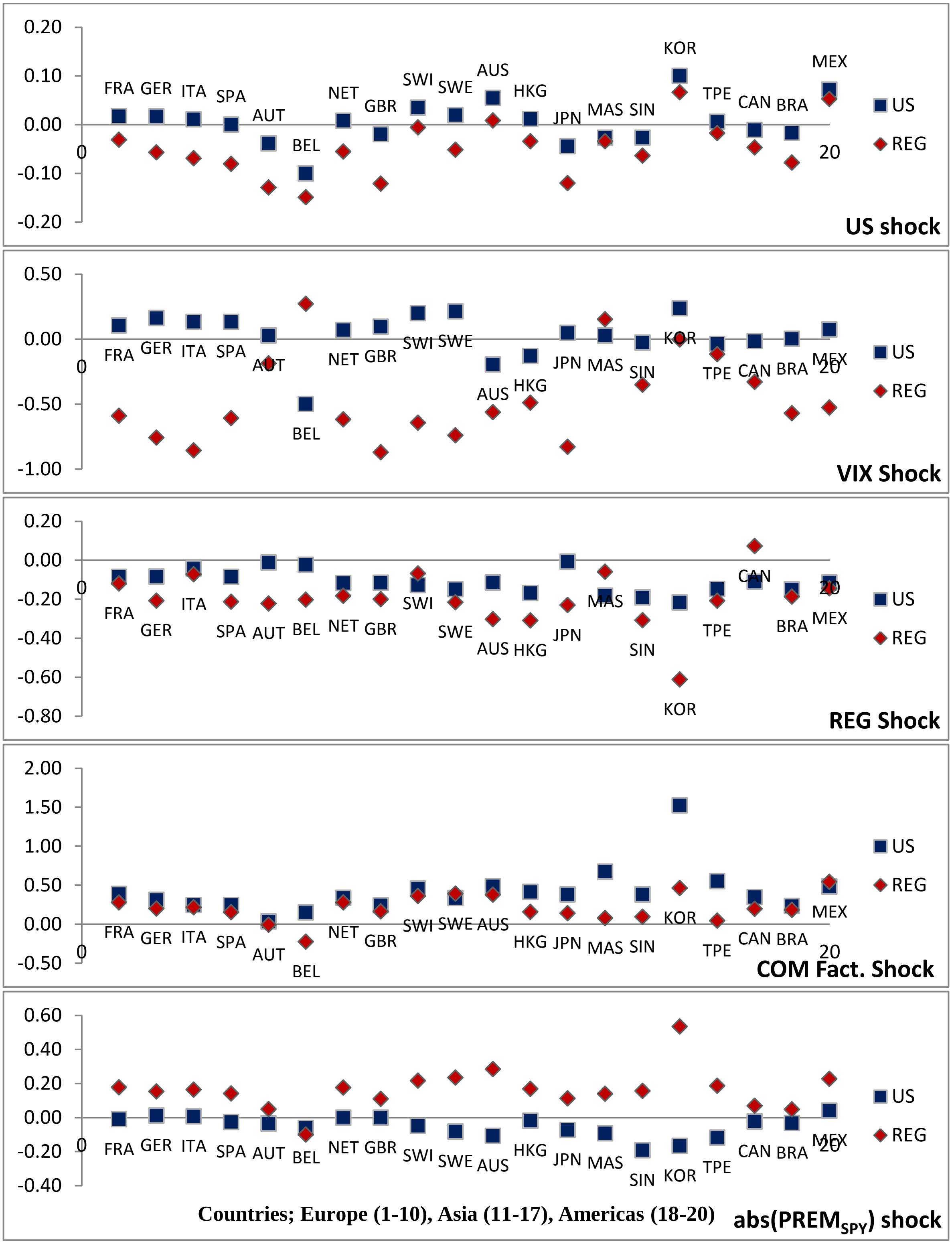

Figure 4: Impact of extreme shock on the factor loading (y-axis: change in factor loading)

Table 1: Descriptive Statistics

		Tracking Deviation (Total)					Tracking Deviation (NAV)				
		Mean	**Med**	**S.D.**	**SK**	**EK**	**Mean**	**Med**	**S.D.**	**SK**	**EK**
1	FRA	-0.02	-0.02	1.24	-0.18	3.70	-0.02	-0.01	0.04	-0.26	6.58
2	GER	-0.01	0.02	1.26	-0.06	2.83	-0.01	-0.01	0.06	0.19	7.42
3	ITA	-0.02	-0.03	1.23	-0.07	2.27	-0.02	-0.01	0.16	0.16	3.06
4	SPA	-0.01	-0.03	1.33	0.11	3.36	-0.01	-0.01	0.29	0.11	3.70
5	AUT	0.05	0.05	1.47	0.01	2.44	0.05	-0.02	0.69	0.96	7.72
6	BEL	0.00	0.01	1.59	-0.84	14.55	0.00	0.00	0.49	-0.93	19.16
7	NET	-0.02	-0.03	1.30	0.02	3.78	-0.02	-0.01	0.25	-0.54	5.83
8	GBR	-0.02	-0.01	1.26	-0.10	3.56	-0.01	-0.01	0.04	-0.22	5.50
9	SWI	-0.01	0.01	1.25	0.13	2.76	-0.01	0.00	0.25	-0.42	2.91
10	SWE	-0.02	0.00	1.66	-0.13	6.41	-0.02	-0.01	0.05	-1.59	9.50
11	AUS	-0.03	0.00	1.72	0.45	6.32	-0.01	-0.01	0.04	0.24	3.33
12	HKG	-0.02	-0.06	1.76	-0.04	7.44	-0.01	-0.01	0.07	0.12	7.74
13	JPN	-0.02	-0.01	1.68	-0.72	10.17	-0.01	-0.01	0.06	0.24	1.31
14	MAS	-0.02	-0.03	1.52	0.18	1.42	-0.01	-0.01	0.08	-1.92	24.42
15	SIN	0.00	-0.07	1.63	0.23	3.53	0.00	0.00	0.12	-0.72	12.35
16	KOR	-0.05	-0.03	2.31	0.19	8.62	-0.03	-0.01	0.26	-0.85	25.92
17	TPE	-0.05	-0.07	2.01	0.55	5.38	-0.03	-0.02	0.07	-0.36	1.75
18	CAN	-0.02	-0.01	0.74	-0.32	4.33	-0.02	-0.02	0.06	-0.06	89.05
19	BRA	-0.04	-0.05	1.41	-0.52	5.15	-0.05	-0.03	0.76	0.00	5.29
20	MEX	0.02	0.04	0.98	-0.12	6.52	0.02	0.01	0.30	0.50	2.88
	AVG	**-0.02**	**-0.02**	**1.47**	**-0.06**	**5.23**	**-0.01**	**-0.01**	**0.21**	**-0.27**	**12.27**

Correlations	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Tracking Deviation (Total)	1.00						
Tracking Deviation (NAV)	0.21	1.00					
U.S. market return shock	-0.12	-0.11	1.00				
VIX shock	0.22	-0.07	0.75	1.00			
Regional market return shock	-0.23	0.05	-0.58	-0.74	1.00		
Average TD shock (EWTD)	0.54	0.03	0.09	0.40	-0.38	1.00	
SPY mispricing shock	0.06	0.03	-0.08	-0.08	0.15	-0.06	1.00

Table 2: Ranking of ETFs by Assets Under Management and Quoted Spread

		AUM (in million $)					QSPR		
		P25	**MED**	**P75**			**P25**	**MED**	**P75**
13	JPN	4523.09	5966.96	9415.35	13	JPN	0.08	0.10	0.14
19	BRA	330.60	3005.88	9044.26	19	BRA	0.04	0.10	0.27
17	TPE	473.08	2004.31	2940.44	16	KOR	0.05	0.13	0.32
16	KOR	363.79	1642.03	3027.86	18	CAN	0.06	0.13	0.33
12	HKG	530.89	1111.43	1889.46	20	MEX	0.07	0.14	0.32
18	CAN	388.17	1078.72	2325.25	2	GER	0.07	0.15	0.35
15	SIN	183.12	751.64	1629.11	17	TPE	0.08	0.15	0.36
8	GBR	437.74	724.47	1007.50	11	AUS	0.07	0.17	0.35
11	AUS	200.55	673.72	1944.67	12	HKG	0.07	0.17	0.29
2	GER	142.92	607.43	1545.73	4	SPA	0.13	0.20	0.39
20	MEX	177.53	548.22	1255.60	8	GBR	0.11	0.22	0.41
14	MAS	260.29	407.76	865.51	14	MAS	0.11	0.23	0.41
9	SWI	45.78	222.44	342.27	15	SIN	0.09	0.23	0.50
1	FRA	58.58	170.18	289.71	1	FRA	0.15	0.24	0.47
4	SPA	53.59	157.49	295.12	5	AUT	0.17	0.25	0.58
10	SWE	30.67	151.04	316.14	7	NET	0.18	0.27	0.56
5	AUT	58.24	145.95	304.84	9	SWI	0.15	0.27	0.56
7	NET	29.92	95.14	171.12	10	SWE	0.14	0.27	0.57
3	ITA	32.45	90.23	146.74	3	ITA	0.17	0.30	0.59
6	BEL	26.39	55.65	112.88	6	BEL	0.20	0.31	0.58

Table 3: Explaining the Tracking Deviation

This table reports a regression of the Tracking Deviation, measured as the difference between the ETF return (or NAV return) and the return for the underlying index. The crisis period refers to 07/2007-03/2009. The explanatory variables are as follows: Equally-weighted Tracking Deviation (*EWTD*), regional market return (*REG*) and the world market return (*WRLD*). Region specific coefficients are estimated for these variables. Standard errors are heteroskedasticity consistent. */**/*** denotes statistical significance at the 1/5/10 % level.

	Tracking Deviation (Total)						**Tracking Deviation (NAV)**					
	Entire Sample			**Non-Crisis**			**Entire Sample**			**Non-Crisis**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
EWTD(EU)	0.781*		0.692*	0.768*		0.691*	1.166*		1.158*	1.149*		1.149*
	(38.747)		(30.383)	(36.248)		(28.571)	(24.438)		(24.188)	(19.3)		(19.401)
EWTD(AS)	1.004*		0.86*	0.939*		0.845*	0.404*		0.41*	0.475*		0.474*
	(32.179)		(27.042)	(31.907)		(27.197)	(4.449)		(4.476)	(4.984)		(5.006)
EWTD(AM)	0.277*		0.264*	0.248*		0.234*	0.819*		0.816*	0.761*		0.759*
	(9.444)		(6.389)	(7.736)		(4.738)	(6.989)		(7.036)	(6.145)		(6.184)
REG(EU)		-0.275*	-0.107*		-0.228*	-0.108*		-0.016**	-0.005		-0.011***	-0.004
		(-23.574)	(-12.172)		(-20.676)	(-12.477)		(-2.591)	(-1.219)		(-1.936)	(-0.951)
REG(AS)		-0.215*	-0.065*		-0.154*	-0.035*		0.006***	0.002		0.009**	0.003
		(-12.913)	(-4.705)		(-9.516)	(-2.816)		(1.779)	(0.431)		(2.089)	(0.721)
REG(AM)		-0.106*	-0.009		-0.067*	0.002		-0.019	-0.015		-0.03**	-0.028*
		(-5.987)	(-0.416)		(-3.747)	(0.1)		(-1.062)	(-0.905)		(-2.54)	(-2.645)
WRLD(EU)		0.104*	0.005		0.079*	-0.002		-0.018*	-0.011*		-0.014*	-0.015*
		(11.017)	(0.504)		(9.149)	(-0.202)		(-5.332)	(-3.749)		(-3.861)	(-5.114)
WRLD(AS)		0.219*	0.108*		0.179*	0.09*		0.01**	0.012*		0.018*	0.019*
		(15.491)	(9.309)		(12.228)	(8.083)		(2.32)	(3.043)		(3.17)	(3.285)
WRLD(AM)		0.043**	0.007		0.049*	0.023		-0.005	-0.001		0.001	0.001
		(2.512)	(0.346)		(3.136)	(1.261)		(-0.384)	(-0.04)		(0.212)	(0.185)
Obs	9960	9960	9960	8260	8260	8260	9960	9960	9960	8260	8260	8260
Adj R2	0.626	0.490	0.643	0.588	0.450	0.605	0.229	0.025	0.231	0.229	0.025	0.235

Table 4: Time-variation in the sensitivity of the Common Factor

This table reports the results for the following regression:

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_r^{REG} REG_t + \beta_r^{WRLD} WRLD_t + \beta_{i,t}^{EW} EWTD_t + e_{TD,i,t}$$

$$\beta_{i,t}^{EWTD} = \beta_{0,i} + \beta_1 TED_{t-1} + \beta_2 VIX_{t-1} + \beta_3 SP500_{t-1} + \beta_4 FIN_{t-1} + \beta_5 SPY$$

where REG is the regional market return, WRLD is the world return, EWTD is the equally-weighted tracking deviation. The factor loading of EWTD is modelled as a linear function of five proxies for the limits to arbitrage: average TED and VIX over the previous week, return on the S&P500, return on the financial sector and the absolute value of SPY mispricing (a measure of the overall level of liquidity for the ETF market). Heteroskedasticity consistent standard errors. */**/*** denotes statistical significance at the 1/5/10 % level.

	Tracking Deviation (Total)						**Tracking Deviation (NAV)**					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
TED	-0.017	-0.033	-0.037	-0.052	-0.023	-0.036	-0.07	-0.153	-0.128	-0.152	-0.178**	-0.21**
	(-0.604)	(-0.9)	(-1.433)	(-1.581)	(-0.87)	(-1.068)	(-0.816)	(-1.452)	(-1.478)	(-1.447)	(-2.139)	(-2.057)
VIX	0.001	0.001	0	0	0.001	0.001	0.001	0.002	0.001	0.001	-0.006	-0.006
	(0.471)	(0.469)	(0.147)	(0.126)	(0.764)	(0.73)	(0.278)	(0.472)	(-0.074)	(-0.023)	(-1.101)	(-1.082)
R3			-0.011*	-0.011*	-0.01*	-0.01*			0.011	0.011	-0.007	-0.008
			(-3.032)	(-3.059)	(-2.704)	(-2.746)			(1.204)	(1.224)	(-0.535)	(-0.562)
Financial Sector			-0.006	-0.007	-0.004	-0.005			0.026***	0.023	0.02	0.016
			(-1.469)	(-1.494)	(-1.038)	(-1.075)			(1.757)	(1.61)	(1.269)	(1.06)
abs(SPY mispricing)					-0.114**	-0.108**					0.26***	0.263***
					(-2.521)	(-2.481)					(1.791)	(1.809)
Crisis Dummy	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Obs	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960
Adj R2	0.650	0.652	0.652	0.653	0.652	0.653	0.239	0.245	0.241	0.247	0.243	0.248

Table 5: Time-variation in the sensitivity to the US and REG factors

This table reports the results for the following regression:

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_t^{REG} REG_t + \beta_t^{WRLD} WRLD_t + e_{TD,i,t}$$

$$\beta_{i,t}^{REG} = \beta_{0,i}^{REG} + \beta_{1,r}^{REG} TED_{t-1} + \beta_{2,r}^{REG} VIX_{t-1} + \beta_{3,r}^{REG} SP500_{t-1} + \beta_{4,r}^{REG} FIN + \beta_{5,r}^{REG} SPY$$

$$\beta_{i,t}^{US} = \beta_{0,i}^{US} + \beta_1^{US} TED_{t-1} + \beta_2^{US} VIX_{t-1} + \beta_3^{US} SP500_{t-1} + \beta_4^{US} FIN + \beta_5^{US} SPY$$

where *REG* is the regional market return, *WRLD* is the world return, *EWTD* is the equally-weighted tracking deviation (excluding *i*). The factor loading of *EWTD* is modelled as a linear function of five proxies for the limits to arbitrage: average TED and VIX over the previous week, return on the S&P500, return on the financial sector (*FIN*) and the absolute value of SPY mispricing (a measure of the overall level of liquidity for the ETF market). Heteroskedasticity consistent standard errors. */**/*** denotes statistical significance at the 1/5/10 % level.

	Tracking Deviation (Total)						**Tracking Deviation (NAV)**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: US factor loading												
TED	0.053*	0.041**	0.074*	0.051*	0.061*	0.043**	-0.008	-0.01	0	-0.001	-0.001	-0.001
	(3.668)	(2.047)	(5.359)	(2.709)	(4.542)	(2.297)	(-1.602)	(-1.453)	(0.069)	(-0.109)	(-0.342)	(-0.094)
VIX	-0.003*	-0.003*	-0.005*	-0.005*	-0.002*	-0.003*	0***	-0.001**	-0.001**	-0.001*	0	0
	(-3.543)	(-4.368)	(-6.257)	(-7.857)	(-3.203)	(-4.548)	(-1.676)	(-2.073)	(-2.462)	(-2.948)	(-0.456)	(-0.885)
S&P 500			-0.004***	-0.005*	-0.004**	-0.006*			0	0	0	0
			(-1.916)	(-2.738)	(-2.384)	(-3.118)			(0.451)	(0.159)	(0.325)	(0.019)
FIN			-0.018*	-0.018*	-0.017*	-0.017*			-0.004*	-0.004*	-0.004*	-0.004*
			(-6.3)	(-6.91)	(-6.936)	(-7.449)			(-3.935)	(-3.978)	(-4.135)	(-4.186)
SPY					-0.148*	-0.143*					-0.031*	-0.03*
					(-9.141)	(-9.247)					(-3.68)	(-3.544)
Crisis Ind.	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Obs	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960
AR2	0.508	0.513	0.518	0.525	0.535	0.541	0.043	0.049	0.049	0.056	0.053	0.060

	Tracking Deviation (Total)						Tracking Deviation (NAV)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel B: REG factor loading												
TED(EU)	0.047**	0.1*	0.066*	0.121*	0.077*	0.138*	-0.009	0.003	-0.01	0.002	-0.004	0.013
	(2.057)	(3.413)	(3.088)	(4.311)	(3.673)	(4.671)	(-1.131)	(0.212)	(-1.161)	(0.146)	(-0.548)	(0.868)
TED(ASIA)	-0.025	0.006	-0.021	0.012	-0.039	-0.011	-0.003	-0.003	0.001	0.003	0.001	0.003
	(-0.751)	(0.133)	(-0.728)	(0.297)	(-1.476)	(-0.313)	(-0.809)	(-0.438)	(0.209)	(0.374)	(0.163)	(0.332)
TED(AM)	-0.019	0.02	-0.002	0.044	0.006	0.045	0.072	0.124**	0.043	0.097**	0.051***	0.113**
	(-0.573)	(0.446)	(-0.063)	(1.085)	(0.185)	(1.034)	(1.628)	(2.146)	(1.579)	(2.127)	(1.747)	(2.298)
VIX(EU)	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	0	0.001	0	0.001	0.001	0.001
	(-6.885)	(-6.867)	(-7.224)	(-7.071)	(-7.27)	(-7.049)	(0.935)	(1.085)	(0.84)	(1.032)	(0.957)	(1.25)
VIX(ASIA)	-0.002	-0.002	-0.001	-0.001	-0.004*	-0.004**	0	0	0	0	-0.001	-0.001
	(-1.184)	(-1.088)	(-0.458)	(-0.355)	(-2.755)	(-2.567)	(-0.227)	(-0.196)	(-0.949)	(-0.956)	(-1.459)	(-1.472)
VIX(AM)	-0.003	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.001	-0.001	0	0	0	0
	(-1.572)	(-1.65)	(-1.733)	(-1.838)	(-1.705)	(-1.863)	(-0.742)	(-0.777)	(-0.061)	(-0.046)	(0.107)	(0.213)
S&P500 (EU)			0.003	0.002	0.003	0.003			-0.005**	-0.005*	-0.004**	-0.005*
			(0.776)	(0.663)	(0.822)	(0.751)			(-2.507)	(-2.816)	(-2.486)	(-2.769)
S&P500 (AS)			0.011**	0.011**	0.005	0.005			0	0	0	0
			(2.37)	(2.541)	(1.257)	(1.368)			(0.155)	(0.368)	(-0.392)	(-0.248)
S&P500 (AM)			0.002	0.005	0.002	0.004			-0.01	-0.01	-0.01	-0.01
			(0.462)	(0.965)	(0.433)	(0.883)			(-1.282)	(-1.427)	(-1.295)	(-1.423)
FIN(EU)			-0.006	-0.005	-0.007**	-0.006***			-0.004***	-0.004**	-0.005**	-0.004**
			(-1.539)	(-1.341)	(-2.117)	(-1.83)			(-1.909)	(-1.961)	(-2.033)	(-2.084)
FIN(AS)			0.018*	0.017*	0.006	0.005			-0.002	-0.002	-0.004**	-0.003***
			(2.958)	(3.045)	(1.096)	(1.052)			(-1.36)	(-1.134)	(-2.162)	(-1.903)
FIN(AM)			-0.004	-0.002	-0.007	-0.005			0.003	0.003	0.003	0.003
			(-0.652)	(-0.394)	(-1.165)	(-0.959)			(0.506)	(0.612)	(0.477)	(0.631)
SPY(EU)					0.033	-0.005					-0.006	-0.023
					(0.927)	(-0.161)					(-0.37)	(-1.31)
SPY(AS)					0.263*	0.255*					0.015	0.014
					(5.447)	(5.477)					(1.409)	(1.319)
SPY(AM)					0.024	0.031					-0.027	-0.052
					(0.367)	(0.485)					(-0.459)	(-0.839)
Crisis Ind.	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Obs	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960	9960
AR2	0.508	0.513	0.518	0.525	0.535	0.541	0.043	0.049	0.049	0.056	0.053	0.060

Table 6: Contagion Test based on the Financial Crisis in 08/2007-03/2009

This table reports the results for the following regression:

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_t^{REG} REG_t + \beta_t^{WRLD} WRLD_t + e_{TD,i,t}$$

$$\beta_{i,t}^{REG} = \beta_{0,i}^{REG} + \boldsymbol{\beta}^{REG} \mathbf{Z}_{t-1} + \beta_{2,i}^{REG} I_{\{08/2008-03/2009\}}$$

$$\beta_{i,t}^{US} = \beta_{0,i}^{US} + \boldsymbol{\beta}^{US} \mathbf{Z}_{t-1} + \beta_{2,i}^{US} I_{\{08/2008-03/2009\}}$$

where *REG* is the regional market return, *WRLD* is the world return. The factor loadings are modelled as a linear function of the five proxies for the limits to arbitrage. In this table I only report the coefficient estimates for the financial crisis dummies (defined as 07/2007-03/2009). Heteroskedasticity consistent standard errors. */**/*** denotes statistical significance at the 1/5/10 % level.

	EWTD		***REG***		***WRLD***	
	Coeff.	**T-stat**	**Coeff.**	**T-stat**	**Coeff.**	**T-stat**
FRA	-0.089	-1.219	-0.114	-1.786	0.073	1.475
GER	0.006	0.079	-0.087	-1.260	0.049	0.883
ITA	-0.008	-0.096	-0.135	-1.990	0.028	0.541
SPA	-0.026	-0.319	-0.160	-2.226	0.051	1.037
AUT	0.108	1.023	-0.282	-3.090	0.014	0.234
BEL	0.112	0.798	-0.253	-2.903	0.104	0.910
NET	-0.030	-0.363	-0.138	-1.943	0.051	0.924
GBR	-0.005	-0.055	-0.162	-2.212	0.070	1.247
SWI	-0.002	-0.019	-0.043	-0.610	0.098	1.875
SWE	-0.085	-0.759	-0.135	-1.483	0.047	0.649
AUS	-0.004	-0.036	-0.006	-0.074	0.119	1.582
HKG	0.208	1.381	-0.190	-2.014	0.118	1.450
JPN	-0.012	-0.080	-0.024	-0.293	0.072	0.936
MAS	-0.053	-0.503	-0.047	-0.585	-0.011	-0.165
SIN	0.168	1.839	-0.126	-1.566	0.125	1.935
KOR	0.140	0.721	-0.207	-1.679	0.189	2.060
TPE	-0.027	-0.181	-0.068	-0.734	0.082	1.068
CAN	-0.018	-0.246	-0.022	-0.301	-0.005	-0.093
BRA	0.391	3.303	-0.257	-2.975	-0.016	-0.213
MEX	-0.031	-0.300	-0.012	-0.174	-0.039	-0.411
AVG	**0.037**	**0.248**	**-0.123**	**-1.495**	**0.061**	**0.896**

Table 7: Timing and magnitude of extreme shocks (top 5)

US shock		**VIX shock**		**REG shock**		**abs($PREM_{SPY}$)**		**EWTD shock**	
20081008	6.348	20110810	5.544	20081008	5.056	**20081126**	6.953	20081008	6.348
20110810	4.574	20080917	3.779	20081112	4.638	20081015	5.402	20110810	4.574
20081112	4.179	**20070228**	3.678	20110810	4.137	**20021009**	4.875	20081112	4.179
20081015	3.529	20081008	3.552	20020724	4.121	20020724	4.445	20081015	3.529
20020724	2.816	**20110316**	3.287	**20090114**	3.899	20080917	4.355	20020724	2.816

Note: The date refers to the Wednesday of a week-end. The shocks are expressed in nr. of standard deviations from zero.

Table 8: 1-Factor Contagion Model for *EWTD*

This table reports the results for the following regression:

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_{i,t}^{EWTD} EWTD_t + \beta_r^{REG} REG_t + \beta_r^{WRLD} WRLD_t + e_{TD,i,t}$$

$$\beta_{i,t}^{EWTD} = \beta_{i,0}^{EWTD} + \boldsymbol{\beta}^{EWTD} \mathbf{Z}_{t-1} + \eta_i^{EWTD} \left(1 + \exp\left\{-\gamma\left(s_{t-1} - c\right)\right\}\right)^{-1}, \gamma > 0$$

where *REG* is the regional market return, *WRLD* is the world return and *EWTD* is the average Tracking Deviation (excluding *i*). The *EWTD* factor loading is modelled as a linear function of the five proxies for the limits to arbitrage (*TED*, *VIX*, S&P500, financial sector return and *SPY* mispricing). Factor loadings also depend non-linearly on five different shocks to financial markets: *US* returns, *US* volatility (*VIX*), *REG* returns, *EWTD* and *SPY* mispricing. Note that all shocks are inverted such that *positive* numbers indicate adverse movements (e.g. negative returns, positive volatility). In this table I only report the signs and significances of the contagion coefficients.

	Tracking Deviation (Total)					**Tracking Deviation (NAV)**				
s_{t-1} =	**US**	**VIX**	**REG**	**COM**	**SPY**	**US**	**VIX**	**REG**	**COM**	**SPY**
FRA	+***	−	+*	−***	−*	−	−	+	−	+*
GER	+*	+	+*	−	−	+	−	+	−	+**
ITA	+*	+	+*	−	−	+	+	+	−	+
SPA	+*	+	+*	+	+*	+	−	+	−	+
AUT	−	−***	−**	+*	+*	+*	+	+*	+*	+*
BEL	−*	−*	−*	+*	+*	−*	+***	+	−*	+*
NET	+**	−	+*	−***	−*	+	+	+	−	+***
GBR	+*	+	+*	+	+*	+	−	+	−	+
SWI	+*	+	+*	−*	−*	−	−	+	−	+*
SWE	+*	+	+*	−*	−**	−	−	+	−	+*
AUS	+*	+***	+*	−*	−*	+	+	+	−	+*
HKG	+*	+*	+*	−***	−*	+	+	+	−	+
JPN	+*	+*	+*	−	+*	+	+	+	−	+**
MAS	−	−	−*	−**	−	+	+	+	−	+**
SIN	+*	+*	+*	−	−	−	−	+	−	−
KOR	+**	+*	+*	−*	−*	−	−	−	−	+*
TPE	+***	+	+**	−**	−	+	+	+	−	+*
CAN	+*	+	+*	+	+*	+	+	+	−	+
BRA	+*	+**	+*	+	−	−*	−*	−*	−*	−*
MEX	+*	+*	+*	−*	−*	+	+	+	−	+
γ	1.56	36.97	2.58	4.78	13.83	1.56	36.97	2.58	4.78	13.83
c	6.32	3.31	5.42	5.41	4.87	6.32	3.31	5.42	5.41	4.87
ΔlogL	125.2*	121.73*	124.55*	123.58*	94.43*	36.43*	15.06***	47.3*	19.99*	166.58*
Adj. R2	0.61	0.61	0.61	0.61	0.61	0.27	0.27	0.28	0.24	0.26

Note: Heteroskedasticity consistent standard errors. */**/*** denotes statistical significance at the 1/5/10 % level.

Table 9: 2-Factor Contagion Model for *WRLD* & *REG*

This table reports the results for the following regression:

$$TD_{i,t} = \sum_{j=1}^{4} \alpha_{i,j} TD_{i,t-j} + \beta_t^{REG} REG_t + \beta_t^{WRLD} WRLD_t + e_{TD,i,t}$$

$$\beta_{i,t}^{k} = \beta_{0,i}^{k} + \boldsymbol{\beta}^{k} \mathbf{Z}_{t-1} + \eta_i^{k} \left(1 + \exp\left\{-\gamma\left(s_{t-1} - c\right)\right\}\right)^{-1}, \gamma > 0 \quad k \in \left\{REG, WRLD\right\}$$

where *REG* is the regional market return, *WRLD* is the world return. The factor loading is modelled as a linear function of the five proxies for the limits to arbitrage (*TED*, *VIX*, S&P500, financial sector return and *SPY* mispricing). Factor loadings also depend non-linearly on five different shocks (s_{t-1}) to financial markets: U.S. returns, U.S. volatility (*VIX*), *REG* returns, average tracking performance (*EWTD*) and *SPY* mispricing. Note that all shocks are *inverted* such that positive numbers indicate adverse movements (e.g. negative returns, positive volatility). In this table I only report the signs and significances of the contagion coefficients.

s_{t-1} =	**US**		**VIX**		**REG**		**EWTD**		**abs(PREM$_{SPY}$)**	
	R_{REG}	**R_{WRLD}**	**R_{REG}**	**R_{WRLD}**	**R_{REG}**	**R_{WRLD}**	**R_{REG}**	**R_{WRLD}**	**R_{REG}**	**R_{WRLD}**
FRA	$-^{*}$	$+^{*}$	$-^{*}$	$+^{***}$	$-$	$-^{***}$	$+^{*}$	$+^{*}$	$+^{*}$	$-$
GER	$-^{*}$	$+^{*}$	$-^{*}$	$+^{***}$	$-^{*}$	$-$	$+^{**}$	$+^{**}$	$+^{*}$	$+$
ITA	$-^{*}$	$+^{*}$	$-^{*}$	$+$	$-$	$-$	$+^{*}$	$+^{***}$	$+^{*}$	$+$
SPA	$-^{*}$	$-$	$-^{*}$	$+$	$-^{*}$	$-^{***}$	$+^{***}$	$+$	$+^{*}$	$-^{**}$
AUT	$-^{*}$	$-^{*}$	$-$	$+$	$-^{***}$	$-$	$-$	$+$	$+$	$-^{**}$
BEL	$-^{*}$	$-^{*}$	$+$	$-^{*}$	$-^{***}$	$-$	$-^{*}$	$+$	$-^{*}$	$-^{*}$
NET	$-^{*}$	$+^{*}$	$-^{*}$	$+$	$-^{**}$	$-^{*}$	$+^{*}$	$+^{**}$	$+^{*}$	$-$
GBR	$-^{*}$	$-^{*}$	$-^{*}$	$+$	$-^{**}$	$-^{*}$	$+^{**}$	$+$	$+^{*}$	$-$
SWI	$-$	$+^{*}$	$-^{*}$	$+^{*}$	$-$	$-^{*}$	$+^{*}$	$+^{*}$	$+^{*}$	$-^{*}$
SWE	$-^{*}$	$+^{*}$	$-^{*}$	$+^{**}$	$-^{***}$	$-^{**}$	$+^{*}$	$+^{**}$	$+^{*}$	$-^{*}$
AUS	$+^{**}$	$+^{*}$	$-^{*}$	$-$	$-^{*}$	$-$	$+^{*}$	$+^{*}$	$+^{*}$	$-^{*}$
HKG	$-^{*}$	$+^{*}$	$-^{***}$	$-$	$-^{*}$	$-^{***}$	$+^{**}$	$+^{*}$	$+^{*}$	$-$
JPN	$-^{*}$	$-^{*}$	$-^{*}$	$+$	$-^{**}$	$-$	$+^{*}$	$+^{*}$	$+^{*}$	$-^{*}$
MAS	$-^{*}$	$-^{*}$	$+$	$+$	$-$	$-^{*}$	$+$	$+^{*}$	$+^{*}$	$-^{*}$
SIN	$-^{*}$	$-^{*}$	$-^{**}$	$-$	$-^{*}$	$-^{*}$	$+$	$+^{*}$	$+^{*}$	$-^{*}$
KOR	$+^{*}$	$+^{*}$	$-$	$+$	$-^{*}$	$-^{**}$	$+^{*}$	$+^{*}$	$+^{*}$	$-^{*}$
TPE	$-^{*}$	$+$	$-$	$-$	$-^{**}$	$-^{***}$	$+$	$+^{*}$	$+^{*}$	$-^{*}$
CAN	$-^{*}$	$-^{*}$	$-^{*}$	$-$	$+$	$-^{*}$	$+^{**}$	$+^{*}$	$+^{*}$	$-^{**}$
BRA	$-^{*}$	$-^{*}$	$-^{*}$	$+$	$-^{***}$	$-$	$+^{***}$	$+$	$+$	$-$
MEX	$+^{*}$	$+^{*}$	$-^{*}$	$+$	$-$	$-$	$+^{*}$	$+^{*}$	$+^{*}$	$+^{*}$
γ	0.90		108.84		4.59		2.97		3.59	
c	6.89		3.43		1.28		3.46		4.71	
ΔlogL	166.23*		115.35*		153.73*		140.35*		211.47*	
Adj. R2	0.55		0.55		0.55		0.55		0.56	

Note: Heteroskedasticity consistent standard errors. */**/*** denotes statistical significance at the 1/5/10 % level.