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Credit, Liquidity and Emerging Market Risk in the Global Equity Market

Abstract: We use data on 78 national market indices over 9 years and show that the world CAPM fails to explain stock market index excess returns both in time-series and in cross-section. We introduce credit, liquidity and emerging market factors and report that the performance of the pricing model is increased, with liquidity and emerging market contributing most. We show that the latter two are not priced by the conventional size, value, momentum, short and long-term reversals factors. The market prices of risk are found to be around 10% per year for liquidity and emerging market and close to 0 for credit and world market. The time-varying prices of risk seem to be consistent with the corresponding economic developments. In order to produce investable factors that reflect the liquidity and emerging market risks, the 'dynamic orthogonalization' concept is applied.

Keywords: Credit Risk, Liquidity Risk, Emerging Market Risk, Asset Pricing Model, Dynamic Orthogonalization, CDS, Autocorrelation

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1 Introduction

The issue of explaining stock market returns is of vital importance for both theoretical and empirical finance. Many authors have attempted to address it, resulting in a number of better- or worse-performing asset pricing models, most of which can be applied to a single market. However, extending a model internationally has proven to be non-trivial and no commonly-accepted well-performing model has been developed yet. Moreover, financial markets are far from perfect or fully integrated and different sources of risk have been shown to impact the cross-section of stock returns. Though the influence of various risk factors has been examined, there is space for further research and improvement.

The literature on international asset pricing models begins with Solnik (1974a, 1974b), first introducing a model linking country indices to the world market. While the framework is intuitively appealing, it is unable to explain the cross-section of equity returns, especially the emerging market ones. This stimulated the development of alternative model specifications capturing not only market, but other risks as well. Out of a number of factors, credit and liquidity are shown to be of high importance for explaining the difference in stock returns across countries (Avramov et al., 2012; Lee, 2011). However, the evidence on their significance and explanatory power remains mixed. At the same time, part of the literature promotes the status of emerging market as futile, after accounting for exposure to such risks (for example, Avramov et al., 2012).

In this paper we add to the literature on credit, liquidity and emerging market risk by assessing whether these factors explain the time-series and cross-section of market index returns. We also check if they are priced by the market and what is the magnitude of their risk premia. Unlike many other authors, we build the global credit risk factor using the data on sovereign credit default swap (CDS) spreads. The factor is constructed as the difference in equity index returns of the countries with the highest and the lowest CDS spreads. The benefit of such an approach is that the spreads adapt much faster to new information than sovereign credit ratings or KMV's expected default probability, two generally used proxies for creditworthiness. The global liquidity factor, inspired by Roll (1984) and similar works, is constructed as the 'dynamically orthogonalized' difference in returns of the emerging countries with high absolute autocorrelation and developed countries with low absolute autocorrelation. The paper also employs an emerging market risk factor, computed as the 'dynamically orthogonalized' difference between the MSCI-

EM index and the risk-free rate.

The analysis is performed weekly on the period from February 5, 2004 to January 23, 2013, while the data is collected starting from January 2, 2001. We use stock market index data for 78 countries and CDS data for a variable number of countries, up to 61 at each point in time, 62 over the whole period. Eleven model specifications are run and three different ways of model estimation are allowed for: unconditional, dynamic unconditional and conditional, the focus being retained by the unconditional one.

We find that the world CAPM fails in our sample both in time-series and in cross-section, while the inclusion of the proposed factors improves the performance of the model. The biggest contributors to the explanatory power increase are the liquidity and emerging market factors. Liquidity risk is consistently positively priced with a premium of about 10% p.a. and is statistically significant, followed by the emerging market risk, which is economically similar, but statistically weaker than the liquidity risk price. The results hold when the models are run for different subperiods, different holding periods for the portfolios underlying the factors, on a 4-week basis rather than weekly or on 16 portfolios sorted on credit and liquidity risk. Moreover, we also use autocovariance instead of autocorrelation in the construction of the liquidity factor and find similar results.

Running the models dynamically, we observe that the price of risk is highly time varying and reflects market developments. When applied on a 4-week basis, we find that the dynamic models explain abnormal returns better, in line with the results of other authors (for example, De Santis and Gerard, 1998).

We compare our factors to those frequently used in the literature, *SMB*, *HML*, *MOM* and short- and long-term reversals, and find that, with the exception of the credit risk factor, they are unable to price the factors used in the paper. Moreover, the combination of our credit, liquidity, emerging market and world market risk factors potentially reduce the abnormal returns of the commonly-used risk factors.

We contribute to the existing literature in several ways. First, we use CDS spreads as a proxy for sovereign creditworthiness when constructing the credit risk factor and apply an innovative approach to the construction of the global liquidity factor when one does not have the opportunity to use established volume-based liquidity measures. Second, to our knowledge, we employ the most extensive dataset in terms of the number of countries. Finally, the analysis is performed on a period containing the latest financial turmoil and the European sovereign debt crisis.

The paper proceeds as follows. Section 2 provides the review of the relevant literature. Section 3 describes the data used in the study. Section 4 presents the motivation for the factors used. Section 5 describes the methodology applied. Section 6 elaborates on the results obtained while Section 7 checks their robustness. Finally, conclusions are drawn and paths for possible further research are suggested.

2 Literature review

The literature on asset pricing models is vast and has a long history. It starts with Sharpe (1964) and the first introduction of CAPM. Solnik (1974a), Sercu (1980) and Adler and Dumas (1983) develop and adapt the CAPM to an international setting. Solnik (1974a, 1974b) is the first to derive and test an international asset pricing model (IAPM) for stocks. Sercu (1980) develops Solnik's model by relaxing the assumptions about the covariance structure of asset returns, while Adler and Dumas (1983) stress the importance of market segmentation/integration.

When building his argument, Solnik (1974b) links the country indices to the world market for the first time, in the spirit of the previously developed CAPM. All the following tests of the international pricing models include the world market as a global risk factor. Ferson and Harvey (1994) test different unconditional factor models on 18 national equity markets and find that the world market is clearly the most important, even though it alone is unsuccessful at fully explaining the cross section of country excess returns. Harvey (2000) tests 18 different international pricing factors and finds that the world beta is valuable in the cross-section. Hou et al. (2011) also find that the global market risk factor, along with momentum and cash flow/price factors, explains well country and industry returns. Using global and local instruments Harvey (1991) documents that time-varying covariances between national markets and the world systematic risk factor explain only partially the country stock returns and points out that the unexplained part could be due to incomplete market integration, model misspecification or existence of more than one source of risk, issues that we approach next.

Firstly, in trying to explain the cross section of country stock returns, some authors (Harvey, 1991; Ferson and Harvey, 1994; Bali and Cakici, 2010) assume full market integration, such that the covariance with the world market is the relevant risk measure (Harvey, 1991; Bali and Cakici, 2010). To different degrees, this assumption can be wrong. Harvey (1991), trying to explain the weak results of his model mentions incomplete market integration. Bali and Cakici (2010) also conclude that markets are not fully integrated. The complete market integration assumption is not necessarily valueless though, especially considering the accelerated globalization we witness today. For example, Brown et al. (2009) observe an increase in the global market correlations, while Dumas and Solnik (1995) could not reject the hypothesis that the world capital market is integrated.

Secondly, a large number of authors affirm that the ICAPM fails because it is implemented unconditionally (for example, Harvey, 1991). Merton (1973) introduces an intertemporal version of the CAPM, which serves as the basis for the later conditional factor models. In their analysis on stock portfolios, Jagannathan and Wang (1996) prove the superiority of the conditional CAPM (with time varying factor exposures and risk premia) over its unconditional version. Dumas and Solnik (1995) stress the importance of testing any asset pricing model in its conditional form, while De Santis and Gerard (1998) explain why unconditional versions of the CAPM are likely to fail.

Finally, it can be that country stock return movements are due to exposure to multiple factors. Fama and French (1993) introduce the SMB and HML mimicking portfolios and show that they explain the cross section of 25 stock portfolios sorted on size and book-to-market. At the same time, they argue that the credit (bond) market factors do not impact the SMB and HML factor loadings and do not help explain stock returns. Jagannathan and Wang (1996) show that inclusion of human capital in the analysis leaves the Fama-French factors with no explanatory power. Bali and Cakici (2010) implement the Fama-French factors at index-level and find that the world systematic risk is not a significant factor, while country-specific and idiosyncratic risks are priced in the equity markets. Fama and French (2012) also conclude that global models based on size and book-to-market are poor in explaining regional or local stock returns. Beyond the Fama-French factors, the literature is rich in attempts to interpret international stock returns on the basis of different explanatory variables. Bansal and Dahlquist (2002) argue that, although for the developed markets the systematic risk seems to be enough to explain excess returns, expropriation risk, which is partially related to the reputation in the global capital markets, explains more than half of the risk premia for emerging countries.

On a newer dataset, Avramov et al. (2012) find that the status of emerging market per se does not explain the return differential between emerging and developed countries and that, once again, we need to look beyond the traditional factors for explaining the cross section of country-level stock returns.

Some authors find evidence that the foreign exchange risk premium explains international stock returns[1]. Opposing results are found by Jorion (1991), who reports that US industries' exposure to foreign exchange risk commands no significant premium. Bailey and Chung (1995) find the unconditional currency risk inexistent in the Mexican stock returns. The unconditional model of Di Iorio and Faff (2002) leads to inconclusive results regarding the significance of the exchange rate risk when implemented on different subperiods on the Australian market. Loudon (1993) and Kodongo and Ojah (2011) also find that the exchange risk is not unconditionally priced in the Australian and African markets respectively.

There are two other major sources of risk that the literature proposes in order to complete the (international) CAPM: credit and liquidity. In the following sub-sections we focus our attention on them and review the main ideas.

2.1 Credit risk

The theoretical motivation of the role of credit risk in equity pricing has been shown by Gomes and Schmid (2010) who derive that, in a general equilibrium model setup, counter-cyclical nature of credit risk generates an endogenous counter-cyclical risk premium which should be priced in the market. Some authors find evidence for the opposite relationship. Having examined sovereign credit default swap (CDS) spreads from 2000 to 2010, Longstaff et al. (2011) find that most of the credit risk is explained by the US stock market and various high-yield risk factors. Also global investors' risk aversion has been shown to have a significant impact on time variation of sovereign credit risk premia (Remolona et al., 2008; Lizarazo, 2013). Contrary to these studies, Avramov et al. (2012) create a factor based on differences in equity returns of 75 countries ranked by their sovereign credit ratings and find that the world credit risk factor explains high returns of emerging markets that could not be explained by other global risk factors both in cross

[1] For example, Korajczyk and Viallet (1992), Ferson and Harvey (1994), Dumas and Solnik (1995), De Santis and Gerard (1998), Choi et al. (1998), Doukas et al. (1999).

section and time series. Moreover, the emerging markets factor, which could explain the difference in equity returns among developed and developing economies, becomes insignificant in the presence of the credit risk factor. The finding is supported by Boons (2012), who finds in his test of the ICAPM that exposures to credit market proxies, such as the default spread or the term spread, are priced in the international stock markets. Bailey and Chung (1996) conclude that credit market, along with global equity and currency factors could explain Philippine stock returns, while the risk exposures may not be constant. However, other evidence on the issue is mixed. In an earlier study using corporate credit ratings of US stocks directly, Avramov et al. (2009) find the importance of credit risk to be time-varying and inexistent during calm times, while Garlappi, Shu and Yan (2008), using the Expected Default Probability of Moody's KMV as a proxy of corporate creditworthiness of non-financial US firms, find that higher default probabilities are not associated with higher expected returns and attribute the difference in equity returns to shareholder's negotiation power in case of default.

Looking at the effects of market integration, several studies document that the impact of changes in credit ratings spill over to other countries (Ferreira and Gama, 2007; Christopher et al., 2012). Moreover, the effect of both changes in rating or rating outlook is more pronounced for downgrades rather than for upgrades (Ferreira and Gama, 2007; Pukthuanthong-Le et al., 2007). There is also some evidence that changes in credit ratings have an effect on higher moments of stock returns. Treepongkaruna and Wu (2012) and Hooper et. al. (2008) find that sovereign rating events have a significant impact on realized stock market volatility, increasing it for downgrades and decreasing it for upgrades.

A growing number of studies use credit default swaps (CDS) when trying to explain and forecast equity returns. Han and Zhou (2011) find the slope of the CDS term structure to predict negative stock returns, but their finding cannot be explained by differences in corporate default risk. Meanwhile, Forte and Loverta (2008) show that stock market seems to lead CDS market in terms of price discovery, yielding mixed evidence on the issue. However, Che and Kapadia (2012) find that credit default swaps cannot be effectively hedged in the equity market and suggest that incomplete market integration over short-term horizons can be the cause of it.

It can be seen that the empirical evidence of the role of the credit risk premium is mixed and no consensus has been reached yet, making it an interesting field for research. Moreover, to our knowledge, usefulness of the CDS spreads in explaining the difference in cross section and time series of equity returns globally has not been widely researched yet[2], thus we want to contribute to this field of study in this paper.

2.2 Liquidity risk

Unlike other risk factors, liquidity is elusive and cannot be observed directly; hence its effects on stock returns are not easily testable (Amihud, 2002). As a result, various measures of liquidity have been proposed. In their survey article, Gabrielsen et al. (2011) divide the liquidity measures into volume-based (for example, trading volume, the index of Martin, the liquidity ratio of Hui and Heubel, the turnover ratio, Amihud's ILLIQ), price variability related (the liquidity measure of Marsh and Rock, the variance ratio) and transaction costs based (the bid-ask spread). However, despite the vast number of liquidity proxies, empirical evidence generally agrees that less liquid stocks command higher risk premia.

In one of the first studies on liquidity, Amihud and Mendelsen (1986) propose the hypothesis that expected stock returns are an increasing concave function of illiquidity, proxied by the bid-ask spread, and support it using the 1961-1980 data on NYSE equities. Numerous studies have tested and strengthened this idea using different liquidity proxies and data from various markets. Amihud (2002) suggests an illiquidity measure based on absolute return and traded dollar volume. He finds that the expected excess returns of the stocks are positively related to expected market illiquidity. Interestingly, he observes that rising expected market illiquidity induces investors to shift from less liquid to more liquid stocks, an effect also documented by Acharya and Pedersen (2005). Several other studies of the US market uncover similar effects of liquidity on expected stock returns. Gibson and Mougeot (2004) find that the liquidity premium is significantly negative and time-varying in the US. Pastor and Stambaugh (2003) also show that the liquidity risk is priced in the US even after controlling for the market, size and value factors, as well as momentum. Acharya and Pedersen (2005) develop a liquidity-adjusted CAPM and report that the model significantly outperforms the ordinary CAPM and, similar to other

[2]Some papers attempt to use CDS spreads of corresponding equities to explain the difference in returns. For example, Steiger (2010) finds that stocks with higher CDS spreads tend to earn a premium over those with lower spreads.

authors, document that positive shocks to illiquidity result in higher expected returns. In addition, Deuskar and Johnson (2009) find a positive significant relationship between market illiquidity and market volatility.

Different studies show that the liquidity risk premium is present in other markets outside the US. Liang and Wei (2012) show that local liquidity is priced in 11 developed markets[3], while Jun et al. (2003) find positive correlation both in the cross-section and in the time-series of aggregate market liquidity and stock returns in 27 emerging markets; however, they do not observe a causal relationship between the two. Other studies that focus on single markets stay in line with the previous literature, suggesting that liquidity risk is priced by the market participants (Martinez et al., 2005; Lam and Tam, 2011). International evidence is further strengthened by Lee (2011) who uses an extensive dataset of 30 000 stocks from 50 countries. His findings confirm that liquidity risk is priced in most of the countries and that it affects prices through channels other than market risk.

Due to the peculiarities of the data available, which are going to be addressed in greater detail later in the text, we are unable to apply the generally used measures based on trading volumes or any other stock-specific information, and have to innovate in finding a liquidity factor. Yet, we do expect to obtain results similar to those of other authors.

3 Data

For the purpose of conducting the study we use weekly Wednesday-to-Wednesday US dollar returns on MSCI country indices. The sample in terms of the number of countries is limited by the data available in Datastream, starting from January 2001[4]. Where the MSCI index is not available, we have the following list of priorities in choosing a country index: the main index of the market, the HSBC index and finally the S&P broad market index. If the MSCI index is available only after the 31st of December 2003, we use the local index, proven that its history is longer. Where the dollar index is not available we use the bilateral exchange rate from Datastream to obtain US dollar-returns from an index denominated in the local currency. For autocorrelation calculations we use the daily returns on the version of each index in the trading currency. Where such a version is not

[3] However, their conclusions are not highly convincing because they obtain different results (in terms of significance) for different liquidity proxies.

[4] Starting earlier is meaningless, as the first CDS observations are available in 2003.

available, we convert the USD-returns to the original trading currency. Since such a series of transformations can lead to rounding errors, we impose a rule that in case a computed return in local currency is below 0.00001 in absolute terms it is forced to zero. Similar to country indices, we collect the sovereign CDS data for all the countries for all the time periods which are available in Datastream. The spreads used in the analysis are for the 5-year USD-denominated credit default swaps.

Some additional clarifications have to be made. There are several issues with the data in the way it has been collected by Datastream. Stock markets in Egypt, Jordan, Kuwait, Oman and Saudi Arabia were open Sunday to Thursday during the period of the study. Datastream, however, does not record the index on Sundays, but saves the Thursday values twice (for Fridays). For the weekly analysis this does not pose any problems, while for autocorrelation calculations all days experiencing exactly 0 returns in local currency are omitted assuming that either no trading had taken place because the market was closed or the data is flawed. The assumption seems viable since it is extremely unlikely that if a market was open the total market index did not change at all during the trading session. There are also several other cases when the index data seems to be faulty, for instance for Bangladesh between Nov. 26, 2001 and Dec. 9, 2003 there are 2 large jumps while the rest of the data is very smooth and seems to have been created artificially, or for Panama where the performance of the index seems to exhibit unusual patterns, which are not observed when comparing the Datastream data to other data providers, e.g. Bloomberg. While the first case does not create any difficulties since the problematic period does not fall within the time span of the research, the second case does result in a problem and requires the country to be excluded from the sample.

As a result, given the construction of the portfolios, the study covers the period from February 5, 2004 to January 23, 2013 for 78 countries[5]. Although the time series are not very long, they should be enough for a weekly analysis; however, the weekly data could be noisy and therefore might constitute a weak point of our analysis.

It is important to note that Thomson Reuters ended the contract with CMA for providing CDS data in 2010 and kept reporting only self-collected CDS spreads. For the period in which the time series of the two providers overlap, we observe that they are

[5]The number of countries for which the data is available for indices and CDS spreads can be seen in Figure S1. The list of countries can be seen in Table 1.

similar, but do not coincide, hence we keep the ones with the highest variation in spreads[6]. It should also be noted that the difference in spreads reported by different data providers is not of serious concern for us, as the relative magnitude of the reported spreads is the same from both providers and we construct portfolios based on the CDS spreads and do not use the spreads directly.

Finally, we use the MSCI World and MSCI Emerging Markets indices in constructing the world market and emerging market factor. The risk-free rate is proxied by the 3-month Treasury bill rate from The Federal Reserve. The weekly risk free rate is calculated as the average of the 5 daily risk free rates (expressed in yearly terms), compounded for 1/52 years. All index returns are computed as arithmetic returns. The asset excess returns are then calculated as the difference between country's weekly index return and the weekly T-bill rate[7]. It should be noted that all statistics and results are reported for weekly and not annualized returns unless specified otherwise.

4 Motivation for the factors

As mentioned earlier, a number of studies have tried to use credit risk-based factors in equity pricing models. However, unlike most of the earlier works, this paper utilizes sovereign credit default swap spreads as a measure of creditworthiness of a particular country. A CDS spread represents a very good proxy for the credit riskiness of the underlying asset since it prices almost exclusively credit risk. Moreover, it adapts much faster to news than the other risk measures used in the literature, such as credit ratings or KMV's expected default probability. Even though the approach has been used in some other studies, it is still novel and requires an investigation of the relationship between sovereign CDS spreads and country equity returns. In order to achieve this, every week t we sort the countries into quartile portfolios using their CDS spreads for that respective week. We hold the portfolio for four weeks starting from the investment date, which results in a holding of four portfolios for each quartile at each point in time or sixteen portfolios in total at each point in time. We then compute weekly average equally-weighted equity market returns for each of the quartile portfolio groups. Table 3 reports the average

[6]It is often the case that spreads from one of the providers change only a couple of times per week or per month while those of the other data provider change every trading day during the same period.

[7]The distribution of summary statistics of the index excess returns can be seen in Figures S2 and S3.

equity returns for the portfolios for the whole sample period as well as for the first four years (corresponding to market expansion) and the remaining five years (which include the market crash and the European sovereign debt crisis) of the sample. Aggregated results for the whole sample are not very conclusive, but provide a starting point for our expectations: the average annualized return for the safest portfolio (denoted *C4* as in Table 2) was 8.64% while that of the riskiest one (*C1*) was 11.11%. Returns of all four portfolios exhibited high variations relative to their means; thus, the differences in returns across portfolios should not be treated as certain. The picture changes when the sample is split into two parts. We split the sample on February 7, 2008 so that the first part, consisting of four years of data, represents the period of economic expansion while the second part contains the financial and the sovereign debt crises. The period until February 6, 2008 provides a much clearer pattern of the difference in equity returns for the risky, middle and safe countries based on their credit risk, the annualized return for the riskiest countries was 38.86% and 20.91% for the safe ones. Even though the volatility of returns was also high, the magnitude of the difference in returns is clearly economically and statistically significant with a t-statistic of 2.82. At the same time the results are almost the opposite for the period starting from February 7, 2008, the lowest average returns were observed for the riskiest countries with the annualized mean returns being -7.24%. However, the other 3 portfolios yield a return consistent with the expectations: the safest (*C4*) averaged -0.37% p.a., *C3* returned 0.14%, while *C2* performed best with 2.37%. In order to better understand the development of returns over time we also report the value of one dollar invested in each of the four portfolios (see Figure 1).

Supporting the results presented above, one can see on the graph that average equity returns for the four portfolios were somewhat differentiated from the beginning of the sample period until the beginning of 2008 with clearly higher returns for the countries with the highest CDS spreads as compared to the rest. Average CDS spreads for the four portfolios remained relatively stable over time in the first sub-sample as well (see Figure 2). The period starting with the end of 2008 yields mixed results for the portfolio returns. As previously, the safest countries in terms of credit riskiness had the lowest equity returns in 2009–mid-2011 while the rest of the portfolios had higher returns. However, the European sovereign debt crisis, which deepened significantly in 2011, resulted in a sharp rise in CDS spreads for heavily indebted and credit risky countries and in capital flights from these markets, leading to strongly negative equity returns. This can also be seen in the graph – the value of money invested in credit-risky countries' stocks (*C1*) deteriorated heavily when the CDS spreads jumped and stabilized. This drop partially explains the low average returns of risky countries for the second part of the sample, the other reason being the market crash of 2008 which affected the credit-unworthy countries most. Despite the somewhat controversial results of 2008-2013, the overall picture suggests that equities of countries with higher sovereign CDS spreads do seem to earn a premium over those of less credit-risky ones, which serves as a motivation for the credit risk factor that is constructed later in the paper.

Similar to the effect of credit risk, the effect of liquidity on equity returns is examined. Our study has a limitation of not having the privilege to use trading volume data for all the countries due to its unavailability for the equity indices used, thus liquidity has to be proxied only with the help of stock market returns. The most straightforward measure that could be computed in this situation is the absolute value of equity returns order 1 autocorrelation, similar in its spirit to the work of Roll (1984) and other authors. In this case the countries with autocorrelation closest to zero, similar to a Wiener process, should be considered to have the most liquid equity markets while those with the values furthest away from zero – the most illiquid ones. It is also commonly accepted that emerging markets on average have lower stock market liquidity than the developed ones (Bekaert et al., 2007). Since the autocorrelation measure itself is not the best proxy for liquidity, we combine it with a classification of advanced and emerging countries. Thus, 4 portfolios of countries are constructed each week: the whole sample is first divided into developed and emerging countries based on the IMF (2012) classification and afterwards each basket is divided in half based on the level of absolute order 1 autocorrelation as in Table 2. Autocorrelations are computed at the end of each Wednesday using the previous 130 non-zero daily observations of equity index returns in the original trading currency of the index, which roughly represents half a year of data. Similar to CDS spread-sorted portfolios, we hold portfolios sorted on absolute values of autocorrelation and emerging market status for four weeks resulting in a simultaneous holding of sixteen portfolios, four for each level of risk. In the end we examine the returns of the portfolios – risky (*E1*) and safe (*E2*) portfolios of emerging markets and risky (*D1*) and safe (*D2*) portfolios of developed markets, value of one dollar invested in which can be observed in Figure 3. As one can see, the difference in returns of developed and emerging market portfolios is rather obvious – emerging markets do seem to command a premium over the developed ones. However, the difference in returns within the emerging and developed groups is not as clear-cut. Assuming that absolute autocorrelation is a good proxy for liquidity, such a result could imply either that there is no significant difference in liquidity within the emerging and developed markets groups or that the difference is there but different portfolios also have different exposures to other risks which add up to the effect of liquidity, risks that are captured due to the double-criterion used in the construction of the portfolios. The first hypothesis proves to be wrong as absolute values of autocorrelations do differ between portfolios (see Figure 5) and the second hypothesis can be tested by orthogonalising the portfolio returns with respect to the other risk factors, the most obvious of which in our case are market and emerging market risks. In order for the portfolios to be investable, we run orthogonalisation dynamically, which will be explained in greater detail further in the methodology section. As for now, we present the average orthogonalised portfolio returns sorted on emerging and developed markets status and absolute autocorrelation (see Table 4). The average returns of supposedly less liquid markets (*E1* and *E2*) are higher during the sample period as compared to the supposedly more liquid markets (*D1* and *D2*). Also the average returns of emerging markets with higher absolute autocorrelation (*E1*) are greater as compared to those with lower absolute serial correlation (*E2*) with 8.19% versus 5.39% in average annualized values, which is consistent with our hypothesis as well but the difference is not large. The pattern is also observed in developed countries with average annualized returns for less liquid (*D1*) and more liquid (*D2*) countries being 0.44% and -2.24% respectively. When splitting the sample into two parts based on the advanced/emerging market status, the general picture remains the same with less liquid markets earning a premium over the more liquid ones; however, the difference in returns within the emerging and developed markets segments is still not clear and could be varying over time. We plot the value of one dollar invested into each of the four portfolios in order to better understand their performance (see Figure 4).

One can observe that the less liquid countries have been outperforming the more liquid ones throughout most of the sample, which supports the conclusions about difference in average returns presented earlier. Moreover, there seems to be a clear difference between all four portfolios with the riskiest one (*E1*) outperforming the other ones most of the time. The most obvious difference in returns of the four portfolios could be observed in the first half of the sample until mid-2008 with riskier countries offering higher premia. With the outbreak of the financial crisis all the portfolios experienced a crash, but it was much more severe for the less liquid ones; again, this is observed after the portfolios are dynamically orthogonalized with respect to world and emerging market risk. Also absolute autocorrelations of the emerging markets returns jumped indicating decreased liquidity in those markets as the investors flew to safer economies (see Figure 5). While from 2009 the difference in returns between the emerging markets portfolios started to behave as predicted again, this is slightly less clear for the developed economies; the performance of more and less liquid developed markets portfolios was very similar. However, when considering the two portfolios with lowest and highest liquidity, i.e. emerging markets with highest absolute autocorrelation (*E1*) and developed markets with the lowest absolute autocorrelation (*D2*), the first one does seem to have higher return in most of the cases as compared to the second one; thus, they should be good candidates for constructing the liquidity factor. Also unlike in the case of plain absolute autocorrelation and country status-sorted portfolios with no orthogonalization, these dynamically orthogonalized portfolios do not suffer ex-ante from possible exposure to world market and emerging market risks, which could bias the results.

One could still argue that both the proposed logic for liquidity and credit risk factors might be flawed since it could be the case that exactly the emerging markets are the least liquid ones and have the highest credit risk exposure. Thus, both factors could be capturing just the so-called emerging market premium. In order to eliminate this potential misjudging of the factors we include an emerging market risk factor in the study, which should capture the emerging market premia in the assets. We discuss the construction of this emerging market factor later in the paper.

5 Methodology

In line with De Santis and Gerard (1998) who found that the local risk was not priced in any of the major stock markets, in this paper we focus on global factors and try to explain the national market stock returns on the basis of world market, credit, liquidity and emerging market risks. We use mimicking portfolios to proxy for credit and liquidity in the spirit of Fama and French (1993) or Avramov et al. (2012). Our models are implemented weekly, as a daily implementation would bring too much noise, while a monthly approach would leave us with too little data. For each of the risk measures, we sort the countries from the least favorable risk measure to the most favorable one, i.e. from high CDS spread to low CDS spread and from low liquidity to high liquidity, as proxied by absolute autocorrelation and emerging market status.

5.1 The factors

Firstly, the world market risk factor (*WMR*) is defined as the weekly risk premium of the MSCI World index over the 3M T-bill rate, similar to Harvey (1991) or Lim (2005), using arithmetic returns.

For constructing the credit factor (*CRD*), each week t we split the countries into four equally-weighted portfolios with the same number of assets, after having sorted them based on the 5Y sovereign CDS spread. In order to ensure some degree of consistency from one week to another and to eliminate possible reversal effects, we hold each weekly-formed portfolio for 4 weeks. Therefore, each week t we have in total 16 portfolios, the earliest 4 being formed in *t-3*, while the latest 4 being formed in that respective week. We regroup the 16 portfolios into 4 portfolios according to the level of credit risk they had in the week when they were formed. More specifically, each week t we group the riskiest portfolios for *t-3*, *t-2*, *t-1* and t into one equally-weighted portfolio. We do the same for the 2$^{\text{nd}}$ riskiest, 2$^{\text{nd}}$ safest and the safest portfolios. We denote the 4 portfolios formed in such a way as *C1, C2, C3* and *C4*, *C1* being the riskiest (corresponding to the countries with the highest CDS spread) and *C4* being the safest. *CRD* is then computed as the weekly return on *C1* minus the weekly return on *C4* (i.e. *CRD* is the return on credit unworthy minus the return on credit worthy countries). *CRD* is investable, being the result of a linear combination of tradable portfolios.

As data for calculating conventional liquidity measures at index level is not easily available, our liquidity factor (*LIQ*) is based on a combination of two criteria: the emerging/advanced market status and the absolute autocorrelation. Roll (1984), Lesmond (2005) and Vayanos and Wang (2009) all consider that the higher negative autocovariance is an indicator of higher illiquidity. Moreover, Roll (1984) bases his method on the strong assumption that the 1$^{\text{st}}$ order autocovariance is negative, proposing the square root of minus autocovariance as an illiquidity measure; Lesmond (2005), following Roll (1984), forces the positive autocovariances to become negative, while Vayanos and Wang (2009) use minus autocovariance as a measure for illiquidity. All these authors' methods fail to accomodate the data we work on and assuming autocovariances to be negative deviates dramatically from reality[8]. An important proportion of both the advanced and emerging market autocovariances is positive; for emerging markets the positive autocovariances even seem to dominate.

Our approach is in the spirit of the aforementioned authors' procedures, but is simpler and adapted to our data. We take the absolute autocorrelation to be the measure of liquidity risk. A high absolute autocorrelation means high illiquidity, while the lower the absolute autocorrelation, the safer the asset should be from a liquidity perspective. We prefer autocorrelation to autocovariance because it standardizes for market volatility. The ranking that it produces is mathematically similar to Roll's square root of minus autocovariance given that all the autocovariances are negative[9]. At the same time, we acknowledge that autocorrelation is not a perfect measure of liquidity and can produce some puzzling rankings of the countries[10]. In an attempt to avoid such effects, we clearly separate the countries according to their status of advanced and emerging and consider that the advanced countries are more liquid by default. This assumption is consistent with Bekaert et al. (2007), who state that the emerging countries are the markets where the liquidity effects may be particularly strong. This means that a criterion based on emerging/developed status contains, besides information about the emerging market risk, also information about the liquidity risk and this information is valuable for us. We acknowledge that a limited number of emerging countries can be more liquid than some advanced countries and postulating that emerging markets are by default less liquid constitutes a limitation of our study.

In light of these arguments, we first split the countries according to IMF World Eco-

[8]See Figure S4. Note that we only present autocorrelation, but the sign of autocorrelation is the same as the sign of autocovariance.

[9]If we used autocovariance, the ranking would be exactly the same as Roll's.

[10]For example Columbia has, at times, a lower absolute autocorrelation than the United States. However, this does not completely undermine the absolute autocorrelation as a measure of liquidity. The majority of the emerging countries do have higher absolute autocorrelations than the developed coutnries; also, absolute autocorrelation predicts that emerging markets are on average less liquid than the advanced markets, which is an economically reasonable fact. In Figure 5 and Figure S4 we do observe that the average absolute autocorrelation within the emerging markets basket is undoubtedly higher compared to the developed bin.

nomics Outlook (2012) into advanced and non-advanced. We obtain 34 advanced countries and 44 non-advanced (emerging), as in Table 1. Each week t, within each of the two groups we sort the countries according to their absolute order 1 autocorrelation of returns, calculated from the previous 130 daily observations, excluding the non-trading days as explained in Section 3 and form two portfolios within each subgroup, containing the same number of countries. As in the credit factor case, we keep the holding period for four weeks and we follow the same procedure for constructing four portfolios. More specifically, the riskiest portfolio in week t would be the equally weighted average of the portfolios of emerging countries with highest absolute autocorrelation for the weeks *t-3*, *t-2*, *t-1* and t. The safest portfolio in week t would be the equally weighted average of the portfolios of advanced countries with lowest absolute autocorrelation for the weeks *t-3*, *t-2*, *t-1* and t. Table 2 illustrates how we construct the portfolios.

The next step in constructing our liquidity factor is taking the difference between the weekly returns of portfolios *E1* and *D2*. Given our methodology, that represents the difference between the most illiquid portfolio, being a portfolio of emerging countries and having the highest absolute autocorrelation within the emerging markets bin and the most liquid portfolio, being advanced and having the lowest absolute autocorrelation within the advanced countries bin. As shown before, in constructing these portfolios we make use of the information contained in the advanced/emerging market status, but this status also brings undesired noise. Therefore, the *E1-D2* difference contains not only the liquidity risk (*LIQ*) premium, but also the emerging market risk (*EMR* – defined later) premium and potentially the premium for different exposures to world market risk (*WMR*), due to the country status of advanced or emerging. In order to be left with liquidity premium, we need to strip this return differential of its emerging and world market part. We do that by 'dynamic orthogonalization'. We first run Regression 1 dynamically using a window of 1.5 years (78 weeks) before the estimation, i.e. for each date t we use the 78 previous observations of *WMR* and *EMR*. The window should be long enough to produce relatively stable beta coefficients but at the same time short enough to capture the changes in exposures to the factors. More precisely, for each date t, for s from *t-78* to *t-1* (including both ends) we run:

$$
\begin{aligned}
(R_{E1}-R_{D2})_s &= (\widehat{\alpha_{E1}-\alpha}_{D2})_{t-78:t-1}+(\widehat{\beta^W_{E1}-\beta^W_{D2}})_{t-78:t-1}WMR_s+\\
&+(\widehat{\beta^E_{E1}-\beta^E_{D2}})_{t-78:t-1}EMR_s+(\varepsilon_{E1}-\varepsilon_{D2})_s\,, \qquad (1)\\
&s=t-78,t-77,...,t-1
\end{aligned}
$$

where $\beta^W$and β^E stand for beta with respect to the world market and emerging market factor and *t-78:t-1* denotes the window for which the coefficients have been estimated. Finally, our liquidity factor at date t (LIQ_t) is the unexplained part in the return differential between *E1* and *D2* ($(R_{E1}-R_{D2})_t$) using the coefficients estimated previously ($(\widehat{\beta^W_{E1}-\beta^W_{D2}})_{t-78:t-1}$ and $(\widehat{\beta^E_{E1}-\beta^E_{D2}})_{t-78:t-1}$) and the time-t *WMR* and *EMR*:

$$
\begin{aligned}
LIQ_t &= (R_{E1}-R_{D2})_t-\left[(\widehat{\beta^W_{E1}-\beta^W_{D2}})_{t-78:t-1}WMR_t+(\widehat{\beta^E_{E1}-\beta^E_{D2}})_{t-78:t-1}EMR_t\right]\\
&= (\alpha_{E1}-\alpha_{D2})_t+(\varepsilon_{E1}-\varepsilon_{D2})_t \qquad (2)
\end{aligned}
$$

We need to emphasize that at no date t do we have the benefit of foresight – we always use historical data for estimating the liquidity factor. Being a linear combination of tradable assets, the factor formed in such a way is a tradable zero-investment portfolio based on the information available at present, rebalanced every week using the previous 0.5 years of daily absolute autocorrelations and 1.5 years of weekly excess returns. We acknowledge that the emerging market factor itself potentially contains a liquidity premium and, by including it in the orthogonalization, not only are we eliminating the emerging risk premium, but also part of the liquidity premium. Although we employ an external emerging market factor unrelated to the way we construct the liquidity one, this remains a limitation of our study.

One might argue that not treating *CRD* in the same way as *LIQ* potentially constitutes a weak point of our analysis. In fact, there are several differences in the construction of the portfolios underlying *CRD* and *LIQ* that impose the 'dynamic orthogonalization' only on *LIQ*. First of all, when building the portfolios for *LIQ* we sort the countries on two criteria, as opposed to one in the case of *CRD*. Sorting them on two criteria implicitly means isolating more than one effect, which is not the case for *CRD*. The portfolios underlying *LIQ* contain differences in absolute autocorrelation and emerging market status, such that the difference in return between the unorthogonalized *E1* and *D2* contains the emerging market effect along with the liquidity effect. On top of that, the differences in world market beta between emerging and advanced countries can be notable, such that chances are high that the return differential between *E1* and *D2* potentially includes return differential due to different exposure to market risk. Hence we consider it necessary to isolate the liquidity effect by accounting for the emerging market and beta exposure effects. This is not the case for *CRD*, where the countries are solely sorted on their sovereign CDS spread and one country could migrate in time from the safest to the riskiest portfolio and vice-versa. Some cases are Greece, Spain, Portugal or Ireland. Therefore, we argue that by sorting the countries on CDS spreads we actually isolate only the credit effect. At the same time, the migration between the top and bottom portfolios composing the liquidity factor is impossible by construction.

Finally, we present the construction of our emerging market risk (*EMR*) factor. We start by collecting the MSCI Emerging Markets index (MSCI-EM) and computing its weekly excess return over the 3-month T-bill rate. We observe that the MSCI-EM excess return captures an important part of the world market movement, having a correlation of 0.86 with *WMR*. In order to obtain a pure emerging market factor, we need to strip it of its world market component. We do that again by 'dynamically orthogonalizing' it as in the case of the liquidity factor, using the same window of 1.5 years (78 weeks). For each date t, for s from t-78 to t-1 we run:

$$\begin{aligned}
(R_{MSCI-EM} - r_f)_s &= \widehat{\alpha}_{MSCI-EM,t-78:t-1} + \widehat{\beta}_{MSCI-EM,t-78:t-1} WMR_s + \varepsilon_{MSCI-EM,s}, \\
& \quad s = t-78, t-77, ..., t-1 \qquad (3)
\end{aligned}$$

Our emerging market factor at date t (EMR_t) is the unexplained part in the MSCI-EM excess return at date t using the previously estimated exposure to the market and the current market return:

$$\begin{aligned}
EMR_t &= (R_{MSCI-EM} - r_f)_t - \hat{\beta}_{MSCI-EM,t-78:t-1} WMR_t \\
&= \alpha_{MSCI-EM,t} + \varepsilon_{MSCI-EM,t} \qquad (4)
\end{aligned}$$

EMR is also a zero-investment tradable portfolio rebalanced every week using 1.5 years of weekly excess returns data. We need to point out that in order to be able to compute *LIQ* we need to have a time-series of *EMR* starting 78 weeks before the start of our *LIQ* factor and in order to compute *EMR* we need a time-series of *WMR* starting at least 78 weeks before the start of our *EMR*.

We further explain the methodology for testing the pricing factors defined above both unconditionally and conditionally.

5.2 The unconditional model

The unconditional model test follows the methodology described in Cochrane (2013) and Sangiorgi (2011). It is composed of two parts: the time-series regressions and the cross-sectional ones.

5.2.1 Time-series analysis

We first estimate the time-series regressions for each country q:

$$(r_t^q - r_t^f) = \hat{\alpha}^q + \sum_{k=1}^{K} \hat{\beta^{kq}} f_t^k + \varepsilon_t^q,\ q = 1, 2, ..., Q \tag{5}$$

where K is the number of factors (up to 4 in our case) and f_t^k denotes them. The market prices of risk in the time series are simply the averages of the factor excess returns over time:

$$\hat{\lambda}^k = \frac{1}{T} \sum_{t=1}^{T} f_t^k \tag{6}$$

Under no autocorrelation of the factors[11], the standard error is:

$$\sigma(\hat{\lambda}^k) = \frac{\sigma(f_t^k)}{\sqrt{T}} \tag{7}$$

A good pricing model should eliminate the abnormal return α of the assets. In order to test for the joint significance of alphas for all the countries we employ the test statistic of Gibbons, Ross and Shanken (GRS) (1989):

[11] Partially proven in Table S4.

$$GRS \equiv \frac{T-Q-K}{Q}\left(1+\bar{f}'\hat{\Sigma}_f^{-1}\bar{f}\right)^{-1}\hat{\alpha}'\hat{\Sigma}_\varepsilon^{-1}\hat{\alpha} \sim F_{Q,T-Q-K} \tag{8}$$

where T is the number of time periods (in our case 468 weeks), Q is the number of assets (78 country indices), K is the number of factors (varying from 1 to 4), $\bar{f}$ is the vector of the sample means of the factors, $\hat{\alpha}$ is the vector of estimated intercepts from the Q time-series regressions, $\hat{\Sigma}_f$ is the estimated factor covariance matrix normalized by T, not $T-1$, while $\hat{\Sigma}_\varepsilon$ is the estimated covariance matrix of the residuals of the time-series regressions, again normalized by T.

We need to point out that the results should be interpreted with caution, as the GRS test requires the time-series regression errors to be normal and i.i.d.. Jarque-Bera tests for all the models show that the hypothesis of error normality is rejected for all the markets at the 5% significance level (not reported). On the other hand, Ljung-Box tests show that usually less than half of the errors exhibit some degree of autocorrelation, regardless of the model, and the number of heteroskedastic errors is usually low[12].

5.2.2 Cross-sectional analysis

We further proceed with the cross-sectional regressions. We regress without an intercept the expectations of the country excess returns on the previously estimated betas to get the cross-sectional market price of risk $\hat{\lambda}^k$:

$$E(r^q - r^f) = \sum_{k=1}^{K} \hat{\lambda}^k \beta^{kq} + \alpha^q,\ q = 1, 2, \ldots, Q \tag{9}$$

α^q are now the error terms. The standard errors of the risk prices are:

$$\sigma(\hat{\lambda}) = \frac{1}{T}\left[(\beta'\beta)^{-1}\beta'\hat{\Sigma}_\varepsilon\beta\,(\beta'\beta)^{-1}\left(1+\hat{\lambda}'\hat{\Sigma}_f^{-1}\hat{\lambda}\right)+\hat{\Sigma}_f\right] \tag{10}$$

where $\hat{\lambda}$ is the vector of market prices of risk and β is the matrix of risk loadings from the time-series regressions. The covariance matrix for the cross-sectional error terms α^q is

$$Cov\left(\hat{\alpha}\right) = \frac{1}{T}\left(I_N - \beta\,(\beta'\beta)^{-1}\beta'\right)\hat{\Sigma}_\epsilon\left(I_N - \beta\,(\beta'\beta)^{-1}\beta'\right)\left(1+\hat{\lambda}'\hat{\Sigma}_f^{-1}\hat{\lambda}\right) \tag{11}$$

$\hat{\alpha}$ denotes the vector of α^q and measures mispricing. We finally test if all α^q are jointly

[12]See Tables S7 and S8.

equal to 0:

$$\chi^2 - statistic \equiv \hat{\alpha}' Cov(\hat{\alpha})^{-1}\hat{\alpha} \sim \chi^2_{Q-K} \tag{12}$$

An important point to be mentioned here is the fact that while in the time-series regressions the R^2 can be used to assess the goodness of fit, the R^2 in our cross-sectional analysis would be ill-defined and, most importantly, not bounded between 0 and 1 because of the exclusion of the intercept from the regression. Therefore, we do not compute R^2 for the cross-sectional regressions.

5.3 The dynamic unconditional model

Numerous authors have noted that even though the unconditional estimation of pricing models seems to be appealing in theory, it is unlikely to produce convincing and significant results in practice[13]. As a result, the natural way to improve upon the unconditional model developed in the previous section is the introduction of time-variability in betas.

A first approach in attempting a time-varying analysis is estimating the unconditional model for consecutive overlapping intervals of 1.5 years (78 weeks). We roll the windows on a weekly basis. For each interval we run the time series regressions (Equation 5), save the factor loadings and use them for estimating the price of risk and the mispricing in the cross-section (Equations 9-12). The main purpose is to observe the evolution of the price of risk and whether our models are improved.

5.4 The conditional model

Following the rolling-window estimation of betas, we apply another model to obtain time-varying beta coefficients and prices of risk as a verification of the results obtained through the previous dynamic estimation. For that purpose dynamic conditional correlation GARCH (DCC-GARCH) of Engle and Sheppard (2001) is used.

The model assumes that the excess returns from the Q+K assets and factors are conditionally multivariate normal with

$$r_t|\mathcal{F}_{t-1} \sim N(0,\ H_t) \tag{13}$$

and

[13]For example, Harvey (1991), Dumas and Solnik (1995), Jagannathan and Wang (1996) and others.

$$H_t \equiv D_t R_t D_t \tag{14}$$

with D_t being a $(Q+K) \times (Q+K)$ diagonal matrix of time-varying standard deviations obtained from GARCH models with $\sqrt{h_{it}}$ on the i^{th} diagonal and R_t being a time-varying correlation matrix. In order to perform the estimation we use a demeaned series of the excess returns for the whole sample period. The elements of the standard deviations matrix take the form of

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q},\ i = 1, 2, ..., Q+K \tag{15}$$

with all the usual GARCH restrictions. It should be noted that Q_i refers to the order of GARCH terms, while Q denotes the number of assets. For each asset and factor we run a series of GARCH(P_i,Q_i) models up to $P_i \leqslant 4$ and $Q_i \leqslant 3$ and employ BIC to choose the parameters to use. Thus, the proposed dynamic correlation structure takes the following form:

$$C_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\bar{C} + \sum_{m=1}^{M} \alpha_m(\varepsilon_{t-m}\varepsilon'_{t-m}) + \sum_{n=1}^{N} \beta_n C_{t-n} \tag{16}$$

$$R_t = C_t^{*-1} C_t C_t^{*-1}$$

with $\bar{C}$ being the unconditional covariance of the standardized residuals from the first stage estimation and

$$C_t^* = \begin{bmatrix} \sqrt{c_{11_t}} & 0 & \cdots & 0 \\ 0 & \sqrt{c_{22_t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \sqrt{c_{(q+k)(q+k)_t}} \end{bmatrix}$$

so that C_t^* is a diagonal matrix containing square roots of the diagonal of C_t. Unfortunately, we have to limit ourselves to only one M and N term in the estimation of DCC parameters due to the lack of computational power to estimate the significance of additional DCC terms introduced to the model. However, the results should not be biased significantly as Engle and Sheppard (2001) report that in most of the cases coefficients on higher DCC terms are insignificant for the selected stocks in the US market.

The covariance matrix obtained from the model can be seen as

$$H_t = \begin{bmatrix} H_t^{QQ} & H_t^{QK} \\ H_t^{KQ} & H_t^{KK} \end{bmatrix} \tag{17}$$

from which a conditional covariance matrix of factor returns, H_t^{KK}, and a conditional covariance matrix of the asset and factor returns, H_t^{KQ}, can be extracted. Following the idea of Lim (2005), we compute the matrix of time-varying betas as

$$\mathbf{B}_t = [H_t^{KK}]^{-1} H_t^{KQ} \tag{18}$$

After the estimation of betas, we compute the risk prices using the logic similar to Fama and MacBeth (1973), i.e. we run cross-sectional regressions of asset returns[14] over the obtained betas for every period. As in the case of the rolling window estimation, we allow for time variability of risk prices; therefore, we do not average them out for the whole sample, but report a time series.

6 Results

6.1 The factors

6.1.1 Statistics for the factors

The data described in Section 3 is used to construct the factors[15] as explained in Section 5.1. For a better understanding of the return performance over time we plot the development of the value of a 1 dollar investment into the factors (see Figure 6). As it can be observed, the average returns of *LIQ* and *EMR* are higher over the whole sample period than those of *WMR* and *CRD*. The returns for all four factors are similar in the first part of the sample until mid-2007; however, the beginning of the financial crisis uncovered the difference in the underlying risks for them. When world markets experienced a crash in 2008, a flight from all the risks can be observed, with drops in both the credit and

[14] It has to be noted that here the actual factor excess returns are used and not the demeaned series used for estimation of DCC-GARCH.

[15] The summary statistics for the factors can be seen in Table S1.

liquidity factors. A clear rise in *LIQ* is observed around the deepening of the European sovereign debt crisis and default of Greece when investors left the credit unworthy countries, but not the most illiquid ones. The development of *CRD* returns also follows a clear pattern, commanding a positive risk premium over the first half of the sample and having negative returns starting from 2011. The latter could possibly be attributed to the above-mentioned European sovereign debt crisis since the investors fled from countries with deteriorated public finances and decreasing creditworthiness. It can also be seen that *EMR* was not affected too much by the crash of 2008 and recovered quickly, implying that the emerging market premium on average stayed positive also during the turmoil. However, the later announced emerging countries slow-down does seem to have an influence on the factor as the returns on it have on average been negative since 2011.

It can also be observed that *CRD* and *LIQ* have a certain degree of negative correlation with WMR, mostly attributable to the period that includes the market crash and the European debt crisis. We also test the factors for normality and autocorrelation. The returns on the factors do not seem to be normally distributed. Autocorrelation tests suggest that *CRD* is not autocorrelated while there is a vague evidence of serial correlation for *WMR* and a somewhat stronger evidence for *EMR* starting with lag 2 and for *LIQ* starting with lag 3[16].

Finally, we run regressions of the *CRD*, *LIQ* and *EMR* factors on the *WMR* factor as well as their various combinations to see if there is any clear linear dependence between them (see Table 5). *CRD* and *LIQ* do seem to be linearly related to *WMR* with a high degree of significance of the betas. This is an indication that the *LIQ* factor is ex-post non-orthogonal with respect to the world market, even though, by construction it is orthogonal ex-ante. However, this should not constitute a problem for our analysis.

When controlling for both *WMR* and *EMR* factors, the explanatory power of the regressions of *CRD* and *LIQ* increases slightly; however, the two regressors (*WMR* and *EMR*) still cannot explain large part of the variation in *CRD* and *LIQ*, which serves as an argument that *CRD* and *LIQ* do not capture world or emerging market risk premia. Similarly, when regressing *LIQ* on different combinations of the other three factors, around 20% of the variation is explained. Most importantly, the alphas are significant for regressions with *LIQ* as explained variable, meaning that *LIQ* experiences abnormal returns

[16]See Tables S2, S3, S4 and S6.

when controlling for the other factors. Finally, even if the the intercepts for *EMR* and *CRD* factors are statistically indistinguishable from zero, most of their variation cannot be replicated using a linear combination of the other factors and although in the time-series they produce no significant abnormal return, they can be valuable in the cross-section.

6.1.2 *CRD*, *LIQ* and *EMR* versus well-established factors

We also check if our factors are capturing any of the effects from other well-known risk factors such as the size (*SMB*) and value (*HML*) factors of Fama and French (1993) or momentum factor (*MOM*) of Carhart (1997). Considering the fact that our analysis is done on weekly data, there is a threat that some of our factors may capture the reversals effect, so short- (ST_REV) and long-term reversals (LT_REV) factors are also included in the analysis. The above-mentioned factors are downloaded from Kenneth French data library. Unfortunately, the database does not contain weekly data for international factors; therefore, we use the factors constructed on the US market. Even though it is a limitation, the international and US factors are known to perform similarly and to capture similar economic forces, thus the results are still interpretable and should serve well the purpose of illustration. The correlations between our factors and the other factors introduced above are generally small in absolute terms, apart from those of *WMR* with the aforementioned factors[17]. Also the results show that *CRD*, *LIQ* and *EMR* do not exhibit positive correlation with the reversals factors implying that these effects are unlikely to be captured by our factors.

We also run a series of regressions trying to see if *CRD*, *LIQ* and *EMR* are explained by the other factors used in the literature and vice versa (see Tables 6 and 7). We observe that the liquidity and emerging market risk factors do not seem to be priced by the combination of the other factors, as the alphas in the regressions are high in economic terms and statistically significant at the 99 and 90% confidence levels respectively (see Table 6). At the same time the alpha of the credit risk factor is small and statistically insignificant implying that the five factors used could price *CRD*. However, the explanatory power of the regression is still low with an R^2 of under 13% which implies that most of the variation in *CRD* cannot be explained by the model. The period used for the study should also be taken into account since it can be the case that the conclusion is different

[17] See Table S5.

for a different sample. Finally, the market and momentum factors are the only ones which retain statistically significant betas for all three of our factors. In addition, the reversal factor betas are not distinguishable from zero.

In our final set of regressions, we check whether the 3 factors we proposed price the other well-established factors. The conclusion could favor our factors: we find evidence that after accounting for *WMR*, *CRD*, *LIQ* and *EMR*, the intercepts of the conventional factors with the exception of *ST_REV* are statistically insignificant with the largest influence coming from the world market risk (Table 7). The only economically significant mispricing is the one of *ST_REV*, at 7.85% per year statistically significant at 90% confidence level. We acknowledge that these results can be sample-specific and the reason for the insignificance of the intercepts could be the low average return over the analyzed period. Indeed, with the exception of *ST_REV*, all the conventional factors have an annualized mean between -2.21% and 2.40% from the 5$^{\text{th}}$ of February 2004 until the 23$^{\text{rd}}$ of January 2013 and are statistically insignificant. However, the mean returns are observed to decrease after accounting for the proposed factors, the most important reduction being observed for the size factor, from 1.76% to 0.24% p.a. The same argument goes also vice-versa, with *CRD* being seemingly explained only because it had a low, insignificant mean return.

Summing up, our proposed factors perform well against the other established risk factors in academia. *LIQ* and *EMR* are not priced by the *SMB*, *HML, MOM*, *ST_REV* or *LT_REV* factors, while the combination of *WMR*, *CRD*, *LIQ* and *EMR* explain part of the alpha in the conventional factors for the period analyzed.

6.2 The unconditional model

6.2.1 Time-series tests

As explained in Section 5, we start by running the time-series regressions for each of the 78 assets (countries) and test for mispricing. We explore the performances of the following 11 models: *WMR*, *CRD*, *LIQ*, *EMR*, *WMR-CRD*, *WMR-LIQ*, *WMR-EMR*, *WMR-CRD-LIQ*, *WMR-CRD-EMR*, *WMR-LIQ-EMR* and *WMR-CRD-LIQ-EMR*. In Table 8 we report the average measure of mispricing (alpha), its maximum and minimum, the number of significant alphas and betas as well as the average, minimum and maximum adjusted R^2.

We observe that the majority of the average annualized alphas is below 10% p.a. and that the minimum and the maximum alphas are not symmetrical around zero. Instead, the maximum alpha is further away than the minimum alpha for all the models, which means that on average the market indices outperform the model predictions. This fact is also confirmed by the small difference between the mean alpha and mean absolute alpha, showing that the majority of alphas are positive. The world CAPM (*WMR* alone) fails to explain the returns of the country indices, leaving an alpha of 5.93% (8.22% in absolute terms) and indicating that we need to use more risk factors. The model that draws our special attention is the one where we use *LIQ* alone. The mean alpha is 15.13% per year, highly economically significant. In the opposite situation we find the model that includes *WMR*, *LIQ* and *EMR*, for which the average alpha is 1.99% per year and the average absolute alpha is the lowest at 5.69%. Overall, the statistics for alphas in Table 8 indicate that the best factor is *EMR* while the poorest is *LIQ* in the time series.

Looking at the statistical significance rather than the economic one, we observe that for various confidence levels the models including *EMR* perform best. When considered alone, *EMR* yields 4 significant alphas at the 95% confidence level and 8 at 90%, while *LIQ* alone is the poorest with 30 significant alphas at the 95% confidence level and 40 at the 90% level. When included along with other factors, *EMR* leaves only 1 significant alpha at the 99% confidence level. The market alone leaves 17 and 13 significant alphas at the 90% and 95% confidence levels, numbers that improve to 10 and 7 when *LIQ* and *EMR* are added. Without the Newey-West correction the ranking of the models does not change.

When we consider the significance of the betas with respect to our factors, *CRD* seems to have a significant impact on the lowest number of assets, while *WMR* exhibits significant betas for almost all countries, being followed by *LIQ*. The conclusions remain unchanged if we do not apply Newey-West corrections. *CRD* also seems to perform poorest when we consider the adjusted R^2, exhibiting a very low mean adjusted coefficient of determination (2.81%) and not improving the adjusted R^2 when added to other models. On the other hand, the variation in *WMR* seems to be best at explaining the variation in the excess returns of the assets, with a mean adjusted R^2 of 38.52%. *LIQ* seems to be the second best again, but its R^2 is only only 5.45%. The highest average adjusted R^2 is 45.37% and corresponds to the model that includes all the regressors. The explanatory power does not increase very much when adding additional risk factors to the world CAPM, consistent with Ferson and Harvey (1994) who report that the world market is the most powerful factor in their unconditional model.

As a robustness check we use the raw MSCI-EM weekly excess return to proxy for emerging market risk and, when used alone, it produces a much higher adjusted R^2 and a slightly higher number of significant betas, but at the same time it generates more significant alphas. It appears that the results for the MSCI-EM model become similar to the ones yielded by *WMR* and, given the correlation between MSCI-EM and *WMR* (86%), we can safely argue that the improvement comes mostly from the world market part of MSCI-EM, proving once again that the raw MSCI-EM alone is a poor proxy for emerging market risk. For the models where MSCI-EM appears with *WMR*, *CRD* and *LIQ* in different combinations, the results do not exhibit important changes.

Given that *CRD* is the only factor that did not undergo any kind of orthogonalization, we also included an orthogonalized[18] version of it with respect to the market, but its performance remained unchanged. Naturally, nothing changes for the models where *CRD* is not stand-alone.

So far we have approached the time-series regressions on an individual basis, but the key of our procedure is testing the joint significance of the pricing errors. An investor holding a diversified portfolio is likely to be interested in the performance of one model versus another overall, not for individual assets. The time-series approach in testing the joint significance of the alphas was proposed by Gibbons, Ross and Shanken (1989) and, as discussed in Section 5, we use their *GRS* statistic. Table 8 presents this statistic and its associated p-value.

We cannot reject the null hypothesis that all alphas are jointly zero for the traditional confidence levels for the models containing *LIQ* and *EMR* individually, while for *CRD* the null cannot be rejected at 95% confidece level. All the other models, which is equivalent to all the models that include *WMR*, leave jointly significant alphas at 99% confidence. The reason for this puzzling result is not the fact that the models without *WMR* decrease the absolute alphas. In fact, as presented before, many of them yield higher absolute alphas. What happens is that the (co)variance of the residuals of the time-series analysis is much higher (4-6 times higher than if we use *WMR*). Consequently, the confidence intervals

[18]This time we did a simple non-dynamic orthogonalization for the whole period, hence we had the benefit of foresight. The orthogonalized *CRD* would therefore not be an investable real-world factor.

are much broader for the three models as compared to the remaining eight containing *WMR*. Hence the probability of observing the joint insignificance of alphas is higher for the models where regressors are *CRD*, *LIQ* or *EMR* alone. Moreover, the saturation ratio as discussed by Gallant and Tauchen (1989) or Dahlquist and Söderlind (1999) is low with a value of 12 and the power of the test is reduced. As warned previously, the GRS results should be regarded with caution[19].

Of the two-regressor models, by far the best one in terms of the p-value is the one with *WMR* and *LIQ*, while of the three-regressor models the best one is, again, *WMR-LIQ-EMR*. When we do not correct for heteroskedastic and autocorrelated errors the p-values become much higher, but we witness the same phenomenon, the covariance remaining relatively high.

Besides, including the MSCI-EM as the raw measure of emerging market risk would shift the results downwards for *EMR*, which would no longer have the same power, while using the orthogonalized version of *CRD* would not change the results in an important fashion.

As an intermediary conclusion, the results presented in Table 8 offer the strongest support for the *WMR-LIQ-EMR* model, hence for the *LIQ* and *EMR* factors.

The price of risk in the time-series approach is simply the average of the risk factor across time. In Table 9 we report the price of risk for each of the factors. The results are in line with Figure 6. The market prices of market risk and credit risk are both economically and statistically insignificant. Indeed, shorting USD 1 worth of T-bills or credit-safe countries' indices and investing it in the world market or the credit-risky countries' indices would result in a very small profit for the period we consider. On the other hand, both *LIQ* and *EMR* have economically significant prices (10.67% p.a. and 8.19% p.a.). With a t-statistic of 1.83, the market price of emerging market risk is only statistically significant at 90% confidence level, while the market price of liquidity risk is strongly statistically significant (*t-stat* = 3.77). The result is consistent with those in other works, e.g. Lee (2011), Pastor and Stambaugh (2003) or Gibson and Mougeot (2004) who found significantly positive premium for holding illiquidity.

Using the orthogonalized (with respect to *WMR*) version of *CRD* does not have an impact on the observed price of credit risk, which increases marginally from 2.29% to

[19] Dahlquist and Söderlind (1999) report that a saturation ratio below 10 often indicates potential problems.

2.9% in the time-series, with a slightly higher t-statistic of 0.83 (vs. 0.63).

6.2.2 Cross-sectional tests

We investigate how each of the models performs in the cross section. As explained in Section 5, we now regress the average excess return of each country on its beta(s) and find the cross-sectional market price of risk (lambda).

As expected, the models including more factors perform better (see Table 10). On a stand-alone basis, *CRD* produces the highest deviations from zero of the alphas, which now represent the errors in the cross-sectional regressions without intercept. *WMR* delivers the lowest number of significant alphas, while the lowest average absolute alpha is produced by *EMR*. The best model in terms of the magnitude of the pricing errors is *WMR-CRD-LIQ-EMR*, while regarding the number of significant alphas produced *WMR-CRD-EMR* performs best.

What we are most interested in is the joint significance of the pricing errors, which is a better measure to judge the performance of a pricing model. In Table 10 we report the χ^2-statistic and its associated p-value. We reject the null at 5% significance for all the models, but *WMR-LIQ-EMR*. We do not reject it at 1% for *WMR-LIQ*, *WMR-CRD-LIQ* and *WMR-CRD-LIQ-EMR*. As in the time-series case, it seems that *LIQ* and *EMR* are the the factors that price the assets best. The results are generally in line with those of the other authors, e.g. Acharya and Pedersen (2005) or Avramov et al. (2012); however, the last ones find emerging market premium to become insignificant in the presence of a credit risk factor, which is not the case for us.

If we consider the results without the Newey-West correction, the World CAPM fails with a p-value of 2.33%, which means that we reject the hypothesis of all alphas being jointly zero at the 95% confidence level. The p-value exhibits an important increase when along with *WMR* we include *LIQ, CRD* and *LIQ, LIQ* and *EMR* or all of our proposed factors. These are the four models for which we cannot reject the null at 10% significance level. Within the one-regressor group of models, only the models based on *LIQ* and *EMR* yield a p-value higher than 5%. Overall, the best model seems to be *WMR-LIQ-EMR*. The performance of the liquidity factor is similar to the one documented by Acharya and Pedersen (2005), who conclude that the international CAPM is significantly improved after adjusting for illiquidity.

The market prices of risk in the cross-section are not very different from the ones obtained in the time-series. The market price of liquidity is the most significant one both in terms of the number of models where it appears significant and the confidence level. Its magnitude is the same as the one we estimated in the time-series (9.42%-11.84% p.a. in cross section and 10.67% p.a. in the time-series) except the case when we estimate it without any additional regressors, where it becomes insignificant both economically and statistically. The explanation we find for this phenomenon lies in the time-series regressions. Let us take the example of *LIQ* alone and *WMR-LIQ* models. The correlation between *WMR* and *LIQ* is negative[20] and we had shown that *LIQ* is not orthogonal ex-post to *WMR*. Many countries had a similar return pattern as the market[21] and therefore it is possible that a model including *LIQ* alone would yield downward biased negative betas (w.r.t. *LIQ*) not because the countries would have a certain exposure to the liquidity factor, but because of the rather high negative correlation of the world market with *LIQ* (-0.31). Indeed, when we include *WMR*, 77 out of 78 *LIQ* betas increase, suggesting that they have been negatively biased before. Therefore, using *LIQ* beta when the market is not included potentially produces flawed rankings of the countries in terms of liquidity exposure. Therefore, when we use these estimated betas in the cross-section, they might contain no real information and, of course, market does not reward lack of information. On the other hand, when the market factor is introduced, the market trend is taken into account and *LIQ* attempts to explain only the remaining variation which is not due to market movements, but to different risks. The beta with respect to *LIQ* becomes more meaningful if the country has some true exposure to liquidity risk and this time the betas contain viable information which the market rewards in cross-section. This could be the case also for *CRD* and *EMR*.

In the *WMR-CRD* model, *CRD* is statistically (5% significance) and economically significant at 13.06% p.a., much higher than the time-series 2.29%. *EMR* is statistically and economically significant in *WMR-EMR* and *WMR-CRD-EMR* with an annual price of more than 13%. Finally, the market risk price remains insignificant both economically and statistically, regardless of the model, but without the exposure to the market risk included all the other risk prices could be biased. The insignificance of market risk price has its roots in the period we are analyzing when the market crash wiped out all the

[20]See Table S2.

[21]76 out of 78 countries have a significant positive beta with respect to the market.

previous and later gains.

An overall conclusion from the unconditional tests is that adding *CRD*, *LIQ* and *EMR* to the world market risk helps reducing the pricing errors. *LIQ* and *EMR* seem to be the best factors from that perspective. The most significantly priced risk over the period analyzed, both in time series and cross-section, is the liquidity risk, followed by the emerging market risk. The poorer performance of the credit factor that we observe is contrary to the results of Avramov et al. (2012) and we find three potential explanations for this phenomenon. First, it can be the case that the public sector, or, more specifically the public debt developments do not have a large influence on the private markets. Second, it is possible that the CDS market does not lead the stock market returns, but vice-versa, an explanation compatible with the conclusions in Forte and Loverta (2008). Finally, the CDS and stock markets might not be completely integrated, as in Che and Kapadia (2012)

6.3 The dynamic unconditional model

For each of the 11 model specifications, we run the rolling windows procedure 390 times (468-78) and present only the most relevant results, i.e. the joint significant of alphas in the cross-section and the evolution of the market prices of risk.

To begin with, the average (across time) p-value that all the alphas are jointly equal to zero is 0 (not reported) for all the models, with and without the Newey-West correction. On a weekly basis, our factors fail to capture the abnormal returns of the assets. As we suggest in Section 7.2.1, this is likely to be the result of the noisy weekly data.

Moving to the prices of risk, we present the estimates from the model including all factors. Although our results are mostly statistically insignificant, the economic results seem strong and the patterns clear. The market risk (Figure 7) is rewarded positively most of the time. During the market crash of 2008 when the risk materialized, investors bearing market risk suffered losses, the estimated price going below 0. After the financial crisis the market started rewarding market risk exposure again, but we observe that the price is pushed downwards by the later sovereign debt crisis. There is also an obvious pattern in the market price of credit risk (Figure 8). Before the market crash investors bearing credit risk were positively rewarded for holding it. Once the financial crisis occurred, the credit risk price became negative. It did show signs of recovery afterward, but one can observe that the credit crisis pushed it back below 0. Holding credit risk returned around -10% per year during the debt crisis. Meanwhile, the price of liquidity risk (Figure 9) is consistently positive (10-20% p.a.), a sign that the market values it highly. During the financial turmoil the liquidity dried up and the price of liquidity risk became negative. However, it recovered fast and not only was it unaffected by the credit crisis, but it actually increased towards the end of our sample. Finally, the price of emerging market risk (Figure 10) performed well during the market crash, maintaining a positive return throughout. Nevertheless, we observe that recently, once the emerging economies started slowing down and the global growing prospects became more pessimistic, the market price of emerging market risk became negative. These graphs prove that the market prices of risk are highly time-varying and approaching them in a static, unconditional manner could lead to improper conclusions.

6.4 The conditional model

Similarly to the rolling betas model, we report the time series plots of the prices of risk for the same sample period. However, unlike in case of the rolling windows, we are unable to present the confidence bounds due to lack of computational power; therefore, only the economic significance and general trends are analyzed. These computational problems prevent us from testing the significance of alphas.

The estimated price of risk following the DCC-GARCH procedure for computing the betas dynamically is very noisy. As a consequence, in order to be able to produce some economic interpretations regarding the market price of risk, we need to apply a filter. For simplicity, we choose an alpha-beta filter, as described by Penoyer (1993). The filter is a simplified form of the Kalman filter and needs to be adjusted to our case. Therefore, we need to exclude the velocity term by setting a β of 0 and initial velocity of 0, but keep the position term positive. This reduced form alpha-beta filter is suitable for the market price of risk, as economically we do not expect it to vary much from one week to another. Applied to λ, the filter can be described as follows:

Firstly, a preliminary estimate of the price of risk for week t is equal to the current estimate.

$$\hat{\lambda}_{t,prelim} = \hat{\lambda}_{t-1}$$

Secondly, the actual price of risk on week t is observed and an error is calculated:

$$\hat{e}_t = \lambda_t - \hat{\lambda}_{t,\,prelim}$$

Finally, the week-t estimate of the market price of risk is:

$$\hat{\lambda}_t = \hat{\lambda}_{t,\,prelim} + \alpha * \hat{e}_t \tag{19}$$

The results are presented for $\alpha = 0.025$ and starting point equal to the mean risk price for the whole period. Whatever the starting point, its influence is lost quickly, as the filter has a sufficient level of convergence in our case. Moreover, we present the results starting with the 78$^{\text{th}}$ week of the analysis to make them visually comparable to the rolling window case, and by that time we also lose the influence of the starting point. This filter is clearly suboptimal, but it serves well our purpose of depicting the economic implications of our model. It captures the longer-term directions of the movements in the market price of risk and at the same time reduces the noise.

It can be observed that the filtered prices of risk obtained via the conditional model experience similar patterns as the ones obtained through the rolling window estimation (see Figure 11). More specifically, the price of market risk is large and economically significant in the period preceding the crash. It drops dramatically in 2008-09 and recovers afterward. Just as in the case of the rolling window estimation, after recovery, the price of market risk starts moving towards zero. The price of credit risk is also positive before the financial turmoil, crashes in 2008, starts recovering in 2009 and suffers another crash corresponding to the European sovereign debt crisis. The same pattern was observed in the rolling window analysis. The price of liquidity risk is generally high and positive, with the exception of the financial crisis, when it reached negative values, just as presented in Section 6.3. The price of emerging market risk struggles at the beginning, it is positive and increasing throughout the crisis and decreases afterward, consistent with the economic slowdown in the emerging countries, confirming once again the observations made previously.

We need to mention the fact that, undoubtedly, there are differences in the level of the risk prices estimated through the two models (rolling window and DCC-GARCH), but the economically significant movements and relative levels are the same. Moreover, these differences might partially be a result of a lagged response of the rolling window model to the innovations in the data.

7 Robustness checks

7.1 The unconditional model

7.1.1 Splitting the sample period into sub-periods

Considering Figures 1, 4 and 6, it seems natural to split the analysis period into two sub-periods, based on economic fundamentals. The first period (February 5, 2004 - February 6, 2008) overlaps a period of economic boom and market expansion. The second period (February 7, 2008 - January 23, 2013) includes the market crash of 2008 and the European sovereign debt crisis. In the first sub-period, the correlations between the factors and the market are lower in absolute value. In the second period the correlations of the three factors with the market keep their full-period sign, but are higher in absolute value.

If we split the sample in the periods described above, our models lose power in explaining alpha for both periods, both in time-series and in cross-section. This effect can be caused by the fact that we use short samples and weekly data, which has some degree of noise. Even so, we do observe some patterns[22]. During calm times (first sub-period) all of the models fail to explain abnormal returns. Compared to the first period, in turbulent times our models perform better in time-series, a result that was found also by Avramov et al. (2009), who argue that during calm times credit risk fails to explain alphas. However, none of the models can explain abnormal returns well enough in the time-series since the hypothesis of all the alphas being jointly equal to zero can be rejected for all models at 95% confidence level. The best models seem to be *CRD*, *LIQ* and *EMR*, the only ones with GRS p-values higher than 1%. However, without adjusting for heteroskedastic and autocorrelated errors, we find that the models containing *CRD* and *EMR* alone are the best with p-values higher than 10% (not reported).

In the cross-section, the impact of our small sample is even higher, χ^2 p-values being reduced even more dramatically. Practically, for both the first and the second period all the models fail. Even so, we can still observe that *WMR-CRD-LIQ-EMR* model yields the lowest χ^2-statistic.

[22]See Table S9

The time-series market prices of risk are better distinguishable this time[23], and they, naturally, vary significantly over the two sub-periods. In the first period the market price of credit risk is highly significant both economically and statistically, its annualized price reaching 14.90%, with a t-statistic of 2.82, from this perspective opposing Avramov et al. (2009) who report that credit risk is not priced during stable times. It is also the case for the market price of emerging market risk, with a statistically significant annualized price of 15.03%. The price of liquidity is higher for the first sub-period and no longer statistically significant in the second one; even so, the economic significance of the liquidity risk price in the second period is highest among all risks, at 6.98% p.a. The market price of market risk remains the least significant for both periods. The price of credit risk becomes negative in the second subperiod while still being economically, but not statistically significant. The emerging market risk becomes the second least significant in economic terms during financial distress periods after the world market risk. The unreported cross sectional prices of risk are broadly in line with the time-series observations, they retain the signs but are somewhat larger in magnitude for the first sub-period and smaller for the second one, which generally strengthens our conclusions.

To sum up, our proposed factors perform better in time-series during periods of financial instability, while the prices of risk reflect the market developments. Moreover, the results presented here should be analyzed remembering that it is likely that our models are the victims of small sample effects.

7.1.2 Using a holding period of 1 week when constructing the credit and liquidity factors

Instead of creating the factors based on a long position in an average of 4 portfolios and a short position in another average of 4 portfolios we run the analysis under a one-week holding period approach. This implies that each week we construct 4 portfolios for each of the two risks, just as before, but this time we offload the previous portfolios. Therefore we use a long position in one portfolio and a short position in another portfolio to create *CRD* and *LIQ*.

The results are very much in line with the ones we presented so far. The *LIQ* and *EMR* factors contribute most to reducing the pricing errors. Moreover, the price of

[23] The time-series prices of risk are reported in Table S10.

risk, both in time-series and in cross-section remains similar to the one estimated before. The statistical and economic significance remain unchanged. The price of liquidity and emerging market risks are the most economically significant, while the price of the liquidity risk is consistently statistically significant. The correlation between *LIQ* and *WMR* stays negative, but increases in absolute terms.

7.1.3 Using autocovariance for constructing the liquidity factor

We run the analysis using the absolute autocovariance instead of absolute autocorrelation when constructing the liquidity factor. Again, the results remain very similar to the ones already presented. The explanatory power of the *LIQ* factor decreases slightly, but does not impact the conclusions in a significant way. Moreover, the market price of liquidity risk in the cross-section remains in the area of 10% per year, statistically significant at 95% confidence level. The important difference that we notice is the market price of liquidity risk in the time-series, which becomes 7.37% (t-stat = 2.36), as opposed to 10.67% (t-stat = 3.77) when we use autocorrelation.

7.1.4 Running the analysis on a 4-week basis

We run the unconditional model also on a 4-week basis. For each 4-week period we compound the weekly returns for the assets and factors; the 4-week periods are not overlapping. We check the joint significance of pricing errors in the cross section and we report the cross-sectional market price of risk for the full model *WMR-CRD-LIQ-EMR*.

We find strong joint significance of alphas, with p-values of 0 for all the 11 models (not reported), which is similar to the results for the weekly analysis. It is possible that the reduced noise effect that we obtain is overcome by the smaller sample effect.

The cross-sectional market prices of risk are consistent to the previously estimated ones, with slight amendments[24]. The market price of market, credit and liquidity risks are 1-2% lower than the ones estimated using weekly returns, reaching now 3.42%, 2.54% and 7.94% p.a. The market and credit risk prices remain statistically insignificant, while the price of liquidity risk is statistically significant at 95% confidence level. The market price of emerging market risk is 11.57%, superior to the previously estimated one, and becomes significant at 90% confidence level (95% without the Newey-West correction).

[24]See Table S11.

Overall, the 4-week based unconditional model fails to explain the abnormal returns of the assets, but supports our findings concerning the market prices of risk.

7.1.5 Running the analysis on 16 portfolios

In the spirit of Fama and French (1993), we also test our models against portfolios formed on the criteria underlying the factors. For that we use the countries for which CDS data is available and first split them into advanced and emerging as in IMF (2012). Within each of these groups we rank the countries according to their level of absolute autocorrelation and separate them into two sub-groups (four in total). Within each of the four sub-groups, we sort the countries according to their CDS-spread levels and split each sub-group into four portfolios[25]. The holding period is one week and the rebalancing is made weekly. We do not simply take the intersection of the countries based on the three criteria because that would yield empty portfolios, while the presented procedure ensures that the 16 portfolios are non-empty and contain approximately the same number of countries.

Running the analysis on 16 portfolios also brings the benefits of an increased number of degrees of freedom for the GRS test, but decreases the number of degrees of freedom for the cross-sectional χ^2-test. However, the main advantage is the improvement in the saturation ratio. The number of parameters to be estimated varies with the square of the number of assets and it decreases dramatically, increasing the saturation ratio from 12 to 56 and making the results of the GRS test more powerful.

The *WMR-EMR* and *WMR-CRD-EMR* models yield no time-series significant alphas at all the common confidence levels, while *EMR* and *WMR-CRD-LIQ* leave the lowest number of significant pricing errors in the cross-section (not reported). In the time-series, the world CAPM yields a p-value of 8.58% that all the abnormal returns are jointly 0, while the best model, *WMR-LIQ-EMR* produces a much higher p-value of 79.1% (Table 12). At the same time, the world CAPM fails in cross section at the 95% confidence level with a p-value of 4.93%, while *WMR-LIQ* produces the highest p-value at 87.81%. These results prove that *EMR* is the best pricing factor in the time-series, while *LIQ* prices the assets best in the cross-section.

Finally, the results concerning the cross-sectional price of risk remain much in line with the previous reported ones. The market price of liquidity is strongly significant in

[25] See Figure S5.

all the models where it is not alone and in economic terms it is approximately 2% higher than previously estimated, ranging from 12% to 15% p.a.. It is followed by emerging market risk, both in terms of statistical and economic significance, while the market and credit risks are mainly insignificant.

7.2 The dynamic unconditional and the conditional models

7.2.1 Running the analysis on a 4-week basis

As in the unconditional model case, we aggregate each 4 consecutive weekly returns into one 4-week return, without overlapping. On this new data set, we run the rolling windows model with a window length of 1.5 years. Table 13 presents the average (across time) probability that all the alphas are jointly zero in the cross-section for each model. The results that we obtain now are much stronger. The world CAPM model produces an average p-value of 13.92%. Adding any of our factors significantly increases the performance of the model such that, when the full model *WMR-CRD-LIQ-EMR* is considered, the average p-value reaches 44.56%.

Two very important observations have to be made here. First, by comparing these results with the ones that we get from the unconditional 4-week based estimation we find that the time-varying model significantly outperforms the static unconditional one, which yielded p-values of 0; this result is in line with the current literature. Second, by comparing the 4-week rolling windows results with the output from the weekly-based rolling windows model, we discover that the 4-week approach produced much better results compared to the weekly rolling windows model's p-values of 0. This means that indeed, weekly data is too noisy and important information could be masked by random movements. This conclusion supports our previous claim that insignificant results might be caused by too much noise in weekly data and also offers an important path for future research. Once the sample period becomes long enough, a monthly replication of our work might lead to strong conclusions.

Doing the 4-week analysis on the DCC-GARCH model, the patterns followed by the prices of risk remain unchanged compared to the weekly implementation, reflecting the financial and economic developments.

8 Conclusions

In this paper we aim at explaining stock market index returns and estimating various risk prices in the global market. For that purpose three pricing factors in addition to the world market are proposed: credit, liquidity and emerging market. Using 78 market indices spanning for a period of approximately 9 years, we test 11 different models based on various combinations of the factors, approaching the analysis in three ways: unconditional, which represents the main part of our study, dynamic unconditional and conditional.

To begin with, the factors are constructed as zero-investment portfolios. In order to isolate the different risk forces and keep the factors tradable based on past information, we make use of the concept of 'dynamic orthogonalization' for estimating the liquidity and emerging market factors.

With alpha t-statistics of 3.65 and 1.68, the proposed liquidity and emerging market factors are not priced by the established factors in the literature at the 99% and 90% confidence level respectively. At the same time, the combination of the factors that we employ in the analysis might partly explain the abnormal return of conventional factors such as size, value, momentum, short and long term reversals.

We find that the world CAPM fails both in time-series and in cross-section and adding the three factors improves the performance of the model significantly on both dimensions. The most important contributors to the explanatory power increase are the liquidity and emerging market factors.

We observe that the market prices of risk are highly time-varying and reflect the market developments, both when estimated through rolling windows and through the conditional model. Although the statistical significance over time is low for all the risk prices, the economic significance is strong and consistent with the expectations. In addition, in the unconditional time-series and cross-section, the liquidity risk is strongly statistically significant with a premium of around 10% per year, followed by the emerging market risk, also with a premium of approximately 10%, but less statistically significant and more volatile from model specification to model specification.

The credit factor performs poorer and the credit risk price is less significant compared to the liquidity and emerging market ones. This makes us believe that either the the public debt evolutions do not influence the private sector to a high degree, the CDS and stock markets are not completely integrated or the sovereign credit market does not lead the stock market.

We also run the analysis for different subperiods, different holding periods for the portfolios underlying the factors, on a 4-week basis rather than weekly and on 16 portfolios of countries sorted on credit and liquidity risk. Moreover, we use autocovariance instead of autocorrelation in the construction of the liquidity factor. The results that we find are very much similar to the base-case. An important observation that we need to make is that implementing the unconditional model dynamically (through the rolling windows) and using a 4-week basis for the analysis improves the cross-sectional power of the tested models dramatically, from a χ^2-statistic p-value of 0 to as much as 45% in the best case. This is consistent with a large part of the current literature[26] reporting that the static, unconditional models yield weaker results than the time-varying ones. At the same time, it suggests that the weekly data potentially contains too much noise. Also, given that the highest p-value is obtained through the full model specification and that it is significantly higher than the second highest p-value, the importance of each risk factor is strengthened.

Our paper contributes to the literature in a number of ways. First and foremost, we construct the factors in a new fashion. The credit factor is based on the sovereign CDS spread, rather than less volatile measures used previously. The liquidity factor is extracted after a double-sorting of the markets and a 'dynamic orthogonalization' procedure, while the emerging market factor is also dynamically adjusted to better reflect emerging market risk, separated from world market. Second, to our knowledge, we employ the most extensive dataset in terms of the number of countries. Finally, our analysis spans across the latest market crash and the current European sovereign debt crisis.

There are some future development opportunities that we observe. The first and the most natural is to check the performance of the proposed factors on different financially turbulent times and also on a longer time period, preferably on a monthly basis. Second, the significance of our liquidity factor opens several doors. It can be applied to different asset classes or, with a different sorting criterion than the advanced market status, it can be applied to individual stocks. Research on the profitability of an investment strategy based on our liquidity factor after accounting for transaction costs might yield interesting conclusions about its real-life applicability. Moreover, we suggest research on cost reducing methods such that an investment strategy based on the liquidity factor could be efficiently

[26] Harvey (1991), Dumas and Solnik (1995), Jagannathan and Wang (1996), De Santis and Gerard (1998), etc.

implemented. Finally, one could check if the explanatory power of the credit factor is improved by using the slope or curvature of the CDS spread term structure, a potentially fruitful idea given the work of Han and Zhou (2011).

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10 Appendix

10.1 Heteroskedasticity and autocorrelation tests for the time-series residuals

The average number of significant autocorrelations up to lag 9 in the unconditional time-series residuals is higher than one only on 3 occasions[27]. Moreover, according to the Durbin-Watson test, approximately half of the countries exhibit no serial correlation, regardless of the model. In addition, for an important number of countries the hypothesis of homoskedastic time-series residuals cannot be rejected[28]. However, Newey-West corrections for heteroskedasticity and autocorrelation might be appropriate. It is important to note that Newey-West benefits come at the expense of loss of efficiency and, more importantly, loss of consistency of the estimators, which can create problems when we try to use the well-established distributions. Since it is customary in the literature and the benefits often outweigh the costs, we present the Newey-West standard errors, but also comment on the the results without the Newey-West adjustment, where appropriate.

[27] See Table S7.

[28] See Table S8.

10.2 Main tables and figures

Table 1: List of countries.
The table reports the list of countries which are used in the study. The IMF (2012) classification is used to divide the countries into advanced and emerging.

	Advanced	
Australia	Hong Kong	Portugal
Austria	Iceland	Republic of Korea
Belgium	Ireland	Singapore
Canada	Israel	Slovakia
Cyprus	Italy	Slovenia
Czech Republic	Japan	Spain
Denmark	Luxembourg	Sweden
Estonia	Malta	Switzerland
Finland	Netherlands	Taiwan
France	New Zealand	United Kingdom
Germany	Norway	United States of America
Greece		
	Emerging	
Argentina	Kenya	Peru
Bahrain	Kuwait	Philippines
Bangladesh	Latvia	Poland
Brazil	Lebanon	Qatar
Bulgaria	Lithuania	Romania
Chile	Macedonia	Russia
China	Malaysia	Saudi Arabia
Colombia	Mauritius	South Africa
Croatia	Mexico	Sri Lanka
Egypt	Montenegro	Thailand
Hungary	Morocco	Tunisia
India	Namibia	Turkey
Indonesia	Nigeria	Venezuela
Jamaica	Oman	Zambia
Jordan	Pakistan	

Table 2: Forming portfolios based on credit and liquidity risks.
The tables show the notation used in the paper for different portfolios sorted on CDS spreads and absolute autocorrelation and emerging market status.

CDS spread-sorted

Riskiest	C1
	C2
	C3
Safest	C4

Absolute autocorrelation and emerging market status-sorted

	Emerging (riskier)	Developed (safer)
Risky	E1	D1
Safe	E2	D2

Table 3: Mean equity returns for the CDS spread-sorted portfolios.

The table reports means and standard deviations of weekly returns of the four CDS spread-sorted portfolios for three time periods within the sample. The first part shows results for the whole sample while the second and the third parts depict equity return values for the first 4 and last 5 years of the sample respectively. Portfolios are formed every week and held for 4 weeks, i.e. at each moment in time four portfolios for each riskiness category or sixteen portfolios in total are held. C1 stands for the average of the four portfolios of countries with the highest CDS spreads while C4 - the lowest. The annualized mean is computed as $(1 + weekly\_mean)^{52} - 1$ *and is presented in percent.*

	C1 (riskiest)	*C2*	*C3*	*C4* (safest)
05.02.2004 - 23.01.2013				
Annualized mean (%)	11.11	12.29	10.54	8.64
Mean	0.002	0.002	0.002	0.002
Standard deviation	0.029	0.027	0.028	0.030
05.02.2004 - 06.02.2008				
Annualized mean (%)	38.86	25.90	24.92	20.91
Mean	0.006	0.004	0.004	0.004
Standard deviation	0.025	0.020	0.021	0.022
07.02.2008 - 23.01.2013				
Annualized mean (%)	-7.24	2.37	0.14	-0.37
Mean	-0.001	0.000	0.000	-0.000
Standard deviation	0.031	0.032	0.032	0.035

Table 4: Mean equity returns for the liquidity-sorted portfolios.

The table reports means and standard deviations of weekly returns of the four dynamically orthogonalized liquidity-sorted portfolios for three time periods within the sample. Portfolios are formed every week and held for 4 weeks, i.e. at each moment in time four portfolios for each riskiness category or sixteen portfolios in total are held. E1 stands for the average of the four portfolios of emerging markets with highest absolute values of autocorrelation, E2 stands for emerging markets with lowest absolute values of autocorrelation, and D1 and D2 stand for developed markets with highest and lowest absolute autocorrelation respectively. Afterward the portfolios are dynamically linearly orthogonalized with respect to the world market and emerging market factors. The first part shows results for the whole sample, while the second and the third parts depict equity return values for the first 4 and last 5 years of the sample respectively. The annualized mean is computed as $(1 + weekly\_mean)^{52} - 1$ *and is presented in percent.*

	E1 (riskiest)	*E2*	*D1*	*D2* (safest)
05.02.2004 - 23.01.2013				
Annualized mean (%)	8.19	5.39	0.44	-2.24
Mean	0.002	0.001	0.000	-0.000
Standard deviation	0.017	0.020	0.014	0.014
05.02.2004 - 06.02.2008				
Annualized mean (%)	23.16	15.71	10.37	6.72
Mean	0.004	0.003	0.002	0.001
Standard deviation	0.010	0.015	0.009	0.010
07.02.2008 - 23.01.2013				
Annualized mean (%)	-2.58	-2.28	-6.92	-8.93
Mean	-0.001	-0.000	-0.001	-0.002
Standard deviation	0.021	0.023	0.016	0.016

Figure 1: Evolution of one dollar invested into CDS spread-sorted portfolios.

The graph depicts how one dollar invested in each of the CDS spread-sorted portfolios developed over time. Portfolios are formed every week and held for 4 weeks, i.e. at each moment in time four portfolios for each riskiness category or sixteen portfolios in total are held. C1 stands for the average of the four portfolios of countries with the highest CDS spreads while C4 - the lowest.

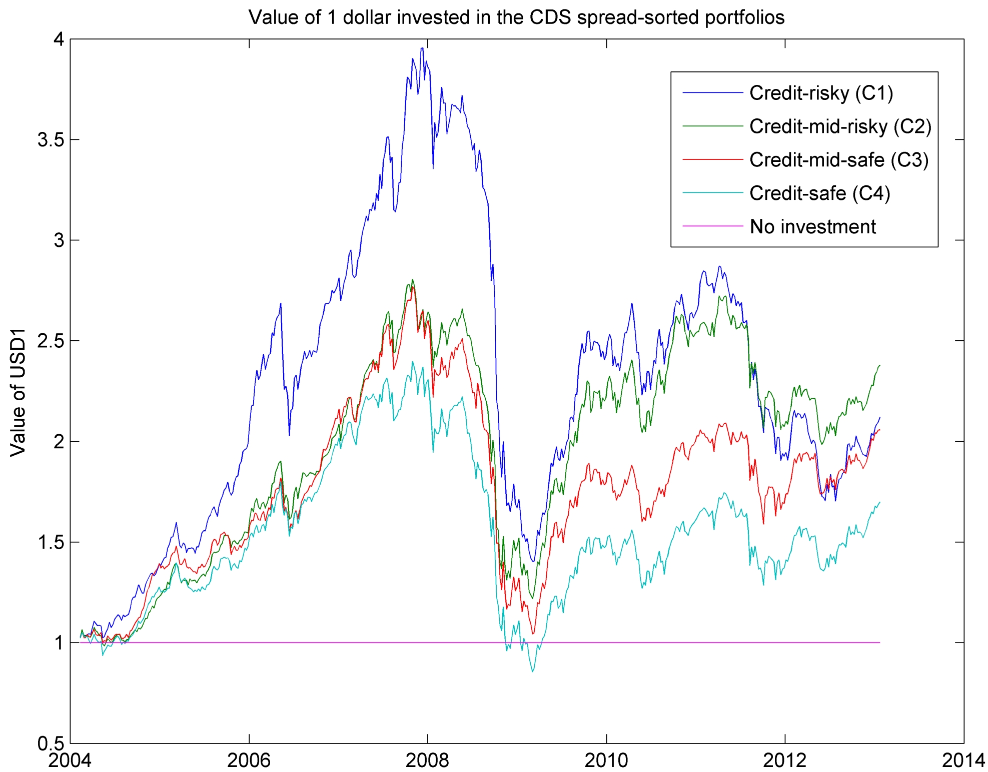

Figure 2: Development of average CDS spread for portfolios sorted on CDS spread.
The graph depicts the evolution of average CDS spreads for each of the CDS spread-sorted portfolios over the sample period. C1 stands for the portfolio of countries with the highest CDS spreads while C4 - the lowest.

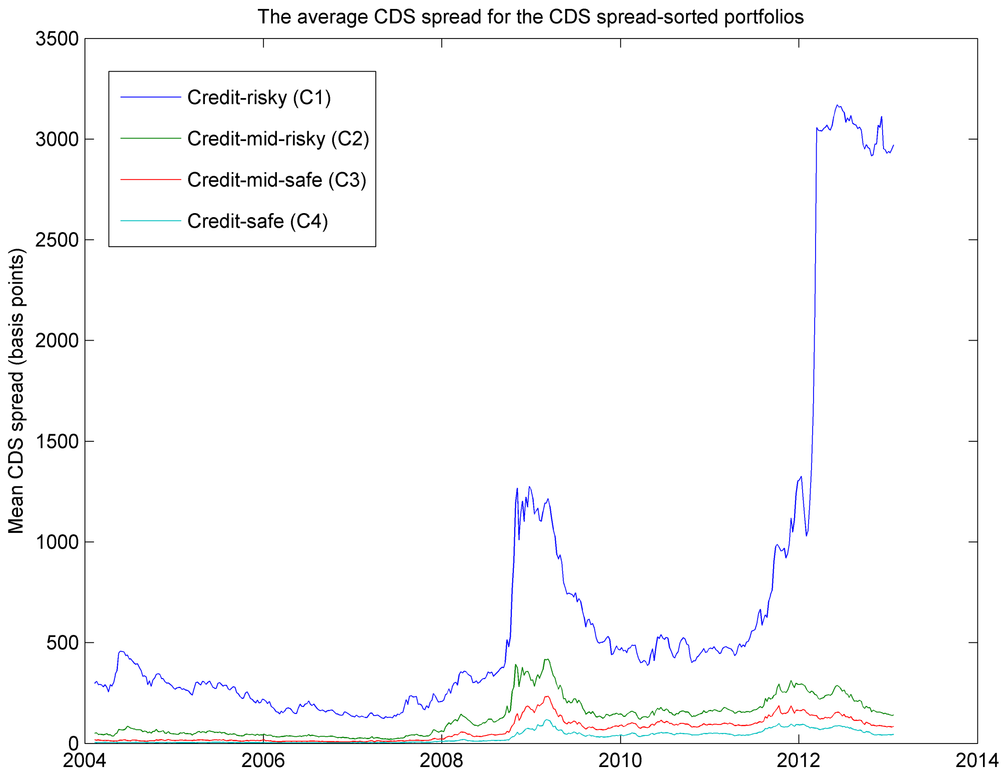

Figure 3: Evolution of one dollar invested into portfolios sorted on autocorrelation and emerging market status.

The graph reports the evolution of a one dollar investment into each of the four autocorrelation and emerging market status-sorted portfolios. Portfolios are formed every week and held for 4 weeks, i.e. at each moment in time four portfolios for each riskiness category or sixteen portfolios in total are held. E1 stands for the average of the four portfolios of emerging markets with highest absolute values of autocorrelation, E2 stands for emerging markets with lowest absolute values of autocorrelation, and D1 and D2 stand for developed markets with highest and lowest absolute autocorrelation respectively. The portfolios are not orthogonalized.

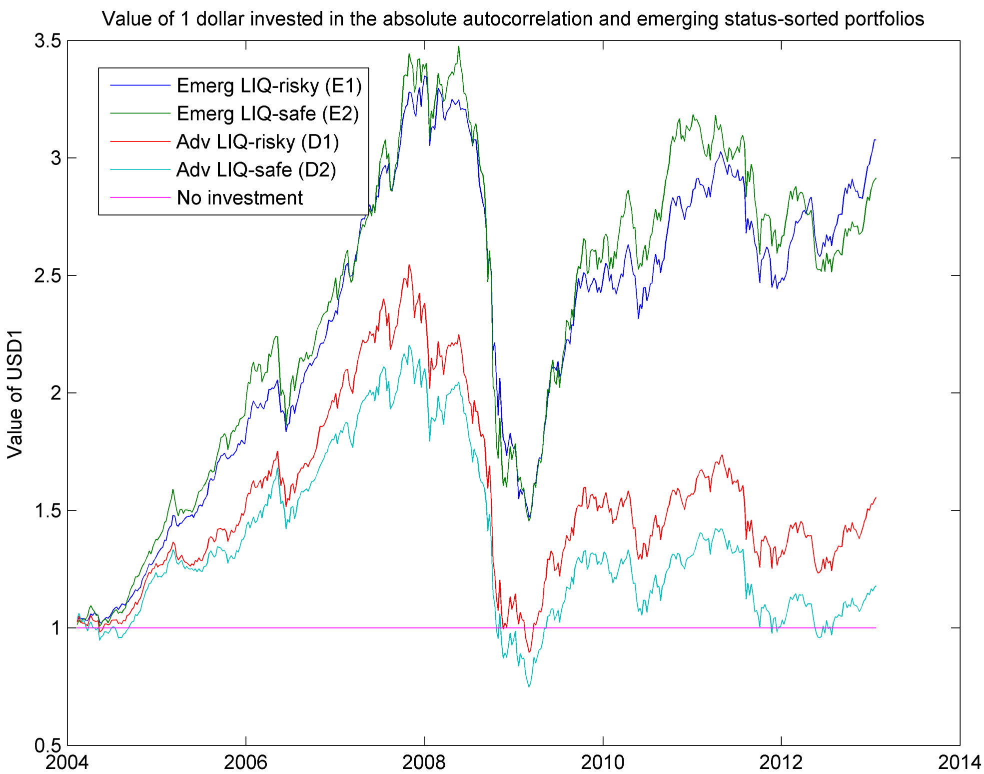

Figure 4: Evolution of one dollar invested into liquidity-sorted portfolios.
The graph reports the evolution of a one dollar investment into each of the four dynamically orthogonalized liquidity-sorted portfolios. Portfolios are formed every week and held for 4 weeks, i.e. at each moment in time four portfolios for each riskiness category or sixteen portfolios in total are held. E1 stands for the average of the four portfolios of emerging markets with highest absolute values of autocorrelation, E2 stands for emerging markets with lowest absolute values of autocorrelation, and D1 and D2 stand for developed markets with highest and lowest absolute autocorrelation respectively. Afterward the portfolios are dynamically linearly orthogonalized with respect to the world market and emerging market factors.

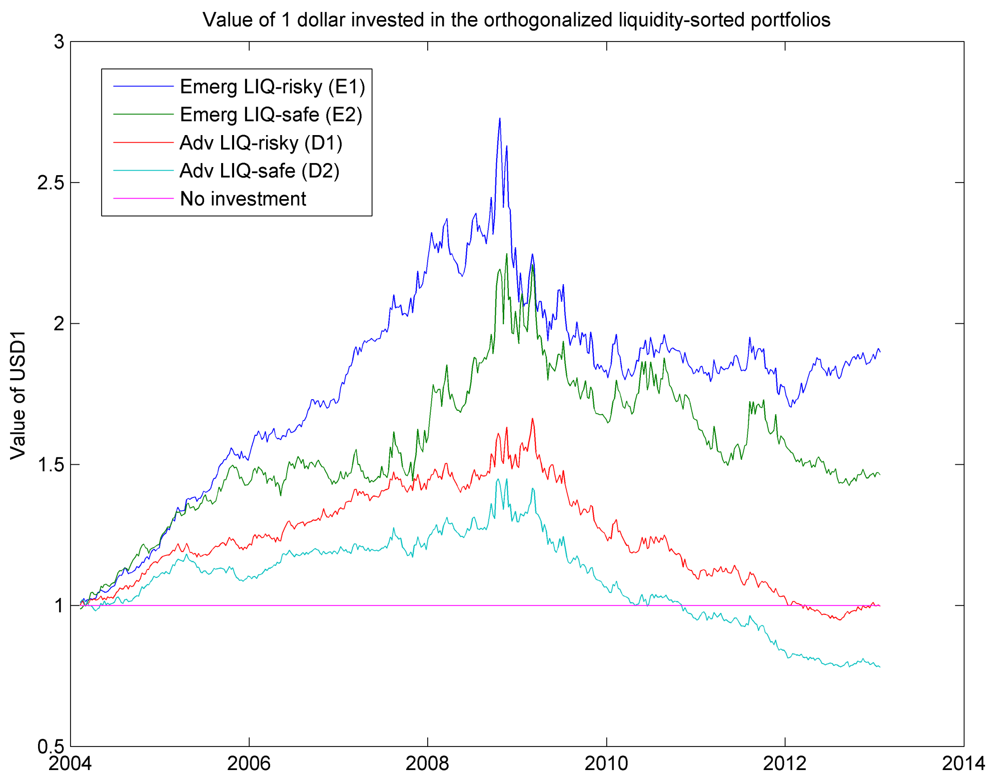

Figure 5: Development of average absolute autocorrelations for portfolios sorted on absolute autocorrelation and emerging market status.

The graph reports the evolution of average absolute autocorrelation for each of the four liquidity-sorted portfolios. E1 stands for emerging markets with highest absolute values of autocorrelation, E2 stands for emerging markets with lowest absolute values of autocorrelation, and D1 and D2 stand for developed markets with highest and lowest absolute autocorrelation respectively.

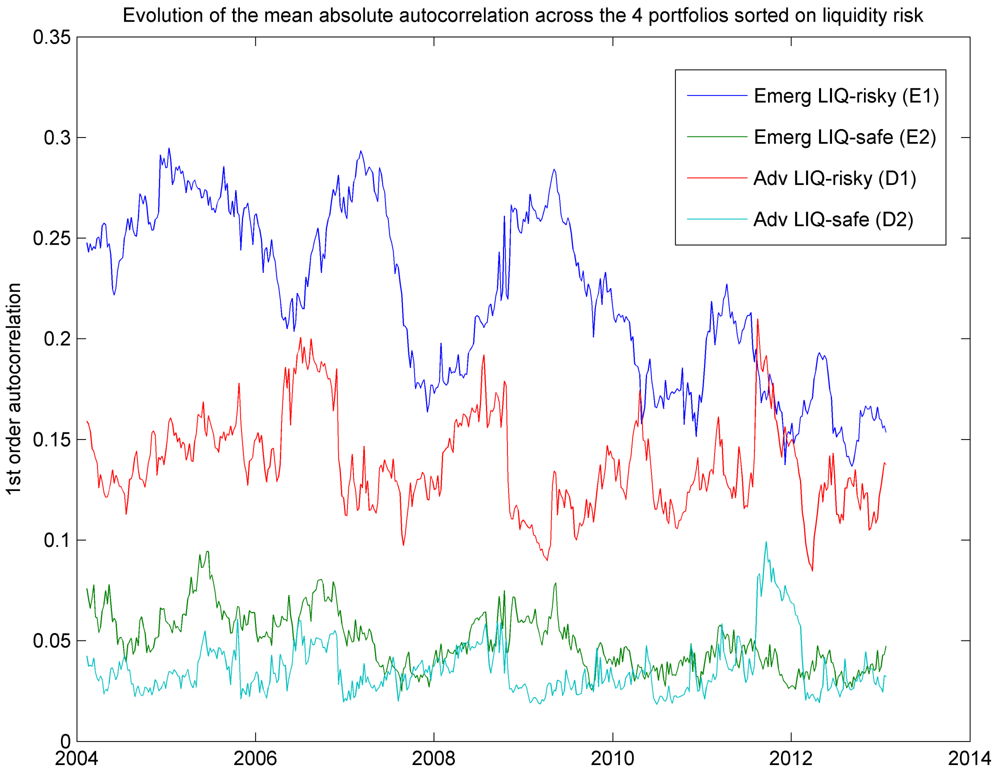

Figure 6: Evolution of one dollar invested in the factors.

The figure plots the evolution of the value of a one dollar investment in the risk factors as constructed in section 5.1. All the risk factors are zero-investment portfolios.

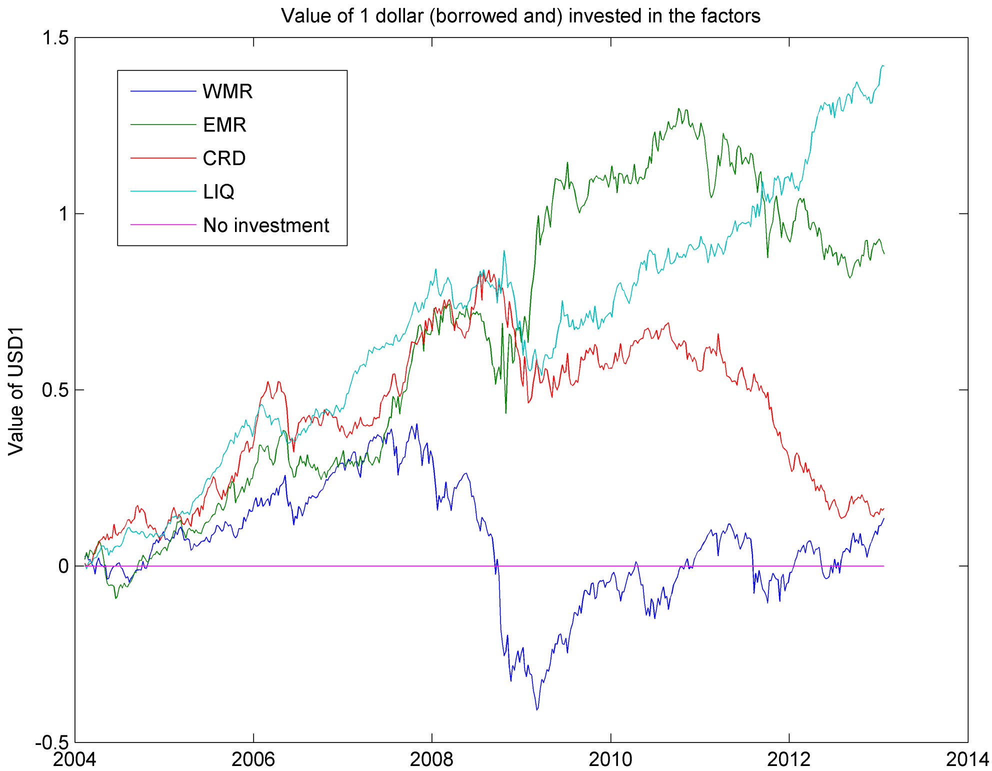

Table 5: Output of factor regressions.

The table presents the regression output of OLS regressions of EMR on WMR (1), CRD on WMR (2), LIQ on WMR (3), CRD on WMR and EMR (4), LIQ on WMR and EMR (5) and LIQ on WMR, EMR and CRD (6). The t-statistics are reported in parentheses. The annualized intercept is calculated as $(1 + weekly\_\alpha)^{52} - 1$ and is presented in percent.

	(1)	(2)	(3)	(4)	(5)	(6)
Annualized intercept (%)	8.11*	2.63	10.95***	1.05	10.95***	10.95***
	(1.85)	(0.84)	(4.13)	(0.33)	(4.11)	(4.28)
WMR	-0.03	-0.19***	-0.14***	-0.18***	-0.14***	-0.08***
	(-0.88)	(-7.40)	(-7.00)	(-7.44)	(-6.99)	(-4.36)
EMR				0.22***	-0.00	-0.07**
				(6.33)	(-0.09)	(-2.44)
CRD						0.28***
						(8.334)
Adjusted R^2	-0.001	0.103	0.093	0.173	0.091	0.208

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 6: Output of regressions of *CRD*, *LIQ* and *EMR* on other factors.

The table presents the regression coefficients of OLS regressions of CRD (1), LIQ (2) and EMR (3) factors on WMR, SMB, HML, MOM, ST_REV and LT_REV factors (together). The t-statistics with Newey-West correction are reported in parentheses. Alphas are reported on an annualized basis as $(1 + weekly\_\alpha)^{52} - 1$ *and are presented in percent.*

	(1)	(2)	(3)
Annualized alpha (%)	2.66	10.84***	7.77*
	(0.64)	(3.65)	(1.68)
WMR	-0.16***	-0.14***	-0.01
	(-3.70)	(-4.39)	(-0.20)
SMB	0.05	0.11**	-0.02
	(0.63)	(2.09)	(-0.14)
HML	0.04	0.05	0.04
	(0.65)	(0.63)	(0.28)
MOM	0.12***	0.05	0.09*
	(2.90)	(1.12)	(1.69)
ST_REV	-0.01	-0.01	0.04
	(-0.48)	(-0.40)	(0.42)
LT_REV	0.00	-0.02	0.00
	(0.03)	(-0.30)	(0.02)
Adjusted R^2	0.127	0.103	0.002

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 7: Output of external factor regressions on *WMR*, *CRD*, *LIQ* and *EMR*.

The table presents the regression coefficients of OLS regressions of SMB (1), HML (2), MOM (3), ST_REV (4) and LT_REV (5) factors on WMR, CRD, LIQ and EMR factors (together). The t-statistics with Newey-West correction are reported in parentheses. Alphas are reported on an annualized basis as $(1 + weekly\_\alpha)^{52} - 1$ *and are presented in percent.*

	(1)	(2)	(3)	(4)	(5)
Annualized alpha (%)	0.24	1.67	-0.41	7.85*	-2.66
	(0.09)	(0.48)	(-0.07)	(1.94)	(-0.77)
WMR	0.14***	0.22***	-0.33***	0.32***	0.11**
	(4.87)	(4.90)	(-2.58)	(3.19)	(1.89)
CRD	0.01	-0.04	0.25**	-0.07	-0.00
	(0.26)	(-0.88)	(2.30)	(-0.73)	(-0.08)
LIQ	0.11*	0.01	0.08	-0.02	0.02
	(1.92)	(0.20)	(0.55)	(-0.16)	(0.25)
EMR	-0.00	-0.00	0.08	0.04	-0.00
	(-0.02)	(-0.09)	(1.00)	(0.42)	(-0.09)
Adjusted R^2	0.080	0.197	0.182	0.154	0.046

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 8: Results of the time-series regressions and GRS tests.

The table reports the results of the time-series regressions and of the GRS test of time-series joint significance of alphas for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The alphas refer to the intercepts in the time-series regressions and are reported on an annualized basis as $(1 + weekly\_\alpha)^{52} - 1$*; they are presented in percent. The results are reported with the Newey-West (1 lag) correction.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Annualized alphas (%)											
Mean	5.93	9.42	15.13	5.93	5.12	5.27	2.65	5.87	2.51	1.99	2.52
Mean absolute	8.22	10.58	16.07	7.74	7.69	7.52	6.30	7.87	6.20	5.69	5.83
Max	33.72	33.00	40.41	33.48	30.72	27.83	32.35	29.67	31.19	24.82	28.47
Min	-14.59	-12.04	-7.37	-13.55	-15.68	-14.87	-17.66	-14.04	-17.94	-12.42	-10.89
Number of significant alphas											
at 10% level	17	15	40	8	15	18	11	23	10	12	11
at 5% level	13	11	30	4	11	10	7	11	7	7	8
at 1% level	3	2	6	2	2	3	1	3	1	1	1
Number of significant betas at 5% significance level											
WMR	74				76	76	75	76	76	76	76
CRD		37			46			45	32		31
LIQ			55			44		40		45	42
EMR				48			58		55	57	54
Adjusted R^2											
Mean	0.385	0.028	0.055	0.039	0.401	0.399	0.433	0.413	0.442	0.447	0.454
Min	-0.002	-0.002	-0.002	-0.002	-0.003	-0.001	-0.003	0.000	0.000	0.000	0.004
Max	0.893	0.145	0.195	0.288	0.893	0.902	0.916	0.904	0.918	0.926	0.925
GRS test											
GRS statistic	2.01***	1.29*	1.15	1.23	2.04***	1.75***	1.93***	1.80***	1.98***	1.67***	1.70***
P-value	0.000	0.062	0.200	0.103	0.000	0.000	0.000	0.000	0.000	0.001	0.001
Number of regressions	78	78	78	78	78	78	78	78	78	78	78
Number of periods[a]	468	468	468	468	468	468	468	468	468	468	468

, ** and * denote significance at 10%, 5% and 1% level respectively.*

[a]One period is the equivalent of one week

Table 9: Time-series prices of risk.

The table reports the time-series weekly prices of risk for the WMR, EMR, CRD and LIQ factors. The price is computed as the average of the return of the factor over time. The annualized price of risk is computed as $(1+weekly\_price)^{52}-1$ *and is presented in percent.*

	WMR	*CRD*	*LIQ*	*EMR*
Annualized price (%)	3.15	2.29	10.67***	8.19*
T-statistic	0.51	0.63	3.77	1.83

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 10: Results of the cross-sectional regressions and the χ^2 cross-sectional test.

The table reports the distribution of alphas and the number of significant alphas in the cross-section, as well as the results of the test of joint significance of alphas in the cross-section for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The alphas refer to the residuals in the cross-sectional regressions with no intercept and are reported on an annualized basis as $(1+weekly\_\alpha)^{52}-1$*; they are presented in percent. The results are reported with the Newey-West (1 lag) correction of the time-series standard errors.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Annualized alphas (%)											
Mean	1.75	7.03	5.97	2.14	0.90	0.00	1.20	0.01	0.87	0.07	0.07
Mean absolute	7.14	9.25	9.01	6.34	6.26	5.81	6.00	5.82	5.78	5.46	5.45
Max	32.25	40.20	36.87	31.85	26.15	23.17	31.64	21.67	25.35	24.74	25.21
Min	-19.77	-13.00	-19.26	-16.98	-21.20	-18.89	-18.70	-19.28	-19.87	-14.18	-13.91
Number of significant alphas											
at 10% level	67	68	70	69	69	67	66	69	66	69	69
at 5% level	66	66	70	68	68	67	65	69	65	67	67
at 1% level	62	66	69	63	63	64	63	67	60	63	63
χ^2-statistic											
χ^2-statistic	120.67***	117.97***	110.33***	112.23***	111.28***	99.45**	112.68***	99.71**	108.76***	95.71*	95.52**
P-value	0.001	0.002	0.008	0.005	0.005	0.037	0.004	0.030	0.007	0.054	0.047
Observations	78	78	78	78	78	78	78	78	78	78	78

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 11: Cross-sectional price of risk.

The table reports the price of risk of the WMR, EMR, CRD and LIQ factors in the cross-section for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The annualized price of risk is computed as $(1 + weekly\_price)^{52} - 1$ *and is presented in percent. T-statistic is obtained using Newey-West (1 lag) adjusted standard errors.*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WMR	Annualized price (%)	7.99				4.78	9.25	1.92	8.44	1.92	5.63	5.75
	T-statistic	1.18				0.73	1.34	0.29	1.25	0.30	0.83	0.85
CRD	Annualized price (%)		-6.68			13.06**			6.42	9.97*		4.67
	T-statistic		-0.63			2.41			1.29	1.91		0.95
LIQ	Annualized price (%)			-4.69			11.84***		11.26***		9.42**	9.51**
	T-statistic			-0.72			3.03		2.87		2.45	2.45
EMR	Annualized price (%)				20.29*			15.25***		13.41***	7.75	7.71
	T-statistic				1.66			2.63		2.34	1.39	1.39

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Figure 7: The market price of market risk.

The figure plots the market price of market risk, estimated using the rolling windows procedure, with a window length of 1.5 years. The estimation is done on a weekly basis and the results presented are annualized as $(1+weekly\_price)^{52}-1$. *The confidence bounds include the Newey-West correction.*

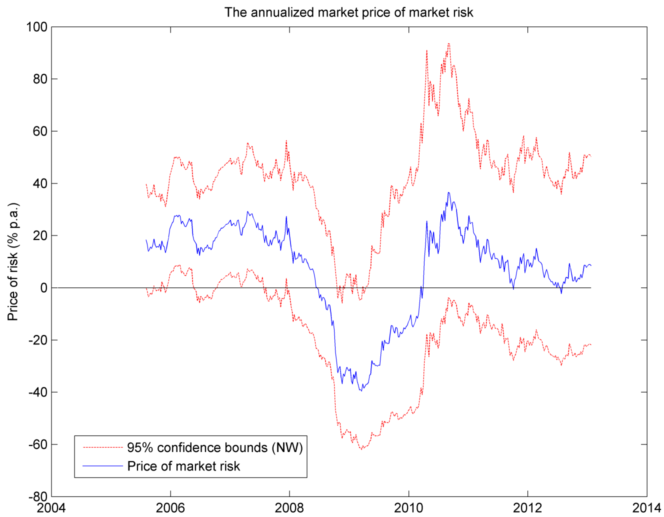

Figure 8: The market price of credit risk.

The figure plots the market price of credit risk, estimated using the rolling windows procedure, with a window length of 1.5 years. The estimation is done on a weekly basis and the results presented are annualized as $(1+weekly\_price)^{52}-1$. *The confidence bounds include the Newey-West correction.*

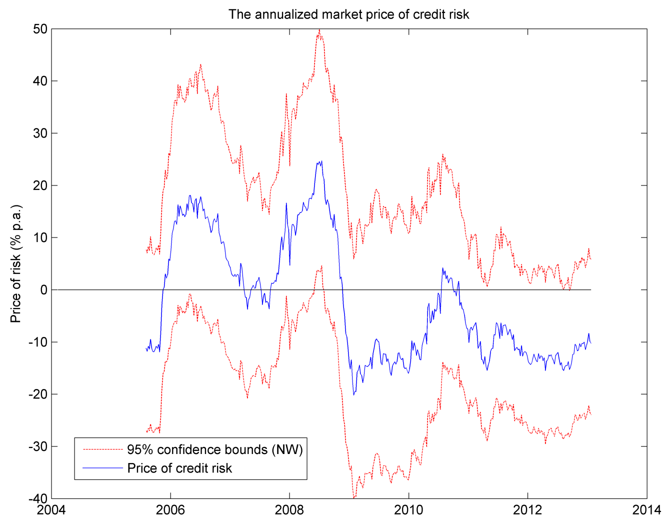

Figure 9: The market price of liquidity risk.

The figure plots the market price of liquidity risk, estimated using the rolling windows procedure, with a window length of 1.5 years. The estimation is done on a weekly basis and the results presented are annualized as $(1 + weekly\_price)^{52} - 1$. *The confidence bounds include the Newey-West correction.*

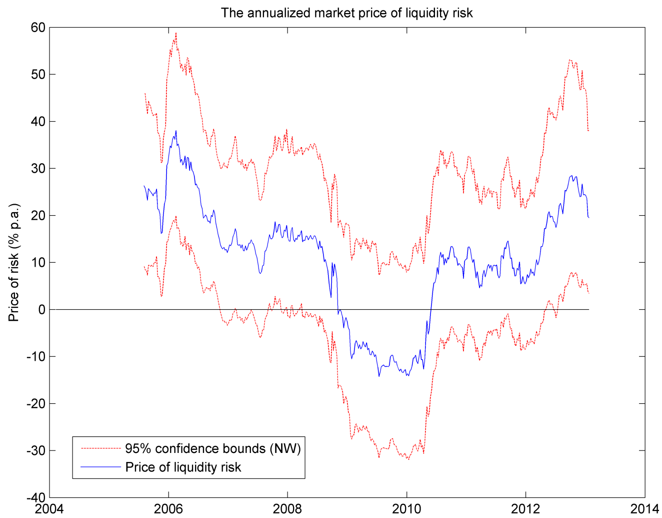

Figure 10: The market price of emerging market risk.

The figure plots the market price of emerging market risk, estimated using the rolling windows procedure, with a window length of 1.5 years. The estimation is done on a weekly basis and the results presented are annualized as $(1 + weekly\_price)^{52} - 1$. *The confidence bounds include the Newey-West correction.*

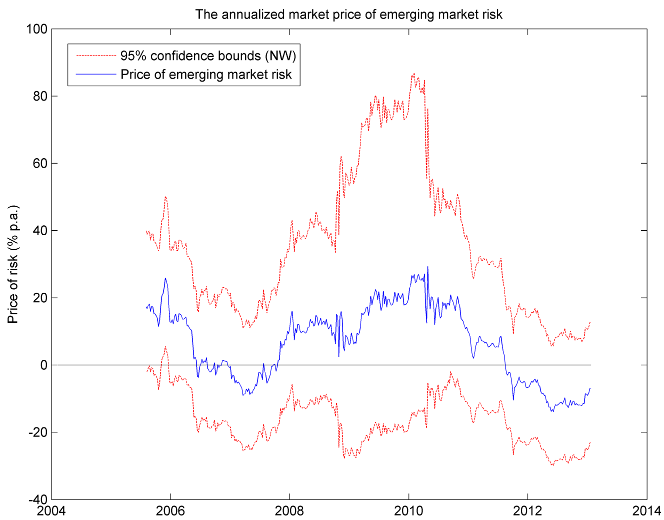

Figure 11: The market prices of market, credit, liquidity and emerging market risks from the conditional model.

The figure plots the market price of market, credit, liquidity and emerging market risk estimated using the DCC-GARCH model. The estimation is done on a weekly basis and the results presented are alpha-beta filtered and annualized as $(1 + weekly\_price)^{52} - 1$.

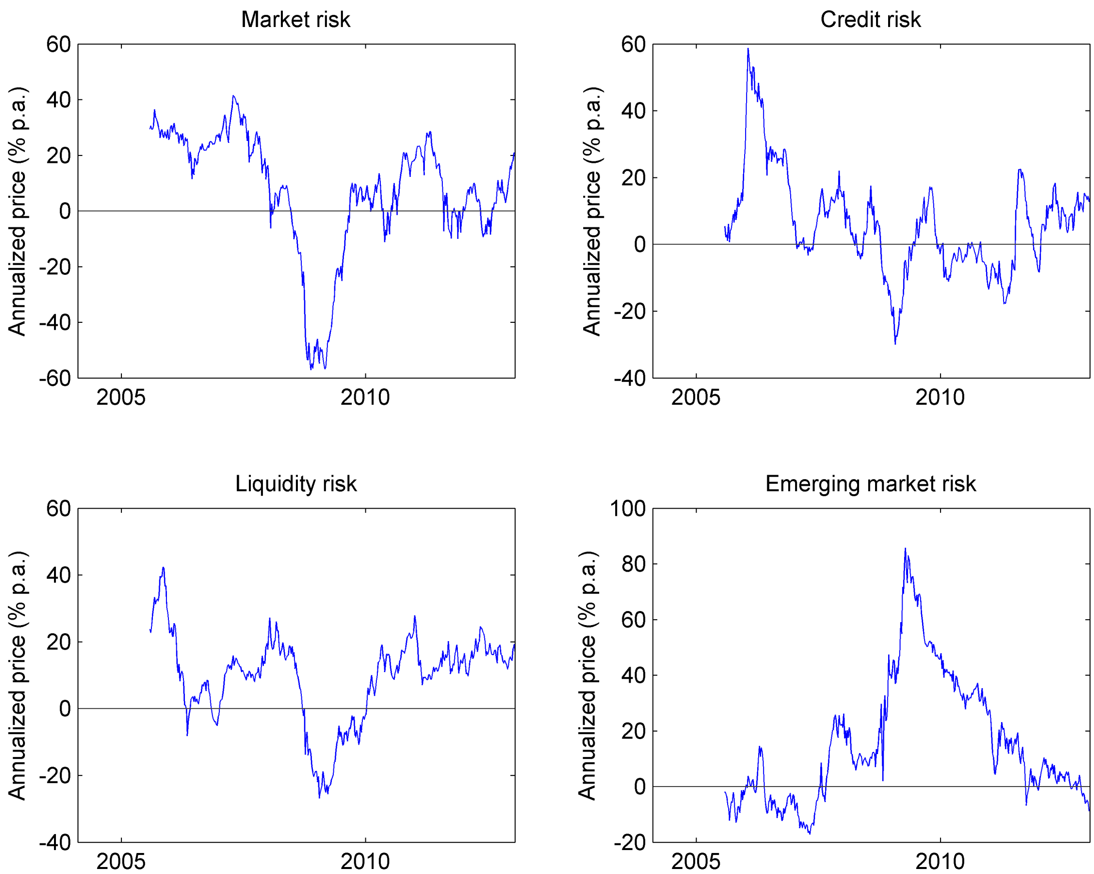

Table 12: Results of the GRS and χ^2 cross-sectional tests for 16 portfolios.

The table reports the results of the GRS and the χ^2 tests of time-series and cross-sectional joint significance of alphas using 16 portfolios of assets for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The results are reported for tests with the Newey-West (1 lag) correction.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GRS test											
GRS statistic	1.53*	1.65*	0.98	1.40	1.64*	0.89	1.40	1.05	1.54*	0.70	0.78
p-value	0.086	0.053	0.474	0.137	0.056	0.577	0.138	0.405	0.083	0.791	0.709
χ^2 test											
χ^2-statistic	25.05**	23.27*	16.61	17.17	20.89	8.21	16.84	7.82	16.55	7.85	7.10
p-value	0.049	0.079	0.342	0.309	0.104	0.878	0.265	0.855	0.221	0.853	0.851

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table 13: Results of the χ^2 cross-sectional test for the rolling windows model based on 4-week periods

The table reports the average (across time) p-value of the test of joint significance of alphas in the cross-section for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The results are reported with the Newey-West correction of the time-series standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Average P-value for the χ^2 -statistic											
Average P-value	0.14	0.13	0.13	0.15	0.24	0.22	0.22	0.33	0.32	0.31	0.45

10.3 Supplementary tables and figures

Figure S1: Number of observations over time.

The figure reports the number of countries for which CDS and stock market index observations are available at each point in time.

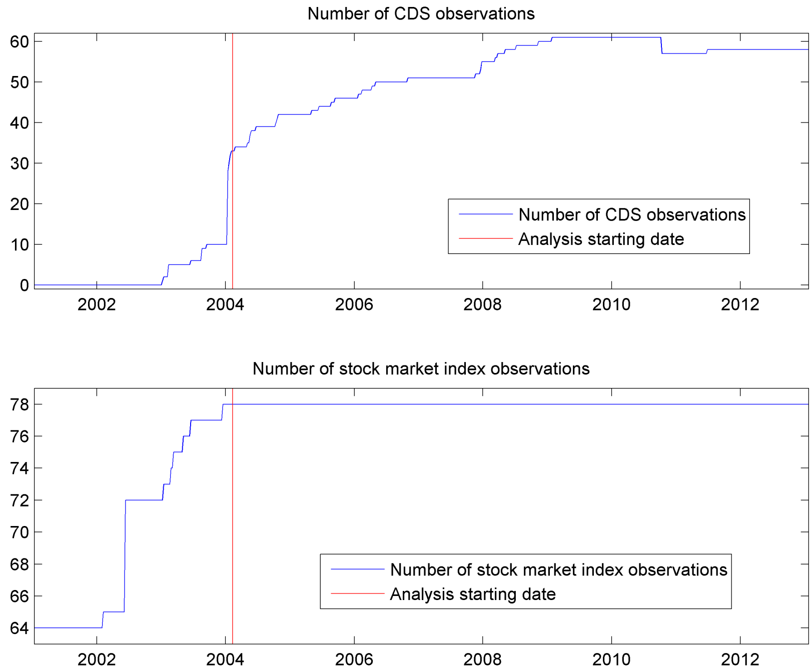

Table S1: Summary statistics for the factors.

The table reports the summary statistics for the factors for the whole sample period.

	WMR	*EMR*	*CRD*	*LIQ*
Mean	0.001	0.002	0.000	0.002
Median	0.003	0.002	0.001	0.002
Variance	0.001	0.000	0.000	0.000
Skewness	-0.896	0.291	0.083	-0.112
Excess Kurtosis	4.343	5.148	0.806	0.951
Min	-0.153	-0.085	-0.054	-0.040
Max	0.079	0.104	0.057	0.041

Figure S2: Means and medians of weekly asset excess returns.
The graphs depict the distributions of means and medians of weekly excess returns for 78 national market indices.

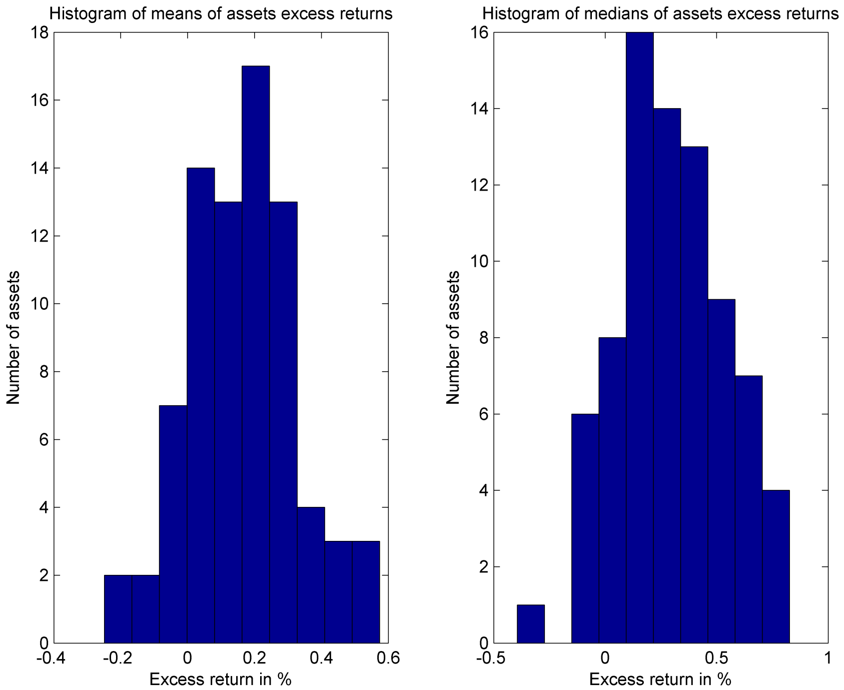

Figure S3: Variances, skewnesses and excess kurtoses of weekly assets excess returns.
The graphs depict the distributions of variances, skewnesses and excess kurtoses of weekly excess returns for 78 national market indices.

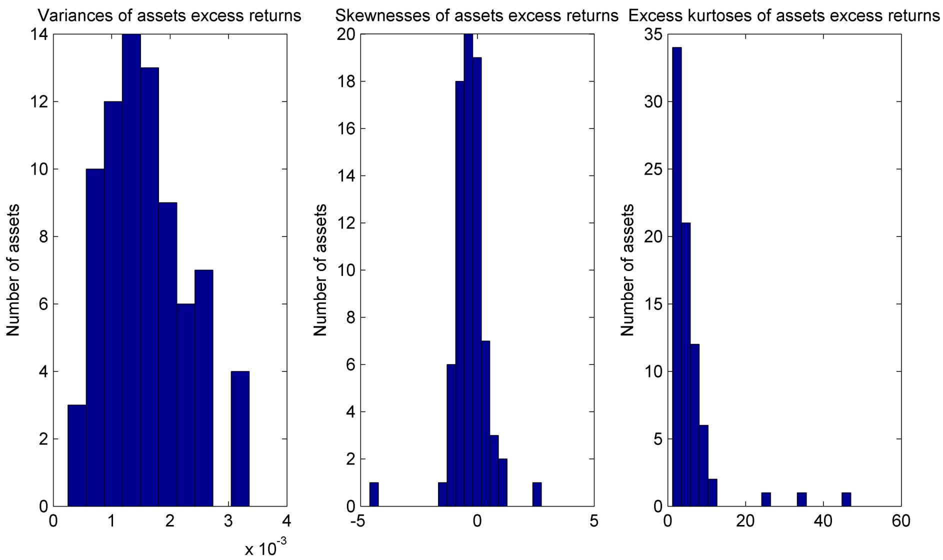

Figure S4: Autocorrelation histogram.

The graphs show the distributions of first order autocorrelations for emerging and advanced markets.

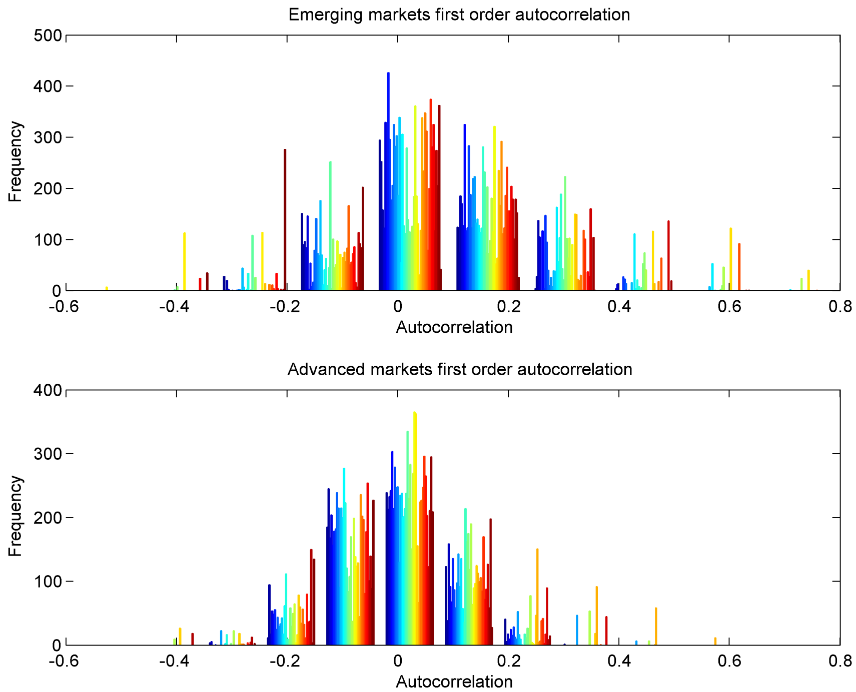

Table S2: Correlation between the factors for the full sample period.

The table shows correlations between the factors for the whole sample period. The factors are constructed as depicted in Section 5.1.

	WMR	*EMR*	*CRD*	*LIQ*
WMR	1.00	-0.04	-0.32	-0.31
EMR	-0.04	1.00	0.28	0.01
CRD	-0.32	0.28	1.00	0.41
LIQ	-0.31	0.01	0.41	1.00

Table S3: Jarque-Berra test of the factors.

The table shows Jarque-Berra normality test results for the factors.

	WMR	*EMR*	*CRD*	*LIQ*
JB statistic	430.39	523.33	13.21	18.60
P-value of JB statistic	0.000	0.000	0.001	0.000

Table S4: Ljung-Box test of autocorrelation of the factors.

The table reports Ljung-Box autocorrelation test results for the factors up to 10 lags.

		Lag									
		1	2	3	4	5	6	7	8	9	10
WMR	Statistic	1.03	1.22	4.55	4.68	6.62	9.51	14.79**	18.42**	19.17**	26.01***
	P-value	0.311	0.542	0.208	0.322	0.251	0.147	0.039	0.018	0.024	0.004
EMR	Statistic	0.16	12.96***	13.89***	15.24***	18.03***	21.04***	23.93***	29.89***	31.11***	33.13***
	P-value	0.691	0.002	0.003	0.004	0.003	0.002	0.001	0.000	0.000	0.000
CRD	Statistic	0.54	0.58	1.86	2.04	2.56	2.74	2.77	2.90	3.87	4.31
	P-value	0.464	0.749	0.602	0.729	0.768	0.840	0.905	0.941	0.920	0.933
LIQ	Statistic	2.00	3.25	10.73**	13.93***	14.45**	17.09***	18.70***	21.78***	23.11***	28.33***
	P-value	0.158	0.197	0.013	0.008	0.013	0.009	0.009	0.005	0.006	0.002

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table S5: Correlations of *WMR*, *CRD*, *LIQ* and *EMR* with other risk factors.

The table presents the correlations between WMR, CRD, LIQ and EMR factors with SMB and HML factors of Fama and French (1993), MOM factor of Carhart (1997), as well as short-term (ST_REV) and long-term (LT_REV) reversals factors. The correlations are computed for the whole sample period, February 5th, 2004 to January 23rd, 2013.

	WMR	*CRD*	*LIQ*	*EMR*
SMB	0.28	-0.04	0.02	-0.01
HML	0.45	-0.19	-0.14	-0.04
MOM	-0.40	0.29	0.20	0.11
ST_REV	0.40	-0.16	-0.15	0.01
LT_REV	0.23	-0.08	-0.06	-0.02

Table S6: Correlation between the factors for the two sub-periods.

The table reports the correlations between the factors for two sub-periods.

	05.02.2004 - 06.02.2008				07.02.2008 - 23.01.2013			
	WMR	*EMR*	*CRD*	*LIQ*	*WMR*	*EMR*	*CRD*	*LIQ*
WMR	1.00	0.05	0.05	-0.01	1.00	-0.07	-0.48	-0.40
EMR	0.05	1.00	0.38	0.02	-0.07	1.00	0.22	0.00
CRD	0.05	0.38	1.00	0.44	-0.48	0.22	1.00	0.39
LIQ	-0.01	0.02	0.44	1.00	-0.40	0.00	0.39	1.00

Table S7: Autocorrelation in the time-series regressions residuals.

This table presents a summary of the analysis of autocorrelation in the time-series regressions residuals. The first part of the table reports the number of countries for which the p-values of the two-sided Durbin-Watson test are below 0.1, 0.05 and 0.01 respectively, i.e. the absence of serial correlation can be rejected. The second part of the table reports the average and the maximum number of significant correlations in residuals per country for the number of lags up to $min(int(1.2T^{1/3}), T)$ *respectively, where int() denotes the integer part. The maximum number of lags equals 9 is our case. The columns represent the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The null hypothesis assumes no serial correlation in the data.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Number of countries with autocorrelated residuals according to the Durbin-Watson test											
DW P-value $\leq$ 0.1	47	24	24	38	47	45	49	47	45	48	47
DW P-value $\leq$ 0.05	36	19	21	28	39	38	39	35	41	42	40
DW P-value $\leq$ 0.01	25	10	12	13	24	20	29	22	25	22	23
Number of countries	78	78	78	78	78	78	78	78	78	78	78
Average number of significant autocorrelations per country											
P-value $\leq$ 0.1	0.56	1.46	1.74	1.21	0.50	0.62	0.65	0.54	0.62	0.67	0.59
P-value $\leq$ 0.05	0.36	0.96	0.95	0.65	0.29	0.29	0.37	0.23	0.29	0.33	0.28
P-value $\leq$ 0.01	0.05	0.26	0.29	0.19	0.06	0.06	0.10	0.06	0.10	0.09	0.10
Maximum number of significant autocorrelations per country											
P-value $\leq$ 0.1	5	5	6	6	4	4	5	3	4	4	4
P-value $\leq$ 0.05	4	4	4	4	3	3	4	2	3	2	2
P-value $\leq$ 0.01	1	2	2	2	1	1	2	1	2	1	1

Table S8: Heteroskedasticity tests for the time-series regressions errors.

The table reports the number of countries for which the p-value of the tests is above 0.05, i.e. homoskedasticity cannot be rejected. The columns represent the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The null hypothesis assumes no heteroskedasticity in the data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Breush-Pagan, Koenker modification test	57	60	30	63	46	42	45	39	38	39	34
White's test	24	21	7	15	19	10	18	9	15	11	11
White, Wooldridge special case test	24	21	7	15	25	25	25	27	22	22	21
Number of countries	78	78	78	78	78	78	78	78	78	78	78

Table S9: Results of the GRS and the χ^2 cross-sectional tests for the two sub-periods.

The table reports the results of the GRS test of time-series joint significance of alphas and of the test of joint significance of alphas in the cross-section for the models with the regressors being: WMR (1), CRD (2), LIQ (3), EMR (4), WMR and CRD (5), WMR and LIQ (6), WMR and EMR (7), WMR, CRD and LIQ (8), WMR, CRD and EMR (9), WMR, LIQ and EMR (10), WMR, CRD, LIQ and EMR (11). The results are reported for tests with the Newey-West (1 lag) correction.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GRS statistic for the period 05.02.2004 - 06.02.2008											
GRS	2.64***	2.12***	2.02***	2.18***	2.51***	2.30***	2.50***	2.30***	2.43***	2.16***	2.18***
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GRS statistic for the period 07.02.2008 - 23.01.2013											
GRS	1.74***	1.47**	1.51**	1.45**	1.70***	1.72***	1.73***	1.64***	1.68***	1.74***	1.63***
P-value	0.001	0.019	0.013	0.022	0.002	0.002	0.002	0.004	0.002	0.001	0.004
χ^2-statistic for the period 05.02.2004 - 06.02.2008											
χ^2	273.58***	240.59***	218.05***	244.25***	257.40***	192.61***	264.88***	176.34***	256.08***	188.81***	175.76***
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
χ^2-statistic for the period 07.02.2008 - 23.01.2013											
χ^2	161.51***	159.58***	163.33***	161.40***	157.03***	160.14***	158.49***	148.32***	150.44***	157.10***	145.09***
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table S10: Time-series prices of risk for the two sub-periods.

The table reports the time-series weekly prices of risk for the WMR, EMR, CRD and LIQ factors. The price is computed as the average of the return of the factor over time. The annualized price of risk is computed as $(1 + weekly\_price)^{52} - 1$ *and is presented in percent.*

	05.02.2004 - 06.02.2008				07.02.2008 - 23.01.2013			
	WMR	*CRD*	*LIQ*	*EMR*	*WMR*	*CRD*	*LIQ*	*EMR*
Annualized price (%)	4.96	14.90***	15.42***	15.03**	1.70	-6.89	6.98	2.96
T-statistic	0.81	2.82	4.57	2.53	0.17	-1.40	1.63	0.46

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Table S11: Cross-sectional prices of risk in the unconditional analysis based on 4-week periods.

The table reports the cross-sectional annualized prices of risk for WMR, CRD, LIQ and EMR, obtained from the model with the factors being WMR, CRD, LIQ and EMR together. The results correspond to the 4-week based analysis. The sample period considered is 05 Feb 2004 - 23 Jan 2013. The annualized price of risk is computed as $(1 + 4\_week\_price)^{52/4} - 1$. *T-statistic is computed using the Newey-West adjustment for the time-series errors.*

	WMR	*CRD*	*LIQ*	*EMR*
Annualized price (%)	3.42	2.54	7.94**	11.57*
T-statistic	0.53	0.50	2.02	1.94

, ** and * denote significance at 10%, 5% and 1% level respectively.*

Figure S5: Formation of the 16 portfolios.

The figure shows how the portfolios used in Section 7.1.5 are formed. Each week all the countries for which CDS spreads are available are split into emerging and developed markets. Each group is then split in half based on the values of absolute autocorrelation computed using daily local currency returns for the preceding 1.5 years – those with lower values are considered most liquid and those with higher values – least liquid. Afterward each of the four liquidity groups is split into quartile portfolios based on the CDS spreads for the respective week – those with the highest CDS spreads are the riskiest, while those with the lowest – the least risky. The portfolios are rebalanced weekly and held for one week.