View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Research Papers in Economics

b
UNIVERSITÄT
BERN

Faculty of Business, Economics
and Social Sciences

Department of Economics

Measuring Co-Movements of CDS Premia during the Greek Debt Crisis

Sergio Andenmatten
Felix Brill

11-04

July 2011

DISCUSSION PAPERS

Schanzeneckstrasse 1
Postfach 8573
CH-3001 Bern, Switzerland
http://www.vwi.unibe.ch

Measuring Co-Movements of CDS Premia during the Greek Debt Crisis

Sergio Andenmatten[*] Felix Brill[†]

July 5, 2011

JEL-Classification: C58, G01, G12, G15
Keywords: CDS market, Contagion, Greek debt crisis, Sovereign credit

Abstract

In this paper we test whether the co-movement of sovereign CDS premia increased significantly after the Greek debt crisis started in October 2009. We perform a bivariate test for contagion that is based on an approach proposed by Forbes and Rigobon (2002). Our sample consists of daily data between October 2008 and July 2010 for 39 countries including both emerging and industrialized countries. Our results indicate that there were periods of contagion for CDS markets during the Greek debt crisis, which is in contrast to the results from Forbes and Rigobon (2002) for equity markets after the Hong Kong crash and their conclusion of "no contagion, only interdependence". Especially for European countries we would instead conclude "both contagion and interdependence".

[*]Sergio Andenmatten (Swiss National Bank, Börsenstrasse 15, CH-8022 Zurich, sergio.andenmatten@snb.ch) is writing his doctoral thesis at the University of Bern and works for the Swiss National Bank.

[†]Felix Brill (Wellershoff & Partners Ltd., Zürichbergstrasse 38, CH-8044 Zurich, felix.brill@wellershoff.ch) is writing his doctoral thesis at the University of Bern and works for Wellershoff & Partners.

The authors would like to thank Klaus Neusser, Klaus Wellershoff, and the participants of the brown-bag seminar of the Department of Economics at the University of Bern for their valuable comments. The content of the publication is the sole responsibility of the authors and does not necessarily reflect the views of the Swiss National Bank or Wellershoff & Partners.

Contents

“Nothing is so well calculated to produce a death-like torpor in the country as an extended system of taxation and a great national debt.”

William Cobbett, letter, Feb. 10, 1804

1 Introduction

Since the financial crisis of 2008 the sovereign CDS market in Europe has been growing strongly. The financial crisis caused public deficits to increase massively due to fiscal stimulus packages, bail-outs and reduced tax revenues. As can be seen in Figure 1, however, the trend of increasing public debt had started already in the 1970s. For instance, the average debt-to-GDP ratio for the G7 countries had risen from a low of about 30% to around 90% in 2007. Since then, the debt-to-GDP has increased by another 20 percentage points.

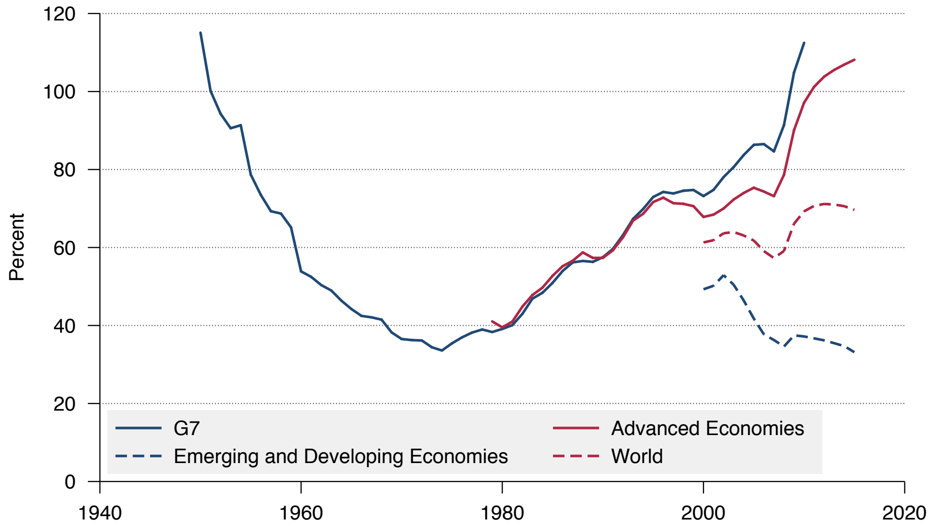

Figure 1: Debt-to-GDP Ratio since 1950. Source: IMF.

Accordingly, fears about the sustainability of this development, accompanied by deteriorating credit quality for some countries, stimulated the needs of market participants to hedge against sovereign default risk. Eventually, this led to a significant increase in the demand for sovereign credit default swaps (CDS). Prior to 2008, sovereign CDS were mainly traded for emerging markets. However, since then CDS markets for industrialized countries have also been developed and have been in the limelight several times. According to the Fitch Solutions liquidity index[1], the liquidity in European sovereign CDS surpassed the liquidity of Latin American emerging economies in several periods after November 2009. In general, as stated by Markit, the liquidity of a credit derivative asset increases when the underlying is show-

[1] As stated by Fitch Solutions, the liquidity index measures "are derived from a proprietary statistical model which produces a liquidity score for each credit derivative asset by modeling a broad set of information taken from the CDS market."

ing signs of financial stress in combination with a significant amount of debt outstanding and/or changes in its capital structure, including new issuance.[2] Entities also tend to be more liquid when there is agreement about present value but disagreement about future value due to heightened uncertainty surrounding the entity.

As discussed in Andenmatten and Brill (2011), CDS are bilateral contracts used to transfer risk among market participants and are basically defined by four parameters: the reference entity, the notional amount, the price (spread or premium), and the maturity. One participant is the so-called protection buyer who wants to buy insurance against the default of a specific entity, the so-called reference entity. The other party is the protection seller, who writes the insurance on the reference entity. To compensate the seller of the insurance for the assumed risk, the protection buyer pays an initially fixed spread every year (or each quarter) on the insured notional value. If a credit event occurs, the CDS is triggered and the protection seller has to pay the difference between the insured notional value and the recovery value.[3] Since 2005, an auction process has been instituted and settlement is almost always made through an auction (either cash or physical delivery), i.e. investors are signed up automatically for all auctions.

A CDS makes it possible to invest in the credit quality of a corporate or a sovereign. If an investor believes that the credit quality of a corporate will decrease in the coming months and that this is not yet priced into the current spreads, he should buy protection. Once the spreads widen, he will profit because his insurance will increase in value. He can close the insurance contract whenever he wants and monetize his gains. Thus, buying protection on Germany does not mean that somebody is speculating on the country going bankrupt. It merely means that somebody believes the credit quality of Germany will decrease in the future. At the same time, the seller of the protection on Germany believes that – given the current spreads – it is attractive to agree to the contract.

The so-called PIGS countries (i.e. Portugal, Ireland, Greece, Spain) have been frequently in the focus of financial markets and the media, especially since October 2009 when Greek officials announced that debt statistics had been forged. As a consequence, financial market participants responded quickly to the deterioration in fiscal positions by requiring higher sovereign default risk premia not only for Greece but also for many other countries with a seemingly unsustainable fiscal situation. This supports previous studies that had shown that sovereign risk premium differentials tend to co-move over time and are mainly driven by a common time-varying factor, which

[2] Interestingly, CDS liquidity for France, Spain and Portugal has consistently been greater than that of Ireland.

[3] The so-called ISDA Credit Derivative Determination Committee – consisting of buy and sell side members – will decide whether the requirements for a credit event are fulfilled. The decision of the determination committee is binding for the whole market.

can be interpreted as a repricing of global risk factors (see for instance Codogno, Favero, & Missale, 2003; Favero, Pagano, & Thadden, 2007; and Geyer, Kossmeier, & Pichler, 2004).

In line with that, in an extensive study of 26 developed and emerging-market countries Longstaff, Pan, Pedersen, and Singleton (2011) find for the period 2000-2007 that sovereign credit risk premia were generally more related to the U.S. stock market and high-yield bond markets, global risk premia, and capital flows than they were to local factors. Accordingly, an investment in sovereign credit is to a large extent a compensation for bearing global risk and there is little or no country specific premium. However, their study does not include a sovereign debt crisis or the sort of credit events we experienced in the 1990s.

In contrast, Sgherri and Zoli (2009) find evidence that since October 2008 markets have become progressively more concerned about the potential fiscal implications of national financial sectors' frailty and future debt dynamics, which would imply that sovereign credit risk premia are driven more by national than global factors.

The recent focus of financial market participants on the fiscal situation in the PIGS countries provides an opportunity to study the developments of CDS premia for "hot-spot" countries. We now have a better data basis for studying the co-movement of CDS premia across countries and regions and testing whether the co-movement of sovereign CDS premia increased significantly after the Greek debt crisis that started in October 2009 – a development which is usually referred to as contagion. However, there does not seem to be any agreement on what contagion exactly means (Rigobon, 2002) and how it manifests itself. For instance, Forbes and Rigobon (2001) declare that "there is no consensus on exactly what constitutes contagion or how it should be defined". In the following analysis, we will define contagion in the restrictive way proposed by Forbes and Rigobon (2002). They define contagion as a significant increase in cross market linkages after a shock to one country.

In the remainder of the paper we proceed as follows: In the next section, we discuss the concept of contagion and describe a bivariate test procedure that was originally proposed by Forbes and Rigobon (2002). In section 3, we apply this test procedure to our sample of daily data between October 2008 and July 2010 for 39 countries including both emerging and industrialized countries. In doing so, we test for contagion stemming from the Greek CDS market (country level analysis) and the regional CDS market for the PIGS countries (regional level analysis), respectively. In section 4, we attempt to explore the common factor and perform first principal component analysis in order to analyze the degree of commonality of inner-regional variation of CDS premia. Finally, section 5 concludes.

2 Propagation of Shocks: Contagion vs. Interdependence

On October 4, 2009, George Papandreou became the new prime minister of Greece after his Panhellenic Socialist Movement (PASOK) party won the general election. At that time, the Greek economy was still faced with the severe repercussions of the financial crisis. Around two weeks later, on October 20, officials from the new government announced that Greek debt statistics had been forged in the past. Instead of a public deficit of 6% of GDP for 2009 the government now expected twice as much to materialize. This was the starting point of the Greek debt crisis that led to radical austerity packages for the Greek economy and an international rescue package.

The crisis also led to a strong increase in risk premia for Greek sovereign debt as reflected, for instance, in CDS premia. While the CDS premium for a Greek government bond with a 5-year maturity and a notional value of USD 10 million was 124 basis points on October 20, 2009, it soared to 1012 basis points by May 7, 2010. This means that the insurance costs against a default of this particular Greek government bond increased by a factor of more than 8 times, i.e. from USD 124,000 to more than USD 1 million. At the same time, CDS premia for many other countries increased strongly as well. Figure 2 illustrates this by comparing the development of the CDS premia for the PIGS countries. As can be seen, the increase for Greek CDS premia was strongest, but these dramatic movements were mirrored in the other three CDS markets as well.

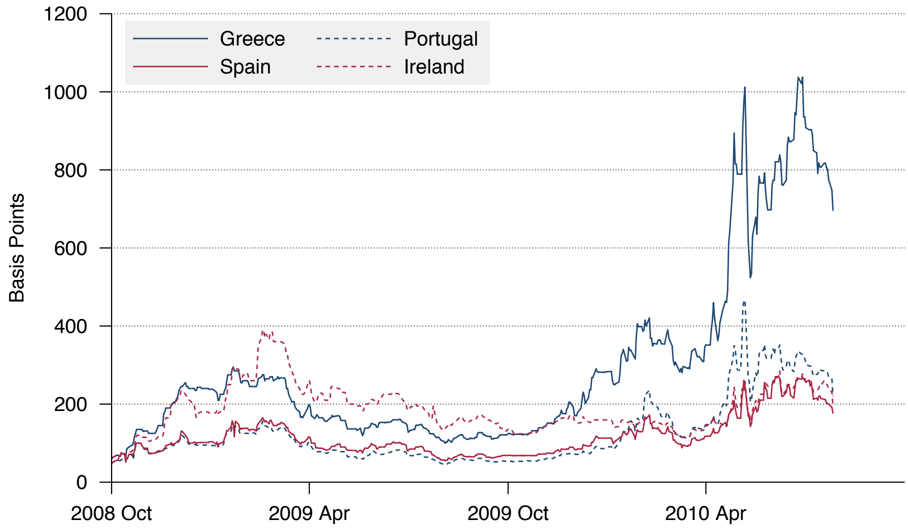

Figure 2: CDS Premia in Basis Points. Source: Thomson Reuters.

This shows that dramatic events in one market can have strong impacts on other markets. The question then is whether a high degree of co-movement during times of crisis already constitutes contagion? Or does this, as Forbes and Rigobon (2002) argue, rather reflect the fact that global markets are "so interdependent that they have similar high rates of co-movement in all states of the world?" Before we can discuss these questions for the Greek debt crisis in section 3, we first introduce the theoretical framework of what contagion constitutes as well as an empirical test procedure based on the approach from Forbes and Rigobon (2002).

2.1 Theory and Literature Review

According to Dornbusch, Park, and Claessens (2000), reasons for contagion can be divided into two groups: on the one hand fundamental based reasons and on the other hand investor behavior-based reasons. While fundamental based contagion works through real and financial linkages across countries, behavior based contagion is more sentiment driven. It seems reasonable to assume that during a financial crisis both types of contagion are present: Firstly, fundamental based because of the strong interrelationship of financial sectors. For instance, during the Greek debt crisis it became apparent that European banks had a significant exposure to Greek government bonds. Hence, a potential restructuring of Greek bonds increased the probability of bail-out packages in different European countries. Secondly, as discussed in Dornbusch et al. (2000), investor behavior-based contagion usually takes effect through liquidity and incentive problems, as well as information asymmetries and coordination problems. As Dornbusch et al. (2000) stated:

> In the absence of better information to the contrary, investors may believe that a financial crisis in one country could lead to similar crises in other countries. A crisis in one country may then induce an attack on the currencies of other countries in which conditions are similar. This type of behavior can reflect rational as well as irrational behavior. If a crisis reflects and reveals weak fundamentals, investors may rationally conclude that similarly situated countries are also likely to face such problems; such reasoning helps explain how crises become contagious. This channel presumes, of course, that investors are imperfectly informed about each country's true characteristics and thus make decisions on the basis of some known indicators, including those revealed in other countries, which may or may not reflect the true state of the subject country's vulnerabilities. The information investors use may include the actions of other investors, which brings us to the effects of informational asymmetries on investor behavior.

There is an extensive literature on potential reasons and transmission channels of contagion[4] as well as on theoretical modeling of contagion.[5] However, little is yet known about the transmission channels and their relative importance.

In addition to that, there is also a large body of literature that focuses on empirical tests for the existence of contagion in a certain stress period, i.e. if there are stronger cross-market linkages in times of crisis. This study belongs to the latter type. In what follows, we will focus on testing for the existence of contagion during the Greek debt crisis.

So far, however, no unifying framework of testing for the existence of contagion during financial crises has been agreed upon. Instead, a broad range of different methodologies has been developed. Dungey, Fry, Gonzalez-Hermosillo, and Martin (2005) offer an extensive review of these methodologies as well as their empirical application for equity markets in 1997-98 during the Asian crisis.[6] According to the authors of this study, the fact that there are so many different methodologies in use makes the assessment of contagion difficult. This seems to be particularly the case for assessing the significance in transmitting crises between countries.

In what follows, we focus on the approach of Forbes and Rigobon (2002), which builds on a correlation analysis. The motivation for focusing on this approach is based on the above mentioned survey from Dungey et al. (2005). In their empirical application of different methodologies Dungey et al. classify the approach from Forbes and Rigobon (2002) as a conservative test as it did not yield any evidence of contagion for equity markets during the Asian crisis in 1997-98. Accordingly, finding evidence for contagion during the Greek debt crisis with such a conservative test would then be a stronger signal than finding evidence for contagion with a less conservative test.

The basic idea of this approach is to test whether the correlation between two variables increases significantly during a crisis period. However, one has to be careful when comparing correlation coefficients between different periods because, as Boyer, Gibson, and Loretan (1997) and Forbes and Rigobon (2002) show, correlation coefficients between markets are conditional on volatility. Hence, during times of increased volatility (i.e. in times of crisis) estimates of correlation coefficients are biased upward.[7] If co-movement tests are not adjusted for that bias, contagion is too easily detected.

[4] For example, see Van Rijckeghem and Weder (2001) and Caramazza, Ricci, and Salgado (2000).

[5] For instance, see Allen and Gale (2000), Calvo and Mendoza (2000), Chue (2002), Kodres and Pritsker (2002), and Kyle and Xiong (2001).

[6] See also Dornbusch et al. (2000) and Pericoli and Sbracia (2003) for an overview of the literature.

[7] Forbes and Rigobon (2002) use a numerical example to show how heteroscedasticity can bias a correlations estimator upward.

A good example for the misleading nature of an uncorrected bias is the paper by King and Wadhwani (1990), which was the first major analysis focusing on co-movement analysis. Here contagion is defined as a significant increase in the correlation coefficient. The paper detects contagion between international stock markets after the U.S. market crash in 1987. However, as Forbes and Rigobon (2002) show, when cross market correlation coefficients are adjusted for heteroscedasticity, there is no longer a significant increase in these correlation coefficients.

Before discussing test procedures for contagion, we first examine potential channels through which correlation between sovereign credit risk and, hence, CDS premia could arise. According to a framework presented by Longstaff et al. (2011) that builds on standard arbitrage arguments[8] one can distinguish between three different channels.

One channel might arise through the correlation between the arrival rates of credit events. This might be induced by a deterioration in the economic situation of the countries in question. For example, the financial crisis of 2008 led to a severe economic slowdown around the globe, dragging many countries into the most severe recession since World War II. In an attempt to stimulate the economy, many governments passed huge rescue packages at the cost of soaring public deficits. Eventually, investors have started to question the ability of some governments to serve their debt. This could be interpreted as an expected increase in the arrival rate of credit events for some of the countries.

Another channel might arise through the correlation between loss rates given a default. This could reflect a worsening of the bargaining situation of creditors due to a deterioration of the economic situation, political turmoil, and legal disputes. As a consequence, governments might face higher refinancing costs.

A third channel might arise through liquidity effects. This can also be illustrated by the recent financial crisis and the flight to quality that took place after the collapse of the investment bank Lehman Brothers (see Longstaff (2004) for an analysis of flights to quality). Other forms of liquidity effects might stem from higher trading costs on illiquid securities for which investors want to be compensated (see Amihud, Mendelson, & Pedersen, 2006) and from the possibility that investors are subject to margin requirements (see Liu & Longstaff, 2004). As a consequence, these funding problems might lead to market illiquidity (Pedersen & Brunnermeier, 2007).

[8] As discussed, among others, in Duffie and Singleton (1999), Dai and Singleton (2003), and Pan and Singleton (2008).

2.2 A Bivariate Test of Contagion

As mentioned in the previous section, correlation is conditional on volatility. Hence, in times of stress correlation coefficients are biased upward. Forbes and Rigobon (2002) present a statistical correction for this conditioning bias and the appropriate procedure to test for contagion (henceforth: FR-test), which we discuss in this section.

We focus on two versions of the bivariate FR-test: that originally developed by Forbes and Rigobon (2002) and another suggested by Dungey et al. (2005). We base our notation on that of Dungey et al. (2005).

First, we define different sample periods:

$$\begin{aligned} x &: \text{period before the crisis} \\ y &: \text{crisis period} \\ z &: \text{whole sample period} \end{aligned}$$

Moreover, we define the following parameters of volatility and correlation:

$$\begin{aligned} \sigma^2_{x,i} &: \text{volatility of country } i's \text{ CDS premia before the crisis } (i = 1, 2) \\ \sigma^2_{y,i} &: \text{volatility of country } i's \text{ CDS premia in the crisis } (i = 1, 2) \\ \rho_x &: \text{correlation between countries 1 and 2 in period } x \\ \rho_y &: \text{correlation between countries 1 and 2 in period } y \\ \rho_z &: \text{correlation between countries 1 and 2 in period } z \end{aligned}$$

Forbes and Rigobon (2002) show that the standard (unadjusted) correlation coefficient is conditional on the variance in the two asset markets. Accordingly, if there is an increase in volatility in country 1 during times of crises, i.e. $\sigma^2_{y,1} > \sigma^2_{x,1}$, it would be misleading to suppose contagion if $\rho_y > \rho_x$. Hence, we have to correct for the upward bias. Forbes and Rigobon quantify this bias and show that the adjusted (unconditional) correlation is given by:[9]

$$\nu_y = \frac{\rho_y}{\sqrt{1 + [(\sigma^2_{y,1} - \sigma^2_{x,1})/\sigma^2_{x,1}](1 - \rho^2_y)}} \tag{1}$$

[9] For a similar approach see Boyer et al. (1997), Corsetti, Pericoli, and Sbracia (2001), Corsetti, Pericoli, and Sbracia (2005), and Loretan and English (2000); for alternative approaches see Karolyi and Stulz (1996), and Longin and Solnik (1995).

As can be seen from (1), the unconditional correlation coefficient, ν_y, is the conditional correlation coefficient, ρ_y, scaled by a function of the change in volatility in asset returns of the source country over the high and low volatility periods. To illustrate this, assume that $\sigma^2_{y,1} > \sigma^2_{x,1}$, i.e. that the volatility of asset returns in country 1 increases from period x to period y. Then, $(\sigma^2_{y,1} - \sigma^2_{x,1})/\sigma^2_{x,1} > 0$ and for any $\rho_y \in (-1;1)$ it follows that

$$\sqrt{1 + [(\sigma^2_{y,1} - \sigma^2_{x,1})/\sigma^2_{x,1}](1 - \rho^2_y)} > 1 \tag{2}$$

With that it follows that $\nu_y < \rho_y$. From (1) it is also immediately apparent that $\nu_y = \rho_x$ if there is no fundamental shift in the relationship between the two asset markets from the low to the high volatility period.

Accordingly, we can formulate the null hypothesis and the alternative hypothesis, respectively, of a test that there is a significant increase in the correlation coefficient in the high volatility period, i.e. that there is contagion, as follows:

$$H_0 : \nu_y = \rho_x \tag{3}$$
$$H_1 : \nu_y > \rho_x \tag{4}$$

We can use a t-test to test this hypothesis where the t-statistic is given by

$$t = \frac{\hat{\nu_y} - \hat{\rho_x}}{\sqrt{Var(\hat{\nu_y} - \hat{\rho_x})}} \tag{5}$$

and where $\hat{\nu_y}$ and $\hat{\rho_x}$ mark the sample estimators of ν_y and ρ_x, respectively. If we assume that the two samples are drawn from independent normal distributions we can transform the standard error in (5) as follows:

$$\begin{aligned} Var(\hat{\nu_y} - \hat{\rho_x}) &= Var(\hat{\nu_y}) + Var(\hat{\rho_x}) - 2Cov(\hat{\nu_y}, \hat{\rho_x}) && (6) \\ &= Var(\hat{\nu_y}) + Var(\hat{\rho_x}) && (7) \\ &\cong (1/T_y) + (1/T_x) && (8) \end{aligned}$$

where T_x (T_y) is the sample size of the low (high) volatility period. To get to (7) we use the independence assumption and (8) follows from the assumption of normality and an asymptotic approximation.[10] With that we get

$$FR = \frac{\hat{\nu_y} - \hat{\rho_x}}{\sqrt{(1/T_y) + (1/T_x)}} \tag{9}$$

[10]For this asymptotic approximation Dungey et al. (2005) refer to Kendall and Stuart (1969).

In a next step, Forbes and Rigobon (2002) suggest using the Fisher transformation, as this improves the finite sample properties of the test statistic.[11] This yields

$$FR = \frac{1/2[log((1+\hat{\nu_y})/(1-\hat{\nu_y})) - log((1+\hat{\rho_x})/(1-\hat{\rho_x}))]}{\sqrt{(1/T_y - 3) + (1/T_x - 3)}} \tag{10}$$

When applying (10) one separates the respective low and high volatility periods from each other, i.e. the two periods do not overlap. This was suggested by Dungey et al. (2005). However, in the original test statistic from Forbes and Rigobon (2002) for testing (3) against (4) the non-crisis period is defined as the whole sample period z, i.e. the non-crisis and the crisis periods overlap. Accordingly, (9) would be formulated as

$$FR = \frac{\hat{\nu_y} - \hat{\rho_z}}{\sqrt{(1/T_y) + (1/T_z)}} \tag{11}$$

and the Fisher adjusted version (10) as

$$FR = \frac{1/2[log((1+\hat{\nu_y})/(1-\hat{\nu_y})) - log((1+\hat{\rho_z})/(1-\hat{\rho_z}))]}{\sqrt{(1/T_y - 3) + (1/T_z - 3)}} \tag{12}$$

As shown, the test statistics (11) and (12) build on the assumption that the variances of $\hat{\nu_y}$ and $\hat{\rho_z}$ are independent. This assumption is violated, however, if the two sample periods overlap. As a result, the covariance term in (6) is most likely not equal to zero and the step from (6) to (7) results in a standard error that is too large, as the negative covariance term is not taken into account. As stated by Dungey et al. (2005), this leads to a downward bias in the t-statistic and, hence, to fewer rejections of the null hypothesis. Nevertheless, in what follows we will apply both versions in order to see if this downward bias leads to fundamentally different results. In terms of notation, we will refer to the overlapping version (12) suggested by Forbes and Rigobon (2002) as FR_O, and to the non-overlapping version suggested by Dungey et al. (2005) as FR_N.

[11] According to Dungey et al. (2005), the Fisher transformation is valid for small values of both the unadjusted and the adjusted correlation coefficient.

3 Contagion during the Greek Debt Crisis

In this section, we apply both versions of the FR-test in order to test for contagion during the Greek debt crisis: first, the original version (12) by Forbes and Rigobon (2002) with overlapping data (FR_O); and second, the alternative version (10) with non-overlapping data (FR_N) suggested by Dungey et al. (2005). We perform the tests not only on a national but also on a regional level after constructing various regional aggregates. Our sample is based on daily data running from October 1, 2008, through July 27, 2010.

3.1 Between Countries

Starting on the national level, Table 1 lists basic descriptive information and the number of observations for CDS premia for 39 countries. We use CDS premia from Thomson Reuters with a notional value of USD 10 million. All prices are based on the standard ISDA contract for physical settlement with a constant 5-year maturity and are expressed in basis points. As can be seen, the average values of the CDS premia range widely across countries and the median is lower than the mean in all 39 cases. Argentina is the country with the highest mean of 2023 basis points, followed by Ukraine at 1718 basis points.

At the other end of the range we find Germany and the United States with means of just 15.3 and 16.8 basis points, respectively. What is more, both the standard deviations and minimum/maximum values indicate that many countries experienced a strong variation in their CDS premia over time. For example, the CDS premia for Greece range from a minimum of 59.5 basis points to a maximum of 1037.6 basis points — more than 17 times the minimum value.

We define October 20, 2009 as the start of the crisis. On this day, officials from the new government in Greece announced irregularities in the Greek debt statistics. However, this choice is somewhat arbitrary, since the reliability of the debt statistics was widely doubted before the irregularities were officially confirmed. In general, defining an exact crisis period seems erratic based on the myriad events surrounding the Greek debt crisis. Similar issues were already recognized by Forbes and Rigobon (2002) during the Asian crisis in the late nineties. When did the crisis period start? When did it end? As Forbes and Rigobon (2002) state, there was "no single event which acts as a clear catalyst behind this turmoil".

To demonstrate these difficulties, we take a look at the developments in Greece since the outbreak of the crisis and their influence on the Greek 5-year CDS. The key events are marked in Figure 3.

Table 1
Descriptive Statistics of CDS Premia

This table lists basic descriptive information and the number of observations for CDS premia in our sample. We use daily CDS premia from Thomson Reuters with a constant 5-year maturity. The data run from October 1, 2008, through July 27, 2010. It is worth mentioning that in all cases the median is lower than the mean. Argentina is the country with both the highest mean and median, followed by Ukraine. At the other end of the range we find Finland, Germany and the United States.

	Obs.	Mean	S.D.	Min.	Median	Max.
Argentina	459	2023.4	1220.6	803.3	1536.1	4841.8
Austria	460	96.7	44.5	19.2	83.0	265.0
Belgium	459	72.2	32.1	30.0	62.8	158.0
Brazil	460	204.9	104.3	109.3	140.7	606.3
Bulgaria	460	340.4	135.2	174.5	300.6	692.7
Chile	453	129.6	68.9	48.5	94.8	310.0
China	460	111.2	57.5	57.5	82.0	284.0
Columbia	460	231.3	108.4	123.7	168.8	668.7
Denmark	458	56.8	32.7	23.2	41.9	146.0
Estonia	453	313.9	194.6	90.0	236.0	732.5
Finland	455	36.2	17.1	14.5	31.0	94.0
France	459	48.6	20.9	21.0	44.0	98.7
Germany	460	37.5	15.3	12.2	34.1	92.5
Greece	460	297.3	234.3	59.5	223.3	1037.6
Hungary	460	321.1	115.4	165.6	305.9	630.7
Indonesia	458	352.9	228.9	147.5	215.0	1240.0
Ireland	455	189.4	62.6	63.0	172.0	390.0
Israel	454	145.3	44.5	99.0	122.5	282.5
Italy	460	122.5	43.4	50.0	111.9	251.7
Japan	453	63.0	21.2	18.0	64.0	120.0
Kazakhstan	455	482.2	350.6	157.0	351.1	1634.1
Malaysia	457	145.9	79.1	69.5	105.0	500.0
Mexico	460	217.4	107.2	101.2	163.7	613.1
Netherlands	458	51.6	26.4	25.0	42.9	130.0
Peru	460	211.5	110.8	107.3	145.9	664.3
Phlippines	456	255.5	119.1	142.5	193.5	840.0
Poland	455	175.8	74.1	86.0	146.8	421.0
Portugal	460	127.0	85.8	45.0	93.5	466.5
Qatar	460	152.4	75.6	76.2	115.0	390.0
Romania	460	380.3	162.3	188.5	308.9	767.7
Russia	454	355.1	237.4	124.0	264.2	1106.0
South Korea	459	194.0	121.5	73.0	138.0	680.0
Spain	460	117.1	51.9	47.2	100.6	270.2
Sweden	457	64.3	31.8	21.0	52.2	159.0
Thailand	460	158.4	76.6	75.0	120.8	500.0
Turkey	455	276.4	126.1	155.5	208.8	835.0
UK	460	82.6	27.0	27.5	79.1	165.0
Ukraine	449	1718.0	1104.7	494.5	1363.0	5300.4
USA	443	42.9	16.8	19.7	38.8	95.0

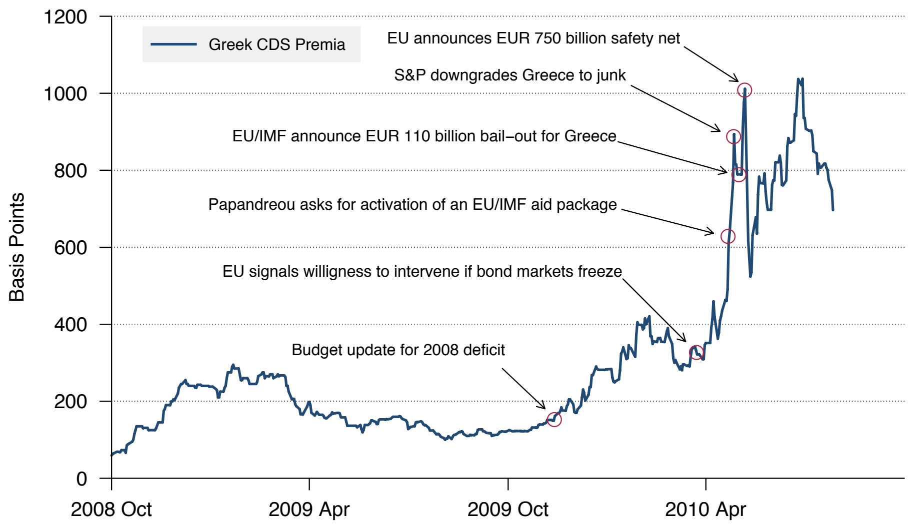

Figure 3: Greek CDS Premia and Key Events During the Greek Debt Crisis

In November 2009, Greece announced its update on the initial budget for 2008. The deficit was, as mentioned previously, more than twice as much as in the initial budget presented in December 2008. Against the background of spreading negative market talk, CDS spreads soared in the following weeks, which led to increasing refinancing costs on bond markets. After a period of reassurance, in spring 2010 the situation worsened again.

A weak bond auction in April 2010 fueled fears that bond issuing was close to a standstill. This forced euro area leaders to signal their willingness to support Greece in case refinancing became blocked. This announcement, however, did not succeed in calming the markets. CDS spreads soon skyrocketed, forcing Papandreou to activate the EU/IMF aid package.

On April 27, S&P downgraded Greek government bonds to junk. At the beginning of May, the EU and the IMF were forced to announce a EUR 110 billion bail-out for Greece. One week later, against the background of further rising spreads across European peripheral countries, the EU announced a EUR 750 billion safety net for potentially troubled states. This had a temporarily calming effect on markets. However, doubts on the sustainability of the bailout for the Greek economy and a general worsening outlook for the European peripheral countries, the Greek CDS in the summer 2010 again soared to new record levels.

This chronologically aggregated summary demonstrates the pulsating nature of a typical crisis, where periods of reassurance and stress periods alternate. Hence, it is reasonable to assume that during 2009/2010 there were several contagious periods — not just one "enduring" period of contagion.

Based on the difficulty of defining a fixed crisis period, we suggest enhancing the Forbes and Rigobon approach by applying the test on rolling windows of periods of turmoil. In the case of the Hong Kong crash, Forbes and Rigobon defined the period of relative stability as lasting almost 22 months, namely from January 1, 1996 to October 16, 1997, and the period of turmoil as the month starting on October 17, 1997. As discussed earlier, we put the start of the Greek debt crisis at October 20, 2009. Accordingly, our period of relative stability lasts from January 1, 2008 to October 19, 2009, i.e. also almost 22 months. However, the period of turmoil might have lasted from October 20, 2009 to the end of our sample, namely July 27, 2010. But even then, one might argue, the debt crisis has not come to an end – as the events in Ireland demonstrate. Instead, the discussion of key events above illustrates that the period after October 20, 2009 can be divided into various sub-periods of relative turmoil and periods of relative calm. But even accounting for this makes it almost impossible to accurately define fixed periods of turmoil. Therefore, we define rolling windows of relative turmoil lasting 20, 40, and 60 days, respectively. The 20-day window corresponds to the 1-month period of relative turmoil defined by Forbes and Rigobon (2002) as 20 business days are a common proxy for a calendar month. The 40-day and 60-day windows account for the long-lasting nature of the Greek debt crisis.

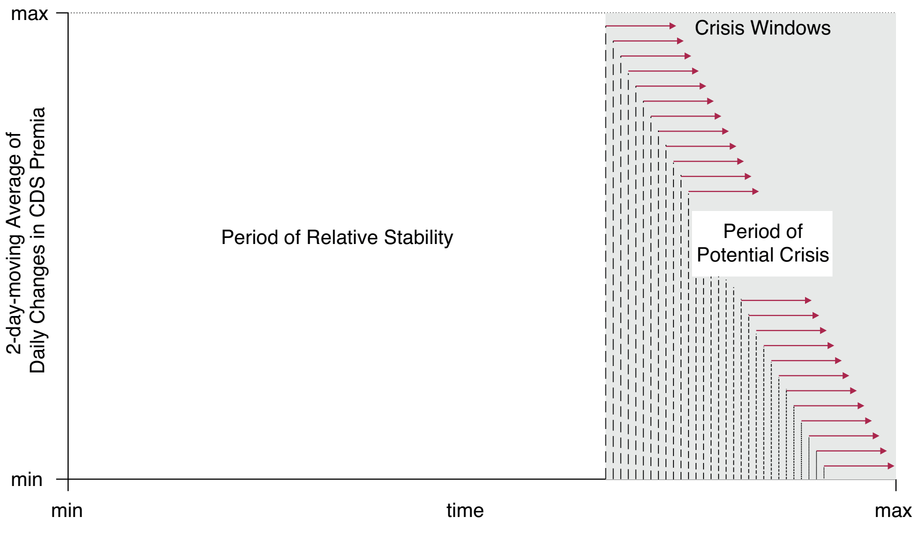

Figure 4: Illustration of the Rolling FR-Test Approach

Before applying the tests, we calculate first differences, i.e. daily changes, of all variables in order to transform the time series into stationary ones. Augmented Dickey-Fuller tests confirm that the variables in first differences are all stationary. Also, as is common practice when testing for contagion, we calculate 2-day-moving averages of the daily changes in the CDS premia.[12] This accounts for the problem that financial markets in different countries are not open at the same time.

We then apply both versions of the FR-test on rolling crisis-windows: first, the original version with overlapping data (FR_O); and second, the alternative version with non-overlapping data (FR_N) suggested by Dungey et al. (2005). For every single crisis window we test for contagion on a five-percent level of significance and count the number of such signals over the test period. Figure 4 illustrates this.

However, for identifying the signals, we cannot rely on the critical t-values of a standard one-sided t-test. Similar to testing for a structural break at an unknown break date, where the so-called sup F-statistic[13] is the largest of many F-statistics and, hence, its distribution is not the same as an individual F-statistic, the distribution of the FR-test statistic is not the same as the standard t-distribution. Based on this, we used Monte Carlo methods to find approximate critical t-values.[14] The results are shown in table 6 in Appendix A. As can be seen, the critical values for the FR-tests are larger than the one for a standard one-sided t-test.

Table 2 reports the number of signals for contagion stemming from the Greek CDS market based on the transferred variables and the rolling-window approach. As can be seen, we obtain signals for contagion for both versions of the FR-test as well as for the three different time windows, if we use the critical values from table 6. We obtain the largest number of signals, namely for 26 out of 38 cases, for the overlapping test, FR_O, for the 20-day window. If we focus on the relative frequency of the signals across countries we find that European countries dominate. For instance, for Spain, Portugal, and Ireland, we get 23, 15, and 12 signals, respectively. However, it is not only the CDS markets of the PIGS countries that seem to be affected by contagion stemming from the Greek market, but also the CDS markets of Germany, France, Italy, the Netherlands, and Austria. Outside the European Union, we obtain most signals for countries in Central and Eastern Europe, such as Kazakhstan, Turkey, and Russia. In Latin America, the number of signals is on average much lower. For Asian countries, we get only a few signals on average and for some countries such as South Korea and the Philippines no signals at all.

[12]For instance, see Corsetti et al. (2001), Dungey et al. (2005), and Forbes and Rigobon (2002).

[13]The term sup F-test is only one of many different ones that are in use for this approach. The idea was originally proposed by Quandt (1960) and, accordingly, the approach is often called the Quandt likelihood ratio (QLR) test. Another term in use is sup-Wald test. For an introduction to this approach, the interested reader is referred to Stock and Watson (2007). For more details, Perron (2005) offers a review of the literature on dealing with structural breaks.

[14]We describe the applied methodology in more detail in Appendix A.

If we focus on the 40-day and 60-day windows, we find that the number of signals decreases across countries but the regional pattern seems to be similar to the 20-day window. With the exceptions of Kazakhstan and Qatar, we find that the signals almost completely break down for countries outside the European Union. Accordingly, one conclusion to draw from the FR_O-test is that we not only find evidence for contagion stemming from the Greek CDS market but also a strong regional pattern. This observation holds true for the FR_N-test as well if we focus on the 20-day window. The FR_N-test seems to be more restrictive compared to the FR_O-test, as the number of countries for which we obtain at least one signal decreases from 26 to 14, and the average number of signals for countries with at least one signal declines from 8.5 to 7.4. As discussed in the previous section, this had to be expected as the standard errors of the FR_O-test are likely to be biased upward due to the overlapping nature of the periods of relative turmoil and relative stability. This becomes even more apparent if we concentrate on the 40-day and 60-day windows. For instance, for the 60-day window the FR_N-test only yields signals for 3 countries while the FR_O yields signals for 15 countries.

Overall, our results for CDS markets during the Greek debt crisis contrast with the results from Forbes and Rigobon (2002) for equity markets after the Hong Kong crash and their conclusion of "no contagion, only interdependence". With the term "interdependence", Forbes and Rigobon (2002) refer to a situation where there is no significant increase in the adjusted correlation coefficient between two markets but a continued high level of co-movement. In their view, this "continued high level of market co-movement suggests strong real linkages between the two economies". Especially for European countries we would instead conclude "both contagion and interdependence". It seems that during the Greek debt crisis there were not only periods of interdependence but also periods which were characterized by a significant increase in the co-movement of sovereign credit risk as measured in CDS premia. This is especially interesting as the approach of Forbes and Rigobon (2002) is, according to Dungey et al. (2005), a conservative test. Their findings are based on a comparison of various contagion tests during the Asian crisis. What is more, even Forbes and Rigobon (2002) state that their result is "controversial". We think that finding evidence for contagion for such a restrictive and, hence, controversial test is a very strong result. One underlying reason for finding evidence for contagion for CDS markets during the Greek debt crisis might be that the developments after the collapse of the investment bank Lehman Brothers had demonstrated how interconnected financial markets and the world economy are nowadays. Accordingly, the risk of Greece becoming a new "Lehman" might have led to contagion rather than just interdependence.

Table 2
Forbes and Rigobon Tests

This table reports the number of signals for contagion stemming from the Greek CDS market based on the bivariate Forbes and Rigobon (2002) approach. We test for rolling crisis-period windows starting on October 20, 2009. Thereby, we apply two version of the test. First, the original version with overlapping data (FR_O). Second, an alternative version with non-overlapping data (FR_N) suggested by Dungey et al. (2005). The signals are based on a five-percent level of significance where we use the approximated critical values from table 6.

	FR_O			FR_N		
	20 days	40 days	60 days	20 days	40 days	60 days
Argentina	0	0	0	0	0	0
Austria	21	12	1	17	3	0
Belgium	6	4	6	6	0	0
Brazil	4	0	0	0	0	0
Bulgaria	0	0	0	0	0	0
Chile	3	0	0	0	0	0
China	0	0	0	0	0	0
Columbia	4	0	0	0	0	0
Denmark	10	6	7	7	3	4
Estonia	0	0	0	0	0	0
Finland	6	3	3	3	0	0
France	7	9	10	5	5	5
Germany	15	15	15	6	2	3
Greece	0	0	0	0	0	0
Hungary	3	0	0	0	0	0
Indonesia	0	0	0	0	0	0
Ireland	12	13	2	1	1	0
Israel	0	0	0	0	0	0
Italy	22	3	0	21	2	0
Japan	0	0	0	0	0	0
Kazakhstan	18	27	17	5	13	0
Malaysia	0	0	0	0	0	0
Mexico	4	0	0	0	0	0
Netherlands	19	7	8	9	0	0
Peru	4	0	0	0	0	0
Phlippines	0	0	0	0	0	0
Poland	2	3	9	0	0	0
Portugal	15	2	0	9	0	0
Qatar	3	4	4	0	0	0
Romania	0	5	0	0	0	0
Russia	5	5	5	1	0	0
South Korea	0	0	0	0	0	0
Spain	23	6	0	13	3	0
Sweden	4	5	6	0	0	0
Thailand	0	0	0	0	0	0
Turkey	5	2	3	0	0	0
UK	1	0	0	1	0	0
Ukraine	1	0	0	0	0	0
USA	4	4	4	0	0	0

3.2 Between Regions

Motivated by the regional pattern of contagion signals we found in the previous section, we also aim to test for contagion on a regional level. We base our analysis on the findings of Longstaff et al. (2011), who performed a cluster analysis to identify significant commonality in sovereign credit spreads on an aggregated level. However, in contrast to Longstaff et al. (2011), we do not construct clusters ex post based on the pairwise correlations in our sample. Instead, we construct ex ante regional aggregates. The motivation of this approach is threefold. First, our data sample covers more countries from various regions than the one in Longstaff et al. (2011). Also, our sample is more balanced between industrial and emerging countries. While in the sample of Longstaff et al. (2011) Japan is the only industrialized country out of 26 countries, in our sample 17 out of 39 countries are industrialized. This allows us to construct a broad range of both geographical and political aggregates. Second, Longstaff et al. (2011) find that there is a strong regional structure in their cluster analysis. In particular, the first cluster is dominated by Eastern Europe and the Mediterranean, the second one by Asian countries, the third one again by Eastern Europe, the fourth one by Latin America, and the sixth one by the Middle East. Thus it seems plausible to construct aggregates along regional lines. Finally, the focus of investors during the Greek debt crisis first on the PIGS countries and later on the euro area as a whole indicates a strong interest in particular aggregates which we would like to address directly.

Accordingly, we construct various aggregates based both on geographical and political criteria. These aggregates are constructed as unweighted averages of CDS premia of countries belonging to the selected region. Table 3 gives an overview of these aggregates and the countries that were included for constructing them. The aggregates are the following: the European Union (EU), the European Monetary Union (EMU), the PIGS countries, Central and Eastern Europe (CEE), the Middle East (ME), Asia, Latin America (LATAM), and an aggregate for the USA, Japan, and Germany (G3).

Based on the national-level approach, we calculate first daily changes of the regional aggregates and then 2-day-moving averages. Panel A of Table 4 reports correlation coefficients between the CDS premia in first differences of the regional aggregates for the whole sample. We excluded the PIGS countries for the regional aggregates of the EU, the EMU, and the world aggregate. In general, one can see that the pairwise correlation coefficients between most regional aggregates are very high. For instance, correlation coefficients for the EU range from 0.68 with Asia to 0.87 with the world aggregate.

Table 3
Definition of Regional Aggregates

This table gives an overview about the regional aggregates and the countries that were included for constructing the aggregates. EU stands for European Union; EMU for the European Monetary Union; PIGS for Portugal, Ireland, Greece, and Spain; CEE for Central and Eastern Europe; ME for Middle East; LATAM for Latin America; and G3 for USA, Japan, and Germany.

	EU	EMU	PIGS	CEE	ME	Asia	LATAM	G3
Argentina							x	
Austria	x	x						
Belgium	x	x						
Brazil							x	
Bulgaria	x			x				
Chile							x	
China						x		
Columbia							x	
Denmark	x							
Estonia	x			x				
Finland	x	x						
France	x	x						
Germany	x	x						x
Greece	x	x	x					
Hungary	x			x				
Indonesia						x		
Ireland	x	x	x					
Israel					x			
Italy	x	x						
Japan								x
Kazakhstan					x			
Malaysia						x		
Mexico							x	
Netherlands	x	x						
Peru							x	
Phlippines						x		
Poland	x			x				
Portugal	x	x	x					
Qatar					x			
Romania	x			x				
Russia				x				
South Korea						x		
Spain	x	x	x					
Sweden	x							
Thailand						x		
Turkey					x			
UK	x							
Ukraine				x				
USA								x

Table 4

Correlation Coefficients and Contagion Signals for Regional Aggregates

Panel A reports correlation coefficients between the CDS premia in first differences of selected regional aggregates for the whole sample. The regional aggregates are constructed as unweighted averages of CDS premia of countries belonging to the selected region. EU stands for European Union (ex PIGS countries); EMU for the European Monetary Union (ex PIGS countries); PIGS for Portugal, Ireland, Greece, and Spain; CEE for Central and Eastern Europe; ME for Middle East; LATAM for Latin America; G3 for USA, Japan, and Germany; and World for the world aggregate (ex PIGS countries).

Panel A: Correlation Coefficients for the Whole Sample Period

	EU	EMU	PIGS	CEE	ME	Asia	LATAM	G3	World
EU	1.00								
EMU	0.74	1.00							
PIGS	0.68	0.86	1.00						
CEE	0.90	0.59	0.53	1.00					
ME	0.79	0.59	0.53	0.82	1.00				
Asia	0.68	0.61	0.53	0.65	0.76	1.00			
LATAM	0.63	0.57	0.51	0.62	0.63	0.68	1.00		
G3	0.66	0.80	0.68	0.59	0.60	0.65	0.50	1.00	
World	0.87	0.73	0.66	0.89	0.88	0.84	0.84	0.71	1.00

Panel B reports the number of signals for contagion stemming from the PIGS aggregate based on the bivariate Forbes and Rigobon (2002) approach. We test for rolling crisis-period windows starting on October 20, 2009. Thereby, we apply two version of the test. First, the original version with overlapping data (FR_O). Second, an alternative version with non-overlapping data (FR_N) suggested by Dungey et al. (2005). The signals are based on a five-percent level of significance where we use the approximated critical values from table 6.

Panel B: Signals for Contagion Stemming from the PIGS Aggregate

	FR_O			FR_N		
	20 days	40 days	60 days	20 days	40 days	60 days
EU	42	57	73	39	53	70
EMU	15	5	7	8	0	2
CEE	0	5	0	1	4	0
ME	21	23	8	18	11	0
Asia	0	0	0	0	0	0
LATAM	0	0	0	0	0	0
G3	0	0	0	0	0	0
World	0	0	0	0	0	0

Panel B of Table 4 reports the number of signals for contagion stemming from the PIGS aggregate based on the same approach as on the national level. Accordingly, we test for rolling crisis-period windows starting on October 20, 2009. We apply both versions of the FR-test: first, the original version with overlapping data (FR_O); and second, the alternative version with non-overlapping data (FR_N) suggested by Dungey et al. (2005). The signals are based on a five-percent level of significance where we use the approximated critical values from table 6.

As can be seen, we also obtain many signals for contagion on the regional level. The regional pattern we found on the national level seems to be confirmed by the regional analysis. While the European aggregates produce the largest number of signals for both versions of the test as well as for the different time windows, the tests also return signals for Central and Eastern Europe and the Middle East. In contrast, we find neither evidence of contagion for Latin America nor for Asia.

If we further compare the results of the regional analysis with those of the national level, we find that the FR_N is again more restrictive except for the EU aggregate.

Overall, the regional analysis supports the findings of the analysis on the national level. For Europe in particular, we can again conclude that there was "both contagion and interdependence" stemming from the PIGS countries. To our knowledge, testing for contagion with regional aggregates is a fairly new approach. Hence, it might be interesting also to apply this approach to past crises such as the Asian crisis at the end of the 1990s.

4 Exploring the Common Factor

In the previous section we found strong evidence for contagion in CDS markets during the Greek debt crisis both on a national and a regional level by applying two versions of the FR-test to rolling crisis windows. These findings are in contrast to the conclusion of "no contagion, only interdependence" from Forbes and Rigobon (2002) for equity markets after the Hong Kong crash. We argued that one reason for this might be that the developments after the collapse of the investment bank Lehman Brothers had demonstrated the close interconnection of financial markets with the world economy. Accordingly, the risk of Greece becoming a new "Lehman" might have led to contagion rather than just interdependence.

Another possible explanation might be that the so-called "common factor" between CDS markets is stronger than it is between equity markets. Corsetti et al. (2001) argue that the strong conclusions from Forbes and Rigobon (2002) follow "from arbitrary assumptions on the variance of the country-specific noise in the market where the crisis originates – assumptions that bias the test towards the null hypothesis of interdependence."

They use a standard factor model of stock market returns to show that the ratio of the variance of common factors to country-specific factors has an influence on test results for contagion. Accounting for this, they find evidence of contagion for at least five countries in the case of the Hong Kong crash. However, the bivariate correlation approach we used in the previous section does not allow the inclusion of country-specific factors. Also, applying the framework from Corsetti et al. (2001) to our sample lies beyond the scope of this paper. Nevertheless, we think it is worth trying to get an idea of the role of the common factor between CDS markets.

To achieve that, we perform principal component analysis (PCA) for the regional aggregates of the CDS premia in first differences, i.e. we perform an analysis to establish whether the patterns of correlations between sovereign CDS premia of a particular aggregate can be explained in terms of a smaller number of common factors. This analysis is motivated by Longstaff et al. (2011). Table 5 summarizes the main results of the PCA analysis for the whole sample (panel A) as well as the two sub-samples (panels B and C).

Like the findings of Longstaff et al. (2011), the results of the PCA analysis indicate that there is a large amount of commonality in the intraregional variation of CDS premia. When all observations are used, we find that the first principal component captures almost half of the variation in the correlation matrix of the world aggregate, i.e. when all countries are included. This value increases to 78% in the case of the PIGS aggregate and 80% in the case of the Asian aggregate. Furthermore, the first three principal components collectively explain 62% of the variation in the correlation matrix of the world aggregate. This is even higher than the 53% that Longstaff et al. (2011) find in their analysis.

The analysis of the two sub-samples indicates that the amount of commonality in the intraregional variation of CDS premia is even larger when we only focus on the period after October 20, 2009 (panel C). The first principal component now explains between 47% (world) and 84% (PIGS) of the variation in the correlation matrix. Similarly, the first three components now collectively explain more than in panels A and B. For instance, the share increases to 65% in the case of the world aggregate.

These observations indicate that the common factor plays a dominant role in CDS markets. For interpreting the first principal component, which might be interpreted as the common factor, we compute time series of the first principal components for the different regional aggregates. Therefore, we take a weighted average of the daily changes in the sovereign CDS premia, where the weight for sovereign i equals the i-th principal component weight divided by the sum of all the principal component weights of the particular regional aggregate. Figure 5 illustrates this by plotting the daily changes of the CDS premia of the PIGS countries, and, in addition, the time series of the first principal component of the PIGS aggregate.

Table 5
Regional Aggregates - Principal Component Analysis

This table reports principal components of inner-regional CDS premia. In addition we list correlation coefficients of the first principal component with selected financial variables. Cum. stands for cumulative; Stks R for the regional stock market index; Stks W for the world stock market index; VIX for the volatility index; and CDS B for the average CDS premium of 18 international banks. Significance of an increase of the adjusted correlation in Panel C compared to the correlation in Panel B at the one-percent, five-percent, ten-percent level is denoted by ***, **, *, respectively.

Panel A: October 1, 2008 until July 27, 2010

	Principal Components				Correlation of Comp1 with			
	Comp1	Comp2	Comp3	Cum.	Stks R	Stks W	VIX	CDS B
EU	0.56	0.10	0.05	0.71	-0.58	-0.45	0.37	0.69
EMU	0.63	0.08	0.05	0.77	-0.51	-0.38	0.32	0.63
PIGS	0.78	0.09	0.08	0.95	-0.50	-0.36	0.34	0.60
CEE	0.59	0.11	0.08	0.78	-0.58	-0.53	0.44	0.61
ME	0.59	0.17	0.16	0.92	-0.54	-0.56	0.46	0.56
Asia	0.80	0.07	0.05	0.92	-0.56	-0.37	0.25	0.44
LATAM	0.74	0.11	0.09	0.95	-0.65	-0.66	0.55	0.55
G3	0.57	0.26	0.18	1.00	-0.29	-0.33	0.25	0.60
World	0.46	0.10	0.06	0.62		-0.56	0.45	0.70

Panel B: October 1, 2008 until October 19, 2009

	Principal Components				Correlation of Comp1 with			
	Comp1	Comp2	Comp3	Cum.	Stks R	Stks W	VIX	CDS B
EU	0.56	0.11	0.04	0.71	-0.57	-0.42	0.27	0.64
EMU	0.63	0.07	0.06	0.76	-0.51	-0.38	0.23	0.57
PIGS	0.71	0.11	0.09	0.91	-0.48	-0.37	0.23	0.54
CEE	0.56	0.12	0.08	0.77	-0.55	-0.49	0.35	0.55
ME	0.61	0.16	0.15	0.92	-0.53	-0.53	0.43	0.51
Asia	0.80	0.08	0.05	0.93	-0.55	-0.37	0.23	0.41
LATAM	0.74	0.12	0.08	0.94	-0.69	-0.64	0.52	0.51
G3	0.59	0.24	0.17	1.00	-0.25	-0.30	0.18	0.58
World	0.47	0.10	0.05	0.62		-0.53	0.37	0.65

Panel C: October 20, 2009 until July 27, 2010

	Principal Components				Adjust. Correlation of Comp1 with			
	Comp1	Comp2	Comp3	Cum.	Stks R	Stks W	VIX	CDS B
EU	0.58	0.09	0.06	0.73	-0.63**	-0.57**	0.48***	0.79***
EMU	0.65	0.09	0.06	0.80	-0.58**	-0.47	0.39**	0.72***
PIGS	0.84	0.07	0.06	0.97	-0.58*	-0.38	0.31	0.61
CEE	0.71	0.08	0.07	0.86	-0.81***	-0.80***	0.71***	0.84***
ME	0.55	0.22	0.18	0.95	-0.74***	-0.83***	0.75***	0.85***
Asia	0.79	0.08	0.05	0.92	-0.70***	-0.52**	0.41**	0.65***
LATAM	0.80	0.09	0.07	0.96	-0.61	-0.91***	0.85***	0.84***
G3	0.54	0.28	0.18	1.00	-0.53**	-0.53***	0.45***	0.72***
World	0.47	0.10	0.08	0.65		-0.76***	0.66***	0.88***

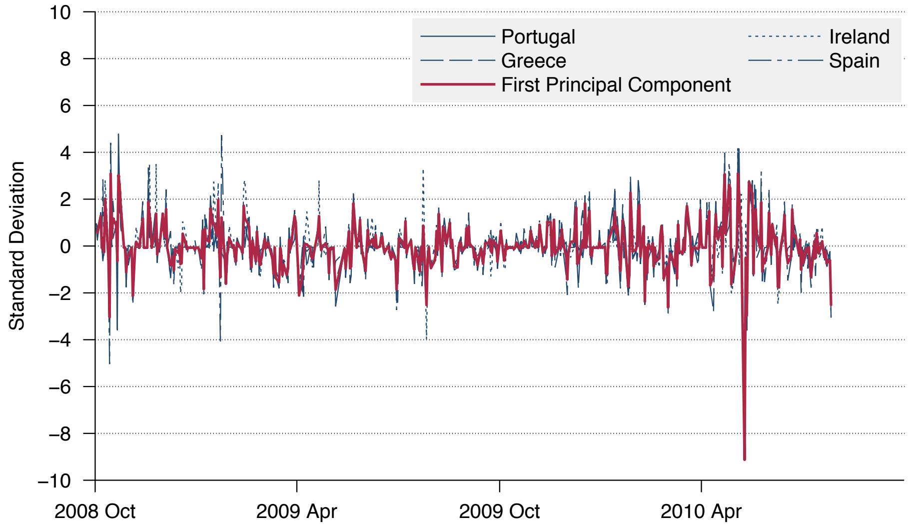

Figure 5: Principal Component Analysis for PIGS Countries

As can be seen, there is a large amount of commonality in the variation within the PIGS aggregate. In addition, and for a better understanding of the large amount of commonality within the regions, we explore the correlation of the first principal component with various financial variables. These variables are as follows:

- Index of regional stock market returns (Stks R): We construct indices of daily regional stock market returns as an unweighted average of daily returns of national MSCI equity market indices that belong to the regional aggregate in question.

- Index of worldwide stock market returns (Stks W): We construct an index of daily worldwide stock market returns as an unweighted average of daily returns of all national MSCI equity market indices in our sample.

- U.S. equity market volatility (VIX): The volatility of the U.S. equity market serves as a proxy for global nervousness of financial markets and is expressed by the popular VIX index, which measures the implied volatility of S&P 500 index options.

- Index of CDS premia for international banks (CDS B): We construct an index of daily changes in CDS premia of banks as an unweighted average of CDS premia for 18 international banks such as Goldman Sachs or UBS.

The results are reported in Table 5 as well. In general, the signs of the correlation coefficients for the selected financial variables with the first principal component of the regional aggregates appear intuitive and consistent. For instance, a positive correlation coefficient with the index for bank CDS premia is intuitive: the higher the risk premia for international banks, the higher the implicit risk for a default of one of these international banks. This, in turn, should increase the implicit risk of negative spillovers to the sovereign level as the collapse of the investment bank Lehman Brothers has clearly demonstrated. Similarly, the higher the risk of default is on a sovereign level the higher the risk premia for banks should be, as they are usually heavily involved in financing the sovereign debt.

Looking at panel A, we find that the correlation of the first principal component is generally highest with the daily changes of the index of CDS premia for international banks when all observations are included. Moreover, correlation is, in absolute terms, also very high for daily changes of the regional and worldwide stock market indices. The correlation coefficients of the stock indices are similar to the one Longstaff et al. (2011) find for the U.S. stock market returns. The results for the VIX index are usually lower compared to the stock market returns. This is most apparent in the case of the Asian aggregate, where the correlation coefficient with the VIX index is only at 0.25 while the correlation coefficient with the regional stock market returns is at -0.56.

What is more, we find that most adjusted (unconditional) correlation coefficients[15] increase significantly if we only focus on the time period after the debt crisis in Greece started (panel C). For instance, correlation between the first principal component for the world aggregate and the VIX index is now at 0.66 while it was only at 0.37 in panel B. This is more consistent with the results from Longstaff et al. (2011), who find a correlation coefficient of 0.659 with the VIX index.

Overall, these results indicate that the principal source of variation of the CDS premia across the sovereigns of a particular region appears to be very highly correlated with global financial variables such as stock market returns and stock market volatility. These results are consistent with Longstaff et al. (2011) and Pan and Singleton (2008) who likewise find a strong relation between sovereign credit spreads and financial market volatility measured in the form of the VIX index. What is more, the adjusted correlation coefficients indicate that the co-movement increased significantly during the Greek debt crisis. This may help to explain why we find evidence for contagion even with the restrictive approach from Forbes and Rigobon (2002).

[15] We apply formula (1) to adjust for higher volatility during the Greek debt crisis.

5 Conclusion

The recent focus of financial market participants on the fiscal situation in the PIGS countries provided us with the possibility to study the developments of CDS premia for "hot-spot" countries. The difficult fiscal situation in Greece led to a strong increase of risk premia for Greek sovereign debt as measured in CDS premia. At the same time, CDS premia for many other countries increased strongly as well. While the increase for Greek CDS premia was strongest, these dramatic movements were also mirrored in the other CDS markets.

This shows that dramatic events in one market can have strong impacts on other markets. The question is, however, whether a high degree of co-movement during times of crisis already constitutes contagion? The aim of this paper was to analyze this question for the Greek debt crisis. Therefore we discuss the theoretical framework of what contagion constitutes as well as an empirical test procedure based on the approach from Forbes and Rigobon (2002).

However, given the difficulty of defining a fixed crisis period, we suggest enhancing the Forbes and Rigobon approach by applying the test on rolling windows of periods of turmoil. We use rolling windows of relative turmoil lasting 20, 40, and 60 days, respectively. As 20 business days are a common proxy for a calendar month, the 20-day window corresponds with the 1-month period of relative turmoil that Forbes and Rigobon (2002) use for testing for contagion after the Hong Kong crash in 1997. The 40-day and 60-day windows account for the long-lasting nature of the Greek debt crisis.

Our results indicate that there were periods of contagion for CDS markets during the Greek debt crisis, which is in contrast to the results from Forbes and Rigobon (2002) for equity markets after the Hong Kong crash and their conclusion of "no contagion, only interdependence". Especially for European countries we would instead conclude "both contagion and interdependence". It seems that during the Greek debt crisis there were not only periods of interdependence but also periods characterized by a significant increase in the co-movement of sovereign credit risk as measured in CDS premia. This is especially interesting as the approach of Forbes and Rigobon (2002) is, according to Dungey et al. (2005), a conservative test. What is more, even Forbes and Rigobon (2002) state that their result is "controversial". We think that finding evidence for contagion for such a restrictive and, hence, controversial test is a very strong result. One underlying reason for finding evidence for contagion for CDS markets during the Greek debt crisis might be that the developments after the collapse of the investment bank Lehman Brothers had demonstrated the close interconnection of financial markets and the world economy. Accordingly, the risk of Greece becoming a new "Lehman" might have led to contagion rather than just interdependence.

Motivated by the regional pattern of contagion signals we found on the national level, we also aimed at testing for contagion on a regional level. We base our analysis on the findings from Longstaff et al. (2011), who performed a cluster analysis to identify significant commonality in sovereign credit spreads on an aggregated level. Applying the same methodology as on the national level yields many signals for contagion on the regional level as well. The regional pattern we found on the national level seems to be confirmed by the regional analysis. While we get most signals for the European aggregates, the tests also return many signals for Central and Eastern Europe and the Middle East. In contrast, we find almost no evidence of contagion for Latin America and no signals at all for Asia.

Accordingly, the regional analysis supports the findings of the analysis on the national level. Especially for Europe we again can conclude that there was "both contagion and interdependence" stemming from the PIGS countries. To our knowledge, testing for contagion with regional aggregates is a fairly new approach. Hence, it might be interesting also to apply this approach to past crises such as the Asian crisis at the end of the 1990s.

Finally, we explore the common factor by conducting a principal component analysis. This analysis is motivated by Corsetti et al. (2001) who argue that the strong conclusions from Forbes and Rigobon (2002) follow "from arbitrary assumptions on the variance of the country-specific noise in the market where the crisis originates – assumptions that bias the test towards the null hypothesis of interdependence."

Our results indicate that there is a large amount of commonality in the intraregional variation of CDS premia. In addition, we find that the principal source of variation of the CDS premia across the sovereigns of a particular region appears to be very highly correlated with regional and global financial variables such as stock market returns and stock market volatility. These results are consistent with Longstaff et al. (2011) and Pan and Singleton (2008), who likewise find a strong relation between sovereign credit spreads and financial market volatility measured in the form of the VIX index. What is more, the adjusted correlation coefficients indicate that the co-movement increased significantly during the Greek debt crisis. This could explain why we found evidence for contagion even with the restrictive approach of Forbes and Rigobon (2002).

References

Allen, F., & Gale, D. (2000). Financial contagion. *The Journal of Political Economy*, *108*(1), 1-33.

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2006). *Liquidity and asset prices.* now Publishers Inc.

Andenmatten, S., & Brill, F. (2011). *Did the CDS market push up risk premia for sovereign credit?* (Forthcoming in Swiss Journal of Economics and Statistics)

Andrews, D. W. K. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, *61*(4), 821-856. (Corrigendum, 71(1), 395-397)

Boyer, B. H., Gibson, M. S., & Loretan, M. (1997). *Pitfalls in tests for changes in correlations* (International Finance Discussion Papers No. 597). Board of Governors of the Federal Reserve System (U.S.).

Calvo, G. A., & Mendoza, E. G. (2000). Rational contagion and the globalization of securities markets. *Journal of International Economics*, *51*(1), 79-113.

Caramazza, F., Ricci, L. A., & Salgado, R. (2000). *Trade and financial contagion in currency crises* (Working Paper No. 00/55). IMF.

Chue, T. K. (2002). Time-varying risk preferences and emerging market co-movements. *Journal of International Money and Finance*, *21*(7), 1053-1072.

Codogno, L., Favero, C., & Missale, A. (2003). Yield spreads on EMU government bonds. *Economic Policy*, *18*(37), 503-532.

Corsetti, G., Pericoli, M., & Sbracia, M. (2001). *Correlation analysis of financial contagion: What one should know before running a test* (Working Paper No. 822). Economic Growth Center, Yale University.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), 1177-1199.

Dai, Q., & Singleton, K. (2003). Term structure dynamics in theory and reality. *The Review of Financial Studies*, *16*(3), 631-678.

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank research observer*, *15*(2), 177-198.

Duffie, D., & Singleton, K. J. (1999). Modeling term structures of defaultable bonds. *The Review of Financial Studies*, *12*(4), 687-720.

Dungey, M., Fry, R., Gonzalez-Hermosillo, B., & Martin, V. L. (2005). Empirical modelling of contagion: a review of methodologies. *Quantitative Finance*, *5*(1), 9-24.

Essaadi, E., Jouini, J., & Khallouli, W. (2007). *The Asian crisis contagion: A dynamic correlation approach analysis* (Working Paper No. 0725). Groupe d'Analyse et de Theorie Economique (GATE).

Favero, C., Pagano, M., & Thadden, E.-L. von. (2007). *How does liquidity affect government bond yields?* (Working Paper No. 323). IGIER (Innocenzo Gasparini Institute for Economic Research), Bocconi University.

Forbes, K., & Rigobon, R. (2001). Contagion in Latin America: Definitions, measurement, and policy implications. *Economia*, *1*(2), 1-46.

Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, *57*(5), 2223-2261.

Geyer, A., Kossmeier, S., & Pichler, S. (2004). Measuring systematic risk in EMU government yield spreads. *Review of Finance*, *8*(2), 171-197.

Hansen, B. E. (1997). Approximate asymptotic p values for structural-change tests. *Journal of Business & Economic Statistics*, *15*(1), 60-67.

Karolyi, G. A., & Stulz, R. M. (1996). Why do markets move together? an investigation of U.S.-Japan stock return comovements. *Journal of Finance*, *51*(3), 951-986.

Kendall, M., & Stuart, A. (1969). *The advanced theory of statistics* (Vol. 1). Charles Griffin and Co.

King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *The Review of Financial Studies*, *3*(1), 5-33.

Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *Journal of Finance*, *57*(2), 769-799.

Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *Journal of Finance*, *56*(4), 1401-1440.

Liu, J., & Longstaff, F. A. (2004). Losing money on arbitrage: Optimal dynamic portfolio choice in markets with arbitrage opportunities. *The Review of Financial Studies*, *17*(3), 611-641.

Longin, F., & Solnik, B. (1995). Is the correlation in international equity returns constant: 1960-1990? *Journal of International Money and Finance*, *14*(1), 3-26.

Longstaff, F. A. (2004). The flight-to-liquidity premium in U.S. treasury bond prices. *The Journal of Business*, *77*(3), 511-526.

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, *3*(2), 75-103.

Loretan, M., & English, W. B. (2000). *Evaluating "correlation breakdowns" during periods of market volatility* (International Finance Discussion Papers No. 658). Board of Governors of the Federal Reserve System (U.S.).

Pan, J., & Singleton, K. J. (2008). Default and recovery implicit in the term structure of sovereign cds spreads. *Journal of Finance*, *63*(5), 2345-2384.

Pedersen, L. H., & Brunnermeier, M. K. (2007). *Market liquidity and funding liquidity* (Working Paper Series No. w12939). NBER.

Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of Economic Surveys*, *17*(4), 571-608.

Perron, P. (2005). Dealing with structural breaks. In T. C. Mills & K. Patterson (Eds.), *Palgrave handbook of econometrics, volume 1: Econometric theory* (chap. IV). Palgrave Macmillan.

Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, *55*(290), 324-330.

Rigobon, R. (2002). Contagion: How to measure it? In S. Edwards & J. A. Frankel (Eds.), *Preventing currency crises in emerging markets* (p. 269-334). University of Chicago Press.

Sgherri, S., & Zoli, E. (2009). *Euro area sovereign risk during the crisis* (Working Paper No. 09/222). IMF.

Stock, J. H., & Watson, M. W. (2007). *Introduction to econometrics* (2nd ed.). Prentice Hall.

Van Rijckeghem, C., & Weder, B. (2001). Sources of contagion: is it finance or trade? *Journal of International Economics*, *54*(2), 293-308.

Appendices

Approximate Critical Values for the Rolling FR-Tests

Similar to testing for a structural break at an unknown break date, where the so-called sup F-statistic is the largest of many F-statistics and, hence, its distribution is not the same as an individual F-statistic, the distribution of the FR-test statistic is not the same as the standard t-distribution. Andrews (1993) derived the asymptotic distribution for a wide class of tests for structural change, among them the sup F-test. However, the asymptotic distribution of these tests is non-standard and depends both on the number of restrictions being tested, i.e. the number of coefficients that are being allowed to break, and the range of the subsample over which the F-statistics are computed. Hansen (1997) developed computationally convenient approximations to the asymptotic p-value functions for the Andrews asymptotic distributions.

Applying the approach of Andrews (1993) and Hansen (1997), respectively, to the rolling FR-test approach is out of scope of this paper. Instead, we use Monte Carlo methods to find approximate critical values for the rolling FR-test statistics.

In order to do that we assume that the sample of daily returns are drawn from a bivariate normal distribution. Then, for a given correlation between the two variables, we draw a sample of the bivariate normal distribution. In order to match the characteristics of our sample of CDS premia, we define the non-crisis period as the first 260 observations. This should be sufficient as Essaadi, Jouini, and Khallouli (2007) show that the minimum for a stable rolling correlation coefficient is 224 observations (on a five-percent level of significance). This is illustrated by figure 6.

We then run both versions of the FR-test for the three different time windows and store the respective test statistics. We repeat this procedure until we have collected for each of the different test versions 10,000 test statistics. Figure 7 illustrates that 10,000 observations should be sufficient to determine stable approximate critical values.

Now, we can determine the approximate critical values for the correlation structure we used for drawing the repeated samples from the bivariate normal distribution. We do that for three different levels of significance, namelely 1, 5, and 10 percent, by using the respective percentiles of the observed distribution of the test statistic.

Finally, we repeat this procedure for different correlation coefficients. The results are presented in table 6.

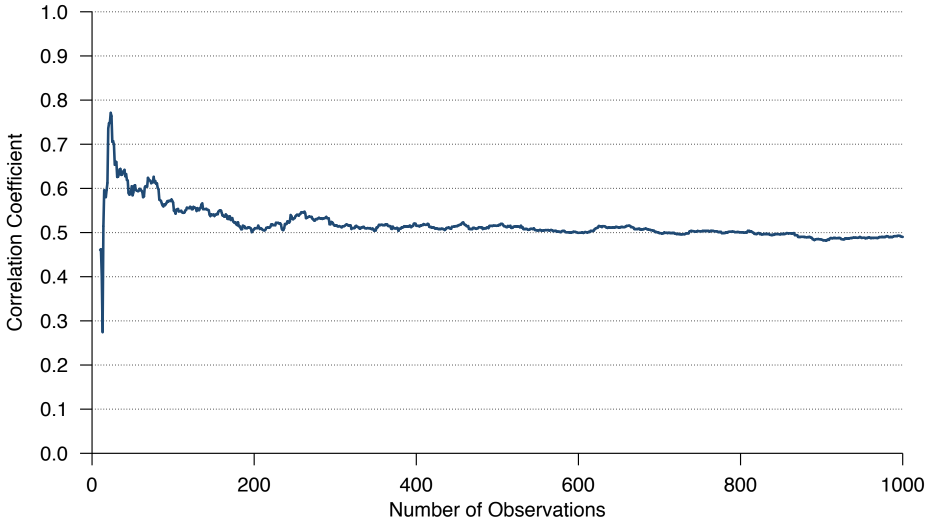

Figure 6: Rolling Correlation Coefficient

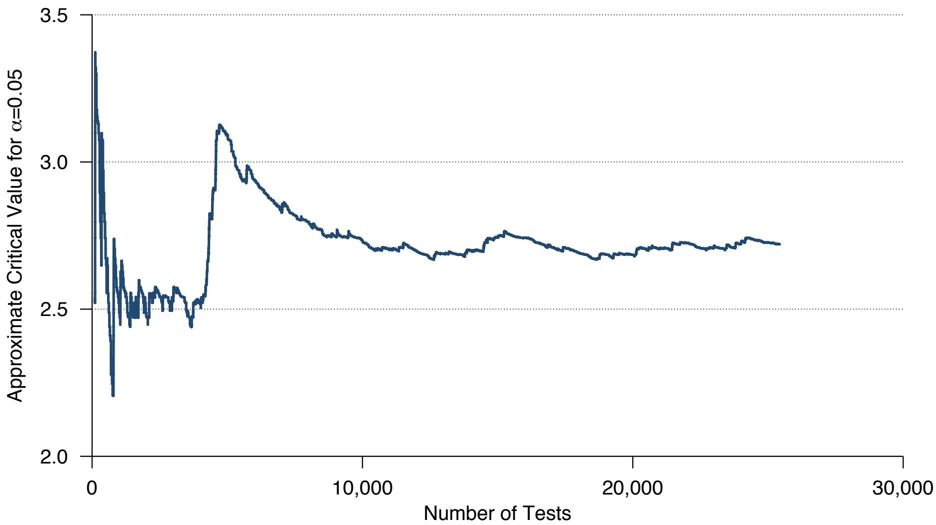

Figure 7: Approximate Critical Value for $\alpha = 0.05$

Table 6
Approximate Critical Values for the Rolling FR-Tests

This table shows approximate critical values for the different versions of the rolling FR-test based on Monte Carlo simulations with 10,000 repeated tests.

Panel A: $\alpha = 0.01$

	FR_O			FR_N		
Correlation coefficient	20 days	40 days	60 days	20 days	40 days	60 days
0.00	3.595	3.081	2.581	3.688	3.375	3.046
0.10	3.827	3.445	3.147	3.937	3.916	3.758
0.20	3.877	3.267	3.073	4.125	3.736	3.439
0.30	3.411	3.209	3.047	3.404	3.248	3.297
0.40	3.584	3.499	3.224	3.684	3.712	3.574
0.50	3.635	3.462	3.467	3.877	3.839	4.218
0.60	3.389	3.093	2.509	3.465	3.188	2.813
0.70	3.380	3.031	2.583	3.528	3.257	2.907
0.80	3.342	3.019	2.830	3.439	3.185	3.103
0.90	3.125	3.016	2.567	3.171	3.056	2.686

Panel B: $\alpha = 0.05$

	FR_O			FR_N		
Correlation coefficient	20 days	40 days	60 days	20 days	40 days	60 days
0.00	2.542	2.147	1.959	2.610	2.349	2.240
0.10	2.679	2.241	2.066	2.747	2.418	2.362
0.20	2.700	2.493	2.251	2.851	2.780	2.624
0.30	2.433	2.255	2.135	2.451	2.422	2.366
0.40	2.735	2.477	2.440	2.805	2.683	2.624
0.50	2.628	2.405	2.363	2.721	2.602	2.689
0.60	2.588	2.107	1.836	2.616	2.221	2.026
0.70	2.433	2.159	1.980	2.530	2.342	2.151
0.80	2.494	2.203	2.059	2.563	2.351	2.365
0.90	2.382	2.078	1.866	2.371	2.200	2.023

Panel C: $\alpha = 0.10$

	FR_O			FR_N		
Correlation coefficient	20 days	40 days	60 days	20 days	40 days	60 days
0.00	1.958	1.647	1.528	2.019	1.819	1.813
0.10	2.030	1.688	1.617	2.100	1.829	1.833
0.20	2.152	1.956	1.889	2.270	2.203	2.148
0.30	1.954	1.791	1.737	1.990	1.858	1.816
0.40	2.217	2.004	1.953	2.298	2.120	2.150
0.50	2.065	1.868	1.787	2.131	1.972	1.941
0.60	2.034	1.633	1.467	2.090	1.749	1.633
0.70	2.000	1.731	1.586	2.040	1.823	1.743
0.80	2.048	1.795	1.720	2.111	1.981	1.952
0.90	1.953	1.645	1.494	1.963	1.706	1.551