Measuring Systemic Vulnerability in European Banking Systems

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March 2017

ABSTRACT

We construct a measure of systemic vulnerability in selected EU banking systems using an indirect measure of the system covariance which is also time-varying. We proceed to examine to what extent the resulting measures of systemic vulnerability provide a convincing narrative of events during the period January 2000 to March 2016. The results provide evidence of: (i) rising vulnerability prior to the outbreak of the international financial crisis in 2007/08 in countries with banks exposed to toxic assets; (ii) vulnerability associated with the euro area sovereign debt crisis from 2009/10; and (iii) continued concerns from 2013 onwards regarding the need for euro area banks to improve their balance sheets and raise new capital at a time of sluggish profitability.

Keywords: euro area financial crisis, systemic vulnerability, financial instability, European banks
JEL Classification: E3, G01, G14, G21

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1. *Introduction*

The idea that systemic vulnerability in the banking system can potentially result in financial instability, with its consequent costs for the real economy, is by no means new. As far back as the mid-1970s, Lamfalussy focused on the potential build-up of macroeconomic imbalances which, he argued, could endanger financial stability[1]. He believed that the financial system had an endogenous capacity to generate crises and emphasized the role of innovation in the financial system in concealing, but not reducing, vulnerability. These ideas were developed by both Crockett (2000) and Knight (2006), with their emphasis on the need for macro-prudential − and not just micro-prudential − regulation of the banking system. The international financial crisis that erupted in 2007/08, followed by the outbreak of the euro area sovereign debt crisis in 2009/10, reinforced interest in the systemic health of the banking system.

Crises such as those mentioned above may be thought of as having two parts. First the financial system must be systemically vulnerable, that is to say the level of interdependence between institutions must be high. Then the system must be hit by a shock such as the subprime loan crises in the US, the collapse in property prices in Spain or the sovereign debt crises in Greece. In this paper we will focus on measuring the first of these, the level of systemic vulnerability in a given banking system. We are not trying to measure overall risk, nor are we trying to predict financial crises. We are trying to provide a tool which will let a bank regulator know if the banking sector is changing in a way which will amplify the consequences of a shock if one occurs.

If central banks are to be able to prevent (or anticipate) systemic vulnerability, the issue arises as to how such vulnerability is to be measured. However, because systemic vulnerability is not well-understood, measurement of systemic vulnerability is obviously challenging (Bisias, Flood, Lo and Valavanis, 2012). In this paper, we provide a measure

[1] See Maes (2009) for an excellent review of Lamfalussy's thinking on the concept of systemic stress, financial stability and the role of macro-prudential policy.

based on the covariance of banks' performance, and we apply the measure to nine European countries: Austria, France, Germany, Greece, Ireland, the Netherlands, Spain, and the United Kingdom. The estimates derived are then compared to events ex post in order to assess their performance. Our proposal has a number of advantages. First, it is consistent with Crockett's insight that systemic vulnerability is effectively a product of correlated failures. Consequently, our measure does not focus on levels or changes in specific financial variables, which are typically thought to provide little information (He and Krishnamurthy, 2014). Second, we use banks' market values, which are readily available and easily updateable, to estimate vulnerability. Third, the analysis of covariance can be conducted easily at several levels. Specifically, we can concentrate on levels of vulnerability in the banking system of a particular country, groups of countries (e.g., core versus periphery of the euro area) and/or the euro area itself. Indeed the technique we outline below can be easily extended to look at systemic vulnerability of sovereigns, other non-bank financial institutions and the interdependence between banks, non-bank financial institutions and soverigns. The empirical results reported below, which focus on individual countries, suggest that our measure provides a practical and reliable indicator of systemic vulnerability in banking systems. It can act to alert regulators and supervisors of impending increases in vulnerability with the aim of triggering measures to prevent financial instability.

2. Measuring systemic vulnerability[2]

What is systemic vulnerability? Broadly, systemic vulnerability can be thought of as a set of circumstances that leads to the failure of a significant part of the financial sector, resulting in a reduction of credit availability that has the potential to adversely affect the real economy (Bisias, Flood, Lo and Valavanis, 2012, p. 1; Acharya, Pederson, Philippon and Richardson, 2010, p. 284).

The empirical literature has employed a large variety of measures that aim to capture systemic vulnerability and risk more generally. An early strand of the literature views systemic vulnerability from the perspective of individual institutions; earlier empirical

[2] Useful literature reviews of the measurement of systemic stress or financial fragility include De Bandt and Hartmann (2000), Galati and Moessner (2011), Bisias, Flood, Lo and Valavanis (2012) and Hansen (2014).

studies focused on interdependencies between banks resulting from credit claims between the banks. Furfine (1999) uses Fedwire transfers to map interbank credit claims in the Federal Funds Market. He then uses these bilateral exposures to generate expected losses based on various simulations of bank failure. Elsinger, Lehar and Summer (2002) build a matrix of interbank connections for the Austrian banking system and conclude that the probability of contagious default from interbank relationships within the system are very small. Iori, Jafarey and Padillah (2003) simulate potential contagion within theoretical banking systems and conclude that the vulnerability of systemic instability stemming from the interbank market is greater when banks are more interdependent, with failing risky banks having the ability to cause safer banks to get into trouble. Those authors concluded that, if banks are strongly interdependent and the banking system contains large institutions, banks are likely to be more fragile. This view is currently known as either the "too interconnected to fail" or "too big to fail".

The more recent literature takes a system perspective. A number of papers seek to build indices of systemic risk. These indices are then used in the early warning literature, in which there is much emphasis on ability to predict crises (Hollo, Kremer and Lo Duca, 2012; Louzis and Vouldis, 2012; Lo Duca and Petonen, 2013). Hollo *et al* combine 15 financial market indicators, covering 5 categories of information, to build an index of systemic risk for the euro area. The five categories are: financial intermediaries, money markets, equity markets, bond markets and foreign exchange markets. The authors compute a separate index for each category and then aggregate the indices, taking into account cross correlations between the sub-indices. Thus heightened vulnerability in all sub-indices has a higher weight than heightened vulnerability in any single market[3].

Other papers which focus on market measures of vulnerability focus on the probability of a tail event occurring over a given horizon. Segoviano and Goodhart (2009) extract the probabilities of distress for individual banks using various financial data. They then combine these individual measures into the probability of distress of a portfolio of banks containing all the banks in a given banking system. Various measures of banking system stability are then produced, including the probability of common distress of the banks in

[3] Lo Duca and Peltonen (2013) construct indices for some 28 emerging and advanced countries, while Louzi and Vouldis (2012) focus on Greece.

the system, the probability of distress between two specific banks and the probability that the system is distressed as a result of one bank being distressed. The authors apply the method to European, US and Latin American banking systems and conclude that the various measures provide a promising explanation of the events associated with the international financial crisis. Adrian and Brunnermeier (2011) use a VaR (Value at Risk) approach, and calculate the contribution of different banks to the riskiness of the entire system. The marginal contribution of bank i to overall systemic risk is calculated as the difference between the VaR for the entire system conditional on i being in distress and the VaR for the entire system conditional on i not being distressed. Acharya, Pederson, Philippon and Richardson (2010, 2013) apply a similar methodology to the US. Finally, Saldias (2012) uses distance to default measures to build a measure of systemic stress. He calculates the average distance to default of individual banks and compares this distance to the distance to default of the banking system (the latter being calculated by aggregating individual banks). The difference between the average distance to default and the portfolio distance to default is driven by interdependence among institutions in the sample and represents a measure of systemic risk/stress.

3. Methodology and data

Our proposed measure of systemic vulnerability is within the spirit of Crockett (2000), viewing vulnerability from a "portfolio" perspective rather than from the perspective of individual institutions. It measures the vulnerability of correlated failures by focusing on covariances and hence also accounts for interdependencies among institutions. The index measures systemic vulnerability at each point in time it does not consider the overall level of risk which is addressed by the literature which focuses on tail events. We begin with the following relation:

$$\frac{Var(\sum bank_i)}{\sum Var(bank_i)} = \frac{\sum Var(bank_i) + \sum 2Cov(bank_i, bank_j)}{\sum Var(bank_i)} \qquad (1)$$

Where *Var* is variance, *Cov* is the covariance, and $bank_i$ is the market value of bank *i*. We focus on the market value of banks. The rationale for this choice is simplicity – we aim to produce a tool that is easily implementable on a real time basis.

What we would ideally like to have is a large time varying covariance matrix for the sector and a simple way to summarize this matrix so that we could determine if there is an increase in positive covariances within the sector. This, however, is not easy to achieve. The natural technique to use would clearly be within the GARCH family of models. A system of GARCH equations would allow us to model the expected value of the banking sector along with the variance and covariance structure. However, such an approach would entail a substantial dimensionality problem, because standard multivariate GARCH models quickly generate very large numbers of parameters as the number of variables in the system increases. To explain, consider the following system:

$$\begin{aligned} &Y_i = \beta_i X + \varepsilon_i \qquad \varepsilon \sim N(0,\Sigma_t) \\ &vech(\Sigma_t) = W + Avech(\varepsilon_{t-1}\varepsilon'_{t-1}) + Bvech(\Sigma_{t-1}) \end{aligned} \tag{2}$$

where *Y* is a vector of n endogenous variable and *X* is a vector of suitable exogenous variables, and we have limited the model to a system GARCH(1,1) specification. This model is a direct generalization of the standard univariate GARCH model, but it is intractable for anything other than a very small number of variables. For example, if the number of variables in the system were 5, the model would require estimation of 465 parameters in the *W*, *A* and *B* matrices; additionally the number of parameters would grow exponentially with n, the number of variables in the model.

There are a number of ways to reduce this problem of dimensionality but none of them are entirely satisfactory. It is possible to make the *A* and *B* matrices diagonal, but this effectively eliminates the interaction between the covariances and severely limits their time variation. A popular model is the BEKK (Baba, Engle, Kraft and Kroner, 1990, referenced in Engle and Kroner,1995, also see Hall, Miles and Taylor 1990) model, given below:

$$\Sigma_t = V'V + A'\varepsilon_{t-1}\varepsilon'_{t-1} A + B'\Sigma_{t-1}B \tag{3}$$

This allows fairly complex interactions between the covariances and also ensures positive semi-definiteness for the covariance matrix, but it still involves a large number of parameters as n rises. For a system where n=5, the model has 75 parameters in the variance equation and this number again grows rapidly as n rises.

Another alternative would be to use factor GARCH models; the assumption here is that there are only a small number of factors underlying the variables being modelled, allowing a much more parsimonious formulation of the model. However, factor GARCH models limit the amount of time variation in the covariances. Moreover, the assumption of a small number of factors may also be questioned. A further common approach is the constant conditional correlation model in which the time-varying conditional covariances are parameterized to be proportional to the product of the corresponding conditional standard deviations. This condition, however, restricts precisely the part of the model we are most interested in and, where this has been tested, this assumption is almost invariably rejected.

In what follows we propose a measure of the covariance structure which sidesteps these complex problems, given that we are not particularly interested in any one covariance term but rather a joint measure of all the covariances. Our procedure only involves univariate GARCH estimation and is, therefore, relatively easy to undertake regardless of the number of banks. In particular, our approach is to derive an *indirect* measure of systemic vulnerability based on an implicit measure of the covariances which is based on equation (1). In fact by repeatedly applying the technique described below in a bivariate setting it would be possible to construct a very large time varying covariance matrix and thus solve the dimensionality problem of GARCH modelling. This is not our objective here, however, since our aim is to derive a summary vulnerability index.

Specifically, we estimate the variance for each individual bank in a country using a GARCH (1,1) process. Then, we add the variances of each individual bank to obtain the sum of all the variances. We also sum the values of all the banks to obtain the variance of the entire banking sector, also using a GARCH (1,1) process. We implicitly calculate the covariance by using the ratio of the total variance of the banking sector to the sum of the individual variances for each bank. A ratio above one indicates that, in total, the covariance terms are positive; a ratio of one implies a net zero covariance; and a ratio of less than one implies net negative covariance. We interpret this ratio as a measure of systemic vulnerability since it captures the covariance among individual parts of the system. It should be stressed that the covariances are conditional on past behaviour. Thus, a rise implies banks' market values start moving together unexpectedly – out of line with past behaviour. The validity of this procedure is investigated using Monte Carlo techniques in Appendix A.

More formally, we restate (1) in a general form where x_i is a vector of bank valuations for i banks

$$R = \frac{Var(\sum_{i=1}^{N} x_i)}{\sum_{i=1}^{n} \mathrm{var}(x_i)} = \frac{\sum_{i=1}^{n} \mathrm{var}(x_i) + \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} 2\,\mathrm{cov}(x_j x_i)}{\sum_{i=1}^{n} \mathrm{var}(x_i)} \qquad (4)$$

One problem with this simple measure of the variance ratio is that it will grow with the number of banks and so we cannot easily compare groupings comprising different numbers of banks. The ratio is suitable for a comparison over time but not for a comparison among countries. The problem with ratio (4) is that the size of the group affects the size of R even if all the covariances are identical. In the extreme case where all the xs move perfectly together, then R=n. That is for n=2 R=2, for n=3 R=3, for n=4 R=4…. and so on.

In order to avoid this occurrence, in what follows we derive an index, R*, which is not affected by the number of banks in any group.

$$R = \frac{\sum_{i=1}^{n} \mathrm{var}(x_i) + \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} 2\,\mathrm{cov}(x_j x_i)}{\sum_{i=1}^{n} \mathrm{var}(x_i)} = 1 + \frac{\sum_{j=1}^{n-1} \sum_{i=j+1}^{n} 2\,\mathrm{cov}(x_j x_i)}{\sum_{i=1}^{n} \mathrm{var}(x_i)} \qquad (5)$$

So

$$R-1=\frac{\sum_{j=1}^{n-1}\sum_{i=j+1}^{n}2\operatorname{cov}(x_j x_i)}{\sum_{i=1}^{n}\operatorname{var}(x_i)} \qquad (6)$$

And

$$(R-1)\sum_{i=1}^{n}\operatorname{var}(x_i)=\sum_{j=1}^{n-1}\sum_{i=j+1}^{n}2\operatorname{cov}(x_j x_i) \qquad (7)$$

And

$$((R-1)\sum_{i=1}^{n}\operatorname{var}(x_i))/(n.(n-1))=(\sum_{j=1}^{n-1}\sum_{i=j+1}^{n}2\operatorname{cov}(x_j x_i))/(n.(n-1))=mean\ \operatorname{cov}ariance \qquad (8)$$

That is, we now have the average covariance among all the banks in the group. Finally, we use this expression for the mean covariance in order to generate an adjusted R which we call R*.

$$R^*=\frac{n(\sum_{j=1}^{n-1}\sum_{i=j+1}^{n}2\operatorname{cov}(x_j x_i))/(n.(n-1))}{\sum_{i=1}^{n}\operatorname{var}(x_i)}+1 \qquad (9)$$

In words, our vulnerability index equals n times the average covariance divided by the sum of all the variances, plus 1. This is not then affected by n as there are n variances and the mean is multiplied by n. If R* takes a value of 1, then the covariance is zero. For values above 1, there is positive covariance; for values below 1, there is negative covariance.

We have collected data at a daily frequency on the market value of banks in nine European countries (Austria, UK, Germany, Italy, Ireland, Greece, Spain, France and the Netherlands) over the period 2000-2016[4]. The sample thus includes a non-euro area country (the UK) as well as core and peripheral euro-area countries.

[4] Source of data is Datastream (Thomson Reuters). The number of banks for each country is as follows:
Austria: 5

In sum, we estimate a time-varying variance using a GARCH(1,1)[5] estimate for each bank individually and for the sum of the market value of banks within a banking system. This procedure provides a daily time-varying estimate of the above ratio.

4. Results

We define systemic vulnerability on an individual country basis. It would be possible to apply the technique to a wider set of banks, such as all EU banks or core and periphery EU banks. However it seems more sensible to focus on individual country baking sectors as, at present, most EU states have banking sectors which are domestically dominated. A summary of the results is presented in Table 1. There is some evidence that systemic vulnerability reaches a local (if not global) peak in around the outbreak of the international financial crisis (end-2007 with the failure of Northern Rock in the UK and throughout 2008 with the rescue of Bear Stearns (March) and the failure of Lehman Brothers (September)). Thus the UK, Germany, France, Ireland and Spain are all cases in point. There is also evidence of high systemic vulnerability during the euro area sovereign debt crisis, most notably in Greece, but also in other euro area countries (France, Germany, Ireland, Italy, Spain). Finally, it is interesting to notice the differences in the average levels of vulnerability. The UK and Greek banking systems exhibit the most vulnerability, with average ratios of close to 1.4 in contrast to that of the Netherlands with averages of close to 1 (that is, zero covariance). The highest peak values of the covariance are found in Ireland – reaching 3 in 2008 on the collapse of Lehman Brothers and 6.5 in 2011 (around the time of the recapitalization of Irish banks).

France:	11
Germany:	6
Greece:	5
Ireland:	3
Italy:	16
Netherlands:	2
Spain:	4
UK:	5

[5] We used a GARCH(1,1) specification as this as found to be the best specification based on the Schwartz information criteria, see appendix B for details.

The individual country results are presented in Figures 1 to 9. In addition to the daily index, we also present a Hodericl-Prescot (H-P) filtered version[6] in order to eliminate excess volatility; since the smoothed series is easier to interpret, that series will be the main focus of the discussion that follows.

Figure 1 depicts our measure of systemic vulnerability in the German banking system. The index exhibits a sharp rise in the years leading up to the international financial crisis, peaking around the time of the collapse of Lehman Brothers in September 2008. It then falls back sharply, reaching a cyclical trough in mid-2009. This sharp fall (also present in other countries) is indicative of market sentiment in the aftermath of the failure of Lehman Brothers; the markets perceived that the crisis had been contained by the swift actions on the part of policy makers. The index's subsequent rise (beginning in late 2009) reflects the start of the Greek debt crisis, followed by a further rise during 2011 as the Greek debt crisis had spread to other euro-area peripheral countries. The index continued to rise through 2012, and it remained at elevated levels, on balance (compared with the levels in the early 2000), during the remainder of the sample period. The latter development reflects the following factors. First, markets focused on the performance of European banks in light of discussions, beginning in 2012, of the creation of a euro-area banking union under which, among other things, larger banks would be subjected to vulnerability-testing; the market's consensus during the period from 2013 to 2015 was that some euro-area banks needed to restructure their balance sheets and to raise additional capital. Second, the weak recovery of the euro-area in the aftermath of the break-out of the euro-area crisis indicated that banks' earnings would remain modest, contributing to the view that the financial positions of some banks would remain fragile in the medium term.

A similar picture is evident for the French banking system. Systemic vulnerability rises up to the outbreak of the international financial crisis, but then recedes slightly. It is worth noting that the overall level of the indicator for France is somewhat lower than that of Germany, but it is nevertheless mainly above 1, indicating positive covariance.

[6] We set λ=6812100

Next, consider two smaller core European countries, The Netherlands and Austria. The overall level of vulnerability in both countries is small -- typically below 1. The general pattern in the Netherlands follows that of Germany and France. However, overall systemic vulnerability is at less-elevated levels than those of Germany. In Austria, systemic vulnerability is also very low; indeed, for most of the sample period, the ratio exhibits values of less than one indicating negative covariance. This could reflect the diversification of the Austrian banking system into Eastern Europe. The 2009 agreement[7] that European banks would not withdraw liquidity from branches and subsidiaries in the region could have played a positive role in this outcome following the international financial crisis.

Figure 5 through 8 present data for Italy, Greece, Ireland, and Spain, respectively. Systemic vulnerability in Italy (Figure 5) exhibits considerable variability around relatively-high levels (in the range of 1.04 to 1.20). After peaking in the third quarter of 2004, vulnerability recedes, only to rise modestly on the eve of the Lehman Brothers failure, and sharply with the outbreak of the euro area debt crisis (just before the experience of contagion in the summer of 2011 and into 2012 from the euro area sovereign debt crisis). The modest reaction to the Lehman Brothers failure could reflect the fact that Italian banks were not directly exposed to the instruments involved, while their funding positions were more secure given their strong domestic retail deposit base (Banca d'Italia, 2008). Finally, the heightened vulnerability, visible in the non-smoothed data, at the end of 2015 and the beginning of 2016 is indeed borne out by developments in the Italian banking system and the setting up of a fund to deal with NPLs.

The indicator for Greece (Figure 6) also varies around elevated levels (mainly, in the range of 1.25 to 1.45). As with Italian banks, vulnerability increases modestly on the eve of the Lehman Brothers failure since Greek banks, which were not directly exposed to the toxic assets, mainly experienced funding pressure. Thereafter, systemic vulnerability peaks again with the outbreak of the Greek debt crisis in 2009-10 and in the aftermath of private sector involvement (PSI) in 2012 when banks required recapitalisation following losses taken on Greek sovereign bonds. Systemic vulnerability fell rapidly in the run-up to, and after, recapitalisation in June 2013. Vulnerability rose again in 2014-15 associated initially

[7] The agreement is known as the Vienna Initiative and was agreed in January 2009 among European banks and governments. It aimed at safeguarding financial stability in emerging Europe.

with political uncertainty and, thereafter, with a prolongation of negotiations between the Greek government and official creditors. Only after agreement in August 2015 was reached did systemic vulnerability start to retreat. The successful further recapitalisation by end-2015 reinforced this trend.

Systemic vulnerability in Ireland (Figure 7) was characterised by a sharp rise in vulnerability from the last quarter of 2005, reflecting Irish banks' increasing exposure to toxic assets (both domestic and foreign), though covariances were still negative. It is noteworthy that systemic vulnerability was often very high, something not reflected in the smoothed series. Systemic vulnerability retreated, first, with the euro area response to the international financial crisis and, then, following a huge peak in the third quarter of 2011, once the Irish banks had been recapitalised in summer/autumn 2011. The brief plateau in 2010 represents the period before the agreement on a Memorandum of Understanding with the EC/IMF which was signed in November 2010.

Spain's banking system was exceptionally exposed to a domestic housing bubble, which eventually burst with the onset of the sub-prime crisis. As with Ireland, systemic vulnerability (Figure 8) starts to build up from mid-2005, only to peak at end-2008. However, unlike the Irish case, systemic vulnerability in the Spanish banking system remained elevated and rose sharply at the end of 2015 and into the beginning of 2016 suggesting a heightened sensitivity to the global turbulence of that period.

Finally, Figure 9 presents the results for the UK. Systemic vulnerability tends to be high in the UK and levels of vulnerability in the banking system are more sensitive to global developments. Thus, rising systemic vulnerability in the second half of 2002 was related to sharp declines in equity markets, higher volatility, a deteriorating macroeconomic outlook and an increase in credit risk indicators (Bank of England, 2002). Vulnerability levels fall back only to start rising again from the beginning of 2005, well before the sub-prime crisis. Indeed, before the sub-prime crisis vulnerability levels reach a peak a full year before the onset of the international financial crisis and it is at this point that, the failure of Northern Rock occurred in September 2007. They remained high throughout 2008. The subsequent peaks relate to the euro area debt crisis – its outbreak in 2010 along with Greek PSI and contagion to Italy and Spain in 2011-2012.

5. *Conclusions*

In this paper, we have constructed a measure of systemic vulnerability for various euro area banking systems using an indirect measure of the system covariance which is also time-varying. The measure has a number of advantages. First, it identifies systemic vulnerability as a product of correlated failures. Second, it is constructed from data on banks' market values, which are readily available and easily updateable. Finally, it allows the analysis to be conducted on several levels – while the work here is only for the banking sector of various EU countries the technique outlined can be applied in other settings, groups of countries and/or the euro area itself and across a wide range of institutions including non-bank financial institutions and sovereigns.

We proceeded to examine to what extent the resulting measures of systemic vulnerability provide a convincing narrative of events during the period. A number of results are worth noting. First, the index captures elevated vulnerability levels prior to certain events. For example, the Irish bank recapitalisation is associated with heightened vulnerability levels. Second, the index often rises before stressful events thus making the outcome of these events worse than it might have been. For example, rising vulnerability is evident prior to the outbreak of the international financial crisis in countries, such as the UK, Germany, France, Ireland and Spain, with banks exposed to toxic assets (whether foreign or domestic). Third, stress associated with the euro area sovereign debt crisis is evident, most prominently in Greece, but also in Italy and Spain. Fourth, stress levels since 2008 have been high and variable. Thus in the aftermath of the international financial crisis, stress levels fell in Germany and France quite sharply in the belief that the crisis had been contained, only to rise again with the outbreak of the sovereign debt crisis. Continued concerns from 2013 about the need for euro area banks to restructure their balance sheets and raise new capital at a time of sluggish profitability have caused levels of stress to remain at elevated levels up to the present time.

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Appendix A, A small Monte Carlo Experiment

In order to test the validity of the procedure proposed in the main text of this paper we have conducted two simple Monte Carlo experiments. In the first we consider the case of two variables which are normally distributed with zero covariance and in the second case we consider two variables which are perfectly correlated.
Case 1.
In this case we draw 1000 realizations of two variables which have a standard normal distribution and are independent of each other. The ratio defined in the main text is therefore equal to.

$$ratio = \frac{\mathrm{var}(x+y)}{\mathrm{var}(x)+\mathrm{var}(y)} = \frac{\mathrm{var}(x)+\mathrm{var}(y)}{\mathrm{var}(x)+\mathrm{var}(y)} = 1$$

We then estimate univariate GARCH(1,1) models for x and y and the sum of x and y. We then calculate the mean ratio over the 1000 replications and store this mean. This process is then repeated 1000 times.

Finally we average the 1000 means together to get our average estimate of the ratio. The resulting average of the means is 0.99995, effectively 1 which is the correct figure.
Case 2
In this case we again draw 1000 realizations of two variables which have a standard normal distribution but in this case they are perfectly correlated. The ratio defined in the main text is therefore equal to.

$$ratio = \frac{\mathrm{var}(x+y)}{\mathrm{var}(x)+\mathrm{var}(y)} = \frac{\mathrm{var}(x+x)}{\mathrm{var}(x)+\mathrm{var}(x)} = \frac{\mathrm{var}(x)+\mathrm{var}(x)+2\,\mathrm{var}(x)}{\mathrm{var}(x)+\mathrm{var}(x)} = 2$$

We then estimate univariate GARCH(1,1) models for x and y and the sum of x and y. We then calculate the mean ratio over the 1000 replications and store this mean. This process is then repeated 1000 times.
Finally we average the 1000 means together to get our average estimate of the ratio. The resulting average of the means is 2.000, which is again the correct figure.
EVIEWS code
The following is the EVIEWS code for the first case

```
vector i(1)=1
for !j=1 to 1000
i(1)=i(1)+1
vector v1=@mnrnd(1000)
mtos(v1,a)
vector v2=@mnrnd(1000)
genr b=0
mtos(v2,b)

equation eq1.arch(backcast=1) a c a(-1) a(-2) a(-3)
eq1.garch (backcast=1)
eq1.makegarch va
```

```
equation eq2.arch(backcast=1) b c b(-1) b(-2) b(-3)
eq2.garch(backcast=1)
eq2.makegarch vb

genr sum=a+b
equation eqsum.arch(backcast=1) sum c sum(-1) sum(-2) sum(-3)
eqsum.garch(backcast=1)
eqsum.makegarch vsum

genr ratio=vsum/(va+vb)
series z(i(1))=@mean(ratio)
next
series y=@mean(z)
```

Appendix B Checking the GARCH Specification

A very robust finding in the GARCH literature is that a GARCH(1,1) specification outperforms most other more general GARCH models. This is not surprising as a GARCH(1,1) is equivalent to an infinite order ARCH model and any higher order GARCH model is simply imposing a slightly different weighting pattern on the infinite order ARCH process. It is nevertheless worth checking this result in the context of this paper. We have done this using the Schwartz models selection criteria and in every case it selects the GARCH(1,1) process in favor of a higher order model. To illustrate this we give the detailed results for the five UK banks selected and the total of the banking sector.

Table XX Test of the GARCH(1,1) specification for the UK Banks

	UK1	UK2	UK3	UK4	UK5	UK total
GARCH(1,1)	17.24	15.817	15.986	16.513	14.691	18.887
GARCH(2,2)	17.25	15.818	15.987	16.517	14.708	18.991

Figures in the table are the Schwartz information criteria value; the preferred model has the smaller value.

In addition, the important point to stress here is that all we are only interested in is the actual estimate of the conditional variance from each of these sets of estimates. The different GARCH models give an almost identical estimate of the conditional variance and hence our results are robust to the specific GARCH model chosen. We illustrate this below by showing a graph for the third UK bank which gives the conditional variance from the GARCH 1,1 and 2,2 models. Only one line can be seen as they are effectively identical. Their correlation coefficient is 0.9968

Figure B1; A comparison of the conditional variance from the two GARCH specifications

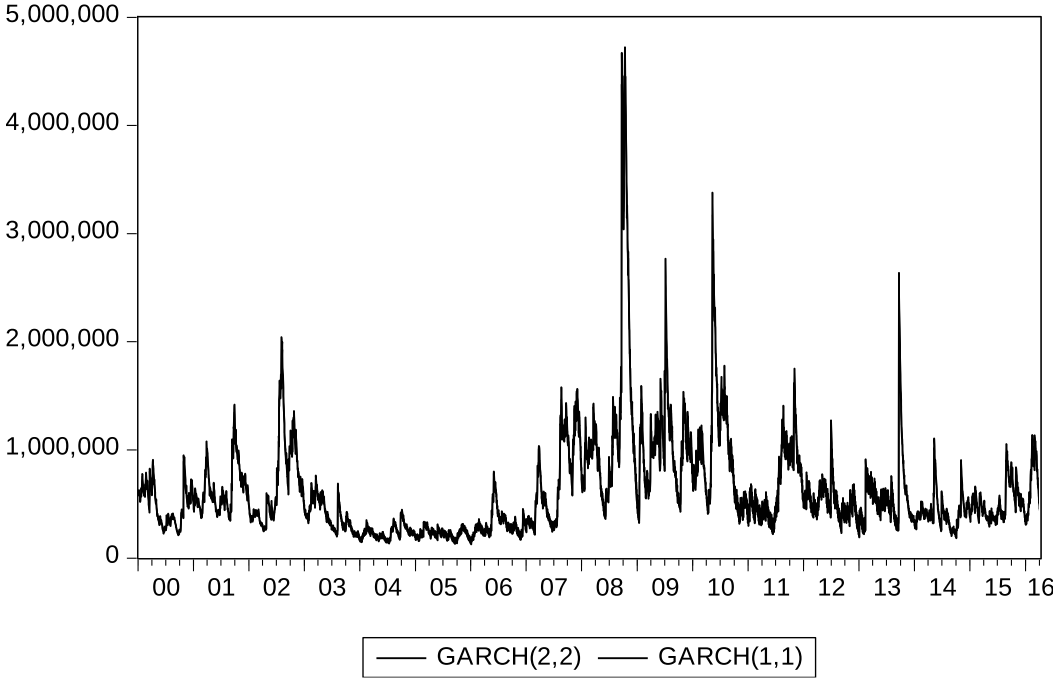
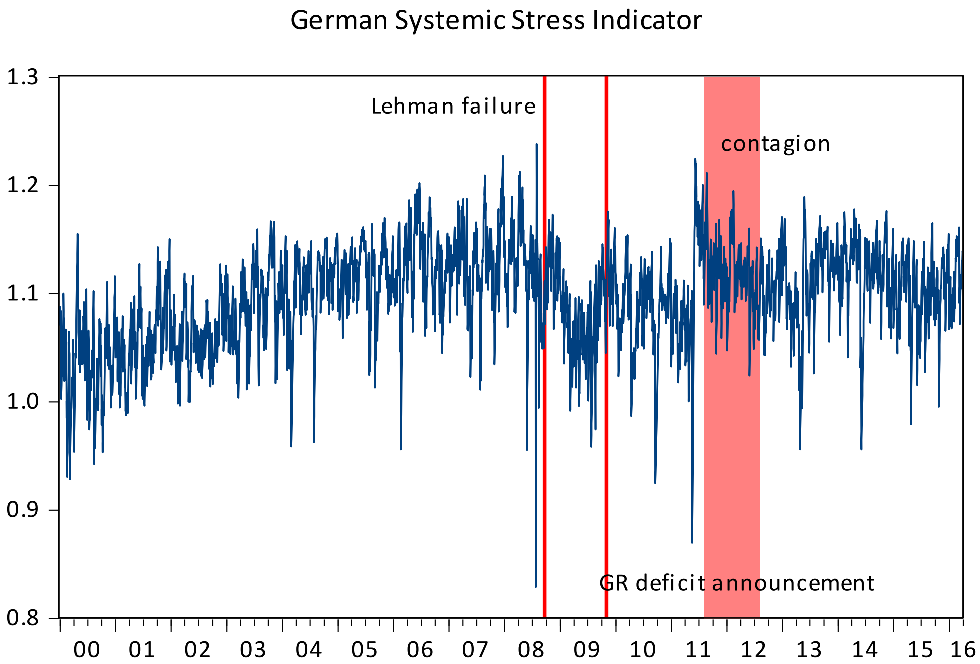


Table 1: Summary of the results				
Country	Range	Mean	Local Peak(s)	Local Troughs
Germany	0.82-1.23	1.09	2008Q1, 2011Q4, 2014Q1	2009Q2
France	0.98-1.16	1.09	2007Q4, 2016Q1	2009Q2
Netherlands	0.95-1.10	1.01	2006Q2	2002Q3
Austria	0.97-1.03	1.00	2005Q1, 2008Q4	2004Q3
Italy	0.93-1.22	1.11	2004Q4, 2013Q1	2008Q4
Greece	0.82-1.57	1.33	2012Q4	2007Q3, 2016Q1
Ireland	0.64-6.50	0.90	2007Q4, 2011Q3, 2014Q1	2010Q3
Spain	0.85-1.70	1.31	2002Q4, 2008Q1, 2016Q1	2005Q3
UK	1.01-2.17	1.41	2002Q3, 2007Q4, 2011Q4	2005Q1, 2014Q2
Note: We do not identify local peaks or troughs from the first observations, since they could simply reflect initial conditions.				

Figure 1


German Systemic Stress Indicator
1.3
1.2
1.1
1.0
0.9
0.8
Lehman failure
contagion
GR deficit announcement
00
01
02
03
04
05
06
07
08
09
10
11
12
13
14
15
16

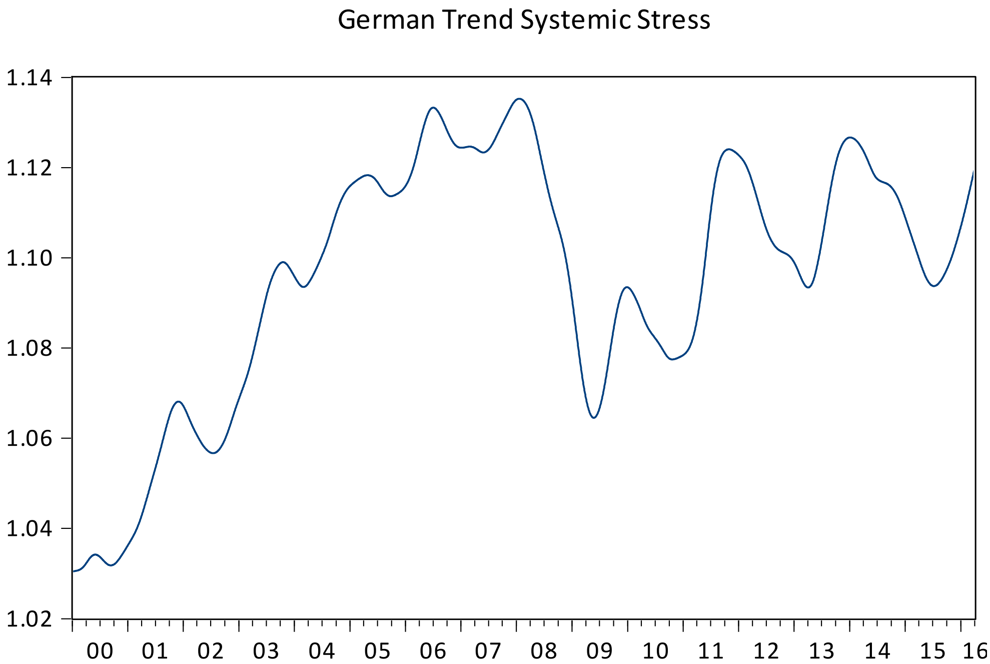
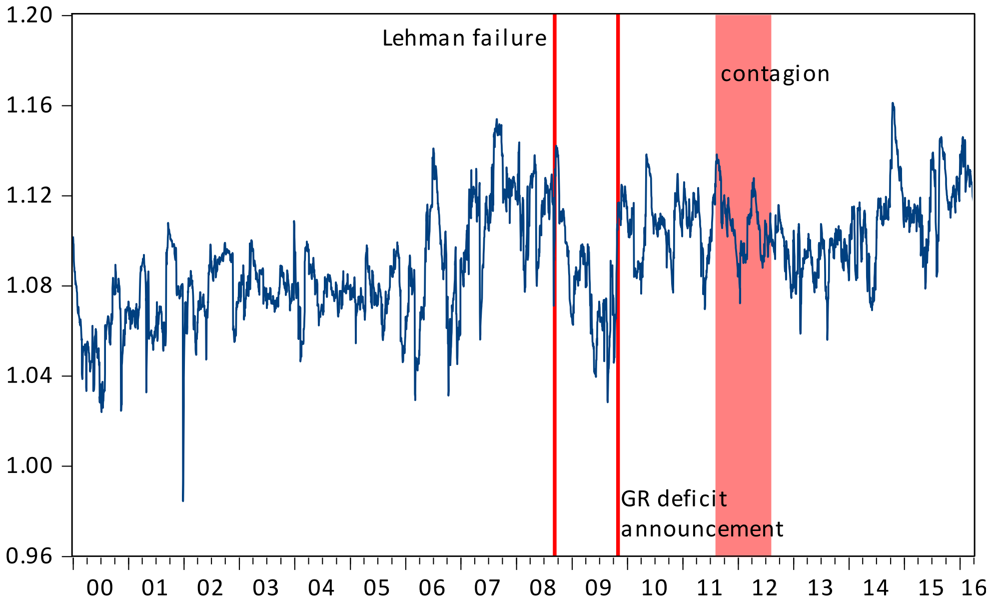

German Trend Systemic Stress
1.14
1.12
1.10
1.08
1.06
1.04
1.02
00
01
02
03
04
05
06
07
08
09
10
11
12
13
14
15
16

Figure 2

French Systemic Stress Index



French Trend Systemic Stress

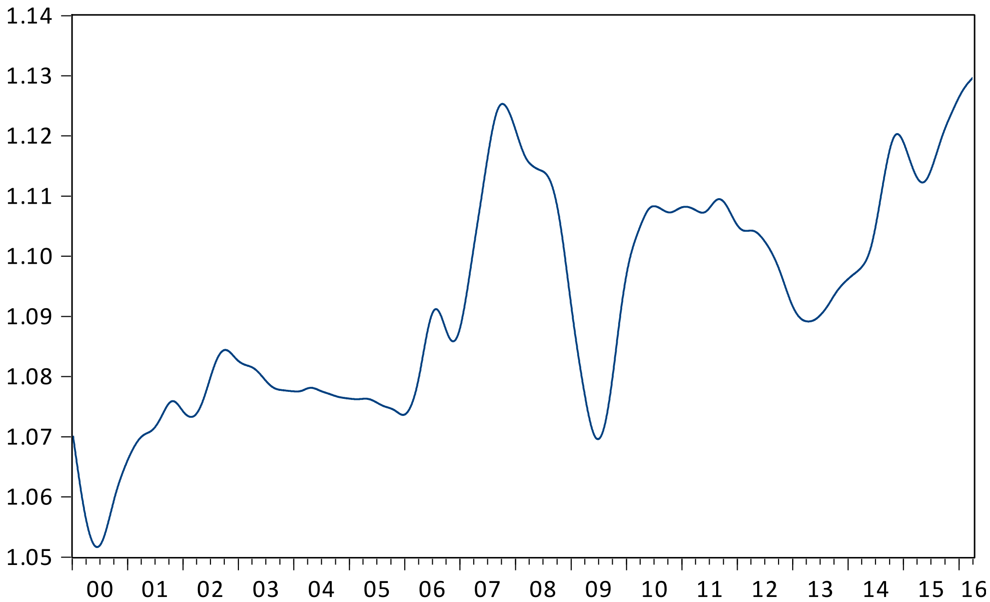
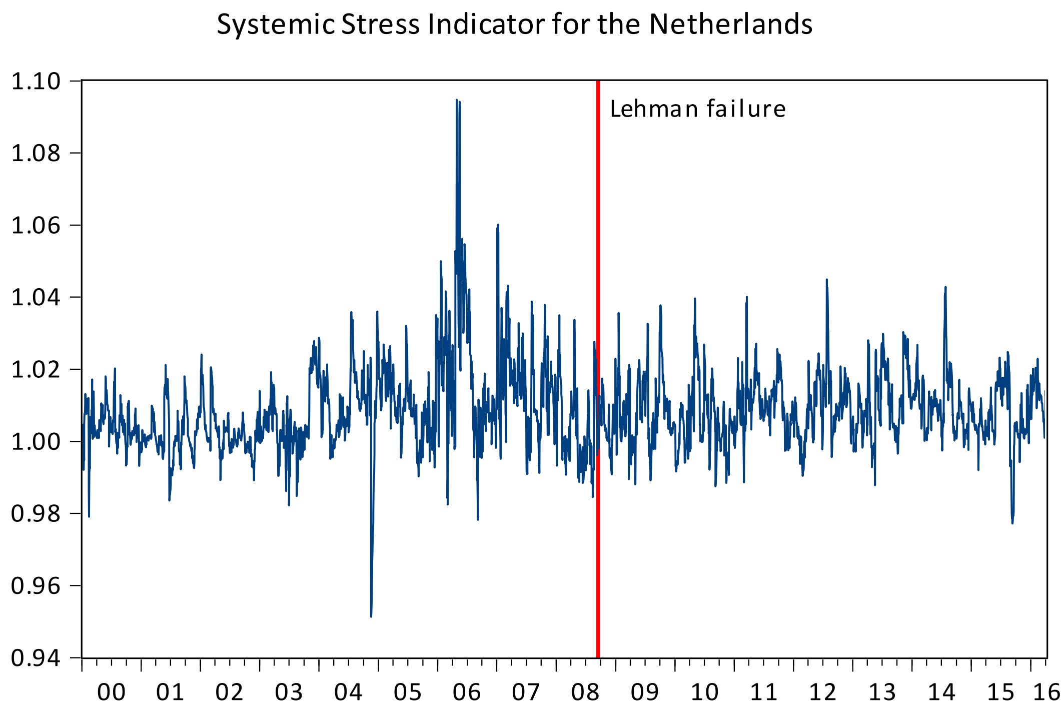
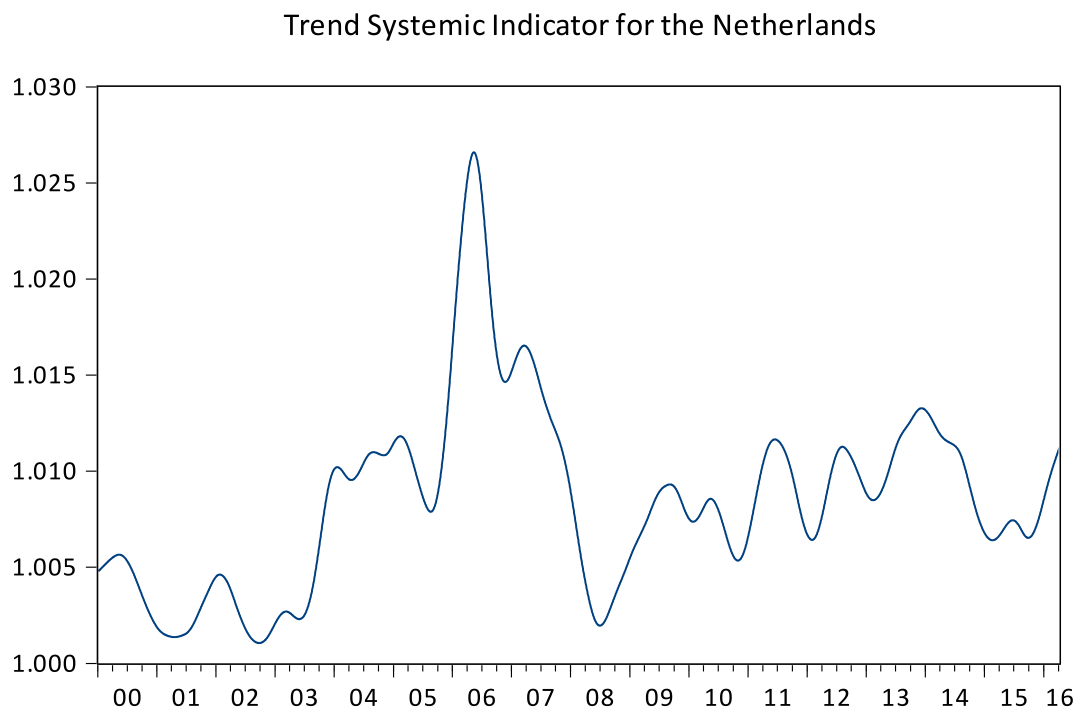


Figure 3

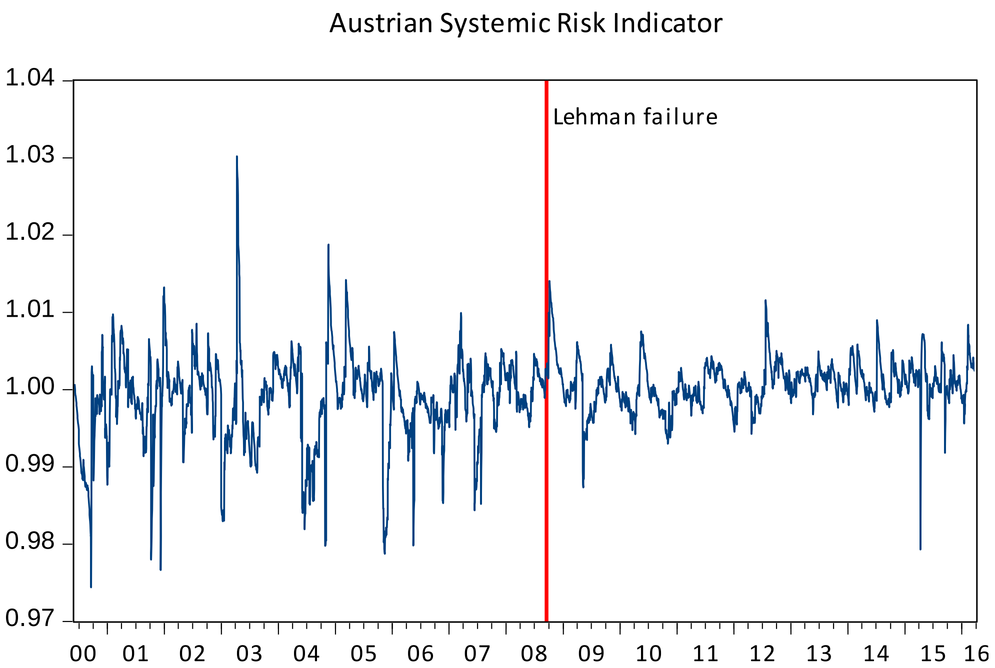


Systemic Stress Indicator for the Netherlands
Lehman failure
1.10
1.08
1.06
1.04
1.02
1.00
0.98
0.96
0.94
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

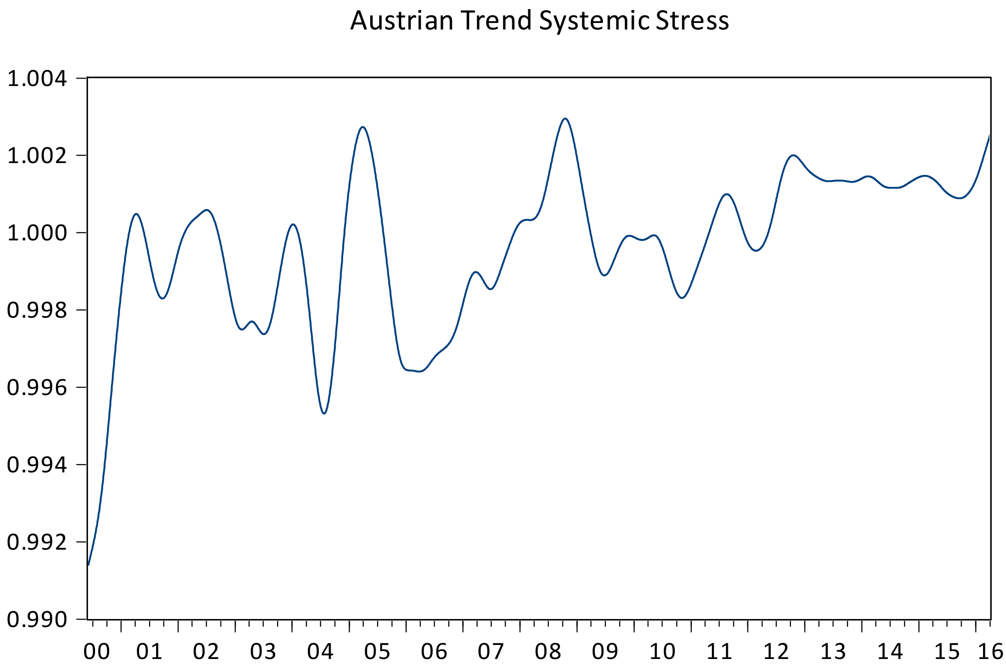


Trend Systemic Indicator for the Netherlands
1.030
1.025
1.020
1.015
1.010
1.005
1.000
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

Figure 4

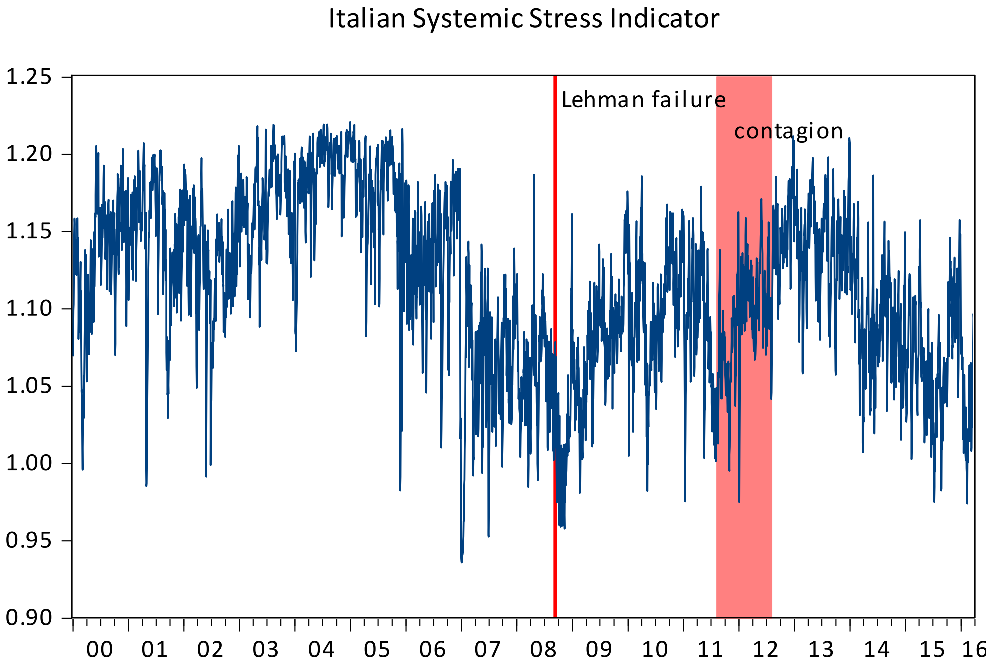


Austrian Systemic Risk Indicator
Lehman failure
1.04
1.03
1.02
1.01
1.00
0.99
0.98
0.97
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

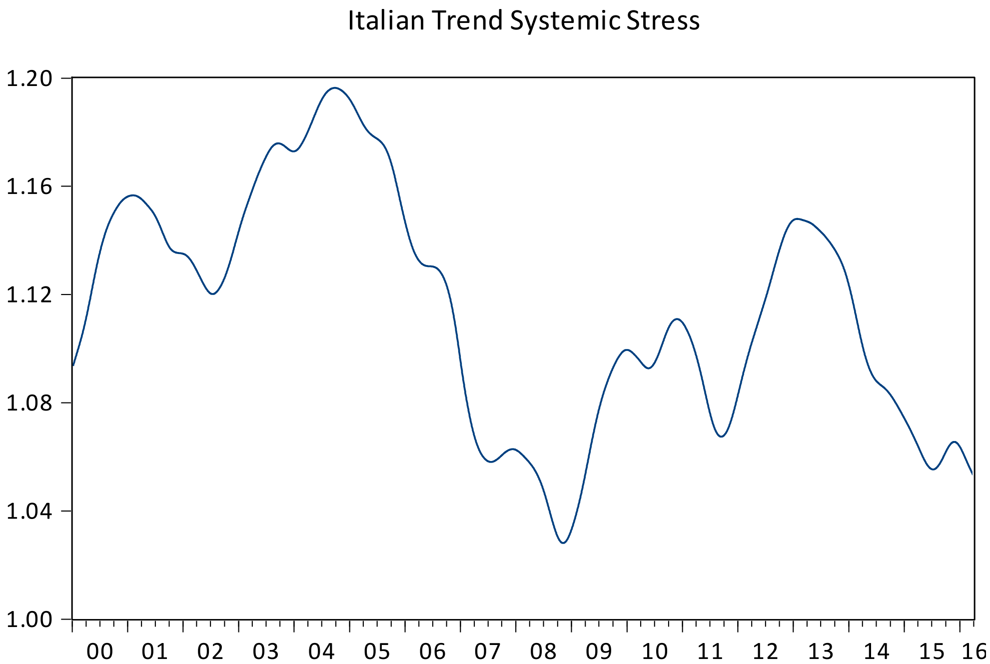


Austrian Trend Systemic Stress
1.004
1.002
1.000
0.998
0.996
0.994
0.992
0.990
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

Figure 5



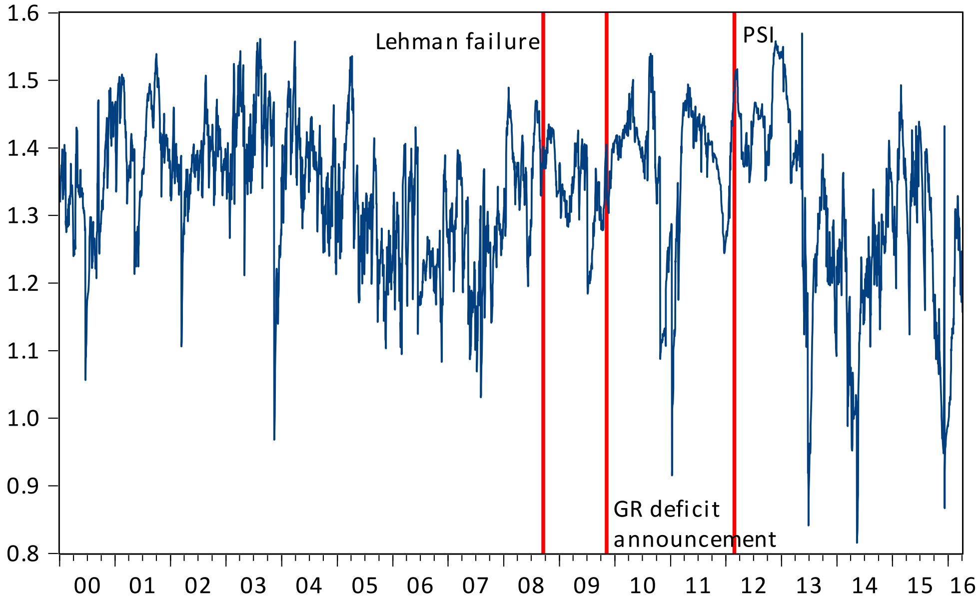
Italian Systemic Stress Indicator
1.25
1.20
1.15
1.10
1.05
1.00
0.95
0.90
Lehman failure
contagion
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16



Italian Trend Systemic Stress
1.20
1.16
1.12
1.08
1.04
1.00
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

Figure 6

Greek Systemic Stress Indicator



Greek Trend Systemic Stress

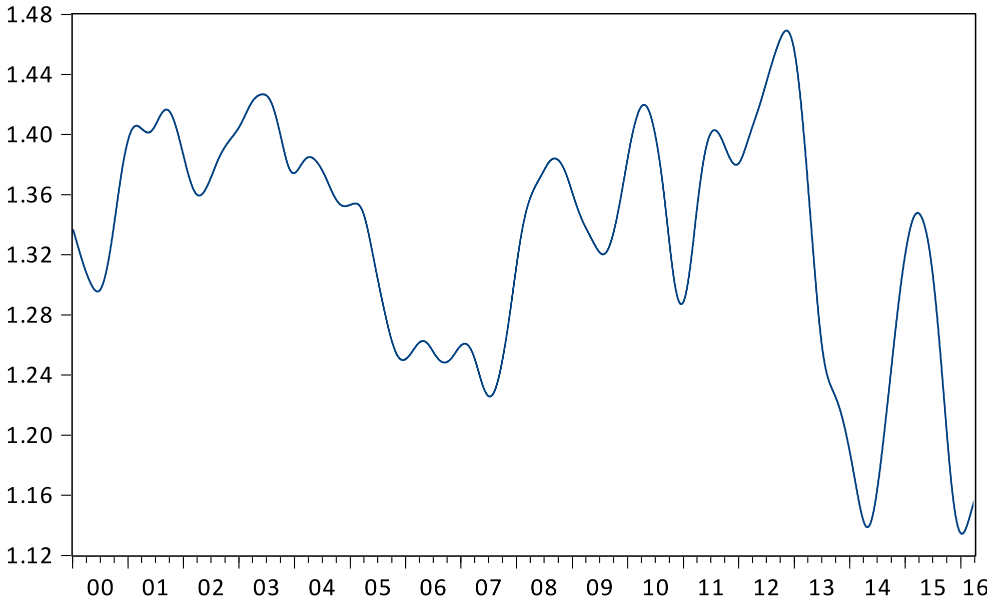
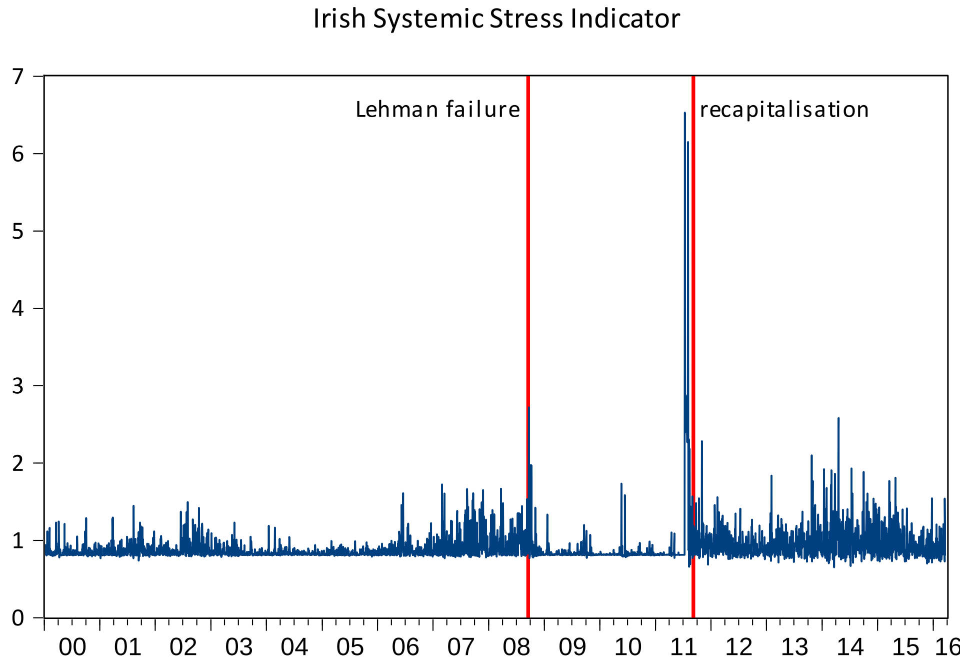


Figure 7


Irish Systemic Stress Indicator
Lehman failure
recapitalisation
7
6
5
4
3
2
1
0
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

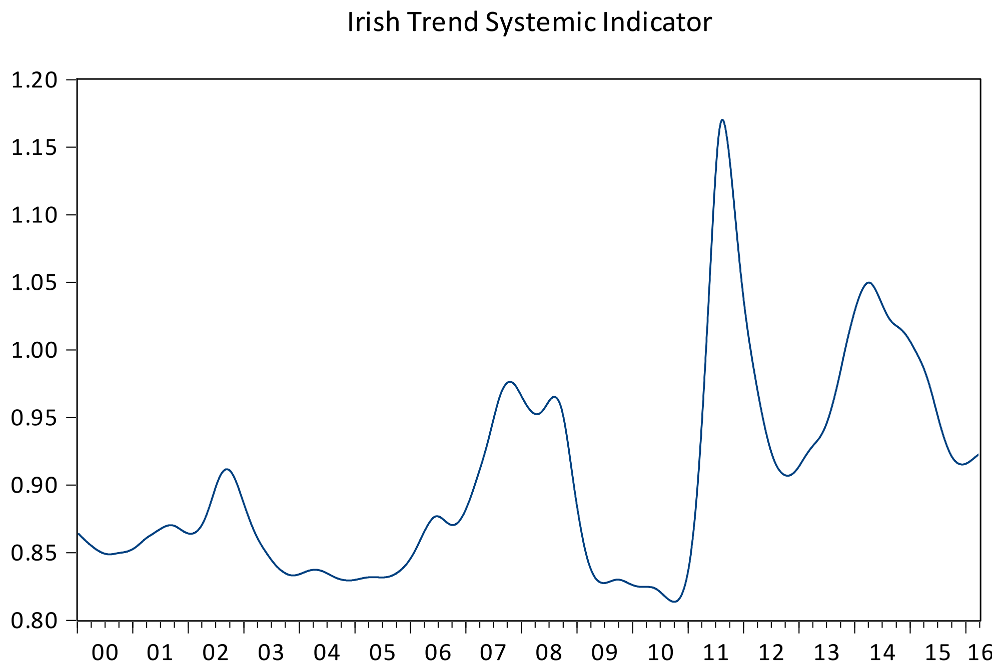
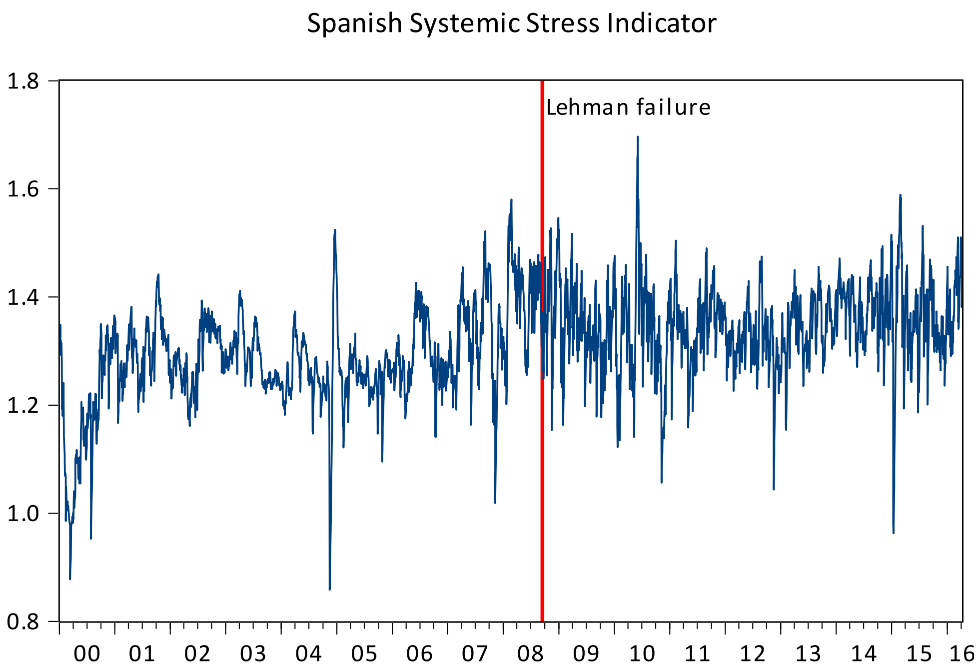

Irish Trend Systemic Indicator
1.20
1.15
1.10
1.05
1.00
0.95
0.90
0.85
0.80
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

Figure 8


Spanish Systemic Stress Indicator
1.8
1.6
1.4
1.2
1.0
0.8
Lehman failure
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

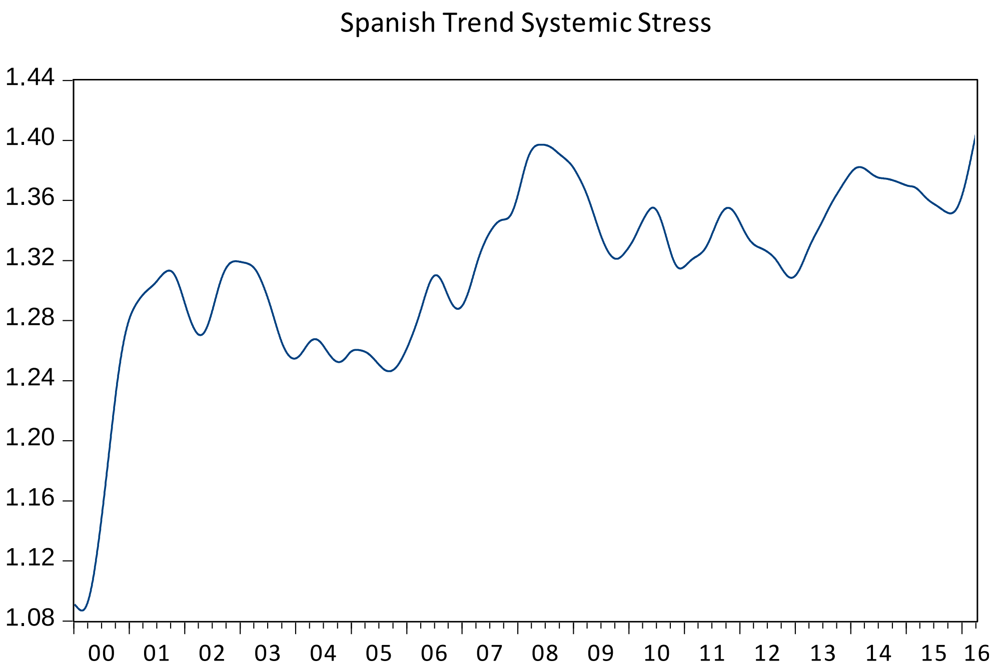
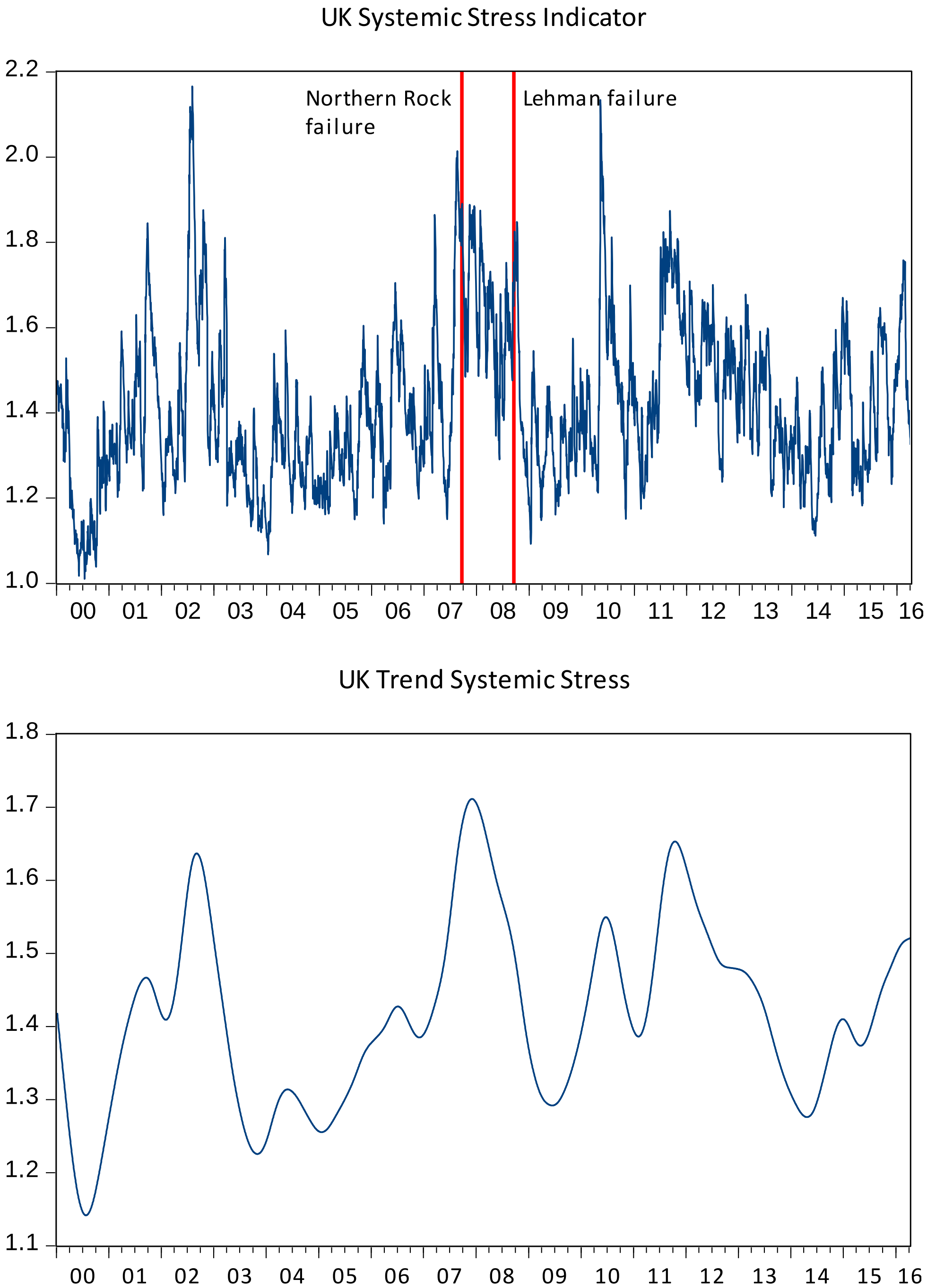

Spanish Trend Systemic Stress
1.44
1.40
1.36
1.32
1.28
1.24
1.20
1.16
1.12
1.08
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

Figure 9


UK Systemic Stress Indicator
Northern Rock failure
Lehman failure
2.2
2.0
1.8
1.6
1.4
1.2
1.0
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16
UK Trend Systemic Stress
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16