

The simple econometrics of tail
dependence

The simple econometrics of tail dependence

Maarten R.C. van Oordt and Chen Zhou*

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 296

May 2011

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

The simple econometrics of tail dependence

Maarten R.C. van Oordt^{*†}

De Nederlandsche Bank

Chen Zhou^{*‡}

De Nederlandsche Bank and Erasmus University Rotterdam

May 6, 2011

Abstract The aim of this paper is to show that measures on tail dependence can be estimated in a convenient way by regression analysis. This yields the same estimates as the non-parametric method within the multivariate Extreme Value Theory framework. The advantage of the regression approach is contained by its straightforward extension to the estimation of higher dimensional tail dependence. We provide an example on international stock markets. The regression approach to tail dependence can be applied to estimate several measures of systemic importance of financial institutions in the literature.

Keywords: Tail dependence, Regression analysis, Extreme Value Theory, Systemic risk.

JEL Classification Numbers: C14, C58.

^{*}Postal address: Economics and Research Division, De Nederlandsche Bank, 1000AB Amsterdam, The Netherlands. Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

[†]Email: M.R.C.vanOordt@DNB.nl

[‡]Email: C.Zhou@DNB.nl, zhou@ese.eur.nl

1 Introduction

Tail dependence refers to the dependence among extreme events. This dependence structure is not necessarily similar to the tail dependence structure among ordinary observations. A fascinating example is observed in financial markets: the dependence among asset returns increases during volatile periods, and especially during strong market downturns, see Longin and Solnik (1995, 2001), Ang and Chen (2002), Ang and Bekaert (2002) among others.

The major difficulty of measuring tail dependence is the scarcity of observations on extreme events. The developments in multivariate Extreme Value Theory (EVT) allow assessing the tail dependence structure based on observations close to the tail. For example, in the applications by Poon et al. (2004) and Hartmann et al. (2004), measuring tail dependence reveals which stock market pairs are likely to crash jointly or which are likely to exhibit *flight-to-quality* phenomenons.

One often applied measure on tail dependence is the τ -measure, see e.g. Straetmans et al. (2008), De Jonghe (2010), Pais and Stork (2010) and Beine et al. (2010).¹ The pairwise τ -measure compares the probability of a joint tail event to that of a tail event of one variable, where ‘tail events’ occur only with very low probability. Formally, the τ -measure for the pairwise dependence between the left tails of two random variables x and y is given by

$$\tau_{y|x} = \lim_{p \rightarrow 0} \frac{\Pr(y < Q_y(p) \text{ and } x < Q_x(p))}{p} = \lim_{p \rightarrow 0} \Pr(y < Q_y(p) | x < Q_x(p)),$$

where $Q_y(p)$ denotes the quantile of the distribution of y at probability level p .² Although the notation $\tau_{y|x}$ can be read as the conditional probability of a tail event of y given the occurrence of a tail event of x , it does not necessarily imply any causality. Similar to correlation, the τ -measure ranges from 0 to 1 indicating the level of tail dependence. The

¹Some studies report manipulations of τ : Hartmann et al. (2004, 2010) and De Vries (2005) report $2/(2 - \tau)$; Garita and Zhou (2009) report $\tau/(2 - \tau)$.

²The definition of τ is sufficiently flexible to define tail dependence among all tail pairs, i.e. to vary among the left and right tails. In addition, several studies choose to replace $Q_y(p)$ and $Q_x(p)$ in the definition of τ by a sufficiently low threshold $-u$. The regression approach can deal with both definitions of τ .

case $\tau_{y|x} = 0$ corresponds to tail independence, while the case $\tau_{y|x} = 1$ corresponds to complete tail dependence.

Under the multivariate EVT framework, the τ -measure can be estimated non-parametrically, see e.g. Embrechts et al. (2000). Our paper provides a simple ordinary least squares (OLS) regression approach to estimate τ . Our estimator exactly coincides with the non-parametric estimator. Because pairwise tail dependence is only a projection of the multidimensional tail dependence structure, it is crucial to have an accessible instrument to investigate multidimensional tail dependence. The advantage of our regression approach is contained by the straightforward extension of analyzing tail dependence to higher dimensional levels. We provide an empirical example on multidimensional tail dependence among international stock markets. Finally, we report how the regression approach can be applied to estimate the measures of systemic importance in the banking system developed in various papers: the Probability of Cascade Effects (PCE) in Segoviano and Goodhart (2009) and the Systemic Impact Index (SII) in Zhou (2010).

2 Indicator regression

The non-parametric estimator of the $\tau_{y|x}$ -measure is calculated as the ratio between the number of observations in which both x and y are extreme and those in which variable x is extreme. Here being *extreme* is defined as having a value below the k -th lowest observation in the sample, given a sufficiently low k , see Embrechts et al. (2000). With observations x_t and y_t for $t = 1, 2, \dots, n$, the non-parametric estimator of $\tau_{y|x}$ is given by

$$\hat{\tau}_{y|x} = \frac{\sum_{t=1}^n I_{y \text{ and } x,t}}{\sum_{t=1}^n I_{x,t}},$$

where $I_{y \text{ and } x,t} = \mathbf{1}(y_t < Q_y(k/n) \text{ and } x_t < Q_x(k/n))$ and $I_{x,t} = \mathbf{1}(x_t < Q_x(k/n))$ with $\mathbf{1}(\cdot)$ denoting the indicator function, and where the quantile function $Q(k/n)$ is usually estimated by the k -th lowest observation. With a similar notation for $I_{y,t}$, we have $I_{y \text{ and } x,t} = I_{y,t}I_{x,t}$,

and rewrite the estimator $\hat{\tau}_{y|x}$ as

$$\hat{\tau}_{y|x} = \frac{\sum_{t=1}^n I_{y,t} I_{x,t}}{\sum_{t=1}^n I_{x,t} I_{x,t}}.$$

Hence, the non-parametric estimator is computationally equivalent to the OLS estimate of the slope coefficient when the indicator for extreme values of y is regressed on the indicator for extreme values of x without intercept. In other words, the OLS estimate of β in the regression

$$I_{y,t} = \beta \times I_{x,t} + \varepsilon_t$$

equals to the non-parametric estimate $\hat{\tau}_{y|x}$.³

Studies in the literature focus on pairwise tail dependence only. However, this is in general not sufficient to reproduce the higher dimensional tail dependence structure. For example, consider a three-dimensional case with random variables y , x_1 and x_2 with all pairwise τ -measures equal to $1/2$, i.e. $\tau_{y|x_1} = \tau_{y|x_2} = \tau_{x_2|x_1} = 1/2$.⁴ Several potential tri-variate dependence structures can lead to such pairwise τ -measures. One possibility is that y is extreme if and only if x_1 and x_2 are both extreme. Another one is that y is extreme if and only if one of x_1 and x_2 is extreme. The two tri-variate dependence structures are very different, and so are their economic consequences. Hence, it is necessary to have an instrument to investigate multidimensional tail dependence.

The indicator regression can be extended to multidimensional analysis. To analyze the tail dependence among random variable y and multiple random variables x_1, \dots, x_m , one should include all possible interactions among the indicators $I_{x_i,t}$ in the indicator regression. The regression then gives a complete figure on tail dependence in the multidimensional case. To illustrate this idea we consider the three-dimensional dependence structure between

³We remark that the usual standard errors of the OLS regression are meaningless. Correct standard errors for $\hat{\tau}$ can be obtained by using a (block) bootstrap. To obtain the standard errors reported in Table 1, we followed Hartmann et al. (2010) and set the optimal block length equal to $n^{1/3}$.

⁴This example is close to the findings of Poon et al. (2004) on pairwise tail dependence among the stock markets of UK, Germany and France.

variable y and variables x and z by estimating the following indicator regression:

$$I_{y,t} = \beta_x I_{x,t} + \beta_z I_{z,t} + \beta_{x,z} I_{x,t} I_{z,t} + \varepsilon_t.$$

Similar to the pairwise case, the interpretation of the multidimensional tail dependence structure follows the interpretation of a usual regression. That is, to get the non-parametric estimate of the conditional probability of y being extreme given a certain scenario on x and z , one has to calculate the predicted expectation of the left hand side indicator given the value of the right hand side indicators under the scenario. A proof is given in the Appendix. For example, for the scenario in which x is extreme and z is not extreme, the conditional probability that y is extreme, $\hat{\tau}_{y|x,\bar{z}}$, equals to $\hat{\beta}_x \cdot 1 + \hat{\beta}_z \cdot 0 + \hat{\beta}_{x,z} \cdot 1 \cdot 0 = \hat{\beta}_x$.⁵ Similarly, the estimate of the probability that y is extreme, conditional on both x and z being extreme, $\hat{\tau}_{y|x,z}$, is given by $\hat{\beta}_x + \hat{\beta}_z + \hat{\beta}_{x,z}$.

The indicator regression in high dimensional cases may involve a large number of higher dimensional interactions. The estimation of a full tail dependence structure suffers from a dimensional curse: with scenarios defined on m variables, $2^m - 1$ parameters must be estimated. Nevertheless, both complete tail dependence and tail independence among regressors provide potential relief to this dimensional curse. First, if two regressors are recognized as completely tail dependent, then the individual regressors can be left out. For instance, suppose that in the three-dimensional example, x and z are completely tail dependent. Then a perfect collinearity problem will occur in the indicator regression, since we have $I_{x,t} = I_{z,t} = I_{x,t} I_{z,t}$. Because the scenario in which only one of x and z is extreme has probability zero, the only meaningful model is to regress $I_{y,t}$ on $I_{x,t} I_{z,t}$. The indicator regression coefficient gives the estimate of $\tau_{y|x,z}$. Second, if two regressors are recognized as tail independent, then the interaction of the two is by definition zero. In this case all interaction terms that include the two regressors can be omitted from the indicator regression. To summarize, identifying

⁵The absence (presence) of the bar on the subscript of $\hat{\tau}$ denotes a scenario with a particular variable being (not) extreme.

completely tail dependent or tail independent regressors before performing the full indicator regression provides relief to the dimensional curse problem.

3 Tail dependence among stock markets

We provide an empirical example of the indicator regression at work by extending some of the pairwise results from Poon et al. (2004) to the multidimensional case.⁶ Poon et al. (2004) estimate the pairwise tail dependence among major stock indices. We replicate their pairwise results on the tail dependence between the U.K. stock market and those of France, Germany and the U.S. with the indicator regression, which gives

$$\hat{\tau}_{UK|US} = 0.29 \quad , \quad \hat{\tau}_{UK|GE} = 0.46 \quad \text{and} \quad \hat{\tau}_{UK|FR} = 0.43.$$

The results on pairwise tail dependence suggest that the U.K. market suffers the least co-crashes with the U.S. stock market, while its tail dependence with the German and French stock market appears to be on a comparable level.

Subsequently, we estimate the full tail dependence structure among the four countries by an indicator regression that includes all possible interactions, which gives

$$\begin{aligned} I_{UK,t} \approx & 0.11 \cdot I_{US,t} + 0.19 \cdot I_{GE,t} + 0.20 \cdot I_{FR,t} + 0.25 \cdot I_{US,t}I_{GE,t} + \\ & -0.06 \cdot I_{US,t}I_{FR,t} + 0.13 \cdot I_{GE,t}I_{FR,t} + 0.18 \cdot I_{US,t}I_{GE,t}I_{FR,t}. \end{aligned}$$

In Table 1 we calculate the conditional probabilities τ for all possible scenarios from the regression coefficients as discussed in Section 2.

⁶The stock market indices are S&P500 for the U.S., FTSE100 for the U.K., DAX30 for Germany and CAC40 for France. Our analysis regards the results on unfiltered data in the third subperiod: from November 28, 1990 to November 12, 2001. The total sample size is $n = 2,859$. With an exception for $\tau_{UK|FR}$ our pairwise estimates equal those in Poon et al. (2004), Table 3. This is due to the different choice of k . To report estimates that are comparable to the multidimensional analysis, we choose a common $k = 87$ for all market pairs.

- TABLE 1 HERE -

Three results follow from the multidimensional analysis. First, considering the scenario in which *only one particular* market suffers an extreme loss, then the U.K. market has the weakest link with the U.S. market, while those with the German and French market are comparable. This result matches the results from the pairwise analysis.

Second, given an extreme loss in the U.S. market, the link of the U.K. market with the German market is stronger than the link with the French market. Hence, from the multidimensional analysis we observe a distinction between the French and German market that does not appear from the pairwise analysis.

Third, we observe that the U.K. market is expected to suffer an extreme loss with almost certainty, if the other three markets are observed to suffer an extreme loss. In contrast to the moderate levels of pairwise tail dependence, the multidimensional analysis reveals a strong linkage among the four markets.

4 Systemic importance of financial institutions

With the failure of the investment bank Lehman Brothers in 2008, the financial system in the US and the EU came close to a complete meltdown. This phenomenon falls in line with the discussion on "tail dependence": crashes of financial institutions are likely to happen simultaneously. Financial institutions that are more likely to co-crash with other institutions within the financial system are sometimes considered as more systemically important. For policymakers, measuring the systemic importance of financial institutions turns to be the key issue in both financial stability assessment and macro-prudential supervision. Recent studies propose a few measures on the systemic importance. For example, Segoviano and Goodhart (2009) propose the Probability of Cascade Effects (PCE), which measures the probability

of having at least one other bank crash given the crash of one specific bank. Zhou (2010) proposes the Systemic Impact Index (SII), which measures the expected number of crashes within the financial system given the crash of one specific bank. We demonstrate that these two systemic importance measures can be estimated with the indicator regression method.

Consider a financial system consisting of d financial institutions, with variables $x_{1,t}, \dots, x_{d,t}$ indicating their statuses in period t . An extremely low value in x_i indicates that bank i is distressed. Examples of such status variables are given by the returns on bank i 's equity or by the returns on providing insurance on bank i 's debt, as reflected by the changes in the price of credit default swaps (CDS). In correspondence with the foregoing, we use $I_{i,t}$ to indicate whether bank i is in distress at period t , i.e. $I_{i,t} = 1(x_{i,t} < Q_i(p))$.

We start with the PCE measure in Segoviano and Goodhart (2009). Segoviano and Goodhart (2009) apply the CIMDO copula approach to estimate the PCE measure, while Zhou (2010) provides a non-parametric estimate of the PCE measure. We show how to apply the indicator regression to produce the non-parametric estimate. It is obvious that the event "having at least one other bank crash" can be indicated by the indicator $I_{\neq i,t} = \max_{j \neq i} I_{j,t}$. Similar to the estimation of τ , one can estimate the OLS regression

$$I_{\neq i,t} = PCE_i \cdot I_{i,t} + \varepsilon_t,$$

to obtain the estimate of the PCE measure for bank i . It is straightforward to see that such an estimate is exactly equal to the non-parametric estimate of the PCE measure.

Next, we discuss the SII measure in Zhou (2010). The non-parametric estimate of the SII measure for bank i equals to the sum of the estimates on $\tau_{j|i}$ which is the τ measure between bank i and any bank j , $j = 1, 2, \dots, d$. From the indicator regression, $\tau_{j|i}$ can be estimated by the OLS regression

$$I_{j,t} = \tau_{j|i} I_{i,t} + \varepsilon_t.$$

By aggregating the regressions, we get that performing a single OLS regression

$$\sum_{j=1}^d I_{j,t} = SII_i \cdot I_{i,t} + \varepsilon_t$$

leads to the non-parametric estimate of the SII measure for bank i . Notice that this is beyond the aforementioned concept of "indicator regressions", because the dependent variable is not an indicator, but a measure for the status of the system.

5 Concluding remark

Because the tail dependence measure is a regression coefficient in an indicator regression, it is possible to incorporate other covariates. De Jonghe (2010) investigates the determinants of the τ -measure between bank equity returns and a banking index by regressing the estimated τ -measure on bank level characteristics. Such a two-step approach may result in a loss of efficiency. Differently, it is possible to combine the indicator regression with the cross-sectional model to construct a one-step approach. Similarly, such a one-step approach can be applied to investigate bank level characteristics of the other systemic importance measures we discussed. This is left for future research.

References

- A. Ang and G. Bekaert. International Asset Allocation With Regime Shifts. *Review of Financial Studies*, 15(4):1137–1187, 2002.
- A. Ang and J. Chen. Asymmetric correlations of equity portfolios. *Journal of Financial Economics*, 63(3):443–494, 2002.
- M. Beine, A. Cosma, and R. Vermeulen. The dark side of global integration: Increasing tail dependence. *Journal of Banking & Finance*, 34(1):184–192, 2010.
- O. De Jonghe. Back to the basics in banking? A micro-analysis of banking system stability. *Journal of Financial Intermediation*, 19(3):387–417, 2010.
- C.G. De Vries. The simple economics of bank fragility. *Journal of Banking & Finance*, 29(4):803–825, 2005.
- P. Embrechts, L. de Haan, and X. Huang. Modelling multivariate extremes. In *Extremes and integrated risk management*, pages 59–67. Risk Waters Group, 2000.
- G. Garita and C. Zhou. Can Open Capital Markets Help Avoid Currency Crises? *DNB Working Papers*, 205, 2009.
- P. Hartmann, S. Straetmans, and C.G. de Vries. Asset Market Linkages in Crisis Periods. *Review of Economics and Statistics*, 86:313–326, 2004.
- P. Hartmann, S. Straetmans, and C.G. de Vries. Heavy tails and currency crises. *Journal of Empirical Finance*, 17(2):241–254, 2010.
- F. Longin and B. Solnik. Is the correlation in international equity returns constant: 1960–1990? *Journal of International Money and Finance*, 14(1):3–26, 1995.
- F. Longin and B. Solnik. Extreme correlation of international equity markets. *Journal of Finance*, 56(2):649–676, 2001.

- A. Pais and P.A. Stork. Contagion risk in the Australian banking and property sectors. *Journal of Banking & Finance*, 35(3):681–697, 2010.
- S.H. Poon, M. Rockinger, and J.A. Tawn. Extreme value dependence in financial markets: Diagnostics, models, and financial implications. *Review of Financial Studies*, 17(2):581–610, 2004.
- M.A. Segoviano and C.A.E. Goodhart. Banking Stability Measures. *IMF Working Papers*, 2009.
- S. Straetmans, W.F.C. Verschoor, and C.C.P. Wolff. Extreme US stock market fluctuations in the wake of 9/11. *Journal of Applied Econometrics*, 23(1):17–42, 2008.
- C. Zhou. Are banks too big to fail? Measuring systemic importance of financial institutions. *International Journal of Central Banking*, 6(4):205–250, 2010.

6 Appendix: Proofs

Define $N_x = \sum I_{x,t}$, $N_{x,z} = \sum I_{x,t}I_{z,t}$, etc, where the sum is over all t . Then the non-parametric estimate that y is extreme, conditional on x and/or z being extreme, is given by

$$\hat{\tau}_{y|x,\bar{z}} = \frac{N_{y,x} - N_{y,x,z}}{N_x - N_{x,z}}, \quad \hat{\tau}_{y|\bar{x},z} = \frac{N_{y,z} - N_{y,x,z}}{N_z - N_{x,z}} \quad \text{and} \quad \hat{\tau}_{y|x,z} = \frac{N_{y,x,z}}{N_{x,z}}.$$

We prove that OLS estimates from

$$I_{y,t} = \beta_x I_{x,t} + \beta_z I_{z,t} + \beta_{x,z} I_{x,t} I_{z,t} + \varepsilon_t$$

leads to the non-parametric estimators as $\hat{\tau}_{y|x,\bar{z}} = \hat{\beta}_x$, $\hat{\tau}_{y|\bar{x},z} = \hat{\beta}_z$ and $\hat{\tau}_{y|x,z} = \hat{\beta}_x + \hat{\beta}_z + \hat{\beta}_{x,z}$.

Proof. Write $\mathbf{Y} = \begin{pmatrix} I_{y,1} \\ \vdots \\ I_{y,n} \end{pmatrix}$ and $\mathbf{X} = \begin{pmatrix} I_{x,1} & I_{z,1} & I_{x,1}I_{z,1} \\ \vdots & \vdots & \vdots \\ I_{x,n} & I_{z,n} & I_{x,n}I_{z,n} \end{pmatrix}$. Then the vector $\beta = (\beta_x, \beta_z, \beta_{x,z})'$ is estimated by $\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$. We start with calculating $(\mathbf{X}'\mathbf{X})^{-1}$:

$$\mathbf{X}'\mathbf{X} = \begin{pmatrix} N_x & N_{x,z} & N_{x,z} \\ N_{x,z} & N_z & N_{x,z} \\ N_{x,z} & N_{x,z} & N_{x,z} \end{pmatrix}.$$

The inverted matrix $(\mathbf{X}'\mathbf{X})^{-1}$ is

$$\frac{1}{N_{x,z}(N_x - N_{x,z})(N_z - N_{x,z})} \begin{pmatrix} N_{x,z}(N_z - N_{x,z}) & 0 & -N_{x,z}(N_z - N_{x,z}) \\ 0 & N_{x,z}(N_x - N_{x,z}) & -N_{x,z}(N_x - N_{x,z}) \\ -N_{x,z}(N_z - N_{x,z}) & -N_{x,z}(N_x - N_{x,z}) & N_x N_z - (N_{x,z})^2 \end{pmatrix}.$$

Multiplying $(\mathbf{X}'\mathbf{X})^{-1}$ with

$$\mathbf{X}'\mathbf{Y} = \begin{pmatrix} N_{y,x} & N_{y,z} & N_{y,x,z} \end{pmatrix}'$$

gives the estimates:

$$\hat{\beta} = \begin{pmatrix} \frac{N_{y,x} - N_{y,x,z}}{N_x - N_{x,z}} \\ \frac{N_{y,z} - N_{y,x,z}}{N_z - N_{x,z}} \\ \frac{N_{y,x,z}}{N_{x,z}} - \frac{N_{y,x} - N_{y,x,z}}{N_x - N_{x,z}} - \frac{N_{y,z} - N_{y,x,z}}{N_z - N_{x,z}} \end{pmatrix} = \begin{pmatrix} \hat{T}_{y|x,\bar{z}} \\ \hat{T}_{y|\bar{x},z} \\ \hat{T}_{y|x,z} - \hat{T}_{y|x,\bar{z}} - \hat{T}_{y|\bar{x},z} \end{pmatrix}.$$

■

In the proof we do not assume a common number of tail observations k . This justifies the remark in footnote 2.

Table 1: Tail dependence among the U.K. and other major equity markets

Regression	Coefficient	Tail dependence	Probability (s.e)
$\hat{\beta}_{US}$	0.105	$\hat{\tau}_{UK US,\overline{GE},\overline{FR}}$	0.105 (0.041)
$\hat{\beta}_{GE}$	0.188	$\hat{\tau}_{UK \overline{US},GE,\overline{FR}}$	0.188 (0.078)
$\hat{\beta}_{FR}$	0.200	$\hat{\tau}_{UK \overline{US},\overline{GE},FR}$	0.200 (0.090)
$\hat{\beta}_{US,GE}$	0.253	$\hat{\tau}_{UK US,GE,\overline{FR}}$	0.545 (0.221)
$\hat{\beta}_{US,FR}$	-0.055	$\hat{\tau}_{UK US,\overline{GE},FR}$	0.250 (0.196)
$\hat{\beta}_{GE,FR}$	0.128	$\hat{\tau}_{UK \overline{US},GE,FR}$	0.515 (0.096)
$\hat{\beta}_{US,GE,FR}$	0.182	$\hat{\tau}_{UK US,GE,FR}$	1.000 (0.110)

Note: The estimates are obtained from an indicator regression based on U.K. stock market returns and U.S., German and French stock market returns. Each returns series runs from November 28, 1990 until November 12, 2001, containing 2,859 daily observations. We choose k at 87. The first column presents the regression coefficients. The second column presents the conditional probabilities of observing an extreme loss in the U.K. market conditional on a scenario in the other three markets. The absence of the bar in the conditioning scenario in the subscript of $\hat{\tau}$ denotes an extreme loss in that particular market.

Previous DNB Working Papers in 2011

- No. 276 **Ronald Heijmans, Richard Heuver and Daniëlle Walraven**, Monitoring the unsecured interbank money market using TARGET2 data
- No. 277 **Jakob Bosma**, Communicating Bailout Policy and Risk Taking in the Banking Industry
- No. 278 **Jakob de Haan and Fabian Amtenbrink**, Credit Rating Agencies
- No. 279 **Ralph de Haas and Neeltje van Horen**, Running for the Exit: International Banks and Crisis Transmission
- No. 280 **I Kadek Dian Sutrisna Artha and Jakob de Haan**, Labor Market Flexibility and the Impact of the Financial Crisis
- No. 281 **Maarten van Oordt and Chen Zhou**, Systematic risk under extremely adverse market conditions
- No. 282 **Jakob de Haan and Tigran Poghosyan**, Bank Size, Market Concentration, and Bank Earnings Volatility in the US
- No. 283 **Gabriele Galati, Peter Heemeijer and Richhild Moessner**, How do inflation expectations form? New insights from a high-frequency survey
- No. 284 **Jan Willem van den End**, Statistical evidence on the mean reversion of interest rates
- No. 285 **Marco Hoeberichts and Ad Stokman**, Price dispersion in Europe: Does the business cycle matter?
- No. 286 **Cai Cai Du, Joan Muysken and Olaf Sleijpen**, Economy wide risk diversification in a three-pillar pension system
- No. 287 **Theoharry Grammatikos and Robert Vermeulen**, Transmission of the Financial and Sovereign Debt Crises to the EMU: Stock Prices, CDS Spreads and Exchange Rates
- No. 288 **Gabriele Galati, Federica Teppa and Rob Alessi**, Macro and micro drivers of house Price dynamics: An application to Dutch data
- No. 289 **Rob Alessie, Maarten van Rooij and Annamaria Lusardi**, Financial Literacy, Retirement Preparation and Pension Expectations in the Netherlands.
- No. 290 **Mara Demertzis**, Public versus Private Information
- No. 291 **Enrico C. Perotti and Javier Suarez**, A Pigovian Approach to Liquidity Regulation
- No. 292 **Jan Willem Slingenberg and Jakob de Haan**, Forecasting Financial Stress
- No. 293 **Leo de Haan and Jan Willem van den Ende**, Banks' responses to funding liquidity shocks: lending adjustment, liquidity hoarding and fire sales
- No. 294 **Janko Gorter and Jacob A. Bikker**, Investment risk taking by institutional investors
- No. 295 **Eric J. Bartelsman, Pieter A. Gautier, and Joris de Wind**, Employment Protection, Technology Choice, and Worker Allocation

