Linking economic shocks and financial vulnerability in Kazakhstan: A portfolio model as a stress testing tool.

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Abstract

In this paper, we develop a two-stage approach which integrates a macro perspective of the economy with the micro-perspective of each individual bank. We apply this tool to the banking system of the Republic of Kazakhstan. In the first stage, we identify the main risk drivers for production growth. These are the sudden drop in the global oil price and the devaluation of the domestic currency. In the second stage, we link the downturn in production to the multifactor portfolio model and simulate the expected losses for each individual bank. Under the scenario, where oil price declines by 35% and the tenge depreciates simultaneously by 30%, 58% of the considered banks would not be able to meet the regulatory capital requirement. We conduct this exercise using a unique and confidential data set, including asset quality measures for different business sectors of the economy of Kazakhstan.

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1 Introduction

Theoretical work on stress testing methodologies, in particular for credit risk, has progressed substantially over the last decade. A recent survey by the Basel Committee on Banking Supervision has confirmed that stress testing has become a key component of the supervisory assessment process as well as a tool for contingency planning and communication. This survey uncovered, however, also wide differences in the sophistication of supervisory stress tests across countries. Nearly half of the participating 28 countries were found to be at an early stage.[1]

In this context our paper provides a feasible stress test methodology geared towards economies in transition which balances the use of an advanced methodology with specificities, particularly data restrictions, typical in such situations. We develop a two-stage approach which integrates a macro-perspective of the economy with the micro-perspective of individual banks and apply our approach to the banking system of the Republic of Kazakhstan. We see the following three aspects as the main contributions of our paper. First, we provide a robust and at the same time very flexible portfolio stress testing tool, which has only parsimonious data requirements. Therefore, the tool can easily be adapted to the data typically available to supervisory authorities and to quantify macroeconomic risk in terms of expected losses for each individual bank. Second, we present a unique and confidential data set for the banking system in Kazakhstan including asset quality measures such as non-performing loans for different business sectors. Finally, the results and the insights from our paper are useful for the risk management of banks in Kazakhstan, the Financial Supervisory Authority (FSA) and the National Bank of the Republic of Kazakhstan (NBRK). Moreover, this paper offers insights which could be useful to the IMF in the context of the implementation of the Financial Sector Assessment Program (FSAP) in transition countries such as Kazakhstan.[2] Furthermore, other transition coun-

[1] See BCBS (2012) Peer review of supervisory authorities' implementation of stress testing principles, April 2012, http://www.bis.org/publ/bcbs218.htm.

[2] An overview of stress testing methodologies used by the IMF within the FSAP missions is given by Moretti, Stolz, and Swinburne (2008).

tries with less developed banking systems could apply this tool by identifying the relevant macroeconomic shocks for their economy and transferring them to the portfolio model.

From a more general perspective, we contribute to the literature on macro stress testing using value-at-risk frameworks based on Merton (1974). Even though the link between credit risk and macroeconomic developments seems obvious, only few credit risk models have an explicit mechanism relating the default probabilities of credit exposures to the relevant macroeconomic factors. Drehmann and Manning (2004) and Pesaran, Schuermann, Teutler, and Weiner (2004) study the relationship between firm default probabilities and macroeconomic fundamentals for stress testing purposes. While Drehmann and Manning (2004) analyze shocks in systematic factors for the UK, Pesaran et al. (2004) estimate a global vector autoregressive model that captures the inter-dependence between business cycles across countries.[3] Our paper offers an application for the model which has been successfully implemented at the Deutsche Bundesbank (see Duellmann and Erdelmeier (2009) and Duellmann and Kick (2012)). Duellmann and Erdelmeier (2009) stress test large German banks by conditioning their portfolios on a downturn of the automobile sector. Duellmann and Kick (2012) include a macroeconomic model to estimate a global cost-of-capital shock (an immediate increase of firms' capital expenses) for German export-dependent production sectors. The flexibility of the model is underlined by the successful adaption of the portfolio model to the macroeconomic environment and the specifics of the banking system of Kazakhstan. This property is a precondition for a useful risk management instrument in a changing macroeconomic environment.

For macroeconomic stress testing, a crucial step is the identification of relevant macroeconomic risks which could have a negative impact on the payment ability and thus on the solvency of firms located in the country concerned. As Kazakhstan is highly dependent on exports of oil and metals (their respective shares in all exported goods are 35% and 33%; the share of exported ores is 12%), the development of global commodity prices is an important risk factor. Another important risk factor is the exchange rate of the domestic

[3]Sorge and Virolainen (2006) provide a comprehensive overview of macro stress-testing methodologies using Merton-type models with application to Finland, pp. 123-135.

currency. After external shocks hit Russia, the top trading partner of Kazakhstan, the NBRK devalued the tenge (national currency of Kazakhstan) substantially in 1998 and 2009 in order to protect the domestic economy. Irrespective of a possible positive net impact of the currency devaluation in the long term, in the short run the constellation of the adverse developments of the two risk factors, the oil price and the exchange rate, are likely to adversely impact on the economy and subsequently the quality of assets in banks' balance sheets.[4]

Under such a scenario, the value of exports falls because of the decreasing global commodity prices; the currency depreciation could stimulate exports but at the same time the imported goods become relatively more expensive, leading to a decrease in domestic demand. As a result, domestic production could decline overall, and lead to delays in loan redemptions. In the worst case, some firms would become unable to repay their loans. The financial sector would consequently realize losses which could ultimately cause some banks to face difficulties in meeting regulatory capital requirements and finally them to become insolvent. This chain of events could have further negative repercussions on the real economy when affected banks reduce credit supply, thus further aggravating the economic downturn.

In this paper, we in the first stage simulate a decline in the oil price of 35% and a depreciation of the domestic currency of 30% and quantify the adverse impact on the economic growth in six major business sectors in Kazakhstan within the framework of the vector autoregression model with exogenous variables (VARX). In the second stage, we link the economic downturn in the affected sectors to the banking system and quantify losses under stress for the majority of the Kazakh banking system. The adverse impact on the banking system is captured by a multifactor credit risk model. In order to assess the

[4]See Podlich, Illyasov, Tsoy, and Shaikh (2010) for an evaluation of the impact of currency devaluation on banks' balance sheet. The authors describe the results of a project which developed a "bottom-up" stress testing tool for Kazakhstan. The project consisted, inter alia, a survey among banks. Banks received a questionnaire including three different stress scenarios: deposit outflow, drop in real estate prices and tenge devaluation. Eight banks, which represent 53% of the whole banking system, assessed a currency devaluation of 20% as dangerous and indicated that overdue repayment and non-performing loan ratios would rise by 124.22% and 84% respectively; profitability measures would shrink by more than 100%.

predicted stress on the stability of the banking system, we analyze the minimum capital requirement for banks.

Our findings from the macro model suggest that the devaluation of the domestic currency has an adverse impact on the Kazakh real economy. As expected, the global oil price has a significant and positive impact on the commodity exporting sector. Moreover, the oil price seems to be an indicator for the common wealth in Kazakhstan. More importantly, the decline in the affected production sectors predicted in the framework of the VARX model - if transferred to the portfolio model - causes a significant increase in the portfolio losses of banks. More specifically, if a loss rate (LGD) of 50% is assumed, 6 banks out of 23 banks (covering 58% of the sample) would be in trouble. In the absolute worst case scenario, when LGD is assumed to be 100%, 88% (or 12 banks) of the considered banks would not be able to meet the regulatory requirements for the capital adequacy ratio. All in all, we receive plausible results from the macro-model and could show that a substantial part of the banking system would significantly be affected by the assumed stress scenario.[5]

The paper is structured as follows: first we introduce the portfolio model, and in the subsequent section we derive the different possibilities for stress testing design. Section 4 includes all the empirical results from the stress testing approach, starting with the description of the data and ending with sensitivity checks of the results. In the final section, we summarize the results and provide some concluding thoughts and remarks for further research.

2 Portfolio Model

The pivotal part of our stress testing framework is based on a commonly used multifactor credit risk model. We model portfolio losses for each individual bank, assuming that the bank's portfolio consists of assets with respect to the distribution across sectors. Here,

[5]We were able to calculate the expected losses for 26 banks which cover ca. 98% of the Kazakh banking system. Due to data constraints, the impact of expected losses on regulatory capital ratio could only be calculated for 23 banks, which approximately cover 95% of the Kazakh banking system.

we consider one-year time period and two different states of the default-trigger variable - default and nondefault - at the end of the period. Corresponding to the classic Merton model, an obligor defaults if the default trigger falls below an exogenously determined default barrier. In order to ease notation we require that all borrowers can be uniquely assigned to individual business sector and that every borrower has only one loan outstanding.

Let N denote the total number of borrowers or loans in a bank's portfolio, S the total number of business sectors and s: $\{1, ..., N\} \to \{1, ..., S\}$ a mapping which assigns every borrower or loan to its specific sector. In this case the unobservable, normalized asset return Y_i of borrower i in sector $s(i)$ for $i \in 1, ..., N$ is given by the following function:

$$Y_i = \theta_{s(i)} \cdot X_{s(i)} + \sqrt{1 - \theta_{s(i)}^2} \cdot \zeta_i. \tag{1}$$

The change in the asset value Y_i is determined by one idiosyncratic and a weighted sum of S standard normal systematic risk factors, which correspond to business sectors.[6] These systematic and independent risk factors - let denote them as Z_k - are linearly combined into $X_{s(i)}$ as follows:

$$X_{s(i)} = \Sigma_{k=1}^{S} \kappa_{s(i),k} Z_k \tag{2}$$

In equation (1) the relative weight of the systematic risk factor is denoted by $\theta_{s(i)}$. The closer the value of the coefficient is to one, the higher is the sensitivity of the borrowers in the particular business sector to systematic risk. The linear coefficients $\kappa_{s(i)}$ are obtained from Cholesky decomposition of the estimated correlation matrix $\Lambda = \{\upsilon_{\omega,\omega\prime}\}_{\omega,\omega\prime=1,...,S}$, which display the inter-sector correlation. The structure of sector dependencies is crucial for the measurement of portfolio risk. The idiosyncratic factor ζ_i is assumed to be independent from the systematic factors and it captures model the remaining (non-systematic) risk of the borrowers. Both risk components are jointly standard normal distributed. In accordance with equation (1) and the definition of the correlation matrix Λ, the asset

[6]Bonti, Kalkbrener, Lotz, and Stahl (2006) show a portfolio model where different systematic factors such as for countries and industries are incorporated.

correlation of any pair of borrowers i and j is equal to:

$$\rho_{i,j} = cor(Y_i, Y_j) = \theta_{s(i)}\theta_{s(j)}\upsilon_{s(i),s(j)}. \tag{3}$$

Here, we assume that $\theta_{s(i)}$ is the same for all borrowers from the same business sector. The coefficient θ can then be calculated by $\sqrt{\rho_{i,j}/\upsilon_{s(i),s(j)}}$ if both parameters are known. We use mean values of both parameters for practical purposes. Based on the function for the unobservable and normalized asset value Y_i, we calculate the total loss function L_n for a bank's individual credit portfolio of n loans as:

$$L_n = \Sigma_{i=1}^{n}\nu_i \cdot LGD_i \cdot 1_{\{Y_i \leq c_i\}}. \tag{4}$$

Here, the loss given default is denoted by LGD_i and the relative share of a single loan in the entire portfolio is ν_i. We calculate ν_i as the share of the i-th loan amount relative to the total credit amount of the portfolio. The indicator function $1_{\{Y_i \leq c_i\}}$ is a binary random variable which takes the value of one if a loan defaults, and otherwise zero. Here, a default event occurs if the normalized asset value Y_i falls below the default point c_i. Since Y_i is assumed to be standard normally distributed, the default barrier $c_i = \Psi^{-1}(PD_i)$ is derived using the inverse of the cumulative normal distribution function of the default probability PD_i.

The distribution of portfolio losses for a given confidence level q is obtained by sampling the loss distribution, given by (1) and (4). We perform 10,000 simulations runs. As mentioned in the introduction, we are primarily interested in the expected losses (EL), which we use to calculate the impact on the regulatory capital ratio.[7] In the next subsection we describe how we use this portfolio model for stress testing purposes.

[7] The economic capital (EC) and the expected shortfall (ES) as further credit risk measures could be calculated with this model.

3 Stress Testing Design

In the literature, the well established designs for portfolio stress testing are those which are based on the adjustment of the model parameters such as probability of default (PD) and/or loss given default (LGD), the correlation structure of the risk parameters (assuming that correlation goes up during turbulent periods) and distribution of the risk factors. In order to construct our stress testing scenario as realistically as possible, we choose a plausible combination of several adjustments.

The key idea of our stress testing methodology, however, is defined as a constraint of the systematic risk factors in the spirit of Bonti et al. (2006). Above all, we are interested in the impact on banks' losses caused by an economic downturn in different parts of the economy of Kazakhstan. The systematic factors in our paper are represented by business sectors of the economy. The adjustment of these factors can be understood here as the cyclical downturn in these sectors. More technically, the state space of the systematic risk factors of the sectors that we want to stress is restricted, and only those samples are considered in the Monte Carlo simulation which satisfy the scenario constraint. Furthermore, the downturn scenario from originally stressed sectors is distributed to other sectors via the correlation matrix Λ. Bonti et al. (2006) emphasize the advantages of designing the stress scenario as a constraint of the state space. One important advantage for stress testing purposes is that the probability of the stress scenario is automatically known, which gives an indication of the severity of the stress scenario.

The guidelines of the European Banking Authority states that stress tests should be based on exceptional, but plausible events.[8] But what exactly is "exceptional, but plausible"? Pesola (2011) shows that the losses during the recent financial crisis could be well forecasted (ex post) if the unanticipated output and interest rate shocks, which are defined as the deviation from the publicly announced forecasts, are incorporated into the model. However, ex ante it is a challenging exercise to assume the appropriate shock, which would be severe enough, especially when the history of the given country does not include finan-

[8]See CEBS guidelines on Stress Testing from 26. August 2010.

cial crisis. In this regard, we are "lucky" to have a very severe crisis in our sample, which took place after the disintegration of the Soviet Union.[9]

We approach the aim of constructing severe but plausible scenarios not only by specifying how far we go into the tails of the distribution of the systematic factors. We obtain greater plausibility, and more importantly we make an effort to understand the relationship between economic stability in the business sectors (systematic factors) and the risk factors that are capable of destabilizing economic growth. To do so, we incorporate a VARX model to estimate a downturn in the business sectors conditional on the adverse change of the exchange rate and the oil price. Additionally, we test the sensitivity of the portfolio model results by comparison with the historical distribution of the systematic factors, which we assumed to be production growth in the business sectors.

Thus, we assume that macroeconomic shocks as systematic drivers adversely impact on the probability of corporate default, which in turn increases banks' expected losses. The latter, if large enough, can increase significantly the banks' probability of default. This shock transmission channel is well known both in the academic literature and in practice. Amongst others, Wilson (1997a) and Wilson (1997b) identify not only idiosyncratic but also macroeconomic factors as systematic risk drivers affecting PDs. The difference is that idiosyncratic factors are uncorrelated across firms. For stress testing purposes, or more generally from the perspective of systemic risk, systematic risk drivers which are correlated among firms are more interesting, since the deterioration of these could lead to a failure of a significant part of the banking system.

The considerable downsizing of the real economy would not only impacts PDs but also increase LGDs. Altman and Karlin (2010) and Frye (2000) show that PDs and LGDs vary together systematically. Frye (2003) presents further evidence that the LGD is sensitive to an economic downturn. In order to further check the sensitivity of our results, in

[9] Breuer, Jandacka, Rheinberger, and Summer (2009) analyze the problem of finding extreme but plausible scenarios in a classical quantitative risk-management framework with the purpose to support the current regulatory framework of the Basel Committee on Banking Supervision. It requires banks to perform stress tests which meet three requirements: plausibility of stress scenarios, severity of stress scenarios, and suggestiveness of risk-reducing action.

addition to the systematic risk factors we use different LGDs. The implementation of all these steps above requires data. In the next section we discuss the important issue - the availability and quality of data.

4 Empirical Results

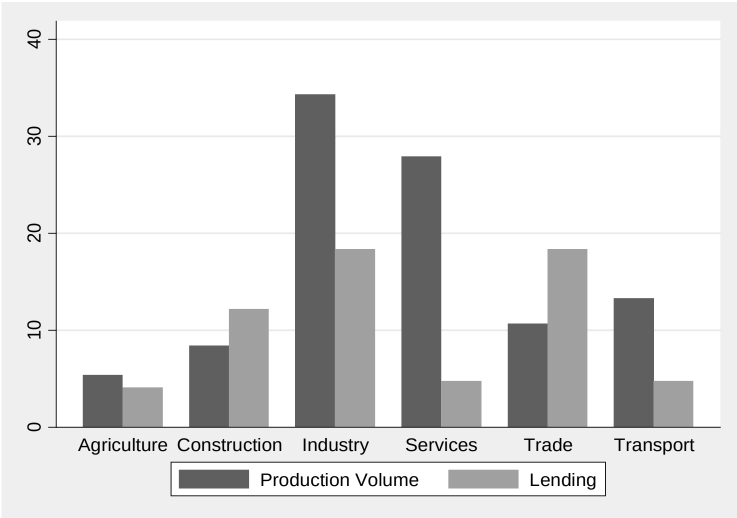
4.1 Data Set

The data set used for our analysis comprises macroeconomic and banks' balance sheet data. We describe the economic situation in different business sectors of the economy and assess the exposures of banks to these sectors following the sector definition used by the NBRK and the FSA. In turn, the FSA assigns the sectoral loans in accordance with the definition applied by the Agency of Statistics of the Republic of Kazakhstan (ASRK), which collects the data on sectoral production.[10] All in all, six major sectors are identified, namely the agricultural sector, industrial production, construction, trade, transport and communication, and services. In terms of production volumes, the industrial sector is the largest production sector in Kazakhstan, as can be shown in the figure 1. It is also the most export-dependent sector.

At the end of 2009 it accounted for approximately 34% of the entire national production. Here, different subsectors are incorporated: mining, the manufacturing industry, the distribution of electricity, gas and oil and the distribution of water and the waste industry. The following four sectors predominantly depend on domestic demand. The sector trade (amounting to approximately 11% of total production) includes the trade of food, beverages, personal and household goods. In terms of loan exposures, the share of the trade sector is the highest and amounts to approximately 32%. In contrast, the share of "industry" accounts for only approximately 18%; this presumably reflects the importance of FDI to this sector. The second largest sector, services, (amounts to approximately 28% of total production and total credit exposures) includes financial services, real estate

[10] More information can be found at www.stat.kz.

Figure 1: Relative sectoral production to total production and sectoral lending in the fourth quarter of 2009



activities, renting of machinery and equipment, tourism, public administration, research and development, and other service activities. The smallest business sector is agriculture, which comprises livestock breeding and plant growing. Its share decreased gradually from 17% in 1994 to 5% in 2009. Agriculture is the second sector, besides "industry", which exports goods. The share of exported agriculture commodities is equivalent to 9% of all exports. [11]

The existence of detailed information on loan quality is a precondition for the results of the portfolio model to be useful for banking supervision purposes. Data on the necessary sectoral loans and their quality measured by non-performing and bad loans is available on a quarterly basis from July 2005 onwards. All non-performing loans, which banks in Kazakhstan are obliged to report, are subdivided into six categories. In order to approximately assess the sectoral default probability, we consider the last two categories; the fifth is designated as "delayed redemption of at least 90 days" and the sixth as "no redemption at all". The data on loans is available only on a sectoral level and not on a borrower level. However, we are able to calculate the sectoral probability of default for each bank individ-

[11] In general, the evolvement of the production shares over time shows that the ranking order we described above remains approximately stable (Appendix A 1). Some exceptions can be observed, first, during the period between the end of 1995 and the first half of 1999 the share for "services" production is above the industrial sector and therefore is the largest production sector during a period of four years. Second, from 2005 onwards the construction sector overtakes the agriculture.

ually. This variation between banks' individual sectoral default probability displays the different borrowers' default risks, which provide useful information for the calculation of the banks' individual loss distribution.[12]

Table 1: Descriptive statistics of macro variables growth rates in %

Variable	Mean	Std. Dev.	Min	Max
Endogenous Variables				
Agriculture	2.08	15.44	-30.02	64.49
Construction	5.18	22.85	-42.59	68.21
Industry	4.08	13.21	-19.50	43.08
Trade	2.53	8.99	-22.22	23.07
Transport and Communication	4.43	13.50	-26.51	55.63
Services	3.55	7.46	-16.33	24.57
Exogenous Variables				
Exchange Rate Tenge/US-Dollar	5.63	24.57	-6.09	187.85
Oil Price	4.68	19.88	-60.83	47.76
Control Variable				
Total monthly wages	2.81	7.14	-18.04	22.25

In order to analyze the impact of the drop in the oil price and the depreciation of the tenge on production, we incorporate growth rates of the production volumes for the six business sectors that we described at the beginning of this section. Table 1 provides descriptive statistics, which were calculated for the period from 1994 to 2009 on a quarterly basis, for all variables which serve as inputs into our macroeconomic model. We use real and seasonally adjusted production volumes. We use growth rates for two reasons: to remove the trend from the data and to simplify the interpretation of the results. According to the Augmented Dickey-Fuller unit-root test, all transformed (exogenous and endogenous) variables are stationary at the 1% significance level. The descriptive statistics indicate that the growth rates of the variables, both endogenous and exogenous, are highly volatile. The entire distribution of the growth rates for sectoral production is provided in A 2.

Table 2 provides descriptive statistics for the aggregated non-performing loans (26 banks) as a percentage of total loans for the period from 2005 to 2009 on a quarterly

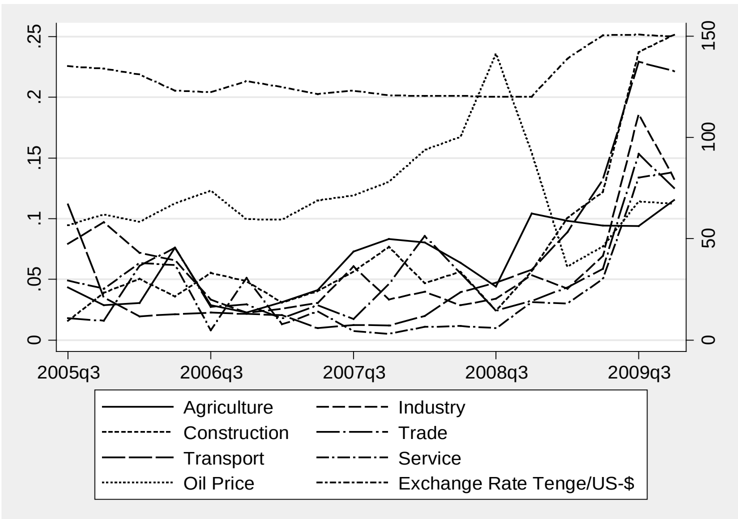
[12] The bankspecific data is confidential. FSA and NBRK provided the data sets temporarily within the framework of the project "Development of an Early Warning System for Kazakhstan" coordinated by Ifo Institute Munich and the National Analytical Center of the Government and the National Bank of Kazakhstan.

Table 2: Descriptive statistics of non-performing loans in % of total loans

Variable	Mean	Std. Dev.	Min	Max
Agriculture	7.57	4.37	2.27	19.55
Industry	8.11	6.29	2.25	20.22
Construction	10.61	10.05	1.58	33.14
Trade	6.88	5.76	1.59	19.50
Transport and Communication	9.03	9.54	0.97	29.70
Services	5.72	5.44	0.51	15.76

basis. Construction can be seen as the most risky sector in comparison to other sectors, while the services sector is the least risky. Figure 2 shows the evolvement of sectoral non-performing loans and the macroeconomic factors, such as the exchange rate (tenge to US-$) and the oil price per barrel, over time. One cannot fail to notice that the shares of non-performing loans to total loans start to rise, short after the oil price started to decline dramatically. The domestic currency was devaluated in the first quarter of 2009. At the end of 2009, all sectoral non-performing loan ratios exceed the threshold of 10%, indicating high tension in the banking system according to Demirgüç-Kunt and Detragiache (1998).[13]

Figure 2: Non-performing loans over total loans by sectors and the macroeconomic factors



Concerning the portfolio model, besides PDs, the correlation between the systematic

[13]The authors define four criteria for the emergence of the banking crisis. One of them is "the ratio of non-performing loans to total loans in the banking systems has exceeded 10%". The other three criteria are: the cost of the rescue operation has been at least 2% of GDP; banking sector problems have resulted in a large scale nationalization of banks; extensive bank runs have taken place. Instead of the last criterion the authors additionally mention emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees have been enacted by the government in response to the crisis.

factors has to be calculated and an assumption about the LGD has to be made. Particularly, the former is difficult to model because the data is scarce and low in quality. The data on LGD for banks in Kazakhstan is not available to us at all. In agreement with the supervisors (FSA and NBRK) of the banking system of Kazakhstan, however, we set the expected loss severity (LGD) in all sectors to 50% as a starting value. Another important block for the portfolio stress test is understanding how systematic factors are correlated with each other. As shown in equation (3), the data for two parameters is needed: the inter and intra-sector correlations. Duellmann and Erdelmeier (2009) use high frequency data on sectoral stock indices to capture the inter-sector correlations and follow Hahnenstein (2004) by setting an empirical value of 0.09 for the intra-sector correlation based on the data for small and medium-sized German corporations. This practice of using the history of stocks returns to capture the two different types of correlation is very common. However, Frye (2008) argue that assuming that the correlation in the model is equal to asset correlation might be an error and result in misleading statements about risk, especially if high values (greater than 10.8%) are incorporated. The author suggests using the observed default rates. The correlation can then be calculated in case one or both assets default. The calculation of the correlation for the model is challenging, not only because there is no default data for firms' assets in Kazakhstan, but also because it is not possible to follow common practice and calculate the correlation using the stocks returns, as only few Kazakhstani corporations are publicly traded, with the result that no stock indices for business sectors are available.[14] We use two data bases to capture approximately the values for both these parameters. For the correlation between sectors we use the unique non-public data set collected by the ASRK (and provided to the NBRK for further use) on profitability of big and medium-sized Kazakhstani companies, which is available from 2005 to 2009 on a quarterly basis. The profitability is measured with return on equity (ROE) and is aggregated for each business sector of the economy of Kazakhstan. Table

[14] Most of the listed firms are either banks or companies which belong to the industrial business sector (oil, gas and mining industry). Kazakhmys, KazakhGold KazMunaiGas, Kazakhstan Kagazy, ENRC Group and ShalkiyaZinc represent the latter. While the business sector "services" is represented by Chagala, a real estate development company, the other four sectors are completely unrepresented.

(3) provides the inter-sector correlation matrix Λ based on this data. The sample available to us is based on 20 observations and is therefore relatively small. Consequently we accept all correlation values which are significant at least at the 15% significance level for the calculation of the average inter-sector correlation. We set all statistically insignificant correlation values to zero. Accordingly, the mean value of the matrix is equal to 0.39. The average intra-sector correlation is set to 0.05. Here, the calculations are based on the NBRK's own data base, which includes ROE for 1782 big and medium-sized companies.[15] Based on these values for inter and intra-sector correlations (see equation 3), the weight for the systematic risk factor is equal to 0.36. We use this value as a starting parameter but check the sensitivity of the results by changing it. In the next section, we describe the results from our macroeconomic model.

Table 3: Inter-sector Correlations

		1	2	3	4	5	6
1	Agriculture	1	0.00	0.00	0.71	0.47	0.30
2	Industry	0.00	1	0.00	0.00	0.46	0.80
3	Construction	0.00	0.00	1	0.00	0.58	0.33
4	Trade	0.71	0.00	0.00	1	0.28	0.00
5	Transport	0.47	0.46	0.58	0.28	1	0.63
6	Service	0.30	0.80	0.33	0.00	0.63	1

Note: This table shows inter-sector correlations for six sectors. The correlations were estimated from sectoral ROE based on 20 observations in the period from 2005 to the end of 2009. Source: NBRK, own calculations

4.2 Results from the Macroeconomic Model

We model the relationship between the different sectors of the economy, including export and import dependent sectors, and the two observable risk factors, which are the oil price (as a proxy for all non-agricultural commodities) and the exchange rate (the tenge against US dollar). We include these two factors with a time lag equal to one quarter, as our intention is to find an indication of how production in these sectors would react to the changes in our risk factors. With this knowledge, we would be able to quantify the

[15]The intra-sector correlation calculated by Hahnenstein (2004) is based on medium and small-sized firms in Germany to assure the homogeneity of the data. We are unfortunately not able to exclude big firms from our data.

impact emanating from the main risk drivers for production in Kazakhstan, which would support us in developing plausible stress scenarios. The two risk factors, designated as OIL and EXCH,[16] enter a VARX model as exogenous variables in the following way:

$$Y_t = v + A^{'}Y_{t-i} + \gamma OIL_{t-1} + \lambda EXCH_{t-1} + \vartheta TMW_t + \mu_t \tag{5}$$

$$Y^{'}_{t-i} = [TRADE_{t-i} IND_{t-i} TRANS_{t-i} SERV_{t-i} CONSTR_{t-i} AGRA_{t-i}] \tag{6}$$

Consequently, the endogenous variables are assumed to be dependent on themselves (Y) and all other business sectors up to four quarters. Here, all other business sectors with their lags enter only the basis specification. In the specification, which we use to estimate the production drop, we put constraints on regression coefficients (in $A^{'}$) which are not significant. We exclude insignificant sector variables without changing the predictive power of the model but saving degrees of freedom.[17] As a control and further exogenous variable, we introduce the costs for production approximated by total monthly wages (TMW), which enter the model contemporaneously.

Table 4: Regression results from the macro model

	Trade	Industry	Construction	Transport	Agriculture	Services
OIL_{t-1}	**0.22*****	**0.32*****	**0.01**	**0.02**	**-0.08**	**0.16*****
	4.07	4.06	0.04	0.39	-0.83	2.83
$EXCH_{t-1}$	**-0.51*****	**-0.31**	**-0.53**	**-0.69*****	**0.09**	**-0.47*****
	-3.00	-1.23	-1.3	-3.89	0.28	-2.72
TMW_t	-0.33*	-1.05***	-0.19	-0.19	-0.44	-0.19
	-1.66	-3.45	-0.32	-0.82	-1.11	-0.92
No. Obs	59	59	59	59	59	59
R-sq	0.68	0.50	0.30	0.69	0.46	0.60
R-sq adj.	0.36	0.21	0.10	0.45	0.15	0.21
Chi-sq	134.36***	58.31***	33.66***	190.32***	49.85***	91.75***

Note: t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 4 provides results for the variables, which we assume to be exogenous to the rest of the model and are included to "stress" the production volume of the business sectors.[18] For the industry sector the global oil price is, as expected, positive significant;

[16] The empirical correlation of these two factors entering the equation with one time lag equal to 2%.

[17] The LR-Test for nested models supported our decision to exclude insignificant variables from the model in all cases.

[18] We refrain from showing all results here due to the size of the table. However the results are available upon request from the authors.

the exchange rate is, as expected, not significant. As the commodities from this sector are traded in US dollar, the devaluation of the tenge does not play a role. Furthermore, the sectors “trade” and “services” obviously benefit from the oil price increase. Higher commodity prices on global markets improve the earning power of households (residents in general) and result in higher domestic demand for goods and services. The exchange rate is negative significant for the production sector “trade”. This sector includes trade of food, beverages, personal and household goods, which to a large extent are imported. Therefore, the more the tenge devalues, the more expensive imported goods are for the residents and the more domestic demand for these goods declines. Production in the sectors “transport and communication” and “services” declines when the tenge devalues. There is no significant impact emanating from the exogenous variables to the sectors “construction” and “agriculture”. The production growth in these sectors seems to be driven by other determinants. For “agriculture” these could be land, labor, agricultural capital, credit availability etc. The sector “construction” has experienced stable growth over the past years, which started in 1997 when Kazakhstan was still in recession. This development was sparked off by the relocation of the capital city. The growth of the construction sector was first driven by government investments.

The control variable TMW has a negative impact on production, as theoretically expected. The higher the production costs, the smaller is the production output. The variable is significant for only two sectors.

In Figure A 3 we show the predictions together with observed values and 95% confidence bands for all six production sectors using the parameters from our VARX model. We observe relatively good forecasting power for the sectors “trade”, “industry”, “transport and communication” and “services”, which is reflected by the fact that no observations lie outside the confidence bands. The adjusted R-squared is relatively high for the sectors “trade” and “transport and communication”.

Using these model parameters we predict a conditional drop in the production for the four sectors (“trade”, “industry”, “transport and communication” and “services”) for the second quarter of the year 2010 as a result of a 35% drop in the global oil price and the depreciation of the national currency by 30%. We develop this scenario using the historical distribution of these two exogenous risk factors. More specifically, we base our scenario on a comparison of the mean value and a 1-standard deviation (see Table 2 for detailed descriptive statistics). Since the production growth rates are linear in OIL and EXCH, the specific numbers for shocks do not have any other impact, as the greater the degree of the tenge's devaluation and the lower the price for oil, the greater is the decrease in sectoral production in "trade", "industry", "transport and communication" and "services", where at least one of the risk factors is significant.[19] In the next section we link stress from the macroeconomic model expressed as the decline in production volume to the portfolio model.

4.3 Mapping between the Macroeconomic Model and the Portfolio Model

As mentioned in the section "Stress Testing Design", the stress impact on the portfolio loss is captured first of all by restricting the distribution of the primary stress sectors. In order to link both models, the macroeconomic and the portfolio model, the estimates of the declines in the four sectors obtained from the macro model are linked to the corresponding four unobservable risk factors of the portfolio model. Since the relationship between the observable risk factor in the macroeconomic model and the unobservable risk factor from the portfolio model is not necessarily linear, we implement this link by the more robust requirement that the probabilities of both risk factors should correspond. In conducting the mapping methodology, we first carry out the kernel density estimation and obtain the continuous distribution of the sectoral production growth rates from 1994Q2 to 2009Q4. The next step is to determine the cut-off value ς_{j^*} for each of the four production indices. We assume the following property of the cut-off value ς_{j^*}:

$$E[\Xi_{j^*}/\Xi_{j^*} \leq \varsigma_{j^*}] = \hat{\varepsilon^*}. \tag{7}$$

[19] We predict the evolvement of the production growth for one quarter. In the literature the predictions are usually made from one to four quarters. If necessary, the whole exercise could be adapted to longer forecast horizon.

Referring to equation 7, the expected value of the sectoral production index Ξ_{j^*} conditional on being below the cut-off point is the predicted stress value ε^* of this sectoral production index. We determine the probability $p(\varsigma_{j^*}) = P(\Xi_{j^*} \leq \varsigma_{j^*})$ from the kernel density distribution for each of the sectoral production. Thereafter, we find the corresponding cut-off point $\Psi^{-1}[p(\varsigma_{j^*})]$ of the corresponding unobservable risk factor X_{j^*}, since the distribution of this systematic risk factor is assumed to be standard normal. Following this procedure, we produce mapping results shown in Table 5.

Table 5: Results from linking macro shocks and the portfolio model

	$\hat{\varepsilon^*}$	ς_{j^*}	$p(\varsigma_{j^*})$	$\Psi^{-1}[p(\varsigma_{j^*})]$
TRADE	-9.40%	-3.65%	23.74%	-0.71
INDUSTRY	-20.56%	-17.92%	3.16%	-1.85
TRANSPORT	-28.17%	-26.03%	0.59%	-2.51
SERVICES	-3.41%	1.66%	39.69%	-0.26

Note: the calculations are based on the sectoral production growth rates.

With regard to the results of the "trade" sector, the value predicted by the macro model for production growth is equal to -9.40%. This value implies a cut-off point -3.65%, which is calculated using the property given in equation (7). The probability that the production volume of the sector "trade" would fall by -3.65%, equals 23.74%, which is relatively high in comparison to the sectors "industry" and "transport and communication". The smaller the probability is, the more severe is the scenario. The corresponding cut-off point on the standard normal distribution of the unobservable systematic risk factor for the sector "trade" is then equal to -0.71. Starting with this value, the left part of the distribution of this risk factor in our portfolio model is constrained in case we want to receive expected losses or other bank's credit risk measures conditional on "trade" production sector being in "stress".[20] In the next section we quantify the impact of this stress scenario on the credit portfolio of each individual bank in our sample.

[20]We are aware that this approach is not a unique solution and offers room for exploring alternatives. For more detailed information on mapping methodology, see Duellmann and Erdelmeier (2009).

4.4 Results for Portfolio Losses

4.4.1 Macroeconomic Downturn in the Business Sectors: Trade, Industry, Transport and Communication, and Services

Table 6 contains descriptive statistics on the expected losses (EL) under normal conditions (baseline) and under stress with two different assumptions for the LGD. Here, stress is defined as a macroeconomic downturn in the four business sectors (as shown in Table 5) and the ELs are given as a percentage of the aggregated nominal value of loans in the banks' credit portfolio. Under stressed macroeconomic conditions in the sectors "trade", "industry", "transport and communication" and "services" the expected losses for the whole credit portfolio of all banks in the sample are on average at 5.15% higher in comparison to the baseline scenario. The maximum increase of expected portfolio losses under the baseline scenario is equal to 11.17%. Whereas the under the stress scenario and under the further assumption that LGD is equal to 50%, the maximum expected loss in our sample is equal to 23.52%.

Table 6: Descriptive statistic on expected losses in baseline and stress scenario

		LGD=50%		LGD=100%	
	Baseline	Stress	Absolute Diff	Stress	Absolute Diff
Minimum	0.53	2.49	1.43	6.03	4.93
25% quantile	1.40	4.29	2.90	10.33	6.97
Median	2.28	6.63	2.90	15.32	9.69
Mean	3.35	8.50	5.15	18.78	11.01
75% quantile	3.86	10.98	7.55	24.56	14.10
Maximum	11.17	23.52	12.34	48.54	25.10

Note: the ELs are given as a percentage of the aggregated nominal value of loans in the banks' credit portfolio.

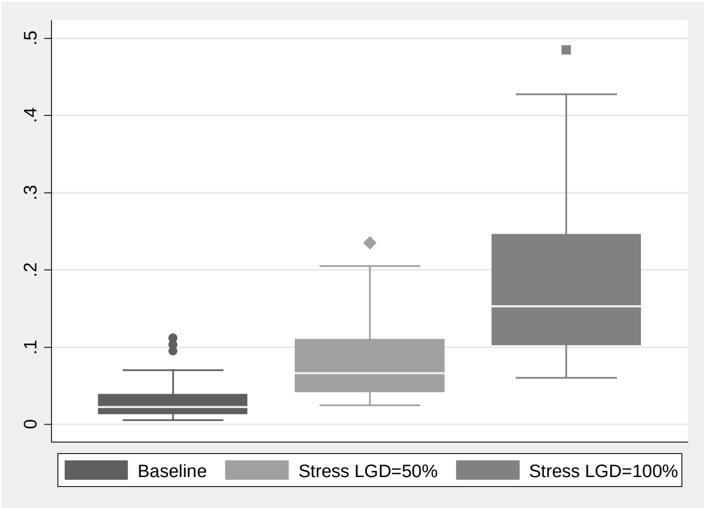
If, in addition to the sizeable downturn in these four sectors, we assume that in the stress scenario the loss rate (LGD) would be equal to its maximum possible value of 100%, one bank from our sample would even expect losses equal to 48.54% of its credit portfolio.[21] To visualize the results, we show the distribution of the expected losses for baseline and stress scenario in the Figure 3.[22] The stress impact is naturally stronger when we

[21]We assume LGD equalling 100% as a maximum possible loss rate, but one should keep in mind that such level is very extreme and unrealistic.

[22]Here, we refer to the portfolio which consists of loan volumes given to the real sector; lending to private households and interbank lending are not considered.

assume 100% loss rate, the results are also much more dispersed across banks, as shown by the inter-quartile range and the greater distance between the whiskers.

Figure 3: Portfolio losses for 26 banks with LGD equalling 50% and 100%



The results from the portfolio model confirm that the assumed scenario is very severe. Considering the fact that the share of bad loans in Kazakhstani banks' balance sheets were high and continued to increase during the time when the country experienced a macroeconomic downturn (2008-2010), the results and therefore the underlying scenario seem plausible. Before we evaluate the impact of the losses on banks' solvency, which is the most important step in conducting stress testing from the perspective of a banking supervisor, we check how sensitive the results from the portfolio model are to changes of the input parameters.

4.4.2 Sensitivity Analysis

As already shown in the previous section, the expected losses would linearly increase if the LGD rises. In order to show how sensitive the results from the portfolio model are to changes in other input parameters, we first change the scenarios for the systematic factor. We assume that all four sectors are in trouble (economic downturn in terms of negative production growth rates) with probability equalling 1%, 5% or 10% respectively. Table 7 provides the corresponding production growth rates. The decrease in production growth is calculated using the property described in equation 7. With regards to the results for the sector "trade", the production decrease is equal to -19.29,-13.10 and -9.22 if the probability for such decreases is set to 1%, 5% and 10% respectively. The corresponding cut-off thresholds of the unobservable systematic factor in the portfolio model is then identical to -2.33, -1.64 and -1.28.

Table 7: Sectoral production growth rates if decline probability is equal to 1%, 5% or 10%

$p(\varsigma_{j^*})$	TRADE	IND	TRANS	SERV	$\Psi^{-1}[p(\varsigma_{j^*})]$
1	-19.29	-21.47	-24.32	-16.25	-2.33
5	-13.10	-15.86	-15.11	-8.62	-1.64
10	-9.22	-12.12	-10.60	-5.10	-1.28

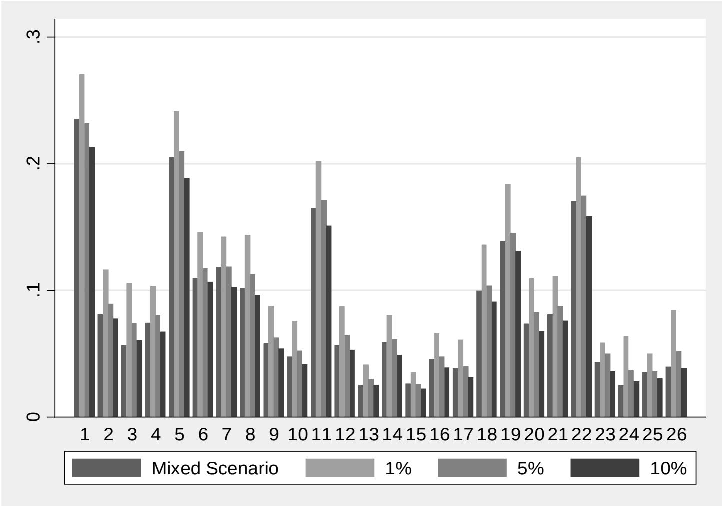
Note: In this table we report all values in %.

Figure 4 shows results for 26 banks. The expected losses are higher if the production growth in all four sectors, for which the risk factors were significant in our macro model, decreased with the probability of 1%, in comparison to the expected losses for the scenario concluded from the macro model. When $p(\varsigma_{j^*})$ is set to 5%, two banks (No 1 and No 15) experience higher losses if the scenario from the macro-model is assumed[23]. With no exception the losses based on the scenario from the macro-model are higher then the scenario where the production would fall with the probability of 10%. These results are plausible since the scenario from the macro model is extreme but only for 2 sectors (for "industry" the probability equals 3.16 and for "transport and communication" the probability equals 0.59).

One of the most challenging exercises in conducting portfolio stress testing is the reliability of the assumed asset correlations. In the section "Stress Testing Design" we refer to general problems regarding the assumptions for the asset correlations. In this section we show the results from the portfolio model if the asset correlation is changed from 5% to 9% in the spirit of Duellmann and Erdelmeier (2009) and to 1% in the spirit of Frye (2008),

[23] In the figure 4 we denote the scenario from the macro-model as "mixed scenario"

Figure 4: Expected losses under the scenario from the macro model vs. ad hoc assumptions



who find that smaller values for the asset correlation are more realistic. The higher the assumed asset correlation, the higher the sensitivity of the losses to the systematic factor.[24]

Table 8: Portfolio losses if the intra-sector correlation takes the values 1%, 5% and 9%

$\rho_{i,j}$	θ	Mean	Std. Dev.	Min	Max
1	16	5.52	4.14	1.26	16.52
5	36	8.50	5.7	2.5	23.51
9	48	11.2	7.0	3.5	29.6

Note: In this table we report all values in %.

Table 8 indicates that the losses are not only higher with the increased $\rho_{i,j}$, but also more dispersed within the sample.

In the next section, we show how losses impact the banks' solvency.

4.5 Impact on Regulatory Capital Ratios

The bank's capital is the reserve that buffers the impact of the potential losses. The commonly used indicator for bank's risk bearing capacity is the regulatory capital ratio. In order to assess the predicted stress in terms of a bank's solvency, we analyze its minimum capital requirement after stress as follows:

$$CR_{Stress} = \frac{RC - \Delta EL}{RWA} \tag{8}$$

[24]The row in the middle, where θ equals to 5% is based on the results which are provided by Table 6.

where $\Delta EL = EL_{Stress} - EL_{Baseline}$.

Pursuant to the Kazakh Banking Act, the capital adequacy ratio defined as the regulatory capital (RC) in terms of the bank's risk weighted assets (RWA) has to be above 12%. We assume that banks have formed provisions for the expected losses and need to buffer the impact from any additional losses coming from a sudden economic downturn. We denote these additional losses with ΔEL. When the sectors "trade", "industry", "transport and communication" and "services" are in stress, as specified above, and an LGD of 50% is assumed, 6 banks would be in trouble. The share of the affected banks (in terms of their RWAs) is equal to 58% of the considered banking system. In the absolute worst case scenario, when LGD is assumed to be 100%, 88% of the considered banks would became insolvent. In comparison, in the baseline scenario (when ΔEL is equal to zero) 2 banks or 28% of all banks' RWAs, would not meet the regulatory requirement.[25]

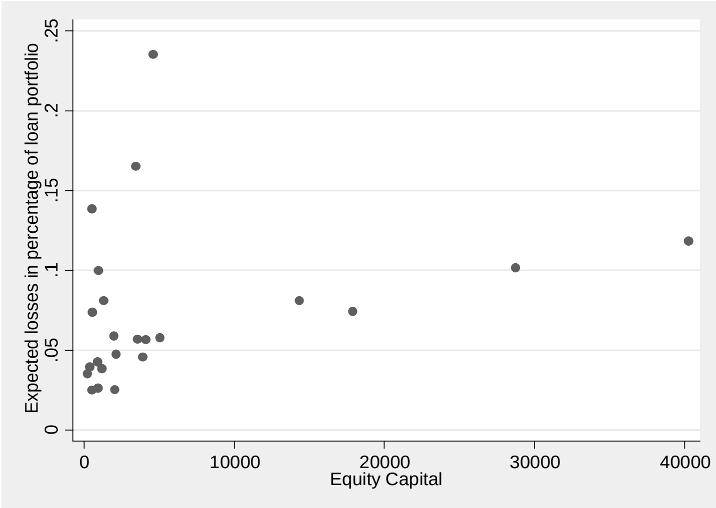
Furthermore, we analyze the relationship between expected losses and the regulatory measures. We find a positive relationship between losses under stress and the risk weighted assets, which indicates that the relatively big banks in the sample would experience relative high losses. Moreover, we find a negative relationship between the size of the equity capital (but also equity capital ratio) and the expected losses under stress. Banks which experience high losses tend to have relatively small amounts of equity capital to buffer losses. As we show in Figure 5, only a few banks have experienced losses and were well capitalized at the same time.

5 Concluding Thoughts

In this paper, we integrate the macro-perspective of the economy with the micro-perspective of each of 26 Kazakh banks in order to stress test banks loan portfolios. In the first stage, we identify the main risk drivers for the production growth in Kazakhstan, which are the sudden drop in the global oil price and the devaluation of the domestic currency. Af-

[25]We receive very similar results if the core capital ratio instead of the equity capital ratio is involved.

Figure 5: Correlation between the equity capital (in thousands of tenge) and the increase of expected losses in stress scenario (2010)



ter that, we quantify the impact of the risk factors on the production growth for the six business sectors (“industry”, “construction”, “agriculture”, “trade”, “transport and communication” and “services”). In a VARX model we predict a production downturn conditional on decline in the price of oil by 35% and the depreciation of the tenge against the US dollar by 30%. In the second stage, we link the downturn in production to the portfolio model and simulate the expected losses for each individual bank. Finally, we assess the bank's stability assuming the hypothetical stress would occur.

We find a significant impact emanating from at least one out of two risk factors on the sectors “trade”, “transport and communication”, “services” and “industry”. After transferring the stress to the portfolio model, we find a significant increase in the conditional expected losses. On average the expected losses increase by 5.15%, when LGD is assumed to be 50%. The consequence of this simulation is that 58% of the considered banks would not be able to meet the regulatory requirement on their capitalization. It also means that these banks would be forced to cut their lending on the economy of Kazakhstan, which would amplify the economic downturn. In the worst case scenario, when LGD is assumed to be 100%, the expected losses increase on average by 11.01% and they are more dispersed within the sample of banks. Under this stress scenario, 88% of the considered banks would fail to meet the regulatory requirement. In this case the repercussions in the form of feedback effects on the economy would be even more substantial. All in all, the results show that the macroeconomic environment, particularly the negative development in the corporate sector, induce a considerable rise in the expected losses in banks' credit portfolios, which could lead to banks' insolvency.

It is important that the supervisory authorities analyze the impact of macroeconomic developments on financial institutions' credit risk and their solvency as part of their on-going supervision. Recent developments in the financial sectors around the world have shown how crucial it is to pay attention to the vulnerabilities of the financial sector from the macro-perspective. Macro-shocks, if severe enough, could destabilize big parts of the financial system. The model presented in the paper, helps to quantify the impact of macro-shocks and therefore it can support the supervisory authorities to take preventive actions. Furthermore, assessing the degree of the financial system' vulnerability to an exchange rate shock would be useful in order to take better informed monetary policy decisions. Thus, macro-stress testing could be useful in addressing monetary policy considerations by incorporating financial stability issues into the monetary policy decision-making process.

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6 Appendix

Figure A 1: Evolvement of the sectoral production shares over time

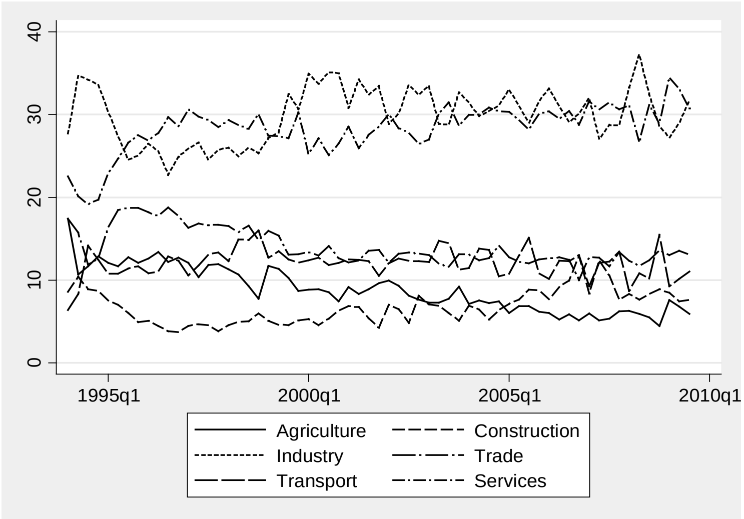

Figure A 2: Distribution of the sectoral production growth rates

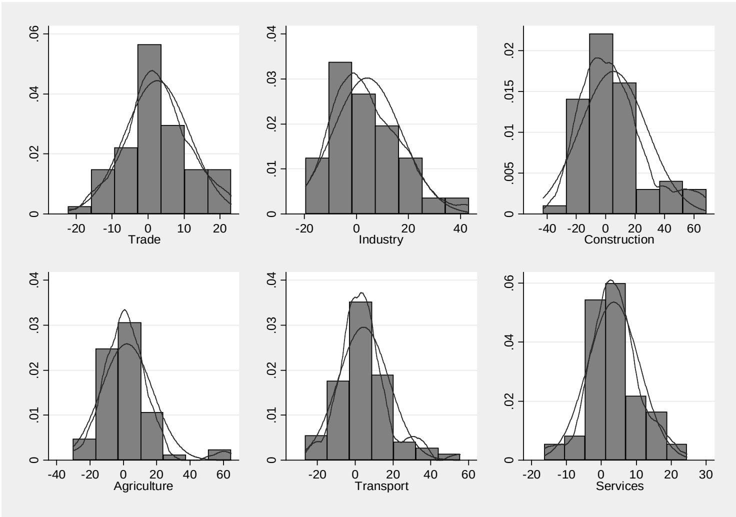

Figure A 3: Forecast vs. observed values for the business sectors “trade”, “industry”, “transport and communication”, “services”, “construction” and “agriculture”