Charles University in Prague
Faculty of Social Sciences

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DISSERTATION

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Credit Risk in the Macroprudential Framework: Three Essays

DISSERTATION

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Declaration

Hereby I declare that I compiled this thesis using only the listed literature and resources.

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The views expressed do not necessarily represent those of the Czech National Bank or Charles University.

Abstract

This thesis focuses on proper credit risk identification with respect to macroprudential policies, which should mitigate systemic risk accumulation and contribute to higher financial stability of the financial sector. The first essay deals with a key credit risk parameter – Loss Given Default (LGD). We illustrate how the LGD can be estimated with the help of an adjusted Mertonian structural approach. We present a derivation of the formula for expected LGD and show its sensitivity analysis with respect to other company structural parameters. Finally, we estimate the five-year expected LGDs for companies listed on Prague Stock Exchange and find that the average LGD for the analyzed sample is around 20–50%.

The second essay examines the issue of how to determine whether the observed level of private sector credit is excessive in the context of the "countercyclical capital buffer", a macroprudential tool proposed in the new regulatory framework of Basel III by the Basel Committee on Banking Supervision. An empirical analysis of selected Central and Eastern European countries, including the Czech Republic, provides alternative estimates of excessive private credit and shows that the HP filter calculation proposed by the Basel Committee is not necessarily a suitable indicator of excessive credit growth for converging countries.

The last paper describes the stress testing framework used in the Czech central bank and focuses on a general question how to calibrate models used to stress test the most important risks in the banking system. The paper argues that stress tests should be calibrated conservatively and rather to overestimate the risks. However, to ensure that the stress test framework is conservative enough over time, verification, i.e. comparison of the actual values of key financial variables with predictions generated by the stress-testing models should become a standard part of the stress-testing framework.

Keywords: loss given default, credit risk, Basel III, countercyclical capital buffer, stress-testing

JEL Codes: C02, E44, E47, G01, G13, G18, G21, G33

Abstrakt (in Czech)

Disertační práce se zabývá identifikací kreditního rizika v souvislosti s makroobezřetnostní politikou, jejíž cílem je zmírnit vznik systémového rizika a přispět k vyšší stabilitě finančního sektoru. První esej se zabývá klíčovým parametrem kreditního rizika – ztrátovostí ze selhání (loss given default – LGD). Podrobně je ilustrováno odvození vzorce pro výpočet očekávaného LGD pomocí upraveného Mertonova modelu a následně je diskutována citlivostní analýza LGD vzhledem k ostatním strukturálním ukazatelům společnosti. Na závěr jsou odhadnuty očekávané LGD v pětiletém horizontu pro vybrané společnosti kotované na Burze cenných papírů Praha. Výpočty ukazují, že průměrné LGD analyzovaného vzorku firem se pohybuje mezi 20–50 %.

Druhý článek se věnuje otázce, jak nejlépe určit, zda pozorované zadlužení privátního sektoru je již nadměrné v souvislosti s makroobezřetnostním nástrojem navrhovaným Basilejským výborem pro bankovní dohled, tzv. proticyklickým kapitálovým polštářem. Empirická analýza na vybraných zemích střední a východní Evropy včetně ČR ukazuje alternativní odhady indikátoru nadměrného zadlužení privátního sektoru a naznačuje, že výpočet pomocí HP filtru navrhovaný Basilejským výborem nemusí být pro konvergující země vhodným indikátorem nadměrného růstu úvěrů.

Poslední esej shrnuje metodologii zátěžových testů bankovního sektoru ČNB a zaměřuje se na otázku kalibrace modelů určených pro odhad rizik v bankovním systému. Text dokládá, že nastavení předpokladů zátěžových testů a využívaných dílčích modelů by mělo být konzervativní a rizika by měla být spíše nadhodnocována. Verifikace zátěžového aparátu využívaného ČNB naznačuje, že model je nastaven správně na pesimistické straně. Článek zároveň shrnuje, že verifikace agregovaných testů by měla být běžnou součástí zátěžového testování a měla by být využita pro další zpřesňování celého aparátu zátěžových testů.

Klíčová slova: ztrátovost ze selhání, kreditní riziko, Basel III, proticyklický kapitálový polštář, zátěžové testy

JEL kód: C02, E44, E47, G01, G13, G18, G21, G33

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List of abbreviations

APR	Absolute Priority Rule
ARDL	Autoregressive Distributive Lag
ARS	Adjusted Relative Spread
BCBS	Basel Committee on Banking Supervision
CAR	Capital Adequacy Ratio
CEE	Central and East European
CNB	Czech National Bank
CPI	Consumer Price Index
CZSO	Czech Statistical Office
DB	Default Barrier
DSGE	Dynamic Stochastic General Equilibrium
EAD	Exposure to Default
EBA	European Banking Authority
ECB	European Central Bank
ELGD	Expected Loss Given Default
ESRB	European Systemic Risk Board
FSAP	Financial Sector Assessment Program
FSB	Financial Stability Board
FSR	Financial Stability Report
FX	Foreign Exchange
HP	Hodrick-Prescott
IAS	International Accounting Standard
IFRS	International Financial Reporting Standard
IMF	International Monetary Fund
IMF-IFS	IMF International Financial Statistics
IRB	Internal Rating-Based
IRS	Internal Rating System
LGD	Loss Given Default
MAE	Mean Absolute Error
MED	Mean Error in Direction
MG	Mean Group
NPL	Non-Performing Loans
OECD	Organization for Economic Co-operation and Development
OOS	Out-Of-Sample
PD	Probability of Default
PMG	Pooled Mean Group
PSE	Prague Stock Exchange
RoE	Return on Equity
RR	Recovery Rate
RWA	Risk-Weighted Assets
UL	Unexpected loss
WB	World Bank
WDI	World Development Indicators

♦ Introduction

The general feature of the financial system is its procyclicality which may lead to unexpected boom and bust cycles amplifying economic fluctuations and threatening its financial stability. Although this endogenous behavior of the financial system is well known and has been thoroughly discussed in a broad range of studies (see for instance Borio and Drehmann, 2009 and references therein), it is still not a straightforward task to determine the current stage of the economy in the cycle and the consequent risk, which may arise therefrom. Procyclical behavior of the financial sector leads to underestimation of risks during the upswing, and turn to exaggerated panic when the cycle reverses.

Indeed, the largest risk is usually accumulated in the "optimistic" phase of the economic cycle (e.g. IMF, 2012 or CNB, 2011). One possible source of systemic risk in the building-up phase of the cycle is also excessive credit growth as a result of lower-risk perception of economic agents – households, companies and government – who are willing to accept higher indebtedness given optimistic income and assets prices prospects. Furthermore, even the supply side of the credit market – financial institutions – may suffer from myopia with regard to the continuing positive income outlook of the borrowers and may not fully take into consideration the accumulating risks when providing credit to the real economy. Subsequent revaluation of the exaggerated expectations by economic agents usually causes the materialization of the risks and adjustments leading to an increase in unpaid loans, bankruptcies, fire sales of the accumulated assets, deleveraging and overall episodes of financial instability.

Therefore, the connecting element of this thesis is proper identification of the credit risk which may arise from inadequate perceptions of selected credit risk parameters of the borrowers and excessive credit growth over the financial cycle. Moreover, the recent global financial crisis cast doubts on the proper functioning of the current regulatory framework and led to an extensive debate about its possible amendments and changes, see for example Eichengreen (2010) or Bank of England (2009). To address this debate, the thesis also deals with some of the regulatory amendments which were proposed to better reflect risks arising in the financial sector and to strengthen financial stability of the system as a whole. In line with these changes, the new regulatory perspective focuses intensively on macroprudential policies which should prevent accumulation of systemic risks and decrease the procyclicality of the financial sector.

Macroprudential polices are focused on limiting system-wide risks and are supposed to supplement fiscal and monetary policies, which may have limited effectiveness in preventing systemic crises due to their possibly different objectives and timeliness of response (IMF, 2012). Macroprudential policies should be also aimed at macro supervision to prevent possible fallacy of composition, which arises when it is assumed that the system as a whole is stable when each of its institutions is stable (Morris and Shin, 2008). As we witnessed during the financial crisis, this assumption may not be valid because of the interconnected balance sheet structure of the institutions, which can lead to contagion and funding shortages when funding and market liquidity disappear, see Borio (2004) or Brunnermeier et al. (2009). As a consequence, macroprudential policies for example include tools to increase capital buffers, limit the loan-to-deposit ratio, leverage or the loan-to-value ratio and maturity mismatches, which may strengthen the financial sector's resilience and its ability to maintain a stable provision of financial services to the real economy and thereby moderate an excessive credit crunch during economic downturns.

Nevertheless, the practical question of implementing the macroprudential regime is also of crucial importance. Some of the proposed regulatory changes have already been implemented including the changes in the EU supervisory architecture, establishing the European Systemic Risk Board (ESRB), and the new banking regulation known as Basel III. National authorities are amending their regulatory frameworks, creating new bodies responsible for macroprudential policies and its operational features (IMF, 2011; Houben et al., 2012). Still, macroprudential policies can not be taken as a panacea and their limitations emerge especially with free capital mobility and cross-border lending. Therefore further analysis and discussion should focus intensively on cross-border spillovers of macroprudential policies and their harmonization across individual states (Cerutti et al., 2012). It follows from the above that macroprudential policies are still an open and not fully defined concept in the current "post"-crisis financial world. An extensive debate is still ahead and this thesis can hopefully contribute slightly to the creation of this new methodological framework brought by recent regulatory proposals and needs for strengthening financial sector's resiliency.

As a result, the first essay of the thesis discusses the method of estimation of the Loss Given Default (LGD) credit risk parameter employing market-observable information. Estimating the LGD credit risk parameter using market prices enables creditors to better predict possible loss in case of the debtor's default, especially for types of borrowers with low-default history, for which LGD parameter could be otherwise undervalued due to insufficient historical experience. However, even correct and precise credit risk management may not be sufficient when the credit bubble burst and the systemic risks materialize. This issue is addressed in the second essay, which is focused on the excessive indebtedness of the private sector in the transition economies and ways of mitigating the procyclicality of the banking sector using a newly proposed macroprudential tool – the countercyclical capital buffer. The last part of the thesis focuses on proper calibration and validation of the stress-testing framework, which is used for the assessment of financial sector resilience with respect not only to the sector's acute risks, but also to its systemic stability (Alessandri et al., 2009), and which is therefore becoming a standard tool in the macroprudential framework across many regulatory authorities (FSB, 2011).

A more detailed summary of the individual essays follows: In the first essay we address credit risk parameter, Loss Given Default (LGD), and we estimate it for selected companies listed on the Prague Stock Exchange (PSE). The importance of estimating LGD stems from the fact that a lender's expected loss is the product of the probability of default (PD), credit exposure at default (EAD), and LGD. However, LGD has received considerable attention only in recent years as Basel regulation identified it as one of the key credit risk parameters and allowed financial institutions to apply their own estimates of LGD in the computation of regulatory capital. Thus, accurate estimation of LGD has become an important problem in current credit risk management because its systemic underestimation may cause significant losses for the creditors when the debtors default.

We do not estimate LGD based on the historical LGD values of defaulted companies. Instead, we try to employ information in the stock market and estimate potential LGD in the case of default for companies which are currently listed on the stock exchange. We employ Merton's structural approach, which models default as the situation where the value of a company's assets is lower than the value of its debt at the time of maturity. Nonetheless, this approach is based on a number of simplifying assumptions. There are no taxes, the company's debt structure is represented by a single zero-coupon bond, and default can occur only on maturity of the debt, which we arbitrarily set at five years for all the companies analyzed.

The 15 most liquid non-financial companies listed on the PSE were analyzed in the time period 1999–2008. We estimated the expected LGDs at the five-year horizon, which were in the range of 20–50% on average. Because of the model's simplifications, there is uncertainty about the precise values of the estimated LGD. However, it can serve as a credit risk indicator capturing the evolution of a company's riskiness over time. Furthermore, the presented results are the first estimates of expected LGD based on market information for companies listed on the PSE and could therefore serve as a stepping stone for further improving such estimates.

The second essay deals with the method for estimating equilibrium indebtedness of the private sector in the Central and Eastern Europe (CEE). The historical experience of the CEE countries with the credit boom in 2004–2007 offers the possibility of applying the method proposed by the Basel Committee within its Basel III regulatory package to calculate and discuss what countercyclical capital buffer level these countries might have had if the newly proposed regulation on the creation of capital buffers had existed before the crisis.

The motivation for this analysis is to determine how suitable the Basel Committee's proposed method for calculating excessive credit using the Hodrick-Prescott (HP) filter for the credit-to-GDP series is for the countries of Central and Eastern Europe. In these countries, rapid credit expansion may simply mean convergence to values typical of the advanced nations, and not excessive borrowing. For this type of country, we propose to use a method involving estimation of the equilibrium private credit level obtained using economic fundamentals.

The HP filter method applied on credit-to-GDP has its drawbacks. A time series trend is dependent to a significant extent on the length of the chosen time series and the calculation is very sensitive to the smoothing parameter (lambda). Complication as regards practical application in macroprudential policy is "end-point bias", which generates a highly unreliable estimate of the trend at the end of the data period. Another relevant question is whether the credit ratio should take into account other denominators besides GDP, such as financial assets or total assets of the private sector.

The paper offers a so-called "out of sample method" (OOS) based on estimating the model on a different sample of countries and applying the elasticities so obtained to the data for the countries for which the equilibrium credit level is being estimated. We draw upon the existing studies on this topic, which use the developed countries of the EU or OECD as appropriate countries for OOS comparison (Kiss et al., 2006; Égert et al., 2006).

We use the PMG (pooled mean group) estimation method, introduced for panel estimates by Pesaran et al. (1999). This method can be used to estimate the long-run relationship between the credit-to-GDP ratio and other variables, which is identical for all countries, whereas the short-run adjustment to this long-run relationship can differ across countries. The PMG model therefore allows heterogeneity of the estimates for individual countries in the short run. However, the long-run relationship of the cointegrated variables is common to all the countries in the sample.

The OOS calculations may in some cases imply significantly different conclusions regarding excessive credit compared to the calculations using the HP filter. According to the HP filter, the credit-to-GDP gap indicates excessive credit in the recent period not only for the Czech Republic, but also, for example, for Slovakia, Lithuania, Romania and Poland, whereas the OOS estimate does not confirm this excessive credit level. By contrast, Bulgaria, Estonia, Latvia and Slovenia had excessive credit-to-GDP ratios according to the OOS method. Finally, the size of the capital buffer was calculated for individual CEE countries using the two alternative methods using the mid-2008 data as the starting point for the buffer calculation.

The third and last essay describes the stress testing framework used in the Czech central bank and focuses on the general question of how to calibrate the models used to stress test the most important risks in the banking system. As stress-tests offer a framework to estimate the impact of adverse developments which may arise not only from a systemic crisis, proper methodology for testing relevant risks should be developed to assess all possible sets of vulnerabilities threatening the financial system.

A general obstacle to stress testing is very problematic verification, since the adverse scenario is very unlikely to materialize. If it does, only a few data points are available, which is hardly sufficient for rigorous empirical verification of stress testing models assumptions and the actual outcomes. This ambiguity leads to the situation where the stress testing models for the sector as a whole are very rarely back-tested and verified. Still, the models can be verified for the baseline scenario, which presents the most probable development. However, since the estimated elasticities of the model may change dramatically in the adverse scenario compared to the baseline scenario, the paper argues that stress tests should be calibrated conservatively and overestimate the risks for the baseline scenario to have a sufficient buffer for the situation where the adverse negative shocks materialize.

1. The Merton Approach to Estimating Loss Given Default

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The Merton Approach to Estimating Loss Given Default:

Application to the Czech Republic

Abstract

This paper focuses on a key credit risk parameter – Loss Given Default (LGD). We illustrate how the LGD can be estimated with the help of an adjusted Mertonian structural approach. We present a derivation of the formula for expected LGD and show its sensitivity analysis with respect to other company structural parameters. Finally, we estimate the five-year expected LGDs for companies listed on Prague Stock Exchange and find that the average LGD for the analyzed sample is around 20–50%.

Abstrakt (*in Czech*)

Tato práce se zabývá klíčovým parametrem kreditního rizika – ztrátovostí ze selhání (loss given default – LGD). Podrobně je ilustrováno odvození vzorce pro výpočet očekávaného LGD pomocí upraveného Mertonova modelu a následně je diskutována citlivostní analýza LGD vzhledem k ostatním strukturálním ukazatelům společnosti. Na závěr jsou odhadnuty očekávané LGD v pětiletém horizontu pro vybrané společnosti kotované na Burze cenných papírů Praha. Výpočty ukazují, že průměrné LGD analyzovaného vzorku firem se pohybuje mezi 20–50 %.

Keywords: *loss given default, credit risk, Merton model*

JEL Codes: C02, G13, G33

1.1. Introduction

Credit risk techniques have undergone significant development in recent decades. This has led to the development of new methods for the estimation of the potential bankruptcy of borrowing entities and parameters specifying possible losses. These parameters include Loss Given Default (LGD), expressing the percentage of an exposure which will not be recovered after a counterparty defaults.[1] While the estimation of the probability of default (PD) has received considerable attention over the past 20 years, LGD has gained greater acceptance only in recent years as the New Basel Accord identified it as one of the key risk parameters.

LGD modeling is still quite a new and open problem in credit risk management and its estimation is not straightforward, because it depends on many driving factors, such as the seniority of the claim, the quality of collateral, and the state of the economy. Moreover, the insufficient database of experienced LGDs makes it more difficult to develop accurate LGD estimates based on historical data. Hence, the extraction of LGD for credit-sensitive securities based on market-observable information is an important issue in the current credit risk area and may produce further improvements in present credit risk management and prevent systemic undervaluation of this parameter for some types of borrowers with low-default history.

This paper therefore discusses this key risk parameter for single corporate exposures and deals with the possibility of LGD extractions from market information. This type of LGD is referred to as *implied market LGD*. We use so-called structural models, which are based on the initial Merton framework, and present the derivation of a closed-form formula for LGD and its sensitivity analysis with respect to other company structural parameters. Furthermore, we empirically implement this contingent claim approach for a set of companies in the Czech Republic. As a result, we estimate five-year expected LGDs for the 15 most liquid companies listed on the Prague Stock Exchange in the period 1999–2008.

1.2. Basic characteristics of LGD

LGD is usually defined as the loss rate experienced by a lender on a credit exposure if the counterparty defaults.[2] Thus, despite default the lender still recovers $1-\text{LGD}$ percent of the exposure. One minus LGD is therefore called the recovery rate (RR). In principle, LGD also comprises other costs related to default of the debtor, and the correct formula should rather be $\text{LGD} = 1 - \text{RR} + \text{Costs}$. Nevertheless, costs are relevant only in a specific type of LGD and are not usually so high as to influence losses markedly in comparison with the recovery rate. Therefore, we use the recovery rate as the complement of LGD in the following text and take these two parameters as being conceptually the same.

[1] Before Basel II formalized the use of LGD, this concept was also called *Severity* (see Stephanou and Mendoza, 2005).

[2] In principle we should denote the loss given default rate as LGDR and use LGD for the absolute amount of the loss. However, LGD is used to indicate the loss rate by many practitioners, including Basel II, while the absolute loss is indicated as LGD.EAD, where EAD is the exposure at default (see BCBS, 1988).

Usually three basic types of LGD for defaulted facilities are used. *Market LGD* employs the price of a bond after default as a proxy for the recovered amount. However, the post-default price is available only for the fraction of the debt that is traded and for which an after-default market exists – very often it is available only for corporate bonds issued by large companies.[1] Market LGD is therefore highly limited for defaulted bank loans, which are traditionally not traded. For them one must turn to another approach.

Workout LGD considers all relevant facts that may influence the final economic value of the recovered part of the exposure arising in the long-running workout process. However, bankruptcy claims are often settled not in cash, but with securities (equity, options, warrants, etc.) with no secondary market, which means that their value will be unclear for years. Another problem is that the appropriate discount rate (which should reflect the risk of holding the defaulted asset) is not known. Computation of workout LGD therefore depends on an unknown and variable discount rate which is difficult to estimate for a particular situation.[2]

The last method of measuring of LGD is the concept of *Implied Market LGD*, which is estimated ex ante from market prices of non-defaulted loans, bonds, or credit default instruments by structural or reduced-form models. The idea is that prices of risky instruments reflect the market's expectation of the loss and may be broken down into PD and LGD. Implied market LGD estimation does not rely on historical data and can be used especially for low-default facilities. Thus, it may help to estimate LGD parameter which could be otherwise undervalued for some types of borrowers due to insufficient historical default experience.

Recovery rates are ultimately determined by the value of the assets that can be seized in the case of default. Because many asset types differ between industries,[3] it is intuitive to assume that the debtor's industry characteristics can influence LGD. Although the type of industry seems like a straightforward determinant of RR, the literature does not give wholly unified answers (see Altman and Kishore, 1996; Grossman et al., 2001 or Acharya et al., 2003). Those studies have broken down the LGD of corporate bonds by industry and have found evidence that some industries, such as *public utilities* and *chemicals*, do evidently better than the others. Nonetheless, they have also shown that the standard deviation of RR per industry and within a given industry is still very large (see Table 1).

[1] What is more, outside the USA the market for defaulted bonds either is non-existent or does not have the required depth and liquidity.

[2] Sometimes a discount rate based on historical values is used. What discount factor should be used is dealt with in detail in, for example, Maclachlan (2005).

[3] For example, firms in some sectors have a large amount of assets that can be easily sold on the market in case of default, while other sectors can be more labor-intensive, for example.

Table 1

Average recoveries per industry

Altman and Kishore			Acharya et al.			Moody's	
1971–1996			1982–1999			1982–2003	
Industry Description	Mean (%)	Std. Dev. (%)	Industry Description	Mean (%)	Std. Dev. (%)	Industry Description	Mean (%)
Public Utilities	70.5	19.5	Utilities	74	18.8	Utility-Gas	51.5
Chemicals*	62.7	27.1	Energy, Resources*	60	31.0	Oil and Oil Service	44.5
Machinery*	48.7	20.1	Financial Institutions	59	44.3	Hospitality	42.5
Services*	46.2	25.0	Healthcare, Chemicals	56	40.8	Utility-Electric	41.4
Food*	45.3	21.7	Building Products	54	42.1	Media and Broadc.*	38.2
Wholesale and retail	44.0	22.1	Telecommunications	53	38.1	Finance and Banking	36.3
Divers. manufacturing	42.3	25.0	Aerospace, Auto*	52	38.1	Industrial	35.4
Casino, hotel*	40.2	25.7	Leisure Time, Media	52	37.2	Retail	34.4
Building material*	38.8	22.9	High Technology*	47	32.4	Automotive	33.4
Transportation*	38.4	27.9	Consumer, Service	47	35.6	Healthcare	32.7
Communication*	37.1	20.8	Transportation	39	36.1	Consumer Goods	32.5
Financial institutions	35.7	25.7	Insurance and Real Es.	37	35.4	Construction	31.9

* Industry description is reduced

Source: Altman and Kishore (1996), Acharya et al. (2003), Moody's (2004)

An opposite view of industry influence is presented by Gupton et al. (2000) and Araten et al. (2004). These studies found no evidence of different LGDs across industries. They state that the use of recovery averages broken down by industry does not capture the industry variability in recovery rates across time. Some sectors may enjoy periods of high recoveries, but can fall below average recoveries at other times. This means that industry recovery distributions change over time and therefore cannot be expected to hold in the future.

These unambiguous results of different studies might be due to cyclicality of LGD in relation to the economic environment. Each industry can be at a different stage of the economic cycle. The cycle can influence LGD more than the industry-type itself because LGD is not stable in time and there is underlying cyclical variability depending on the macroeconomic conditions. Acharya et al. (2003) showed that when the industry is in distress, the mean LGD is 10–20% higher on average than otherwise.

Behind the cyclical variation is the fact that as the economy enters into recession, default rates increase. Recoveries from collateral will depend on the possibility of selling the relevant assets. We can generally suppose that a greater supply of collateral assets will lead to lower prices of those assets, of course depending on the market size and structure observed for the particular asset. Moreover, the demand for these assets declines because non-defaulted companies are not able to invest the same amount of money in a recession as during an expansion. The result is that the macroeconomic situation can significantly influence the recovery rate. This has been demonstrated by several authors (see Araten et al., 2004, or Altman et al., 2005).

Also, when a firm goes into bankruptcy[1] and there is no other option than liquidation, the capital structure of the firm and the absolute priority rule (APR)[1] are important deter-

[1] Bankruptcy takes the form of either reorganization or liquidation.

minants of the recovery rate. This means that the rate of recovery of a defaulted bond depends on where the claims are in the firm's capital structure. Empirical evidence on recovery rates is usually based on defaulted bonds because the LGD data are simply available. The results of several empirical studies have confirmed that RR increases with the seniority and security of the defaulted bond and decreases with the degree of subordination. The results also tend to be rather similar in terms of average recovery rates – for bank loans (70–84%) and for bonds: senior secured (53–66%), senior unsecured (48–50%), senior subordinated (34–38%), and subordinated (26–33%). All studies also reported a high standard deviation characterizing the recovery rate across all bond debt classes, regularly exceeding 20% (see Altman and Kishore, 1996; Castle and Keisman, 1999; and Keenan et al., 2000).

As said earlier, LGD is influenced by many factors, such as the facility's seniority and the presence of collateral, the borrower's industry characteristics, and more general factors such as the macroeconomic conditions. However, previous research gives ambiguous results concerning some LGD properties. The relatively rare occurrence of default events for some facilities can cause the research to be based on relatively small empirical samples. It is clear that further research is needed, and hopefully with the adoption of the Basel II accord, which sets rules for LGD data gathering and estimation, this research will be based on better data samples offering more exact outcomes. However, a major difficulty of such information is its complete dependence on historical data. LGD predictions based on past LGD data are not thus necessarily consistent with the evolution of fundamentals across time and can result in inaccurate estimates that cannot capture the real trend in the economy.

1.3. LGD modeling

In this part we focus on analytical tools enabling forward-looking estimates of LGD to be obtained from market-observable information. We employ asset pricing models, which aim at determining the equilibrium arbitrage-free price of risky assets. Each risky asset should offer an expected return corresponding to its degree of risk; therefore, all risky parameters must be evaluated by the market in order to get the equilibrium price. This assumption that prices include all information is then used by credit risk pricing models, which use market information (e.g. share or bond prices) to measure credit risk and try to extract the key risk parameters such as PD or LGD from the prices. Those models are forward-looking, estimating the risk parameters which are expected by the market in the future and not those that occurred in the past. From the nature of this method such estimate of LGD is called *implied market LGD*.

These credit risk pricing models can be further classified as *structural* and *reduced-form* models. The category of structural-form models is based on the framework developed by Merton in 1974 using the theory of option pricing presented by Black and Scholes (1973). The intuition behind this model is quite straightforward: a company defaults when the value of its

[1] Eberhart and Weiss (1998) confirm that the APR is routinely violated because of speed of resolution. Creditors agree to violate the APR to resolve bankruptcies faster.

assets is lower than that of its liabilities when the debt matures. For that reason, the default process is driven by the value of the company's assets and the risk of default is explicitly related to asset variability.[1]

In contrast, *reduced-form* models generally assume that default is possible and is driven by some exogenous random variable. The result is that default and recovery are modeled independently of the firm's structural features, which lacks the clear economic intuition behind the default event. The basic input parameters for extracting LGD in the reduced-form approach are the prices of risky corporate bonds. However, companies in the Czech Republic are still using traditional bank loans more than bond issuance as a source of finance (see Dvořáková, 2003). As a result, the domestic corporate debt market is rather illiquid and incomplete and can hence barely reflect market expectations about the default and recovery risk of particular companies or their securities. The result is that reduced-form models which employ prices of corporate bonds are currently hardly applicable for LGD estimation in the Czech Republic.

The stock market provides an alternative source of information, assuming that share prices incorporate all available information, including the future prospects of the company and its creditworthiness.[2] Structural models for extracting a company's default risk typically use observed stock prices, stock volatility, and specifics about the company's capital structure. Even if the number of listed companies in the Czech Republic is also limited,[3] for some of them it seems to be sufficiently liquid to apply structural models and estimate the required credit risk parameters. As a result, we will use Merton's structural approach to derive a formula for implied market LGD for particular companies.

The seminal structural Merton (1974) model relies on many hypotheses, most of which derive from the Black–Scholes option-pricing theory. Some of them became sources of criticism and were later relaxed.[4] The original framework in which the process of valuing a firm's assets is embedded requires many assumptions for the application of standard corporate credit risk pricing. There are no transaction costs, taxes, or short-selling restrictions. The term structure of the risk-free interest rate is flat and known with certainty. The price of a riskless

[1] The term structural comes from the fact that these models focus on structural characteristics of the company, such as asset volatility or leverage, which determine the relevant credit risk elements. Default and RR are a function of those variables.

[2] This is true only if the efficiency hypothesis holds, which has been doubted by some studies (see, for example, Sloan, 1996). There is also a question whether the volatility of stock prices is caused solely by the incorporation of new information about future stock returns, or if it is caused largely by trading itself (see French, 1980, or French and Roll, 1986).

[3] More about the stock market efficiency of the PSE can be found in, for example, Filacek et al. (1998) and Hájek (2007).

[4] Alternative approaches have been developed in an attempt to remove one or more of the drawbacks of the seminal model. Black and Cox (1976) introduced the possibility of a more complex capital structure of the company's liabilities, Geske (1977) introduced interest-paying debt, and Vasicek (1984) established a distinction between short and long-term debt. All these authors also enhanced the model by treating default as an event that can occur any time before debt maturity. More recent improvements, such as in the papers by Longstaff and Schwartz (1995) and Hull and White (1995), reject the constant risk-free interest rate and consider the interest rate as a stochastic variable instead. For a detailed account of later structural models, see, for example, Altman et al. (2005) and the references therein.

bond paying \$1 at time T is hence $B_0(T) = \exp[-rT]$, where r is the instantaneous riskless interest rate. The total value of firm V is financed by equity E and one zero-coupon non-callable debt contract D, maturing at time T with face value F. It also holds that $V_t = D_t + E_t$. With the no-taxes assumption this implies that the value of the firm and the values of assets are identical and do not depend on the capital structure itself (the Modigliani–Miller theorem).

The dynamics of the firm's value through time can be described by a stochastic differential equation called geometric Brownian motion:

$$dV_t = \mu_V V_t dt + \sigma_V V_t dW_t^V$$

where μ_V is asset drift (i.e., the instantaneous expected rate of return on the firm's value V per unit time), σ_V is the standard deviation of its return, and dW_t^V is a standard Gauss–Wiener process.

Based on these assumptions, credit risk concerns the possibility that the stochastically evolving value of the company on the maturity day T will be less than the repayment value of the loan F. The debt holders receive at T either the value F (if $V_T > F$) or the entire value of the firm and the owners of the firm receive nothing (if $V_T < F$). The risk of default is therefore explicitly linked to the volatility in the firm's asset value. Merton's contingent claim analysis shows how this risk should be priced. Merton derived a fundamental differential equation which determines the value of the debt at any time t as a function of the value of the firm. We use Merton's famous conclusion that the value of equity is identical to the formula for pricing "...*a European call option on a non-dividend-paying common stock where firm value corresponds to stock price and F corresponds to the exercise price*" (Merton 1974, p. 10). This is given as

$$E(V,0) = \max[0; V - F]. \tag{1}$$

Indeed, at maturity time T, the equity holders will exercise the option and pay the debt holders the face value of liabilities if $V_T \geq F$, otherwise they let this option expire. By applying the Black–Scholes option pricing formula it is straightforward to get the solution for equation (1) as

$$E(V,\tau) = V\Phi(d_1) - Fe^{-r\tau}\Phi(d_2) \tag{2}$$

where $d_1 = \dfrac{\ln\dfrac{V}{F} + \left(r + \dfrac{1}{2}\sigma_V^2\right)\tau}{\sigma_V\sqrt{\tau}}$, $d_2 = d_1 - \sigma_V\sqrt{\tau} = \dfrac{\ln\dfrac{V}{F} + \left(r - \dfrac{1}{2}\sigma_V^2\right)\tau}{\sigma_V\sqrt{\tau}}$, and Φ (.) is the cumulative standard normal distribution. And since $V = D(V,\tau) + E(V,\tau)$, where $\tau = T - t$ is the length of time until maturity, we can express the value of the debt at time τ as

$$D(V,\tau) = V\Phi(-d_1) + Fe^{-r\tau}\Phi(d_2).$$

Now we are able to clarify how credit risk parameters such as PD and RR can be extracted. Default occurs when the firm's value drops below some *default barrier* (DB), which in the seminal Merton model is represented by the face value of the debt F at its maturity. The probability of default is therefore simply expressed as

$$PD = \Pr(V_T \le F)\ . \tag{3}$$

To obtain this probability, more information about the probability distribution of V has to be known. However, we can use the assumption that the value of the firm V is log-normally distributed, which according to Crouhy et al. (2000) is quite a robust hypothesis confirmed by actual data, and we can obtain the probability distribution of $\ln V_T$,[1] which is

$$\ln V_T \sim \Phi\left[\ln V_0 + \left(\mu_V - 0{,}5\sigma_V^2\right)T, \sigma_V^2 T\right]. \tag{4}$$

From the properties of the natural logarithm, one can obtain the probability (3) expressed as

$$PD = \Pr(\ln V_T \le \ln F)$$

Combining this equation with (4) we can get

$$PD = \Phi\left(-\frac{\ln\frac{V_0}{F} + \left(\mu_V - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}\right) = \Phi(-d_2^*) \tag{5}$$

which is the PD of the company at the time of maturity T expected at time $t = 0,\ (\tau = T)$, when the value of the firm V_0 is known with certainty.[2] $\Phi(d_2)$ is the probability that the European call option will be exercised by equity holders and the company will not default. The term $1-\Phi(d_2) = \Phi(-d_2)$ then characterizes the default probability. However, while $\Phi(-d_2^*)$ in (5) gives the real-world (physical) probability of default, $\Phi(-d_2)$ represents the default probability in the risk-neutral world. This is caused by using the riskless interest rate r instead of the expected rate of return μ_V in the formula for d_2. In the real world, investors demand more than the risk-free rate of return and therefore $d_2^* > d_2$, which implies $\Phi(-d_2^*) < \Phi(-d_2)$ and the fact that the risk-neutral PD overstates its physical measure. Similarly, one has to distinguish between the physical and risk-neutral RR.[3]

The recovery rate, assuming no liquidation costs after default, will be given by the ratio of the firm's value at T to the debt F, (V_T/F). More formally expressed as

[1] Itô's Lemma can again be used to get the dynamics for $d\ln V_t$, and from that the parameters of the normal distribution for $\ln V_t$ can be determined.

[2] From (5) it can be seen that PD is a function of the distance between the current V_0 and the face value of the debt F, adjusted for the expected growth of asset μ_V relative to its volatility σ_V^2. d_2^* is thus called the distance to default (DD) and the higher it is, the lower is PD.

[3] As, for example, Delianedis and Geske (2003) state, the risk-neutral default probabilities can serve as an upper bound to the physical default probabilities. For recoveries the reverse relation holds – the risk-neutral expected recovery rate is less than its physical (real-world) counterpart (see Madan et al., 2006, p. 5).

$$RR = E\left(\frac{V_T}{F}\middle| V_T < F\right) = \frac{1}{F} E\left(V_T \middle| V_T < F\right) \tag{6}$$

as was already mentioned, V is the log-normal variable. Therefore, to get an explicit formula for RR we can use the method presented in Liu et al. (1997), which derives the conditional mean for a log-normal distributed variable, which is exactly the case of equation (6) (see Resti and Sironi, 2007).

Let's suppose that variable Y is log-normal and $\ln Y$ is normally distributed with mean μ and variance σ^2. Then variable $Z=(\ln Y-\mu)/\sigma$ has a standard normal distribution. The conditional mean of Y, given $Y<c$, can then be expressed as follows:

$$E\left(Y \middle| Y < c\right) = E\left(\exp\left[\sigma Z + \mu\right] \middle| \exp\left[\sigma Z + \mu\right] < c\right)$$

$$= E\left(\exp\left[\sigma Z + \mu\right] \middle| Z < \left(\ln c - \mu\right)/\sigma\right). \tag{7}$$

To simplify this expression, let's define $g = \left(\ln c - \mu\right)/\sigma$ and $h = \Phi(g)$, where Φ (.) is the normal c.d.f. With these notations, equation (7) becomes

$$E\left(Y \middle| Y < c\right) = h^{-1} \int_{-\infty}^{g} \exp[\sigma Z + \mu] \left(2\pi\right)^{-1/2} \exp[-z^2/2] dz$$

$$= \exp[\mu + \sigma^2/2] h^{-1} \int_{-\infty}^{g} \left(2\pi\right)^{-1/2} \exp[-(z-\sigma)^2/2] dz$$

$$= \exp[\mu + \sigma^2/2] \frac{\Phi\left(\left(\ln c - \mu\right)/\sigma - \sigma\right)}{\Phi\left(\left(\ln c - \mu\right)/\sigma\right)}.$$

Considering the parameters of the normal distribution of $\ln V$ stated in (4), we can express the mean of V_T, conditional on $V_T<F$, as

$$E\left(V_T \middle| V_T < F\right) = \exp[\mu_v^* + \sigma_V^{*2}/2] \frac{\Phi\left(\left(\ln F - \mu_v^*\right)/\sigma_V^* - \sigma_V^*\right)}{\Phi\left(\left(\ln F - \mu_v^*\right)/\sigma_V^*\right)}$$

where $\mu_v^* = \ln V_0 + \left(\mu_V - 0{,}5\sigma_V^2\right)T$ and $\sigma_V^{*2} = \sigma_V^2 T$. After substituting and rearranging we get

$$E\left(V_T \middle| V_T < F\right) = \exp\left[\ln V_0 + \mu_V T\right] \frac{\Phi\left(-\dfrac{\ln\left(V_0/F\right) + \left(\mu_V + 0{,}5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}\right)}{\Phi\left(-\dfrac{\ln\left(V_0/F\right) + \left(\mu_V - 0{,}5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}\right)}$$

$$= V_0 \exp[\mu_V T] \frac{\Phi(-d_1^*)}{\Phi(-d_2^*)}.$$

Using the term in equation (6) we get the final expression for the expected recovery rate at time $t=0$ in the form

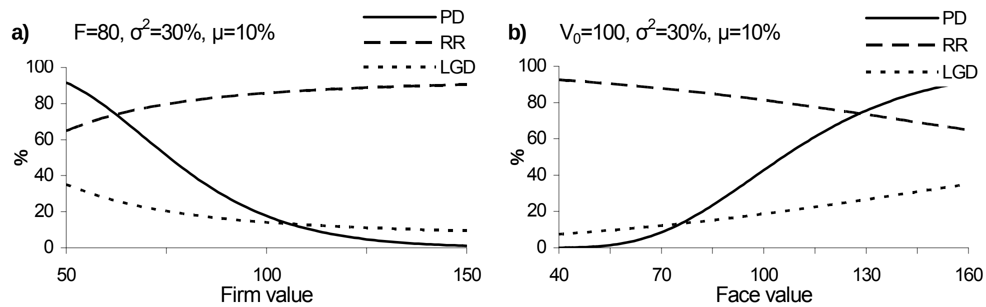
$$RR = \frac{1}{F} E\left(V_T \middle| V_T < F\right) = \frac{V_0}{F} \exp[\mu_V T] \frac{\Phi(-d_1^*)}{\Phi(-d_2^*)} \tag{8}$$

which is the physical recovery rate, and the risk-neutral RR would be obtained by replacing μ_V with r. The RR function is homogeneous of degree zero in V_0 and F, which means that a proportional change in those variables does not influence its value (ceteris paribus). Moreover, RR, like PD, is dependent on the uncertain development of the firm's value and therefore is not constant through time but stochastic.

Using the expression presented for PD and RR, sensitivity analyses can be made with respect to other company structural parameters. Consider a firm with given $F = 80$, $V_0 = 100$, $\sigma^2 = 30\%$, $\mu = 10\%$, and $T = 1$. The variables will be shocked to see how PD and RR change.

Figure 1

Sensitivity analysis for PD and RR (LGD) – part 1

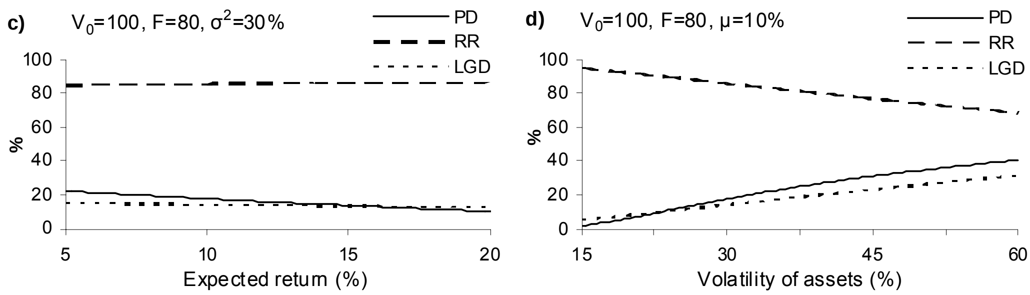


Source: computed from eq. (5) and (8)

The figure presents the results for RR and PD for the physical measure. It shows that the higher is the firm's value at the time of prediction of the risk parameters, the lower is the expected LGD and lower is PD (part a); the link is the reverse for the value of debt F (part b). An increase in the firm's leverage brings about higher both PD and LGD. An increase in asset volatility (leaving leverage unchanged) has a similar impact, causing higher uncertainty of the future value of the firm at maturity T and therefore a fall in RR.

Figure 2

Sensitivity analysis for PD and RR (LGD) – part 2



Source: computed from eq. (5) and (8)

In summary, Merton's approach evidently generates a negative correlation between PD and RR because both variables depend on the same structural characteristics of the firm. RR is significantly determined by the value of the firm's assets at the maturity time T.

However, the original Merton model does not include any payouts to security holders. Since the interest payouts occur over the life of the debt and are considerably lower than the principal amount, they represent lower default risk. However, disregarding the dividend stream, as Hillegeist et al. (2004) state, could introduce significant errors into the estimation of the current market value of the firm and its volatility and thereby influence the resulting LGD estimate.[1] Therefore, it is necessary to modify the seminal Merton approach and incorporate the payout of dividends into the model.

If we define the dividend rate δ as the ratio of the sum of the prior year's common and preferred dividends to the market value of the firm's assets, then the equation for the equity value reflecting the dividend stream paid by the firm accruing to equity holders would change as proposed by Hillegeist et al. (2004) into

$$E(V,T) = V\exp[-\delta T]\Phi\left(d_1\right) - Fe^{-rT}\Phi\left(d_2\right) + (1-\exp[-\delta T])V \tag{9}$$

where the additional $\exp[-\delta T]$ in the first term accounts for the reduction in asset value due to dividends distributed before maturity T. The last expression $(1-\exp[-\delta T])V$ does not appear in the traditional equation for the call option on a dividend-paying stock since dividends do not accrue to option holders. Equation (9) is derived under the risk-neutral measure, therefore the risk-free rate is taken to be the expected rate of return on the firm's value. This rate, however, is lowered by the dividend rate and hence the terms d_1 and d_2 have to be modified to

$$d_1 = \frac{\ln(V_0/F) + \left(r - \delta + 0,5\sigma_V^2\right)T}{\sigma_V\sqrt{T}},\ d_2 = d_1 - \sigma_V\sqrt{T}$$

where all parameters are as defined above.

1.4. Implementation of the model

The empirical use of any structural model is based on variables which are not directly observable. Similarly, in our case, the market value of assets V and also asset volatility σ_V must be estimated in order to compute the expected LGD.[2] A procedure for estimating these variables was first proposed by Jones et al. (1984) for publicly listed companies, exploiting the prices of their shares. Their approach is based on simultaneously solving two equations which match the value of equity E and its volatility σ_E with two unknown variables V and σ_V. Equity data is generally used since actual daily prices are observable and equity is the firm's most liquid security.

[1] We are more concerned about dividend payouts, since they lower the value of the company by transferring it to the shareholders, which implies a lower recovered amount for the debt holders if default occurs.

[2] The market value of the firm is the sum of the market value of its equity and its debt. However, the market value of the debt is not usually available since companies are not financed entirely by traded debt.

Jones et al. (1984) used relation (2) as the first equation. However, this equation does not consider dividend payouts and we will thus use a modified equation (9). The second equation linking the observable and unknown values is in the form

$$\sigma_E E = \sigma_V \exp[-\delta T] V \Phi(d_1) \tag{10}$$

and its derivation uses Itô's lemma and the expression for equity delta (see Hillegeist et al., 2004). This system of two equations has to be solved to arrive at the unobservable market value of the firm's assets and its volatility. Due to the non-linearity of those equations it is necessary to solve the system iteratively.[1]

The accuracy of the expected LGD estimate is therefore dependent on the estimates of the parameters in equation (8). Although some of them, such as the face value[2] or maturity of the debt, are observable, some assumptions must be made about them to be able to implement Merton's simplifying approach. For example, the model requires us to reduce the firm's capital structure into a single liability. Since a large share of the firm's debt is not traded very often, we have to use book values as a proxy. As a result, the book value of total liabilities reported in firms' balance sheets is used as the notional face value of the zero coupon bond. This approach is often used because equity holders earn the residual value of the firm once all debt is paid off (see, for example, Helwege et al., 2004 or Hillegeist et al., 2004).[3]

To determine the maturity time of the zero coupon bond representing all the firm's liabilities, we could compute the weighted maturity of the individual claims' maturities.[4] However, our intention is to provide LGD comparable across the sample of the companies analyzed, which would hardly be practicable in case of different maturities (see the sensitivity analysis section). Therefore, we will assume a five-year debt maturity for all companies, which should take into consideration both short-term and long-term debt maturity.[5]

From our previous discussion it is obvious that the estimates of V and σ_V are highly dependent through the system of two equations on the value of equity and its volatility. While the market value of equity E is simply obtained as the closing price of shares at the end of the fiscal year multiplied by the outstanding number of stocks, the equity volatility value depends

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1 To solve two non-linear equations of the form $F(x,y) = 0$ and $G(x,y) = 0$ we need to minimize the function $[F(x,y)]^2 + [G(x,y)]^2$ (see Kulkarni et al., 2005).

2 This holds only if the debt is traded.

3 Employed approach in this paper is similar to Moody's KMV model for estimating expected default frequencies, which specifies the notional default point as the book value of short-term liabilities plus half of the value of long-term liabilities (see Crosbie and Bohn, 2003). It means that KMV puts a greater weight on short-term obligations because debts due in the near term are more likely to cause a default. However, this approach is probably more convenient in the first-passage time models than in seminal Merton, where the default may occur only at debt maturity.

4 Another method widely used among academics is to group the short-term and long-term obligations and find out the maturity by weighting the maturities of those two groups. For example, Dalianedis and Geske (2001) made an assumption of 1-year maturity for short-term debt and 10-year maturity for long-term debt. The weights would be the book values of claims.

5 By setting the longer time horizon we should also avoid inaccuracies due to the fact that we use a poor diffusion process without possible jumps for the firm's asset value dynamics.

on the estimation method chosen. For that reason, it is desirable to use different types of estimation techniques for comparison.

The standard approaches for estimating σ_E are based on the historical data of stock prices or on exploiting bond prices to obtain the so-called implied volatility. The implied volatility of a bond is obtained when one chooses the asset volatility such that the price generated by our model fits the bond's actual market value.[1] Nevertheless, since this volatility estimate incorporates all possible errors of the model used, and also considering our discussion about the illiquid and insufficient bond market, we will use only the historical approach based on stock returns.

Let P_i denote the closing price of the stock on day i. Then the continuously compounded one-day return r_i is defined as $r_i = lnP_i - lnP_{i-1}$ and the unbiased estimate of the one-day volatility using the m observations of r_i is

$$\sigma_E = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(r_i - \overline{r}\right)^2}$$

where $\overline{r}$ denotes the mean of the r_i's (see Hull, 2003). The appropriate observation interval depends on the time horizon which we are dealing with. Since we set the maturity time to five years, we should also use the long-term volatility for our predictions. For that reason we used a volatility of five trading years.[2] In addition, to take into account possible changes in volatility in the shorter term, we also estimate the last 250 trading days' volatility, similarly to, for example, Kulkarni et al. (2005).

An improvement over these traditional volatility estimation methods, which give equal weights to each observation, is estimation using the exponentially weighted moving average (EWMA), where more recent observations carry higher weights. This method, capturing the volatility dynamics better, is recommended in RiskMetrics™ (1996). For a given set of m observations, the exponentially weighted volatility can be computed as

$$\sigma_E = \sqrt{(1-\lambda)\sum_{i=1}^{m}\lambda^{i-1}\left(r_i - \overline{r}\right)^2}\ ,\ 0 < \lambda < 1$$

where λ is referred to as the *decay factor*, which determines the relative weights for particular observations. For our sample of companies we use monthly observations over five years with a decay factor equal to 0.97. This value is based on the analysis relating to optimal λ provided in RiskMetrics™ (1996).

The fourth and last method that we used is GARCH(1,1), which takes into account the fact that the variance of a time series returns tends to revert to its long-run average over time

[1] Similarly, one could get the option-implied volatility for companies with options written on their stock by using the standard Black–Scholes formula for pricing options (see Hull, 2002).

[2] In the case of insufficiently long time series, we use the longest available one. This holds also for the other five-year estimates computed later in this section.

(see Bollerslev, 1986). We estimate the GARCH(1,1) model for daily data over a five-year interval in the form

$$\sigma_t^2 = b + \alpha_1 r_{t-1}^2 + \alpha_2 \sigma_{t-1}^2\,,\ \alpha_0 > 0, \alpha_1 \geq 0, \alpha_2 \geq 0$$

where $b = \alpha_0 \sigma_{LR}^2$, σ_{LR}^2 represents the long-run unconditional variance of the daily returns r and $\alpha_0, \alpha_1, \alpha_2$ are the weights, whose sum is equal to 1. Since we are concentrating on the long-run volatility, we use only the long-run average variance σ^2_{LR} to which the process will convert in the future. The long-run volatility is therefore computed from the estimated parameters as

$$\sigma_E = \sqrt{\frac{b}{1-\alpha_1-\alpha_2}}\ .$$

However, for some companies we did not estimate the long-run GARCH volatility, since their return time series were not weakly stationary. Also, the GARCH is unstable when the fitted parameters $\hat{\alpha}_1 + \hat{\alpha}_2$ are close to 1. This leads to an integrated IGARCH(1,1) model with the additional constraint $\alpha_1 + \alpha_2 = 1$. However, the unconditional variance σ^2_{LR} is not defined in this case. Nonetheless, as can be found in Tsay (2005), this special IGARCH(1,1) model can be rewritten as the EWMA formula with which we have already estimated σ_E.

For most of the companies in our sample we estimated four types of daily equity volatility by the aforementioned methods. These still need to be scaled to obtain the annualized volatility used in later computations.

All estimates are presented in Table A1 in the Appendix. Since higher volatility of equity results in higher volatility of the firm's value and higher default risk, the choice of estimated σ_E can significantly influence the further results. As a rule of prudence, however, we consider it more desirable to provide overstated rather than understated values of LGD. Therefore, we use the average of the two highest σ_E estimates, σ_E^*, as the parameter entering the system of two equations.

As the firm's expected rate of return, the system derived for obtaining the unobservable values of V and σ_V exploits the risk-free rate r_f, for which we used the yield of the five-year government bond. Therefore, the last parameter that must be estimated in order to solve the equations is the dividend rate δ. Nonetheless, to acquire δ, one needs to obtain the market value of the firm V. Hence, we use the approximate market value V' as the sum of the market value of equity E and the book value of debt.[1] Since we are estimating the five-year horizon, in the computations we will use the adjusted rate δ^*, capturing the dividend stream in the last five years, instead of the one-year dividend rate δ.[2]

[1] This approach, as Wong and Li (2004) show, overestimates the true market value of the firm.

[2] We used the exponentially weighted average with decay factor $\lambda = 0.9$.

We solved the two equations simultaneously using the iterative Newton search algorithm. The approximate value V' and the equity volatility were used as the starting values for V and σ_V, respectively. In almost all cases, the process converges within ten iterations. Note that the equation linking equity and asset volatility given by equation (10) holds only instantaneously, which causes bias in the V and σ_V estimates when the leverage changes. Crosbie and Bohn (2003) assert that a quick decrease in the leverage would lead to overestimation of asset volatility and that, conversely, a rapid increase would lead to underestimation.[1]

Note that the dynamics of the estimated σ_V follow the equity volatility σ_E^*; nevertheless, σ_V is always lower than σ_E^*. This is caused by the presence of leverage, since the debt is considered to be non-traded. With increasing leverage, the equity occupies a lower share in the overall value of the firm and therefore V is less volatile than E.

To estimate the expected LGD for the risk-neutral measure we already know all the necessary parameters. However, as the risk-free rate can significantly differ from the firm's real rate of return, we also estimate the expected market return on assets, μ_V, as the return on assets during the previous year. We can easily use the estimated values of the firm's market value V and obtain the one-year return μ_V as

$$\mu_V(t) = \frac{V(t) + Div(t) - V(t-1)}{V(t-1)}$$

where $V(t)$ is the firm's market value at the end of year t and $Div(t)$ denotes the sum of the common and preferred dividends declared during this year. Since the five-year expected return will not be based solely on a one-year observation only, in our calculations we use the adjusted μ_V^* as the five-year weighted average, in which recent years carry more weight to react faster to current information.

1.5. Estimate of LGD in the Czech Republic

We implement the aforementioned methods on a sample of the most liquid firms listed on the Prague Stock Exchange (PSE) and present the dynamics of the five-year expected LGD for each company between 1999 and 2008. We restrict our sample to non-financial firms so that the leverage ratios are comparable across them. In addition, we exclude enterprises that became listed after 2007 to obtain the long time series of share prices necessary to estimate asset volatility. The 15 companies analyzed account for around 7% of the corporate sector's total assets.

Income statements and balance-sheet items for our set of PSE corporations were obtained from the Magnus (2009) database, and for some of them the information was supplemented with data from company annual reports. Share prices, dividend yields, and the number of shares outstanding are available on the PSE website.[2] We use the time series of share prices

[1] The impact of a change in the firm's leverage on ELGD is presented later, in the sensitivity analysis section.
[2] The information is also available for the Czech companies in the Magnus (2009) database.

from the beginning of 1999 to the end of 2008 and accounting information reported at the end of the fiscal year. The series of five-year risk-free interest rates comes from the ARAD database of the Czech National Bank (CNB).

The non-existence of dividend payouts in the seminal Merton model was modified in the last section. Still, one should also incorporate the costs of bankruptcy, which result in debt holders receiving less than the total firm value in the event of default. Additional default costs also arise from deviations in APR where equity holders gain at the expense of bondholders. While Betker (1997) estimated the direct administration costs relating to bankruptcy at around 5% of firm value, a study by Andrade and Kaplan (1998) indicates higher costs of financial distress, in the range of 15–20%. Based on those empirical studies we consider exogenous common bankruptcy costs $(1-\varphi)$ equal to 10%.[1]

The final formula for the five-year expected LGD at the beginning of year t for the physical measure, including both dividend payouts and bankruptcy costs, is then

$$ELGD_t = 1-\varphi \frac{V_t}{F_t} \exp[(\mu^*_{V,t} - \delta^*_t)T] \frac{\Phi(-d^*_1)}{\Phi(-d^*_2)} \tag{11}$$

$$d^*_1 = \frac{\ln(V_t / F_t) + \left((\mu^*_{V,t} - \delta^*_t) + 0,5\sigma^2_{V,t}\right)T}{\sigma_{V,t}\sqrt{T}}, \text{ and } d^*_2 = d^*_1 - \sigma_{V,t}\sqrt{T}$$

where the time indexes represent particular values at the beginning of year t (the end of the previous year), and $\mu_{V,t}{}^*$, $\delta_t{}^*$ denotes adjusted rates considering five-year historical observations. One can get the expected risk-neutral LGD by replacing $\mu_{V,t}{}^*$ by r_f.

The results are given in Table 2, which presents the expected LGD for each company estimated at the end of every year during the period 1999–2008 for both the risk-neutral and physical measure.[2] All the parameters used for the computations are given in Table A1 in the Appendix.

In the theoretical framework the risk-neutral LGD is always an upper bound to its physical counterpart. Nevertheless, this holds only if asset drift μ_V is greater than the risk-free rate. In the conventional analysis rate r_f is supposed to be always less than drift μ_V. For example, Hillegeist et al. (2004) compute μ_V for PD estimates and use r_f as a minimum bound for μ_V, since they claim that lower expected growth rates than r_f are inconsistent with asset pricing theory. Allowing μ_V to be lower than the risk-free rate may therefore seem to be an arbitrage-free opportunity. However, we try to evaluate the possible expected value of the company from the viewpoint of the creditor, whose recovery rate will depend also on the negative evolution of the company's market value. As a result, letting the risk free rate be the minimum bound for μ_V can

[1] However, there is quite high uncertainty about the value of this parameter, which may be country specific and depend on the legal system of the particular country.

[2] The estimates for the physical measure begin from the year 2000 since we lost one observation for acquiring the firm's growth rate.

result in highly underestimated values of LGD if the real growth rate is lower than r_f. This can be demonstrated using the given results.

Table 2

The five-year expected LGD in the period 1999–2008.

	Expected LGD (%) – risk neutral measure										Expected LGD (%) – physical measure								
Company	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2000	2001	2002	2003	2004	2005	2006	2007	2008
CETV	–	–	–	–	–	–	18.0	22.5	21.4	52.7	-	-	-	-	-	-	23.1	18.0	62.7
ČEZ	24.1	27.7	34.4	35.7	35.3	30.7	29.3	29.2	24.1	40.3	32.7	47.1	39.3	29.6	21.2	18.1	18.7	16.7	27.0
ECM	–	–	–	–	–	–	–	13.8	27.7	47.3	-	-	-	-	-	-	-	18.8	43.6
JČ PAPÍRNY VĚT.	29.2	23.7	26.3	26.5	21.3	32.4	23.1	23.0	33.6	38.9	30.3	52.6	33.2	57.9	33.2	13.0	14.1	36.2	22.3
ORCO	–	–	–	–	–	–	21.3	22.5	29.5	62.8	-	-	-	-	-	-	13.2	16.7	73.8
PARAMO	30.4	17.6	16.2	20.5	19.5	23.8	25.0	21.4	22.5	25.1	78.4	65.4	44.3	16.5	20.6	19.1	18.7	19.6	26.0
PEGAS	–	–	–	–	–	–	–	28.4	19.0	47.2	-	-	-	-	-	-	-	20.4	78.2
PHILIP MORRIS	–	17.0	25.4	36.9	32.1	31.1	28.9	32.5	43.5	46.0	-	15.8	21.7	18.8	20.8	21.0	29.5	44.5	51.2
PR. ENERGETIKA	51.5	40.8	42.5	44.0	35.9	28.8	25.1	22.9	21.9	25.0	52.7	53.5	40.4	28.5	22.0	18.5	17.4	15.9	16.7
SPOL. CH.H. VÝR.	20.0	16.2	23.0	23.4	24.9	22.4	25.5	22.0	33.5	36.3	70.1	37.8	28.1	23.9	15.8	14.5	13.7	21.1	21.8
SPOLANA	33.3	33.5	36.1	34.2	35.0	34.9	27.8	27.5	26.6	22.8	42.9	76.6	58.5	44.3	45.0	28.9	27.1	30.0	25.6
TELEFÓNICA	23.9	32.5	36.7	36.0	33.4	33.3	26.3	22.9	43.4	39.1	40.2	49.5	51.7	35.4	32.7	23.0	20.9	37.1	33.5
TOMA	29.9	29.1	23.0	23.5	21.0	19.7	23.5	21.4	18.7	19.1	67.5	24.2	29.6	18.4	15.6	16.5	15.8	13.4	13.5
UNIPETROL	36.1	30.1	26.5	24.8	26.4	29.8	35.0	36.3	34.1	59.6	24.0	25.3	23.4	22.1	27.0	18.8	22.3	23.2	49.9
ZENTIVA	–	–	–	–	–	18.6	22.6	22.9	24.6	25.3	-	-	-	-	-	15.3	18.7	19.6	22.8
Mean (%)	30.9	26.8	29.0	30.6	28.5	27.8	25.5	24.6	28.3	39.2	48.8	44.8	37.0	29.6	25.4	18.8	19.5	23.4	37.9
Std. Dev. (%)	9.2	8.1	8.1	7.8	6.5	5.7	4.2	5.4	7.9	13.6	19.4	19.1	12.1	13.2	9.2	4.4	5.0	9.2	20.9

Source: computed from eq. (11)

Paramo ended 2000 with a loss of more than CZK 430 million and an almost 24% drop in its market value. This negative result has no impact on the expected risk-neutral LGD at the end of 2000 and its value is even below average for that year. However, the physical estimate captures the huge deterioration in the firm's asset value, which leads to a more than four times higher expected LGD. Moreover, Spolana recorded losses of about CZK 700 million in 2001 as a result of a downswing in the plastics market. The subsequent year it was negatively affected by floods, which led to further losses. While the risk-neutral LGDs in these years do not incorporate any problem compared to the estimates for other years, the physical measure counterparts indicate the company's poor performance quite well. The same situation can be found in the case of Papírny Větřní in 2001 and 2003. By contrast, when the growth rate of a firm's assets μ_V is higher than r_f, the risk-neutral estimates overstate ELGD.

The relatively high ELGD for both measures for ČEZ at the end of 2001 might seem contradictory, since ČEZ ended 2001 successfully with an increase in net profit of over 26% to more than CZK 9 billion. However, its share price dropped from an initial CZK 101 at the end of 2000 to CZK 77.5 at the end of 2001, which led to a more than 23% decrease in the market value of its equity. This, together with a high dividend rate, was reflected in an almost 14% deterioration in asset value and led to a significant increase in ELGD. Similarly, a large decrease in the market value of equity caused the predictions for Telefónica to worsen in 2001 and 2002. Nonetheless, the sharp rise of ELGD in 2007 is due solely to a sharp increase in asset volatility.

The expected downswing in economic activity due to global and domestic factors was not incorporated enough into share prices at the end of 2007. Therefore, the average ELGD at the end of 2007 is relatively small, still capturing the good economic trend in recent years.

For some of the companies analyzed, however, the expected slowdown in economic growth resulted in a drop in the market prices of equity. As a result, the average ELGD estimate at the end of 2008 rose to 38%, indicating a considerable increase in credit risk in the non-financial corporations sector.[1] However, while some companies showed only moderate LGD growth differing little from the previous years' values (ČEZ, Pr. Energetika, and Zentiva), or even the same or decreasing values of ELGD (Spolana, Toma, and Telefónica), some companies recorded sharp increases several times higher than the historical values (CETV, ECM, ORCO, and PEGAS). The latter were mostly companies that had been listed on the PSE for a short time only and property developers, which were one of the sectors hardest hit by the crisis, as the housing market was declining significantly. The unfavorable situation on the market was reflected in negative market sentiment, drops in companies' share prices, and consequent declines in the market values of companies. Also, equity volatility increased in 2008 for almost all companies, although for newly listed companies it reached very high levels (see Table A1).

The comparison of our estimates with the realized LGDs is not straightforward, since the literature about historical LGDs concentrates on different facilities in different countries and is based on diverse sample sizes across different time periods. What is more, our sample of companies comprises better rated companies with rare occurrence of defaults, so a historical database is not available. Grunert and Weber (2005) summarized 25 empirical studies regarding historical values of LGD and found an average LGD of about 30%, which corresponds to our results. CNB (2008) gives LGDs for large companies of around 34% for secured claims and 48% for unsecured claims. Also, the aforementioned studies by Altman and Kishore (1996), Castle and Keisman (1999), and Keenan et al. (2000) give average LGDs of around 50%. However, since the average indebtedness of our sample is lower than the indebtedness of the whole non-financial corporate sector, the average ELGDs of our sample under analysis should be lower than the aforementioned values.[2]

The risk-neutral estimates are based on the same company structural values relating to credit risk as the physical estimates, except for different assumptions about expected growth of company assets. Nevertheless, as was demonstrated, the risk-neutral estimates do not properly characterize the company's actual riskiness. The more μ_V differs from r_f, the more inaccurate results they provide compared to their physical counterpart. Therefore, creditors trying to appraise their possible recovered amounts in the event of an obligor defaulting should consider the real future growth rate of the firm's assets μ_V as the main determinant of the future LGD,[3]

[1] Seidler and Jakubík (2009) present only preliminary expected LGDs for 2008, which are still based on the accounting information from the previous year. Still, since the results do not differ significantly for most of the companies (e.g. CETV 74 vs. 63%, Orco 65 vs. 73.8, and Pegas 70 vs. 78.2%) we can conclude that the stock market was the main factor influencing the estimates of LGD in 2008, and that financial statements (mainly indebtedness) played a relatively minor role.

[2] The comparison is based on the economic results of non-financial corporations with more than 100 employees provided by the Czech Statistical Office.

[3] Also, the risk-neutral estimates consider changes in the market value of a company's assets through the leverage ratio. Still, as we saw, it does not seem to be sufficient.

even if the average values of the physical and risk-neutral measures are almost identical (Table 2). From this point of view, it is more desirable to use real physical estimates.

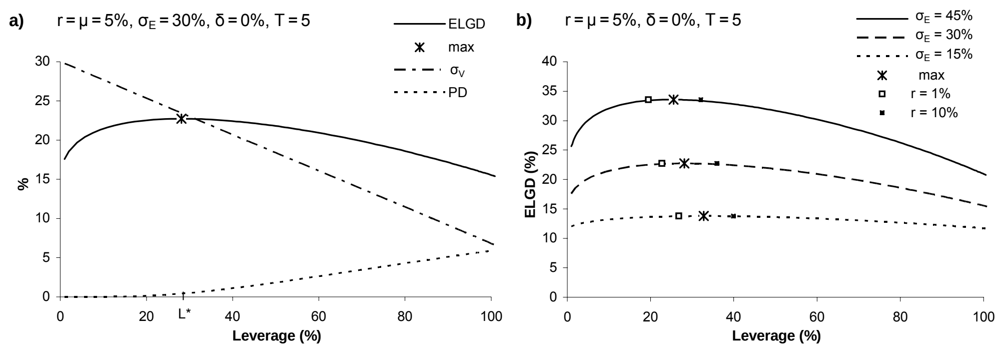
1.6. Sensitivity analysis

The sensitivity analysis relating to Merton's initial model discussed in the theoretical section assumed that all the necessary structural variables are known. However, as already said, the value of a firm's assets and its volatility are not directly observable and they have to be estimated through a system of two equations which hold only at a given time. Therefore, the following analysis concentrates on the sensitivity of ELGD due to potential changes in the structural variables of a company influencing also the estimates of σ_V and V. Emphasis is put on leverage, defined as the ratio of total liabilities to the market value of all assets (F/V).

Before we present the ELGD sensitivity for the individual companies in the sample analyzed, we provide a general theoretical discussion based on different input parameter scenarios. The main difference between the current analysis and the previous one illustrated in Figure 2 is due to the fact that a change in leverage influences the estimate of the firm's asset volatility σ_V. Thus, if the leverage increases, the weight of equity in the firm's value declines and the volatility decreases. The rate of decline for a given set of parameters is presented in the first part of Figure 3.

Figure 3

Sensitivity analysis for ELGD – part 1



Source: computed from eq. (11) and system (9) and (10)

This figure also illustrates the impact of an increase in the firm's leverage on PD and ELGD. However, while growth in leverage has a positive unambiguous effect on PD, ELGD peaks for a particular leverage ratio and then starts to decrease.

The negative relation between ELGD and leverage may look counterintuitive; however, it is caused by decreasing asset volatility σ_V.[1] Although PD increases with increasing leverage, the expected value of the firm's assets at maturity T, conditioned by default ($V_T < F$), in-

[1] The previous analysis reported in Figure 2 shows a strictly positive correlation between ELGD and leverage. However, σ_V was taken as a constant and did not change with leverage.

creases with respect to the given leverage. In other words, due to lower volatility σ_V it is less likely that the firm's expected value will be excessively below the default barrier F at time T and therefore the expected recovery ratio (V_T/F) in the case of default has increased.

The result is that by leaving the initial volatility of equity constant,[1] an increase in leverage causes a decline in asset volatility, which generates a negative correlation between PD and ELGD starting from a particular leverage ratio (L^* – the breakpoint). Nevertheless, for all the scenarios presented the increase in PD outweighs the decline in LGD and the expected loss for a unit of exposure (PD.ELGD) is therefore strictly increasing with leverage.

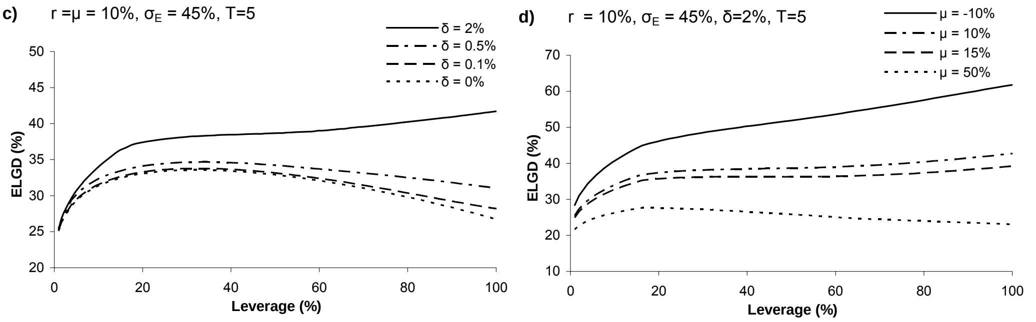
Pursuing the issue further, we analyze the changes in breakpoints with respect to other parameters. The maximum ELGD points are presented for three different values of r_f and σ_E. As can be seen, a decline in the risk-free interest rate shifts the max ELGD points to the left, similarly as an increase in equity volatility (Figure 3b). It is evident that any increase in σ_E will lead (because of higher uncertainty) ceteris paribus to higher values of ELGD. However, the figure also presents the variability of potential ELGDs along the whole range of leverages. While for σ_E=45% the ELGDs vary from 22 to 33 percent, the volatility for σ_E=30% is only 7 percentage points, and in the case of σ_E=15% the variability of possible ELGDs is minimal. This further highlights the importance of volatility as a crucial variable for LGD predictions and indicates that companies with identical leverage ratios can have substantially different ELGD sensitivity.

The existence of the dividend rate in the system of equations lowers the estimated market value of the company V, since part of its value is paid out to the equity holders. Supposing the same value of equity, the presence of dividends increases the estimated asset volatility compared to the state with a zero dividend rate. Thus, dividends offset the initial lowering of σ_V given by an increase in leverage, which results in higher ELGD and consequently a lower ELGD decrease behind the breakpoint. Moreover, the increase in asset volatility given by a sufficiently high dividend rate outweighs the decline in volatility after the breakpoint and the overall effect of increase in leverage on ELGD is positive (see Figure 4c).

[1] A change in leverage will also affect the equity volatility. However, since we use the long-run volatility σ_E^* for the computation, in which sudden short-term changes do not take effect, the assumption of constant σ_E in the sensitivity analysis is maintainable.

Figure 4

Sensitivity analysis for ELGD – part 2



Source: computed from eq. (11) and system (9) and (10)

Until now we have not considered any differences between the physical and risk-neutral measures in the analysis of the sensitivity of ELGD to leverage. Since real asset growth μ_V does not figure in the estimation of V and σ_V, it may seem that the physical ELGD will differ for a given set of parameters only in absolute terms, keeping the same rate of change with respect to leverage. The right-hand side of Figure 4 displays the evolution of ELGD for various growth rates relating to the increasing ELGD sensitivity curve from the previous figure (2% dividend rate). As we can see, μ_V also affects the slope of the ELGD curve and not only its parallel shift. Bad company performance, represented by small and negative μ_V, will raise the rate of growth of ELGD, while good performance will offset the presence of the dividend payout and the curve will become downward-sloping from the breakpoint again.

The result is that the ELGD under the physical measure has a lower growth rate in leverage for $\mu_V > r_f$, and for sufficiently high values of μ_V the initial growth rate may from some point even invert from increasing to decreasing (see part d, $\mu_V = 50\%$). This also holds in the opposite direction for low and negative values of μ_V.

The empirical results for the sample analyzed are reported in the following table, which shows the leverage elasticity of ELGD for both measures at the beginning of 2008.

Table 3

Elasticity of ELGD with respect to leverage

Company	$\varepsilon^{ELGD^Q}_{Leverage}$	$\varepsilon^{ELGD}_{Leverage}$	Company	$\varepsilon^{ELGD^Q}_{Leverage}$	$\varepsilon^{ELGD}_{Leverage}$	Company	$\varepsilon^{ELGD^Q}_{Leverage}$	$\varepsilon^{ELGD}_{Leverage}$
CETV	0.071	0.022	PARAMO	-0.393	-0.498	SPOLANA	-0.647	-0.477
ČEZ	0.078	-0.034	PEGAS	0.341	0.405	TELEFÓNICA	0.175	0.150
ECM	-0.607	-0.643	PHILIP MORRIS	0.403	0.403	TOMA	-0.093	-0.179
JČ PAPÍRNY VĚTŘNÍ	0.116	0.129	PR. ENERGETIKA	0.268	0.128	UNIPETROL	-0.025	-0.148
ORCO	0.344	-0.128	SPOL. CH.HUT.VÝR.	-1.072	-1.095	ZENTIVA	0.012	-0.109

Source: computed from eq. (11) and system (9) and (10)

As can be seen, most of the companies analyzed have inelastic ELGD with respect to leverage. Only Spolek pro chem. a hut. výrobu has a negative elasticity, slightly exceeding 1. Based on our previous discussion we can analyze the differences in risk-neutral (ε^Q) and physical (ε^P) elasticity with respect to other parameters. For example, CET and Pr. Služby, companies with a zero dividend rate and low leverage at the beginning of 2008, are located on the rising parts of their ELGD sensitivity curves. However, because μ_V lowers the ELGD growth rate and the expected asset rate μ_V is higher than r_f for both companies, their "physical" elasticity is lower than ε^Q. By contrast, Č. Nám. Plavba and JČ Papírny show an inverse inequality between ε^P and ε^Q since their $\mu_V < r_f$.[1]

The sensitivity analysis further illustrates the differences already pointed out between the risk-neutral and physical measures. However, a more important finding seems to be that ELGD is quite inelastic with respect to leverage and sudden changes in it do not incur significantly large turns in the expected LGD. Possible inaccuracies in the estimation of V and σ_V, as mentioned by Crosbie and Bohn (2003), caused by change in leverage might be more relevant to the PD estimate, but should not cause important changes in the predictions of ELGD.

Another sensitivity analysis presented here concerns debt maturity, which was arbitrary set at five years for all companies, as already mentioned in the section on model implementation. The following table compares ELGDs for three different debt maturities estimated in one particular year, where the values for five-year maturity (5Y) are identical to the estimates from Table 2 in 2008. As we can see, the estimates of ELGD increase significantly with time to debt maturity, as the uncertainty about the firm's future value increases with longer time horizons. The sensitivity of ELGD with regard to maturity T is rather high, especially for increases in T from low initial values. However, the relationship is not linear and the elasticity decreases with higher T.[2]

Table 4

ELGD for the physical measure for different debt maturities

ELGD in 2008 – physical measure

	ELGD (%) for maturity:				ELGD (%) for maturity:				ELGD (%) for maturity:		
Company	1Y	5Y	10Y	Company	1Y	5Y	10Y	Company	1Y	5Y	10Y
CETV	35.0	62.7	77.4	PARAMO	16.5	26.0	32.3	SPOLANA	15.7	25.6	31.4
ČEZ	21.0	27.0	45.1	PEGAS	45.3	78.2	83.0	TELEFÓNICA	24.2	33.5	46.5
ECM	19.3	43.6	49.4	PHILIP MORRIS	25.1	51.2	68.4	TOMA	12.1	13.5	14.2
JČ PAPÍRNY VĚTŘNÍ	14.4	22.3	32.1	PR. ENERGETIKA	14.2	16.7	18.1	UNIPETROL	30.9	49.9	60.1
ORCO	44.0	73.8	85.3	SPOL.CH.HUT.VÝR.	16.7	21.8	22.9	ZENTIVA	15.4	22.8	28.3

Source: computed from eq. (11) and system (9) and (10)

Even if the assumption of five-year debt maturity is rather strong, we set it arbitrarily for all companies to have comparable ELGD results across the whole sample. For most firms the average debt maturity is shorter in reality (Jakubík and Seidler, 2009, p. 624). However, the longer time period was chosen also for conservative prudential reasons in order to ensure that the LGD estimates obtained were slightly overestimated. The other limits and shortcomings of the estimates presented are discussed in more detail in the next section.

[1] The values of leverage and expected asset growth are reported in Table A1 in the Appendix.
[2] This may be caused by the fact that the process of modeling the firm's asset value dynamics is a poor diffusion process with no possible jumps and low maturity does not enable significant fluctuations in the firm's asset value.

1.7. Criticism and limitations

The first implementation of Merton's model, applied by Jones et al. (1984), Ogden (1987), and Franks and Torous (1989), suggested that the model generates lower credit spreads than those observed on the market. Similarly, more recent studies by Lyden and Saraniti and Helwege et al. (2004) showed that the basic Mertonian contingent claim model underpredicts the actual bond spread, especially for low-leveraged and low-volatility companies. Based on these findings, our ELGD estimates would be undervalued. However, considering that bond spreads also reflect market risk, tax, and liquidity effects, the aforementioned studies only confirmed Merton's inability to capture other components of debt spread, saying nothing about the model's ability to reveal default and recovery risk.

This issue is confirmed by Longstaff (2000), who has argued that corporate bond markets are much more illiquid than government bond and stock markets, so it seems likely that credit spread is only partly due to default risk. In spite of these well-known complications and imperfections, the majority of the literature empirically testing the structural models has presumed that credit spread is primarily due to default risk, since the other components are hardly tractable.[1] Sarig and Warga (1989) compared not the absolute values of theoretical corporate bond spreads, but only their rates of change with respect to change in the bond's actual default riskiness and praised the good predictive power of Merton's model. Furthermore, Dalianedis and Geske (2001) termed the difference between the observed and modeled spread the residual spread and empirically confirmed that the spreads estimated by the Merton approach correctly evaluate the default risk and that the residual spread is driven by liquidity, tax, and other effects.[2] These conclusions suggest that our LGD estimates are correct, since the accuracy of the ELGDs is based on capturing the company's default risk.

If we assume that share prices reflect all relevant information regarding the future development of the company as well as the expected conditions for the given industry or economy, these expectations are also incorporated into our ELGDs, since they are dependent on the development of the stock market. Thus, ELGDs based on the market value of equity are forward-looking estimates which may be used to instantaneously monitor a company's riskiness and can serve as an early-warning indicator. Nevertheless, the stock market dependence of ELGDs can also embody excessive movements in share prices caused by market bubbles. Also, the stock market may not efficiently incorporate all publicly available information about the default probability, especially in the case of a young market such as the Czech one.[3]

[1] This idea stems from the theoretical assumption that corporate bond markets are perfect and complete and trading takes place continuously (see Dalianedis and Geske, 2001).
[2] Structural models may also understate spreads in the short run, since the pure diffusion process is not able to capture unpredicted extreme changes in a firm's asset value given by a shock. Therefore, it is also possible to add a jump process to Brownian motion or to model asset value as a discontinuous Lévy process.
[3] We are also aware of possible sample bias, as a company with very bad performance approaching default would probably be withdrawn from the stock market.

The model treats default as an event that cannot occur before debt maturity. In practice, liabilities are repaid more frequently and default can be observed anytime before maturity of the debt. Allowing default to occur before maturity would hedge debt holders against high losses in the event of the borrower's assets continuing to decrease. In that case, the remaining value of the company would be higher at the time of default than at debt maturity, which implies lower LGD. The simplifying assumption of no default occurrence before maturity therefore overstates the expected LGD. However, as a rule of prudence, we prefer to provide overstated rather than understated values of LGD.

Furthermore, the definition of default used in the model corresponds more to the state of bankruptcy than to the obligor's ninety days past due obligation defined under Basel II. Thus, the model's definition of default also leads to overstated ELGD; however, the companies analyzed should have a high ability to raise funds. So, if a company is past due more than 90 days on its obligation, it has probably exhausted all means to raise the funds and bankruptcy will follow.

The computations also do not consider any debt priority, therefore ELGDs for secured and more senior claims should be lower than the presented estimates and, conversely, those for subordinated debt should be higher. However, the distribution of the value of a bankrupt firm also depends on violation of the APR, which is difficult to predict for single cases. The bankruptcy costs were determined by using other empirical studies, but bankruptcy laws and other procedures differ substantially by country and may therefore differ in the Czech Republic. We are aware, that calibration on an empirical sample would be needed to obtain more accurate estimates more usable in business area, however, no appropriate data sample is available owing to a low number of defaults of comparable companies in the Czech Republic.

The computed ELGDs also suffer from other shortcomings, such as the assumption of a constant interest rate and no tax shield, and other simplifications arising from the seminal Mertonian approach. On the other hand, more sophisticated models require a higher number of parameters, which have to be estimated. This increases the computational complexity and might therefore produce higher errors. Also, some amendments relating, for example, to stochastic interest rates have unambiguous effects and sometimes have only little impact on the results (Lyden and Saraniti, 2000). Nevertheless, the empirical application of more complex models will be the goal of further research.

In spite of all the aforementioned limitations, the presented results are the first estimates of expected LGD based on market information for single companies listed on the Prague Stock Exchange. However, because of the many exogenous and simplifying assumptions, the presented estimates should serve more as a stepping stone for further improvements or as some kind of warning indicator and cannot substitute for estimated LGD values based on historical data as required under Basel II.

1.8. Conclusion

The intensively studied topics in quantitative finance currently include the concept of Loss Given Default, which is rather unexplored territory in the credit risk area. Especially with the implementation of the New Capital Accord, LGD has received increased attention and has become a frequent object of empirical and theoretical research. The goal of this paper was to present the basic knowledge concerning this key input parameter of credit risk analysis and primarily to introduce a modeling technique which enables estimation of forward-looking LGDs from market-observable data.

We exploited the information embedded in the stock market and used the Mertonian structural approach based on contingent claim analysis, which considers the remaining value of a firm's assets as the recovered amount in the case of default. This demonstrates that LGD is stochastic even in Merton's initial framework, since it depends on the uncertain development of asset value. We also pointed out the joint dependence between PD and LGD, which implies that those parameters should not be treated as independent in credit risk modeling.

We analyzed 15 companies listed on the Prague Stock Exchange in the 1999–2008 period and computed the expected LGD for every single company in a given year. The average LGD of the sample across time was estimated in the range of around 20–50%. We also described estimation procedures exploiting prices of equity and their volatility and showed that LGD is relatively inelastic with respect to leverage of the company. By contrast, the LGD estimates are highly elastic with respect to debt maturity, which was arbitrarily set at five years for all companies in the sample analyzed. The presented approach is based on some simplifying assumptions, hence we are aware of the uncertainty regarding the precise values of the LGD estimates presented. Still, the computed estimates can serve as an indicator of the evolution of a company's riskiness over time and should be taken as the first attempt to estimate LGD using the Mertonian approach for companies listed on the Prague Stock Exchange. These estimates can be further developed and improved.

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Appendix

Table A1

All relevant parameters for the sample of companies analyzed – part 1

		Estimates of equity volatility					Parameters used for ELGD computation						Other parameters used				
Company	End of year	σ_E MA(5y)	σ_E MA(1y)	σ_E EWMA	σ_E GARCH	σ^*_E	r_f	μ^*	δ^*	σ_V	V	F	δ	μ	Leverage	V′	Equity
		(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(bill. CZK)	(bill. CZK)	(%)	(%)	(%)	(bill. CZK)	(bill. CZK)
CETV	2005	22,7	22,7	21,9	22,8	22,7	3,1	-	0,0	17,5	62,94	16,99	0,0	-	27,0	65,35	48,36
	2006	28,2	30,7	27,5	28,7	29,7	3,3	7,2	0,0	24,2	73,04	15,91	0,0	7,2	21,8	75,45	59,54
	2007	28,4	28,6	27,5	28,7	28,7	4,0	26,3	0,0	24,9	102,67	16,52	0,0	40,6	16,1	105,63	89,12
	2008	57,6	97,5	22,5	42,8	77,5	3,7	-13,7	0,0	41,9	34,73	23,96	0,0	-66,2	69,0	40,13	16,17
ČEZ	1999	35,6	35,6	31,2	39,0	37,3	6,7	-	0,0	17,9	113,76	84,34	0,0	-	74,1	136,83	52,49
	2000	36,0	36,4	33,1	36,7	36,5	6,8	-0,2	0,5	21,1	112,36	81,61	0,8	-0,2	72,6	141,49	59,87
	2001	38,1	41,7	35,2	41,9	41,8	4,8	-8,0	0,8	24,6	95,30	76,45	1,2	-13,9	80,2	122,37	45,92
	2002	36,9	33,3	34,0	39,9	38,4	3,2	-1,3	1,3	26,2	99,83	69,54	2,1	7,5	69,7	124,30	54,76
	2003	34,2	20,9	29,1	41,1	37,7	3,8	14,6	1,8	28,4	137,20	78,22	2,9	42,2	57,0	164,51	86,29
	2004	32,8	27,6	28,1	38,3	35,5	3,4	41,5	2,0	30,2	264,57	79,22	1,9	96,7	29,9	280,99	201,77
	2005	31,9	32,1	28,4	36,4	34,2	3,1	67,1	1,9	30,3	546,00	132,92	1,6	109,7	24,3	568,96	436,04
	2006	29,0	29,6	27,4	39,6	34,6	3,3	61,5	1,9	30,8	701,40	161,00	1,6	30,6	23,0	729,52	568,52
	2007	27,7	27,0	26,7	29,4	28,6	4,0	57,9	2,0	26,9	942,99	169,56	0,0	37,8	18,0	976,15	806,59
	2008	37,1	58,6	40,5	35,1	49,6	3,7	29,3	2,6	32,1	602,50	287,77	0,0	-33,3	47,8	709,98	422,21
ECM	2006	16,0	16,0	16,0	15,0	16,0	3,3	-	0,0	8,7	11,16	5,98	0,0	-	53,6	12,07	6,09
	2007	25,8	26,3	23,6	33,5	29,9	4,0	26,6	0,0	19,1	14,13	10,91	0,0	26,6	77,3	16,03	5,12
	2008	52,5	70,1	56,9	0,0	63,5	3,7	8,1	0,0	31,7	13,30	14,54	0,0	-5,8	109,3	16,33	1,79
JČ PAPÍRNY VĚTŘNÍ	1999	44,8	44,8	41,6	45,2	45,0	6,7	-	0,0	22,9	0,43	0,30	0,0	-	71,3	0,51	0,20
	2000	41,1	37,0	35,3	40,7	40,9	6,8	-0,9	0,0	15,7	0,42	0,38	0,0	-0,9	89,1	0,53	0,15
	2001	43,4	47,8	39,0	44,5	46,1	4,8	-15,6	0,0	17,7	0,31	0,25	0,0	-26,7	81,9	0,36	0,11
	2002	40,0	27,2	31,4	40,9	40,4	3,2	-6,1	0,0	20,4	0,33	0,20	0,0	6,4	59,6	0,35	0,16
	2003	39,8	38,6	30,2	42,0	40,9	3,8	-18,0	0,0	12,3	0,20	0,18	0,0	-38,6	86,8	0,23	0,06
	2004	42,0	53,5	35,7	45,7	49,6	3,4	2,2	0,0	26,1	0,29	0,17	0,0	43,5	59,1	0,31	0,14
	2005	45,6	54,2	41,7	49,3	51,8	3,1	43,0	0,0	12,5	0,65	0,61	0,0	126,1	92,5	0,74	0,13
	2006	45,8	48,7	42,9	51,8	50,2	3,3	30,6	0,0	12,7	0,58	0,53	0,0	-11,5	92,2	0,66	0,12
	2007	50,9	56,7	47,6	51,3	54,0	4,0	-8,0	0,0	53,1	0,04	0,001	0,0	-92,8	2,0	0,04	0,04
	2008	54,0	55,9	51,9	53,5	54,9	3,7	-21,4	0,0	53,2	0,02	0,001	0,0	-56,2	3,1	0,02	0,02
ORCO	2005	21,0	21,0	19,6	35,9	28,5	3,1	-	0,0	18,9	29,57	11,58	0,0	-	39,2	31,18	19,60
	2006	25,8	29,6	24,6	31,7	30,7	3,3	76,4	0,2	18,1	51,91	26,72	0,4	76,4	51,5	56,57	29,86
	2007	26,7	28,1	25,6	28,8	28,4	4,0	34,4	0,4	17,0	53,07	52,69	0,0	3,0	99,3	76,15	23,46
	2008	54,6	96,8	63,8	64,8	80,8	3,7	-5,9	0,6	28,1	21,45	50,87	0,0	-58,9	237,1	52,75	1,89
PARAMO	1999	50,1	50,1	48,8	49,9	50,1	6,7	-	0,0	22,4	2,68	2,18	0,0	-	81,5	3,27	1,09
	2000	46,1	40,9	40,3	51,3	48,7	6,8	-24,3	0,0	7,0	2,03	2,51	0,0	-24,3	123,7	2,74	0,24
	2001	40,9	27,4	32,7	42,7	41,8	4,8	-17,1	0,0	6,1	1,79	1,98	0,0	-11,6	110,7	2,21	0,23
	2002	39,1	33,1	28,3	44,0	41,5	3,2	-11,7	0,0	11,1	1,71	1,51	0,0	-4,7	88,2	1,91	0,41
	2003	37,1	27,0	24,6	39,7	38,4	3,8	9,6	0,0	10,5	2,50	2,24	0,0	46,5	89,6	2,87	0,63
	2004	32,2	28,2	22,8	39,3	35,8	3,4	11,3	0,0	18,2	2,87	1,69	0,0	15,0	58,9	3,12	1,42
	2005	33,0	45,5	29,6	39,2	42,4	3,1	16,7	0,0	17,0	3,42	2,47	0,0	19,1	72,0	3,74	1,28
	2006	34,2	33,8	30,6	35,8	35,0	3,3	9,5	0,0	14,2	3,01	2,14	0,0	-12,0	71,1	3,32	1,18
	2007	33,2	27,6	28,8	34,8	34,0	4,0	11,2	0,0	16,6	3,35	2,12	0,0	11,2	63,2	3,71	1,60
	2008	32,8	24,2	24,5	37,5	35,1	3,7	-0,2	0,0	17,3	2,85	1,85	0,0	-15,0	64,9	3,19	1,35
PEGAS	2006	28,6	28,6	28,6	25,3	28,6	3,3	-	1,7	23,3	9,63	4,78	1,7	-	49,6	11,73	6,95
	2007	20,9	20,6	20,2	20,6	20,7	4,0	0,3	0,7	15,4	9,66	4,47	0,0	0,3	46,3	11,40	6,93
	2008	40,5	53,4	41,1	37,5	47,3	3,7	-29,3	1,8	32,1	4,49	3,72	0,0	-51,5	82,8	5,87	2,15
PHILIP MORRIS	2000	13,8	13,8	10,5	12,5	13,8	6,8	-	12,4	13,8	12,74	3,46	12,4	-	27,2	14,47	11,01
	2001	23,3	24,0	20,3	n.a.	23,7	4,8	63,8	15,5	23,7	17,46	3,21	17,9	63,8	18,4	19,06	15,85
	2002	29,2	34,5	26,8	33,3	33,9	3,2	60,7	15,4	33,9	23,69	4,69	15,3	58,5	19,8	26,03	21,34
	2003	28,3	26,2	25,8	29,5	28,9	3,8	61,0	14,0	28,9	33,90	7,61	11,5	61,4	22,4	37,70	30,10
	2004	28,9	31,0	26,9	29,4	30,2	3,4	44,9	13,2	30,2	35,24	6,27	11,5	16,9	17,8	38,37	32,10
	2005	29,0	28,4	26,9	29,1	29,1	3,1	35,7	11,3	29,1	38,14	6,42	7,4	16,9	16,8	41,34	34,93
	2006	30,6	32,0	27,6	29,9	31,3	3,3	10,6	9,2	31,3	23,39	5,28	6,3	-34,4	22,6	26,03	20,74
	2007	28,6	25,0	26,0	29,9	29,3	4,0	2,8	8,6	29,3	18,55	12,38	0,1	-3,4	66,8	27,56	15,18
	2008	32,0	41,2	33,0	32,7	37,1	3,7	-9,4	7,7	37,1	13,61	4,96	0,1	-20,8	36,5	16,50	11,53

Source: author's computation, Magnus (2009), Prague Stock Exchange

Table A1

All relevant parameters for the sample of companies analyzed – part 2

		Estimates of equity volatility					Parameters used for ELGD computation						Other parameters used				
Company	End of year	σ_E MA(5y)	σ_E MA(1y)	σ_E EWMA	σ_E GARCH	σ^*_E	r_f	μ*	δ*	σ_V	V	F	δ	μ	Leverage	V´	Equity
		(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(bill. CZK)	(bill. CZK)	(%)	(%)	(%)	(bill. CZK)	(bill. CZK)
PR. ENERGETIKA	1999	50,1	50,1	44,0	48,3	50,1	6,7	-	4,7	47,8	6,77	3,24	4,7	-	47,9	7,88	4,64
	2000	38,1	19,5	26,5	28,5	33,3	6,8	-4,4	4,7	33,3	5,86	3,52	4,7	-4,4	60,0	7,86	4,35
	2001	33,0	19,0	20,9	26,7	29,9	4,8	-0,3	5,0	29,9	5,12	3,87	5,5	2,9	75,6	7,79	3,92
	2002	33,5	35,0	21,0	31,0	34,3	3,2	7,0	6,2	34,3	5,92	3,22	8,3	16,6	54,4	7,79	4,57
	2003	30,6	14,3	17,2	25,3	28,0	3,8	21,6	6,4	28,0	7,27	3,56	6,8	46,8	49,0	10,16	6,60
	2004	21,8	14,7	12,7	22,9	22,4	3,4	22,5	6,5	22,4	8,23	3,64	6,3	24,5	44,2	11,52	7,88
	2005	21,8	19,3	13,8	24,7	23,2	3,1	30,5	6,5	23,2	11,31	3,08	5,9	40,4	27,3	14,32	11,24
	2006	21,1	14,7	12,6	18,9	20,0	3,3	25,4	7,6	20,0	10,91	3,20	9,8	8,3	29,4	14,06	10,86
	2007	16,7	19,8	13,5	20,1	20,0	4,0	37,4	9,3	20,0	15,07	3,67	0,1	60,1	24,3	18,71	15,04
	2008	16,6	13,5	10,2	19,1	17,9	3,7	26,9	6,4	17,9	15,78	6,49	0,0	4,7	41,1	21,94	15,45
SPOL.CH.HUT.VÝR.	1999	47,3	47,3	44,4	46,6	47,3	6,7	-	0,0	9,7	1,43	1,63	0,0	-	114,6	1,88	0,25
	2000	41,3	34,2	36,9	41,0	41,2	6,8	-18,1	0,0	6,1	1,17	1,42	0,0	-18,1	121,7	1,57	0,15
	2001	41,5	41,5	38,0	41,4	41,5	4,8	-8,0	0,0	14,5	1,16	0,99	0,0	-0,4	85,5	1,37	0,37
	2002	41,7	42,3	37,2	42,5	42,4	3,2	-2,4	0,0	14,8	1,22	0,96	0,0	5,0	78,8	1,35	0,39
	2003	39,3	28,0	31,5	40,4	39,9	3,8	5,5	0,0	17,9	1,45	0,99	0,0	19,1	68,2	1,61	0,62
	2004	35,7	30,1	28,3	40,9	38,3	3,4	23,6	0,0	14,5	2,34	1,76	0,0	60,8	75,1	2,59	0,83
	2005	39,8	52,3	35,4	43,8	48,1	3,1	45,1	0,0	16,2	4,19	3,39	0,0	79,3	80,9	4,64	1,25
	2006	39,1	37,8	35,5	46,4	42,7	3,3	34,8	0,0	12,8	4,31	3,67	0,0	2,8	85,2	4,84	1,16
	2007	36,7	30,1	32,9	40,4	38,5	4,0	24,0	0,3	18,8	4,03	4,38	0,0	-5,3	108,7	5,68	1,30
	2008	34,6	0,0	13,5	0,3	24,0	3,7	18,8	0,2	15,6	4,31	5,87	0,0	6,9	136,4	7,17	1,30
SPOLANA	1999	44,0	44,0	39,4	44,4	44,2	6,7	-	0,0	18,4	5,29	6,79	0,0	-	128,5	7,20	0,40
	2000	39,4	34,2	31,8	40,1	39,8	6,8	-0,7	0,0	19,0	5,25	6,59	0,0	-0,7	125,5	7,13	0,54
	2001	40,2	41,7	34,2	40,5	41,1	4,8	-26,3	0,0	23,0	2,86	2,94	0,0	-45,5	102,6	3,48	0,54
	2002	40,5	41,7	32,9	43,3	42,5	3,2	-13,8	0,0	19,8	2,94	3,05	0,0	2,7	103,7	3,37	0,33
	2003	37,3	19,2	24,8	39,9	38,6	3,8	-4,5	0,0	21,7	3,28	3,26	0,0	11,4	99,4	3,82	0,56
	2004	33,7	25,9	21,7	38,9	36,3	3,4	-5,8	0,0	22,2	3,00	2,82	0,0	-8,4	94,0	3,42	0,60
	2005	37,8	50,9	29,7	51,7	51,3	3,1	1,6	0,0	18,3	3,54	2,80	0,0	18,0	79,2	3,91	1,11
	2006	36,2	34,4	28,9	62,2	49,2	3,3	3,9	0,0	18,6	3,45	2,67	0,0	-2,5	77,3	3,83	1,16
	2007	32,5	21,9	24,9	57,0	44,8	4,0	-0,5	0,0	18,7	3,11	2,29	0,0	-10,0	73,8	3,49	1,20
	2008	32,6	19,9	19,7	36,2	34,4	3,7	-1,5	0,0	14,1	3,09	2,33	0,0	-0,7	75,5	3,53	1,20
TELEFÓNICA	1999	31,9	31,9	28,7	32,0	32,0	6,7	-	0,0	26,8	221,55	49,96	0,0	-	22,6	235,65	185,68
	2000	38,2	43,8	36,4	39,9	41,9	6,8	-10,4	0,7	36,2	196,08	45,58	1,2	-10,4	23,2	208,95	163,36
	2001	43,2	51,8	42,9	44,4	48,1	4,8	-18,5	0,4	39,1	147,99	38,95	0,0	-24,5	26,3	155,71	116,76
	2002	42,8	41,7	41,6	43,3	43,1	3,2	-18,0	6,2	32,5	103,75	34,19	16,4	-17,4	33,0	113,01	78,82
	2003	41,8	37,6	39,1	42,3	42,0	3,8	0,5	5,4	28,1	132,06	55,46	3,7	32,6	42,0	149,28	93,82
	2004	40,7	24,0	34,0	40,3	40,5	3,4	4,8	4,0	33,3	149,91	38,74	0,0	13,5	25,8	157,65	118,92
	2005	36,6	17,8	26,6	n.a.	31,6	3,1	16,4	5,3	29,1	190,22	29,24	7,3	36,6	15,4	198,17	168,94
	2006	30,1	22,0	22,8	n.a.	26,4	3,3	13,1	6,9	23,5	168,01	29,40	8,8	-3,2	17,5	182,71	153,31
	2007	25,0	18,2	19,9	80,4	52,7	4,0	22,3	6,5	48,6	200,88	30,76	0,1	38,0	15,3	206,23	175,47
	2008	26,1	41,2	28,4	45,0	43,1	3,7	9,2	7,8	38,2	154,37	25,46	0,1	-15,1	16,5	162,05	136,60
TOMA	1999	28,1	28,1	22,7	27,6	28,1	6,7	-	0,0	20,1	0,22	0,20	0,0	-	94,9	0,27	0,07
	2000	26,3	24,4	21,7	25,9	26,1	6,8	-21,1	0,0	19,5	0,17	0,16	0,0	-21,1	95,0	0,22	0,05
	2001	32,1	41,4	28,9	31,7	36,8	4,8	2,9	0,0	16,2	0,21	0,15	0,0	20,9	72,8	0,24	0,09
	2002	30,9	27,0	24,9	31,6	31,3	3,2	-13,3	0,0	25,8	0,13	0,03	0,0	-34,5	20,6	0,14	0,11
	2003	29,1	20,0	20,5	29,9	29,5	3,8	24,4	0,0	27,3	0,26	0,02	0,0	89,7	8,9	0,26	0,24
	2004	29,3	28,8	21,6	31,2	30,3	3,4	64,0	0,0	29,4	0,63	0,02	0,0	145,3	3,3	0,63	0,61
	2005	29,6	26,4	20,8	32,8	31,2	3,1	54,4	0,0	25,8	0,72	0,15	0,0	14,4	20,3	0,74	0,59
	2006	24,6	18,4	16,9	31,4	28,0	3,3	41,4	0,0	21,7	0,76	0,20	0,0	6,8	26,7	0,80	0,59
	2007	22,9	18,4	16,3	25,8	24,4	4,0	48,6	0,0	16,1	1,11	0,46	0,0	45,5	41,6	1,20	0,73
	2008	22,7	18,6	13,0	22,9	22,8	3,7	39,6	0,0	15,3	1,46	0,60	0,0	30,9	41,3	1,58	0,97
UNIPETROL	1999	47,5	47,5	42,7	55,0	51,3	6,7	-	0,0	32,7	15,23	8,09	0,0	-	53,1	17,36	9,27
	2000	41,4	34,1	36,6	44,1	42,7	6,8	23,2	0,0	26,5	18,76	10,32	0,0	23,2	55,0	21,59	11,27
	2001	40,2	37,7	36,2	42,4	41,3	4,8	7,0	0,0	20,0	17,80	12,06	0,0	-5,1	67,8	20,23	8,17
	2002	41,1	44,0	37,9	43,5	43,8	3,2	5,4	0,0	16,4	18,38	13,99	0,0	3,3	76,1	20,26	6,27
	2003	38,5	25,2	32,9	40,7	39,6	3,8	14,1	0,0	20,9	23,73	13,88	0,0	29,1	58,5	25,93	12,05
	2004	33,8	23,2	27,1	47,0	40,4	3,4	11,0	0,0	29,3	24,88	8,23	0,0	4,8	33,1	26,04	17,81
	2005	38,6	53,7	33,8	47,9	50,8	3,1	71,9	0,0	30,4	74,49	36,75	0,0	199,4	49,3	78,91	42,16
	2006	37,8	33,8	31,6	64,8	51,3	3,3	52,0	0,0	33,0	69,26	30,75	0,0	-7,0	44,4	73,23	42,49
	2007	34,2	24,8	28,2	50,0	42,1	4,0	45,7	1,2	34,4	80,82	24,00	0,0	21,3	29,7	85,22	61,22
	2008	43,3	64,3	46,0	82,7	73,5	3,7	16,5	0,9	54,4	42,51	19,78	0,0	-47,4	46,5	46,97	27,19
ZENTIVA	2004	24,1	24,1	23,2	25,2	24,7	3,4	-	1,0	24,4	30,70	2,14	1,0	-	7,0	31,03	28,89
	2005	27,7	29,4	25,6	28,0	28,7	3,1	68,2	0,8	25,2	51,28	9,29	0,7	68,2	18,1	52,61	43,32
	2006	28,3	29,2	25,4	30,8	30,0	3,3	32,3	0,8	28,2	53,59	6,17	0,8	5,4	11,5	54,53	48,36
	2007	29,6	32,4	9,7	29,8	31,1	4,0	20,8	0,7	21,4	56,31	24,97	0,0	5,6	44,3	62,04	37,07
	2008	29,6	32,4	9,7	29,8	31,1	4,0	20,8	0,7	21,4	56,31	24,97	0,0	5,6	44,3	62,04	37,07

Source: author's computation, Magnus (2009), Prague Stock Exchange

2. Credit Growth and Countercyclical Capital Buffers

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Credit Growth and Countercyclical Capital Buffers:

Empirical Evidence from Central and Eastern European Countries

Abstract

Excessive credit growth is often considered to be an indicator of future problems in the financial sector. This paper examines the issue of how to determine whether the observed level of private sector credit is excessive in the context of the "countercyclical capital buffer", a macroprudential tool proposed in the new regulatory framework of Basel III by the Basel Committee on Banking Supervision. An empirical analysis of selected Central and Eastern European countries, including the Czech Republic, provides alternative estimates of excessive private credit and shows that the HP filter calculation proposed by the Basel Committee is not necessarily a suitable indicator of excessive credit growth for converging countries.

Abstrakt (*in Czech*)

Nadměrný růst úvěrů je často považován za indikátor budoucích problémů ve finančním sektoru. Tento článek se věnuje otázce, jak nejlépe určit, zda pozorované zadlužení privátního sektoru je již nadměrné v souvislosti s makroobezřetnostním nástrojem navrhovaným Basilejským výborem pro bankovní dohled, tzv. proticyklickým kapitálovým polštářem. Empirická analýza na vybraných zemích střední a východní Evropy včetně ČR ukazuje alternativní odhady indikátoru nadměrného zadlužení privátního sektoru a naznačuje, že výpočet pomocí HP filtru navrhovaný Basilejským výborem nemusí být pro konvergující země vhodným indikátorem nadměrného růstu úvěrů.

Keywords: credit growth, financial crisis countercyclical capital buffer, Basel regulation

JEL Codes: G01, G18, G21

2.1. Introduction

The Basel III reforms to the banking sector regulatory framework agreed in 2010 contain an important macroprudential element intended to dampen the potential procyclicality of the previous capital regulation. The Basel Committee on Banking Supervision (BCBS, 2010a) has introduced a “countercyclical capital buffer” aimed at protecting the banking sector from periods of excessive credit growth, which have often been associated with growth in systemic risk. In good times, banks will – in accordance with set rules – create a capital reserve which can then be used to moderate contractions in the supply of credit by banks in times of recession.

One region that recorded a boom in lending to the private sector in the lead-up to the global financial crisis was the Central and East European (CEE) countries.[1] The observed credit expansion was driven by many factors relating to both the demand and supply side of the credit market. Although the credit growth in these transition economies started from very low levels, the rate of growth in many countries has raised concerns about how sustainable such growth is in the medium term and whether it poses significant risks to the stability of the financial sector.

This paper aims to draw on the historical experience of the CEE countries with credit expansion and, using the method proposed by the Basel Committee, to calculate and discuss what the countercyclical capital buffer level these countries might have had if the newly proposed regulation on the creation of capital buffers had existed before the crisis. The motivation for this analysis is to determine how suitable the Basel Committee’s proposed method for calculating excessive credit using the Hodrick-Prescott (HP) filter is for the countries of Central and Eastern Europe. In these countries, rapid credit expansion may simply mean convergence to values typical of the advanced nations, and not excessive borrowing. For this type of country, we propose to use a method involving estimation of the equilibrium private credit level computed using economic fundamentals. Given that different countries have different characteristics, the Basel Committee allows national regulators to exercise discretion and specify different methods for setting the countercyclical capital buffer.

The paper is structured as follows. Section 2 discusses the risks associated with excessive credit expansion, looks at the situation in selected EU countries before the global financial crisis broke out, and briefly examines the logic of the countercyclical capital buffer as proposed by the Basel Committee. Section 3 takes a closer look at the disadvantages of applying the HP filter method and proposes an alternative technique for calculating excessive credit – the out-of-sample method. Both these calculation methods are then used on data for ten CEE countries. Section 4 illustrates the different implications of the alternative indicators of excessive credit growth for the countercyclical capital buffer settings of the banking sectors of the coun-

[1] In this study, the group of CEE countries consists of Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.

tries analysed. The conclusion attempts to generalise the results of the analysis and formulate recommendations for the national authorities responsible for macroprudential policy.

2.2. Excessive credit growth

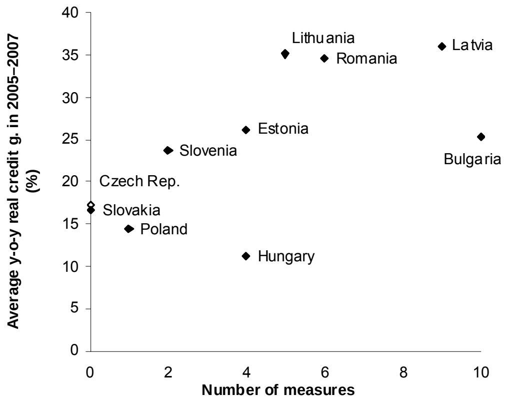
Credit growth in CEE countries has caught the attention of many studies over the past decade. These studies have tried to identify not only the determinants of credit growth, but also its equilibrium level (e.g. Brzoza-Brzezina, 2005; Égert et al., 2006; Enoch and Ötker-Robe, 2007). The credit boom in some transition economies was strong enough to raise concerns about whether this trend was simply a manifestation of convergence to the average credit levels in advanced nations, or whether it was a case of excessive growth posing a risk to macroeconomic and financial stability (Hilbers et al., 2005).

The central banks and supervisory authorities of some countries even assessed the situation as critical and in 2004–2007 introduced a series of tools for limiting credit growth (Dragulin, 2008; Herzberg, 2008). These tools generally included monetary policy tools (increases in official interest rates or reserve requirements justified by policymakers with reference to “rapid credit growth”), regulatory measures (increased risk weights on selected loans, restrictions on loan-to-value and/or debt-to-income ratios, increases in provisioning rates, tighter regulation of large exposures and tougher rules on collateral valuation), soft non-binding measures (the introduction of guidelines and recommendations) and also very “hard” administrative restrictions on credit portfolio growth (as applied, for example, in Bulgaria). The extent of the measures, as measured by the number of different tools used to limit credit growth in individual countries, was correlated to a large degree with the credit growth rate (see Figure 1). While the number of policy measures might not be the best proxy for the degree of policy interventions, given the available data and information it at least serves as a relatively reliable indicator of policymakers’ effort.

At the same time, it is difficult to assess the effectiveness of the tools used, since most of them were applied just before the global financial crisis erupted. The decline in credit growth observed since then may thus have been due more to the sharp economic contraction and reduced demand for loans. The studies conducted up to now tend to conclude that the aforementioned tools are rather ineffective and that credit booms can be limited in only a very limited way during good times (Kraft, 2005; Herzberg, 2008).

Figure 1

Credit growth and number of tools applied to limit credit booms

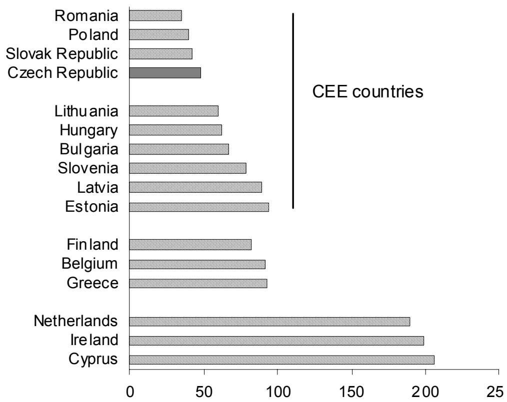


Source: IMF, national authorities' websites

Figure 2

Private credit ratios in selected EU countries

(as % of GDP; 2007 Q4)



Source: IMF IFS, authors' calculations

Despite the comparatively strong credit boom observed in 2003–2007, the stock of loans in many CEE countries in the pre-crisis year 2007 was still relatively low, especially in comparison with other EU countries (see Figure 2 and Table A3 in the Appendix). Nevertheless, in terms of the private-credit-to-GDP ratio, some countries of the region had reached levels typical of some euro area countries. The question therefore arises whether they were already showing excessive credit levels. One limitation of this comparison is that is based solely on data on domestic bank loans. This indicator understates total private credit, as it neglects loans provided by non-bank financial intermediaries and loans provided directly from abroad.

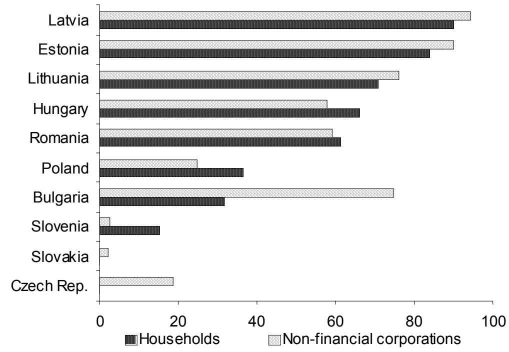
Excessive credit growth can threaten macroeconomic stability in many ways. Given that lending supports consumption, growth in private sector loans can over-stimulate aggregate demand beyond the framework of potential output and cause the economy to overheat, with knock-on effects on inflation, the current account deficit, interest rates and the real exchange rate (Bakker and Gulde, 2010).

At the same time, lending institutions can, in an economic growth phase, have over-optimistic expectations about borrowers' future ability to repay their debts and therefore very often lend to high-risk borrowers. The upshot is that the bulk of "potentially" bad loans arise during upward phases of the credit cycle. In some CEE countries, private loans were provided in foreign currency because foreign interest rates were lower (see Figure 3). This further increases the risks for the banking sector, because if the domestic currency depreciates, the volume of credit expressed in the domestic currency rises, debt servicing costs go up, and foreign exchange risk turns into credit risk. In many cases, therefore, the aforementioned measures to contain credit growth were targeted primarily at reducing growth in foreign currency loans (Steiner, 2011). Furthermore, if a domestic credit boom is financed from foreign sources, as was the case in several CEE countries (except for the Czech Republic, Slovakia and Poland), the risk of the domestic banking sector having insufficient balance-sheet liquidity (roll-over risk) increases. In economic bad times, domestic banks face a high risk of outflows of short-term foreign funds that cannot be financed by the sale of liquid assets (Hilbers et al., 2005).[1] Although this study, focusing on excessive credit growth, would benefit from an analysis of different loan types, such detailed disaggregated data is not available in a sufficiently long time series for the countries under examination.

Figure 3

Shares of foreign currency bank loans

(as of end-2009; as % of total loans to given sector)



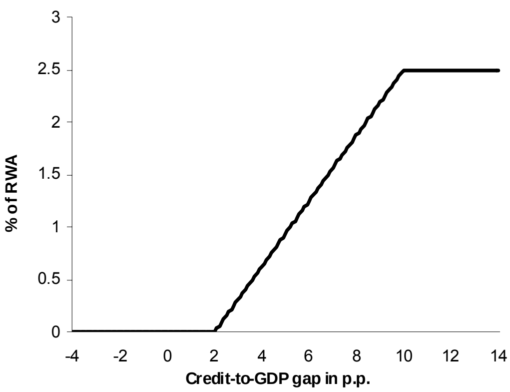
Note: Slovak Republic and Slovenia were already members of the euro area in 2009, so their foreign currency loans comprise currencies other than EUR.

Source: ECB

Figure 4

Countercyclical capital buffer

(% of RWA as function of credit-to-GDP gap)



Source: CNB

A bursting of the credit bubble and negative macroeconomic developments, leading to external financing constraints and growth in non-performing loans (NPLs), can therefore cause the banking sector serious difficulties. IMF (2004) estimates that more than 75% of credit booms were followed by banking or currency crises. This fear is consistent with existing studies in the field of early warning signals, according to which excessive credit growth can be considered one of the most reliable indicators of future problems in the banking sector (Borio and Lowe, 2002; Borio and Drehmann, 2009; FSB, 2008; Jimenez and Saurina, 2006; Saurina et al., 2008; Drehmann et al., 2010).[2]

As part of the preparation of the new Basel III regulatory framework for banks, the Basel Committee (BCBS, 2010a) has proposed several tools for reducing the procyclical behaviour of the banking sector.[3] One of the key tools is a proposal for banks to create countercyclical capital buffers during credit booms.[4] Such buffers, expressed as a percentage of risk-

[1] In this regard, the Czech Republic has a very favourable deposit-to-loan ratio. For a comparison with other EU countries, see CNB (2010, section 1.3.1).

[2] However, an identification of proper early warning indicator is still only partially-solved problem, which attracted a lot of research in recent years, see e.g. Babecky et al. (2011) and references therein.

[3] The issue of procyclicality of the financial system and its sources and potential consequences was discussed in Geršl and Jakubík (2012).

[4] With regard to the objective of reducing the procyclicality of the financial system, the Basel Committee stated explicitly in its December 2009 consultative document (BCBS, 2009) that the aim of this buffer was to "achieve the broader macroprudential goal of protecting the banking sector from periods of excess credit growth".

weighted assets (RWA) and covered by high quality capital (Tier 1, or even core Tier 1), would be set by the regulator within the range of 0% to 2.5%. As a guide for the setting of the buffer, the Basel Committee is proposing to use and regularly publish the difference between the current private credit ratio as a percentage of GDP and its trend value estimated using the HP filter (the "credit-to-GDP gap"). However, regulators may also use other methods to calculate the trend and other variables, such as the prices of various relevant assets and credit conditions. In bad times, this capital buffer would be "released" in order to slow any fall in the credit supply and thereby reduce the procyclicality of the financial system.

The Basel Committee document itself (BCBS, 2010b) proposes to use the aforementioned guide as follows. The capital buffer would start to be created when the credit-to-GDP gap exceeded two percentage points. If the gap reached 10 percentage points or more, the buffer would reach the aforementioned maximum of 2.5% of RWA. For gaps of between 2 and 10 percentage points, the buffer would vary linearly between 0% and 2.5%. For example, for a gap of six percentage points the buffer would be 1.25% of RWA (see Figure 4). For cross-border exposures, the buffer set by the regulator in the foreign jurisdiction would apply. For cross-border banking groups, the capital buffer would be applied on both a solo and a consolidated basis.

It became clear during the discussion phase within the Basel Committee that a simple filtering technique would in many cases not necessarily lead to reliable estimates of excessive credit, so the final version of Basel III (BCBS, 2010b) gives regulators considerable discretion to set the buffer. The need of other relevant indicators for identifying risky episodes highlighted other studies, as credit-to-GDP alone may note be sufficient (IMF, 2011). The primary aim of the buffer, however, is not to restrict credit growth, but to create a capital reserve to give the banking sector greater protection from sudden changes in the credit cycle. At the same time, the Basel Committee documents emphasise the complementarity of this buffer with other macroprudential tools (BCBS, 2010b, p. 5), such as various limits on key indicators of borrowers' ability to repay loans (the loan-to-collateral and loan-to-income ratios).

2.3. Methods for estimating the equilibrium credit level

A major problem in constructing an excessive credit growth indicator is determining what level of credit is excessive and might pose a threat to the financial sector. One traditional method is to apply the statistical Hodrick-Prescott (HP) filter, which obtains the trend from a time series. By comparing the actual credit-to-GDP ratio with its long-term trend obtained using the HP filter we can then estimate whether or not the credit level is excessive. This method is used quite routinely in the literature (Borio and Lowe, 2002; Borio and Drehmann, 2009). Hilbers et al. (2005), for example, consider a credit-to-GDP gap of greater than five percentage points to be an indicator of excessive credit in the economy.

Although the HP filter method is used quite often to determine trends in macroeconomic variables, it does have its drawbacks. A time series trend is dependent to a significant extent on the length of the chosen time series and the calculation is very sensitive to the smoothing parameter (lambda). Complication as regards practical application in macroprudential policy is “end-point bias”, which generates a highly unreliable estimate of the trend at the end of the data period.[1] Macroprudential policy, which, by contrast, requires assessment of the trend on the basis of current (i.e. end-of-period) data, would therefore be reliant on indicators subject to a high degree of uncertainty. In the case of some CEE countries with relatively short time series, credit growth is incorporated directly into the trend itself by the HP filter, i.e. excess credit growth is counted as a trend (Cottarelli et al., 2005). Another relevant question is whether the credit ratio should take into account other denominators besides GDP, such as financial assets or total assets of the private sector. Although GDP is correlated to a significant extent with private sector income and therefore serves as an indicator of the ability to repay a given amount of loans, holdings of financial assets (deposits and securities investments) and non-financial assets (e.g. real estate) are also relevant to the evaluation of excessive credit.

Figure 5 presents credit gaps with alternative denominators (GDP and financial assets and total assets of the private sector) calculated using the HP filter on data for bank loans in the Czech Republic with a high lambda parameter equal to 400,000. Such a high value of lambda was proposed in Basel III with the argument that the credit cycle is usually longer than the business cycle.[2] The filter is applied to quarterly data for the period 1998–2010, which, however, is regarded as relatively short from the international perspective (Basel III recommends at least a 20-year period). The estimates indicate that the current level of bank loans is above the long-term trend. However, the trend estimate is subject to a range of problems related to the short time series and above all to extraordinary factors linked with a fall in credit volume in 1998–2002 caused by a banking crisis in the 1990s and the clean-up of bank balance sheets ahead of the privatisation of large banks. Similar results are indicated even for lower values of lambda parameter (see the Appendix, Figure A1 and A2).

As regards simulating possible macroprudential policy in the past, it makes more sense to apply the HP filter recursively, i.e. in each past period using only the data that were available in that period (at the end of 2005, for example, the trend value and therefore also the gap between the observed credit level and the trend is calculated on 1998–2005 data). This simulates the situation that the macroprudential policy-maker would hypothetically have found itself in had it been required to decide whether excessive credit growth was emerging. The calculated credit gaps expressed as a percentage of GDP indicate that the Czech Republic would have found itself in a situation of excessive credit as early as 2004 (see Figure 5) and the same conclusions apply for recursive HP filter using lower values of lambda parameter (Figure A3

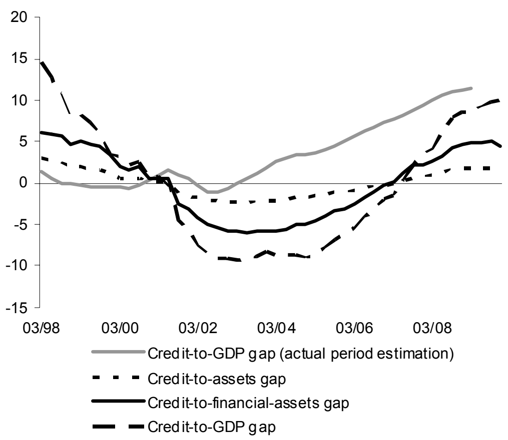
[1] One way of dealing with end-point bias is to extend the time series into the future by means of prediction. This, however, can introduce further uncertainty into the estimate linked with the quality of the prediction.

[2] Drehmann et al. (2010) suppose that the credit cycle is between three to four times longer than the business cycle. Consequently, using Ravn and Uhlig (2002) rule for setting the lambda parameter in HP filter they derived value of lambda equal to 400 000, see Drehmann et al. (2010, p. 28).

and A4). However, the aforementioned drawbacks of the HP filter play an even greater role in the calculated gap, as the problem period of 1998–2002 influences the trend.

Figure 5

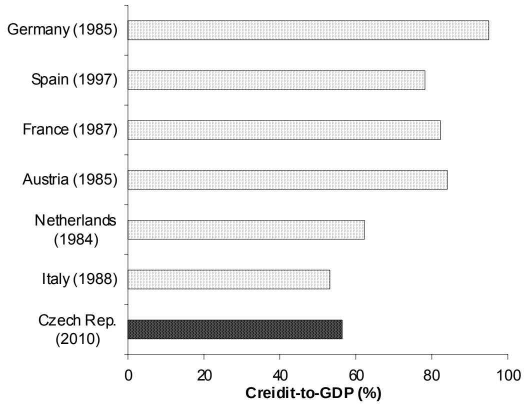
Credit gaps in the Czech Republic with alternative denominators



Source: CNB, authors' calculations

Figure 6

Credit-to-GDP ratios for a similar level of economic development



Note: approx. 22 500 GDP per capita in PPP constant 2005 international $ as Czech Rep. in 2010.

Source: IMF IFS, WB WDI, authors' calculations

The main criticism of the HP filter technique, however, is that it does not take into account economic fundamentals that affect the equilibrium stock of loans.[1] An alternative method is to estimate the equilibrium private credit level in relation to key economic variables (such as the level of development of the economy measured in terms of real GDP per capita). This method says that if GDP per capita – as a proxy for the standard of living of an economy – is the main and only economic fundamental, all countries with the same level of development should have a similar equilibrium credit level. Poorer countries should have a lower equilibrium credit level than wealthier countries. A positive linkage between the credit-to-GDP ratio and the economic development of a country is referred to as financial deepening (see Terrones and Mendoza, 2004). A comparison of bank loans as a percentage of GDP for the Czech Republic in 2010 and selected euro area countries in years when they were at a similar level of economic development indicates, in contrast to the HP filter findings, that the credit ratio in the Czech Republic is below the level consistent with its economic level (see Figure 6).

Other economic fundamentals besides the above-mentioned GDP per capita should also be considered as factors influencing the equilibrium credit level in a particular country, and a suitable econometric model should therefore be employed. However, given that the CEE countries started from very low private credit levels, the estimation of such a model on data for

[1] The same caveat, however, applies also for other simple filtering techniques, such as Band-Pass filter. As presents Figures A5 and A6 in the Appendix, credit-to-GDP trend and gap estimated by Band-Pass method provides us with similar results as HP-filter. Also, results are highly sensitive to the credit cycle length, which is not straightforward to determine for countries with short time series, see e.g. Christiano and Fitzgerald (1999), Baxter and King (1995) and Cogley and Nason (1993) for more details about limitations of both filtering techniques. See Borio et al. (2012) for other frequency-based filter analysis of financial cycle.

these countries would capture the rapid growth caused by convergence towards the average level of the advanced nations. As Égert et al. (2006, p. 14) point out, such estimated elasticities of the relationships between fundamentals and credit would be overstated. At the same time, the estimates would reflect not the equilibrium level, but only the present relationship between economic fundamentals and private credit.

For this reason, the existing literature suggests using out-of-sample (OOS) panel estimation, i.e. estimating the model on a different sample of countries ("in-sample countries") and applying the elasticities obtained to the data for the countries for which the equilibrium credit level is being estimated ("out-of-sample countries"). This approach assumes a priori that the stock of credit of the in-sample countries, which serve for estimating elasticities, is at equilibrium on average, which is quite a significant assumption. Therefore, one needs to choose a suitable group of "in-sample" countries that best meets the need to estimate the correct equilibrium relationships between economic fundamentals and private credit. The existing studies on this topic therefore normally use the developed countries of the EU or OECD as appropriate countries for comparison (Kiss et al., 2006; Égert et al., 2006). For this study, the advanced EU countries were used as in-sample countries. While a possible approach would be to narrow down the number of sample countries to the ones similar in structure to the CEE countries, the econometric methodology used and the availability of data in the time dimension do not allow us to significantly reduce the number of in-sample countries. However, owing to the current debate regarding the excessive debt of the PIIGS[1] countries, these countries were omitted from the calculation of the equilibrium credit level.[2]

However, to estimate the equilibrium elasticities for the given countries, the proper set of fundamental variables influencing the credit-to-GDP ratio must be found. As the analysis of possible credit determinants is beyond the scope of this paper, we refer to previous studies for a comprehensive discussion regarding possible credit determinants; see, for instance, Égert et al. (2006) and the references therein. Based on these studies, we use data on aggregate household consumption, government debt, short-term interest rates, unemployment, inflation measured by the GDP deflator and the CPI index, and GDP per capita.

The data were mostly obtained from the International Monetary Fund's IFS (International Financial Statistics) database, which provides the required macroeconomic data with a sufficient history (which is vital for estimating long-run relationships). For this reason, we used data for a 30-year period (1980–2010). The available statistics on bank loans to the private sector were used as the credit indicator. As stated earlier, these statistics slightly underestimate the total credit of the private sector, as they do not include non-bank financial intermediaries (e.g.

[1] Portugal, Italy, Ireland, Greece and Spain.

[2] However, nations that are structurally quite different from the CEE countries, such as the United Kingdom, remain in the sample of control countries. This may skew the results of the analysis towards higher equilibrium credit values for a given set of economic fundamentals. Nevertheless, the method used (see later in the text) would control for the cyclical component of excessive debt in the sample of countries used.

leasing) and cross-border loans.[1] However, as the financial system in CEE countries is primarily bank-based, using bank credit only should not introduce considerable bias into our estimates.

We applied a set of panel unit root tests for the above-mentioned variables, and some of them were found to be nonstationary in levels, i.e. I(1) processes. A more detailed summary of the results is provided in the Appendix (Table A2). Further, cointegration was tested for selected groups of variables using the Johansen Fisher Panel Cointegration Test. The results confirmed one cointegration relationship between the credit-to-GDP ratio, the household consumption-to-GDP ratio and GDP per capita for the set of in-sample countries. As discussed above, the presence of the GDP per capita variable in the long-run relationship is desirable as it captures the different degree of wealth of the economy, which therefore also influences the equilibrium private credit level (Terrones and Mendoza, 2004).

A variety of econometric methods can be used for OOS estimation. Nevertheless, given the properties of the variables used, traditional panel methods run into the problem of nonstationary time series, mutual regression of which can lead to spurious results. The traditional solution to the problem of nonstationarity of variables involves differentiating them. This step allows us to obtain the short-run relationship between the variables by regression, but the longer-run relationship is lost in the differentiation. The long-run relationship between nonstationary variables can be better estimated if the variables are cointegrated. This fact is used by the ECM (error correction model) method, which estimates not only the long-run relationship between the cointegrated variables, but also the potential deviation from this long-run relationship, which is gradually corrected through short-run adjustments.

Based on the characteristics of the time series used and the character of our study, focusing on the long-term equilibrium credit level, we employ the PMG (pooled mean group) estimation method, introduced for panel estimates by Pesaran et al. (1999). The PMG estimator is an error correction form of the autoregressive distributive lag ARDL (p,q,...,q) model, where the dependent variable in its first differences is explained by the lagged independent and dependent variables in both levels and first differences. This method can be used to estimate the long-run relationship between the credit-to-GDP ratio and other variables, which is identical for all countries, whereas the short-run adjustment to this long-run relationship can differ across countries. The PMG model therefore allows heterogeneity of the estimates for individual countries in the short run. However, the long-run relationship of the cointegrated variables is common to all the countries in the sample. The error-correction equation for N cross-sectional units over T time periods is expressed as follows:

[1] A detailed description of the available data is provided in the Appendix (Table A1).

$$\Delta y_{i,t} = \rho_i (y_{i,t-1} - \sum_{h=1}^{v} \alpha_{i,h} x_{i,h,t}) + \sum_{j=1}^{p-1} \beta_{i,j} \Delta y_{i,t-j} + \sum_{h=1}^{v} \sum_{j=0}^{q-1} \gamma_{i,h,j} \Delta x_{i,h,t-j} + c_i + \varepsilon_{i,t}\,, \qquad \begin{matrix} i = 1,\dots, N, \\ t = 1,\dots, T, \end{matrix} \quad (1)$$

where $\forall i \in \{1,\dots,N\}$, y represents dependent variable and $x_1,\dots,x_v$ independent variables, p and q are the maximum lags used for dependent and independent variables respectively. Coefficients $\alpha_1,\dots,a_v$ represent the long-term relationship among variables y and $x_1,\dots,x_v$, while $\beta_1,\dots, \beta_v$ and $\gamma_1,\dots,\gamma_v$ are the short-run dynamics coefficients capturing adjustment towards the long-term equilibrium. Parameter ρ is the country specific error correction term, i.e. the speed of adjustment towards the equilibrium. As was mentioned, PMG estimator constrains the long-run elasticities $\alpha_1,\dots,a_v$ to be the same across all panels, while parameters for short-run dynamics and error correction term differs across countries. Without this restriction, we would obtain N individual estimates for long-term relationship. Unweighted mean of these N individual regression coefficients is so called mean-group (MG) estimator. For more details see Pesaran et al. (1999).

The long-term relationship of the given equation is taken as a cointegrated relationship, which was found for the credit-to-GDP ratio, the household consumption-to-GDP ratio and GDP per capita. We also employed a different set of other variables and their lags that might affect the short-run adjustment of the credit-to-GDP ratio to its long-run relationship. For example, the government debt-to-GDP ratio might capture any crowding out of bank lending to the private sector.[1] Also, the real interest rate, or changes therein, should, as the cost of financing, be in a negative relationship with the explained variable. However, these variables were not significant even at the 15% level.

The following equation gives the final estimates of the coefficients of the long-run relationship between the cointegrated variables and the values of the coefficients and the constant term in the short run, which are presented below as the mean of all the estimates for the countries concerned.[2]

[1] For this reason, we would expect a negative relationship between the government debt ratio and loans to the private sector. The fact that a less indebted government sector would be able to provide more significant support if the banking sector ran into serious problems is relevant for assessing whether the current private sector credit level is excessive with regard to financial stability.

[2] Based on the Hausman test, we cannot reject the null hypothesis of PMG being an efficient estimator, so PMG is preferred over its mean-group (MG) counterpart. The MG estimator is the simple non-weighted mean of the regression estimates for each country. The Hausman statistic $\chi^2(2)$ is equal to 0.9 (p-value = 0.637). Furthermore, only those variables which were significant at least at the 10% confidence level were kept in the estimated equation. Also, a more empirical approach was used as in Sekine (2001), so inflation is present in the short-run part of the equation but not in the long-run part. Moreover, the low value of the correlation coefficient between *cons/gdp* and *gdp/pop* indicates no possible multicollinearity problem.

$\Delta\,(\text{credit/gdp})_t =$

$$\underset{(**)}{-0.035}(\text{credit/gdp}_{t-1} - (\underset{(***)}{0.7}\text{cons/gdp}_t + \underset{(***)}{0.013}\text{gdp/pop}_t)) + \quad \}\text{long-run relationship}$$

$$+ \underset{(**)}{0.87}\Delta(\text{cons/gdp})_t - \underset{(*)}{0.07}\text{inf}_t + \underset{(***)}{0.014} \quad \}\text{short-run adjustments}$$

Note: *, ** and *** denote significance of the estimated coefficients at the 10, 5 and 1% levels respectively.

Credit/gdp represents the ratio of private sector credit to GDP, *cons/gdp* denotes the ratio of household consumption to GDP, *gdp/pop* is GDP per capita in thousands of US dollars and *inf* is the change in the price level, expressed as the year-on-year change in the GDP deflator.

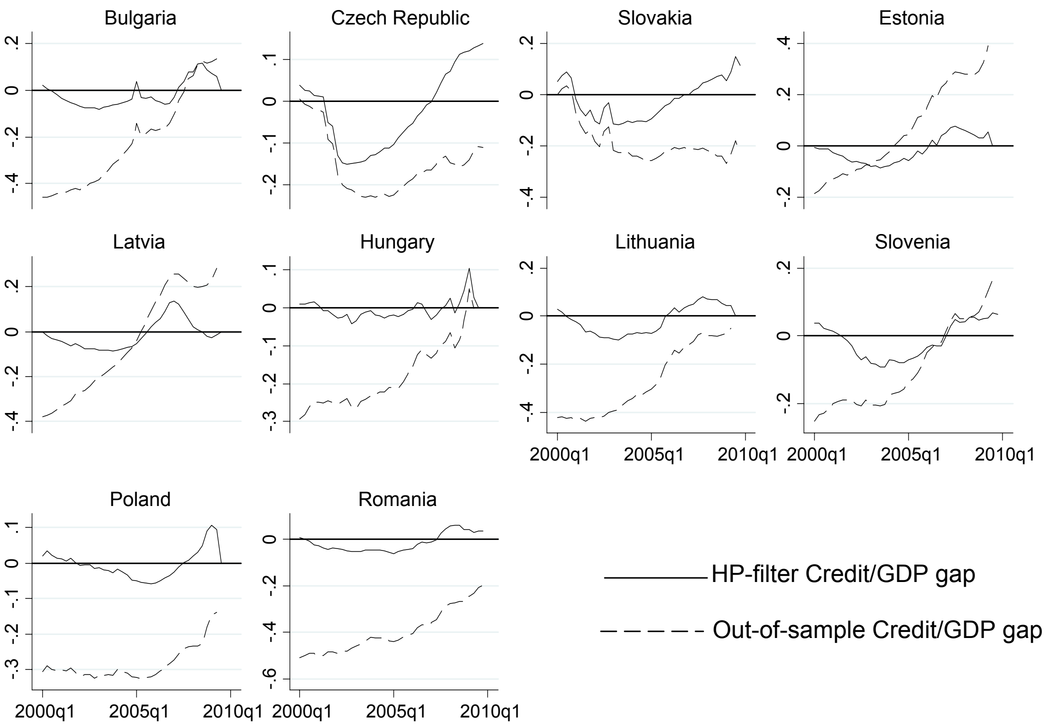
On the basis of the model, short-run adjustment dynamics towards the long-run trend is given as a function of the change in the consumption-to-GDP ratio and as a function of inflation. Based on the estimated coefficients, we can conclude that in the long-run relationship the credit-to-GDP ratio increases with increasing wealth of the economy and with an increasing consumption-to-GDP ratio. This factor then positively affects the explained variable in the short-run relationship as well, while inflation acts in the opposite direction. These conclusions are in accordance with intuition as regards the effects of the variables used on the credit-to-GDP ratio.

The estimated parameters of the model were applied to the data for the CEE countries to obtain values of the "equilibrium" credit ratio. As we are interested in the long-run fundamental-based level of the credit-to-GDP ratio, we used only the coefficients of the estimated long-run relationship between the cointegrated variables. This approach controls in parallel for the credit cycle of in-sample countries, as only equilibrium sensitivities between credit and economic fundamentals are extracted. The results indicate that the OOS calculations may in some cases imply significantly different conclusions regarding excessive credit compared to the HP filter values computed on the end-2009 data (see Figure 7). According to the HP filter, the credit-to-GDP gap indicates excessive credit in the recent period not only for the Czech Republic, but also, for example, for Slovakia, Lithuania, Romania and Poland, whereas the econometric estimate does not confirm this excessive credit level (values in the positive part of the figure indicates excessive private credit-to-GDP ratios). By contrast, Bulgaria, Estonia, Latvia and Slovenia now have excessive credit-to-GDP ratios according to the OOS method. It is clear, therefore, that the two calculation methods used give contradictory results in some cases.

Figure 7

Comparison of credit-to-GDP gaps for various calculation methods

(in p.p.)



Source: IMF IFS, authors' calculations

As mentioned at the beginning of the study, further refinement of the estimates with respect to different loan types and their currency denomination would be desirable. However, current data limitations leave this additional analysis as a future research question.

2.4. Implications for the size of the capital buffer

One of the questions associated with the new Basel III rules is whether the requirement to create a countercyclical capital buffer would contribute to the creation of capital reserves in those CEE countries which experienced significant problems in their banking sectors during the global financial crisis. In the following simulation, the size of the capital buffer is calculated for individual CEE countries using the two aforementioned methods, i.e. the HP filter method and the econometric OOS method. As the crisis did not manifest itself fully in the CEE countries until late 2008 and (in particular) 2009, i.e. after the collapse of Lehman Brothers in September 2008, we set mid-2008 as the starting point for the buffer calculation.

Table 1

Simulation of countercyclical buffer calculation

(data as of 2008 Q2)

	Credit-to-GDP gap (%)		Countercyclical capital buffer (% of RWA)	
	HP filter	Out-of-sample	HP filter	Out-of-sample
Bulgaria	11.4	10.8	2.5	2.5
Czech Rep.	9.5	-15.0	2.4	0.0
Estonia	5.3	27.9	1.0	2.5
Lithuania	6.9	-8.3	1.5	0.0
Latvia	1.0	19.6	0.0	2.5
Hungary	-1.4	-10.7	0.0	0.0
Poland	3.0	-23.3	0.3	0.0
Romania	6.1	-27.3	1.3	0.0
Slovakia	6.1	-22.8	1.3	0.0
Slovenia	5.4	5.5	1.1	1.1

Source: authors' calculations

The results of this simple simulation indicate that only four countries needed a countercyclical capital buffer according to the OOS method (Bulgaria, Estonia and Latvia needed the maximum possible 2.5% of RWA, while Slovenia needed 1.1% of RWA).

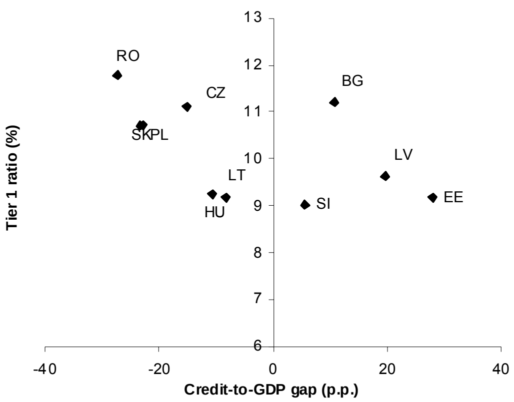
It is relevant to ask whether the banking sectors of these countries had a sufficient capital reserve already in 2008 and were building a "would-be" capital buffer composed of high-quality loss-bearing capital (such as common shares and retained earnings, i.e. in essence a major part of Tier 1 capital) in anticipation of possible problems in the banking sector due to the credit boom. Figure 8 indicates that the countries identified by the OOS method as having excessive credit ratios (i.e. Estonia, Latvia and Slovenia) had relatively low Tier 1 capitalisation. The only exception was Bulgaria, which had set its minimum regulatory limit for total capital adequacy at a higher level (12%) than the traditional 8%, a fact which is also reflected in a higher observed Tier 1 ratio.

Several indicators can be used to compare the impacts of the crisis on the banking sectors of individual countries. In this paper, we look at the change in banking sector profits between 2008 and 2009 (in p.p. of return on equity, RoE), as profitability reflects both credit and market losses as well as the impact of possible higher funding costs on pre-provision income. A simple graphical analysis reveals that two countries identified by the OOS method as having excessive credit ratios (Estonia and Latvia) recorded large losses in their banking sectors in 2009, causing the RoE to decline dramatically (see Figure 9). Two of the countries identified, namely Latvia and Slovenia, saw their governments stepping in and providing public support in 2009. It is worth mentioning that the HP method would not have identified the problems building up in the Latvian and Estonian economies, which were hit hard by the crisis and, especially in the case of Latvia, suffered very high real costs.

It follows from the above that conclusions given by the credit-to-GDP gap computed by HP-filter and OOS method may differ significantly. This problematic was recognized also by other studies, e.g. Repullo and Saurina (2011), which argues that the mechanical application of the credit-to-GDP rule using HP filter – as was initially proposed by the Basel Committee – may lead to unreliable results. However, also BCBS (2010b) argues that the proposed method is only guidance and national authorities are expected to use additional indicators. Nevertheless, finding such indicators being able to transparently identify correct time for setting the buffer without providing false signals is not straightforward and proper calibration based on the historical data is needed, see for instance Laeven and Valencia (2010), IMF (2011, Box 3.2) or Borio et al. (2012), who explore broader range of variables characterizing the financial cycle.

Figure 8

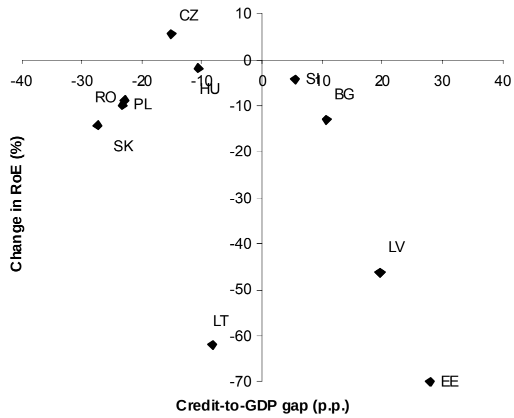
Credit-to-GDP gap via OOS and Tier 1 ratio in 2008



Source: IMF IFS, authors' calculations

Figure 9

Credit-to-GDP gap via OOS and change in RoE



Source: IMF IFS, authors' calculations

Consequently, the setting of the framework for countercyclical buffer decision rule will not be straightforward for authorities in countries with limited length of times series. In this perspective, our method can bring additional insight about country's position in the credit cycle; of course, additional available indicators should be also employed.[1] Still, these authorities will probably need some discretion and expert judgement for setting the threshold that triggers countercyclical buffers, since proper analysis based on the short historical data may not be sufficient.

Another specific issue related to the countercyclical buffers is also correct timing for its release. This is an important but still unsolved problem, as determining accurate timing will influence the meaningfulness of the proposed regulation as it determines to which extent it will prevent the supply of credit being constrained in time of economic distress. As a result, proper conditioning variables which could guide to release of capital must be identified, since credit-to-GDP ratio may be lagging indicator (Table A3). Different set of proxies can be used, for example banks' charge–offs, non-performing loans, or information from bank landing surveys about tightening of credit standards, however, recent analysis also shows, that expert judgement will be necessary (Drehmann et al., 2010).

[1] For example, IMF (2012) suggests employing stress-testing framework as an additional tool for setting countercyclical buffers in the Czech Republic. Prediction of credit growth can be used to limit HP-filter's end-point bias. Both HP-filter and OOS credit-to-GDP indicate that Czech Republic is under its long-term credit-to-GDP ratio (see CNB, 2012, p. 83).

2.5. Conclusions and policy lessons

This paper discusses methods for calculating excessive private sector credit in the Central and Eastern European countries and their suitability as regards the input needed to calculate the countercyclical capital buffer introduced by the Basel Committee on Banking Supervision (BCBS, 2010a). The BCBS has recommended the use of an excessive credit indicator based on the Hodrick-Prescott (HP) filter technique as a guide for setting this buffer.

The paper shows that the HP filter-based calculation of the excessive credit indicator is not necessarily appropriate in certain cases. For the CEE countries in particular, rapid credit expansion may simply mean convergence to values typical of the advanced nations, and not excessive borrowing. As an alternative, the paper suggests considering excessive credit calculation methods that better reflect the evolution of a country's economic fundamentals. One such method is an out-of-sample technique based on estimates for advanced EU countries which are subsequently used to calculate the equilibrium credit levels of the CEE countries.

Although statistical filtering techniques such as the HP filter do have a role to play in the analysis as a first step in the interpretation of the available data, a broader set of indicators and methods should be employed to determine a country's position in the credit cycle. Our chosen method, based on economic fundamentals, would have better identified the problem of excessive credit in those CEE countries whose banking sectors recorded serious problems during the crisis. Although this calculation technique also has its limitations and could be further developed, it can at least be considered by the macroprudential authority responsible for setting capital buffers as a complementary indicator of excessive credit, especially for small converging economies.

There is a clear policy lesson arising from our analysis for macroprudential policy, in which countercyclical buffers will serve as one of the main instruments: national authorities cannot rely on a single indicator only and have to apply judgement, ideally supported by a variety of analyses that help them to identify the position of the economy in the credit cycle with respect to economic fundamentals. Given the current preparatory phase for the implementation of Basel III, including the countercyclical capital buffer, it is crucial to start building a robust, credible and transparent buffer regime that policymakers will apply through the credit cycle once Basel III is fully implemented.

This issue is especially important within the EU where the implementation of Basel III will be based on the idea of a "single rulebook" (or "maximum harmonisation"). This could limit the discretion of policymakers in individual EU countries regarding the methods and variables used to estimate the excessiveness of credit in the economy and thus also the buffer rate, as it requires the set of variables to be agreed on within the European Systemic Risk Board, a new European supranational body charged with the objective of macroprudential surveillance for the EU as a whole.

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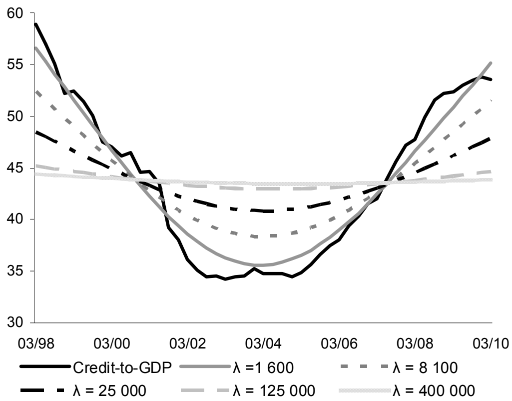
Appendix

A) Sensitivity of Credit-to-GDP gap by HP filter with respect to parameter lambda

Figure A1

Credit-to-GDP trend by HP filter with respect to parameter lambda

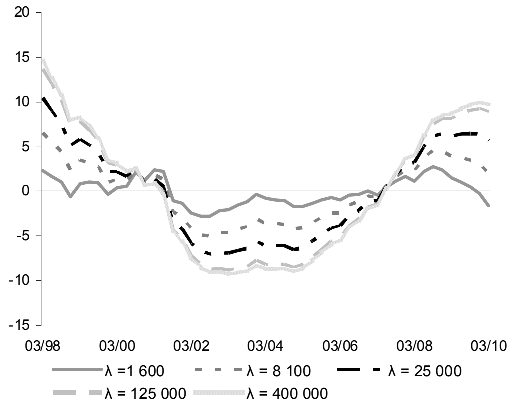
(%)



Source: CNB, authors' calculations

Figure A2

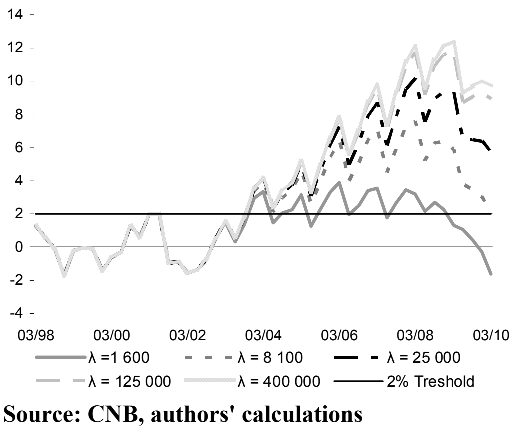
Credit-to-GDP gap for different values of lambda parameter



Source: CNB, authors' calculations

Figure A3

Recursive credit-to-GDP gap for different values of lambda parameter

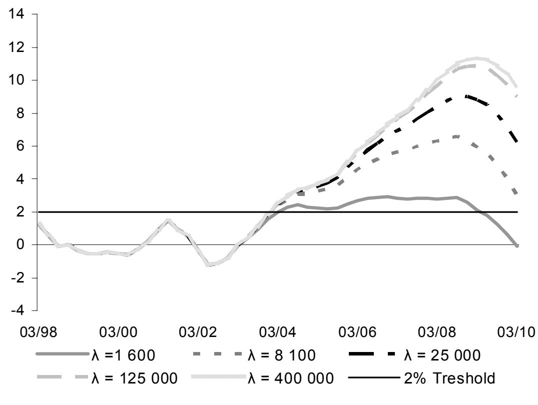


Source: CNB, authors' calculations

Figure A4

Recursive credit-to-GDP gap for different values of lambda parameter

moving average – MA(4)



Source: CNB, authors' calculations

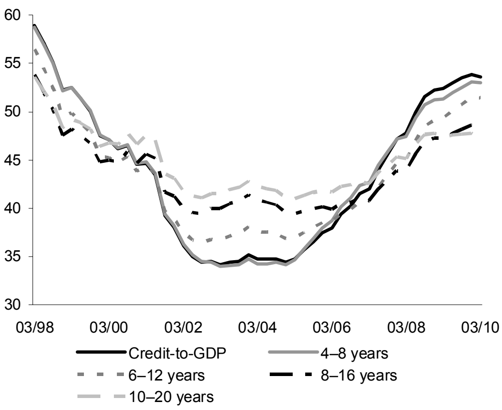
Note: Values of parameter lambda correspond to the assumption that the credit cycle is *x*-times longer than the business cycle. Values of lambda equal to 1 600, 8 100, 25 000, 125 000 and 400 000 corresponds to *x* equal to 1, 1.5, 2, 3 a 4 respectively; see Drehmann et al. (2010).

B) Credit-to-GDP gap by Band-Pass filter

Figure A5

Credit-to-GDP trend by Band-Pass filter for different length of credit cycle

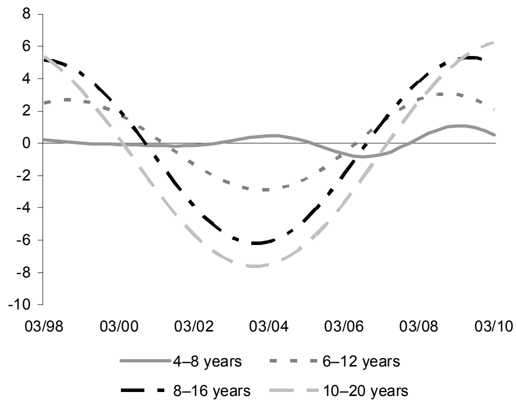
(%)



Source: CNB, authors' calculations

Figure A6

Credit-to-GDP gap based on Band-Pass filter for different length of credit cycle



Source: CNB, authors' calculations

Note: Length of the credit cycle is based on the assumption that the duration of the business cycle ranges from 4 to 8 years in OECD countries, see Drehmann et al. (2010).

C) Detailed description of the data time series used:

Table A1

Detailed description of the data time series used

Time Series' Codes	Description
IMF IFS: AF.ZF...	National Currency per US Dollar average period
IMF IFS: 22D..Z IMF IFS: 32D..ZF...	Claims on private sector
IMF IFS: 32AN.ZW...	Claims on general government (net)
IMF IFS: 222A..ZF...	Claims on general government (net)
IMF IFS: 60P..ZF...	Interest rate
IMF IFS: 64...ZF...	Index CPI
IMF IFS: 67R..ZF...	Unemployment rate
IMF IFS: 99Z..ZF...	Population
IMF IFS: 96F..ZW...	Household consumption expenditures (incl. NPISH) *
IMF IFS: 99BIPZF...	Deflator HDP (base year = 2005)
IMF IFS: 99B..ZF...	Gross Domestic Product in the National Currency
WB WDI: NY.GDP.PCAP.PP.KD	GDP per capita, PPP (constant 2005 international $) **

Source: IMF IFS Database, WB WDI Database
Note: * NPISH = Non-Profit Institutions Serving Households, ** Linearly interpolated from yearly to quarterly frequency.

Time series of interest rates for some countries were completed using the ECB and Eurostat databases and data provided by national central banks.

D) Panel unit root tests:

The standard set of panel unit root tests was applied, i.e. Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin (2003) and Fisher-type tests using ADF and PP tests – see Maddala and Wu (1999) and Choi (2001). Since the set of tests generates extensive output, the results are presented parsimoniously as a summary table for particular variables. However, detailed results are available upon request.

Table A2

Unit root tests

Variable	Result	Note
consumption / gdp	I(1)	Not confirmed by LLCH
credit / gdp	I(1)	
gdp per capita	I(1)	
gdp per capita in PPP	I(1)	
government debt / gdp	I(0)	
inflation (cpi)	I(0)	Not confirmed by LLCH
inflation (deflator)	I(0)	
lending rate	I(0)	Not confirmed by LLCH
real lending rate	I(0)	
unemployment rate	I(0)	

Source: authors' computation

Note: LLCH = Levin, Lin and Chu test for common unit roots across countries.

E) Credit-to-GDP ratios for EU countries

Table A3

Credit-to-GDP ratios for EU countries

(%)

	1995	2000	2005	2008	2009	2010	2011
Austria	92.8	102.7	113.6	119.4	125.7	121.5	118.7
Belgium	72.8	80.7	73.8	94.0	97.6	94.9	92.8
Cyprus	122.7	158.9	164.5	253.8	271.0	285.6	298.1
Denmark	105.3	121.3	154.6	216.6	223.4	216.4	208.7
Finland	61.3	52.3	75.1	86.0	93.6	94.8	95.3
France	86.0	85.6	92.3	108.8	111.3	114.5	116.2
Germany	100.4	117.9	111.9	108.8	113.5	108.0	105.5
Greece	n.a.	n.a.	78.5	97.4	93.9	115.8	118.0
Ireland	n.a.	107.1	160.8	220.3	234.5	215.0	207.6
Italy	56.0	72.9	88.9	104.5	110.7	122.0	122.1
Luxembourg	86.2	103.4	129.0	183.6	187.3	185.3	n.a.
Malta	95.8	109.8	106.4	124.6	134.0	133.6	133.6
Netherlands	93.2	135.9	165.0	193.1	214.8	199.3	197.4
Portugal	66.7	129.5	145.5	173.6	186.7	190.9	n.a.
Slovenia	25.9	36.2	58.6	85.3	92.9	94.4	91.3
Spain	72.3	95.0	145.7	202.8	211.8	213.5	203.5
Sweden	n.a.	n.a.	107.9	128.1	136.2	135.7	136.1
United Kingdom	113.1	126.5	159.1	211.3	213.3	202.6	187.5
Average	**83.4**	**102.2**	**118.4**	**150.7**	**158.5**	**158.0**	**152.0**
Bulgaria	39.9	12.5	43.4	71.6	75.4	74.0	72.0
Czech Republic	70.7	48.3	36.1	50.4	52.1	53.2	55.8
Estonia	16.2	34.5	69.7	97.1	107.2	97.2	n.a.
Hungary	21.9	30.6	51.3	69.8	69.5	68.8	65.0
Latvia	8.0	17.8	68.2	91.1	104.7	99.3	82.7
Lithuania	14.6	12.9	40.9	62.4	69.8	63.6	53.7
Poland	16.9	26.8	28.9	49.6	50.4	52.0	55.0
Romania	n.a.	8.0	19.9	37.7	39.2	39.6	38.0
Slovak Republic	36.4	53.5	35.1	44.7	48.4	48.2	49.7
Average	**28.1**	**27.2**	**43.7**	**63.8**	**68.5**	**66.2**	**59.0**

Source: IMF IFS

3. Stress-tests Verification

Published as

Seidler, J., Geršl, A. (2010): Stress-tests Verification, Financial Stability Report 2009/2010, Czech National Bank, 2010, pp. 92–101, ISBN: 978-80-87225-24-0.

Stress Testing:

Conservative Calibration and Verification

Abstract

This paper describes the stress testing framework used in the Czech central bank and focuses on a general question how to calibrate models used to stress test the most important risks in the banking system. The paper argues that stress tests should be calibrated conservatively and overestimate the risks to have sufficient buffer for the adverse shocks realization. However, to ensure that the stress test framework is conservative enough over time, a verification, i.e. comparison of the actual values of key financial variables with predictions generated by the stress-testing models should become a standard part of the stress-testing framework.

Abstrakt (*in Czech*)

Předkládaný článek shrnuje metodologii zátěžových testů bankovního sektoru ČNB a zaměřuje se na otázku kalibrace modelů určených pro odhad rizik v bankovním systému. Text dokládá, že nastavení předpokladů zátěžových testů a využívaných dílčích modelů by mělo být konzervativní a rizika by měla být spíše nadhodnocována. Verifikace zátěžového aparátu využívaného ČNB naznačuje, že model je nastaven správně na pesimistické straně. Článek zároveň shrnuje, že verifikace agregovaných testů by měla být běžnou součástí zátěžového testování a měla by být využita pro další zpřesňování celého aparátu zátěžových testů.

Keywords: stress testing, credit risk, bank capital

JEL Codes: E44, E47, G21

3.1. Introduction

The Stress tests are used by commercial financial institutions, regulators and central banks as a means of testing the resilience of individual portfolios and institutions or the entire sector to adverse changes in the economic environment. This paper focuses on the so called macro stress tests of the banking sector, which have became a standard tool among central banks and regulatory authorities to assess vulnerabilities of the banking sector as a whole, see e.g. Foglia (2009) or Drehmann (2009) and references therein. However, general methodological problems apply also to macro stress tests for other financial industries (pension funds, insurance companies, credit unions, etc.).

The earliest banking sector stress testing models, which were initially based on the simple historical scenarios linking macroeconomic development with financial sector's variables (e.g. Blaschke et al., 2001), were developed into more sophisticated models integrating market, credit, interest rate risk, and capturing inter-institutions contagion and feedback effect between financial sector and real economy. These relatively complex models become regular tools for analyzing resilience of the financial sector, see e.g. Danmarks Nationalbank (2010, p. 45), Oesterreichische Nationalbank (2010, p. 51), Norges Bank (2010, p. 49), RAMSI model (Risk Assessment Model for Systemic Institutions) of Bank of England (Aikman et al., 2009) or European Banking Authority (2011).

Nevertheless, the global financial crisis uncovered the deficiencies of the stress-testing methodologies used in many countries. Before the crisis, many tests were wrongly indicating that the sector would remain stable even in the event of sizeable shocks (Haldane, 2009; Borio et al., 2012). These deficiencies related not only to the configuration of the adverse scenarios used, which had initially seemed implausibly strong but were often exceeded in reality, but also to the shock combination assumed, which had not been adequately anticipated in the scenarios (Čihák et al., 2009; Breuer et al., 2009). A role was also played by deficiencies in model calibration and in the assumed behaviour of banks and markets, and by the absence of testing of liquidity risk alongside traditional financial risks (in particular credit risk and interest rate risk), since distress after the Lehman failure confirmed the importance of the spiral between market and funding liquidity and its fragile link to the solvency of the institution (Gorton, 2009; Brunnermeier et al., 2009). This problem in stress-testing frameworks also demonstrates Ong and Čihák (2010) using an example of Iceland, where the banking sector collapsed in the fall of 2008, though stress-tests from mid-2008 confirmed its stability.

Consequently, the assumptions and parameters used in stress tests are gradually being re-examined so that the tests can better analyse the impacts of strong shocks to the financial system and stress tests are becoming a standard tool in the new macroprudential framework (FSB, 2011), though there are some doubts about their ability to serve as early warning device (see Borio et al., 2012). In defence of stress testing, however, it should be mentioned that this is a relatively new tool[1] and hence it still requires ongoing methodological development and refinement.[2] And the recent financial turbulences have suggested clearly possible ways for improving their methodology.

This paper focuses on how to calibrate models used to stress test the most important risks in the banking system. We argue that stress tests should be calibrated conservatively and slightly overestimate the risks. However, to ensure that the stress test framework is conservative enough over time, a process of verification, i.e. comparison of the actual values of key banking sector variables with predictions generated by the stress-testing models should become a standard part of the stress-testing framework. Direct verification of adverse scenarios is in majority of cases (i.e. non-crisis periods) not possible. Thus, the verification should be performed on baseline scenarios. However, the whole stress-testing model should be calibrated conservatively in order to take into account the uncertainty related to the possible changes in estimated relationships in the case of adverse economic development. Hence, ex-post comparison between reality and predictions generated by baseline scenarios should indicate systematic risk overestimation.

To illustrate our point we present the results of the verification of the Czech National Bank's (CNB) stress testing framework. The CNB has been performing bank stress tests since 2003 and has significantly expanded its methodology over the past few years. The most recent major update was done in mid-2009 and involved and introduction of dynamic features in the system (see section 2). On this occasion, a verification of the overall stress-testing methodology was conducted in the context of the aforementioned international debate on the reliability of the predictions of the impacts of shocks to the banking sector. The aims were to demonstrate whether the stress test assumptions were correctly configured and to identify any deficiencies in those assumptions.

The analysis reveals that the current CNB stress-testing system generally errs on the right – i.e. pessimistic – side and slightly overestimates the risks. This leads on average to estimates of key financial soundness indicators (in particular capital adequacy) that are lower (more conservative) than the actual values. Some verification results were used to further develop the stress tests. To our knowledge, there is no other study that would systematically and transparently present the verification of someone's stress testing methodology. With this paper we would like to make a contribution to the debate on how to develop and calibrate reliable stress testing frameworks.

The paper is structured as follows. Section 2 briefly describes the CNB's stress-testing methodology that was subsequently verified. Section 3 summarises the verification

[1] Tools based on various types of financial soundness indicators have traditionally been used to assess the resilience of financial institutions (Geršl and Heřmánek, 2008).

[2] The formal obligation of commercial banks to conduct stress tests on their own portfolios was only introduced by Basel II (for banks using advanced methods for calculating capital requirements), which was implemented in the EU in 2006–2007. However, nowadays, there is a set of guidelines by CEBS/EBA related to stress testing in commercial banks (see Committee of European Banking Supervisors – CEBS, 2009).

methodology and presents summary conclusions of the verification for capital adequacy (including its two main constituents, i.e. regulatory capital and risk-weighted assets, RWA) and some other key banking sector variables used in the stress tests. This section also contains a summary of the main improvements introduced following the verification and a brief description of the next steps planned for the development of the banking sector stress tests. The conclusion summarises the verification results and proposes a medium-term plan for further developing the tests.

3.2. Current banking sector stress-testing methodology of the CNB

The original banking sector stress-testing methodology applied at the CNB was based on the IMF methodology used for FSAP missions (e.g. Blaschke et al., 2001; Čihák, 2005; Čihák and Heřmánek, 2005).[1] The CNB later switched from testing historical ad-hoc scenarios defined by a combination of shocks (e.g. a 20% rise in non-performing loans, a 15% exchange rate depreciation) to using consistent macroeconomic scenarios generated by the CNB's prediction model and related credit risk and credit growth sub-models (Čihák at al., 2007; Jakubík and Schmieder, 2008; Jakubík and Heřmánek, 2008). This framework was used for the Financial Stability Report 2008/2009 (CNB, 2009).

In the second half of 2009, the CNB significantly updated the banking sector stress-testing methodology in three respects. First, the tests were "dynamised", in the sense of switching to quarterly modelling of shocks and their impacts on banks' portfolios. This change was described in a box in the CNB Financial Stability Report 2008/2009 (CNB, 2009, pp. 63–64). Second, in the credit risk area there was a changeover to "Basel II terminology", i.e. to capturing the credit risk of several separate portfolios using the standard parameters PD, LGD and EAD and relating risk-weighted assets to those parameters using procedures specified in the IRB approach to calculating capital requirements.[2] The final major innovation was the extension of the shock impact horizon from one to two years (or eight subsequent quarters).

Abovementioned changes were motivated by the best practise of other central banks and supervisory authorities, which made an effort to develop specific expertise in the filed of macro-to-micro linkages in assessing banking sector ability to withstand negative adverse scenarios.

- **Alternative macroeconomic scenarios**

Alternative macroeconomic scenarios still serve as the starting point for stress testing in the updated methodological framework. The scenarios are designed using the CNB's official prediction model (currently dynamic stochastic general equilibrium model – DSGE, see Brázdik et al., 2011) supplemented with an estimate of the evolution of some additional variables, which

[1] The methodology of IMF FSAP missions for stress-testing also developed considerably, and the current stress-testing framework is described in Schmieder et al. (2011).

[2] PD – probability of default; LGD – loss given default; EAD – exposure at default; IRB – internal ratings based.

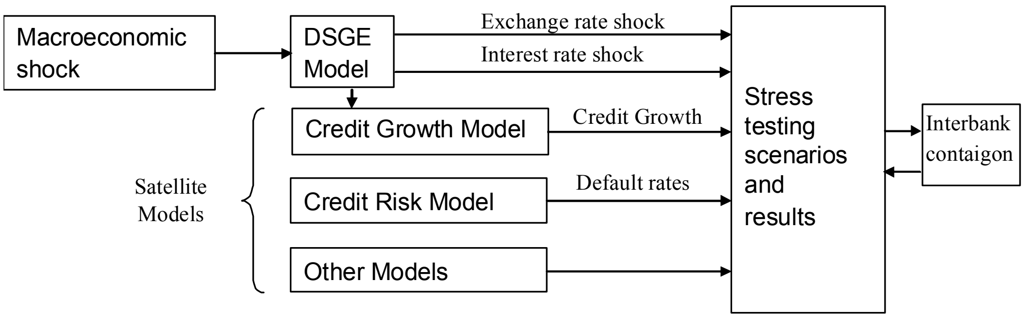
are not directly generated by the model (so called "satellite models"). Stress scenarios are constructed based on the identification of risks to the Czech economy in the near future. To compare the stress outcome with the most probable outcome, the stress tests use a baseline scenario, i.e. the current official macroeconomic prediction of the CNB.

The predictions for GDP growth, inflation and other macroeconomic variables enter credit risk, credit growth and other satellite models, which transform macroeconomic development into the financial sector variables and thereby capture changes in banks' credit portfolios, credit risk, interest income, etc. The stress tests work explicitly with the four main loan portfolio segments by debtor and/or credit type (non-financial corporations, loans to households for house purchase, consumer credit and other loans), to which the sub-models are also adjusted. The credit risk models are used to predict PD for the individual loan segments, whereas the credit growth models are used to estimate the growth in bank portfolios in relation to the macroeconomic situation and (after certain adjustments) to estimate the evolution of risk-weighted assets.

The architecture of the stress-testing framework as a whole is described in the following scheme, which illustrates how macroeconomic model of CNB and satellite models generate alternative scenarios for the banking sector. The part "Other Models" consists of the set of models for property prices development, yield curve, or net interest income.

Scheme 1

Architecture of stress tests



Source: CNB (2007), authors

In the stress tests, the prediction for macroeconomic and financial variables for individual quarters is reflected directly in the prediction for the main balance-sheet and flow indicators of banks. The tests are dynamic, i.e. for each item of assets, liabilities, income and expenditure there is an initial (the last actually known) stock, to which the impact of the shock in one quarter is added/deducted, and this final stock is then used as the initial stock for the following quarter. This logic is repeated in all eight quarters for which the prediction is being prepared. The consistency between stocks and flows is thus ensured.

- **Credit risk**

Credit risk testing is the most important area of stress testing. This testing is based on the use of PD for each of the four main segments of the loan portfolio. The second credit risk parameter is LGD, which is currently determined by expert judgement, with different amounts being set for different scenarios and different credit segments in line with the regulatory rules, commercial bank practices, the approaches applied by some rating agencies (Moody's, 2009) and existing estimates based on market data (Seidler and Jakubík, 2009). The third parameter is EAD, which is determined as the volume of the non-default part of the portfolio (i.e. excluding non-performing loans).

An increase in PD and LGD has two main effects on individual banks.

First, the expected loan losses (in CZK millions), against which banks will create new provisions of an equal amount and record them on the expenses side of the profit and loss statement as impairment losses, are calculated as the product of PD, LGD and EAD for each credit segment and quarter.[1] Total assets are then symmetrically reduced by the amount of these expenses.

The product of PD and the volume of the non-default portfolio forms the volume of new non-performing loans (NPLs) for each quarter. This allows us to generate the volume of total NPLs in the following eight quarters for each bank, and subsequently for the banking sector as a whole, according to the following equation:

$$NPL_{t+1} = NPL_t + \sum_{i=1}^{4} PD_{t+1,i} NP_{ti} - aNPL_t \tag{1}$$

where *NPL* are non-performing loans, *PD* is the probability of default, *NP* is the non-default portfolio in the four segments defined above and *a* is an NPL outflow parameter (i.e. write-offs or sales of existing NPLs, i.e. the default part of the portfolio). Parameter *a* is set by expert judgement at 15% for all segments, i.e. 15% of NPLs are written off/sold each quarter and subsequently disappear from the total volume of NPLs and (gross) assets of the bank. This calibration was chosen on the basis of discussions with commercial banks and estimates conducted as part of the verification, which are described in more detail at the end of the next section.

The credit growth model leads to an estimate of the gross volume of loans in individual segments. Using relation (1) for NPL modelling, this allows us to determine for each bank, and subsequently for the banking sector as a whole, the NPL/total loans ratio, a standard indicator of the banking sector's health.

[1] According the relevant CNB decree and IFRS, banks are not required immediately to create provisions exactly equal to expected losses, but rather they must create provisions equal to realised losses, i.e. for new NPLs. However, if the loans are gradually reclassified during the quarter into the NPL (i.e. default) category to the extent predicted by PD, banks will ultimately create these provisions in the originally estimated amount.

Second, in the case of banks applying the Basel II IRB approach to the calculation of capital requirements for credit risk, the capital requirements (or risk-weighted assets, RWA[1]) for credit risk are a function of PD, LGD and EAD. Given that the largest banks in the Czech Republic apply this approach, this relation is applied to all banks for the sake of simplicity. Given a constant non-default portfolio volume, i.e. EAD, an increase in PD and LGD thus generally results in an increase in RWA and therefore a decrease in capital adequacy.[2]

- **Interest rate and currency risk**

The macroeconomic scenarios contain a prediction of the evolution of the simplified koruna and euro yield curves (rates with 3M, 1Y and 5Y maturities). A change in interest rates has a direct effect on bank balance sheets in two main items, namely interest profit and the value of bond holdings.[3] A rise in short-term rates thus reduces the interest rate profit of those banks which have an excess of short-term liabilities over short-term assets. However, the calculation is adjusted by expert judgement to take account of the business policies of commercial banks, which respond relatively little to market interest rate changes on the deposit side.

The prediction for long-term interest rates is used to estimate profits/losses from the revaluation of bond holdings (except for bonds held to maturity and bonds with a variable coupon dependent on interest rates). The calculation is based on the estimated duration of the bond portfolios, which is calculated by expert judgement on the basis of a more detailed knowledge of the maturity structure. Account is also taken of bond portfolio hedging using IRS (interest rate swaps), which for some banks lessens the impact of interest rate changes.

The quarter-on-quarter change in the CZK/EUR exchange rate is applied to the net open foreign currency position (including off-balance-sheet items), generating either a loss or a profit depending on the sign of the net open position and the direction of the exchange rate change.[4]

- **Interbank contagion risk**

Interbank contagion risk is modelled in two selected periods (in the fourth and eighth quarters). The test uses data on interbank exposures, with the capital adequacy of individual banks being used to determine their probability of default (PD).[5] As interbank exposures are mostly unsecured, LGD is assumed to be 100%. The expected losses due to interbank exposures are calculated for each bank according to the formula PD×LGD×EAD, where EAD is the net interbank exposure. If these losses are relatively high and will lead to a reduction in the bank's

[1] Risk-weighted assets = capital requirements (in CZK millions)×12.5.

[2] This channel of the impact of increased PD and/or LGD on banks is one of the main sources of the much-criticised procyclicality of Basel II (see Geršl and Jakubík, 2010).

[3] At the same time, however, interest rate changes have an indirect effect on credit risk via their effect on the PD estimate.

[4] For example, a positive open foreign currency position and appreciation of the koruna leads to losses.

[5] The PD values in relation to capital adequacy ratios (CAR) are set by expert judgement as follows: PD = 100% for negative CAR; PD = 25% for CAR between 0% and 5%; PD = 15% for CAR between 5% and 8%; PD = 5% for CAR between 8% and 10%; PD = 0.5% for CAR greater than 10%.

capital adequacy and thus an increase in its PD, there follows another iteration of the transmission of the negative effects to other banks through an increase in the expected losses. These iterations are performed until this "domino effect" of interbank contagion stops, i.e. until the rise in PD induced in one bank or group of banks does not lead to a rise in the PD of other banks.

- **Profit, regulatory capital and capital adequacy**

The stress test assumes that banks will continue to generate revenues even in the stress period, particularly net interest income (interest profit) and net fee income. For these purposes, an analytical item of the profit and loss account called "adjusted operating profit" has been constructed. This consists of interest profit (+), fee profit (+), administrative expenses (–) and some other (non-shock) items.[1] The volume of adjusted operating profit was initially determined by expert judgment for the individual scenarios. A model estimate of this item was introduced only in mid-2010 (CNB, 2010).

Regulatory capital is modelled in accordance with the applicable CNB regulations. Each bank enters the first predicted quarter with initial capital equal to that recorded in the last known quarter. If a bank generates a profit in the first predicted quarter (i.e. its adjusted operating profit is higher than its losses due to the shocks), its regulatory capital remains at the same level (is not increased). If, however, it generates a loss, its regulatory capital is reduced by the amount of that loss. The impacts of the shocks are thus reflected in a reduction of capital only if they exceed adjusted operating profit and the bank generates a loss.

It is assumed that those banks which generate a profit for the entire financial year will decide on profit distribution and dividend payments in the second quarter of the following year. Here we assume that each bank, when increasing its capital from retained earnings of the previous financial year, will try to get to its initial capital adequacy ratio if its previous year's profits are sufficient.[2] Depending on the change in RWA, several scenarios are thus possible:

- the bank distributes the entire profit and does not strengthen its regulatory capital (in the event of unchanged RWA);
- the bank uses part of its profit to strengthen its capital and distributes the remainder (in the event of an increase in RWA; however, the entire retained earnings of the previous year will not be needed to reach the initial level of capital);
- the bank uses the entire profit to strengthen its capital (in the event of a relatively sizeable increase in RWA); depending on the size of the increase in RWA, however, it may not reach the original capital adequacy ratio;

[1] In previous Financial Stability Reports this adjusted operating profit was called "net income". Adjusted operating profit is broadly equivalent to the item "pre-provision profit", i.e. operating profit gross of losses on non-performing loans, but differs in that it does not include the impacts of other (interest rate and exchange rate) shocks, whereas pre-provision profit does.

[2] This assumption may not be very realistic at certain times, as banks may decide to pay higher dividends and reduce their capital adequacy ratio below the initial level.

- the bank pays dividends that exceed the profit generated (in the event of a decrease in RWA) and thereby also distributes part of retained earnings of previous years.

Total capital adequacy is then calculated for the individual quarters as the ratio of regulatory capital to total RWA. The portion of RWA relating to credit risk is modelled on the basis of the credit risk parameters (see above), while the other components of RWA (or of the capital requirements for other risks) for the individual quarters are determined by expert judgement.

3.3. Verification of the stress tests

The objective of the verification is to examine to what extent the assumptions and sub-models used in the stress testing framework are in line with reality. A problematic aspect of the verification is that the tests use stress – i.e. unlikely – scenarios, which may not occur in reality. Hence, we cannot subsequently compare predictions based on adverse scenarios with reality. For this reason, only the scenario that represents the most likely evolution of the economic environment, i.e. the no-stress baseline scenario of the CNB forecast, could be used for the verification.[1]

The prediction using the baseline (i.e. likely) scenario should indicate slightly higher risks than those that occur in reality. This is because the whole system should have a "conservative" buffer to offset the uncertainty associated with estimating losses given adverse economic developments, when relations (for example between GDP growth and risk parameters such as PD) estimated by standard econometric techniques on data from mainly calm periods can change suddenly for the worse. This requirement implies that stress test prediction errors should be evaluated differently from the errors of standard macroeconomic predictions, where deviations in either direction are regarded as "equally bad". In verifications using baseline scenarios, it is appropriate to apply an asymmetric view in the stress tests and tolerate prediction errors towards modest overestimation of the risks.

The verification was conducted on quarterly data in the period 2004 Q4–2009 Q2, i.e. for 19 periods in all. The actual values of key variables for the banking sector as a whole are compared with the predictions generated by the current stress-testing methodology for the individual quarters using the relevant baseline scenario of the forecast. As the updated stress-testing methodology allows us to create a prediction for the next eight quarters, it was necessary to choose a prediction horizon. The results presented in this paper are based on a one-year prediction.[2] The predictions for past quarters were therefore created subsequently using the updated

[1] The first attempt to verify the stress tests using the baseline forecast scenario was made back in 2007 (Čihák et al., 2007), when the capital adequacy ratio and NPL growth predictions generated by the 2006 stress-testing methodology were compared with their real counterparts.

[2] This means, for example, that the actual outcome in 2007 Q4 was compared with the prediction for that quarter made one year earlier, i.e. on bank portfolios as of 2006 Q4 using the January 2007 baseline scenario. In-

stress-testing methodology in order to verify that methodology and do not match the values published in CNB Financial Stability Reports.

Two statistics based on the mean prediction errors were used to verify the selected variables: the mean absolute error (MAE) defined by equation (2):

$$\frac{1}{n}\sum_{t=1}^{n}\left|P_t - A_t\right| \tag{2}$$

and the mean error in direction (MED) defined as:

$$\frac{1}{n}\sum_{t=1}^{n}\frac{P_t - A_t}{\left|A_t\right|} \tag{3}$$

where P_t denotes the value of the prediction of the estimated variable for the given quarter, A_t denotes the actual value and t represents the quarter for which the prediction is being made.[1]

MAE serves for simple presentation of the mean prediction error in the units in which the given variable is expressed, while MED expresses whether the given variable was overestimated or underestimated on average and thus gives the degree of "conservativism".

The prediction error of the capital adequacy ratio and other key banking sector variables can be split into two main factors. The first is the potential prediction error caused by inaccuracy in the estimates of the macroeconomic variables entering the stress-testing mechanism (interest rates and the exchange rate), and the second concerns the assumptions and sub-models used in the stress test itself (e.g. the assumptions about how the bank raises its regulatory capital, what interest and non-interest yields it achieves and how sensitive it is to interest rate risk). The macroeconomic prediction error can be eliminated in the verification by using the actual (ex post) values of macroeconomic variables. The residual error is then due to inaccuracies in the assumptions and sub-models of the stress-testing framework and the intentional conservative buffer.

The most important output variable of the tests is the estimate of the capital adequacy ratio (CAR). The mean absolute deviation (MAE) for CAR equates to roughly 1.6 p.p. of the capital adequacy ratio (see Table 1). This means, for example, that the test predicts CAR of 11.4% instead of 13%.

ternally, however, the verification was performed for all prediction horizons and the results are qualitatively similar (see the Appendix).

[1] As part of the verification we also computed other prediction error statistics, e.g. the mean percentage error, the mean weighted percentage error, the mean quadratic error and the mean percentage quadratic error. The verification results using these statistics, however, did not differ significantly from the results using MAE and MED, which are easier to interpret.

Table 1

Deviation of capital adequacy ratio estimate

Estimate for 1-year horizon

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test	1.6	1.0	0.8	1.6	2.1	1.9
Prediction – known macro	1.5	0.9	0.6	1.1	2.0	2.5
Mean error in direction (MED) in %						
Prediction – stress test	-10.8	-1.7	-6.5	-13.1	-17.2	-15.3
Prediction – known macro	-8.8	1.9	-1.3	-7.1	-16.3	-20.0

Source: authors' computation

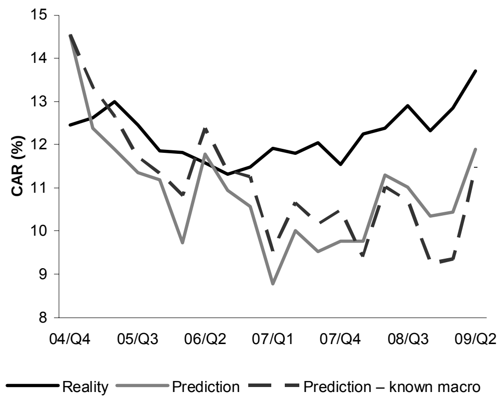
This prediction error equates to roughly 1.8 standard deviations. In the individual shorter periods this error gradually shrinks to 0.8 p.p. (i.e. 1 standard deviation) but then grows again slightly from 2007 onwards. Only a small part of the error is due to errors in the macroeconomic forecast, as the MAE statistic decreases only modestly with knowledge of actual macroeconomic developments.

The negative MED statistic of -10.8% shows that the real values were higher on average in the period as a whole and the stress tests thus tended to generate overvalued CAR estimates (see Table 1). This fact is also demonstrated by Figure 1, which reveals that a lower-than-actual CAR is predicted from the end of 2006 onwards. The resulting CAR was thus underestimated for most periods, in line with the conservative design of the tests. This conclusion remains valid even when the predictions are adjusted for the error in the prediction of macroeconomic variables. Similar results are obtained even for different prediction horizons (the Appendix Table A1, where also two-quarters and six-quarters horizons are compared).

Figure 1

Verification of CAR estimate

(estimate for 1-year horizon)

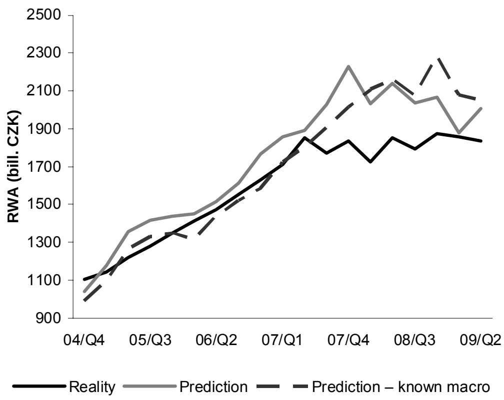


Source: authors' calculations

Figure 2

Verification of RWA estimate

(estimate for 1-year horizon)



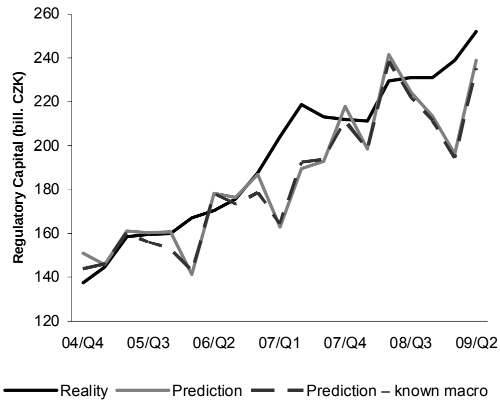
Source: authors' calculations

The estimate of a lower-than-actual CAR is due to inaccuracy in the estimate of both RWA and regulatory capital. With few exceptions the stress test overestimated RWA (see Figure 2) and simultaneously tended to underestimate regulatory capital (see Figure 3). The decomposition of the error in the CAR estimate into the part caused by inaccurate prediction of RWA and the part caused by inaccurate prediction of regulatory capital shows that the contributions of the two items to the error are from 65 % balanced on average caused by risk-weighted-assets (see the Figure A1 and A2 in the Appendix for the detailed decomposition of the error). The overestimation of risk-weighted assets has two sources: first, the credit growth model tends to predict higher credit volumes than the ex-post turnout. While on a first sight an underestimation of credit growth seems to be the conservative calibration, the opposite is true at least from the point of view of risk-weighted assets. Second, the framework uses the estimates of PDs and LGDs as a base of risk weights (IRB approach) which are also overestimated.

Figure 3

Verification of regulatory capital estimate

(estimate for 1-year horizon)

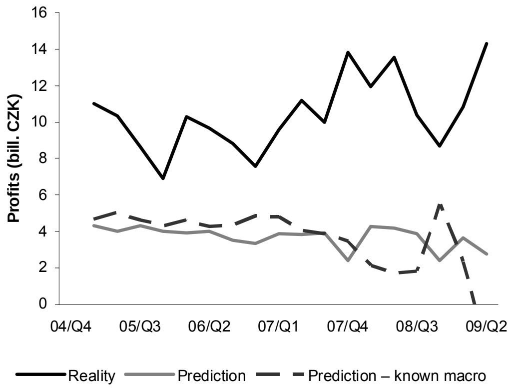


Source: authors' calculations

Figure 4

Verification of profits estimate

(quarterly values, estimate for 1-year horizon)



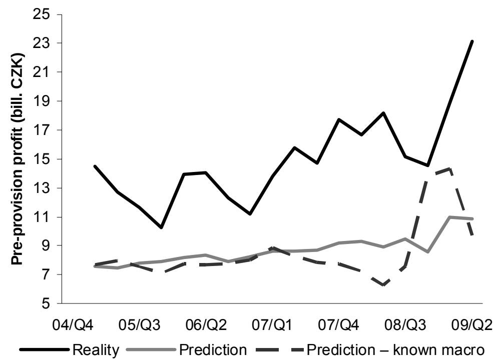
Source: authors' calculations

Regulatory capital is regularly increased out of after-tax profits, so the estimate of profits is an important parameter for the evolution of capital. Profits are calculated as the difference between adjusted operating profit and losses due to the individual shocks tested (see section 2). The verification of this variable revealed that the stress test systematically underestimates after-tax profit (Figure 4). This is due to two factors. First, the test systematically underestimates adjusted operating profit directly through the assumption about its level (for the baseline it was assumed that adjusted operating profit will be 90% of the average for the previous two years).

Figure 5

Verification of pre-provision profit estimate

(quarterly values, estimate for 1-year horizon)



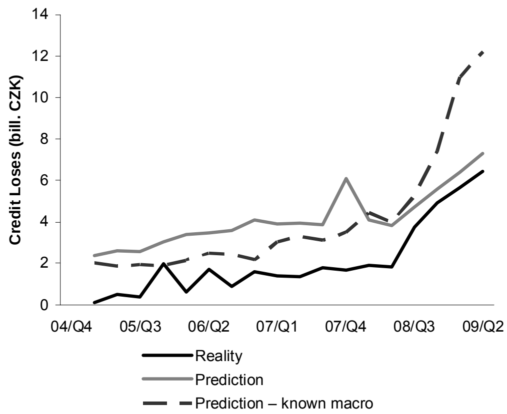
Note: Pre-provision profit equals adjusted operating profit + impact of market profits/losses (interest rate and FX risk).

Source: authors' calculations

Figure 6

Verification of credit losses estimate

(quarterly values; estimate for 1-year horizon)



Source: authors' calculations

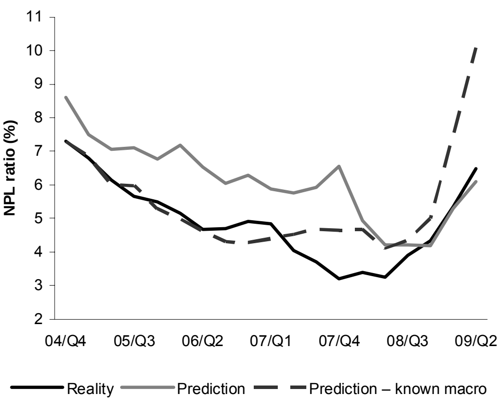
This is also in line with the more conservative approach to risk assessment (Figure 5). The second cause is that the stress test tends to overestimate the impact of the main risk tested, i.e. credit risk, in the form of higher-than-actual PD and related higher provisioning for NPLs (recorded in the "losses from impairment" category), partly also due to a too conservative expert estimates of LGD (Figure 6).

The NPL ratio is a closely monitored financial stability indicator. We therefore present detailed verification results for this variable as well. A comparison of the actual NPL ratios with their predicted values reveals overshooting of the estimates, especially since the end of 2007, for both non-financial corporations (see Figure 7) and households (see Figure 8).

Figure 7

Verification of NPL ratio – corporations

(estimate for 1-year horizon)

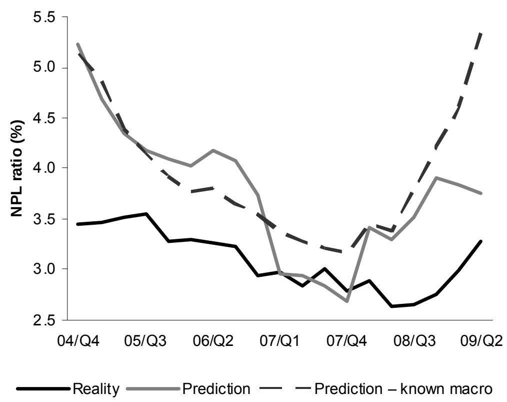


Source: authors' calculations

Figure 8

Verification of NPL ratio – households

(in %; estimate for 1-year horizon)



Source: authors' calculations

Table 2 shows that MAE was around 1.3 p.p. for non-financial corporations and 0.7 for households. While the NPL estimates for corporations improve significantly with knowledge of the macroeconomic environment, the opposite is true for households in some periods. In overall comparison, however, the household NPL estimate is more accurate. This conclusion applies even for different horizons of prediction (the Appendix, Table A2 and A3).

Table 2

Deviation of NPL ratio estimate for corporations and households

Estimate for 1-year horizon

NPL ratio – corporations

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test	1.3	1.1	1.4	1.9	1.4	0.6
Prediction – known macro	0.8	0.1	0.2	0.6	0.8	1.5
Mean error in direction (MED) in %						
Prediction – stress test	27.8	18.3	26.2	45.5	38.5	12.1
Prediction – known macro	12.3	-0.1	-3.2	6.1	20.6	31.0

NPL ratio – households

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test	0.7	1.1	0.8	0.5	0.4	0.8
Prediction – known macro	0.9	1.1	0.7	0.4	0.7	1.3
Mean error in direction (MED) in %						
Prediction – stress test	21.6	30.7	25.6	12.1	13.9	26.7
Prediction – known macro	27.7	30.5	21.0	14.2	24.1	43.5

Source: authors' computation

The overestimation of the NPL ratio is due both to the aforementioned conservative calibration of the PD risk parameter and, to some extent, to underestimation of outflow parameter *a* from equation (1). To determined the optimum value of *a*, numerical minimisation of the MAE error statistic was performed in various time intervals of 2004–2009. The optimum outflow *a* for the entire period under review was 20% on average. Owing to the deliberate overestimation of the potential risks this parameter was conservatively set at 15% in the tests.[1]

Despite the relatively positive message of the verification results, further gradual refinement of the predictions is desirable. The main problem in the credit risk area is with the submodels and assumptions used, as they excessively overestimate the impact of credit risk in the form of losses on impaired loans. While the direction towards overestimation is correct, the degree of overestimation should be held in a reasonable range.[2] At the same time, the conservative prediction of adjusted operating income (and, as a result, overall profits) seems to be too far from the ex-post reality, so adjustments in this area are also needed.

[1] The sensitivity of the NPL ratio estimate to change in *a* reveals that an increase in *a* of 5 p.p. (i.e. from the 15% used to the optimum value of 20%) – i.e. a faster outflow of NPLs from banks' balance sheets – causes on average a decline in the NPL ratio of one-tenth (e.g. from 10% to 9%).

[2] The results of verification of other key variables (not reported here, but available from authors upon request) indicated that next to a large overestimation of credit losses, market losses (FX and bond revaluations) are also to some extent overestimated.

Following the verification, the CNB has started to modify the stress testing framework in order to bring estimates closer to the reality, while still preserving a certain degree of conservativism (CNB, 2010). In the credit risk area, this involved a recalibration of the credit risk models, linking the parameter LGD to the macroeconomic environment and better prediction of risk-weighted assets. In the profits area, a new bank income model linking adjusted operating profit to developments in the macroeconomic environment was developed (CNB, 2010, Box 7).

When recalibrating and adjusting the overall stress testing framework, there are four main ways to preserve a conservative buffer in estimates. The CNB has been using all of them in combination. First, if a parameter is set expertly (such as adjusted operating profits or the LGDs in the verified version of the framework), it should be set conservatively. Second, if a parameter is estimated via a model, a more conservative definition of the estimated parameter (i.e. the dependent variable) could be used. The CNB has for example used a PD that was based on 30+ days in arrears definition of default rate which is generally higher than the standard Basel 90+ days definition.[1] Third, if the parameter (dependent variable) is correctly calculated, the buffer can be achieved by changing (to the worse) some of the coefficients (elasticities) estimated within an econometric model that is usually using data over a calm period. And finally, while the model itself is estimated by a traditional econometric method, predictions could be adjusted by one standard deviation of the volatility of dependent variable (in the conservative direction). The last way has been used in the new modelling of adjusted operating income of banks in order to intentionally underestimate the income capacity of banks in the stress periods.

The further development of the stress tests should be based on regular verification. This should become an integral part of the banking sector stress-testing framework to enable ongoing assessment of whether the assumptions are realistic and a conservative buffer is being maintained in the risk predictions.[2]

3.4. Conclusion

This paper focused on how to calibrate parameters used in banking sector stress tests. It argued that the parameters should be calibrated conservatively and should slightly overestimate risks in order to take into account the uncertainty related to the possible changes in estimated elasticities in the case of adverse economic development. This means that the ex-post comparison between reality and predictions generated by baseline scenarios should indicate systematic risk overestimation.

We used the case study of the CNB's banking sector stress-testing methodology and presented the results of a verification of that methodology. Such verification is a tool that

[1] Given the results of the verification as to the large overestimation of credit losses, the CNB changed to the standard 90+ definition of default rate from June 2010 (CNB, 2010). However, it still includes some conservative margin.

[2] Regular verification – i.e. retrospective assessment of prediction performance – is also routinely performed as part of the creation of predictions for monetary policy purposes – see for example CNB (2008).

should be used regularly as a guide for refining the assumptions and models used. The results of the verification, conducted at the end of 2009, reveal that the CNB stress tests err on the right – i.e. pessimistic – side and slightly overestimate the risks. This leads on average to capital adequacy estimates that are lower (more conservative) than the actual values. This is consistent with the design of the stress tests, which should be built on conservative assumptions. However, account should be taken of the fact that the level of conservatism, i.e. the degree of overestimation of the risks, in the methodology can only be fully assessed after the effects of the current recession disappear. Also, more attention should be focused on the probability assessment and precise quantification of the needed stress-testing conservatism, however, this issue is left for other research.

The verification results also indicated areas where further refinement of the stress tests is desirable. The main such areas are credit risk (more accurate estimates of PD and LGD), modelling of bank income in relation to the macroeconomic scenario, better estimation of risk-weighted assets, and certain enhancements in calculating the impacts of market risks. These areas were already to some extent tackled in the newest version of the CNB's stress testing framework as presented in the FSR 2009/2010 (CNB, 2010).

As to further development of banking sector stress-testing framework as applied by the central banks, there remain three main medium-term challenges which were not discussed in detail in the paper. The first challenge is to incorporate the feedback effect of a weakened banking sector on the economy in the form of a radical decline in the supply of loans – known as deleveraging – and the related impact on the economy. A first attempt of incorporating a feedback effect for the CNB stress testing framework has been presented in Geršl and Jakubík (2010). The second challenge is to integrate credit, market and balance-sheet/funding liquidity risks in one overall framework, ideally in parallel with the interbank contagion test. Last but not least, CNB stress-testing framework could be also used as an auxiliary tool for the calibration of the countercyclical capital buffers in the Czech Republic, which was also proposed by IMF (2012), since stress-test may offer a tool for estimating capital surcharges needed, when adverse shock materializes and may have an important role as a crisis management tool (Bank of England, 2009; Drehmann et al., 2012).

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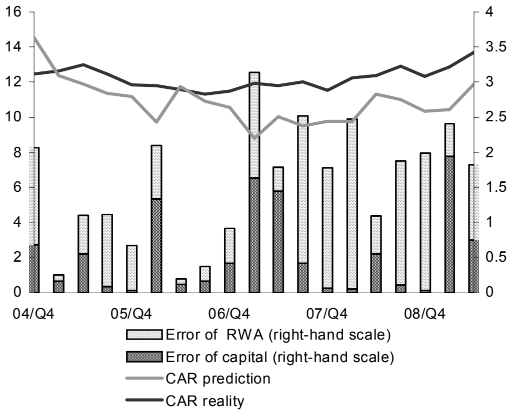
Appendix

Figure A1

Decomposition of the error in CAR estimate into RWA and capital

(% on left-hand scale, p.p. on right-hand scale)

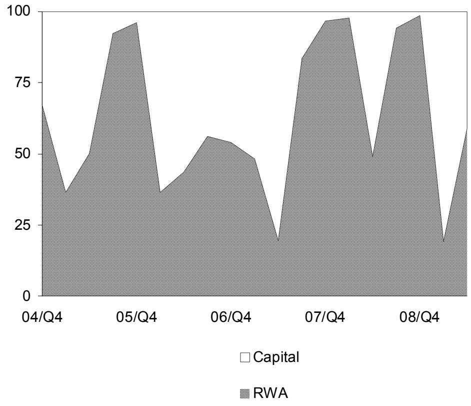


Source: authors' calculations

Figure A2

Percentage decomposition of the error in CAR estimate into RWA and capital

(%)



Source: authors' calculations

Table A1

Detailed deviation of capital adequacy ratio estimate

Estimate for different horizons

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test						
two-quarter horizon	1.4	1.5	1.7	1.5	1.2	1.0
four-quarter horizon	1.6	1.0	0.8	1.6	2.1	1.9
six-quarter horizon	1.6	0.6	0.5	1.1	2.1	2.7
Prediction – known macro						
two-quarter horizon	0.9	0.9	0.8	0.9	1.0	0.9
four-quarter horizon	1.5	0.9	0.6	1.1	2.0	2.5
six-quarter horizon	1.7	0.8	0.5	0.9	2.1	3.3
Mean error in direction (MED) in %						
Prediction – stress test						
two-quarter horizon	-9.8	-11.0	-14.1	-13.1	-9.2	-4.0
four-quarter horizon	-10.8	-1.7	-6.5	-13.1	-17.2	-15.3
six-quarter horizon	-11.2	1.0	-1.3	-8.7	-16.9	-20.7
Prediction – known macro						
two-quarter horizon	-6.5	-4.8	-6.5	-7.4	-8.4	-7.2
four-quarter horizon	-8.8	1.9	-1.3	-7.1	-16.3	-20.0
six-quarter horizon	-11.7	3.0	0.9	-7.0	-17.1	-25.4

Note: four-quarter horizon corresponds to values in Table 1

Source: authors' computation

Table A2

Deviation of NPL ratio estimate for corporations

Estimate for different horizons

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test						
two-quarter horizon	0.7	0.8	0.8	0.9	0.7	0.4
four-quarter horizon	1.3	1.1	1.4	1.9	1.4	0.6
six-quarter horizon	1.8	1.2	1.6	2.1	2.1	1.6
Prediction – known macro						
two-quarter horizon	0.6	0.2	0.3	0.6	0.5	1.3
four-quarter horizon	0.8	0.1	0.2	0.6	0.8	1.5
six-quarter horizon	0.9	0.2	0.3	0.5	1.0	1.9
Mean error in direction (MED) in %						
Prediction – stress test						
two-quarter horizon	14.8	12.0	14.6	22.0	18.3	8.4
four-quarter horizon	27.8	18.3	26.2	45.5	38.5	12.1
six-quarter horizon	39.3	21.4	31.4	49.6	59.6	34.7
Prediction – known macro						
two-quarter horizon	8.6	-1.2	-3.9	6.1	13.8	23.5
four-quarter horizon	12.3	-0.1	-3.2	6.1	20.6	31.0
six-quarter horizon	15.8	-1.9	-4.2	4.2	24.0	40.0

Note: four-quarter horizon corresponds to values in Table 2

Source: authors' computation

Table A3

Deviation of NPL ratio estimate for households

Estimate for different horizons

Mean absolute error (MAE)	2004–2009	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009
Prediction – stress test						
two-quarter horizon	0.4	0.4	0.3	0.2	0.3	0.6
four-quarter horizon	0.7	1.1	0.8	0.5	0.4	0.8
six-quarter horizon	0.9	1.4	1.2	0.9	0.6	0.6
Prediction – known macro						
two-quarter horizon	0.4	0.4	0.2	0.1	0.4	0.9
four-quarter horizon	0.9	1.1	0.7	0.4	0.7	1.3
six-quarter horizon	1.0	1.2	0.9	0.7	0.9	1.5
Mean error in direction (MED) in %						
Prediction – stress test						
two-quarter horizon	10.8	12.4	6.1	2.6	10.9	20.0
four-quarter horizon	21.6	30.7	25.6	12.1	13.9	26.7
six-quarter horizon	27.5	39.9	37.5	26.8	18.8	22.2
Prediction – known macro						
two-quarter horizon	13.3	10.7	4.2	3.2	13.8	29.8
four-quarter horizon	27.7	30.5	21.0	14.2	24.1	43.5
six-quarter horizon	34.4	35.1	28.1	22.0	31.0	50.5

Note: four-quarter horizon corresponds to values in Table 2

Source: authors' computation

♦ References to the Introduction

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