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Conference Paper

A Model of Mortgage Losses and its Applications for Macroprudential Instruments

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik
- Session: Financial Frictions, the Business Cycle, and Stabilization Policy, No. E07-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Hott, Christian (2014) : A Model of Mortgage Losses and its Applications for Macroprudential Instruments, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik - Session: Financial Frictions, the Business Cycle, and Stabilization Policy, No. E07-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/100553>

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A Model of Mortgage Losses and its Applications for Macroprudential Instruments

Abstract

We develop a theoretical model of mortgage loss rates that evaluates their main underlying risk factors. Following the model, loss rates are positively influenced by the house price level, the loan-to-value of mortgages, interest rates, and the unemployment rate. They are negatively influenced by the growth of house prices and the income level. The calibration of the model for the US and Switzerland demonstrates that it is able to describe the overall development of actual mortgage loss rates. In addition, we show potential applications of the model for different macroprudential instruments: stress tests, countercyclical buffer, and setting risk weights for mortgages with different loan-to-value and loan-to-income ratios.

JEL-Classifications: E5, G21.

Keywords: Mortgage Market, Credit Risk, Macroprudential Instruments.

1 Introduction

Loss rates on mortgages have increased substantially in the US and many other countries during the financial crisis. At the same time, financial institutions were heavily exposed to the mortgage market when the crisis started. Figure 1 displays the relationship between mortgages and charge-off rates in the US. As we can see, mortgages increased strongly as long as charge-off rates were low. Therefore, the banks' exposure was at its peak when the bubble burst and charge-off rates suddenly increased strongly. As a result, many banks suffered high losses or even failed. In 2009 the FDIC recorded 140 bank failures for the US. As a comparison, in 2008 there were 25 bank failures and from 2002 to 2007 only 21.

One reason for this was that financial institutions underestimated the risk associated with mortgages. The development of the lending standards of banks and their the mortgage supply¹ indicates that financial institutions base their risk models on the past performance of mortgages rather than on the main economic risk drivers. Among others, these risk drivers are the income of borrowers and the development of house prices.

[Insert Figure 1 about here.]

Another reason for the extent of the crisis was that also existing banking regulation and capital requirements did not adequately capture the build-up of risks in the mortgage market and the resulting systemic impact. As a reaction, we see increasing international efforts (especially by the Financial Stability Board, the BIS and the IMF) to enhance macroprudential instruments in order to identify and monitor systemic risks and to limit the build-up and/or the impact of these risks.² The process is still ongoing; however, key methodologies to identify systemic risks are constructing aggregated indicators for systemic imbalances like the credit-to-GDP ratio and conducting macro stress tests. The most prominent macroprudential instrument is the countercyclical capital buffer, under which banks have to hold more capital in boom phases and can use the buffer to cover losses in a downturn phase. A further instrument is the limitation of loan-to-value and loan-to-income ratios, which are important parameters for banks to influence the risk profile of their mortgage loan portfolio.

¹Lown and Morgan (2006) show that lending standards (as measured by the Loan Officer Opinion Survey of the Federal Reserve) are a key driver of loans.

²See e.g. Financial Stability Board (2011).

Various papers evaluate the driving forces behind mortgage defaults and the resulting losses. Campbell and Cocco (2011), for example, examine default risks and develop a model where households maximize their discounted future utility from consumption and housing. They finance their house by a mortgage and decide in each period whether or not to default on the mortgage. The authors assume that the mortgage lender has no recourse to the defaulter's income or savings. Following their model, households decide to default when their home equity turns negative, meaning the value of the house becomes smaller than the outstanding mortgage loan. However, the authors show that if borrowing constraints are less binding (due to a higher income), households might decide not to default even when home equity is negative.

Deng, Yongheng, Quigley, and Van Order (2000) argue that a mortgage borrower has two separate options: a prepayment option and a default option. The authors develop a unified model of these two options and show that the simultaneity of the two options can help to explain borrower behavior. However, since in many countries there are prepayment penalties and lenders have recourse to defaulters' income, the results are mainly relevant for some US states like California.

Haughwout, Peach, and Tracy (2008) evaluate possible reasons for the strong increase in early mortgage defaults in the US in 2006 and 2007. In their empirical estimation they use credit risk variables like loan-to-value ratios and debt service-to-income ratios as well as variables that capture the economic conditions like regional unemployment rates or house prices. Their results indicate that both bad credit standards and bad economic conditions contributed to the increase in defaults and that the economic conditions had the largest impact. However, the empirical model only predicts less than half of the strong increase in early defaults after 2006.

While most studies focus on default rates of mortgages, Qi and Yang (2009) evaluate different influence factors of the loss given default. Their empirical study is based on a large pre-crisis loan level data set and indicates that the current loan-to-value ratio is the single most important determinant of the loss given default.

The aim and main contribution of this paper is to develop a theoretical model of mortgage loss rates which should serve as a foundation for macroprudential instruments like countercyclical buffers. We develop a theoretical model of mortgage losses by Hott (2011) further in order to be able to calibrate loss rates and to transform it in forms that make it applicable for macroprudential instruments.

In the theoretical model, banks provide mortgages to *a priori* identical households. A heterogenous development of the households' income and house prices leads to the default of some households in the following period. In order to demonstrate the empirical relevance of the model, we calibrate it for two countries that experienced pronounced real estate crises within the past 25 years but had a different development: the US and Switzerland. The results of the calibration are used to demonstrate the ability of the model to estimate the impact of stress scenarios on mortgage losses, to calculate the size and development of countercyclical buffers, and to set standards for risk weights on mortgages with different loan-to-values and loan-to-incomes.

The paper is organized as follows: in the next section we develop the theoretical model, in section 3 we calibrate the model, section 4 shows potential applications of the model for macroprudential instruments, and section 5 offers some concluding remarks.

2 The Model

In this section we develop a theoretical two-period model that enables us to calculate loss rates for mortgage loans. The basic setting of the model is very similar to Hott (2011): in period $t = 1$ banks provide mortgages to *a priori* identical households. In period $t = 2$ each household receives a random labor income and defaults if this labor income plus the value of the house is too low to fulfill the mortgage duties. In contrast to Hott (2011), however, we assume that the constant loan-to-value of mortgages is less than 100%. In addition, we consider unemployment, maintenance costs for houses, foreclosure costs, and a heterogenous development of house prices. By introducing these additional features, the model becomes more realistic and, hence, more suitable for describing actual loss rates on mortgages.

2.1 Basic Assumptions

2.1.1 Houses

There are S_1 *ex ante* identical houses and in period $t = 1$ the price of house i is $P_1^i = P_1$, where $i=1,\dots,S$. Therefore, the value of the entire housing stock is $S_1 P_1$. Further, we assume that houses are subject to depreciation and that owning a house leads to maintenance costs. The sum of the depreciation and the maintenance costs (as a fraction of the house price) is assumed to be $1 > \rho' \geq 0$.

In period $t = 2$ the price of house i is assumed to be uniformly distributed between $(1 - \delta)P_2$ and $(1 + \delta)P_2$, where P_2 is the average house price in $t = 2$ and $\delta > 0$ is the maximum relative deviation from this average price. Therefore, in $t = 2$ the value of the existing housing stock is S_1P_2 .

2.1.2 Mortgages

In period $t = 1$ banks provide mortgages to households at the interest rate $m_1 > 0$. Since banks cannot *ex ante* differentiate between different households and different houses, this mortgage rate is identical for each household. The loan-to-value (LTV) of a mortgage that is granted is the constant l , where $0 < l < 1$.³ Therefore, in period $t = 1$ the amount of all mortgages is lS_1P_1 . The maturity of each mortgage loan is assumed to be one year. This implies that households have to refinance their mortgage every year. However, after this year the LTV of the old mortgage is different for each mortgage borrower and between $lP_1/(1 + \delta)P_2$ and $lP_1/(1 - \delta)P_2$.

When a mortgage borrower defaults, the house goes into the ownership of the bank. We assume that the foreclosure and change in ownership causes costs. These foreclosure costs are assumed to be a fixed fraction ϕ of the amount of the mortgage. We further assume that the bank has recourse to the defaulter's income.⁴ Therefore, we do not consider strategic defaults.

2.1.3 Households

In period $t = 1$ there are N_1 *ex ante* identical households. We assume that the demand for houses equals the supply and, therefore, that $N_1 = S_1$. Each of the households buys the same fraction of the housing stock: $S_1/N_1 = 1$.⁵ It uses its entire wealth to finance the fraction $(1 - l)$ of its housing investment. To finance the rest of the investment, each household takes out a mortgage in the amount of lP_1 .

³Iacoviello (2005) and Kiyotaki and Moore (1997) also assume fixed LTV ratios when evaluating the link between real estate prices and output. Campbell and Cocco (2011) show that in the US, LTV ratios were relatively stable between 1984 and 2008.

⁴This might not be the case in some US states. However, following the results of Campbell and Cocco (2011), income also matters if there is no recourse. In addition, as we will see, our model provides relatively good results also for the US (see section 3).

⁵We therefore assume a home ownership of 100%. An alternative would be to assume that the fraction $1/h$ of the households buys h houses each. These households live in one house and rent out the remaining $h - 1$ houses. If we ignore diversification effects from owning different houses, P could be interpreted as the price of h houses. The rent income of the housing investors is independent of the price development of the specific houses and could therefore be seen as part of the household income. As a result, the assumption of a lower home ownership rate would lead to the same results.

On the one hand, in period $t = 2$ each household bears depreciation and maintenance costs of $\rho l P_1$, where $\rho = \rho'/l$. In addition, each household has to pay the mortgage rate and has to pay back the mortgage: $(1 + m_1)lP_1$. Hence, its total expenses are: $(1 + \rho + m_1)lP_1$. Further we assume that depreciation and maintenance costs are senior to the mortgage payments.

On the other hand, household i owns a house which can be sold at the price P_2^i , where P_2^i is uniformly distributed between $(1 - \delta)P_2$ and $(1 + \delta)P_2$. In addition, we assume that in $t = 2$ household i receives a labor income Y_2^i that is uniformly distributed between zero and Y_2 . With probability u_2 a household becomes unemployed and receives an income of zero. In reality, in most countries the minimum (transfer) income is greater than zero. However, since we do not consider consumption expenditures, we assume that the minimum income is used for an autonomous consumption and can, therefore, not be used for mortgage payments.

Household i becomes insolvent in $t = 2$ if:

$$P_2^i + Y_2^i < (1 + \rho + m_1)lP_1 \quad \text{or} \\ Y_2^i < \left(\rho + m_1 - \frac{P_2^i - lP_1}{lP_1} \right) lP_1. \quad (1)$$

The right-hand side of equation (1) is also known as the imputed rent for housing. This imputed rent is in line with the assumptions of many other studies on real estate and mortgage markets. Poterba (1984 and 1992), McCarthy and Peach (2004), Himmelberg, Mayer, and Sinai (2005), and Hott and Monnin (2008), for example, use very similar factors to define imputed rents. In our model we do not consider the possibility to save in addition to the housing investments $((1 - l)P)$. Hence, we assume that the difference between the left and the right side of equation (1) is used for consumption exceeding autonomous consumption.

2.2 Calculation of Loss Rates

To calculate loss rates on mortgage loans, we first calculate the default probability (PD) and the loss given default (LGD) of mortgages independently. The expected loss rate is given by the multiplication of the PD and the LGD .

The calculation of the PD and the LGD depends strongly on the development

of house prices in $t = 2$. There are two extreme cases. In the first case, house prices increase so strongly that no household defaults ($PD = 0$). This is the case if $(1 - \delta)P_2 \geq (1 + \rho + m_1)lP_1$. In the other extreme case, house prices fall so strongly that all households default ($PD = 1$). This is the case if $(1 + \delta)P_2 + Y_2 \leq (1 + \rho + m_1)lP_1$. Both cases are not very realistic and will, therefore, not be considered. The intermediate case can be divided into several subcases as well. However, we will only consider the following case as the relevant case:⁶

$$\frac{(1 + \rho + m_1)lP_1}{1 + \delta} \leq P_2 \leq \frac{(1 + \rho + m_1)lP_1}{1 - \delta}$$

and $\frac{(1 + \rho + m_1)lP_1 - Y_2}{1 - \delta} \leq P_2.$ (2)

In this range, neither households with the best performing houses ($P_2^i = (1 + \delta)P_2$) nor households with the highest labor income ($Y_2^i = Y_2$) default. However, there are always at least some households that default.

2.2.1 Probability of Default

Figure 2 illustrates which households default and which stay solvent. As we can see, for a household with a labor income greater than $[(1 + \rho + m_1)lP_1 - (1 - \delta)P_2]$, the probability of a default is zero. Therefore, the probability that an employed household has an income that leads to a positive default probability $\Pr(PD > 0 | employed)$ is:

$$\Pr(PD > 0 | employed) = \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{Y_2}. \quad (3)$$

Following condition (2), $0 \leq \Pr(PD > 0 | employed) \leq 1$. If a household is unemployed, this probability is one.

[Insert Figure 2 about here.]

For households that can default ($PD > 0$), the default probability decreases with labor income. For an unemployed household with zero labor income ($Y_2^i = 0$), the probability of default is:

⁶The calibration of the model confirms that this is the relevant case. See also Hott (2011).

$$PD(Y_2^i = 0) = \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{2\delta P_2}. \quad (4)$$

Under the condition that the labor income of an employed household is in a range where there is a positive default probability, the default probability is 50% of $PD(Y_2^i = 0)$.⁷ Multiplied by the probability $\Pr(PD > 0|employed)$ from equation (3) we obtain the default probability of an employed household:

$$PD(employed) = \frac{[(1 + \rho + m_1)lP_1 - (1 - \delta)P_2]^2}{4\delta P_2 Y_2}. \quad (5)$$

The unconditional PD is given by:

$$PD = u_2 \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{2\delta P_2} + (1 - u_2) \frac{[(1 + \rho + m_1)lP_1 - (1 - \delta)P_2]^2}{4\delta P_2 Y_2}. \quad (6)$$

As we can see, the PD depends positively on the unemployment rate (u_2), the depreciation and maintenance costs (ρ), the LTV, the mortgage rate (m_1), the house price level in $t = 1$ (P_1), and the maximum deviation from the average house price in $t = 2$ (δ).⁸ It depends negatively on the house price increase ($P_2 - P_1$) and on income (Y_2). Note that condition (2) assures that (3) to (6) lie between 0 and 1.

2.2.2 Loss Given Default

There are two factors that have an influence on losses for a bank when a mortgage borrower defaults. Firstly, the difference between the outstanding mortgage (lP_1) plus interest, depreciation and maintenance costs⁹ ($(\rho + m_1)lP_1$), and the value of the house in period 2 (P_2^i) plus the income of the house (Y_2^i). The second factor are the foreclosure costs (ϕlP_1). As a result, the loss given default (LGD) of a mortgage to household i is:

⁷Since each income in this range is equally likely.

⁸The relationship between δ and PD depends on the development of the house price. In the relevant range, however, $\partial PD / \partial \delta$ is positive.

⁹Depreciation and maintenance costs have to be borne by the household or the bank. However, in both cases the loss for the bank would be the same.

$$LGD(P_2^i, Y_2^i) = \frac{(1 + \rho + m_1)lP_1 - P_2^i - Y_2^i}{lP_1} + \phi \quad (7)$$

For an unemployed household with zero income, the LGD can vary between ϕ and $[(1 + \rho + m_1)lP_1 - (1 - \delta)P_2]/[lP_1] + \phi$. Since each of the LGD in this range is equally likely, the expected LGD of an unemployed household is:

$$LGD(Y_2^i = 0) = \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{2lP_1} + \phi \quad (8)$$

The LGD of a mortgage to an employed household decreases linearly with the labor income of the borrower. It varies between ϕ for $Y_2^i = (1 + \rho + m_1)lP_1 - (1 - \delta)P_2$ (the maximum income for a PD greater than zero) and $LGD(Y_2^i = 0)$ for an employed household with zero income. As we have seen in section 2.2.1, the different LGD s are not equally likely, however. The probability that a household defaults varies between zero and the result of equation (4). The expected LGD of a mortgage to an employed household is therefore:

$$LGD(employed) = \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{3lP_1} + \phi. \quad (9)$$

This LGD depends positively on ϕ , ρ , m_1 , l , δ , and P_1 , it depends negatively on P_2 and it is independent of the maximum income Y_2 . Condition (2) assures that the LGD is not negative. However, note that, although the fraction on the right hand side of equation (9) is well below one, the LGD could get greater than one.¹⁰

2.2.3 Expected Loss Rate

The expected loss rate in period $t = 2$ (EL_2) is given by the weighted average of the product of the PD and LGD for unemployed and employed households:

$$EL_2 = u_2 \frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{2\delta P_2} \left[\frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{2lP_1} + \phi \right] + (1 - u_2) \frac{[(1 + \rho + m_1)lP_1 - (1 - \delta)P_2]^2}{4\delta P_2 Y_2} \left[\frac{(1 + \rho + m_1)lP_1 - (1 - \delta)P_2}{3lP_1} + \phi \right]. \quad (10)$$

¹⁰According to our calibration results, the LGD is always well below one. See Figure 5.

As we can see, the expected loss rate depends negatively on income (Y_2) and on the house price increase ($P_2 - P_1$) and it depends positively on the unemployment rate (u_2), the foreclosure costs (ϕ), the house price level (P_1), the loan-to-value (l), and the mortgage rate (m_1). Furthermore, in the relevant range¹¹ the expected loss rate also depends positively on the heterogeneity of the house price development (δ).

These results are in line with the usual empirical findings. Deng et al. (2000), for example, find empirical evidence that increasing interest rates and decreasing house prices increase the probability of default. Furthermore, the authors find evidence that a higher LTV leads to higher defaults. Qi and Yang (2009) examine defaults in the US mortgage market and find the current LTV is the most important determinant of the loss given default of a mortgage. Lambrecht, Perraudi, and Satchell (1997) examine the UK mortgage market and find a positive relationship between interest rates and default probabilities and a negative relationship between income and default probabilities. Surprisingly, the authors also find a negative relationship between the LTV and default probabilities. One explanation for this finding could be that high LTV mortgages are only provided to households with low credit risk.

3 Model Calibration

To examine the empirical relevance of the model, we calibrate it for two different countries: the US and Switzerland. Both countries have experienced a major real estate crisis within the past 25 years. However, the overall development of the two mortgage markets was rather different. Besides an in sample calibration we also calibrate the crisis development out of sample, i.e. using only data up to 2005 Q4.

3.1 Data

According to equation (10) we need data on mortgage rates (m_t), house prices (P_t), unemployment rates (u_t), and the maximum household income (Y_t) to calibrate loss rates. The maximum household income is calculated as $(2GDP_t)/[(1 - u_t)N_t]$ and by using nominal GDP and population data (N_t). To compare the resulting theoretical expected loss rates with reality, we also need data on actual loss rates (L_t). The frequency of most data series is quarterly. Annual population data and the annual

¹¹See equation (2).

loss rates for Switzerland are transformed into quarterly data by linear interpolation. Table 1 provides a brief description of the data, the sources, and transformations.

[Insert Table 1 about here.]

3.2 Parameter Values

According to equation (10) we need parameter values for the *LTV* (l), the heterogeneity of the house price development (δ), the depreciation and maintenance rate (ρ), and the foreclosure costs (ϕ) for both countries. In addition, we need a conversion factor α to adjust the level of GDP to the house price level ($Y_t = \alpha 2GDP_t / [(1 - u_t)N_t]$). Firstly, house prices (index values) and GDP are not expressed in the same unit and, secondly, Y reflects only the (constant) fraction of the income that is available for housing expenditures.

The first parameter is the loan-to-value (l). According to Green and Wachter (2005), in the US the average *LTV* is 75% but it can go up to 97%. For the calibration we use $l = 0.75$ for the average *LTV* in the US. In Switzerland a mortgage usually has a *LTV* of 67% and it can go up to 100%. We use $l = 0.67$ for the calibration. To capture the variation of the loan-to-value in both countries, we consider the difference between the maximum and the average *LTV* in the heterogeneity of the house price development (δ).

The second parameter is the heterogeneity of the house price development (δ). When calibrating a mortgage model for the UK, Miles (2005) uses 12.5% as the standard deviation of house price growth. Campbell and Cocco (2003) consider 11.5% when evaluating the US mortgage market. This would imply around 22% for our parameter δ .¹² As already mentioned, we will also consider the difference between the maximum and the average *LTV* in the parameter δ . We assume that the difference between the maximum and the average *LTV* is equal to three standard deviations of the *LTV*. Therefore, the add-on for δ (maximum of a uniform distribution) is $\sqrt{3}/3 = 1/\sqrt{3}$ times the difference between the maximum and the average *LTV*. For the US the resulting δ is 35%, and for Switzerland it is 41%.

¹²The maximum deviation of the uniformly distributed heterogeneity of the house price development is $\sqrt{3}$ times the standard deviation.

The literature offers different estimates of the depreciation and maintenance rate. Harding, Rosenthal, and Sirmans (2006) estimate that the annual rate is between 2.4 and 2.9 percent. McCarthy and Peach (2004) assume that the depreciation rate plus repairs is 2.5 percent per year and Poterba (1992) assumes that the sum of depreciation and maintenance rate is four percent. For simplicity, we use $\rho' = 2.5\%$ for each of the two countries. Therefore, we obtain $\rho = \rho'/l = 3.3\%$ for the US and $\rho = \rho'/l = 3.7\%$ for Switzerland.

Foreclosure costs (ϕ) involve legal fees, taxes, insurance, commissions etc. Although these costs might vary between countries, for simplicity, we assume that they are 15% in both countries. This figure is based on anecdotal evidence from contacts with banks.

The fifth parameter is the conversion factor α . For this parameter we do not have an *a priori* assumption (except that it is positive). Therefore, we chose a parameter value for α that solves the following minimization problem:

$$\min_{\alpha} \sum_{t=0}^T [EL_t - L_{t+k}]^2 \quad (11)$$

subject to $\alpha > 0$. While $T - k$ is equal to the end of the data sample (2010 Q4 for Switzerland and 2011 Q2 for the US) in our in sample calibration, it is 2005 Q4 in our out of sample calibration. The parameter k reflects the lead of the theoretical series compared to the actual series expressed as the number of quarters. The lead is derived by looking at the maximum cross correlation of the two series. The choice of the different parameter values is summarized in Table 2.

[Insert Table 2 about here.]

3.3 Calibration Results

Figure 3 displays the development of actual (L_t) and theoretical expected (EL_t) loss rates for the US and Switzerland. As we can see, the fit between actual and theoretical loss rates is quite good. In particular the model is able to mirror the high loss rates during the crisis episodes: The current real estate crisis in the US and the crisis in the early 1990s in Switzerland. According to Table 2, the theoretical expected losses have a lead of $k = 4$ quarters. This reflects that in reality it can take several periods until a bank knows how high the losses from a defaulted mortgage really are. In addition,

Figure 3 displays the development of the calibrated PDs and $LGDs$. In the US as well as in Switzerland, the PDs fluctuate between 0 and 10% and the $LGDs$ between 15% and 30%.

[Insert Figure 3 about here.]

To evaluate the performance of our model, Figure 4 shows the results of the out-of sample calibration as well as the in- and out-of sample results of the following simple regression:

$$L = c + \alpha_1 delP + \alpha_2 delY + \alpha_3 delM + \alpha_4 P/Y + \alpha_5 u + \alpha_6 m + \epsilon, \quad (12)$$

where c is a constant, $delP$ is the annual log change of the house price, $delY$ the annual log change of nominal GDP, $delM$ the annual change of mortgage volumes, P/Y is the fraction of the house price index to the nominal GDP (according to our model a measure of the affordability). In order to consider potential lead-lag relations, we chose the lagged or leading variables which produce the highest R^2 . Following Table 3, the resulting coefficients have the expected signs and most of them are highly significant - especially for Switzerland and the in-sample regression for the US. While the R^2 for the Swiss and the in-sample US regressions are above 90%, it is only 70% for the reduced time sample in the US.

For Switzerland, the difference between the in and out of sample calibrated expected loss rates is negligible. For the US, however, we can observe a difference. This is no surprise, since charge-off rates in the US experienced an unprecedented strong increase after the end of 2005 and, therefore, the end of the considered data for the out of sample calibration. Nevertheless, even the out of sample calibration of the crisis leads to a relatively good fit with the actual development. Especially in comparison with the out-of sample performance of the regression which would have predicted losses up to 0.77% in the recent crisis compared to 2.21% out-of sample calibrated and 2.81% actual peak losses. While the fit of the regression is better than the fit of the calibration for Switzerland (mean squared error $0.04 * 10^{-5}$ vs. $0.25 * 10^{-5}$ in sample and $0.05 * 10^{-5}$ vs. $0.25 * 10^{-5}$ out of sample) and in-sample for the US ($0.41 * 10^{-5}$ vs. $0.93 * 10^{-5}$), it is better for the calibrated out-of sample estimate of US mortgage losses ($2.67 * 10^{-5}$ vs. $2.97 * 10^{-5}$). The out of sample fit of the calibration would be even better if we

would assume the same lag ($k = 4$) as for the in-sample calibration, keeping all other parameter-values constant (mean squared error $1.12 * 10^{-5}$). This indicates that the model is suitable for risk management purposes where the actual timing of the losses is less important than their extent. For trading activities, however, the instable lead-lag relationship of the calibration would be a major drawback.

[Insert Figure 4 about here.]

[Insert Table 3 about here.]

In order to evaluate the sensitivity of the calibration to changes in the parameter values, Figure 5 displays the in sample calibration results for alternative parameter values. The biggest influence has a change in the assumed LTV ratio. However, even with higher or lower LTV ratios (that are still in line with condition (2) and lead to positive PDs), the results do not deviate substantially.

[Insert Figure 5 about here.]

4 Macroprudential Applications of the Model

Our model and its calibration give us information about the impact of macroeconomic developments on mortgage losses. This information can be used as an input for macroprudential instruments. Important examples of macroprudential instruments are conducting stress tests, introducing countercyclical buffers, and setting risk weights for mortgages with different loan-to-value and loan-to-income ratios.

4.1 Stress Tests

As a reaction to the recent crisis and in order to identify systemic risks, banking supervisors and central banks are conducting more and more stress tests. In these stress tests banks are asked to calculate the impact of an adverse combination of macroeconomic shocks on their profits and losses and, therefore, on their capital needs.

For the regulator it is important to benchmark the loss estimates for the different asset classes with own estimates. Our model can provide an alternative estimate of

the impact of an adverse scenario on mortgages. To demonstrate this, we calculate the aggregated impact of the adverse scenarios from the 2009 Supervisory Capital Assessment Program (SCAP) of the Federal Reserve Board for the US and the adverse scenario from the 2011 EU-wide stress test of the European Banking Authority (EBA) for the UK.¹³ The scenarios are summarized in Table 4.

The impact of the scenarios on expected losses (EL_t) is presented in Figure 6. The solid (SCAP) and the broken grey (EBA) lines indicate that both scenarios lead to an increase in expected losses. As we can see, the impact of the SCAP scenario is much stronger than the impact of the EBA scenario. This is not a surprise since the assumed GDP and house price declines are much higher. Another noteworthy outcome is that both scenarios have a stronger impact on expected losses in the US than on expected losses in Switzerland. The main reason for this is that we assume a higher LTV for the US.

Compared to the estimates of the Fed with regard to the impact of the SCAP scenario on US banks, our expected loss rates are relatively low. While the Fed estimates indicate an aggregated two year loss rate of 7 to 8.5%,¹⁴ our model indicates only 5% with an annual maximum of 3.3%. One reason for this might be that we are calculating the expected losses under an adverse scenario and not adverse losses under this scenario. According to Table 2, the difference between our estimate and the Fed estimate is about three times the average difference between the expected and actual loss rates.

[Insert Figure 6 about here.]

[Insert Table 4 about here.]

4.2 Countercyclical Buffers

With a countercyclical buffer, banks have to hold more capital when imbalances in the credit market are building up. The aim of this additional requirement is that banks have a higher capital buffer which they can use when the bubble bursts. Therefore, the countercyclical buffer should compensate for the additional risk that arises from the

¹³The EBA stress test included scenarios for all EU countries. However, we only consider the scenario for the UK.

¹⁴See Federal Reserve Board (2009b).

increasing imbalances. A further potential effect of the countercyclical buffer is that it can help to lean against emerging bubbles.

The Basel Committee on Banking Supervision (BCBS, 2010) proposes monitoring the ratio of credit to GDP and the deviation from its trend to assess the phase of the cycle and the build-up of the imbalances. The size of the buffer should then increase with this indicator between zero and a (more or less arbitrary) maximum buffer size. While the main idea of the countercyclical buffer is to capture imbalances in the entire credit market, the tool can also be used to target specific kinds of loans on a macro level (i.e. not on an individual bank level). Switzerland, for example, has turned on a countercyclical buffer on mortgage loans in 2013 to capture the special developments in this market.

In our model the credit (or mortgage) volume is defined as a constant fraction l of the house price P_t multiplied by the housing stock $S = N$. GDP, on the other hand, is given by $(1 - u_t)NY_t/2$. Hence, the ratio of credit to GDP (i_t) is given by:

$$i_t = \frac{2SlP_t}{(1 - u_t)NY_t} = \frac{2lP_t}{(1 - u_t)Y_t}. \quad (13)$$

As an indicator for imbalances we take the difference between i_t and its average $i^{average}$. To determine the size of the countercyclical buffer, we look at the impact of an above-average i_t on expected losses (EL_t). We rewrite equation (10) to:

$$EL_t = u_t \frac{lR_{t-1} - (1-\delta)(1+w_t)}{2\delta(1+w_t)} \left[\frac{lR_{t-1} - (1-\delta)(1+w_t)}{2l} + \phi \right] + i_t(1 - u_t)^2 \frac{[lR_{t-1} - (1-\delta)(1+w_t)]^2}{8\delta l(1+w_t)} \left[\frac{lR_{t-1} - (1-\delta)(1+w_t)}{3l} + \phi \right], \quad (14)$$

where $R_{t-1} = 1 + \rho + m_{t-1}$ and $1 + w_t = P_t/P_{t-1}$. The impact of an above-average i_t on expected losses is then given by:

$$buffer\ size = \Delta EL_t = (i_t - i^{average})(1 - u_t)^2 \frac{[lR_{t-1} - (1-\delta)(1+w_t)]^2}{8\delta l(1+w_t)} \left[\frac{lR_{t-1} - (1-\delta)(1+w_t)}{3l} + \phi \right]. \quad (15)$$

Capital requirements should make sure that banks hold enough capital to cover losses in stress events. As a stress scenario for the capital requirements we take the strongest historical drop in real estate prices in combination with the average mortgage rate or

R_t , respectively. According to equation (15), the unemployment rate has a negative effect on the buffer size. One reason for this is that the loan-to-income (LTI) is only important for households that are employed. With a lower unemployment rate the LTI is relevant for a higher fraction of the population. Another reason is that, given a level of GDP, the income of an employed household has to be higher the higher the unemployment rate is. Hence, for the stress scenario we take the average unemployment rate. The scenarios for the two countries are summarized in Table 5.

Figure 7 shows the evolution of the resulting buffer size. It is assumed (as in the BCBS proposal) that the buffer cannot be negative. As we can see, the countercyclical buffer increases before the crises begin and loss rates increase. Hence, banks can use the capital buffer to cover losses and the buffer requirements are gradually reduced to zero.

The maximum buffer size is about 0.47% of the mortgage volume in the US and about 0.25% in Switzerland. Reasons for the higher buffer size in the US are the more adverse scenario and a higher LTV but also a greater imbalance during the stress episodes. In contrast to the BCBS proposal, our buffer is not based on risk-weighted assets but on loan volumes. If we assume average risk weights of about 35%, the buffer size would reach a maximum value of about 1.34% in the US and about 0.71% in Switzerland.

[Insert Figure 7 about here.]

[Insert Table 5 about here.]

4.3 Risk Weights

The loan-to-value and the loan-to-income are the most important parameters for banks to influence the risk profile of their mortgage loan book. According to equation (14), both parameters have a positive effect on expected losses. Hence, risk weights for capital requirements should increase with LTV and LTI.

Our model can help to estimate to which extent risk weights should increase with both parameters and how strong the tradeoff between both parameters is. Figure 8 shows the impact of a change in LTV on expected losses for different LTI. These expected losses are calculated according to equation (14). As in section 4.2 we consider

a stress scenario with the strongest historical drop in real estate prices and an average interest rate level. Since the unemployment rate has a negative effect on expected losses, we take the highest historical unemployment rate (US: 10.7%, Switzerland: 5.4%).

According to Figure 8, expected losses are higher in the US than in Switzerland. The main reason for this is that the US scenario assumes a much higher drop in real estate prices. In general, however, the relationship between LTV, LTI, and expected losses is very similar: Expected losses increase with increasing LTV and with increasing LTI. In addition, we can see that the impact of an increasing LTV is stronger when the LTI is higher. These effects should be reflected when risk weights for capital requirements for mortgages loans are set.

[Insert Figure 8 about here.]

5 Conclusions

In this paper we develop a theoretical model of mortgage loss rates which serves as a foundation for macroprudential instruments. Following the model, loss rates are positively influenced by the house price level, the unemployment rate, the loan-to-value, and interest rates. They are negatively influenced by the income level and the growth of house prices. The calibration of the model for the US and Switzerland has demonstrated that it is well able to describe the overall development of the actual loss rates.

In addition, we have demonstrated that the model can be used to calibrate loss rates under stress events, to calculate the size and development of countercyclical buffer, and to set of risk weights for different combinations of loan-to-value and loan-to-income.

The model has two main shortcomings: the maturity of mortgage loans is assumed to be only one year and all the parameters are assumed to be constant. In spite of these simplifying assumptions, however, the model is able to explain the main developments of mortgage loss rates in the US and Switzerland. In addition, it can serve as a basis for various macroprudential instruments. Efforts to make the model more realistic should be aligned to the specific needs of its application.

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Figure 1: Mortgages and Charge-Off Rates in the US

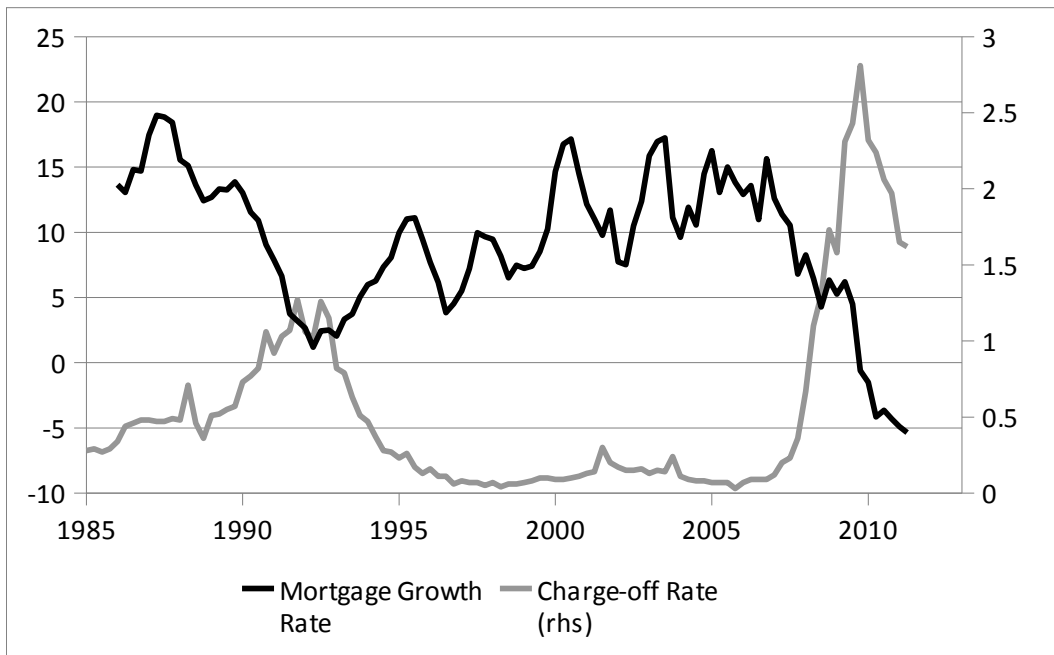


Figure 2: Income, Mortgage Payments and Defaults

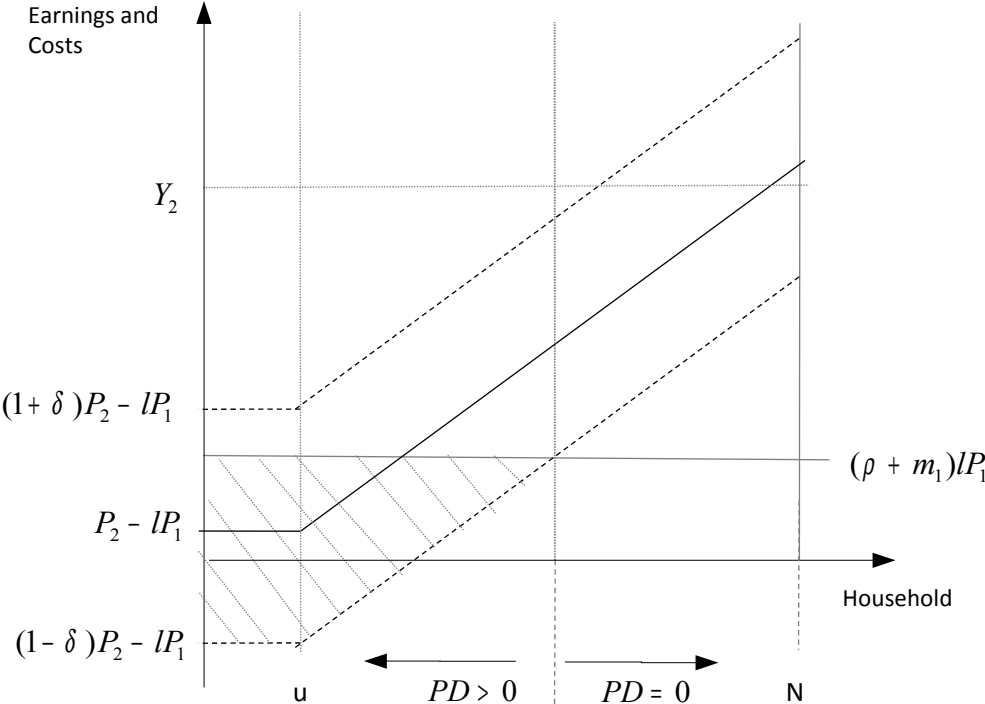


Figure 3: Actual (L) and Calibrated (EL) Mortgage Loss Rates as well as Calibrated Probability of Default (PD) and Loss Given Default (LGD).

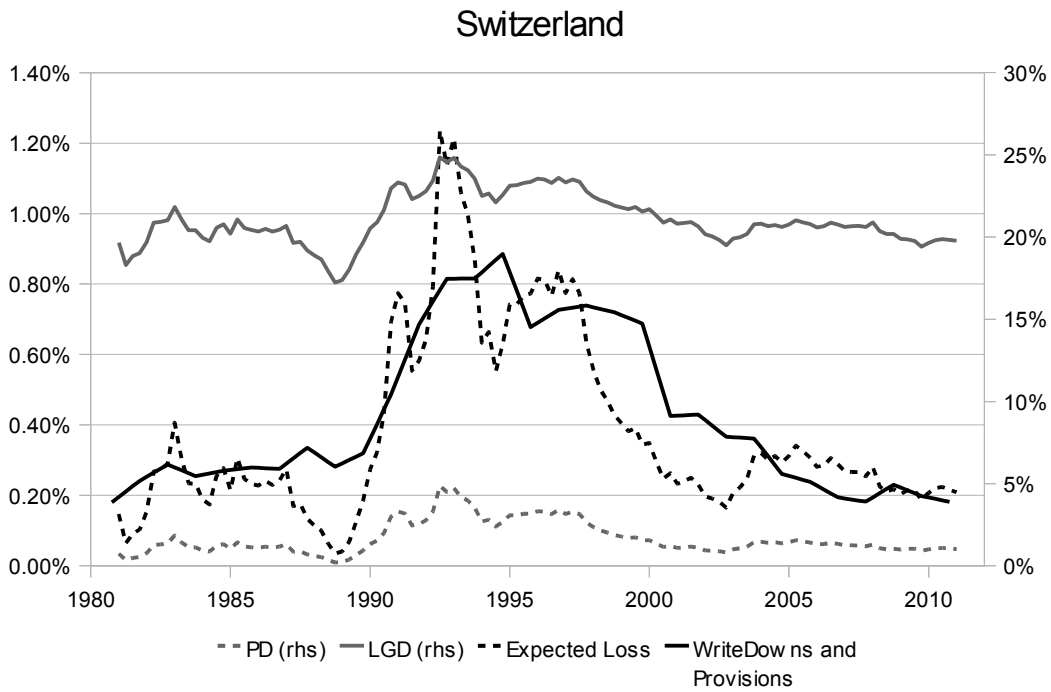
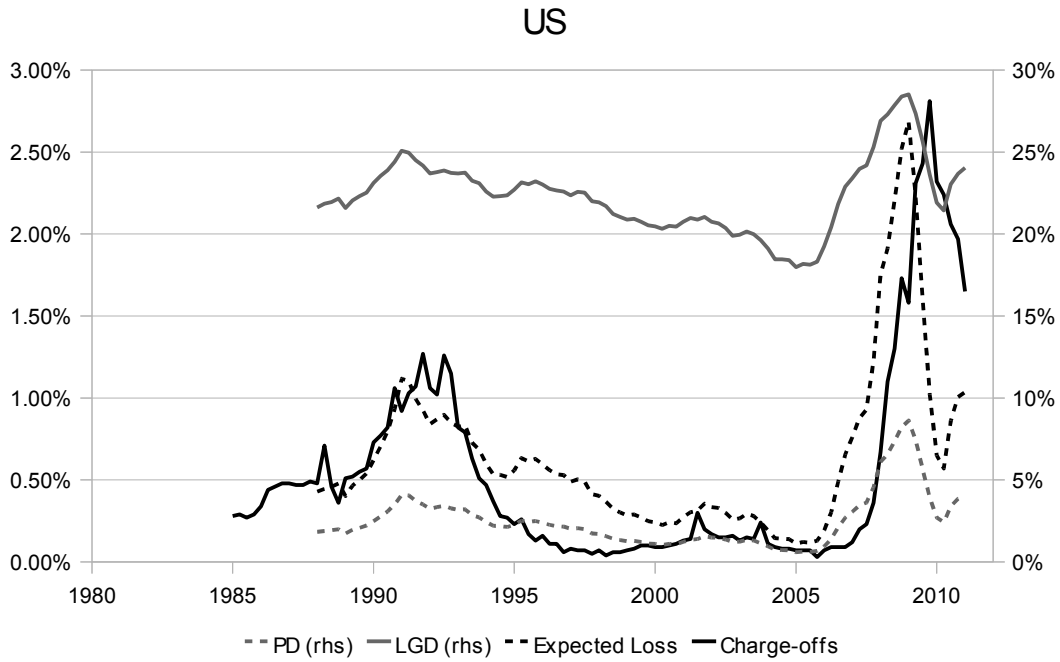


Figure 4: Actual (L) and In and Out of Sample Calibrated (EL) Mortgage Loss Rates as well as In and Out of Sample Regression Results.

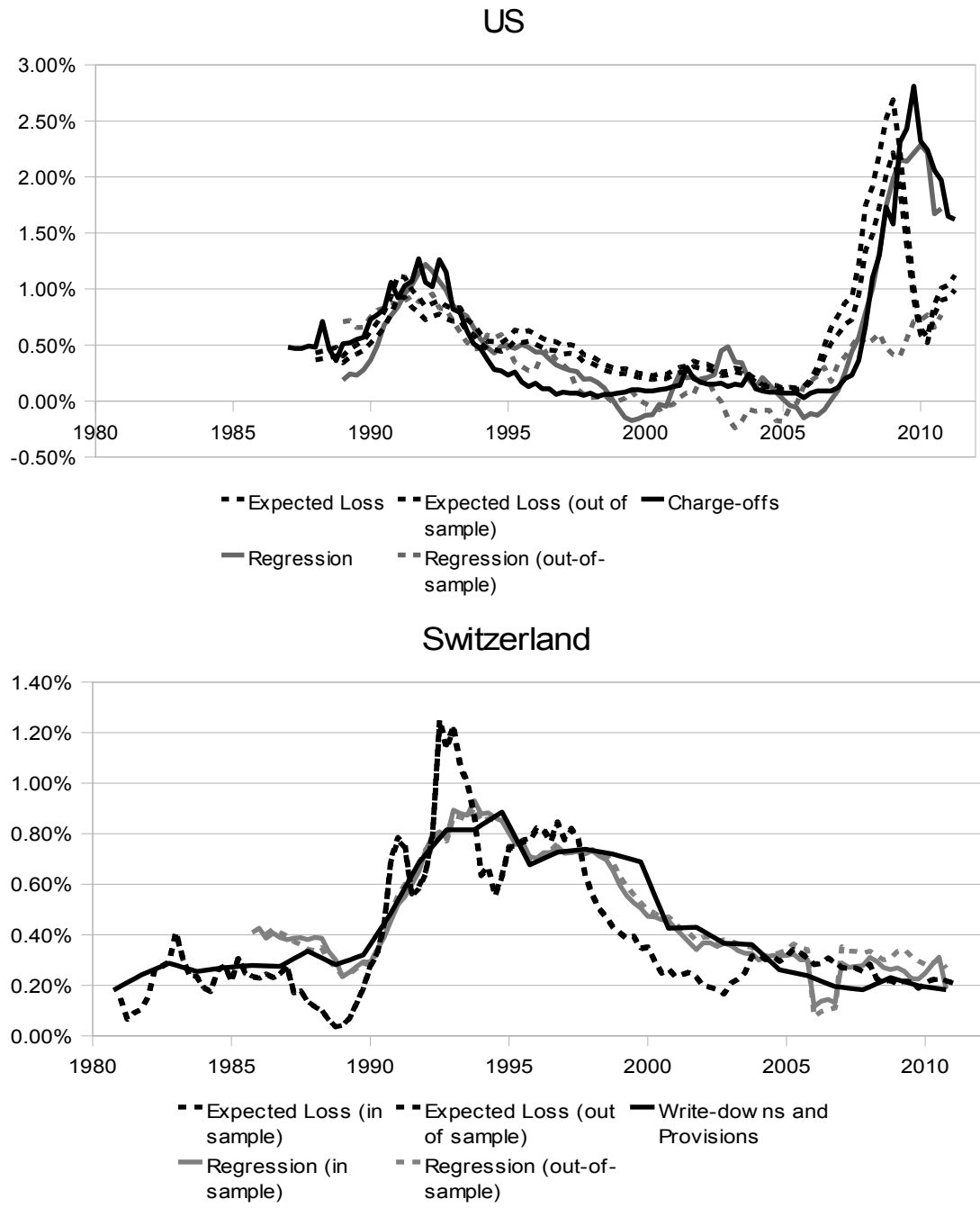
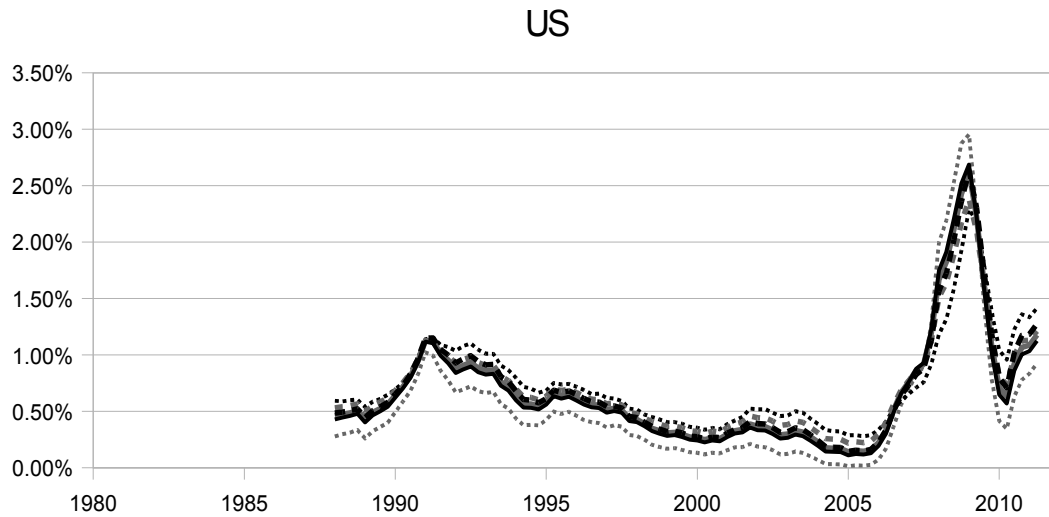
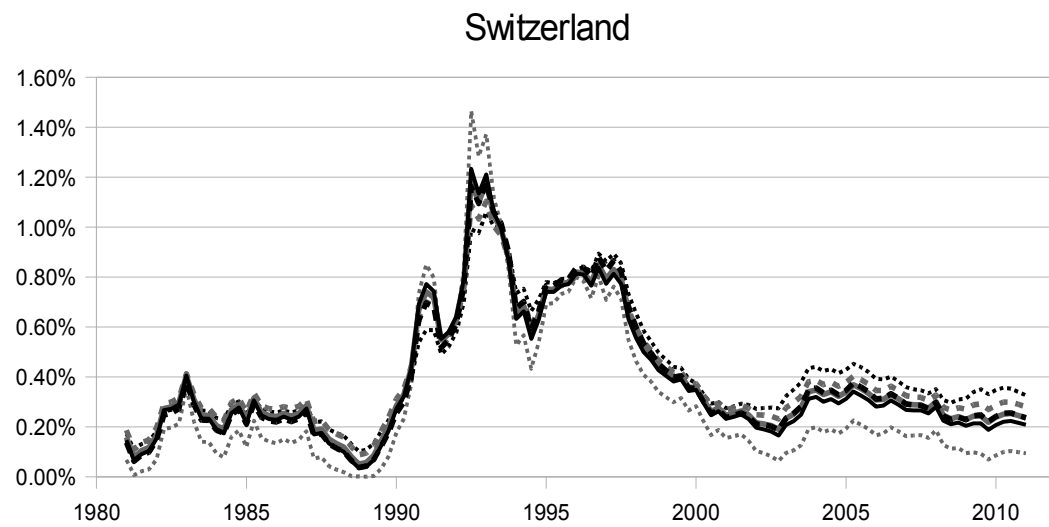


Figure 5: Sensitivity of Calibrated (EL) Mortgage Loss Rates to Changes in Parameter Values.



- Expected Loss - - - Expected Loss (phi=25%) — Expected Loss (maintenance 4%)
- - - Expected Loss (del=40%) ···· Expected Loss (l=85%) ···· Expected Loss (l=70%)



- Expected Loss - - - Expected Loss (phi=25%) — Expected Loss (maintenance 6.5%)
- - - Expected Loss (del=45%) ···· Expected Loss (l=75%) ···· Expected Loss (l=62%)

Figure 6: The Impact of Adverse Scenarios on Expected Losses

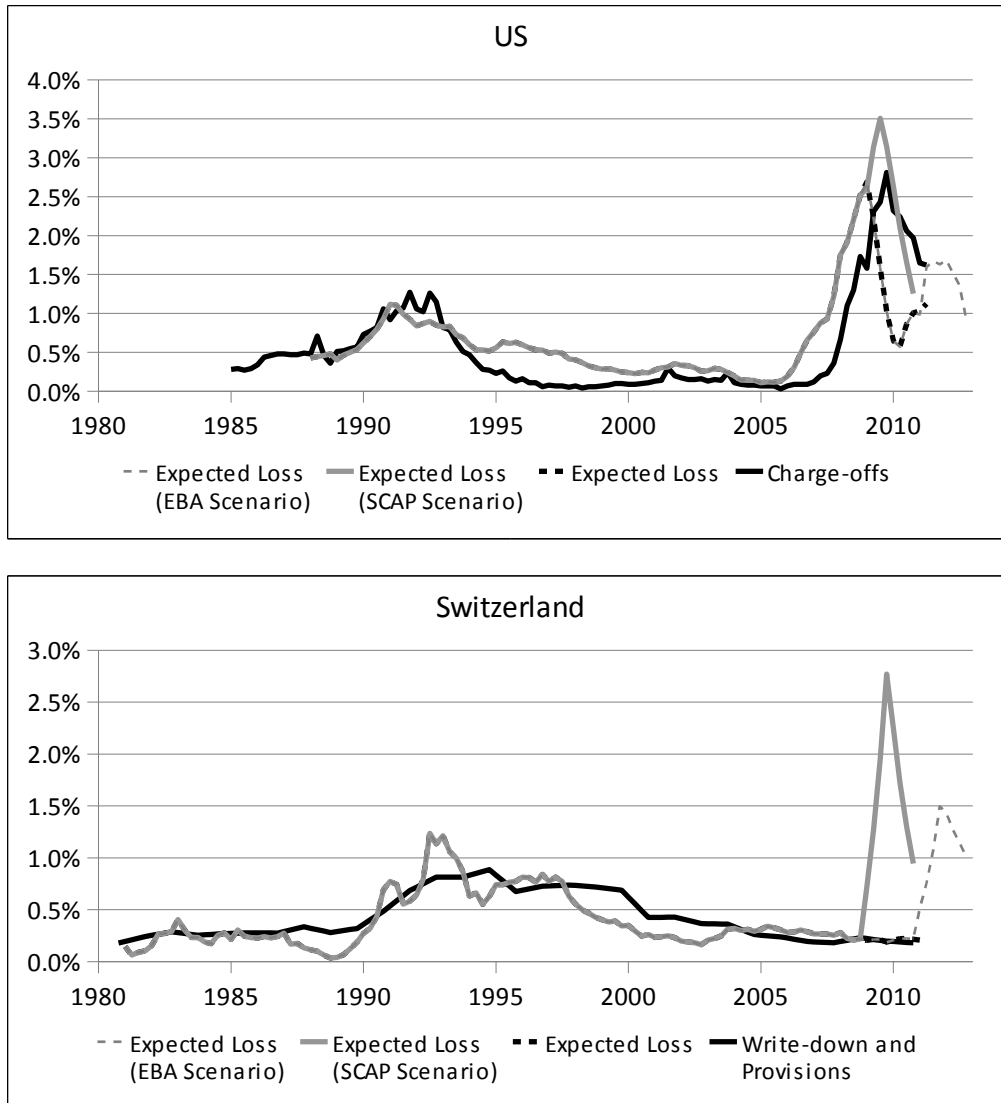


Figure 7: Development of the Countercyclical Buffer

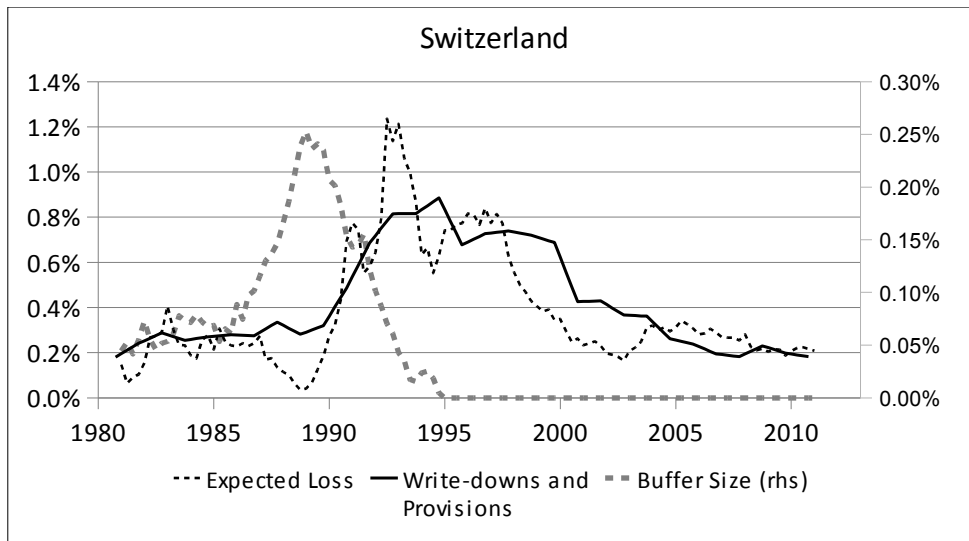
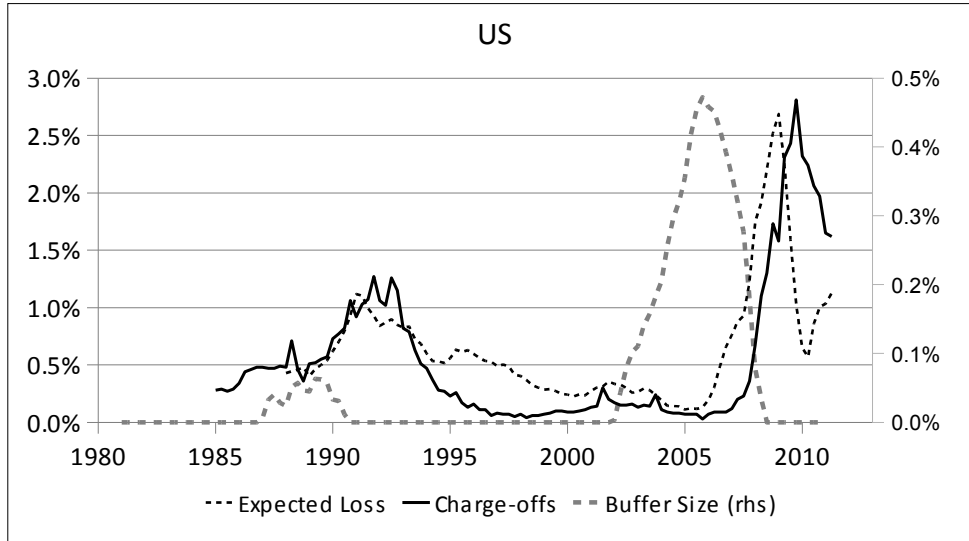


Figure 8: Impact of LTV on Expected Losses for Different LTI

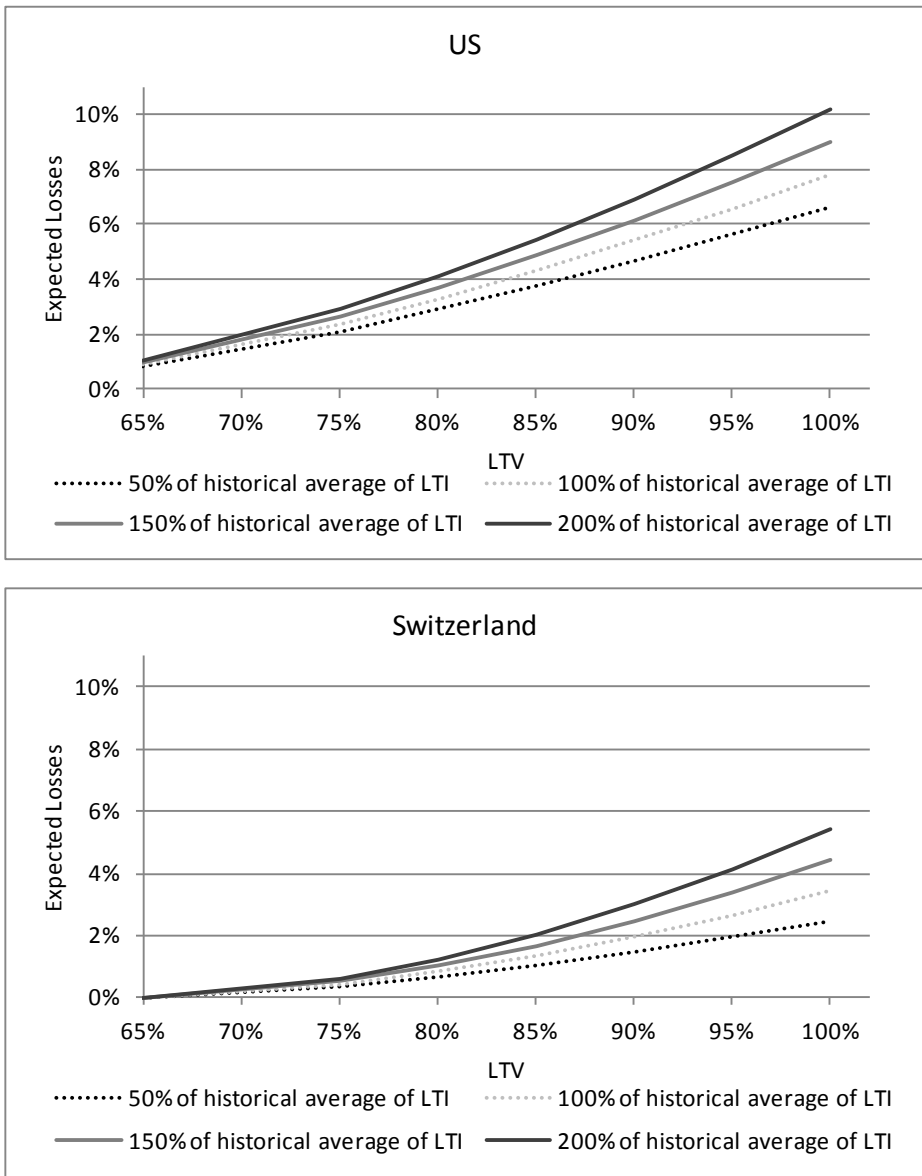


Table 1: **Data description**

	US	CH
m_t	<i>name:</i> Interest rate on conventional mortgages, 30 years <i>source:</i> BIS	Average mortgage rate Swiss National Bank
P_t	<i>name:</i> Case-Shiller National Seasonally Adjusted Home Price Values <i>source:</i> Standard & Poors	Residential Prop. Pr., All One Family Houses Wuest & Partner
GDP_t	<i>name:</i> Gross Domestic Product SA <i>source:</i> IMF (IFS)	Gross Domestic Product SA IMF (IFS)
N_t	<i>name:</i> Population <i>source:</i> IMF (IFS) <i>transf.:</i> Annual data is transformed into quarterly data by linear interpolation.	Population IMF (IFS) Annual data is transformed into quarterly data by linear interpolation.
u_t	<i>name:</i> Unemployment Rate SA <i>source:</i> IMF (IFS)	Unemployment Rate SA IMF (IFS)
L_t	<i>name:</i> Charge-off rate on real estate loans <i>source:</i> Federal Reserve Board <i>transf.:</i>	Write-downs and Provisions Rate Swiss National Bank Write-downs and provisions to total credits of Regional Banks and Raiffeisen banks (more than 90% mortgages in their loan portfolio); annual into quarterly data by linear interpolation.

Table 2: **Parameter values for conversion factor α , heterogeneity of house price development δ , LTV l , foreclosure costs ϕ , maintenance costs ρ and number of lags k in quarters.**

	US	CH
δ	35%	41%
l	75%	67%
ϕ	15%	15%
ρ	3.3%	3.7%
α in sample	6.5830	0.0022
k in sample	4	4
α out of sample	10.688	0.0022
k out of sample	-1	4

Table 3: **Parameter values of the regression.**
(Signif. codes: *** 0.001 ** 0.01 * 0.05 . 0.1)

	US		CH	
	in sample	out-of sample	in sample	out-of sample
	(lead/lag)	(lead/lag)	(lead/lag)	(lead/lag)
<i>c</i>	-0.007**	-0.014**	-0.003***	-0.0014**
<i>delP</i>	-0.026*** (-4)	-0.016 (4)	-0.012*** (-5)	1.3*10 ⁻⁵ *** (-5)
<i>delY</i>	-0.024 (-5)	-0.014*** (2)	-0.009* (-5)	-0.005 (0)
<i>delM</i>	-0.020** (4)	-0.025* (-1)	-0.014*** (2)	-0.020*** (2)
<i>P/Y</i>	0.196*** (-4)	0.340*** (0)	0.047 (-1)	0.084** (-1)
<i>u</i>	0.215*** (2)	0.103* (0)	0.051*** (-4)	0.053*** (-4)
<i>m</i>	0.004 (-4)	0.141*** (0)	0.133-0.014*** (-4)	0.105*** (-4)
R ²	0.91	0.70	0.91	0.93

Table 4: **Adverse scenarios for the SCAP and the EBA exercise. Source: Federal Reserve Board (2009a) and European Central Bank (2011).**

		GDP (Y on Y)	Unemployment Rate (Level)	House Prices (Y on Y)
SCAP	2009	-3.30%	8.9%	-22.00%
	2010	0.50%	10.3%	-7.00%
EBA UK adverse scenario	2011	-0.70%	9.0%	-12.50%
	2012	0.90%	10.6%	-7.00%

Table 5: **Scenario for the calculation of the countercyclical buffer.**

	US	CH
<i>w</i>	-18.9%	-7.4%
<i>m</i>	8.9%	4.7%
<i>u</i>	5.9%	2.5%