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Stress testing the German mortgage market

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Non-technical summary

Research Question

This paper presents a methodology for assessing credit risks from the residential real estate (RRE) lending of German banks. This methodology allows us to quantify potential credit losses in the RRE loan portfolios conditional on an adverse macroeconomic scenario. To this end we calculate based on current collateral values losses given default (LGD) and estimate probabilities of default (PD) using a panel time series model.

Contribution

Due to limited data availability, so far there is little empirical analysis of credit risks in the real estate loan portfolios of German banks. The proposed methodology allows us to estimate expected losses from RRE loans to households for the whole German banking system in the aggregate as well as for individual banks. Due to the lack of granular data, we estimate PD, LGD and outstanding RRE loan amounts (EAD) relying on satellite models using various macroeconomic and regulatory data. We show a significant link between default rates, RRE price dynamics and the unemployment rate in Germany. Moreover, we demonstrate the direct impact of lending standards and RRE prices on credit losses.

Results

Our stress test for the years 2018 to 2020 suggests that in an adverse macroeconomic scenario with a strong reversal in the RRE prices and a significant increase in the unemployment rate credit losses rise considerably at the bank-individual and the aggregate level. The increase in losses is particularly driven by high LTV-loans. Our results show that the majority of banks would face a significant increase in the estimated expected losses in their RRE loan portfolios implying that large parts of the banking system would be affected by an adverse shock if the assumed scenario were to materialize.

Nichttechnische Zusammenfassung

Fragestellung

Dieses Papier stellt einen Ansatz vor, mit dem Kreditrisiken aus der Wohnimmobilienkreditvergabe deutscher Banken abgeschätzt werden können. Mit Hilfe dieses Ansatzes können wir die potentiellen Verluste in den Wohnimmobilienkreditportfolien quantifizieren, die in einem adversen makroökonomischen Szenario entstehen. Dazu berechnen wir aus dem aktuellen Wert der Immobilien, die als Sicherheiten dienen, die erwartete Verlustquote (LGD) und schätzen die Ausfallwahrscheinlichkeiten (PD) mit Hilfe eines panelökonometrischen Zeitreihenmodells.

Beitrag

Kreditrisiken aus den Immobilienkreditportfolien deutscher Banken sind bislang aufgrund der eingeschränkten Datenverfügbarkeit empirisch kaum untersucht. Der vorgeschlagene Ansatz erlaubt es, die möglichen Verluste aus Wohnimmobilienkrediten an Privatpersonen für das gesamte deutsche Bankensystem sowohl auf aggregierter Ebene als auch für die einzelnen Banken zu schätzen. Da granulare Daten zu Wohnimmobilienkrediten auf Einzelbankebene nicht vorliegen, schätzen wir PD, LGD und ausstehende Immobilienkreditvolumina (EAD) mit Hilfe von Satelliten-Modellen auf Basis verschiedener makroökonomischer und aufsichtlicher Daten. Wir zeigen einen signifikanten Zusammenhang zwischen den Ausfallraten, der Immobilienpreisentwicklung und der Arbeitslosenquote in Deutschland. Darüber hinaus verdeutlichen wir den direkten Einfluss von Kreditvergabestandards und Immobilienpreisen auf Verlustquoten.

Ergebnisse

Unser Stresstest für die Jahre 2018 bis 2020 legt nahe, dass in einem adversen makroökonomischen Szenario mit einem starken Einbruch der Hauspreise und einem deutlichen Anstieg der Arbeitslosenquote die Verluste – sowohl auf Einzelbankebene als auch im Aggregat der Banken – beachtlich ansteigen. Der Verlustanstieg wird insbesondere durch Kredite mit hohem Beleihungssatz getrieben. Laut unseren Ergebnissen wäre die Mehrheit der Banken mit einem deutlichen Anstieg der Verlustquoten in ihren Wohnimmobilienkreditportfolios konfrontiert. Dies deutet darauf hin, das weite Teile des Bankensystems von einem adversen Schock getroffen sein dürfen, sollte sich das unterstellte makroökomische Szenario materialisieren.

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Stress testing the German mortgage market *

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Abstract

This paper presents a framework for estimating losses in the residential real estate mortgage portfolios of German banks. We develop an EL model where LGD estimates are based on current collateral values and PD dynamics are estimated using a structural PVAR approach. We confirm empirically that foreclosure rates are rising with the unemployment rate and are inversely related to house price inflation. Being consistent with our expectation that strategic defaults do not play a central role given the full personal liability of German households, the results give broad support for the double-trigger hypothesis of mortgage defaults. In order to analyse the possible credit losses stemming from residential mortgage lending we then use the model to run a top-down stress test and simulate losses on the individual bank level for the years from 2018 to 2020 for the whole German banking sector. Our results show that loss rates in the residential mortgage portfolios of German banks do increase significantly in an adverse economic environment. The estimated expected losses are widely distributed in the banking system leading, on average, to a 0.4 percentage points reduction in the CET1 ratio over the simulation period.

Keywords: Residential real estate, mortgages, credit risk, stress testing, German banks

JEL classification: G01, G17, G21, G28.

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1 Introduction

The recent financial crisis has highlighted that housing markets can be an important source of systemic risk. Not only in the US, but also in several European countries, house price bubbles with excessive credit growth and a deterioration of credit standards have contributed to a build-up of systemic risks. Subsequently, when these risks materialized, large losses occurred, which destabilized the financial system with immense negative spillovers to the real economy. The national banking systems were mostly affected by the housing downturns due to the large direct exposures banks had towards residential real estate (Goodhart and Hofmann, 2007). But imprudent securitisation and cross-border trade of such products were important channels through which risks from national housing markets propagated in the global financial system.

As real estate markets are generally prone to boom-bust cycles they can play a key role for financial stability. Moreover, due to the importance of debt instruments in the housing market, recessions following a real estate bust are in general more severe and affect the macroeconomy at a broader scale (see for instance Ambrose, Eichholtz, and Lindenthal (2013), Jordà, Schularick, and Taylor (2015), Mian and Sufi (2018) and Gertler and Gilchrist (2018)). Gorton and Metrick (2012) and Seyfried (2010) argue that the bursting of real estate bubbles in the United States as well as European countries after 2007 may have triggered the worst economic crisis since World War Two.

In contrast to several other countries, where residential real estate markets have experienced strong upswings in the 2000s, house prices in Germany have been relatively flat in nominal terms, implying real house price decreases. While the last German housing market boom dates back to the early nineties after the German reunification, in 2010 prices started to raise again. Since then house prices in Germany have increased by 5% p.a. on average until the end of 2017 with urban areas experiencing particularly strong increases of 7% p.a. on average during the same period. These house price increases do not necessarily reflect risks for financial stability. As Koetter and Poghosyan (2010) points that an important indicator for systemic risk is the deviation of the price development from the respective fundamentals. Looking at the recent price developments in Germany, fundamental factors can explain some part of the price increases, but historically low interest rates and a flight to assets perceived as relatively safe have also contributed to the upswing. In particular in urban areas, valuations appear to be stretched and overvaluations are estimated for some markets (Kajuth, Knetsch, and Pinkwart, 2016).[1] Bundesbank's estimations point at overvaluations of 15 to 30% for residential properties in urban areas in 2017 (Bundesbank, 2018b). The price developments have been accompanied by accelerating credit dynamics with nominal annual growth of loans to households for house purchase increasing from less then 1% p.a. in 2010 to 4.4% p.a. in the third quarter 2018.[2] These levels are not yet particularly elevated compared to historical data in Germany or in particular in comparison with mortgage growth rates observed in other European countries during the build-up of real estate bubbles. While growth rates are moderate, the overall size of exposures is significant. Currently, there are about EUR 1.2 trillion loans to German households for house purchase outstanding which account for about 44% of

[1] This regional heterogeneity is not a new phenomenon or unique to the German housing market. Glaeser, Gottlieb, and Tobio (2012) find large regional variations in house prices for the US.

[2] Seasonally adjusted and including loans to non-profit organisations. See Bundesbank (2018a).

the total credit exposure to domestic firms and households. The large size of real estate related exposures and the significant price increases over recent years hence call for a close monitoring of the real estate market, mortgage lending and the credit risk of underlying portfolios. Especially the risks of a potential housing market downturn and its effects on banks' losses needs to be assessed. However, due to limited data availability, so far there is little empirical analysis of credit risks in the real estate loan portfolios of German banks.

We propose a methodology that allows estimating expected losses from RRE loans to households for the whole German banking system in the aggregate and for individual banks. To assess the credit losses stemming from RRE loans originated by German banks we develop an EL (expected loss) model in which the LGD (loss given default) is calculated based on current collateral values and PD (probability of default) dynamics are estimated using a structural panel VAR (PVAR) model. Furthermore, our EAD-estimation approach allows a semi-dynamic modelling of the outstanding volume of the RRE loans. Due to the lack of granular data, we estimate PD, LGD and outstanding housing loan amounts (EAD) relying on satellite models and using various macroeconomic and regulatory data. The models are specified so that structural features of the German housing market and RRE lending are taken into account.

The German housing market is characterised by a relatively low home ownership rate of 48% and a strong rental market. Interest payments for mortgages are only tax deductable for buy-to-let properties, but not for owner-occupied real estate. Due to the full recourse of mortgages in Germany, collateral values are less likely to act as a trigger of strategic defaults in case of negative home equity but mainly affect the loss given default.

The current very low level of interest rates is an important driver of demand for housing and mortgages and a normalisation of monetary policy and interest rate levels could significantly affect mortgage demand in Germany. Considering existing mortgages, interest rate risk for households in Germany is less relevant compared to other countries as contracts usually have medium-long interest rate fixation periods. Around 80% of loans for house purchase have a fixed interest period of more than 5 years. Over the last years, the percentage of new loans with an interest rate fixation for more than 10 years has increased from around 30% to over 40%. Hence, given the predominance of the medium-long fixed interest rate fixation periods, most existing mortgage contracts should not be immediately affected by changes in interest rate. We therefore do not explicitly model interest rate risk as driver of mortgage defaults in the stress test since changes in the interest rate are expected to primarily affect the house price change and new lending decisions.

Our results show a significant link between default rates, house price dynamics and the unemployment rate in Germany, confirming that the currently observable low default and foreclosure rates are driven by the favourable macroeconomic environment. Moreover, we demonstrate that lending standards and RRE prices have a direct impact on mortgage loss rates. Overall, our results for the German mortgage market are in line with the double-trigger hypothesis which attributes mortgage default to the joint occurrence of negative equity and adverse shocks to the borrowers' payment ability (compare Schelkle, 2018). In the case of a significant increase in the unemployment rate and a strong reversal in house prices our model predicts a significant increase of mortgage losses, particularly driven by loans with high loan-to-value (LTV) ratio. The distribution of cumulative losses relative to the regulatory capital requirements suggests that the stress effects are not limited to few banks but spread widely in the banking system.

The reminder of the paper is organized as follows. In the next section we discuss the empirical literature that is related to our modelling approach. We then turn to an in-depth discussion of our stress test model. In Section 3 we discuss the underlying data and model calibration before we discuss in Section 4 our results.

1.1 Empirical literature on mortgage credit risks

There are very few empirical studies for the German mortgage market as there is almost no granular data available which is essential for an analysis of mortgage risks at the borrower level.

In contrast, there is ample empirical research on the performance of the US mortgage market driven by the experience of the subprime crisis and supported by the availability of granular mortgage data. A large part of the literature for the US can be interpreted in the light of the 'equity' vs 'ability to pay' default hypotheses (Jackson and Kaserman, 1980). According to the equity hypothesis, borrowers default decision will depend solely on the net housing equity value. Such strategic household defaults are modeled for instance by Cocco, Campbell, et al. (2004). In contrast to the 'equity' hypothesis, the 'ability to pay' hypothesis predicts that borrowers will default when they are hit by an income shock such that their income is insufficient to service their mortgage. Generally speaking, a negative impact of residential real estate (RRE) prices on probability of default can be interpreted as evidence for the equity hypothesis while an effect of an unemployment shock gives support to the 'ability-to-pay' hypothesis. Deng, Quigley, and Order (2000) and Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) are two studies that give empirical support to the hypothesis that simple option models in the spirit of the 'equity' hypothesis are not sufficient to model default rates.

However, we expect strategic default decision to be less relevant in Germany given the full recourse of mortgages. Therefore, we do not expect strategic defaults as a driving force for mortgage defaults in Germany. Rather, a negative relation between house price changes and default probabilities might stem from the fact that households with negative income shocks find it easier to avoid personal insolvency by selling their house in a boom market rather than during a bust ('double-trigger' hypothesis, compare Schelkle, 2018). A stylised theoretical model of this transmission channel can be found in Hott (2015).

Empirical evidence using granular mortgage data for European RRE markets is starting to evolve but is still relatively scarce (see Rodriguez and Trucharte, 2007, Dietsch and Welter-Nicol, 2014 and Gaffney, Kelly, and McCann, 2014 for the Spanish, French and Irish housing markets respectively). Alternatively, Hott (2015) uses a calibrated macro-model to explain mortgage losses for Switzerland. Focusing on the determinants of the recovery rates of a portfolio of 1,236 defaulted mortgages, Ingermann, Hesse, Bélorgey, and Pfingsten (2016) is one of the few studies looking at the German retail mortgage market. Other studies use debt-to-income or debt service variables from household surveys to identify vulnerable households and approximate potential risk exposures (see e.g. Bundesbank, 2013, Ampudia and Ehrmann, 2014, Albacete, Eidenberger, Krenn, Lindner, and Sigmund, 2014). Read, Stewart, La Cava, et al., 2014 use Australian household-level data for the years 2006 and 2010 and find that the probability to miss a payment is particularly high for households with relatively high debt service ratios. Consistently, Fuster and Zafar (2015) show for the US that the delinquency rate drops more than half when cutting the required payment by half.

Stress testing methods based on household or banking data are a natural extension to quantify risks from the RRE markets. Using bank-specific information from the 2017 low-interest-rate environment (LIRE) survey Siemsen and Vilsmeier (2017) assess the impact of a severe decline in house prices on the solvency of German less significant institutions (LSIs). Djoudad (2012), Dey, Djoudad, Terajima, et al. (2008) and Faruqui, Liu, and Roberts (2012) assess the vulnerability of private households in an adverse scenario as debt service variables play a decisive role in the default process. Another strand of the literature then assesses the financial sectors potential exposure against such vulnerable households and estimates their loss given default and expected losses. For instance, mortgages losses might increase not only because of the effect of worsening of debt-service-to-income ratios on default probabilities but also through a fall in the house prices and declining collateral values. Comprehensive stress tests usually involve the decline of various housing related indicators, such as income, unemployment and house prices (see, for instance, EBA, 2014, EBA, 2016 and EBA, 2018). The empirical research on modeling US loss severities generally point towards the predominant importance of current LTVs for determining LGDs, see e.g. Clauretie and Herzog (1990), Lekkas, Quigley, and Order (1993), Calem and LaCour-Little (2004), Pennington-Cross (2010), and Qi and Yang (2009). Also Ampudia and Ehrmann (2014) find that the LGD at the level of the household is particularly sensitive to the value of the house.

2 Empirical Model

In this section we describe the general framework of our stress test approach. As mentioned above, we are thereby focussing on the direct risk transmission channel and aim at quantifying the potential credit losses in RRE mortgage portfolios of German banks. Conceptually, our stress testing framework is similar to a classical expected loss (EL) model, with probability of default (PD), loss given default (LGD), and exposure at default (EAD) model inputs based on the prevailing macroeconomic environment.

First, we estimate the effects of changing house prices and employment rates on default rates. Second, we simulate LGDs based on the undercollaterized part of housing loans which are dynamically updated based on past price movements and amortisation payments. Third, we calculate the amount of outstanding housing loans (EAD) based on past mortgage volumes and historical amortization rates.

Applying an adverse economic scenario to our combined EL-model, we estimate the potential future provisioning needs for the time period 2018-2020 for all German banks with an outstanding RRE private mortgage portfolio larger than EUR 5mm and assess the scenarios' impact on the banks' capital ratios.

Yet, given the lack of granular mortgage data, we cannot estimate and calibrate standard credit risk models at the individual loan level (e.g. Logit- or Probit-models for PD estimates) but must derive equivalent inputs from satellite models using more aggregate data.

In the following, we explain the different satellite models and calibration assumptions in more detail.

2.1 Estimation of expected mortgage losses

The Euro amount of expected losses (EL_t^j) for the mortgage portfolio of each bank j in year t is calculated as the product of the probability of default (PD_t^j), the loss given default ($LGD_{t,T}^{a,s,K}$), and exposures at default ($EAD_{t,T}^{a,j,s,K}$), summed up over all relevant geographical regions s, vintages T, (initial) amortisation rate a and LTV buckets K,

$$EL_t^j = \sum_{a,s,T,K} PD_t^j \cdot LGD_{t,T}^{a,s,K} \cdot EAD_{t,T}^{a,j,s,K} \tag{1}$$

2.1.1 Modeling mortgage default probabilities

Ideally, mortgage PDs and LGDs should be calibrated based on borrower specific or loan-level data. However, no such database is publicly available at the moment for Germany.[3] Instead, we model the PD dynamics of the banks' mortgage portfolio based on aggregated German state-level foreclosure data from the Federal statistics office.

$$\widetilde{PD}_t^j = \overline{PD}_{2016}^j + \Delta\widetilde{PD}_{t,2016} \tag{2}$$

$$= \overline{PD}_{2016}^j + \frac{\Delta\widetilde{FCR}_{t,2016}(U, \Delta P)}{1 - \omega_{cure}} \tag{3}$$

where $\overline{PD}_{2016}^j$ is a bank's average PD of its RRE portfolio in the starting year (2016) as reported in COREP.[4] Furthermore, $\Delta\widetilde{FCR}_{t,2016}$ is the forecasted change in the aggregate foreclosure rate between the starting year 2016 and the simulated year t based on the underlying macroeconomic scenario. The term $1 - \omega_{cure}$ takes into account that a certain fraction of defaulted mortgages are cured and do not end in an official foreclosure procedure.[5]

In order to derive the change in the foreclosure rate $\Delta\widetilde{FCR}_{t,2016}$ conditional on the macroeconomic environment, we estimate the following PVAR model:

$$X_{s,t} = \Phi X_{s,t-1} + \epsilon_{s,t} \tag{4}$$

with $X_{s,t} = [\ln(FCR_{s,t}), \Delta P_{s,t}, U_{s,t}]$ and $\epsilon_{s,t} = [\epsilon_{s,t}^{\ln FCR}, \epsilon_{s,t}^{RRE}, \epsilon_{s,t}^{Unemployment}]$, where $\Delta P_{s,t}$ is the relative price change in state s and $U_{s,t}$ the regional unemployment rate.[6] The model is estimated with fixed effects and uses a standard Cholesky decomposition in order to identify the shocks. In a second step, we calculate the response functions of the foreclosure rate after unemployment or RRE price shocks. Table 1 states the expected

[3] The Household Finance and Consumption Survey (HFCS) of the Eurosystem for Germany collects information on missed or late payments but not on defaults.

[4] As this value is only reported for IRB banks, for banks under the standard approach we use the average value of all IRB banks.

[5] Implicitly, this approximation assumes that the share of defaulted mortgages which are foreclosed remains constant. However, we allow the fraction of cured mortgages to vary conditional on macroeconomic scenario. For a further discussion, see also Section 3.

[6] We also estimated a specification including the level of FCR. However, this specification yielded a worse fit compared to the specification using $\log FCR$.

signs of the impulse response functions.[7] The expected signs are not part of the actual shock identification scheme but rather serve as a benchmark for assessing the validity of the modeling approach using the above mentioned standard Cholesky decomposition identification scheme.

As can be seen in Equation (2), we do not include an additional explicit markup for higher initial LTVs or model the effect of loan age on the PD (see e.g. Lambrecht, Perraudin, and Satchell (1997)). While there is a substantial amount of empirical evidence for higher default probabilities of higher LTV loans (see e.g. Elul et al. (2010), Calhoun and Deng (2002), Deng et al. (2000) or Gaffney et al. (2014)), we simply lack the necessary granular data to calibrate such effects. A one-off survey from 2013 covering RRE lending activities in 24 German cities did not show any significant PD differences for mortgages with a initial LTV at loan origination[8] above 80%. On the other hand, the EBA portfolio benchmarking exercise data gives support to the hypothesis of a hump-shaped relation between current LTVs and default rates (see Figure 11). This is in line with most of the empirical literature which highlights the importance of the current LTV, which takes into account mortgage amortisations and in particular house price appreciations. Even though not modeled on a loan-by-loan basis, the later effect is implicitly captured by the term $\Delta\widetilde{FCR}$ which includes the effect of declining house prices on foreclosure rates and default probabilities.

2.1.2 LGD modeling approach

We model losses conditional on default by the sum of default fixed costs LGD_{FC} and expected losses from foreclosure at time t, multiplied by the conditional probability of a defaulted RRE mortgage not being cured $(1 - \omega_{cure})$, i.e. being foreclosed,

$$LGD^{a,s,K}_{t,T} = LGD_{FC} + (1 - \omega_{cure}) \cdot E(LGD^{a,s,K}_{t,T}|Foreclosure) \tag{5}$$

where T denotes the year of loan origination and default fixed costs LGD_{FC} are incurred by the bank irrespective of the workout process.

The expected loss from foreclosing a real estate is negatively related to the recovery value from foreclosures, which in turn depends on the ratio of the current foreclosure price of the property to the outstanding loan amount, i.e.,

$$\begin{aligned} E(LGD^{a,s,K}_{t,T}|Foreclosure) &= 1 - Foreclosed\ Recovery\ rate^{a,s,K}_{t,T} \\ &= 1 - \min(1, \frac{p_{s,t} \cdot (1 - \Delta f_{s,t}) \cdot \exp^{(-\delta\cdot(t-T+1))}}{L^K_{s,T} \cdot (1 - Amort^a_{t,T})}). \end{aligned} \tag{6}$$

were $p_{s,t}$ corresponds to the real estate price level in region s at time t and Δf_t equates to the time-varying discount of the property's price on the market value in case of foreclosure, while $\exp^{(-\delta\cdot(t-T+1))}$ is the property's depreciation factor between T and t

[7]Table 1 also suggests that a sign restricted identification approach is less suited for this application due to the similar shock patterns.

[8]In this survey, the value used for calculating LTV ratio is the German mortgage lending value (MLV). The MLV is intended to reflect the property's long-term sustainable value. For details on the survey see Bundesbank (2014).

and $(1 - Amort_{t,T})$ is the part of the loan that has not yet been amortised between T and t. In addition, the following relation between initial LTVs ($ILTV$) and current LTVs ($CLTV$) holds by definition:

$$CLTV^{a,s,K}_{t,T} \equiv \frac{ILTV_K \cdot (1 - Amort^a_{t,T})}{(1 + \Delta P_{s,t,T}) \cdot \exp^{(-\delta \cdot (t-T+1))}} \tag{7}$$

where $\Delta P_{s,t,T} = \frac{p_{s,t} - p_{s,T}}{p_{s,T}}$ denotes the cumulative percentage increase in real estate prices in region s between T and t and $ILTV_K \equiv \frac{P_{s,T}}{L^K_{s,T}}$.

Hence, the expected loss in foreclosure is mainly driven by the current LTV ($CLTV$) and the prevailing foreclosure discount. This is in line with Qi and Yang (2009) who show that the current LTV ratio is the single most important LGD determinant. As such, our LGD model is an extension of the model used in Bundesbank Financial Stability Reviews (see Bundesbank, 2014 and Bundesbank, 2015) and is very similar in spirit to the approach used by Gaffney et al. (2014) for the Irish mortgage market.

Combining Equations (5-7) yields

$$\begin{aligned} LGD^{a,s,K}_{t,T} &= LGD_{FC} + (1 - \omega_{cure}) \cdot E(LGD^{a,s,K}_{t,T} | Foreclosure) \\ &= LGD_{FC} + (1 - \omega_{cure}) \cdot [1 - \min(1, \frac{1 - \Delta f_{s,t}}{CLTV^{a,s,K}_{t,T}})] \\ &= LGD_{FC} + (1 - \omega_{cure}) \cdot [1 - \min(1, \frac{(1 + \Delta P_{s,t,T}) \cdot (1 - \Delta f_{s,t}) \cdot \exp^{(-\delta \cdot (t-T+1))}}{ILTV_K \cdot (1 - Amort^a_{t,T})})]. \end{aligned} \tag{8}$$

In general, the LGD formula is the same for all banks but average estimated LGDs are different across banks depending on their lending standards (initial LTVs and amortisation payments) as well as the location of the collateral.

Furthermore, claims of building societies frequently enter in the land register on a subordinate basis. Assuming that half of the building society loans are subordinated, the expected losses from foreclosures for subordinated loans is calculated as:

$$E(LGD^{a,s,K}_{t,T} | Foreclosure, lev) = 1 - \min(1, \frac{(1 + \Delta P_{s,t,T}) \cdot (1 - \Delta f_t) \cdot \exp^{(-\delta \cdot (t-T+1))}}{ILTV_K \cdot (1 - Amort_{t,T})} \cdot lev) \tag{9}$$

$$lev \equiv \frac{ILTV_K}{ILTV_K - ILTV_{Sen}} \tag{10}$$

where $ILTV_S$ and $ILTV_K$ are the initial LTVs of the assumed prior lien (senior) mortgage and the LTV of the total mortgage financing amount at origination. In general, subordinated loans are inherently more leveraged by the factor $\frac{ILTV_K}{ILTV_K - ILTV_S}$ while on the other hand losses of buildings societies are limited by the fact that in general their loans cannot exceed total loan-to-mortgage lending values of 80%.[9]

2.1.3 EAD modeling approach

In principal, we model the EAD as the historical mortgage lending volumes, adjusted for amortizations, prolongations and impairments, i.e.,

$$EAD^{s,K}_{j,t,T} = Lending^{s,K}_{j,T} \cdot net\,outstanding_{j,t,T}. \tag{11}$$

However, neither the historical lending volumes nor the currently outstanding share of the loan are known at a sufficiently granular data basis and must hence be estimated from more aggregate data sources.

Generally speaking, the stock of net outstanding mortgages of vintage T is reduced every year by impairments, voluntary down payments, prolongations and refinancings as well as ordinary amortisation payments. In particular, given information on the past RRE impairment rate $Imp_{j,t}$ of bank j in year t, the share of mortgages with a partial prepayment right of up to $x\%$ of their mortgage ($w_{PPP,x,T}$), as well as the share of historical RRE lending with an interest rate fixation period up to one year ($IRFIX1_{j,t}$) or above one year and up to five years ($IRFIX5_{j,t}$), we can approximate the outstanding loan share by:

$$\begin{aligned} net\,\widetilde{outstanding}_{j,t,T} = {} & [1 - \sum_{z=T}^{t} Imp_{j,z}] \cdot [1 - Prob_{PPP} \cdot \sum_{x=0}^{1} (w_{PPP,x,T} \cdot (t-T) \cdot x)] \cdot \\ & [1 - D1_{t,T} \cdot IRFIX1_{j,T} - D5_{t,T} \cdot IRFIX5_{j,T} - D10_{t,T}] \cdot [\sum_{a} w_{a,T} \cdot AF_{a,i_{j,T},t,T}] \end{aligned} \tag{12}$$

where $D1_{t,T}$,$D5_{t,T}$ and $D10_{t,T}$ are dummy variably that are one if the $t-T$ is smaller than one, five or 10 years respectively, or zero otherwise. Implicitly, Equation (12) assumes that all loans are refinanced or prolonged at the end of their interest rate fixation period but no later than ten years.[10] Additionally, we include the simplifying assumption that the probability of exercising the partial prepayment option ($Prob_{PPP}$) is independent of the size of the prepayment right x. Furthermore, $AF_{a,i_j,t,T}$ is the theoretically outstanding amount of a vintage T mortgage in t, based on the annuity formula with initial amortization rate a and the bank's average interest rate charged for RRE mortgages $i_{j,T}$ and $w_{a,T}$ is the share of initial amortization rate a in historical lending volumes of vintage T.

The estimation of EADs is further complicated that there is no disaggregated historical lending data at the regional level. In addition, the only available representative data source on historical RRE lending volumes since 2003, the MIR-statistics, only contains

[9]Implicitly, this assumes that the amortisation rates of the the senior and junior loan are similar. Anecdotal evidence suggests that amortization rates for building society loans might be higher than for ordinary mortgages but there is no data to quantify the differential.

[10]By law, German creditors have the right to renegotiate or early redeem their loans after ten years. Given the continuous fall of mortgage interest rates over the last decade, rational behavior would imply that German customers have used this opportunity to secure significantly lower interest rate costs.

data for a representative sample of currently 240 German banks while stock data of RRE mortgages is available for all German banks from the Borrower Statistics.

As a starting point for estimating the aggregate lending volume for the banks not included in the MIR-statistics sample, imagine the following simple stock-flow model:

$$Stock_{j,t} \equiv Stock_{j,t-1} \times (1 - \alpha_{j,t}) + Lending_{j,t} \tag{13}$$

where $\alpha_{i,t}$ is the average annual net amortisation rate for RRE mortgages. Note, however, that similar to Equation (12) it includes not only regular down payments but also voluntary prepayments and impairments. Furthermore, because the lending aggregate (based on MIR-statistics) is gross of loan refinancing and prolongations, $\alpha_{i,t}$ also includes corresponding effects. By simple re-arranging of Equation (13) we can write:

$$\frac{Lending_{j,t}}{Stock_{j,t-1}} \equiv g_{j,t} + \alpha_{j,t} = M_{j,t} \tag{14}$$

with $1 + g_{j,t} \equiv \frac{Stock_{j,t}}{Stock_{j,t-1}}$.

The historical lending of bank j can hence be written as :

$$Lending_{j,t} \equiv Stock_{j,t-1} \times M_{j,t}. \tag{15}$$

Now, we can estimate $M_{j,t}$ via the following regression based on the MIR-statistics bank sample for the time period 2003 to 2017:

$$\frac{Lending_{j,t}}{Stock_{j,t-1}} \equiv M_{j,t} = \gamma \times g_{j,t} + constant + \sum_{i=2}^{I} \beta_i \times D_{j,i} + \sum_{T=2004}^{2017} \beta_T \times D_{t,T} + \epsilon_{j,t} \tag{16}$$

with $D_{j,i}$ and $D_{t,T}$ being banking group and time period dummies. This allows us to predict the historical lending volume for the banks outside the MIR-statistics sample by:

$$\widetilde{Lending}_{j,T} = \max(\widetilde{M}_{j,T} \cdot Stock_{j,T-1}, 0). \tag{17}$$

Finally, we make the following two simplifying assumptions. First, the initial LTV distribution only depends on the vintage but is the same for all banks and regions. Second, the regional distribution of RRE mortgages for each bank is proportional to its branch network in 2016.[11] Hence, historical lending volumes by region and ILTV can be approximated as

$$\widetilde{Lending}^{s,K}_{j,T} = w^K_T \cdot w^s_j \cdot \widetilde{Lending}_{j,T}, \tag{18}$$

where w^K_T is the average share of loans from ILTV bucket K for vintage T and w^s_j is the share of branches of bank j in region s relative to all of the bank's branches.

[11] At the time the analysis was completed, information on the branch network for 2017 was not available.

3 Data and model calibration

As outlined before, the dataset underlying this stress test stems from various sources. The first part of our dataset, which covers the EAD estimation for the time period 2003-2017, is built on the borrower statistics on the one hand, containing data on the volume of outstanding mortgages, and the MFI interest rate (MIR) statistics on the other hand, which provides data on volumes and interest rates of new mortgage lending. The borrower statistics includes bank-by-bank data for all German banks while the MIR-statistics covers only a representative sample of about 240 German banks.[12] Information on the banks' branch network is taken from a directory that covers the location of branches of all German banks within Germany.[13] We supplement these information with distributional data about initial LTVs and amortisation rates as well as prepayment rights from Europace.[14]

Second, to calculate current LTVs, which are an important determinant of LGD, we employ regional house price data from from bulwiengesa AG for the 401 German districts since 2004. This allows us to quantify changes in collateral values since loan origination.

Third, as outlined in Section 2.1.1, starting point PDs are based on IRB bank estimates reported under COREP for December 2017. Due to the insufficient time series length of COREP reports and the lack of alternative historical PD data, we derive PD dynamics from the macroeconomic foreclosure sensitivities based on a PVAR model (compare Equation 4). For the estimation of the PVAR, we use regional data on annual house price changes, employment and foreclosures for the 16 German federal states for the period 1991-2016. The time series of annual house price changes in the 16 German states $\Delta P_{s,t}$ are based on data from the bulwiengesa AG since 1991. Before 2004, proxies for state level aggregates are computed based on individual time series for 127 German cities, from 2004 onwards state-level price changes are based on aggregating data for the 401 German districts. The official foreclosure and employment data are obtained from the Federal Statistics Office and the Federal Employment Agency for the time period 1991-2016.[15] The unemployment rate $U_{i,t}$ in state i during year t is constructed according to the ILO

[12] Due to the longer time series, we use the MIR statistic's total new lending definition which includes prolongations (available since 2003) rather than the lending definition without prolongations (available only since 2014). At the individual bank level, monthly lending volumes are aggregate to annual values, annual growth rates are based on end of year figures. Afterwards, the combined MIR and borrower statistics sample was cleaned for missing or irregular data points as well as outliers. Observations from banks involved in mergers or acquisitions were dropped from the sample. Furthermore, we exclude data points when the increase of the stock was larger than the observed lending volume or when the difference between $M_{j,t}$ und $g_{j,t}$ was larger than 50 percentage points. Further observations were excluded due to obvious data inconsistency problems. Overall, due to the data cleansing 787 of the original 3,183 observations were dropped from the final sample. Out of those 787 omitted observations, 81 data points indicated mortgage growth rates of less -20%.

[13] Hoppenstedt Banken Ortslexikon, as of 2016; the information is further complemented by own research.

[14] EUROPACE-Baufinanzierungs-Index (EBIx), https://report.europace.de/ebix-etb/europace-ebix/. Strictly speaking, the LTV ratios reported by EUROPACE are based on mortgage lending value (MLV) instead of market value. According to our estimations, a loan-to-MLV ratio of 80% corresponds to a market price based LTV of approx. 70-75%.

[15] The data can be downloaded from the website of the Federal Employment Agency.

definition. The foreclosure rate FCR is defined as

$$FCR_{i,t} = \frac{n_{foreclosures,i,t}}{n_{households,i,t} \cdot w_{mortgages,i}} \tag{19}$$

with $n_{foreclosures,i,t}$ being the official number of initiated foreclosures reported by the Federal Statistics Office in state i in year t.[16] $n_{households,i,t}$ is the number of respective households and $w_{mortgages,i}$ being the share of households with mortgage debt. $n_{households,i,t}$ is estimated as the fraction of total population and the number of persons per household in state i. Estimates for the state-specific (albeit time-indifferent) share of households with mortgage debt and the number of persons per household are derived from the German HFCS. See Figure 2 for a historical time series of the average German foreclosure rate.

It should be mentioned that the time period covered by the data used to estimate the macroeconomic sensitivities of foreclosure rates includes one episode of pronounced macroeconomic distress between 2001 and 2005 accompanied by declining nominal house prices and rising unemployment and foreclosure rates. Furthermore, in 1999 an amendment of the private insolvency law took place in Germany allowing private persons an easier way to become debt free if they apply for bankruptcy, which may have contributed to the significant increase in the foreclosure rates observed in the data (see Figure 2). Since 2006 the data feature a steady improvement of macroeconomic conditions with steadily declining unemployment and foreclosure rates and, from 2010 on, accelerating house price inflation.

Finally, Table 4 shows the parameter choices for the model calibration. The default fixed costs are set at 3%, which is in line with recent EBA Portfolio Benchmarking LGD data for low LTV mortgages (compare Figure 11). As mentioned before, we assume that half of the building society loans are subordinated by 20%. The share of cured mortgages is set at $\omega_{cure} = 0.4$, which is broadly in line with the currently reported PDs and the historical foreclosure rates. The PD for outstanding mortgages in 2014 was around 1% on average while the foreclosure rate was close to 0.6%, suggesting a probability of being cured of approximately 40%.

In addition, we assume that the foreclosure discount is time-varying and depends on the general macroeconomic environment and real estate market conditions. In particular, it is reasonable to expect that the discount is smaller during a housing upturn when demand exceeds supply and, in turn, will increase during the downturn when supply outpaces demand. For the US, evidence for disclosure discounts between 0 and 50% are reported by Frame (2010), depending on location and time period, and average discount rates in the range between 10% and 20% are estimated by Clauretie and Daneshvary, 2009. Based on these findings, we model the foreclosure discount as a function of current RRE price change, i.e.

$$\Delta f_{i,t} = \max(0, \min(0.5, 0.25 - 2.5 \cdot \Delta p_{i,t})) \tag{20}$$

[16] Strictly speaking, the number of initiated foreclosures reported by the Federal statistics office includes all foreclosure procedures of immovable properties, including but not limited to foreclosures of residential real estate. While a breakdown by the type of underlying property is not available, it is most likely that the vast majority of cases refers to residential real estate. Even in the presence of a broader foreclosure definition, the shape and the relative impact of the estimated shocks remain unaffected as long as the ratio between residential real estate and other foreclosures is constant over time.

with $\Delta p_{i,t} = \frac{p_{i,t}}{p_{i,t-1}} - 1$ and a natural lower bound at zero and a maximum discount rate of 50% in the most adverse possible market environment. The implied value of 25% for the years 2006-2011, when average house price were flat in Germany, corresponds well with the average recovery values of 78% reported by Ingermann et al. (2016) for a portfolio of 1,236 defaulted German properties for the same time period. Finally, the time-invariant annual depreciation rate δ is set to be 1.5%.[17]

4 Results

We break this section down into five subsections. We begin with the discussion of the estimation of the PD and then turn to the results of the EAD model estimation. In the third subsection we present the results for the LGD model. The subsection is followed by a presentation of the overall results for the combined (EL) model. The section ends by discussing the distribution of credit losses among German banks.

4.1 Results for the PD model

In this section we discuss the results of the PD model. We start with our Panel-VAR estimation and then turn to the implied PD dynamics which depend on the macroeconomic scenario and sensitivities estimated with the PVAR model.

4.1.1 Results of the PVAR estimation

Table 2 displays the regression results while Figure 1 depicts the impulse response functions from the estimated PVAR based on regional data for the 16 German federal states for the time period 1991-2016.[18] All impulse responses have the expected signs (compare Table 1) and are statistically significant. Focusing again on the response functions of the foreclosure rate, the results confirm that negative price shocks and positive unemployment shocks lead to a positive change in the foreclosure rate. The foreclosure rate reacts strongly to contemporaneous shocks to RRE prices and the unemployment rate, with the effect gradually declining and becoming insignificant after two to three years. Furthermore, the effects are not only statistically but also economically significant. According to these estimates, a house prices shock of one standard deviation increases the foreclosure rate by up 0.7% and a one standard deviation shock to the unemployment rate increases the foreclosure rate by 0.5%. We see these results as strong support for the double-trigger hypothesis since for a household experiencing a negative income or unemployment shock,

[17] According to OECD2013 estimates of housing depreciation rates (including both structures and land) are generally in the range 1 to 2% per year. The depreciation rate for structures alone is estimated to be 1.5% per year.

[18] The panel, however, is not strictly balanced as regional foreclosure data is not available for the early years of the sample for the five eastern states. As a robustness analysis, we repeat the PVAR analysis based on the representative and fully balanced panel county-level price data from 2005 onwards. Quantitatively, the estimated individual impulse response functions are slightly smaller, probably due to shorter time span which excludes the buildup of the last RRE bubble and the peak of the last crisis. Nevertheless, the results give broad support to the validity and robustness of the PVAR approach. While individual impulse response functions vary somewhat quantitatively, overall the results give broad support to the validity and robustness of the PVAR approach.

it is easier to avoid foreclosure by selling a house in a boom rather than a bust housing market environment.

4.1.2 PD dynamics based on macroeconomic scenarios

Conditional on the macroeconomic scenario presented in Table 5, we forecast the path for the aggregate foreclosure rate based on the approach by Camba-Mendez (2012).[19] Figure 2 depicts the historical time series of the average foreclosure rate for Germany as well as the forecasted values for the simulation period, based on the macroeconomic scenarios. The simulated foreclosure rate strongly increases over the course of the adverse scenario as prices decline and the unemployment rate starts to rise.

The chosen scenario is thereby more conservative than recent stress testing exercises by the EBA and the IMF (compare Table 8 in Appendix A.3.2).[20] In particular, simulation results from the PVAR using the data since 1991 suggests that the implied macroeconomic path of the stress scenario corresponds to the 75% percentile for the unemployment rate and foreclosure rates and exceeds the 99% percentile for RRE prices.[21]

Finally, we proxy the aggregate PD by the scaled change in the aggregate foreclosure rate (compare Equation (3)). Following the 6 PP increase in the unemployment rate in our stress scenario the aggregate PD increases from 0.91% in the last boom year to 1.87% at the end of the forecast horizon (see Figure 3).

4.2 Results for the EAD model

As described in Section 2.1.3, the original dataset contains only information on the flow of historical mortgage volumes for the subset of the German banking sector, while they must be forecasted for all banks outside the MIR sample based on the regression results from Equation (16). Table 6 shows the respective regression results while summary statistics of the MIR sample can be found in Table 3.

The first two columns of Table 6 report the results of the estimation where new lending also includes prolongations; columns (3) and (4) show results for new lending only, i.e. excluding prolongations. As shown in column (1), the coefficient of the growth rate ($g_{i,t}$) is statistically significant. Its magnitude of 0.75 comes close to the hypothetically expected value of 1.[22] The banking group and time period dummies clearly show that the amortisation rate ($\alpha_{i,t}$) varies significantly across banking groups and with time. One possible explanation of the variation is that $\alpha_{i,t}$ includes also prolongations. Furthermore, increased down payments due to uncertainty regarding the performance of other assets after the financial crisis of 2007/2008 may have also contributed to the variation. Column (2) shows the results of the estimation without the growth rate ($g_{i,t}$). This specification has a considerably lower explanatory power. The R^2 goes up from of 29% to 60% when the growth rate ($g_{i,t}$) is included. This suggests that a better out-of-sample forecast (for the banks outside the MIR sample) can be achieved when the growth rate $g_{i,t}$ is taken into account.

[19]We thank Frieder Mokinski for providing the forecasting code.

[20]The assumed cumulative price drop of roughly 30% over the entire simulation period is similar to Siemsen and Vilsmeier (2017).

[21]The comparable quantiles are even higher when estimated using the data since 2004.

[22]However, the difference is statistically significant.

In the following, we estimate the total historical mortgage lending volume based on Equation (17) for all German banks and compare it to the official MIR statistics estimate.[23] As can be seen in Figure 4, our total estimate is almost identical to the official MIR statistics estimate since 2011, while deviating somewhat in the early years. The largest deviations can be seen in the first two years, which might be due to the significantly smaller coefficients of the early years' dummies (compare Table 6).

Besides comparing the aggregate volumes of historical lending activities, we are very interested in the reliability of the exposure estimations at the individual bank level. In a perfect prediction model, the current outstanding stock of mortgages should be equal to the sum of all net outstanding historical lending flows, i.e.

$$Stock_{j,t} \equiv \sum_K \sum_s \sum_T Lending_{j,T}^{s,K,*} \cdot net\ outstanding_{j,t,T}^{*} \tag{21}$$

Hence, we define $EAD\ fit_j$ as the ratio between the actual mortgage stock of a bank and the sum of its model-implied outstanding past lending flows, i.e.,

$$EAD\ fit_j = \frac{Stock_{j,t}}{\sum_K \sum_s \sum_T \widetilde{Lending}_{j,T}^{s,K} \cdot net\ \widetilde{outstanding}_{j,t,T}}, \tag{22}$$

which can be interpreted as a measure of goodness of fit. For that reason, we keep in our final banking sample only those banks where $EAD\ fit_j$ is in the range $[0.5; 1.5]$. This condition results in the removal of 16 smaller banks with a share of less than 1% of the overall German mortgage market.[24]

In order to further gauge the reliability of our model, Figure 5 depicts the histogram and the empirical cumulative distribution function (ECDF) of that same ratio for the final banking sample. Figure 5 suggests that approximately two thirds of the individual banks in the sample are well approximated by the model. Here, the size of the simulated mortgage portfolios deviates by less than 10%. Approximately 90% of the sample have a deviation of less than 20%. Most importantly, the median of the estimated ratio is close to one, implying that the aggregate mortgage market size is matched very well.

4.3 Results for the LGD model

Figure 6 depicts average LGD values (conditional on foreclosure, compare Equation (6)) of the whole banking sector over the simulation horizon (left panel) as well as for each vintage and LTV-at-origination-bucket (right panel), estimated at the end of the simulation period of the stress scenario. With respect to the LGD calculations, Equation (8) clearly shows the non-linear link between the recovery value and initial LTV values and amortization assumptions as well as the evolution of house prices over time. For the interpretation of the LGD values in Figure 6, it is important to keep in mind that the model estimates are

[23] See Bundesbank (2017) for a description of the MIR statistics estimation approach which is based on the same sample.

[24] Most of the time, the removals are caused by large declines in the reported size of the mortgage portfolio which cannot be explained by ordinary mortgage business and which indicate disinvestments from that business segment and/or reclassification of credit portfolios.

essentially based on the mortgages' current LTVs and can be interpreted as an implicit put option. As a consequence, in an environment of past house price increases, the estimated LGDs are monotonically decreasing and at some point zero for older vintages and for mortgages with lower initial LTVs.[25]

The expected non-linear effect can be seen in the simulation results. The left panel of Figure 6 suggests that, as expected, average LGD values are increasing over the whole simulation period. Yet, the LGD increase is particularly pronounced in the second and the third year of the stress test when the put option-like effects of the mortgage credit risk comes into full effect. In the right panel of Figure 6, the monotone behaviour of the LGD with respect to the LTV at origination can be clearly seen. Generally speaking, higher LTV at origination are associated with higher LGDs for any given mortgage vintage. The results suggest, in particular, considerably lower credit risk for mortgages below LTV of 80%. While the monotone behaviour of the LGD with respect to the LTV at origination is economically intuitive, the shape of the LGD curve depends on the underlying macroeconomic stress scenario. As long as house prices changes are positive or zero (until 2018), the LGD function is decreasing in the age of the mortgage. Essentially, the 2017 vintage mortgages were assumed to be issued at the peak of the house price boom. Hence, in our simulation, subsequent mortgages are issued at lower prices and, hence, decline less in value until 2020. On the other hand, younger vintages have experienced shorter amortization periods, which increases their LGDs. As a consequence, the shape of the LGD function depends on the relative size of the price changes and amortization rates. The curve is positively sloped as long as the amortization rate is smaller than the house price decline and negatively sloped otherwise.

4.4 Overall results for the combined (EL) model

The left panel of Figure 7 shows the average of expected loss estimations over the simulation horizon as well as expected losses for each vintage and LTV-at-origination-bucket (right panel) estimated at the end of the simulation period of the assumed stress scenario and averaged over the whole banking sector. Regarding the evolution of the average EL-curve in the left panel, its shape takes into account both the rising LGDs over time and the increasing PDs. At the end of the simulation period, the aggregate loss rate amounts to 0.45% of the total mortgage exposure of the German banking sector. Figure 8 puts the expected loss estimates into the perspective of historical mortgage loss measures. The severity of the stress test losses is considerably higher than in the last housing downturn experienced during the late 1990's and early 2000's which was characterized by a less steep decline in housing prices but higher unemployment rates.[26]

Looking at the expected losses at the end of the simulation period (right panel of Figure 7), the shape of the EL function is equivalent to the shape of the LGD function in the initial LTV dimension. In the vintage dimension, the expected loss is first increasing as the LGD is increasing and the PD for older vintages is decreasing.[27]

[25]Note, however, that these model estimates are based on assumed amortization rates. Hence, individual mortgages within each bucket, e.g. with low past amortization rates, might still be subject to credit risk.

[26]When instead of the adverse scenario, a favorable scenario with positive housing and job market developments is assumed, our model predicts for the years 2018-2020 on-going low expected losses.

[27]A pronounced dent in the EL-curve for the vintage 2015 reflects a sharp decrease of the historical

4.5 Distribution of stress effects among banks

We measure the severity of the stress effects in terms of own funds' reductions. For the final banking sample of 1,338 banks, the average Common Equity Tier 1 ($CET1$) ratio drops over the course of the stress testing from 15.9% (unweighted mean) and 15.1% (median) to 15.5% and 14.8%, respectively.[28] The average Total Capital (TC) ratio on a fully loaded basis drops over the simulation horizon from 18.4% (unweighted mean) and 17.6% (median) to 18.1% and 17.3%, respectively. Hence, on average, the direct impact of this rather severe adverse housing scenario seems to be significant but not critical. However, the average values are not fully representative for the whole German banking sector as only banks with a sufficiently large residential mortgage portfolio are included in the sample.

To put the reductions of funds into perspective, we compare them to the regulatory thresholds of Basel III. Specifically, we calculate two versions of the excess capital ratio. The first one is defined as the difference between the observed $CET1$ ratio and the regulatory threshold of 4.5%.[29] The second one is the difference between the observed $CET1$ ratio and the regulatory threshold of 4.5% plus the capital conservation buffer of 2.5%. Figure 9 depicts the respective distributions of the estimated percentage reduction of excess capital across all banks in the final sample at the end of the stress test. Under the simulated adverse scenario, the majority of the banks in the sample will be faced with a reduction of up to 15% of their excess capital ratio. While no bank falls below the above mentioned regulatory threshold, one bank experiences a reduction of its excess capital position of at least 50%.[30] Overall, the results suggest that the stress effects are not concentrated on a few banks but are rather widely spread in the German banking sector.

5 Macroprudential perspective and policy considerations

The presented stress test offers a useful tool to analyse and quantify expected losses in the mortgage portfolios of German banks conditional on a macroeconomic scenario. It can help to detect potential vulnerabilities in the German banking sector and, therefore, provides valuable input to the surveillance of risks stemming from residential real estate markets as well as to policy considerations. However, its narrow focus on credit losses in the residential mortgage portfolios without accounting for potential contagion and second-round effects in the course of a severe macroeconomic downturn as well as data shortcomings need to be taken into account when interpreting the results in terms of risks

PDs reported in the COREP data.

[28] The estimated capital reductions consider only credit losses; adjustments of risk weighted assets, e.g. due to changes risk weights, are not taken into account.

[29] As an illustrative example, if a bank has a $CET1$ ratio of 10.5% and it loses 3pp during the stress test, the percentage reduction of excess $CET1$ ratio is 50%. A reduction of 100% suggests that prevailing capital will not be sufficient to accommodate regulatory requirements.

[30] Please note however that these values should be seen as a lower bound for the excess capital impact as O-SII and G-SII buffers as well as Pillar 2 requirements (P2R) and Pillar 2 guidances (P2G) are not reflected.

to financial stability and potential policy implications.

First of all, the presented stress test framework only covers residential real estate loans to private households and does not take into account exposures and respective losses from RRE and CRE loans to enterprises.[31] We excluded the latter from the analysis due to limited data availability and comparability between RRE loans to private households and commercial enterprises. While Figure 10 suggests that provisioning rates for RRE loans to enterprises were similar for RRE loans to private households and enterprises since 2003, provisioning rates for the CRE loans after the peak of the last German real estate cycle were more than twice as high as for the RRE exposures. Due to potential correlation between different real estate market segments, the simulated shock should not only have affected the RRE mortgages to private households but would have an impact on the entire real estate loan portfolio of the German banks. Hence, the stress test effects should have been significantly higher if all real estate related exposures were considered.

Second, the estimated stress test effects do not account for possible repercussions with the microprudential regulatory framework like potential changes of risk weights triggered by rising default rates and losses in the assumed macroeconomic scenario. The effects of the simulated shock on the mortgage risk weights and RWAs are likely to be significant. Further analysis is, however, needed to quantify these effects especially with regard to the implications of interactions between PDs and LGDs on risk weights.[32]

Furthermore, in order to interpret our results in a systemic risk context, the expected losses have to be seen in broader macroeconomic environment and the general profitability of the German banking sector. In an otherwise positive environment, the results suggest that banks could absorb the aggregate losses from our mortgage stress test by other profits. But in the context of a broader macroeconomic recession or a financial crisis that goes beyond the housing sector, the cumulative losses would further erode the risk-bearing capacity of the German banking sector. This is particular relevant, as an isolated residential real estate shock without broader macroeconomic implications appears to be an unlikely scenario. The results from the macroeconomic PVAR analysis suggest that significant spillover effects exist from the housing market on macroeconomic variables such as for instance the unemployment rate. Rising unemployment in turn might induce higher loss rates not only for the RRE mortgage portfolio but also for other loans to private households. Moreover, a housing market downturn is likely to occur in parallel with a significant decline in corporate credit portfolios, in particular in the construction sector. This broader macroeconomic view is supported by various empirical studies for the United States[33] and other OECD countries[34]. These studies suggest a close link between national housing markets, macroeconomic performance and monetary policy. In addition, housing market shocks can have an even wider collateral effect on consumption through wealth effects.[35] These macroeconomic feedback loops between the housing market and

[31] Residential real estate mortgages to commercial enterprises account for approximately 12% of outstanding RRE mortgages for German banks.

[32] Impact assessments at the portfolio level are complicated by the concavity of the Basel formula according to Art. 154 CRR and the non-linear LGD impact due to the 10% LGD-floor according to Art. 164(4) CRR.

[33] See Iacoviello (2005)

[34] See Iacoviello (2000), Goodhart and Hofmann (2008), Assenmacher-Wesche, Gerlach, et al. (2008) and Igan and Loungani (2012)

[35] See Iacoviello (2011) and Case, Quigley, and Shiller (2013)

the broader economy have to be kept in mind when assessing of the severity of the stress effects. Due to the limitations described above, the results of this stress test should be rather seen as a lower bound of the possible impact of an adverse macroeconomic shock for the German banking sector.

Nevertheless, regarding the borrower-based macroprudential measures, the analysis highlights the importance of LTVs as drivers for LGDs and credit losses in the mortgage portfolio. Further work is needed for a thorough model calibration of how potential LTV restrictions would influence lending policies and ultimately borrower and mortgage characteristics. In particular, more analyses on the link between initial and current LTVs and PDs are needed. For instance, there is strong evidence that PDs and LGDs are correlated not only in the time dimension but also in the cross section in a downturn. Empirical studies suggest in particular that overly indebted households with high LTVs were prone to default on their mortgage debts which leads to high losses on these loans (see e.g. Elul et al., 2010, Qi and Yang, 2009 or Gaffney et al., 2014). On the other hand, high LTV loans might be predominantly issued to households with sufficiently high and stable income or other types of guarantees (see e.g. Lambrecht et al., 1997), effectively suggesting a lower PD-LGD correlation. The data from the EBA portfolio benchmarking exercise suggestst a hump-shaped relation between current LTVs and default rates (see Figure 11), at least for the sample of German IRB banks. Yet, without a better understanding of the multivariate risk parameter distributions, such correlations remain unaccounted for and might bias the results towards one side or the other.[36] Last but not least, more research is needed regarding the link between DTI and DSTI ratios and PDs.

[36]Figure 7 highlights the stress test limits with univariate distributions. Essentially, the right panels of Figures 6 and 7 have the same shape in the x-dimension as the LGD values of each LTV bucket are multiplied with the same probability of default.

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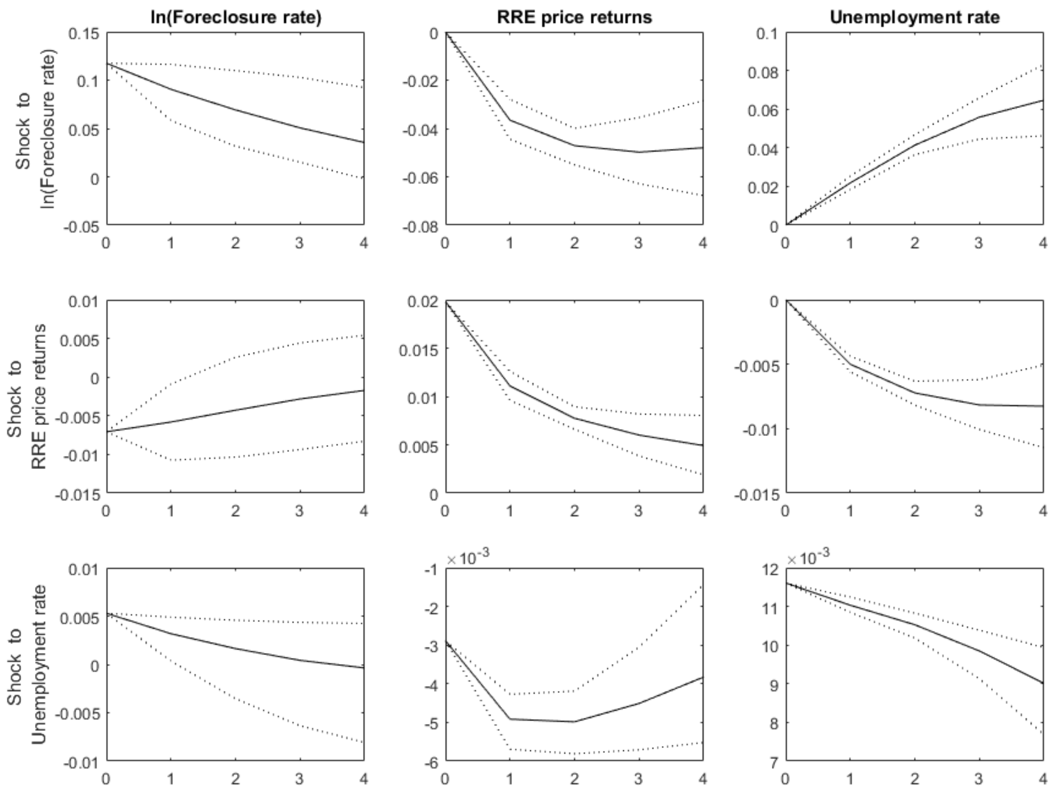
A Appendices

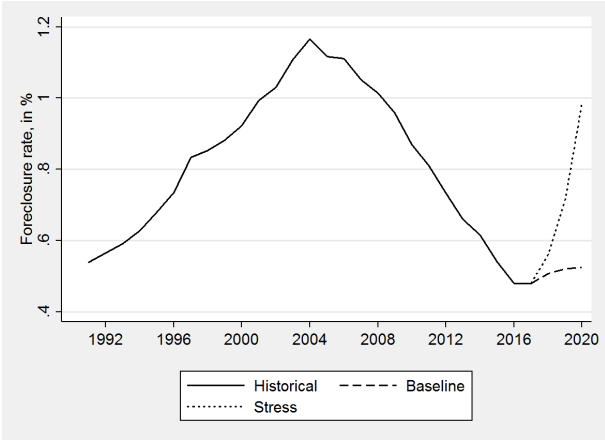
A.1 Figures

Figure 1: Impulse response functions for foreclosure rate, house price changes and unemployment rate



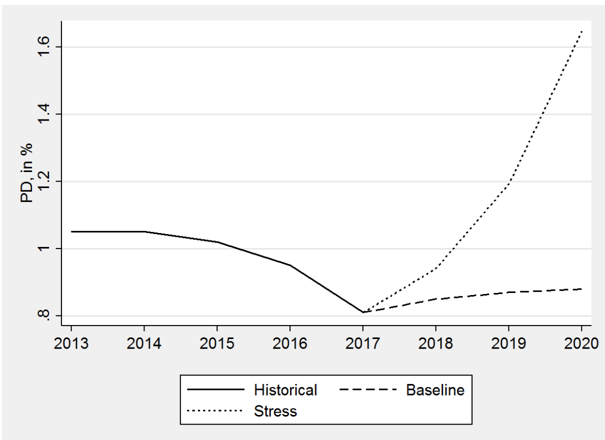
Note: The plots show responses to shocks of one standard deviation in the variables. The response functions are estimated using regional price data for 16 German federal states for the time period 1991-2016. Dotted lines indicate the 90% confidence intervals.

Figure 2: Historical and forecasted aggregate foreclosure rates for Germany over time



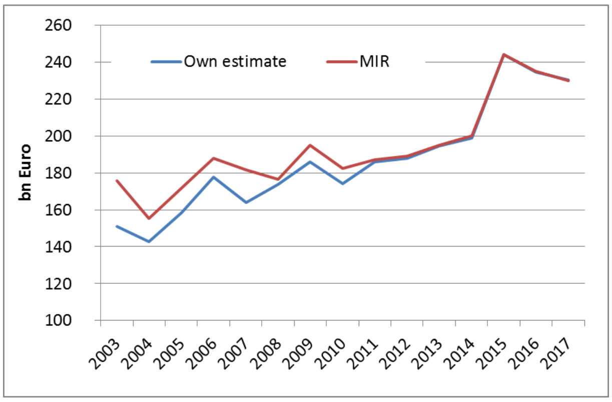
Note: Historical foreclosure rate estimates are based on the state-specific information on the number of foreclosures reported by the Federal Statistics Office, and the state-specific information on the share of households with mortgaged debt and the number of persons per household derived from the German Household Finance and Consumption Survey (HFCS). The forecasts are based on the estimated PVAR and conditional on the prevailing macroeconomic scenario, baseline or stress.

Figure 3: Historical and forecasted aggregate PDs over time



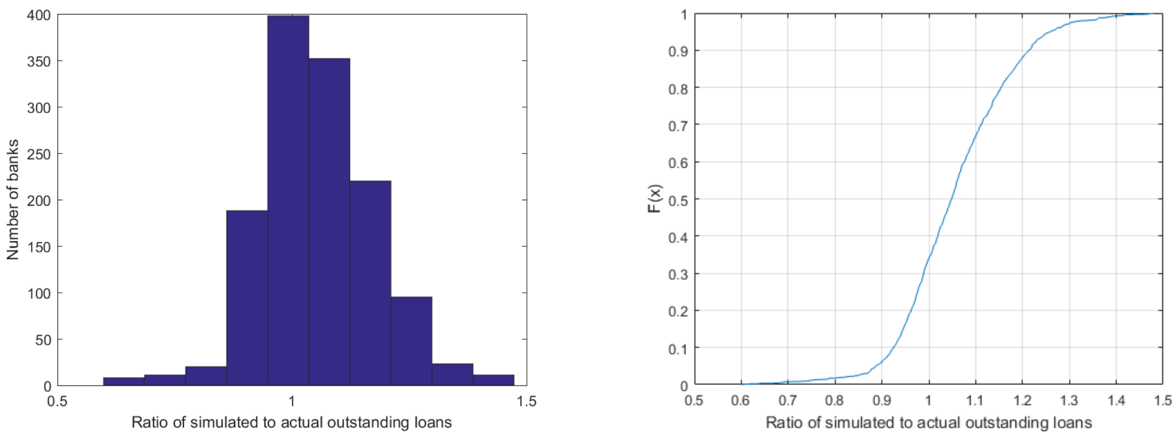
Note: Historical PDs are based on IRB bank estimates reported under COREP. The forecasts are calculated based on the forecasted aggregate foreclosure rates.

Figure 4: Aggregate mortgage lending volume since 2003 for Germany



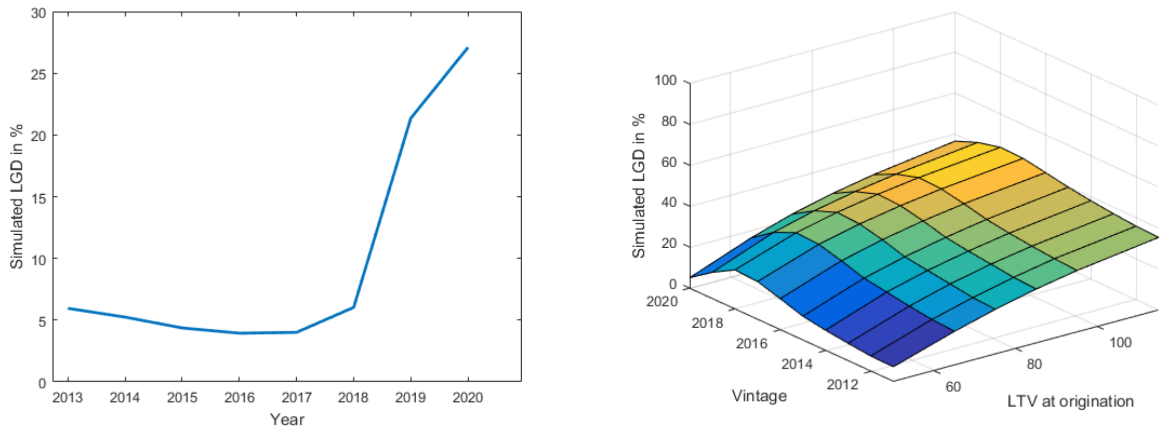
Note: Annual mortgage credit flows to private households on the basis of MIR statistics (red line) are gross of prolongations and refinancing; the estimated annual credit flows (blue line) are based on regression model (see Equation 16).

Figure 5: Histogram (left) and empirical CDF (right) of the estimated ratio between simulated and actual outstanding mortgages



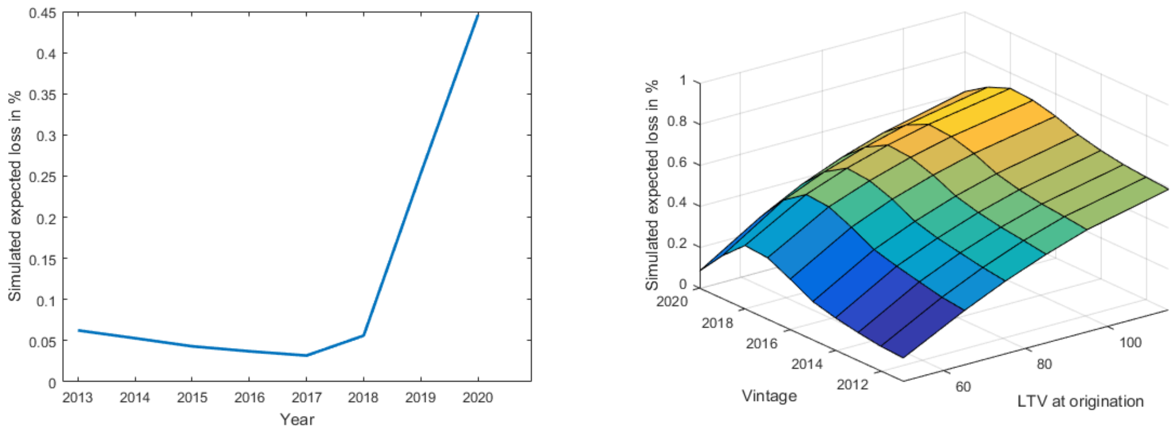
Note: The ratio is estimated based on data for the final sample of banks for the year 2017. Actual outstanding mortgage volume are derived from borrower statistics; simulated mortgage volumes are calculated as outstanding past lending flows (see Equation 22).

Figure 6: Estimated LGDs (in %) over the whole stress scenario (left) and by LTV bucket and mortgage issuance year (vintage) at the end of the stress scenario (right)



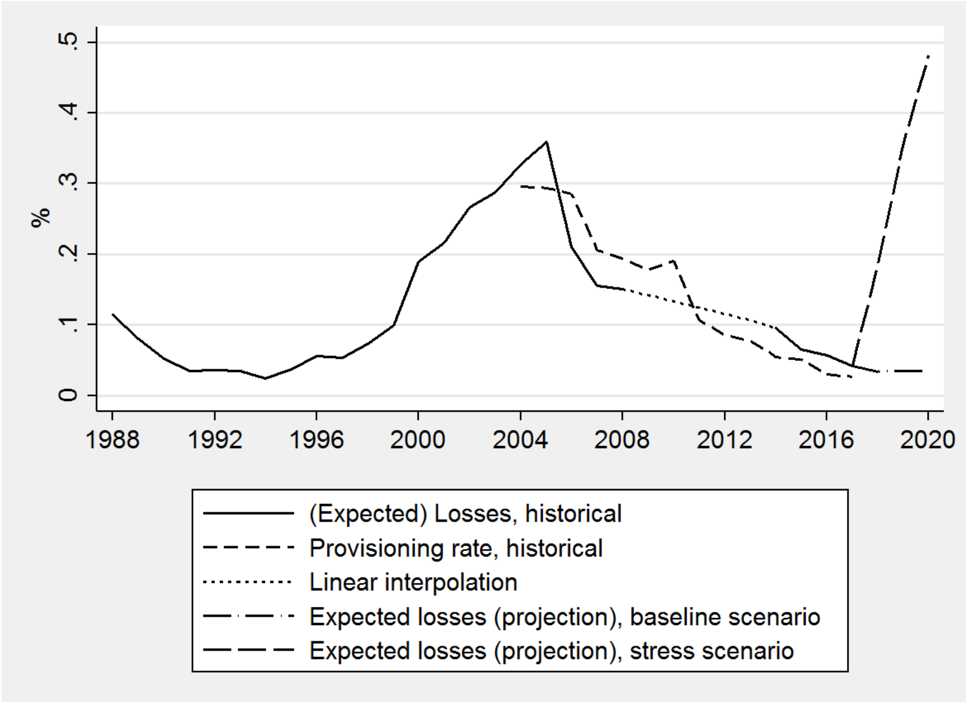
Note: Plotted are the EAD-weighted averages of the estimated LGD values (see Equation 8) for the final sample of banks.

Figure 7: Estimated ELs (in %) over the whole stress scenario (left) and by LTV bucket and mortgage issuance year (vintage) at the end of the stress scenario (right)



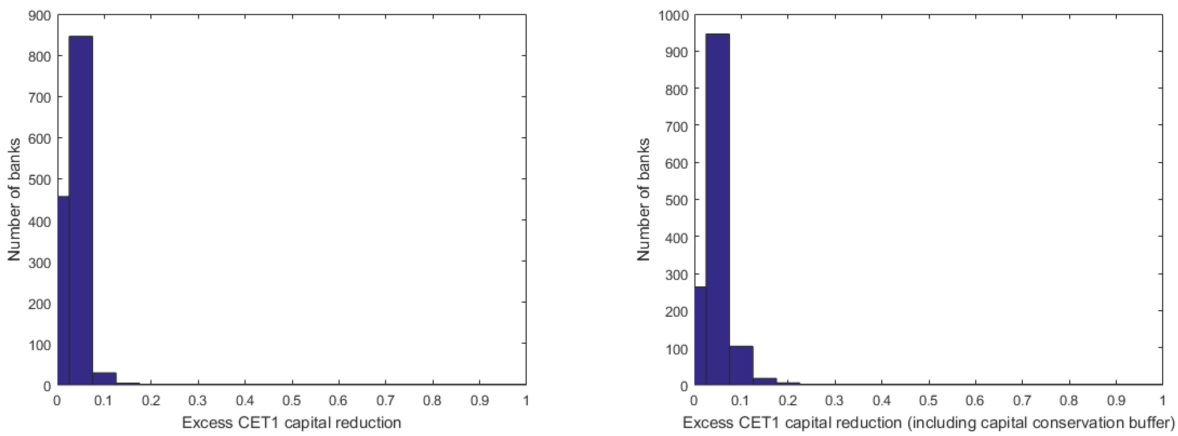
Note: Plotted are the EAD-weighted averages of the estimated expected losses for the final sample of banks.

Figure 8: Historical and stress testing loss estimates



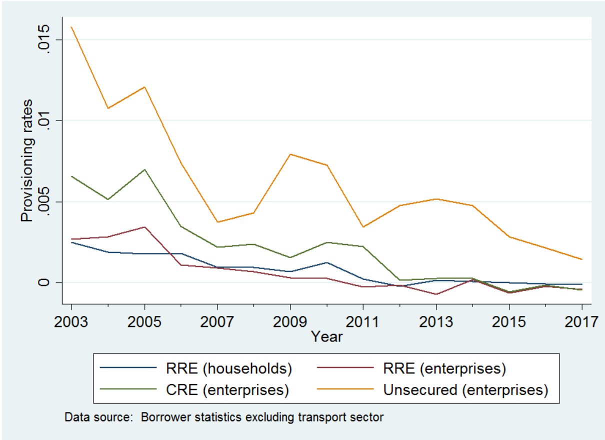
Note: Historical expected losses until 2008 are based on estimates provided by the German banking association; figures for 2014-2017 are based on COREP data; values for 2009-2013 (dotted line) are set by linear interpolation between the estimate of the German banking association for 2008 and COREP data reported for 2014. The historical provisioning rate is derived from the borrower statistics.

Figure 9: Histogram of estimated excess capital ratio reductions



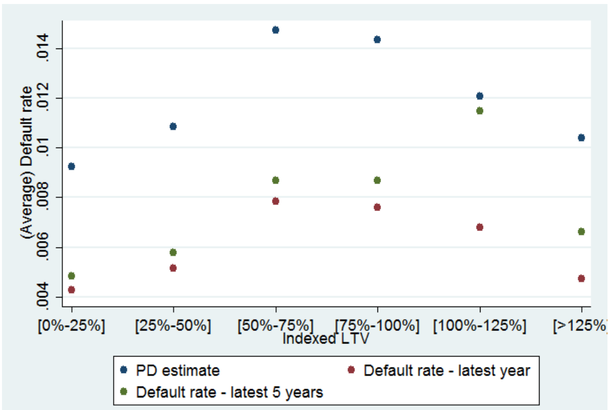
Note: Plotted are cumulative percentage capital reductions for the final sample of banks over the entire simulated period.

Figure 10: Average provisioning rates for loans to private households and enterprises in Germany



Note: Provisioning rates are calculated based on borrower statistics for the following four loan types: residential real estate (RRE) loans to private households including self-employed persons, RRE loans to enterprises, commercial real estate (CRE) loans to enterprises and unsecured loans to enterprises.

Figure 11: Bank internal PD estimates and historical default rates by Current-LTV bucket



Note: Own calculations based on the EBA portfolio benchmarking exercise data for German IRB banks as of Q4 2015, frequency weighted.

A.2 Tables

Table 1: Expected signs of estimated PVAR impulse-response functions

Impulse/Response	$\ln(FCR)$	ΔP	U
$\ln(FCR)$	+	?	?
ΔP	-/0	+	-
U	+	-	+

Table 2: Estimation results for the PVAR model including foreclosure rate, house price changes and unemployment rate

	$\ln(FCR_t)$	ΔP_t	U_t
constant	0.002	0.000	-0.001
	(0.005)	(0.001)	(0.000)
$\ln(FCR_{t-1})$	0.617	-0.005	-0.019
	(0.029)	(0.005)	(0.003)
ΔP_{t-1}	-1.509	0.498	-0.106
	(0.273)	(0.049)	(0.031)
U_{t-1}	1.985	-0.426	0.949
	(0.256)	(0.046)	(0.029)

Note: Estimation is based on regional price data for 16 German states for the time period 1991-2016. Estimated standard errors in parentheses.

Table 3: Summary statistics for the final MIR bank sample.

	Sample	No of observations	Mean	Std.
$\Delta Stock_t/Stock_{t-1}(g_t)$	2003–2017	2,394	0.021	0.074
$Lending_t/Stock_{t-1}$	2003–2017	2,394	0.203	0.089

Note: $Stock_t$ refers to the stock of outstanding residential real estate loans to private households (including self-employed persons). $Lending_t$ denotes new lending gross of loan refinancing and prolongations. Source: Borrower statistics and MIR statistics.

Table 4: Parameter choices for model calibration.

LGD parameters		
Default fixed costs	LGD_{FC}	3%
Cured share	ω_{cure}	40%
Depreciation rate	δ	1.5%
Share of subordinated building society mortgages		50%
Subordination for building society mortgages	$LTV_K - LTV_S$	20%
EAD parameters		
Probability of exercising partial prepayment option	$Prob_{PPP}$	40%
Parameters based on PHF survey		
Average share of households with mortgage	$w_{mortgage}$	18%
Average number of persons in households	$n_{persons\,per\,HH}$	2.05

Table 5: Macroeconomic scenarios.

		Last	Baseline			Stress		
		2017	2018	2019	2020	2018	2019	2020
RRE price index	ΔP	7.0%	7.0%	7.0%	7.0%	0.0%	-14.0%	-18.0%
Unemployment rate	U	4.1%	4.1%	4.1%	4.1%	7.0%	8.0%	10.0%

Note: Unemployment rate based on ILO-definition.

Table 6: Estimation results for regression model specified in Equation (16)

	Lending incl. (1)	prolongatios (2)	Lending excl. (3)	prolongatios (4)
g_t	0.747***		0.894***	
	(0.017)		(0.028)	
Year dummies:				
2004	-0.011	-0.018*		
	(0.007)	(0.009)		
2005	0.002	-0.013		
	(0.007)	(0.009)		
2006	0.024***	0.009		
	(0.007)	(0.009)		
2007	0.019***	-0.009		
	(0.007)	(0.009)		
2008	0.036***	0.011		
	(0.007)	(0.009)		
2009	0.057***	0.041***		
	(0.007)	(0.009)		
2010	0.029***	0.016*		
	(0.007)	(0.009)		
2011	0.035***	0.031***		
	(0.007)	(0.009)		
2012	0.026***	0.022**		
	(0.007)	(0.009)		
2013	0.033***	0.029***		
	(0.007)	(0.009)		
2014	0.029***	0.029***		
	(0.007)	(0.009)		
2015	0.057***	0.061***		
	(0.007)	(0.009)		
2016	0.036***	0.043***	-0.014***	-0.013*
	(0.007)	(0.009)	(0.004)	(0.007)
2017	0.023***	0.023**	-0.024***	-0.030***
	(0.007)	(0.009)	(0.004)	(0.007)
Banking group dummies	+	+	+	+
Constant	0.159***	0.135***	0.145***	0.127***
	(0.007)	(0.009)	(0.007)	(0.012)
Observations	2394	2394	511	509
R^2	0.607	0.293	0.761	0.265

Note: Dependent variable is the ratio $Lending_t/Stock_{t-1}$. Columns (1) and (2) report the results for the specification where lending includes prolongations; columns (3) and (4) show results for true new lending, i.e. excluding prolongations. All four regression specifications include banking group dummies. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A.3 Robustness analysis

A.3.1 Macroeconomic PD sensitivities based on SOEP unemployment data

In order to complement the results of the PVAR, we approximate the change in the default probabilities by a matrix of employment transition probabilites based on the Socio-Economic Panel (SOEP) data from 1998 to 2012 (see Table 7).[37] Here, we run a series of static and dynamic time series regressions (based on levels and 4-quarter changes) in order to estimate the PD_{SOEP}-sensitivity with respect to the general unemployment rate.

In general, we assume that there two distinct components to default probabilities at the aggregated level. There is a structural time-invariant component, $\overline{PD}_S$, and a cyclical component, PD_C, which is driven by aggregate macroeconomic factors affecting the households income situation, in particular changes in the employment status.

$$PD = \overline{PD}^S + PD^C \tag{23}$$

In order to estimate the required macroeconomic sensitivities on the total default probability it is therefore sufficient to estimate the sensitivities of the later component as the structural component is assumed to be time-invariant. In a first step, we estimate the quarterly probability transition matrix for German individuals for becoming employed and unemployed for each quarter based on SOEP data for the time period 1998 to 2012.

Table 7: Average quarterly employment probability transition matrix: based on SOEP data for the time period 1998 to 2012

	Employed	Unemployed
Employed	0.994	0.006
Unemployed	0.004	0.959

As a second step, we then calculate the one-year forward looking default probability PD_{SOEP} as the probability of an individual becoming unemployed some time during the last year and not being employed again within 3 quarters, i.e. remaining unemployed for at least one year:

$$PD_{SOEP} = \sum_{i=0}^{3} p_{EU,t-i} \cdot p_{UU,t+1-i} \cdot p_{UU,t+2-i} \cdot p_{UU,t+3-i} \tag{24}$$

with p_{EU} and p_{UU} being the transition probabilities between the states *employed* and *unemployed* and staying unemployed. This yields an average estimate of $PD_{SOEP} = 2.2\%$ for the cyclical component PD_C over the entire time period.

As a final step, we run a series of static and dynamic time series regressions (based on levels and 4-quarter changes) in order to estimate the PD_{SOEP}-sensitivity with respect to the general unemployment rate. According to the results, the PD_{SOEP}-estimate increases by 15bps for each percentage point increase in the unemployment rate. This suggests the following law of motion for the estimated default probabilities:

[37] The SOEP data used in this paper are derived from the Socio-Economic Panel (SOEP) Version 30 (1984-2013) provided by the Deutschen Institut für Wirtschaftsforschung (DIW Berlin). For details on the SOEP Study see Goebel, Grabka, Liebig, Kroh, Richter, Schröder, and Schupp (2018).

$$PD_t = PD_{t-1} + \Delta PD_t^C + \Delta PD_t^S \tag{25}$$
$$= PD_{t-1} + \Delta PD_t^C + \epsilon_t^S \tag{26}$$
$$= PD_{t-1} + 0.15\Delta U_t + \epsilon_t^C + \epsilon_t^S \tag{27}$$

where ϵ_C would include other cyclical (macroeconomic) impact factors. According to this law of motion, an 6 PP increase in the unemployment rate in our stress scenario is associated with a 0.88 PP increase in the probability of default, which is very close to the predicted unemployment effects of 0.96PP obtained using the PVAR. Hence, the results of the regression analysis using the SOEP-data confirm the findings from the PVAR approach.

A.3.2 Macroeconomic scenarios of other stress tests

Table 8: Macroeconomic scenarios of other recent stress testing exercises.

		Baseline			Stress		
EBA stress test 2016		2016	2017	2018	2016	2017	2018
RRE price index	ΔP	5.6%	6.3%	5.7%	-5.4%	-0.5%	1.4%
Unemployment rate	U	4.9%	5.2%	5.4%	5.4%	6.5%	7.3%
EBA stress test 2018		2018	2019	2020	2018	2019	2020
RRE price index	ΔP	4.8%	4.0%	3.8%	-8.8%	-9.5%	0.2%
Unemployment rate	U	3.3%	3.1%	2.9%	4.2%	5.5%	6.1%
IMF stress test 2016		2016	2017	2018	2016	2017	2018
RRE price index	ΔP	4.0%	2.9%	2.8%	-1.0%	-2.0%	-7.2%
Unemployment rate (Adverse Scenario 1)	U_1	4.7%	4.7%	4.7%	6.0%	6.7%	6.0%
Unemployment rate (Adverse Scenario 2)	U_2				5.9%	6.5%	5.9%