One policy to rule them all? On the effectiveness of LTV, DTI and DSTI ratio limits as macroprudential policy tools

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We employ household-level microdata to assess the effectiveness of macroprudential policy tools in identifying vulnerable households. We evaluate loan-to-value (LTV), debt-to-income (DTI) and debt service-to-income (DSTI) limits with regard to their impact on the following two potential errors: denying nonvulnerable households access to credit (type I) and not preventing vulnerable households from obtaining credit (type II). Therefore our analysis also takes into account the potential costs of falsely restricting credit access to financially sound households. Our data allow us to measure vulnerability based on current values the macroprudential tools refer to, as well as classical vulnerability measures not related to these tools. We find that policymakers' awareness of their own goals and preferences in terms of weights of type I and II errors are crucial to effectively use the macroprudential tools at hand. Our analysis delivers qualitative results to better understand the mechanics of macroprudential policy measures as well as a tool for their evaluation in terms of costs and benefits. However, to employ our tool for actually steering policy limits, a far larger sample or register data would be necessary, as an estimation based on our relatively small survey sample is not precise enough.

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Loan-to-value (LTV), debt service-to-income (DSTI) and debt-to-income (DTI) ratios are among the most widely discussed macroprudential policy tools. Especially the DSTI has been used for a long time in a relatively large and rising number of countries (Lim et al., 2011). Since summer 2017, legislation has been in force in Austria that enables supervisors to use these policy tools in the future.

In this paper we try to assess the potential effectiveness of these policy instruments in preventing (potentially) vulnerable households from taking up excessive debt, while not restraining financially sound households from getting credit. These two effects are the main motives of using LTV, DSTI and DTI limits. If the application of these ratios is effective, they prevent all (potentially) vulnerable households from borrowing, but at the same time do not prevent financially sound ones from taking out loans. Both failing to prevent vulnerable households from borrowing and erroneously denying sound households access to credit are potentially costly negative side effects of such policies.

There are only very few studies taking into account and analyzing the potential costs of introducing macroprudential policy tools. We follow an approach used by Banbula et al. (2016) to identify both error types: (1) type I, the incorrect identification of nonvulnerable households as vulnerable, which entails denying access to credit to households that should not be constrained in getting credit; and (2) type II, the incorrect identification of vulnerable households as nonvulnerable, which entails giving access to credit to households that should not be allowed to

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take out loans. Neither error can be prevented if a small number of (potential combinations of) indicators are used. However, the preferences of the regulator with regard to weighting type I and II errors are important as together with their distribution, they imply the optimal limits to LTVs, DSTIs and DTIs.

In this paper we employ Household Finance and Consumption Survey (HFCS) data to analyze the effectiveness (as defined above) of LTV, DSTI and DTI limits. To do so, it is crucial to have access to borrower-level data. Borrower vulnerability among households depends on many characteristics at the household level. So far, the HFCS is the only source that provides a dataset which includes representative information with regard to all outstanding mortgage debt as well as all other debt of households at the borrower level. At the same time, it includes a large number of socioeconomic characteristics of these borrowers necessary for an analysis of risk. In particular, it includes household income as well as household balance sheets (including all assets and liabilities), which allow a calculation of exposure at default (EAD) and loss given default (LGD). Such calculations are necessary for an assessment of risk. The dataset also allows an assessment of vulnerability according to the (academic) literature but independent from LTV, DTI or DSTI ratios, which is a prerequisite for assessing the predictive quality of these measures with regard to vulnerability.

We employ nonlinear regression-based methods to examine the predictive capacity of the LTV, DTI and DSTI ratios and construct receiver operating characteristic (ROC) curves to illustrate this capacity. One advantage of this approach is that it allows a simulation-based evaluation of different sets of regulator preferences. Furthermore, it allows calculating the overlap between the three policy instruments with regard to errors I and II. Finally, HFCS data allow us to combine debt information at the time of the receipt of the loan with measures of household vulnerability as well as current EADs and LGDs. This is of utmost importance as what is relevant for financial stability is the resilience of households during the full life cycle of all of their loans and not only their resilience at the time of the receipt of one loan.

So our main questions are the following:

- Given a choice of a policy out of the policy set of LTV, DTI and DSTI limits, what is the quantitative size of error I, i.e. nonvulnerable households not obtaining a loan although they should obtain a loan?
- Given a choice of a policy out of the policy set of LTV, DTI and DSTI limits, what is the quantitative size of error II, i.e. households obtaining a loan although they should not obtain a loan?
- Questions (1) and (2) depend on the vulnerability measure used to identify a household as vulnerable. Therefore we use
  - standard measures independent of LTV, DTI and DSTI to evaluate (1) and (2)
  - the policy tools at hand to evaluate which of the measures (LTV, DTI, DSTI) is most representative of the joint consideration of the measures themselves. Put differently, if one considers all three measures to be similarly informative in terms of future risk, which one is the most effective ratio to use as policy tool?

The remainder of this paper is structured as follows. In section 1, we briefly summarize the relevant theoretical considerations and empirical challenges for an evaluation of LTV, DTI and DSTI for Austria. In section 2, we lay out the data we use as well as our estimation strategy. Section 3 discusses all results. Section 4 summarizes and concludes.

1 Theoretical considerations and empirical challenges

In subsection 1.1 we summarize basic theoretical considerations that we believe to be necessary to understand the problem of setting LTV, DTI or DSTI limits. Subsection 1.2 discusses the data restrictions we face when evaluating these policy tools and their potential effects.

1.1 Theoretical considerations

The basic idea of these macroprudential tools is to prevent households from taking out loans which have a relatively high probability of turning out to be unsustainable.

An LTV limit caps the amount of debt that may be taken out to finance a certain asset (mostly a house or an apartment); it sets a lower bound for the capital a borrower needs to purchase a property in relation to the value of the property. Under the assumption of stable prices, this threshold limits the maximum loss given default (LGD) in case of borrower default in the long run.

A DTI limit caps the amount of debt relative to a borrower's annual income. Therefore, it directly targets the borrower's debt sustainability in the medium term.

A DSTI limit directly caps a borrower's debt service and therefore, implicitly in combination with the maturity and interest rate, it also caps the debt level as such.

When analyzing these policy tools, the following aspects are important to note:

– *The relevant unit of analysis.* The relevant unit is the borrower, not the credit. It is the borrower's income and the borrower's assets which are relevant for calculating these measures. An LTV, a DTI or a DSTI ratio is reasonable only at the borrower level. The borrower owns the collateral whose value is used in the LTV, the income in the DTI, and DSTI is the income of the borrower. Neither does refer to the loan itself. This is especially important as many borrowers have multiple loans. Calculating the DSTI or DTI ratio at the loan level is not informative without adjustment (of income or loans) for multiple loans. The same also holds for the LTV ratio. If multiple loans are used to finance one collateral, the sum of all the loans has to be taken into account for calculating the LTV; otherwise statistics at the loan level are not informative. A consolidated borrower perspective as proposed in the ESRB (2014) handbook prevents such pitfalls: In most cases, the household is the relevant borrower unit. It might have multiple sources of income and multiple loans. All loans and all income sources of all household members have to be taken into account to produce meaningful statistics for LTV, DTI and DSTI ratios. To assess the potential impact of defaults on financial stability, all assets of all household members must be used to calculate the EAD and LGD.
– *The interconnectedness of the policy tools.* The three macroprudential policy tools under consideration – the LTV, the DTI, the DSTI – are connected to each other in different ways. Given a certain household with a certain income level and a certain residential property that the household wants to use as collateral, a higher loan level translates into a higher LTV, a higher DTI and a higher DSTI. This layer of interconnectedness implies a positive correlation of the three measures by their definition. However, given a bank's risk assessment, a bank might allow one measure to be relatively high if the other measures are relatively low. Or it might ignore one extreme value with good reason if the other measures are particularly low. This is not necessarily bad practice; on the contrary, it might be a sign of good risk assessment. To illustrate that, let us

assume a simple but – for the sake of outlay – rather extreme example. A household with rather low income inherits a property in an expensive area. The household wants to take out a loan to renovate the property and to be able to partly rent it out. Think of a house with several apartments in an Austrian tourist region. Such a household might have extremely high current DSTI and DTI ratios (due to their low actual income) but a rather low LTV ratio (due to the inherited property). It might be reasonable to grant credit to the household as the collateral in case of default is large and, therefore, the risk implied by LGD low. Also, the probability of default might be low as the income generated by renting out apartments to tourists after the necessary renovation will allow the household to easily sustain the debt. Such situations lead to a negative correlation between the three measures, especially at the tails of their distributions, induced by the bank's (correct) risk assessment.

– *The micro- and the macroprudential perspectives.* While generally it might make sense to control lending by introducing general lending standards to achieve a macroprudential goal, such as preventing debt-driven real estate booms, flexibility at the microprudential level is important because no single policy tool fits all micro-level situations (see example above). It may be reasonable to partly restrict competition between banks in order to prevent banks with sustainable risk assessment from being crowded out by those that do not assess risks adequately. It is, however, important to allow enough flexibility by means of exceptions in order not to exclude borrowers that are able to service their debt. The challenge is to create exceptions which still allow competition but do not restrain credit supply to those households that have been deemed nonvulnerable ex post and prevent costly bailouts of banks at the same time. The major problem is that the future development of household income, real estate prices, interest rates and economic variables in general at the point of receipt of the loan is unknown and can be estimated only roughly. That is why any choice of a certain policy rule should be as informed as possible and evaluated continuously.

1.2 Empirical challenges

A major problem when evaluating (potential) policy effects of macroprudential policy tools in Austria is the lack of adequate data. Austrian credit registers do not include any household loans below EUR 350,000, which implies that almost all mortgages are not included in credit registers. We therefore do not know the distribution of outstanding loans (including mortgages) of households based on register data. This will not change after the implementation of AnaCredit,[2] as it will not include loans to natural persons, including households in Austria. However, even if these register data include loans and their collateral, it would still be a challenge to consolidate them at the household/borrower level in order to produce real borrower-level LTV ratios. As the credit register does not include any information on borrowers' (current) incomes, useful DTI or DSTI ratios cannot be calculated. Besides, register data also lack information to create other

[2] *AnaCredit is a relatively new international effort to gather microdata concerning debt and borrower characteristics. For further information on AnaCredit, see https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html.*

standard measures of household vulnerability, such as financial margins or minimum income requirements, as well as information on households' other assets, which is necessary for an assessment of risks by means of EADs and LGDs.

Because of this lack of information, the OeNB started to gather additional information on LTVs, DTIs and DSTIs of the mortgages granted by banks to households on a quarterly basis. One major problem here is that this information is available not at the borrower (i.e. the household) level, but at the loan level. It comes in the form of summary statistics instead of loan-level data, which makes it impossible to create any necessary combination of information on the borrower level, such as the joint distribution of LTV, DTI and DSTI ratios. This is a prerequisite for any comparative impact analysis of macroprudential policy, however. Neither does the information include all mortgages taken out in a certain quarter in Austria; it only refers to those granted by certain banks. Furthermore, it remains unclear what the terms income and household actually mean at the loan level. Finally, there is no information about outstanding mortgages or any other information on the stock of assets or liabilities at the loan level, which would be needed for estimates of EAD or LGD or any vulnerability measure for current outstanding debt.

Unfortunately, register data or other supervisory data are not available in a form suitable for an analysis of the effectiveness of the macroprudential policy tools discussed here. That is why we use data from the HFCS, a survey which gathers data on the complete household balance sheet across the euro area and beyond. Of course, there are several important downsides to survey data. Among the most severe ones is sample size. As the HFCS covers the overall household population in Austria, its design is not particularly suitable for analyzing the relatively small subset of Austrian mortgage holders. Any analysis is therefore limited with regard to depth and detail. Another disadvantage of survey data are potential measurement errors. Some households do not answer at all (unit nonresponse), and some do not answer particular questions (item nonresponse). Even though the HFCS tackles these problems with state-of-the-art methodology, such as multiple imputations and complex weighting, it still creates a fair amount of uncertainty with regard to all estimates. Nevertheless, the HFCS is the only data source in Austria which includes all the relevant information for a basic assessment of the effectiveness (as defined above) of macroprudential policy tools. The situation with regard to data on loans at the borrower level is generally similar – albeit not that bad – in many euro area countries. That is the reason why in recent years the HFCS became the major workhorse for analyzing questions of financial stability concerning households not only at the OeNB but at most central banks in the euro area as well as at the ECB (see e.g. Albacete et al., 2016a; Bendel et al., 2016; Christelis et al., 2015; Gross, M. and J. Población, 2017). Note that our analysis should be seen as qualitative assessment of the underlying mechanics and not as a quantitative assessment with the aim of coming up with an optimal policy. It would require a far larger survey sample or register data to be able to estimate optimal policies with the necessary precision.

2 Data and estimation strategy

In subsection 2.1, we briefly summarize information on the HFCS Austria 2014, which we use to conduct our analysis. Subsection 2.2 defines all necessary variables used as well as our estimation strategy.

2.1 Data

We use the second wave of the HFCS in Austria,[3] which was conducted 2014. The HFCS is a euro area-wide project which gathers information on the complete balance sheet of households along with a rich set of socioeconomic variables. The unit of observation is the household, which is usually the relevant borrower level in mortgages.[4] In particular, the HFCS includes information on all outstanding loans of households, including information on the loan at the time of loan receipt but also at the time the survey took place. It therefore allows us to take into account all the outstanding loans of all households in the sample, thereby providing a picture of total outstanding debt of households, of which the largest part (80%) by far are mortgages used to finance the household's main residence. Additionally, the HFCS also includes the value of the collateral at the time of its acquisition as well as an estimate of the value (market price) at the time of the survey interview. It also includes direct questions on the household's monthly debt service, including interest payments.

Furthermore, the HFCS covers all other assets and liabilities of the household as well as the income of all household members, which can be aggregated to the household level in order to calculate household income. Household vulnerability is assessed by a number of different measures commonly used in the international literature on household finance and related financial stability issues. The HFCS was designed to provide the necessary information to calculate most of them, such as financial margins based on basic consumption needs.

While the set of information gathered is almost ideal for analyzing questions of financial stability related to households, sample size is a major problem. The sample of 2,997 households is generally relatively large for Austria (by comparison, the Survey of Consumer Finances used at the Federal Reserve comprises about 6,500 observations to represent the U.S. household population, and the HFCS equivalent in Germany includes about 4,500 observation to represent a household population that is ten times the size of Austria's). At the same time, the subset of indebted households is still relatively small, as only 34% of Austrian households have any debt at all, and only 17% or roughly 400 households hold outstanding mortgage debt. Even though it is clearly preferable to have a relatively small number of arguably representative households and not a large number of households not representing the population of interest, the rather small sample size limits the potential detail in which we are able to analyze the data. This is the reason why we limit ourselves to

[3] *A complete documentation of the methods used in the HFCS can be found in Albacete et al., 2016b, first results are reported in Fessler et al., 2016.*

[4] *We have no information on which household member is actually the person who took out the loan. However, as the focus of the analysis are mortgages which are secured by the home where all household members are living, the relevant unit of analysis is the household. Furthermore, in Austria, borrowers have full personal liability in case of default, which affects all their resources (i.e. present and future income and wealth), which they usually share with all other household members.*

the general questions we posed in the introduction and must refrain from a more detailed socioeconomic characterization of the identified subgroups.

2.2 Estimation strategy

In our empirical setup, we closely follow the method first used by Banbula et al. (2016) to assess the effectiveness of macroprudential policy tools. Formally, we observe a cross section draw of indebted households $i \in I$ and the joint distribution of certain household-level characteristics $P(V,M)$, where V denotes indicator variables indicating household vulnerability by means of standard measures of vulnerability, such as the financial margin, and M denotes our three macroprudential policy tools, LTV, DSTI and DTI. Note that we observe all variables for the actual point in time when the survey took place and additionally estimate LTV, DSTI and DTI ratios for the point in time when the household received the loan by employing the approach followed by Albacete and Lindner (2017), which uses retrospective information collected in the survey as well as Austrian national accounts statistics time series. However, the bulk of outstanding loans was taken out in the last 15 years (almost 70% of the first mortgages on households' main residences were taken out in 1999 or later).

Our main workhorse is a logistic regression of the form

$$P(V = 1|M) = \frac{1}{1 + e^{-(\alpha + M\beta)}},$$

in which we estimate the probability of being vulnerable (V=1) using a constant (α) and the level of a macroprudential policy measure (M). The resulting estimate of β, $\hat{\beta}$ then informs us about the relationship of the policy measure with regard to vulnerability. Furthermore, the estimated propensity scores $\widehat{ps}_i$ for all households allow us to evaluate the predictive capacity of the policy measure in terms of sorting the households into the vulnerable or the nonvulnerable group. This predictive capacity is the main object of interest of our analysis as it informs us about how well a certain policy measure, which in fact is a loan characteristic at the time of acquisition of the loan, can predict if a household is vulnerable today. Particularly, we can evaluate how many households are sorted wrongly and identify the type of error they can be assigned to. A type I error occurs when households are predicted to be vulnerable even though they are not, and a type II error occurs when households are not predicted to be vulnerable even though they actually are (see table 1). By moving the threshold at which a household is considered to be vulnerable, i.e. denied credit, we can evaluate different policy regimes defined by different LTV, DTI and DSTI limits or any combination of those.

To indicate household vulnerability, we use two standard vulnerability measures: 1) the expenses-above-income measure, which indicates that a household directly responds that its expenses are regularly above its income when asked the corresponding question (see annex); and 2) the financial margin, which is based on a calculation of basic

Table 1

Error types

	True state: vulnerable	True state: not vulnerable
Model result: vulnerable	True positive	False positive (type I error)
Model result: not vulnerable	False negative (type II error)	True negative

Source: OeNB.

living expenses and debt service recorded. If the sum of basic living expenses and debt service exceeds household net income, the financial margin is negative and the household is considered to be financially vulnerable. Both of these measures are information at the time of the interview, and the item debt service in the latter one takes into account all liabilities of the household.

In addition to that, this framework allows an easy evaluation of the correlations between policy measures and, therefore, their potential effectiveness. By defining vulnerability as failing to stay below certain thresholds of one or more of the other debt ratios, we can analyze which policy measure might be the most effective one to steer lending given the assumption that all are similarly good proxies of sustainable credit. Specifically, the setting allows us to test certain combinations of thresholds. On the basis of the existing literature (see e.g. Albacete and Lindner, 2013; Bankowska et al., 2017; or Giordana and Ziegelmeyer, 2017), we define the threshold for debt to assets (DTA) as 90%, the threshold for DSTI as 40% and the threshold for DTI as 5 years. A household is defined to be vulnerable, if at least one debt ratio[5] exceeds the corresponding threshold (first definition), or if at least two debt ratios exceed their corresponding threshold (second definition), or if all three debt ratios exceed their corresponding threshold (third definition).[6] Note that all of these analyses are only feasible given the joint distribution of all the measures and, therefore, the availability of all underlying variables at the borrower level (see section 1.1). As above, vulnerability is measured at the time of the interview and all assets or liabilities of the household are taken into account.

The definitions of all relevant variables can be found in table A1 in the annex.

The estimation of the probability of being vulnerable allows a graphical representation of the policy tools' predictive capacity at the time of the loan receipt for vulnerability observed at the time of the survey; this representation is known as the receiver operator characteristic (ROC) curve. For the readers' convenience, we shortly describe how the curve is constructed. The propensity score ps_i can be described as a realization of a continuous random variable PS. Given the threshold ps^*, a household is classified as vulnerable if $PS > ps^*$ and nonvulnerable otherwise. PS therefore follows a propability density $f_t(ps)$ if the household classified as vulnerable actually is vulnerable and $f_f(ps)$ if it is not. The rate at which households are correctly and falsely classified as vulnerable are then given by

$$RC(ps^*) = \int_{ps^*}^{\infty} f_t(ps),$$

and

$$RW(ps^*) = \int_{ps^*}^{\infty} f_f(ps),$$

respectively. The ROC curve then plots $RC(ps^*)$ against $RW(ps^*)$ with the threshold ps^* as the (implicitly) varying parameter. As the threshold in our case refers to the

[5] *Although, strictly speaking, the stock of debt is only used in one of these indicators, all three of them are based on information about the debt of the borrower and hence for the ease of reading are called debt ratios.*

[6] *The vulnerability measure based on the LTV takes into account the wealth position of a particular household whereas the other two measures – DSTI and DTI – take into account income information. As is common in the literature, we do not combine income and wealth at this stage, e.g. by taking DTI and looking at additional financial wealth (Gross and Población, 2017), but instead combine the three measures taking into account whether a household is vulnerable according to one, two or all three of the outlined indicators.*

parameter of the policy choice at the time of loan origin, the ROC directly relates the choice of LTV, DTI or DSTI limit to the correctly and falsely denied share of household loans implied by the data – and also to vulnerability measured at the time of the survey. Note that implicitly, this also includes those households which are correctly and falsely granted credit. The ROC is therefore an ideal tool for analyzing the policy tools at hand as it is straightforward to implement and allows to directly interpret the effectiveness of the policy tools. We also model the preferences of policymakers by introducing weights for type I and type II errors and by assuming that they maximize the difference between the true positive rate and the false positive rate over all possible limit values of a given debt ratio. This criterion is known as the Youden index, which is maximized as follows:

$$\max_{ps^*}\{[1-(\varphi)*RWII(ps^*)]-[(1-\varphi)*RW(ps^*)]\}$$

where φ is the weight for the type II error and $RWII$ is the false negative rate. See subsection 3.2 for results.

3 Results

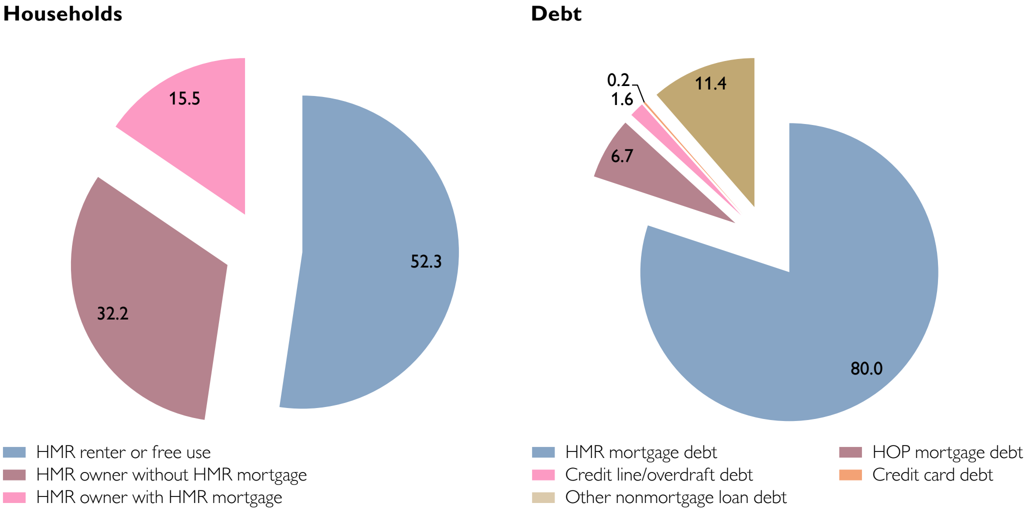
In subsection 3.1, we report descriptive results for household indebtedness and household vulnerability. Section 3.2 includes the results of our logistic estimations and the implied ROC curves.

3.1 Household indebtedness

Roughly 48% of Austrian households own their main residence. About two-thirds of this share have no outstanding debt at all. About 15.5% of all households are owner-occupiers with outstanding mortgages (see left-hand panel of chart 1). About 80% of all household debt is mortgage debt related to Austrian households' main residences (HMR). Another 7% refers to mortgages collateralized by other property than main residences (HOP). Only about 13% of total household debt is uncollateralized (see right-hand panel of chart 1).

Chart 1

Distribution of households and their debt

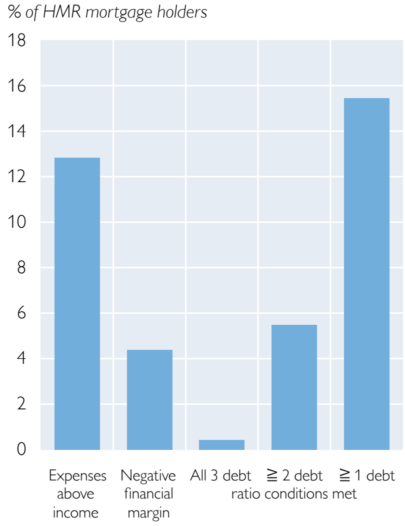


Source: HFCS Austria 2014, OeNB.

The set of HMR mortgage holders is the sample we analyze in this study. Chart 2 shows the prevalence of vulnerable households among these mortgage holders according to the different definitions under consideration. While 13% of HMR mortgage holders indicate that they had higher expenses than income during the last 12 months, only 4% have a negative financial margin at the time of the interview. The definition of financial margin follows a standard procedure from the literature, i.e. we take net income and deduct basic consumption expenditure and debt payment. Furthermore, almost 16% are vulnerable according to at least one out of the three debt ratios (DTA, DSTI and DTI), but only a tiny part (0.4%) are vulnerable according to all three ratios together. Here, we again use the standard definitions for a vulnerable household given by DTA over 90%, DSTI over 40% and DTI over 5 (see also section 2.2).

Chart 2

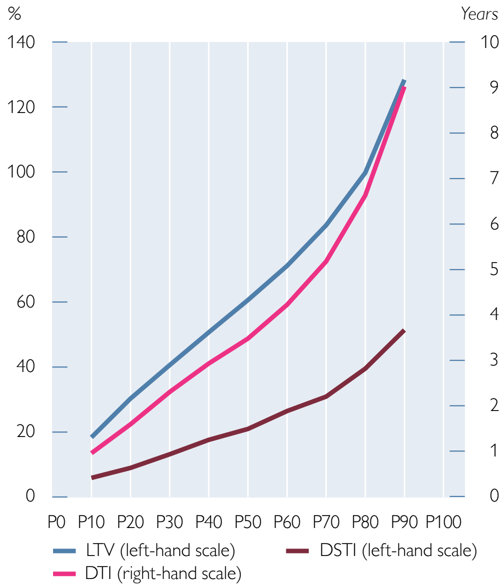
Share of households characterized by different vulnerability measures



Source: HFCS Austria 2014, OeNB.

Chart 3

HMR mortgage holders: percentiles of debt ratios at the time when the mortgage was taken



Source: HFCS Austria 2014, OeNB.

Chart 3 shows the distribution of the LTV, DSTI and DTI measures at the point of loan origination. This chart provides information on where in the distribution we would find a policy measure based on (one of) these three indicators. The HFCS collects information on initial and outstanding amounts of mortgages as well as on the value of real estate both at the time of ownership transfer and at the time of the interview. The former information can be used to estimate initial LTV and its distribution. For the income-based measures, "initial" income needs to be derived from current income and the aggregate change of income in the economy (see section 2.2). The estimated median initial LTV among current Austrian HMR mortgage holders equals 61% (chart 3 at P50), the median initial DSTI equals 21% and the median initial DTI equals 3.5. The DSTI ranges from about 5% to about 50% of income, reflecting the fact that some income is used for living expenses. Around 25% of HMR mortgage holders have LTVs higher than 90% and around 20% of HMR mortgage holders have DSTIs higher than 40% or DTIs longer than about 6.5 years.

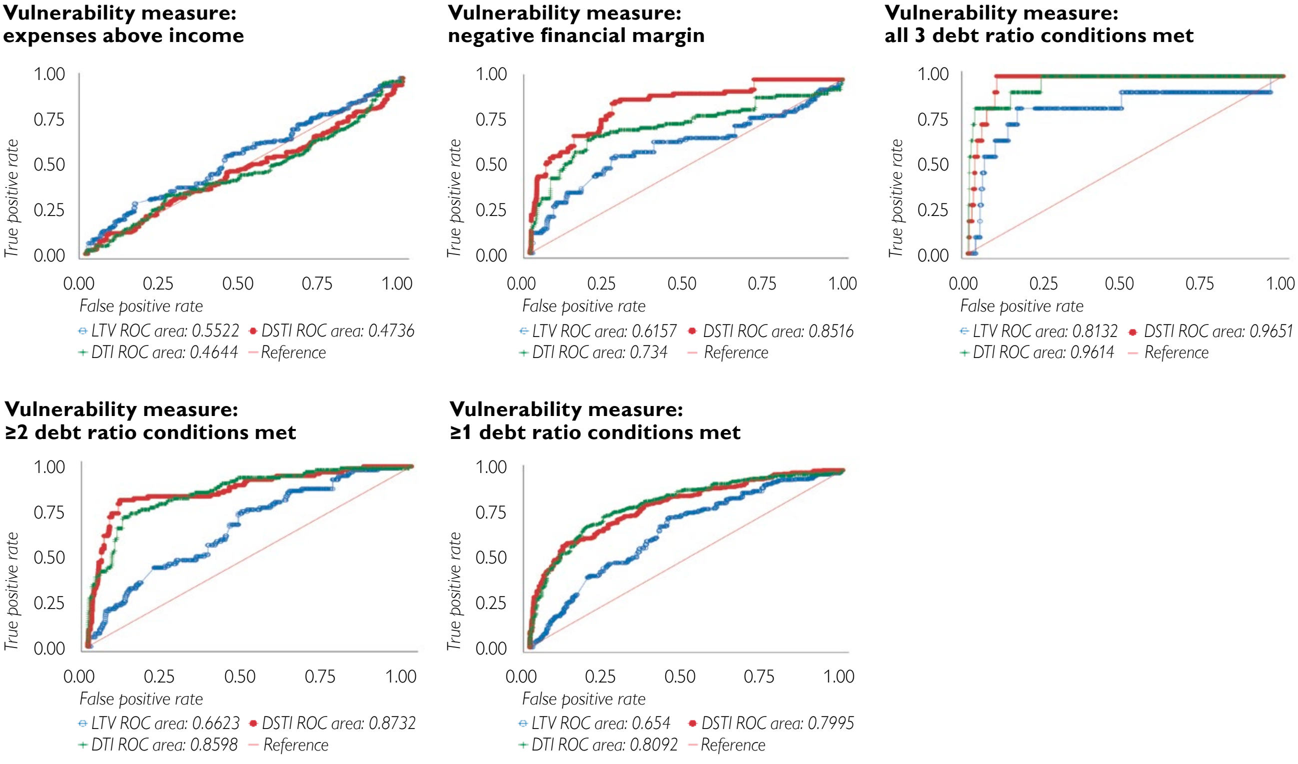
3.2 Effectiveness of policy tools

The basis of the following analysis is the estimation of the logit regressions described in section 2.2. One example of a distribution of the resulting predicted probabilities, i.e. propensity scores, based on one of these regressions is shown in chart A1 in the annex. It can be seen that in general, there is a positive correlation between each of the ratios – LTV, DTI and DSTI – and the indicator being classified as vulnerable. This means that, e.g., a higher LTV at loan origination is associated with a higher likelihood of being vulnerable ex post, as was expected. This translates into a rightward-shifted predicted probability distribution for households classified as vulnerable compared to their nonvulnerable counterparts.

Chart 4 shows the ROC curve and the ROC area statistic for the three policy instruments and for each vulnerability measure. The ROC curve coordinates are estimated as described in section 2.2. The curve shows the share of false positive (i.e. households that would be wrongly excluded from the mortgage market given a policy) against the share of true positive (i.e. households that have been denied credit and turn out to be vulnerable). The 45-degree line is the line of nondiscrimination, i.e. a policy on this line does not separate households in a meaningful way. The area under the ROC curve (ranges theoretically between 0.5 and 1) provides information of how effective a policy is to discriminate households that turn out to be vulnerable from those that are not. All five subfigures consider all three macroprudential policy variables and take several measures (expenses above income, negative financial margin, DTA of 90%, DTI of 5 years and DSTI of 40% as well as

Chart 4

ROC curve and ROC area for three debt ratios



Source: OeNB, HFCS Austria 2014.

combinations of the latter three) to define vulnerability. We find that the income-based policy variables (DSTI and DTI) reflect vulnerability relatively better than the asset-based ones (LTV). Except when measuring vulnerability by expenses above income, the ROC curves of DSTI and DTI always show much higher predictive power for vulnerability than the ROC curves of LTV. This can be seen from the higher ROC curves as well as the higher ROC area statistic.

The inner workings of the ROC curves can be understood from the following example. Suppose that one aims to reach a false positive rate not higher than 0.25. At this point, 25% of nonvulnerable HMR mortgage holders are wrongly classified as vulnerable. Suppose further that vulnerability is defined by the all-debt-ratios-conditions-met measure. This brings us to the subfigure headed "all three conditions met." If the only macroprudential policy instrument available would be the LTV, then the ROC curve tells us that the true positive rate that could be reached would be 0.82 at the highest, meaning that 82% of the vulnerable HMR mortgage holders are correctly classified as vulnerable, or, the other way round, 18% of vulnerable households are wrongly classified as nonvulnerable. The implicit LTV limit behind these two rates would be 90%. However, if the only macroprudential policy instrument would be the DSTI, the reachable true positive rate would be 100% and the implicit DSTI limit would be 33%. And, finally, if the only macroprudential policy instrument would be the DTI, the corresponding true positive rate would be 100%, and the implicit DTI limit would be about 5.7 years. Thus, this example shows that it would be less costly to reach a false positive rate of 0.25 by using DSTI or DTI as a macroprudential tool rather than LTV.

Expenses above income does not seem to be a good measure of household vulnerability, as the ROC curves of the three macroprudential instruments all appear along the diagonal line; this means that the policy tools are as good as flipping a coin to explain this concrete measure of vulnerability. These findings are in line with Banbula et al. (2016), who find that DSTI appears to better reflect vulnerability measured by financial margin rather than by self-assessment. This vulnerability measure is, therefore, excluded for the remaining analysis.

An important element in policymaking are policymakers' preferences. In the case of macroprudential policy using LTV, DTI or DSTI limits, this translates into the question of (implicitly) weighting type I and type II errors. Another element is the question of what to maximize. Let us assume that the policymaker maximizes the difference between the true positive rate and the false positive rate over all possible limit values of a given debt ratio (see section 2.2). Intuitively, this criterion reflects the intention to maximize the rate at which households are correctly classified as vulnerable and not vulnerable.[7]

Table 2 shows the corresponding optimal debt ratios resulting from this maximization depending on the weight that one puts on type I error and type II error. If vulnerability is defined according to the negative financial margin measure and both types of errors are equally weighted (φ=0.5) then the optimal LTV limit would be 84%, the optimal DSTI limit would be 30% and the optimal DTI limit 6 years. If less weight is put on type II error, which means that it is preferable to

[7] *There are also other criteria of what to maximize. For example, minimizing the distance between the point (0,1) and the ROC curve or maximizing the product of true positive and false negative rates.*

Table 2

Optimal debt ratios according to the Youden index depending on weight for the type II error (FNR)

	φ=0.75			φ=0.5			φ=0.25		
Vulnerability measure	LTV	DSTI	DTI	LTV	DSTI	DTI	LTV	DSTI	DTI
Negative financial margin	4.5	29.6	0.2	84.1	30.4	6.4	672.7	67.3	9.8
All 3 debt ratio conditions met	106.2	49.6	5.9	106.2	49.6	16.4	181.3	49.6	16.4
≧ 2 debt ratio conditions met	28.1	44.8	3.6	60.7	44.8	7.6	155.6	49.4	7.6
≧ 1 debt ratio conditions met	29.1	9.2	2.8	60.7	39.6	5.1	1,594.5	49.4	8.5

Source: HFCS Austria 2014, OeNB.

Note: The Youden index equals the difference between the true positive rate and the false positive rate over all possible limit values of a given debt ratio.

avoid false positive cases (nonvulnerable HMR mortgage holders wrongly classified as vulnerable), then the optimal limits will generally increase.

Table 2 clearly shows that for the Austrian population of households with a mortgage, the LTV is not a very effective tool to reach policy goals. It produces unrealistically low LTV limits that would be necessary if the policymaker put more weight on preventing type II errors, i.e. not identifying vulnerable households. It also produces unrealistically high LTV limits that would be necessary if the policymaker put more weight on preventing type I errors, i.e. denying credit to nonvulnerable households.

Risks to financial stability can be reduced most effectively by policies putting more effort into preventing the error of not identifying vulnerable households (type II error). However, at the same time, these policies will increase the occurrence of the error of denying credit to nonvulnerable households (type I error), which harms economic welfare. In order to quantify this trade-off one can take the following example (shown in box 1) illustrating how a certain tool can inform policy.

Box 1

Suppose that vulnerability is defined by the "1-debt-ratio-conditions-met measure." In that case the risk to financial stability in terms of LGD is estimated to be 3.4% of total Austrian HMR mortgage debt.

Suppose further that in order to reduce this risk, the policymaker introduces an LTV limit of 61%, which corresponds to the optimal limit estimated in table 2 in case that both types of errors are equally weighted (φ=0.5). Then the rate at which vulnerable households would be correctly classified as such would equal 74%, and LGD would be reduced from 3.4% to 0.5%. However, the rate at which nonvulnerable households would be wrongly classified as vulnerable would equal 45%, which corresponds to 37% of Austrian HMR mortgage debt.

If the policymaker introduced the optimal DSTI limit of 40% instead of the LTV limit, then the correct classification rate of vulnerable households would equal 62%, the LGD would be reduced from 3.4% to 1.8%, and the wrong classification rate of nonvulnerable households would equal 12%, which corresponds to only 7% of HMR mortgage debt.

Finally, if the policymaker introduced the optimal DTI limit of 5 years, then the correct classification rate of vulnerable households would equal 75%, the LGD would be reduced from 3.4% to 1%, and the wrong classification rate of nonvulnerable households would equal 19%, which corresponds to 20% of HMR mortgage debt. In this scenario, DTI would seem a reasonable policy tool because it combines a strong reduction in LGD with a better classification rate of nonvulnerable households, implying less economic cost.

In general, given that banks also use their own models to assess the creditworthiness of borrowers, it seems reasonable to put less weight on avoiding the type II error and more weight on avoiding the type I error since a vulnerable household that is not identified as such by macroprudential policy (type II error) still has to pass the creditworthiness analysis of the banks, but a nonvulnerable household wrongly identified as vulnerable by macroprudential policy (type I error) has no more chance to get a credit. To allow a certain volume of exceptions is another policy option to mitigate this problem and allow for more competition. However, it comes with many follow-up questions, which complicate policy evaluation.

4 Summary and concluding remarks

In this paper, we adapt the approach of Banbula et al. (2016) and apply it to Austria. It provides a tool that lets us discuss the effectiveness of macroprudential policy tools in ex post discriminating households identified as vulnerable from their nonvulnerable counterparts. Like any policy measure, macroprudential policies may also affect households that are not targeted (false positive – type I – error) as well as miss some vulnerable households (false negative – type II – error); and these side effect should be taken into account when designing and applying the policy tools.

We find that DSTI and DTI have a much higher predictive power for vulnerability than LTV has. This suggests a higher effectiveness of income-based macroprudential policy tools compared to asset-based ones. Furthermore, policymakers' awareness of their goals and preferences in terms of weights of type I and II errors are crucial to effectively use any macroprudential tools. Our analysis delivers qualitative results to better understand the mechanics of macroprudential policy measures as well as a tool for their evaluation in terms of costs and benefits. If policymakers put more weight on avoiding the situation in which vulnerable households are classified as nonvulnerable (type II error) they will reduce the risks to financial stability more effectively. However, at the same time they will increase the risk that nonvulnerable households are classified as vulnerable (type I error), which could harm economic welfare. It might be reasonable to put less weight on avoiding type II errors and more weight on avoiding type I errors since a vulnerable household that has not been identified as such by macroprudential tools still has to pass the creditworthiness analysis of banks; on the other hand, a nonvulnerable household wrongly identified as vulnerable by macroprudential tools has no chance of getting a loan. An alternative policy option would be allowing a certain level of exceptions to mitigate this problem and to increase competition. But such an alternative option would provoke many follow-up questions, which, in turn, would complicate policy evaluation.

While generally it might make sense to control lending by introducing general lending standards to achieve a macroprudential goal, such as preventing debt-driven real estate booms, flexibility at the microprudential level is important as no single policy tool fits all micro-level situations (see example above). It may be reasonable to partly restrict competition between banks in order to prevent banks with a sustainable risk assessment from being crowded out by those that do not assess risks adequately. It is, however, important to allow enough flexibility – by means of exceptions – in order not to exclude borrowers who are able to service their debt.

Employing our tool for actually steering policy limits would require far more sample or register data, as an estimation based on our sample is not precise enough.

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Annex

Wording of the HFCS question on expenses above income:

"Again aside from any purchases of assets, over the last 12 months would you say that your (household's) regular expenses were higher than your (household's) income, just about the same as your (household's) income or that (you/your household) spent less than (your/its) income?"

Coding:
1 – Expenses exceeded income
2 – Expenses about the same as income
3 – Expenses less than income

Table A1

Definition of variables

Variable name	Variable definition
Dependent variables	
Expenses above income	1=expenses exceed income; 0=otherwise (see wording of the question in the annex)
Negative financial margin	1=the sum of total household debt service (from collateralized and noncollateralized debt) and estimated total household nondurable consumption exceed estimated total household net income; 0=otherwise
All 3 debt ratio conditions met	1=all of the following conditions met: current DTA[1]>90%, current DSTI[2]>40%, current DTI[3]>5 years; 0=otherwise
≧ 2 debt ratio conditions met	1=at least two of the following conditions met: current DTA[1]>90%, current DSTI[2]>40%, current DTI[3]>5 years; 0=otherwise
≧ 1 debt ratio conditions met	1=at least one of the following conditions met: current DTA[1]>90%, current DSTI[2]>40%, current DTI[3]>5 years; 0=otherwise
Explanatory variables	
LTV	HMR mortgage amount at the time when the highest mortgage was taken out divided by the value of the property at the time of its acquisition
DSTI	Annual HMR mortgage repayment divided by total household annual net income at the time when the highest mortgage was taken out
DTI	HMR mortgage amount at the time when the highest mortgage was taken out divided by total household annual net income at the time when the highest mortgage was taken out

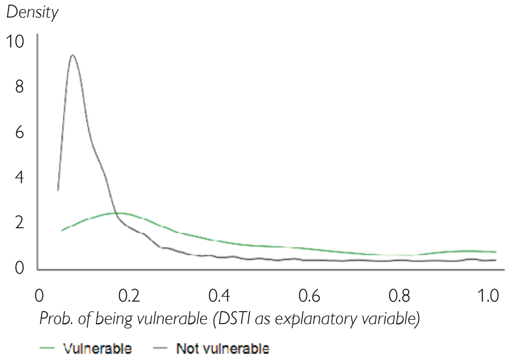
[1] Current DTA is defined as total current household debt (collateralized and noncollateralized) divided by total current household assets (financial and real).
[2] Current DSTI is defined as total current household debt service (from collateralized and noncollateralized debt) divided by total current household net income.
[3] Current DTI is defined as total current household debt (collateralized and noncollateralized) divided by total current household annual net income.

Source: Authors' compilation.

Chart A1

Distribution of predicted probabilities by vulnerability status

Vulnerability measure:
≧ 1 debt ratio conditions met



Source: OeNB, HFCS Austria 2014