Risk Buffer Profiles of Foreign Currency Mortgage Holders

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In Austria, the share of foreign currency mortgages in total household debt has been increasing since the late 1990s. Today about one-third of household credit debt is denominated in foreign currency, mostly in Swiss francs. A major issue with regard to the resulting implications for financial stability is the vulnerability of indebted households. Do foreign currency borrowers opt for foreign currency loans because they cannot afford a given loan in domestic currency? Or are foreign currency borrowers just less risk averse and better able to absorb risks than their domestic currency counterparts?

We employ a subsample of the Household Survey on Housing Wealth 2008 for the first borrower analysis of this kind for Austria. Using simple linear regression techniques may be misleading given the heterogeneity of borrowers' characteristics and the heterogeneity of differences along risk buffers. Hence we estimate conditional counterfactual distributions in order to calculate the differences in terms of risk buffers between foreign currency borrowers and their domestic currency counterparts over the entire marginal distributions of the risk buffers. We find that foreign currency borrowers have substantially higher risk buffers than their domestic currency counterparts and therefore reject the hypothesis that most of them have loans in foreign currency because they would not be able to afford the same amounts in domestic currency on account of the higher interest rate burden.

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Household debt has increased in almost all OECD countries in recent decades (see e.g. Girouard et al., 2006). Such an overall observation is, however, not very meaningful as such. Neither does a rise in debt ratios necessarily imply higher instability of financial markets nor do those figures say anything about the adequateness of risk buffers and debt forms. As far as financial stability is concerned the crucial question is whether the debt holders have got adequate resources to absorb the underlying risks. Assessments of financial stability with regard to household debt will therefore need to look into debt holders' vulnerability to certain shocks and the distribution of vulnerability among them.

The scope of aggregate data for analyzing risks for financial stability is very limited. Aggregate data do not allow distinguishing between households who hold debt and those who do not, and it is not possible to balance household debt with household assets in a reasonable way. Yet as the recent subprime crisis has documented even a relatively small number of indebted households can produce heavy turmoil if the sustainability of their household debt is in question (see Beer and Schürz, 2007, and Albacete and Fessler, 2010, for a literature review and results for Austrian households).

In Austria foreign currency mortgages (FCMs), i.e. foreign currency loans taken out to finance real estate transactions, have been popular with borrowers. FCMs, especially those denominated in Swiss francs, became more and more common from the late 1990s onward. Today about one-third of household credit debt is denominated in a foreign

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currency (chart 1). These loans tend to be bullet loans, meaning that the holders make regular payments toward a repayment vehicle to save for the day when they need to pay back the loan in a single payment. This construction implies that the holder basically acts like a carry trader (Beer et al., 2010), implying two additional risk channels compared to domestic currency counterparts: exchange rate risk, and the risk of changes in the value of the repayment vehicle or in the interest rate.

This paper examines whether these additional risks have been accounted for by households and/or banks, i.e. whether risk-bearing capacities are indeed higher among those households who took greater risks. To this effect it is necessary to estimate the size of the differences in risk buffers. After all, households who could not afford a given loan in domestic currency might have found FCMs attractive simply because of their lower interest rates, which would then imply that risk buffers are even lower for FCM holders than for domestic currency loan holders.

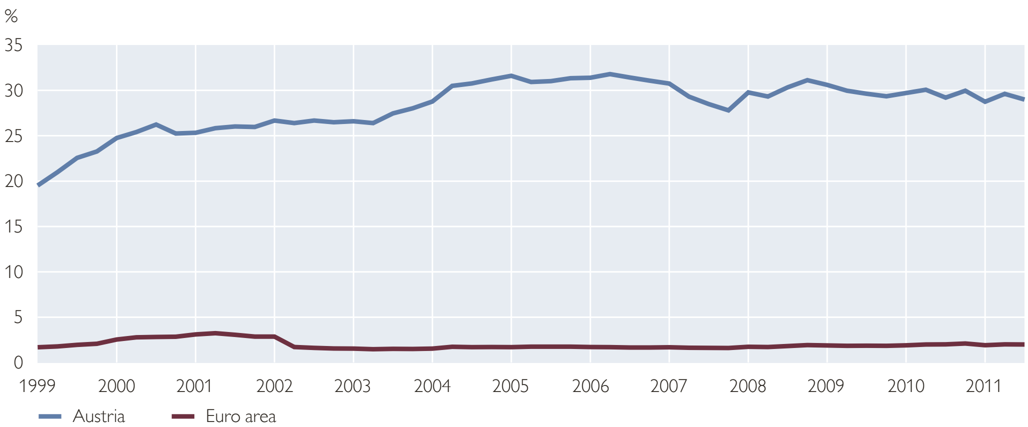
The marketing practices of Austrian banks in Central, Eastern and Southeastern Europe[2] indicate that such considerations have to be taken seriously. It is quite important to look at the marginal distribution of risk buffers and not only at the mean. Some households (banks) may be very careful with taking out (granting) loans while other may not. Some households may have opted for FCMs mainly because of the lower interest rates, failing to adequately take into account the underlying exchange rate and repayment vehicle risks.

Attempts to assess those possible differences in risk buffers are, however, fraught with methodological difficulties.

First, we know very little about the loan granting decisions, which are mainly based on internal data, such as product information, loan-to-value ratios, household income (as far as known to the banks), maturities and probabilities of default and loss-given default of the past by country and products. Furthermore banks may use data on creditworthiness provided by the *Kreditschutzverband* (association for the protection of credi-

Chart 1

Share of Household Debt Denominated in Foreign Currency



Source: OeNB.

[2] *(http://derstandard.at/1319183860502/Kredit-ohne-Fragen-Ein-alter-Werbespot-der-Raiffeisen-kursiert-im-Net), http://www.youtube.com/watch?feature=player_embedded&v=0jXl61uKq8c (retrieved on February 6, 2012).*

tors). As far as we know they have no access to any kind of register data, and they do not use other, survey-based information on households. Under specific assumptions about the future living expenses and behavior of these households they will come to a conclusion about the loan level to be granted. Usually this assessment exercise is undertaken only once, before a loan is granted. Yet the duration of loan repayment may be as long as 25 to 30 years and the financial situation of a household will inevitably change because of instances of unemployment, illness, divorce, inheritance and other unexpected events. To keep up with changing risks, banks would therefore have to reassess the financial situations of their indebted customers periodically. See Fessler and Albacete (2010) for a more detailed discussion of the problem.

Banks assessing their debtors' future risk buffers and ability to repay should ask for higher risk buffers when granting a FCL than when granting the same amount in domestic currency. On the other hand it may be possible that households themselves are self-selecting loan types given their risk appetite and their assessment of their prospective risk-bearing ability. Given the available data, there is no way of disentangling those effects. Instead, we assess the differences in certain risk buffers conditional on a set of covariates at the time when the loan was granted. To allow for heterogeneity with regard to these differences we estimate them over the full marginal distribution.

We employ recently developed methods of inference on counterfactual distributions (see Chernozukov, Fernández-Val and Melly, 2009) closely related to the literature of program evaluation and causal inference (see e.g. Morgan and Winship, 2007; Abring and Heckman, 2007; Blundell and Dias, 2002; Imbens and Wooldridge, 2009; and Fortin et al., 2009). We use these techniques as tools to eliminate confounding factors and to compare FCM holders with their correct domestic currency counterparts.

In section 1 we provide an overview of FCMs of households and introduce the subsample of the Household Survey on Housing Wealth (HSHW) 2008 which we will use for our empirical exercise. Section 2 provides a description of the estimation strategy we use to get inference on the counterfactual distributions. We discuss the relevant results in section 3 and conclude in section 4.

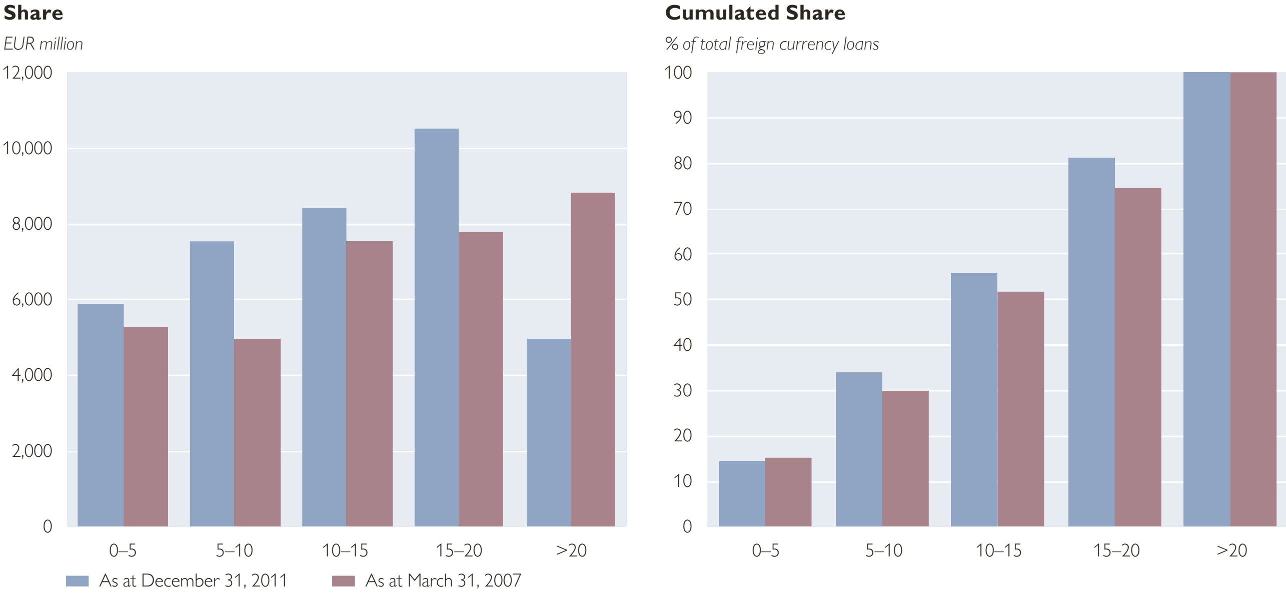
1 Foreign Currency Mortgages

National accounts data allow observing the aggregate volume of FCMs over time. Furthermore data gathered from banks provide details about the distribution of maturities, which are especially important given that most FCMs are constructed as bullet loans (see chart 2). As FCMs are a relatively new phenomenon it will take a few more years until the bulk of outstanding FCMs is due for amortization.

We use a subsample of the Household Survey on Housing Wealth 2008 (HSHW, 2008). The HSHW 2008 was conducted as a pilot project for the comprehensive Eurosystem household survey on finance and consumption (HFCS). It is a representative household survey investigating the housing wealth of Austrian households. The respondents were either the owners or tenants of the respective household's real estate at the time of the interview. The survey focused on the ownership of the respective house/apartment and of additional real estate belonging to any of the household members as well as on the related liabilities owned by the household. Furthermore, detailed socioeconomic characteristics and data concerning intergenerational transfers

Chart 2

Remaining Time to Maturity for Foreign Currency Loans



Source: OeNB.

in connection with housing wealth were compiled (see Wagner and Zottel, 2009; and Fessler et al., 2009). In order to deal with item nonresponse, missing observations were multiply imputed using chained equations (see Albacete, 2012)[3]. Our subsample consists of all households who had taken out a mortgage using their primary residence as collateral. This subsample seems to be the ideal starting point of our analysis to compare risk buffers of FCM holders with risk buffers of domestic currency mortgage (DCM) holders.

The HSHW consists of a sample of 2,081 households. We disregard all tenants, which leaves us with 1,085 homeowners of which 623 used a mortgage to finance their primary residence. Note that we do not take into account how much of the loan has already been repaid, as in the case of bullet loans the total amount or the total amount plus interest is not paid back until the end of the maturity. What we call FCM or DCM holders are therefore households who indicated in 2008 that they had taken out a mortgage to finance their primary residence, disregarding whether this mortgage has already been paid back or not. We follow this strategy as our prime interest is in the loan decision. Moreover, FCMs are a relatively new phenomenon and none of the households with FCMs in the sample have as yet repaid their loan, i.e. this choice is only relevant for our control group, the DCM holders. Finally, this strategy also allows us to keep more observations in the sample we analyze.

[3] *For simplicity, we use only one implicate. However we ran the analysis on all five implicates with no significant differences in the results. In datasets with single imputations the given standard errors do not account for uncertainty with regard to imputations.*

Table 1

Descriptive Statistics

	DCM holders (n=521)		FCM holders (n=102)	
	median	mean	median	mean
Risk buffer measures				
Real estate wealth	230,000	381,479	235,000	276,029
Household income	2,500	3,059	2,848	3,535
Estimated potential rental income	610	696	700	767
Covariates				
Total mortgage taken out	58,932	95,560	145,173	190,654
Number of household members	2.0	2.7	3.0	3.0
Age	51.0	51.6	42.0	42.2
Years since mortgage	19.0	20.5	8.0	10.8
Primary school		0.12		0.02
Apprenticeship, vocational school		0.39		0.47
Medium school, secondary school		0.19		0.23
High school leaving certificate		0.15		0.15
University, college		0.14		0.14

Source: OeNB.

Note: DCM = domestic currency mortgage; FCM = foreign currency mortgage.

Table 1 shows descriptive statistics of our variables of interest for the subsample we analyze.[4]

As risk buffer measures we use total real estate wealth, household income and estimated potential rental income. Estimated potential rental income is the value provided by respondents, on the question how much they might receive if they were to rent out their primary residence to somebody else. While being far from optimal, these measures of vulnerability should capture (controlled for a number of other characteristics) (i) how well off the household is compared to other households and therefore (ii) how vulnerable the household is, i.e. how well it can deal with certain shocks, like temporary unemployment, a negative income shock, a decrease in financial wealth, or – in the case of FCM holders – an appreciation of the foreign currency. The vulnerability of households is in general a multidimensional concept and might be measured by various means. Our approach is to include all available aspects and hope that the resulting evidence points in the same direction in order to shed some light on the questions at hand.

We choose covariates in a way that should ensure as much homogeneity as possible – when averaging the conditional differences given our restricted dataset – with relation to loan and household characteristics at the time of the loan decision. We use the total amount of debt taken out to finance the primary residence as well as variables which are themselves not an outcome of the mortgage decision but might well be relevant for the bank's assessment of the ability to repay the loan. In addition, we use the number of persons living in a household as a measure of possible family planning as a reason for becoming a homeowner. Family planning might signal stability and engagement to a bank and increase the trustworthiness of a possible debtor. However as children might have already left the home it is necessary to control for the age of the homeowner. Finally, along with education the age of the homeowner is also an important proxy for actual and future income. Furthermore, as financing conditions change over time, we also control for the years since the mortgage was taken out. As education is pretty stable over the lifecycle and most people finish their education before becoming homeowners we use educational attainment to control for ability to pay and as a signal of possible rising future income at the time the loan was granted.

With regard to risk buffer measures, FCM holders are better off regarding

[4] *Note that results hardly change if we use only households which have not yet repaid their loan, as this choice only affects the control group and the estimation of the counterfactual distribution in terms of sample size.*

income and estimated potential rental income. Evidence for real estate wealth – where FCM holders have a slightly higher median but at the same time a slightly lower mean than DCM holders – is mixed (table 1). At any rate, FCM holders would not seem to be worse off concerning risk buffers.

Concerning the covariates, FCM holders take out higher mortgages, live in larger households, and are on average around ten years younger, which can also be seen from the shorter time span that has lapsed since they took out their mortgage. Furthermore they are slightly better educated than DCM holders. Especially differences in mortgage value are driven by the fact that FCM loans are on average much more recent.

The descriptive statistics reveals that a simple comparison of means and medians of FCM holders and DCM holders will be misleading as they are very different with relation to the covariates at hand. A direct comparison would be confounded by these factors. We therefore need to control for possible confoundedness and test which of the following possible scenarios is dominant. To do so we define two possible types of FCM holders:

a) FCM Holders are of Type A.

FCM holders have higher values in all risk buffer variables if (i) banks accounted for the additional risk in FCMs and their assessment was right, or (ii) households self-selected towards the amount of risk they are able to bear and use FCMs as a certain type of investment strategy; we cannot disentangle the possible effects (i) and (ii).

b) FCM Holders are of Type B.

FCM holders have lower values in all risk buffer variables, as it might be that households who could not afford a certain amount in the form of a DCM might be able to afford it in the form of a FCM because of lower interest rates, when disregarding the additional risk and extrapolating past exchange rate changes.

Scenario (a) would imply relatively lower financial stability risks than situation (b). But as we know that even a small number of very vulnerable households could lead to severe problems, testing which scenario is dominant may not be enough. We do not know if all FCM holders are of one type (either A or B) or what the share of households of either type is in case both types coexist, which seems more likely. To assess the situation we therefore need to estimate the difference of the risk buffers between FCM and DCM holders over the full marginal distribution of the risk buffers at hand to prevent certain heterogeneous effects from distorting the overall picture. A method to do so is the estimation of conditional counterfactual distributions.

2 Estimation Strategy

We are not aiming at estimating a causal effect of holding a FCM on our risk buffers but instead use the applied methods as tools to control for certain covariates and identify the correct counterfactual to compare FCM holders with DCM holders, i.e. we estimate conditional differences. To illustrate why we care about the complete marginal conditional distributions and not only the mean we estimate the following ordinary least squares (OLS) regression using total real estate wealth *(rew)* as our main risk buffer measure,

$$log(rew_i) = \alpha + \beta D_i + X' \gamma + \varepsilon_i , \quad (1)$$

where α is a constant, D_i a dummy variable taking the value 1 for FCM holders and *0* otherwise, X' the covariate vector according to table 1 with related parameters γ and ε an error term with mean 0 and variance σ^2. The parameter β and its OLS estimate $\hat{\beta}$ should therefore capture the difference in the log real estate wealth of FCM holders compared to DCM holders – given the linear control for covariates. Of course the model is very restrictive in the sense that it is linear, and it does not allow the difference with regard to being a FCM holder to be heterogeneous over the set of covariate combinations. However this approach might be the most common first attempt to tackle the question at hand. The resulting $\hat{\beta}$ is –0.15 and significant at a 5% significance level.[5] One could conclude that when controlled for all these covariates in general, the risk buffers of FCM holders are lower than the ones of their DCM holders' counterparts. This would mean that FCMs are mostly used by households of type B who could not afford a DCM, implying higher risk with regard to financial stability.

However, this assessment might be misleading as the model employed is based on very restrictive linearity assumptions and extrapolation outside the common support. Thus, FCM holders are compared with DCM holders, which might have a completely different joint distribution of the covariates. Furthermore, the way the OLS estimate is constructed it provides us with a mean effect. But the differences between FCM and DCM holders might be heterogeneous over the covariates as well as the risk buffers.

In the following we estimate counterfactual distributions to get deeper insights into the differences in risk buffers between FCM and DCM holders over their complete conditional marginal distributions. So the question we want to answer is the following: "How would the distribution of risk buffers of FCM holders look like if they were DCM holders." If FCM holders have lower risk buffers than their constructed DCM holder counterparts, they obviously opted for FCMs as an alternative if DCMs were not affordable and/or the higher risk was not accounted for (scenario b). If their risk buffers are higher, then obviously the higher risk is/was accounted for in some way, even though we still would not know in which way (scenario a).

Let us denote the conditional distribution of a certain risk buffer by $F^D(Y^D|X^D)$, where $D \in \{0,1\}$ is 0 for DCM and 1 for FCM holders. Given those observed distributions we are interested in the counterfactual distribution of a certain risk buffer of the FCM holders if they were DCM holders, i.e. we are holding the outcome function of the DCM holders fixed (subscript) and use the covariate distribution of the FCM holders to estimate their hypothetical outcome as potential DCM holders; in short, we create comparable DCM holders,

$$F^*(Y) = F_0^1(Y^0 \mid X^1) := \\ := \int F^0(Y^0 \mid X^0)\, d F^1(X^1). \qquad (2)$$

The change from $F^*(Y)$ to $F^1(Y^1|X^1)$ can then be interpreted as the difference in risk buffers for those who opt for/get a FCM instead of a DCM, calculated as the difference between the observed distribution $F^1(Y^1|X^1)$ and the estimated counterfactual distribution $F^*(Y)$ of the risk buffers for FCM holders if they were DCM holders instead.

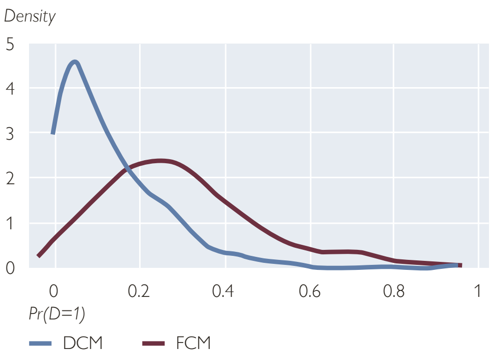
[5] *Furthermore real estate wealth is rising with the total mortgage taken out, income, education, and age (all significant at least on a 10% significance level). The time since taking out the mortgage is positively but insignificantly related to real estate wealth.*

This requires that we can evaluate the outcome function of the DCM holders at each point x in support of X^1. So either we are confronted with $X^1 \in X^0$, or we extrapolate the outcome function outside the support of X^0. The statistical problem at hand is therefore estimating an outcome function for the DCM holders, which can be used to estimate the FCM holders' hypothetical outcome if they were DCM holders by plugging in their covariates X^1. To do so we follow procedures proposed by Chernozhukov, Fernández-Val and Melly (2009)[6], where all of these methods are explained in great detail.

To check the overlapping region of X^1 and X^0 we estimate a logit model where D is regressed on all covariates. We then plot the common support of the resulting propensity scores for FCM and DCM holders. The supports overlap on nearly the full range implying that extrapolating outside of the support of X^0 should not be too problematic when estimating $F^*(Y)$.

Chart 3

Kernel Density Estimate of Propensity Scores



Source: OeNB.

First we use the location scale model to estimate the conditional quantile function of the DCM holders, $Q_0^0(u|X^0) = m(x) + \sigma(x)\, Q_R(u)$, where $m(x)$ is a conditional mean, $\sigma(x)$ is a positive scale function and $Q_R(u)$ is the quantile function of the error term (see Chernozhukov, Fernández-Val and Melly, 2009, as well as Koenker and Xiao, 2002, for details). In this model a change in the covariates can already have heterogeneous effects – via conditional mean and scale function – on the entire distribution of the outcome.

Second we use linear quantile regressions based on the estimator of Koenker and Bassett (1978) to estimate the conditional quantile function of the DCM holders, $Q_0^0(u|X^0)$, where $u \in (0,1)$ are the quantiles. Keeping the conditional distribution of the outcome fixed we plug in X^1 to calculate the counterfactual conditional quantile function for FCM holders' $Q_0^1(u|X^1)$.

Then the estimated counterfactual conditional quantile function is monotonized using the re-arrangement method suggested by Chernozhukov et al. (2010) in order to be able to invert it to obtain an estimate of the counterfactual conditional distribution function $\hat{F}^*(Y) = \hat{F}_0^1(Y^0|X^1) = \hat{Q}_0^{1,-1}(u|X^1)$.

For both models the estimated difference at a certain quantile of the risk buffer at hand is given by the quantile conditional difference,[7]

$$qcd(u) = Q_1^1(u) - \hat{Q}_0^1(u) \quad \forall u \in (0,1). \tag{3}$$

[6] *Companion software – which is used for this paper – developed by Chernozhukov, Fernández-Val and Melly is available from Blaise Melly.*

[7] *Usually this is referred to as "quantile treatment effect," but as we are not estimating a causal effect but only differences in a descriptive way we choose to use the term "quantile conditional difference" instead.*

3 Results

We evaluate *qcd(u)* at 19 quantiles of each risk buffer starting at 0.05 and going in 0.05 steps to 0.95. The resulting *qcds* show the difference between the hypothetical value of the risk buffer of FCM holders if they were DCM holders and their actual risk buffer value. In other words they compare FCM holders with their correct DCM holder counterparts over the full distribution of the risk buffer analyzed. It is not possible to further analyze whether these differences result from self-selection in terms of risk-taking or from the banks' allocation of loans and their assessment of risk-bearing capacities of households.

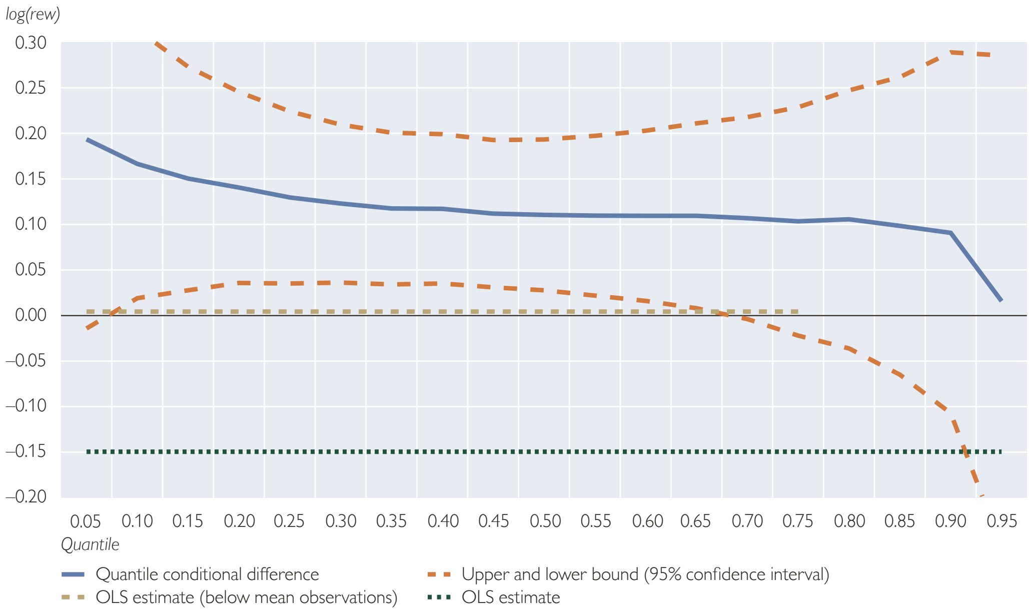
The effects are shown in charts (4a) to (6b), where "a" refers to our first estimation method of the conditional distributions – a location scale model – and "b" refers to our second, more flexible estimation method of the conditional distribution – quantile regressions. Furthermore a (point-wise) bootstrapped 95% confidence band is provided for the estimated differences,[8] as well as two OLS estimates resulting from equation (1) estimated (i) using all observations and (ii) using only observations below the mean of the analyzed risk buffer.

Risk Buffer I – Household Real Estate Wealth

Charts 4a and 4b show the differences for (log) household real estate wealth. In contrast to our OLS specification where we found a significant negative effect the difference is positive along the whole distribution. The negative effect provided by the OLS estimate in

Chart 4a

Real Estate Wealth, Location Scale-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM



Source: HSHW (2008).

[8] *However, it does not include uncertainty of imputations as we only use single imputations in this empirical exercise.*

section 2 can be rejected. FCM holders seem to have – for most part of the distribution – significantly (at the 5% level) higher real estate wealth holdings than their DCM counterparts. If any, households of the discussed type B, who used FCMs because they could not afford the amount based on the respective DCM interest rate, might only be found at the very top of the real estate wealth distribution. As both specifications, even though very different concerning their construction, lead to a similar size and shape of the differences estimated, the result seems to be pretty robust. The huge difference to the OLS estimate might result from the fact that the latter is influenced by a fraction of older DCM holders who have had much more time to build up real estate wealth whereas those are disregarded in the case of our counterfactual estimate, as no or very few counterparts will be found in the group of FCM holders. The OLS estimate using only below mean values (which are in that case around 75% of all values) points in that direction. This also explains why standard errors are largest at the right end of the real estate wealth distribution.

Risk Buffer II – Household Income

Charts 5a and 5b show the differences for (log) household income. In this case the differences do not seem to be very heterogeneous over covariate combinations, as the effects are very close to the OLS case (5a) and do not change over the distribution. In our more flexible estimation of the counterfactual distribution (5b) we see a slight change of the profile, implying somewhat rising differences except at the very bottom of the income distribution. This might be a hint for slightly higher income requirements for getting FCMs rather than DCMs. Again the difference is – robustly in both specifications –

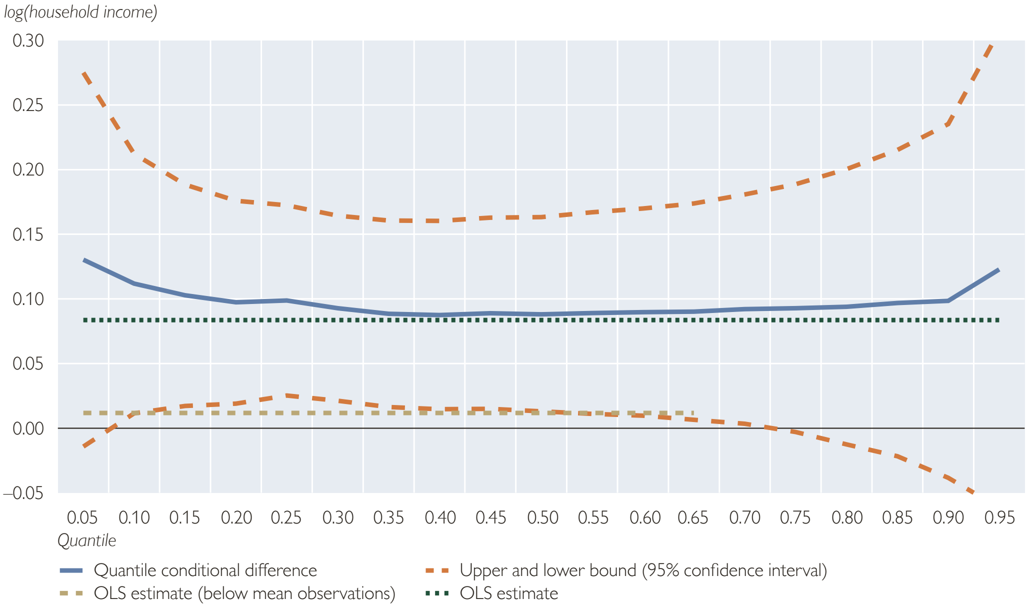
Chart 4b

Real Estate Wealth, Quantile Regression-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM

Source: HSHW (2008).

Chart 5a

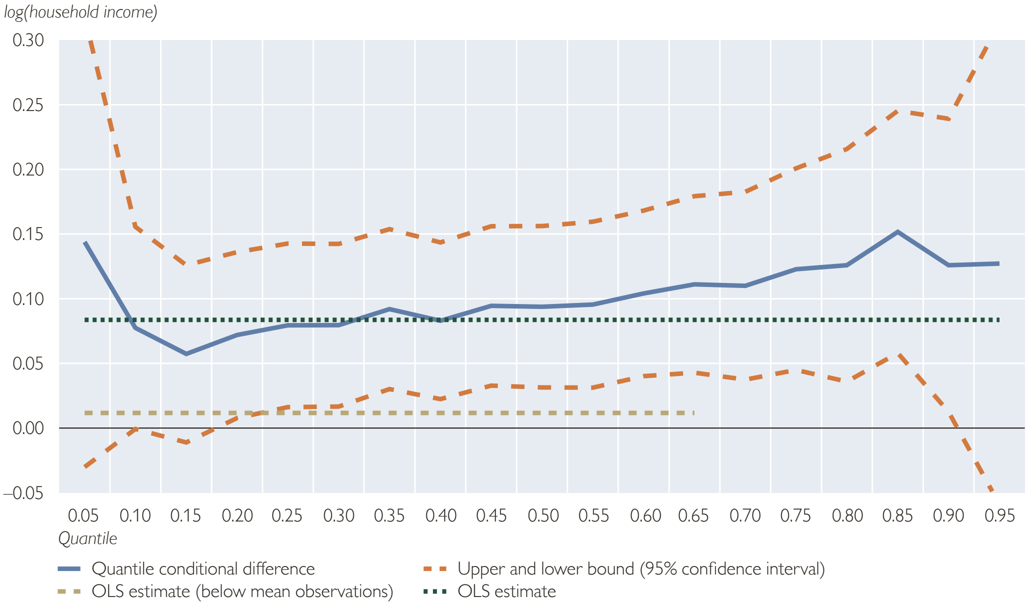
Household Income, Location Scale-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM



Source: HSHW (2008).

Chart 5b

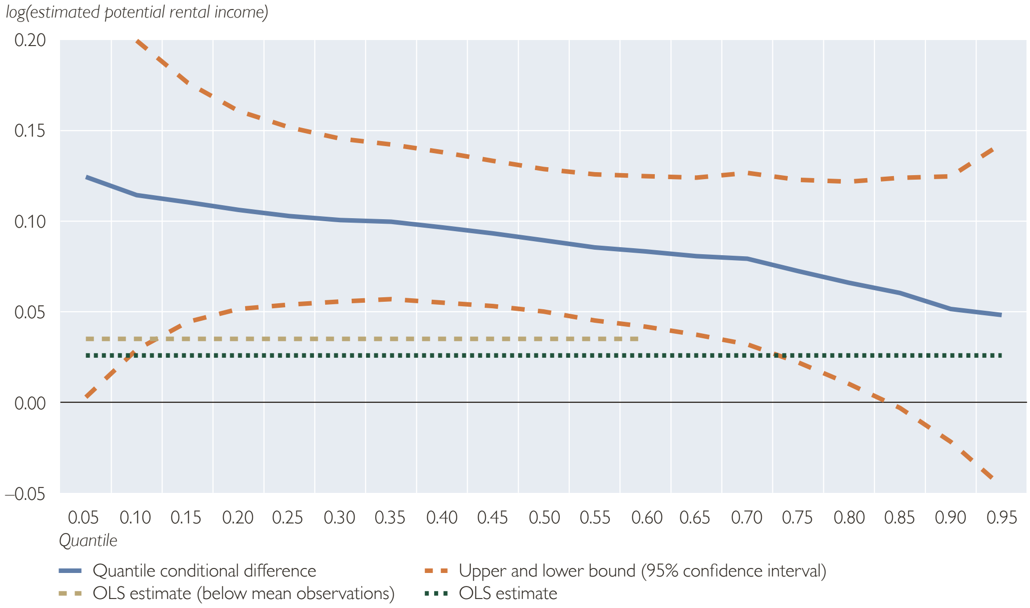
Household Income, Quantile Regression-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM



Source: HSHW (2008).

Chart 6a

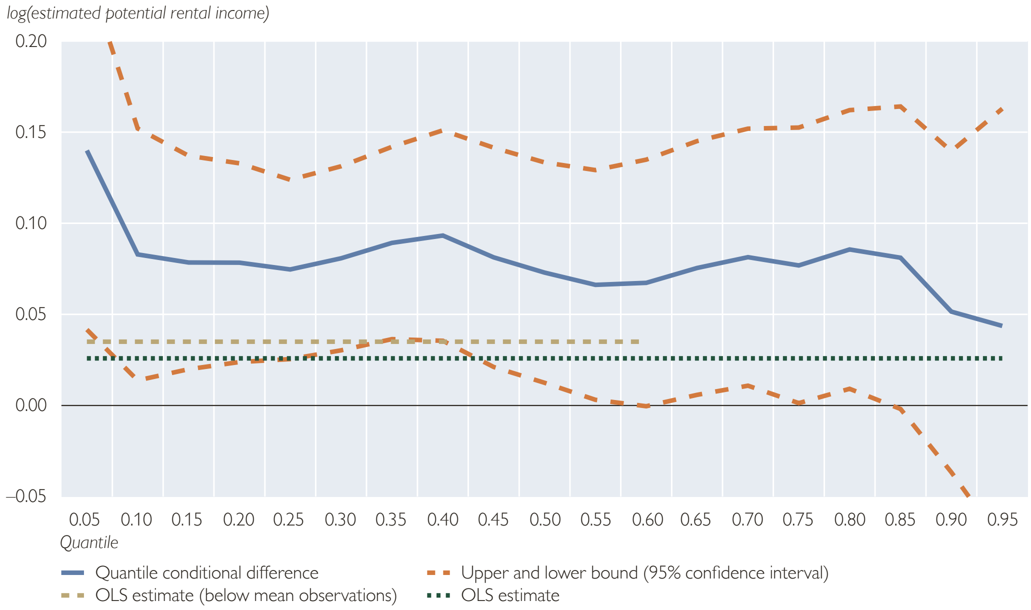
Estimated Potential Rental Income, Location Scale-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM



Source: HSHW (2008).

Chart 6b

Estimated Potential Rental Income, Quantile Regression-Based Counterfactual, Quantile Conditional Difference of FCM vs. DCM



Source: HSHW (2008).

positive over the whole distribution, which implies that the dominance of type B households can be rejected for all income levels.

Risk Buffer III – Estimated Potential Rental Income

Charts 6a and 6b show the differences for (log) estimated potential rental income, which is another measure of the value of the primary residence. Both specifications show FCM holders to have higher values than their DCM counterparts. This implies that given the same amounts of loan taken out and same characteristics, the estimated potential rental income for the primary residence is higher. That points towards more own resources and a ratio of the actual value of the primary residence divided by the loan which is higher for FCM holders. Again the OLS also points towards a positive difference. However both OLS estimates are not significant whereas the estimated differences using counterfactual analysis are significant for a huge part of the distribution.

4 Conclusions

The question if FCM holders took out their FCMs because they could not afford the respective loan amounts based on a DCM or whether they are more able to absorb the additional risk is crucial for financial stability evaluations and the assessment of banks' and households' risk orientation.

We show that using unconditional comparisons and OLS regressions would lead to misleading results at least for one of three risk buffers.

Therefore we employed recently developed methods from the literature of program evaluation and causal inference. We used those techniques instead of identifying a causal effect just for the construction of a reasonable counterfactual to compare FCM holders with DCM holders.

Comparing three risk buffers, namely real estate wealth, household income and estimated potential rental income for the primary residence, we found that FCM holders exhibit higher levels of all risk buffers at hand. Comparing the differences in risk buffers not only at the mean but over their full conditional distribution we can additionally reject the possibility that the results are being driven by heterogeneous effects – as in linear OLS. However data availability is still very limited. The forthcoming euro area-wide Household Finance and Consumption Survey (www.hfcs.at) will allow for much deeper analyses of this topic. Finally, we reject the hypothesis that most FCMs have loans in foreign currency because they would not be able to afford the same amounts in domestic currency on account of the higher interest rate burden.

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