An Analysis of Credit to the Household Sector in Austria

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This article provides an econometric analysis of the determinants of the aggregate level of credit to the household sector in Austria. These are our most important results:

An error correction model explaining real credit shows that the development of this variable has been in line with fundamental macro data in the last years. Thus, contrary to what could be observed for the euro area as a whole, there has been no loan overhang or shortfall over the last years in Austria.

A growth decomposition shows that the largest contribution to real credit growth comes from real GDP. Furthermore, in our case, univariate models are doing better in forecasting real credit than vector error correction models.

JEL classification: C22, C32, C53, E51
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1 Introduction

This article provides an econometric analysis of the determinants of the aggregate level of credit to households in Austria. There are two fields in which our analysis can be applied: First, private sector loans are regularly forecast in the context of the semiannual Broad Macroeconomic Projection Exercise. Our paper evaluates the forecast accuracy of univariate and multivariate models.

Second, the semiannual Financial Stability Report of the Oesterreichische Nationalbank (OeNB) periodically evaluates the development of loans to households[2] from the financial stability perspective. Our paper proposes new indicators which can be used in the Financial Stability Report on a regular basis. We suggest a quantitative measure for long-run equilibrium loans to households that enables us to evaluate whether these loans develop in line with fundamental macroeconomic variables (GDP, financing costs). The suggested indicator is properly specified from an econometric point of view. However, it should be complemented with additional judgmental information or information from data not applicable to our econometric analysis.[3] The indicator is a quantitative measure of the degree of financial (in)stability. The ECB regularly uses a similar indicator in its financial market assessments for the euro area. Therefore, it would also be possible to compare OeNB and ECB results and also to draw conclusions about whether sources of unbalanced credit growth are domestic or not.

Additionally, an econometric model of household loan developments allows for systematic quantification of the impact of macroeconomic developments on household credit growth over the business cycle. Hence, possible sources of unbalanced credit growth can further be broken down and attribtued to macroeconomic developments such as GDP growth or financing costs.

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[2] *We use the terms loans or credit to households to denote MFI (monetary financial institution) loans to the household sector.*

[3] *For instance, additional indicators on financing conditions (from the Bank Lending Survey), information on private sector wealth (e.g. housing wealth) and information on housing prices. However, the time period for which the mentioned data is available is too short to be applicable to our econometric analysis.*

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Eva Ubl, OeNB

We follow more or less the same approach as Calza et al. (2003a and 2003b), who conduct an analysis for the euro area as a whole. They show, in line with other studies,[4] that the development of private sector loans[5] in the euro area can be reasonably explained by aggregate macroeconomic variables and find evidence for a stable long-run relationship between real loans, GDP and real interest rate variables.

These papers employ log-linear relationships between a credit variable and its determinants. In our paper we also find weak evidence for a log-linear cointegration relationship in our econometric specification. Hence, we did not conduct a threshold cointegration analysis accounting for possible nonlinearities in lending.[6]

In section 2, we provide a short literature overview on empirical work explaining credit variables and argue our choices with respect to included variables and specifications. After univariate analysis of our credit data in section 3 and unit root testing, we conduct a cointegration analysis in section 4. In section 5 we discuss the implications for financial stability. In section 6 we decompose credit growth into contributions by GDP, inflation, and the interest rate. We compare forecasts of multivariate models with univariate models in section 7. Section 8 concludes.

2 Model Specification

2.1 What Others Have Done

Not very many previous studies on the determinants of household (or private sector) credit development are available for Austria.[7] Kaufmann and Valderrama (2004) investigate the relation of interest rate and demand variables to household loans and in particular the asymmetry of the reaction of lending to these variables over the business cycle within a Markov-switching vector autoregressive model. They conclude that spending and interest rate variables have an insignificant or low effect on lending. Furthermore, Kaufmann (2001) reveals asymmetric effects of monetary policy on bank lending over the business cycle in Austria. During the economic recovery from the second quarter of 1993 to the second quarter of 1998 the effect of interest rate changes on bank lending is insignificant, while from the second quarter of 1990 to the first quarter of 1993 interest rate changes have a significant, albeit counterintuitively positive, effect on bank lending.

However, numerous econometric studies of other countries' credit variables have been conducted. The abovementioned papers by Calza et al. (2003a and 2003b) both estimate a vector error correction model (VECM) for the euro area with the log of the real credit stock, the log of real GDP and cost variables (both a long-term and a short-term real interest rate in the former study and a constructed composite real interest rate in the latter). Other studies using a VECM or an error correction model (ECM) with one cointegrating relation where a credit variable is explained by an income variable and a cost variable have been done by

[4] *A short literature overview on similar studies of aggregate credit data follows below.*

[5] *They looked at credit to the whole private sector, so in contrast to our study their data also included credit to private nonfinancial firms.*

[6] *Furthermore, applying a nonlinear model to forecasting would require that the nonlinear feature found in the historical sample is also present beyond the sample forecasting period.*

[7] *In this overview we solely focus on papers explaining credit to households and/or the entire private sector. Papers looking at credit to private corporations only, such as Friedman et al. (1993), are therefore not included.*

Blundell-Wignall and Gizycki (1992), Brzoza-Brzezina (2005), Hofmann (2001), and Fitzpatrick and McQuinn (2007); the latter two also included a variable for property prices. Kiss et al. (2006), Backé et al. (2006) and Boissay et al. (2005) proceed similarly but look at the ratio of credit to GDP, all in the context of the rapid credit growth in some of the CEE countries. Safaei and Cameron (2003) analyze similar variables but they estimate a vector autoregressive (VAR) model in first differences. Furthermore, Suzuki (2004) and Jeanfils (2000) both estimate equations explaining the level of credit variables as part of macroeconometric models, the former as a part of a structural VAR model in levels for Japan and the latter ECMs with mortgage and consumption credit for Belgium.

One problem in most of the studies mentioned so far is that the estimated demand equations may also capture supply effects. This is also mentioned by several of their respective authors. Kakes (2000) for the Netherlands and Hülsewig et al. (2004) for Germany try to account for that. Both estimate a VECM with a larger number of variables. Most importantly, they include two interest rates: one as a proxy for the rate to be paid for the loan and one at which the lending banks can borrow money themselves. In both studies, the cointegration rank is larger than one. By imposing restrictions on the cointegrating vectors, the authors are able to identify demand and supply equations. The former includes the interest rate to be paid for loans and GDP and the latter the differential between the two interest rates (plus aggregate banks' equity in Hülsewig et al., 2004, and a time trend in Kakes, 2000).

2.2 Our Choice of Specification

We will follow the majority of the above-mentioned papers and try to explain our credit variable of interest with an ECM using one proxy for economic activity and one proxy for the cost of credit. An ECM specification would be very attractive in our case, as one of the outcomes would be one or more equilibrium relationship(s) between the above-mentioned variables. They can be interpreted in the light of financial stability because larger deviations from the equilibrium relationship(s) may point toward tensions in the financial market. For instance, if a stable long-run relationship between real credit and real growth as well as real financing costs can be found, faster actual real credit growth than expected from this long-run relation signals increasing financial instability.[8]

The Financial Accounts are our data source for the credit granted to Austrian household sector by monetary financial institutions. The series starts in the last quarter of 1981. We consider stocks rather than flows due to the higher importance for financial stability issues. Unlike many other authors, such as Calza et al. (2003a and 2003b), we look at households only instead of the whole private sector; this has both pros and cons: On the one hand, the factors affecting corporate and household loan demand, respectively, can be expected to differ substantially. For example, firms have access to sources of external finance other than credit – the share of capital market instruments has

[8] *Furthermore, if there is an equilibrium relationship between these variables, a VAR in differences only would be misspecified anyway (see for example Hamilton, 1994, p. 652).*

grown recently in Austria.[9] Hence, it makes more sense to model household credit separately from corporate credit, as due to the data limitations in the Austrian case, explaining the latter subcomponent may be very difficult. On the other hand, reclassifications between the household and the nonfinancial business sector were performed in Q2/2004 and Q4/2005. However, our series is adjusted for that factor as well as for the effects of changes in the exchange rate on existing loans in foreign currency.[10]

Our proxy for income and economic activity in general is real GDP; the GDP deflator is also used to calculate the real stock of credit out of the nominal data. As a cost variable, we use real interest rates where expected inflation is replaced by the relative yearly difference of either the CPI or the GDP deflator. We will compare specifications based on both deflators in terms of forecasting performance. The choice of the nominal interest rate was heavily constrained: the only nominal interest rates available from the early 1980s on are a three-month money market rate and the overall secondary market rate of federal government bonds (from 1986 on, data on the ten-year-secondary market yield would also be available).

In the future, more detailed analyses will be possible, as then the length of available data series on subcomponents of credit to households and the corresponding interest rates (like the interest rate for housing credit) will be sufficient. A simple correlation analysis indicates that the secondary market rate of federal government bonds may be a better choice than the three-month interest rate.[11]

We chose a quarterly frequency, which is standard in the literature. The data series start in 1981, so we have about 100 observations for estimation. Monthly data on credit are available only from 11/2001 onward, meaning that the number of available periods is lower than for quarterly data. In addition, the slight increase in information on the time from late 2001 on would come at the price of having to use data which is estimated (GDP) or highly volatile (industrial production as a proxy for GDP).

Both the ECB (2007) and Hofmann (2001) conclude that standard macroeconomic determinants as mentioned above miss the fact that loans to households are largely a reflection of borrowing for house purchases (in our data, housing loans currently make up around two-thirds of total household loans). Consequently, the former authors add household wealth (financial plus housing wealth) and the latter house prices as an additional explanatory factor. However, in Austria there has not been a housing boom since the early 1980s, so we do not think it is necessary to include a house price index.

We will not follow the approach of Hülsewig et al. (2004) and Kakes (2000) of having separate demand and supply equations in our dynamic system. First, according to the econometric evidence Frühwirth-Schnatter and Kaufmann (2006) provide, supply effects are only minor in Austria. And even if they were larger, this would

9 *See for example Andreasch et al. (2006, p. 13–14).*

10 *The adjustment was made by linking the stock data analyzed here to flow data on newly granted loans (many thanks again to Michael Andreasch).*

11 *The correlation of the secondary market rate (monthly data from 12/1995 until 11/2007) with housing and consumption credits is much higher (both around 0.85) than the correlation of the three-month rate with these two rates (both around 0.7).*

change "only" the interpretation of the coefficients in the cointegration relationship(s). The coefficients could not be interpreted as demand elasticities anymore, but would still capture an equilibrium relationship.

3 Univariate Analysis of the Data[12]

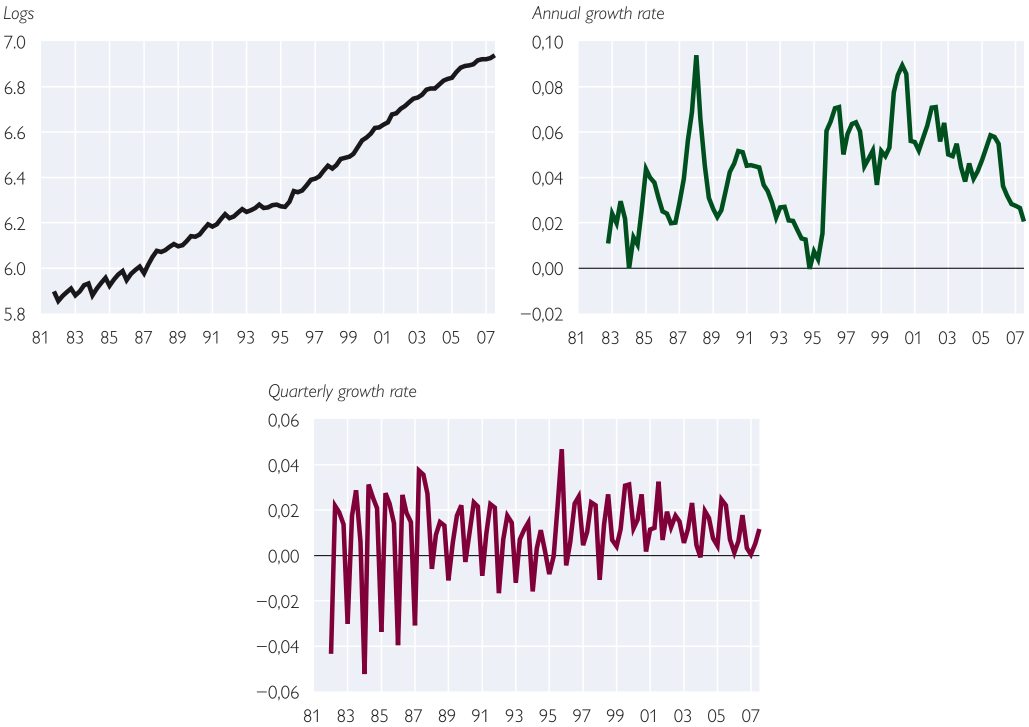
3.1 A First Look at Credit to Households

Chart 1 shows the level of Austrian loans to households deflated by the GDP deflator together with the quarterly and annual difference of real loans. What stands out is that the time series show a considerable change in the slope of the trend after the third quarter of 1995, which may be due to changes in the primary statistics. Furthermore, real interest rates have been trending downward since regulatory changes were made in the wake of Austria's EU accession.

The first differences of real loans to households (in logs) show a clear albeit evolving seasonal pattern. There are at least three periods of varying seasonality. The first period until about 1988 exhibits the strongest seasonal fluctuations, the intermediate period until about 1995 more moderate seasonal fluctuations and the period from 1995 up to now shows seasonal fluctuations that are less pronounced than in the intermediate period. Taking fourth differences (the annual growth rate) of real loans removes much of the seasonality.

Chart 1

Real Loans to the Household Sector



Source: OeNB, WIFO.

[12] Unit root tests and the multivariate analysis in section 5 were done with JMulti, a public domain software (http://www.jmulti.de).

3.2 Unit Root Tests

One difference compared to the papers mentioned in the literature overview is that – following the suggestion of Franses and McAleer (1998) – we do not use seasonally adjusted data. According to their literature overview on seasonality, seasonal adjustment can lead to changes in the persistence properties of the univariate series and weaker evidence of cointegration.

As we deal with data not adjusted for seasonality, we conduct not only standard but also seasonal unit root tests. As a standard unit root test we applied the Augmented Dickey-Fuller (ADF) test. It suggests that (the log of) nominal credit, (the log of) real credit $\ln(K_t)$, (the log of) real GDP $\ln(Y_t)$, the secondary market yield of government bonds (SMR of govt. R_t), and the three-month-interest rate R3 should be modeled as I(1) variables. The seasonal unit root tests (HEGY tests)[13] confirm these results and further indicate that the logs of real GDP and real credit seem to have seasonal unit roots as well. The evidence that the fourth differences of (the log of) the GDP deflator π_t and of the CPI are I(1) is weaker. In case of the fourth difference of (the log of) the GDP deflator, nonstationarity – necessary for π_t qualifying as an I(1) variable – was not rejected at the 5% significance level but at the 10% level. The case of the fourth difference of the CPI is similar, as rejection of nonstationarity depends on the number of included endogenous lags in the ADF test.[14]

4 Multivariate (Cointegration) Analysis

Now, as we have found evidence for regular (zero frequency) nonstationarity of all analyzed variables, we investigate whether there is an equilibrium (cointegration) relationship between them. Here we follow again a recommendation of Franses and McAleer (1998) according to which even in the case of seasonal cointegration standard VECMs or ECMs can do very well in short-run forecasts when using seasonal dummies. Therefore, we do not conduct an analysis of seasonal cointegration.[15] Like our main references, we test for the cointegration rank (and later specify an ECM) with a trend in the data but without trend in the cointegration relation.

In this section, we use the secondary market yield of government bonds as an interest rate variable and the annual growth rate of the GDP deflator as an inflation variable.

4.1 Rank Tests

First, we have to estimate the cointegration rank. Table 1 shows the result for the Saikonnen and Lütkepohl test with five lags in levels and shift dummies starting in the first quarter of 1988 (because of the break in the GDP deflator mentioned earlier)[16] and in the

[13] *HEGY refers to the work of Hylleberg, Engle, Granger and Yoo (1990), who proposed a test for unit roots at seasonal frequencies (in our case these would be the semiannual and the annual frequency). ADF tests are tests for regular or zero frequency unit roots only.*

[14] *With four endogenous lags (as suggested by the Akaike and final prediction error criteria), the ADF test rejects nonstationarity of the fourth difference of the CPI but not without endogenous lags (as suggested by the Hannan-Quinn and Schwarz criteria).*

[15] *Furthermore, of our included variables, only real credit and real GDP have common seasonal unit roots.*

[16] *The break in Q1/1988 is due to the GDP deflator, which was calculated on the basis of GDP series according to ESA 1995 (from Q1/1988) and SNA 68 GDP series (up to Q4/1987). Both series were linked with a level shift, as no homogeneous GDP series from 1982 until now is available.*

Table 1

Cointegration Rank Test with Standard Variables

Rank	Likelihood ratio	P-value	90% critical value	95% critical value	99% critical value
r=0	35.65	0.0514	32.89	35.76	41.58
r≥=1	14.40	0.3025	18.67	20.96	25.71
r≤=2	4.70	0.3725	8.18	9.84	13.48

Source: Authors' calculations.

Note: Saikonnen and Lütkepohl test.
Variables: log of real credit and GDP, secondary market yield and yearly difference of the GDP deflator.
Specification: trend orthogonal to cointegration relation, five lags in levels – as suggested by the Hannan-Quinn Criterion – and seasonal dummies, two shift dummies (Q1/1988 to Q3/2007; Q4/1995 to Q3/2007).
Sample range: Q3/1983 to Q3/2007, T = 97.

fourth quarter of 1995 (because of the break in the credit series).

This may be one of the most plausible specifications, but unfortunately its result is not robust with regard to the cointegration test used (the Saikonnen and Lütkepohl or the Johansen test) nor to the choice of lag length.[17] Thus there is only weak evidence for an equilibrium relationship. Using nominal variables only (and excluding the inflation proxy) to avoid a "spurious" cointegration relationship mainly driven by the GDP deflator yields a relatively similar picture.

4.2 Error Correction Model

Given this (weak) evidence for rank 1 in our system, we have the following cointegration relationship where the residuals should be stationary:

$$\ln(K_t) + \beta_2 \ln(Y_t) + \beta_3 R_t + \beta_4 \pi_t + \\ + CONST + S1 + S2 + S3 = u_t \quad (1)$$

where $\ln(K_t)$ is the log of real credit, $\ln(Y_t)$ is the log of real GDP, R_t is the secondary market yield of government bonds, π_t is our measure for inflation (the fourth difference of the log of the GDP deflator), *CONST* is a constant and $S1$, $S2$, $S3$ are seasonal dummies for quarters 1, 2 and 3. The results are shown in table 2.

It shows that the estimated equilibrium elasticity of real credit with regard to real GDP is 1.662, which is in line with most estimates of the previously mentioned studies.[18] This means that along the implied equilibrium path, the growth rate of real credit has to be higher than that of real GDP, which is also the case in our data. The semielasticity of the (nominal) interest rate[19] is relatively high. We try to capture the breaks with impulse dummies outside the cointegration relation only. Using shift variables inside the relation would artificially decrease the estimated elasticity for output below 1.

[17] *Furthermore, the result is not to the use of real interest rates instead of nominal interest rates and inflation separately.*

[18] *Calza et al. (2003a and 2003b) get lower estimates that are still significantly larger than 1. In the study of Hofmann (2001) covering several countries (Austria is not included), some elasticities are higher and some are lower. Blundell-Wignall and Gizycki (1992) obtain an estimate very similar to ours using nominal variables. Hülsewig et al. (2004) and Kakes (2000) obtain estimates of 1 and 1.7 in their demand equations.*

[19] *Imposing the restriction $\beta_3 = -\beta_4$ like most of the above-mentioned papers does not change the result very much. The semielasticity with regard to real interest rates would be 0.0648, and according to a Wald Test, this restriction cannot be rejected at the 10% level.*

Table 2

Key Coefficients of the Error Correction Model[1]

	Coefficient	Standard deviation	P-value	T-statsitic
	Equilibrium relationship			
$\ln(K_t)$	1.000	×	×	×
$\ln(Y_t)$ (β_2)	−1.662	0.105	0.000	−15.870
R_t (β_3)	0.060	0.011	0.000	5.296
π_t (β_4)	−0.076	0.012	0.000	−6.321
	Adjustment coefficient of the EC term			
	−0.057	0.017	0.001	−3.415

Source: Authors' calculations.

[1] The entire error correction model is available on demand.

Note: Reduced-rank maximum likelihood estimation.
Specification: includes trend orthogonal to cointegration relation, four lags in differences as suggested by the Hannan-Quinn criterion, seasonal dummies, two shifts orthogonal to cointegration relation (Q1/1988 to Q3/2007; Q4/1995 to Q3/2007).
Sample range: Q3/1983 to Q3/2007, T = 97.

However, the results of the specification tests are not completely satisfying. Lagrange-Multiplier-type and Portmanteau tests indicate that the autocorrelation of the residuals (for lags larger than four) of the whole VECM is significantly different from zero. This restricts the possible uses of the model presented above: it is unlikely to perform well in forecasting, and impulse responses will be unreliable.

5 Implications for Financial Stability

However, the error correction model has its uses. Looking at the autocorrelation of the residuals of the real credit equation only, one can see that the residuals are not significantly different from zero. Furthermore, as table 2 indicates, the adjustment coefficient in the ECM explaining real credit is significantly negative. So there is evidence

Chart 2

Error Correction Term

Source: Authors' calculations.

Note: Error correction term printed by JMULTI, recalculated in the EViews-way by regression on a constant and seasonal dummies.

that equation 1 still captures an equilibrium relationship to which real credit adjusts. The error correction term is plotted in chart 2. It shows that there has not been a significant loan overhang or shortfall in Austria in the last years.[20]

This has important implications for financial stability in Austria. Unlike in other euro area countries such as Spain or Ireland, real credit to the household sector seems to have developed in line with macroeconomic fundamentals in Austria. Variables like property prices (which played a role for credit development in other countries; this is also indicated in ECB, 2007) are not needed to obtain an error correction term (the "loan overhang or shortfall") close to zero in the last years.

6 Decomposition of Contributions to Growth

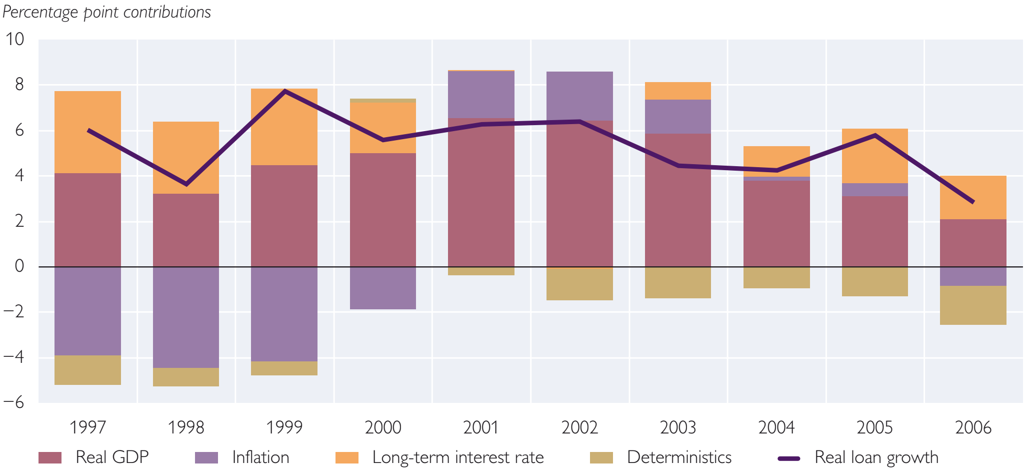
Our preferred ECM can be used to calculate the contributions of the explanatory variables to the growth of real credit. In dynamic specifications like ours, lagged endogenous variables must be taken into account, as they are functions of the explanatory variables. Hence, the lagged endogenous variables were recursively substituted out.[21] The growth contributions are plotted in chart 3.

Our ECM does not explain part of real loan growth (not shown in the chart). The growth contribution of this residual is fairly small from 2002 onward (about 0.16 percentage points of real loan growth).

Real GDP made the biggest contribution to real loan growth over the period from 1997 to 2007.[22] More recently, however, the growth contribution of the long-term interest rates has been growing on account of the strong decrease in nominal interest rates from the beginning of 2000 until about 2005. Inflation (as measured by the

Chart 3

Household Loan Growth Decomposition



Source: Authors' calculations.

Note: "Deterministics" is defined as the growth contributions of the initial conditions and the impulse dummies accounting for the breaks in the series.

[20] *Unless one argues that credit has grown too strongly over most of the sample period.*

[21] *The complexity of this task increases heavily with the number of recursive substitutions of lagged endogenous variables. Therefore, we stopped at 20 recursions implying that the initial conditions for calculating growth contributions are five years in the past.*

[22] *We do not report on the growth decomposition before 1997, as it seems to be less meaningful due to the use of the time dummies in the ECM mentioned before.*

GDP deflator) had a sizable negative effect on credit growth at the end of the 1990s after a period of prolonged downward movement of inflation (lower inflation expectations mean higher real interest rates).

7 Forecast Evaluation

7.1 Univariate Processes to Forecast Real Household Loans

Given the results of section 4, we also look at the performance of univariate models in forecasting. These models are an important benchmark, as they need relatively little information. Probably the most popular univariate process accounting for stochastic trends and seasonality is the Box and Jenkins (1970) airline model:

$$\Delta\Delta_4 \ln(K_t) = (1-\theta_1 L)(1-\theta_2 L^4)u_t \quad (2)$$

where Δ_i is the difference operator defined as $\Delta_i y_t := y_t - y_{t-i}$ and L^i is the lag operator defined as $L^i y_t := y_{t-i}$. The other variables are defined in section 4.2. The airline model captures the data-generating process well. However, it proves to be sufficient to apply first differences to yield a stationary series.

We estimate three competing ARIMA (Auto-Regressive-Integrated Moving-Average) models in first differences. All ARIMA models are free of residual autocorrelation.

7.2 Comparison of VECMs and ARIMAs

We then conduct a detailed analysis of the accuracy of forecasting of four VECMs and four ARIMA models. The VECMs differ in the price variables[23] and the long-term interest rate used: VECM1 (including the CPI and the SMR), VECM2 (including the CPI and a constructed interest rate weighted with outstanding volumes of foreign currency loans), VECM3 (including the GDP deflator and the SMR) and VECM4 (including the GDP deflator and the interest rate weighted with outstanding volumes of foreign currency loans).[24] The ARIMAs include the airline model and three ARIMAs (AR1, AR2, AR3)[25].

Our objects of interest are the prediction errors one to eight quarters ahead; we calculate the root mean squared prediction errors (RMSPE) for these quarters. The sampling scheme is recursive, i.e. the sample used to estimate the model parameters grows as predictions for successive periods are made. More precisely, we use the observations until Q3/2001 to construct an initial set of parameter estimates that are then used for the first prediction for the period from Q4/2001 to Q3/2003. We then estimate the models with observations up to Q4/2001 and make the second prediction eight quarters ahead. The final prediction from Q4/2005 to Q3/2007 is performed with parameter estimates based on the observations up to Q3/2005.

Comparing the competing models (see chart 4 for a plot of the RMSPEs), we can state the following results: All VECMs broadly perform worse than the ARIMAs. This does not come as a big surprise, given the disappointing results of the specification tests of our VECM. The AR2 and AR3 models are

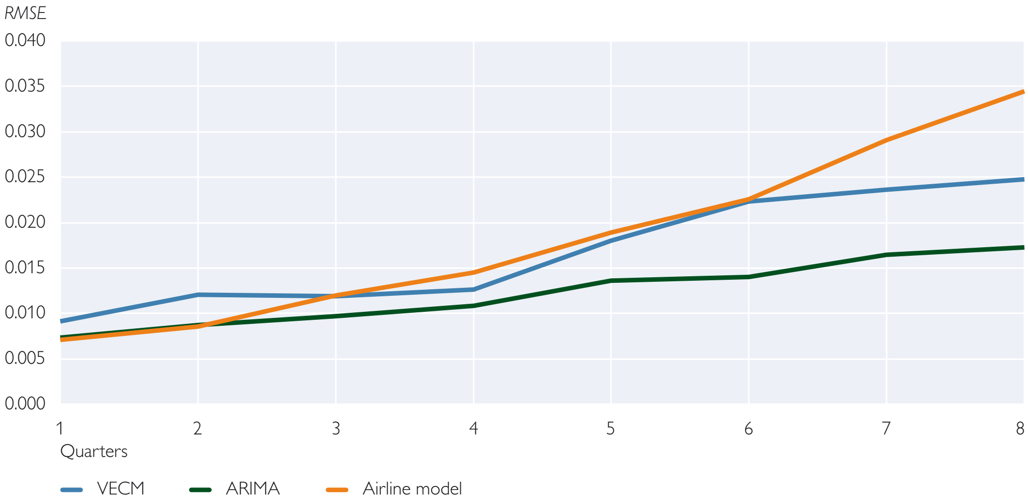
[23] *Credit to households, however, is always deflated by the GDP deflator.*

[24] *This rate is constructed by weighing the secondary market yield of Austria, Japan and Switzerland by the share of their respective currencies in credit of the previous quarter. This accounts for the fact that since the late 1990s a significant part of Austrian credit to households is in foreign currency.*

[25] *AR1: autoregressive term at lag 4, seasonal dummies and constant;*
AR2: autregressive process of order 3, moving average process of order 3 and constant;
AR3: autregressive terms at lags 2 and 4, moving average term at lag 2, seasonal dummy at lag 1 and constant.

Chart 4

Root Mean Squared Prediction Errors of Competing Models



Source: Authors' calculations.

Note: ARIMA model: autoregressive terms at lags 2 and 4, the second order component of a moving average term at lag 2 and a seasonal dummy at quarter 1; the variables in the VECM are real loans to households, real GDP, the annual growth rate of the GDP deflator and the secondary market yield; the Airline model as defined in equation 2.

best in terms of forecast performance for three to eight quarters ahead. The airline model is best for one and two quarters ahead; however, the RMSPEs quickly increase. The forecast performance of the VECMs with different interest rates does not differ very much. The inflation measure based on the GDP deflator does better than the one based on the CPI on short horizons and worse on longer ones.

8 Conclusion

In this paper, we analyze credit to households in Austria. We find weak evidence for cointegration between real credit, real GDP, a nominal interest rate and inflation. Unfortunately, a VECM including these variables does not pass the most important specification tests. This may be one of the main reasons why ARIMA models are doing much better in forecasting the level of real credit, and this even over a two-year horizon. Against this background, we suggest using univariate models to forecast loans to households. However, an ECM with a credit equation only is well specified and can be used for other purposes.

The EC model indicates that, contrary to what could be observed for the euro area as a whole, there has been no loan overhang or shortfall over the last years in Austria. A growth decomposition shows that the largest contribution to real credit growth comes from real GDP.

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