Disaggregated Credit Flows and Growth in Central Europe

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ABSTRACT

The aim of this paper is to explore the link between credit and output in the context of a developed transition economy. Salient credit market features of these economies are (i) credit market imperfections leading to constraints on growth and (ii) the rapidly growing importance during transition of their financial sectors (the insurance, pension funds and real estate sectors). We develop a framework of credit and output including separate measures for credit to the real sector and financial sectors and for credit constraints, taking account of the role of trade credit. In our empirical work we focus on the Czech Republic because of the level of its financial development and data quality. In VAR and ARIMA analyses we find that our disaggregated measures for credit flows are better predictors of nominal growth than traditional, aggregate measures.

JEL codes: E44, G21

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Disaggregated Credit Flows and Growth in Central Europe*

'Theories of credit are useful for understanding the business cycle'.

Nobuhiro Kyotaki, 1998

ABSTRACT

The aim of this paper is to explore the link between credit and output in the context of a developed transition economy. A salient feature of these economies is the recent development of their financial sectors. We develop a framework that reflects this, where we distinguish between credit to the real sector and to the financial sector firms. In our empirical work we focus on the Czech Republic because of the level of its financial development and data quality. We find that disaggregated measures for credit flows exhibit better short-term correlation and causation to output growth than do traditional, aggregate measures of credit and money. Our measure also appears to be a better annual predictor of nominal growth.

1. Introduction

A large literature researches the link between financial development and output. Much of it has focused on the relation between bank credit expansion and growth in GDP. A common finding is that higher credit-to-GDP ratios, indicating financial deepening, accompany higher per capita GDP. While establishing causality is complicated, most studies suggest that financial deepening causes GDP (see Beck, Levine and Loyaza, 2000 and Rajan and Zingales, 2001, for overviews).

The relation between bank credit and GDP is especially relevant to Central European economies where credit growth has outpaced GDP growth in recent years. While this is unsurprising given previous financial underdevelopment, credit booms have fuelled worries about credit bubbles. A number of studies aim to asses the sustainability of Central European credit growth (see e.g. Balasz et al, 2006; Sirtaine and Skamnlos, 2007). A second issue especially relevant to the Central European economies is credit constraints, which have been shown to be among the major impediments on growth in the region, especially for domestic firms. Thus, the study of the credit-growth relation in Central European economies revolves around (i) support of the credit system to *sustainability* of growth, preventing volatility through asset price bubbles, and (ii) support of the credit system to the *rate* of growth (mitigating). The first concern is about credit flows towards asset markets, which should not grow so large as to set of an asset boom and bubble. The second concern is about credit flows to real-sector firms, with an indirect but important role also credit flows towards asset markets in support of the real sector via financing and risk smoothing.

These two separate concerns suggest that it is unhelpful to think of 'credit' as a homogeneous resource flow. Part of the bank credit supply is directed to asset markets, not directly to output growth (although clearly asset market have indirect effects on growth). In the next section we develop the distinction underlying this disaggregation of credit flows, using a modified equation of exchange framework. We label the volume of credit directed to GDP growth C_R and the flow into asset markets C_F. C_R is more correlated to growth than aggregate measures such as the total credit supply or the credit-to-GDP ratio. Further, a temporary wedge between C_R and GDP growth. We will ague that this may indicate a credit constraint which constitutes a drag on growth, so that C_R not only correlates with but also Granger-causes GDP. Following this conceptual framework in section 2, in section 3 we suggest a method to observe disaggregated credit flows from Central Bank data, and implement the analysis for the Czech Republic in section 4. We conclude in section 5 with a summary and some reflections.

2. Conceptual Approach

As convenient starting point to illustrate our approach is the well known quantity equation (Fisher, 1911):

$$MV = PT \tag{1}$$

where *M* stands for the quantity of money in circulation used for transactions, *V* for the transactions velocity, *T* for the number of transactions and *P* for the price paid per transaction. The equation states that in a fully monetised economy, the value of all transactions in the real economy must by definition be equal to the total value of money used for transacting in the real economy. Starting with Pigou (1917), total nominal expenditures *PT* have often (but incorrectly) been interpreted as total nominal income *Y*. This is how the equation is commonly encountered in the textbooks:

$$MV = PY \tag{1'}$$

Total nominal income *Y* was and is typically measured by nominal GNP (or, later, GDP). This is a biased measure since GDP transactions (*PY*) are only a subset of all transactions (*PT*), the other part being financial and real estate transactions. The returns on these transactions are not part of recorded GDP since they are asset price gains (or 'holding gains'). In the *System of National Accounts* that underpins GDP calculations, these are not profits which are included in GDP (although financial firms do make an accounting profit, as a typically minor part of their total returns). Financial-sector transactions are part of wealth, not income[1]. To the extent that they do affect GDP, this will run though different channels than the per-definition relation to GDP of liquidity for real-sector transactions. To account for this, we break both sides of the equation down into money used for transactions that are part of GDP (denoted M_RV_R, with subscript *R* for 'real-sector') and those that are not (M_FV_F, with subscript *F* for 'financial-sector' including real estate). Similarly we disaggregate *PQ* into the value of transactions that are part of GDP ($P_RQ_R = P_RY$), and those that are not (P_FQ_F):

$$MV = M_RV_R + M_FV_F \tag{2}$$

$$PQ = P_RQ_R + P_FQ_F \tag{3}$$

[1] A confusion may arise because 'taxes on capital gains are treated as taxes on income'(UN 1993), and as such are included as a sub category within *System of National Accounts* entry D51. But specialists have emphasized time and again that holding gains, while taxed as income '… are not included in the SNA definition of income' (UN, 1993). Again, another confusion may arise by considering holdings gains as part of property income. But the *System of National Accounts* '…draws a distinction between property income and holding gains and losses. The latter are changes in value of an asset due to changes in its price that constitute neither transactions nor income' (Schreyer and Stauffer, 2004). '[T]he SNA definition of income excludes holding gains' (Lequiller, 2004). 'In the SNA, … holding gains and losses are neither the result of production nor income…' (Nordin, 2005). Instead, holding gains are included in the item 'change in real national net worth', defined as '…[t]he sum of changes in net worth of all resident institutional sectors less the neutral holding gains/losses (that is, in proportion to the general price level)….' (UN, 2003). Financial-sector transactions are part of wealth, not income.

so that

$$M_R V_R = P_R Q_R = P_R Y \tag{4}$$

$$M_F V_F = P_F Q_F \tag{5}$$

Where P_R stands for the GDP deflator. This states, correctly, that in a fully monetised economy, money used for GDP transactions ($M_R V_R$) must be equal to nominal GDP ($P_R Q_R$). In flow terms:

$$\Delta MV = \Delta M_R V_R + \Delta M_F V_F \tag{6}$$

$$\Delta(PQ) = \Delta(P_R Y) + \Delta(P_F Q_F) \tag{7}$$

The flow of additional money ΔM to stock M does not circulate. It is added once to the stock of money (which then circulates with some velocity that does not enter into our flow equations). Hence V drops out (V equals one) in the flow equations (6) and (7). We combine (6) and (7) into

$$\Delta(M_R V_R) = \Delta(P_R Y) \tag{8}$$

which states that the rise (fall) in the amount of money used for GDP transactions is per definition equal to the rise (fall) in nominal GDP.

An increase in the amount of money ΔM originates with banks, which create money by extending credit to firms, households and the government: '[b]anks actually create money when they lend it' (FRBD, 2009). Thus the change in the money supply is determined by the quantity of credit supplied by banks: a change in the stock of money ΔM occurs through an identical change in bank credit ΔC. Substituting therefore credit C for money M in equation (8) and nominal GDP (denoted *nGDP*) for ($P_R Y$) gives the relation between a rise (fall) in bank credit extended to the real sector and a rise (fall) in nominal GDP in a fully monetised economy. Equation (9) states that every (say) Dollar in fresh credit creation is matched by an additional Dollar used in GDP transactions. This is, still by definition, a simple one-on-one relation:

$$\Delta C_R = \Delta(P_R Y) = \Delta nGDP \tag{9}$$

The intuition is that borrowers either spend on final goods (in which case this is counted into GDP) or on intermediate goods in which case with constant inventories – an assumption we relax below – agents receiving the money will spend it again. This may occur many times on intermediary products or services but ultimately it will be spent once on a final or imported good or service, and so be counted into GDP. (If the money is invested in a financial asset it becomes, by definition, part of M_F.) Thus, per time unit ΔC_R equals $\Delta nGDP$ (Werner 1992; 1997).

We now consider non-bank credit. GDP growth in some period can be larger than real-sector bank credit growth (denoted $\Delta C_{R,B}$) if part of GDP transactions are nonbank-financed. Instead, they may be facilitated by trade credit, customer card credit, net inventory changes or other forms of non-bank credit. Any such transactions not supported by money imply that the economy is intertemporally not completely monetised. This is no negligible phenomenon: in industrialized economies, trade credit transactions account for about a quarter of all transactions in goods and services (Mateut, 2005). Similarly, in the short term changes in inventories may be substantial. The net total of nonbank credit plus inventory growth (contraction) contributes to an increase (decrease) in the value of real-sector final transactions (*nGDP*) without a corresponding growth in bank credit. Therefore both bank credit growth $\Delta C_{R,B}$ and nonbank credit growth (denoted $\Delta C_{R,N}$) are in effect part of the total real-sector credit supply ΔC_R:

$$\Delta C_R = \Delta C_{R,B} + \Delta C_{R,N} \tag{10}$$

Bank credit and nonbank credit are substitutes, as documented by Mateut (2005). With larger bank credit constraints, the use of trade credit increases. Lagged $\Delta C_{R,N}$ may therefore be interpreted as a proxy for bank credit constraints. To the extent that movements in bank credit constraints are a causal factor in the business cycle, lagged $\Delta C_{R,N}$ will be a predictor for growth. This is in line with the 'business cycle as credit cycle' literature, which has shown how changes in bank credit constraints are important in explaining output movements (e.g. Kiyotaki and Moore 1997; Mendicino, 2007). In support, Benk et al (2005), building on Uhlig

(2003), identify credit shocks as candidate shocks that matter in determining GDP. Kyotaki (1998) explains how the credit system intermediates and amplifies technology or wealth shocks into output movements. Caporale and Howells (2001) analyse the interactions between bank loans, bank deposits and total transactions in the economy. They conclude that "loans cause deposits and that those deposits cause an expansion of wealth/GDP transactions" (Caporale and Howells, 2001:555).

On the basis of the above analysis we specify the effect of credit on growth as running through two channels. Firms and households need credit to directly finance transactions (ΔC_R) and to purchase and sell financial market instruments (ΔC_F). Accordingly, we specify the total effetof credit flows on the conomy as running through two channels: (1) the effect of possible constraint on ΔC_R, captured in $\Delta C_{R,N}$, and (2) the effet of financial-market liquidity measured by ΔC_F . IN the notation introduced above:

$$\Delta nGDP_t = f\,(-\Delta C_{R,N}, \Delta C_F)_{t-j} = f\,\{-\,(\Delta nGDP - \Delta C_{R,B}), \Delta C_F)_{t-j} \qquad \textit{with}\ f' > 0 \qquad (11)$$

which states that GDP growth is some positive function f of lagged nonbank real-sector credit contraction ($-\Delta C_{R,N}$), which indicates relaxing bank credit constraints; and of lagged financial-market liquidity. In effect, we pose a link between current growth with its own lag and with lagged real-sector and financial-market bank credit flows. This disaggregation is the novel contribution of the present study compared to other studies on the link between credit and growth generally. This has three important advantages. First, financial-sector loans, which affect GDP through different channels than does credit to the real sector, is accordingly treated separately in the analysis. This disaggregation should therefore provide better correlation of credit and GDP. Second, it should also allow for better identification of causation. The total credit supply includes both credit extended to the real sector ΔC_R (which is arguable one factor causing GDP) and credit extended to the financial sector ΔC_F (which reflects changes in wealth and thus is more likely to be resulting from GDP movements). This lumping together of ΔC_F and ΔC_R - of credit causing income growth and of lending resulting from income growth - makes it more difficult to establish temporal causality between credit and GDP. Third, since $\Delta C_{R,N}$ is interpreted as a lagged business cycle indicator, it should be also a useful out-of-sample predictor of growth. Below, then, we use disaggregated credit flows to analyse correlation, causal relation and predictive power of credit flows with respect to *nGDP*. We compare this analysis to identical analysis of the total credit supply ΔC.

3. Application to the Czech Republic: Data and Exploration

The Czech banking sector was transformed from 1989 onward from a one-tier, monobank to a two-tier, commercial banking system. The number of banks grew rapidly in the first half of the 1990s, to 55 (plus the central bank) in 1995. The Czech currency crisis of 1996-7 was followed by a mild banking crisis, in which many banks were liquidated and their number decreased to 40 in 2000. Privatisation, which had been implemented in the rest of the economy in the early 1990s, started in earnest in banking in 1997. This increased foreign participation from 23 % in 1995 to 55 % in 2000 (Hájková et al, 2002). Since 2002, the sector is stable in terms of number of banks, growing in terms of bank size, and improving its profitability – net profit per employee turned from negative to positive in 1999 and tripled in nominal terms between 2001 and 2005. The share of nonperforming loans went down from close to 25 % in 2000 to 5 % in 2005 (Bárta and Singer, 2006). Current Czech financial markets are different from those of many other Central European economies in that there is no credit boom, according to several authors (Sirtaine and Skamnelos 2007; Egert *et al* 2006) - although below we shall see that the credit stock is rising relative to GDP.

We now identify empirical measures for the right-hand side components of equation (11) and use them to explore development on Czech credit markets. Data were collected from the Czech National Bank (CNB) on bank loans denominated in Czech Crowns (CZK) to resident and non-resident households and firms and to the government[2], from 1992Q1 to 2007Q3 . (More recent data are not used as they are likely to still undergo large revisions.) We also collected quarterly nominal GDP data (at purchaser prices and not seasonally adjusted), available from 1995Q1 to 2097Q3[3].

The major challenge in this study is to empirically disaggregate credit into real-sector and financial-sector flows. Our solution is to study the type of lenders. The CNB reports real-sector loans to households and to firms in 26 sector categories comprising manufacturing, agriculture, natural resources and services. As to business loans, we define credit flow to

[2] Note that we include credit extended to both public and private institutions, as both may contribute to GDP growth. Many studies employ a private-credit-to-GDP ratio.

[3] GDP data for 1993Q1-1994Q4 were not provided by CNB and were separately collected from the Czech Statistical Office. We doubt that both sources are consistent given a large discontinuity from 1994Q4 to 1995Q1. For consistency, we include only data from 1995Q1 in our description and analysis.

sectors that engage in financial transactions - non-bank financial institutions (such as pension funds and insurance companies) and real estate - as part of ΔC_F and credit flows to manufacturing, agriculture, natural resources and other services as $\Delta C_{R,B}$. Household loans were disaggregated into lending for real estate investment (most of which were mortgages) and consumption lending. Finally, government credit was all counted into real-sector credit. Obviously, this is an imperfect disaggregation as, for instance, real-sector firms use some of their funds in asset transactions (for instance, in servicing loans taken out for purchase of real estate and also the government also invests in land and buildings). Further, households may take out loans mortgaged with their real estate for consumption purposes. But in broad brush, the bulk of credit to asset investment is captured by household mortgage lending and nonbank financial services. While in principle these data can be generated more accurately by adapting Central Bank reporting formats to become more detailed, within present reporting conventions our method is the closest approximation possible.

Figure 1 depicts the development of credit, money and growth. It shows year-on-year growth over 1996Q1-2007Q3 of the total credit supply, the private credit supply, real-sector credit $C_{R,,B}$, nominal GDP growth *nGDP* and money *M3* (since 2002). On visual inspection, none of the credit or money variables closely tracks GDP growth. Until mid-2004 there is no consistent difference between real-sector credit and the total credit supply. Since then, the total credit supply outstrips real-sector credit. This is due to the rise of financial-sector credit, especially mortgage lending. The growth of real-sector credit is smaller than *nGDP* growth until end-2004, but afterwards a positive, persistent and growing gap opens up between real-sector credit growth and *nGDP* growth. In the terminology introduced above, this suggests that $\Delta C_{R,N}$ (the divergence of real-sector credit and *nGDP*) is positive until end-2004 (there is net nonbank credit creation) but negative thereafter (there is net nonbank credit repayment).

<insert Figure 1>
<insert Figure 2>

This is further illustrated in Figure 2 where we examine the cumulative year-on-year growth in our measure for bank credit constraints $\Delta C_{R,N}$. We observe a build-up of nonbank credit to 2003, and a steep decline from mid-2004. This turning point coincides with an upward shift of *nGDP* growth in 2002-2007 compared to 1995-2001, as we will further explore below. Cumulative $\Delta \mathrm{C}_{\mathrm{R,N}}$ growth is near zero over our period of observation, as woul be expected of trade credit and inventory growth as proxy for the business cycle. In money terms, $\Delta C_{R,B}$ equals CZK 1,931 thousand and $\Delta nGDP$ equals CZK 1,923 thousand, yielding a 99 % quantity correspondence. Again, this is in line with the temporary nature of trade credit. All recorded transactions are eventually being settled in money so that $\Delta C_{R,N}$ sums to zero over the long term.

As credit constraints correlate with (and possibly cause) the business cycle, we expect that $\Delta C_{R,N}$ movements are systematically related to output movements as in equation (11) . Figure 3 suggests that two-quarter lagged nonbank credit contraction (- $\Delta C_{R,N(t-2)}$) maps reasonably well on current nominal output growth $\Delta nGDPC_{(t)}$. Their bivariate correlation coefficient is minus 0.78 over our observation sample. *nGDP* growth appears to accelerate from mid-2004 in percentage terms (nominal growth increases from 7.4 % to 8.0 % from 1995Q1-2004Q2 to 2005Q1-2007Q3). This coincides with ΔC_R turning from mostly negative in 1995Q1-2004Q2 to positive during 2004Q3-2007Q3. We explore this correlation, and any causation, more rigorously below.

<insert Figure 3>

Finally figure 4 shows credit-stock-to-GDP ratios, confirming the 2002 turning point in another way. While all ratios gradually decline from high levels in the early 1990s, we see that the ratio of bank credit to the realsector to GDP ($C_{R,B}/nGDP$) continues to decline till mid-2003, but the total-credit-GDP ratio (*C/nGDP*)bottoms out already in 2002. This is due to the shift of the financial-sector credit stock to a higher level during 2001, and its gradual growth afterwards, pointing to financial deepening. But as the $C_{R,B}$ */nGDP* ratio is still growing faster than the C_F */nGDP* ratio, there is no evidence for a credit-fuelled real estate or stock market bubble in excess of real-sector growth.

4. Analysis I: shocks in disaggregated credit flows

Following equation (11), we estimate the time series-relation of nominal GDP growth with its own lags and with lags of three credit aggregates: the total bank credit supply C; the private-credit supply ΔC_P; the real-sector bank credit supply $\Delta C_{R,B}$; and the financial-sector bank credit supply ΔC_F.

Analysis of GDP and credit presents five statistical challenges: of serial autocorrelation – as both credit flows and GDP growth are partly determined by past realisations -, of seasonal fluctuations, of endogeneity, of cointegration of money and output series, and of time-varying volatility in the series. In the face of these complications, the relation between credit aggregates and output has been analysed in three frameworks, each of which addresses the challenges in different ways. One option is to model the co-integrated time series of money and output and their lags, in a vector auto regression (VAR) system of equations. This allows for endogeneity of both variables and to test for the direction of causality, if any. Another approach is to estimate a regression of output on money in an equation with autoregressive and moving-average terms (ARMA), accounting for seasonality and serial autocorrelation. A third method is to correct for heteroskedasticity over time in an autoregressive conditional heteroskedasticity (ARCH) specification. As each is theoretically justifiable, we explored each of these alternatives. The VAR approach captures most of the issues and, importantly, best enables us to address the cointegration and endogeneity issues. It also allows for assessing Granger causality. Below we therefore report VAR estimation results, while later in the forecasting section we utilise an ARIMA framework[4].

Both credit variables and GDP exhibit strong seasonality and non-stationarity. Philips-Perron tests indicated that seasonally differencing the logarithms resulted in variables still exhibiting non-stationarity. We then differenced once more, by one quarter, to achieve stationarity. Thus we are analysing the quarterly change in the year-on-year growth rates of credit and GDP logarithms. Taking total-credit stocks C as example, formally we study $c = \ln(C_t/C_{t-4}) - \ln(C_{t-1}/C_{t-5})$ and $gdp = \ln(nGDP_t/nGDP_{t-4}) - \ln(nGDP_{t-1}/nGDP_{t-5})$. Some seasonality may survive in this transformation, as we will see in an ARMA analysis below. Table 1 presents overview statistics.

[4] Additional estimation findings using ARCH methods are available on request. They show qualitative findings similar to the results reported below

<*insert Table 1*>

where y and c are the quarterly change in the year-on-year growth rates of GDP and credit / money aggregates in the Czech economy. We estimate the reduced form of the dynamic simultaneous equations of credit and output in two or three VAR equations of output y and one or two credit variable(s) c:

$$y_t = v + A_{(1i)}y_{t-i} + A_{(2i)}m_{t-i} + A_{(3i)}c_{t-i} + e_t \qquad (t = 1,2, \ldots 24; i= 1,2,3,4,5,6)$$

where y_t, v and e_t are all 3x1 vectors, $A_{(i)}$ are coefficient matrices of size 3 x 3, and e_t is white noise. The model is dynamic in that it relates each of the two or three variables nGDP and (total, real of financial) credit growth in year t to their own lags in years t-1 up to t-6 (the lag length selected using Akaike and Schwartz information criteria), and six lags of the other two variables. The two variables on the right-hand side included for y are the change in the year-on-year log growth rates of credit c and growth in GDP logarithms y. We estimate models where for c we substitute C, $C_{R,B}$ and C_P . Note that we need not estimate a model for $c = C_N$ as this would be identical to the $c = C_{R,B} - nGDP$ model (we ran this and found that they are identical indeed).

Individual estimated coefficients and tests for Granger causality were studied and, while of the expected size and significance, they give only an initial indication of the effects of interest since these are the net results of interactions in the system. These effects are better explored in graphs of the orthogonalized impulse response functions resulting from the VAR analyses, for the relations of interest. But this requires Choleski decomposed vectors which imply an ordering in the VAR, which so far was not structured as we are theoretically agnostic on the ordering. For instance, with an x-over-y Choleski vector, it is implied that x drives y, so that a structure is imposed on the VAR. This may be misleading if in reality causality between x and y is unclear, or runs in reverse direction. Sims (1980) suggested that an implicit ordering may be justified by Granger causality from x to y. This is what we first explore (table 2).

<*insert Table 2*>

Using a 1 % level of significance for the Chi-square statistic of the Granger causality test, we find clear evidence of unidirectional causality from real-sector bank credit $C_{R,B}$ to *nGDP* (model 1). This is not the case in a bivariate model with *nGDP* and financial-sector credit C_F (model 2). But in a trivariate model with *nGDP*, C_R and C_F, we observe Granger causality from both C_R and C_F to GDP, as well as bidirectional causality between C_R and C_F (model 3). The $C_{R,B}$ effect is robust to adding the total-credit flow C or the private credit fow C_P (models 5 and 7); the C_F effect is not (model not reported here). Note that a four-variable model with C, C_R or C_F is not feasible as it would be multicollear). Finally, bivariate models of only total credit C or only private credit C_P with *nGDP* yield no evidence of causality either way[5] (models 4 and 6)

In sum, these causality explorations support that disaggregated credit flows C_R and C_F. jointly cause output while the total-credit or private-credit flows C and C_P do not. Real-sector credit by itself appears a causal factor for nGDP while financial-sector credit is not, but it does play a role in conjuction with real-sector credit. The findings so support orthogonalized impulse reponse functions (IRFs) based on Choleski decomposed vectors of C_R over C_F over *nGDP*. The graphs of these IRFs are reported below in Figures 5 and 6.

<insert Figure 5>
<insert Figure 6>

A positive shock to C_R has a direct, positive and significant impact on growth in the first two quarters and no significant long-term impacts. Interestingly, a positive shock to C_F has initially no significant effect on nGDP in the first two quarters, but a sizeable and significant positive effects in the third and fourth quarter. But credit to asset markets are the main culprit of credit bubbles fuelling unsustainable growth, and this shows in the 8th and 9th quarters of the IRF simulation, where a positive shock to C_F detracts from nGDP growth, though not to the same amount as the earlier growth bonus. This is in line with Tornell and Westerman (2005) who show that financial liberalization and the larger credit flows this brings leads to more crises in emerging economies, but on average also to higher growth.

Formulating a C over *nGDP* Choleski vector was not supported in the above table. The resulting IRF would be hard to interpret given the absence of Granger causality from C to

[5] Note that this specification tests for both the total (private) credit supply C and the (private) credit-to-GDP ratio C/GDP, since ln(GDP) = a*ln(C/GDP) is identical to ln(GDP) = (a/(1+a))*ln (C).

nGDP; and as the above leads one to expect, no significant IRF result in response variable *nGDP* could be produced for a shock in impulse variable C (Figure 7).

<insert Figure 7>

5. Analysis II: Growth Forecasting

Our findings suggest that disaggregated credit should not only have good in-sample correlation to output, but also be a strong out-of-sample predictor of GDP. So we now proceed to put our conclusion to the test by implementing a disaggregated-credit based out-of-sample prediction of GDP. Its quality should be evaluated against the alternatives of an aggregate-credit model and a univariate autoregressive model, as model (1) in table 2[6]. The latter test is truly a hard one. Faust (2001) comments after evaluating a wide range of forecasting models applied to the US economy:

> "We find the surprising result that no model clearly outperforms the univariate autoregressive model. This is one of the simplest possible models: it basically forecasts in every period that the GDP growth will simply follow its historical average rate back to the mean. This may be sobering for not only the Fed but for the macroeconomics profession as a whole: knowledge of interest rates, labour market conditions, capacity utilisation, inflation, or any of about 50 additional variables does not systematically improve our ability to foretell where real activity is headed."

Preliminary analysis indicates that an ARIMA specification works best for prediction purposes. We calculated out-of-sample *nGDP* forecasts 4 quarters ahead for the last five years in your sample (2002Q3-2007Q2). In our preferred model we predict output growth y_t with its lags y_{t-4} and y_{t-5} and with lags of disaggregated credit, i.e. lags of real-sector bank credit growth $c_{R,B,t--4}$ and $c_{R,B,t-5}$ and financial-sector bank credit growth $c_{F,t--4}$ and $c_{F,t-5}$.. We compare prediction performance of this model to the alternatives of the naive model and an aggregate-credit model, including lags c_{t-4} and c_{t-5}.

Formally, for the disaggregated credit model we estimate a structural equation of the form

[6] For brevity we do not also report predictions private-credit based models but results are available on request from the authors. These findings do not affect the conclusions below.

$$y_t = C + b_1 \cdot y_{t-4} + b_2 \cdot y_{t-5} + b_3 \cdot c_{R,B,t-4} + b_4 \cdot c_{R,B,t-4} + b_5 \cdot c_{F,t-4} + b_6 \cdot c_{F,t-5} + u_t \qquad (t = 1,2, \ldots 46)$$

and for the aggregate credit model we estimate a structural equation of the form

$$y_t = C + b_1 \cdot y_{t-4} + b_2 \cdot y_{t-5} + b_3 \cdot c_{t-4} + b_4 \cdot c_{t-5} + u_t \qquad (t = 1,2, \ldots 46)$$

while the naive model is

$$y_t = C + b_1 \cdot y_{t-4} + b_2 \cdot y_{t-5} + u_t \qquad (t = 1,2, \ldots 46)$$

where *b*'s are parameters on output and credit and *u* is the disturbance term. In each of these models, a first-order autoregressive AR(1) term and a 4^{th}-lag moving average MA(4) term are included by estimating the disturbance equation:

$$u_t = p \cdot u_{t-1} + s \cdot e_{t-4} + e_t \qquad (t = 1,2, \ldots 46)$$

where *p* is the first-order autoregressive parameter, *s* is the 4^{th}-lag moving average parameter and *e* is a white-noise disturbance term[7].

The transformation of original data for prediction purposes merits separate consideration. While in the in-sample VAR estimation reported in table 2 we used twice differenced logarithms in order to achieve stationarity, this is not necessarily the preferred transformation for prediction purposes. Twice differencing (once annually, once quarterly) necessitates the construction of recursive annual forecasts, i.e. predictions based on predicted values, which introduces multiple errors in the final estimate[8]. This is not necessary with once (annually) differenced data. In our exploratory work we found indeed that predictions based on annually differenced data are superior to those based on twice differenced data and this is the transformation we will use below. Hence with 50 quarterly observations from 1995Q1 – 2007Q2, we use 46 observations of growth data from 1996Q1 – 2007Q so that t = 1,2, … 46 in the above ARMA model equations.

[7] We include only two lags for reasons of data availability. We experimented with different lags from t-1 to t-4 and found that the ar(1) ma (4) model performs best, as expected.

[8] To be sure, ARIMA forecasts themselves are already recursively constructed regardless of data transformation. So actually twice differencing would necessitate twice using recursive calculations.

In our limited time series, feasibility of prediction using the 1996Q1-2007Q2 data is limited by the need for a sufficient number of data points preceding the first predicted value, allowing for reliable estimation of regression coefficients underlying the prediction. Figure 8 below therefore shows the Czech nGDP growth rate as well as its one-year-ahead forecasts, for the last five sample years 2002Q3-2007Q2 of our 1996Q1 – 2007Q3 sample. Thus our first predicted value is for 2002Q3, based on the preceding 30 observations. We chose this cut-off point as additional analysis showed that constructing earlier estimates (2002Q2) - using yet fewer preceding data points - leads to rapidly deteriorating prediction quality.

<*insert Figure 8*>

As it is, performance of particularly the parameter rich C_RC_F model is already weak for the first six quarters of predicted values. We assess prediction performance of the three models by calculating their Roots of Mean Square Errors (RMSEs). If calculated over the entire prediction window for which we also observe nGDP (2002Q3-2007Q3), the RSMEs are 1.21 for the naive model, 1.10 for the C-model and 1.63 for the C_RC_F-model. This would suggest that a credit-based model is superior to the naive model, confirming our theoretical focus on credit; but also that credit disaggregation neither improves over an aggregated-credit model, nor outperforms the naive model.

However, these results are heavily influenced by high RMSE values of the C_RC_F-model for the first six quarters. In order to study prediction performance over time, in Figure 9 we also present the moving-average RMSEs over prediction window t to 2007Q2, with quarter t running from 2002Q3 (producing a 5-year RMSE) to 2006Q3 (yielding a 1-year RSME). For these 20 prediction windows we find that the C-model consistently outperforms the naive model, with a fairly constant and highly significant difference in RMSE of around 0.1. Moreover, this graph also shows that the C_RC_F-model is the weakest model for the first 8 quarters t = 2002Q3 through to t =2004Q2, but in contrast provides the best predictions for the 12 later windows to 2007Q2. Starting from a very high RSME level of above 2 for the 5-year RMSE 2002Q3-2007Q2, its moving-average RMSEs steeply drops over the first six quarters. It first achieves an RMSE value lower than that of the naive-model for the 2003Q4-2007Q2 window, and this remains so for all subsequent prediction windows. From the

2004Q3-2007Q2 window and onwards it also outperforms the C-model, with a highly significant[9] ($p < 0.01$) difference in RSME between the $C_R C_F$-model and the C-model.

<insert Figure 9>

There are three possible explanations for the initially high RMSE values of the $C_R C_F$-model for early *t* and its much better performance afterwards. One is the data need problem noted above: the $C_R C_F$-model, having two more parameters and therefore greater data needs, can be expected to perform more weakly than the other, simpler models at earlier points in time, where there are fewer preceding observations on which to base the predictions. This explanation would imply that the appropriate cut-off point of prediction construction for the $C_R C_F$-model is around 2004Q2. Two other complementary explanations are not statistical but substantive. In the theoretical section we have noted that there is long-run correspondence but short-term divergence of C_R and nGDP. This would be reflected in better model fit over longer time periods, quite regardless of the separate effect of more data points. Yet another explanation concerns the rise of financial-sector credit C_F in the Czech economy we observed in the descriptive section 2. The disaggregated $C_R C_F$ model increasingly captures the reality of banks catering to both real-sector and financial-sector firms, and therefore its predictions perform increasingly well relative to the C-model. To illustrate this last point, Figure 10 plots, in one graph, the share of financial credit C_F in GDP and the ratio of the $C_R C_F$-model RSME to the naive-model RSME, both for the *t* to 2007Q2 window. Their clear negative relation over time is evidenced by a bivariate correlation coefficient of both time series of -0.81.

<insert Figure 10>

[9] The Wilcoxon z-statistic for the difference in RSME between the $C_R C_F$-model and the C-model takes a value 3.040, with a critical value for a directional tests at the 1 % level of z = 2.326.

6. Discussion and Conclusion

The aim of this paper was to suggest a framework to explore the link between credit and output in the context of a developed transition economy such as the Czech Republic, and to implement it. A salient features of these economies is the prevalence of credit constraints (especially in the early phases of the transition) and the recent development of new types of credit flows, transforming their financial sectors. We develop a framework that is capable of reflecting these developments, where we distinguish between bank credit flows to the real sector and credit to financial-sector firms (such those in the insurance, pension funds and real estate sectors). In our empirical work we find that this disaggregated measure for credit flows exhibits better short-term correlation and causation to output growth than traditional, aggregate measures of credit and money. Our measure also appears to be a better annual predictor of nominal growth.

The results we obtained are encouraging. The suggestion supported by this result is to move away from studying overall credit aggregates in researching the finance-growth nexus. It appears more useful to study disaggregated credit flows so as to understand their differential impacts on growth. Their major limitation in our empirical work is data availability. The new EU member states have only about 10 years of reliable data, which is a limitation also when using quarterly observations. Another challenge is the imperfect disaggregation of credit flows, imposed by data collection conventions. Within these limitations, we aim to further pursue this line of research by application to other emerging markets where the relative magnitude of real-sector and financial-sector credit flows are rapidly changing and our framework is likely to be helpful. This will also shed light on the generalisability of our framework across countries. A theme that merits further conceptual development is the role of credit for asset markets C_F. Since a major issue in the study of credit markets in emerging economies is the possibility of credit booms and bubbles, and as such bubbles are typically asset price bubbles, the magnitude of C_F relative to GDP is likely to be relevant in the study of growth sustainability.

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Tables and Graphs

Table 1: overview statistics of output and credit/money aggregates, 1996Q4-2007Q2 (M3:2003Q4-2007Q2)

Variable	# obs	mean	std. dev.	Minimum	Maximum
Y	45	-0.0009	0.0147	-0.0478	0.0363
C_R	45	0.0032	0.0487	-0.1695	0.1130
C_F	45	-0.0041	0.2399	-0.62013	0.7985
C	45	-0.0022	0.1955	-0.4912	0.4841
C_P	45	-0.0022	0.1990	-0.6604	0.5709

Note: Variables are twice differenced logarithms of original data.

Source: Czech National Bank

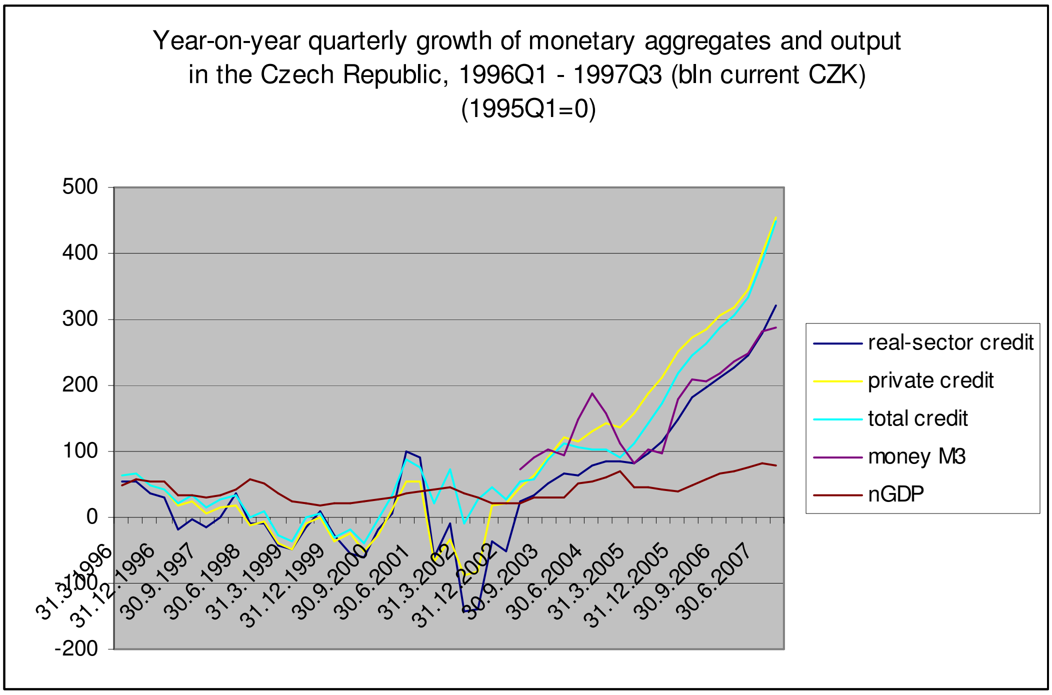
Table 2: Granger test results from VAR estimation of output and credit aggregates, 1996Q4-2007Q2. Dependent: nGDP$_t$

	Model						
	1	*2*	*3*	*4*	*5*	*6*	*7*
Credit aggregate							
$C_{R,B}$	22.97***		42.83***		22.92***		23.54***
C_F		8.2	24.15***				
C				5.2	5.2		
C_P						4.63	5.03
R2	0.58	0.45	0.74	0.41	0.62	0.40	0.63

Notes: All significant Granger causality evidence is unidirectional from credit to output. All models have 39 quarterly observations and six lags.

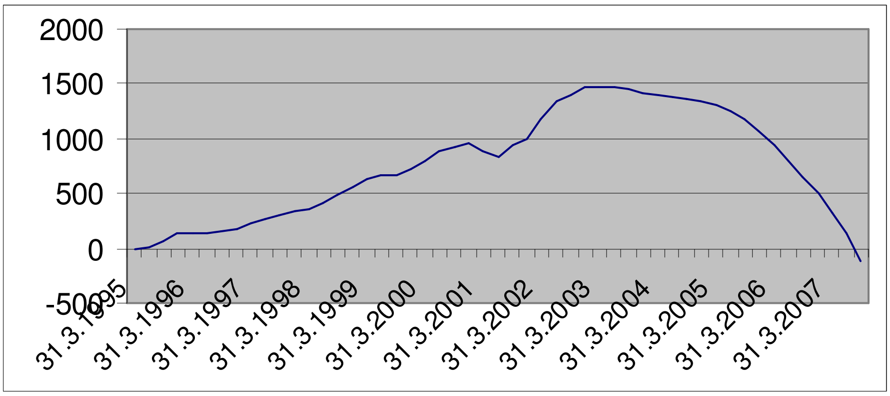
Source: Czech National Bank

Figure 1: monetary aggregates and output growth, 1996 – 2007



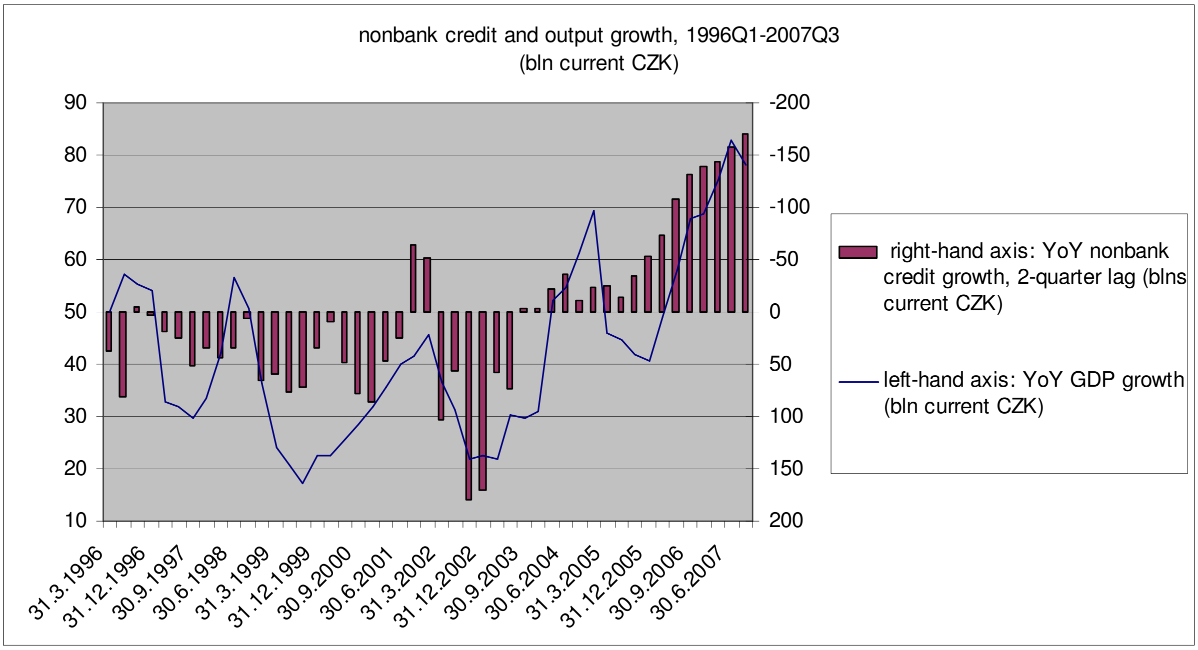
Source: Czech National Bank and authors' calculations. M3 is available from start 2002.

Figure 2: Cumulative Year-On-Year Growth in nonbank credit $\Delta C_{R,N}$



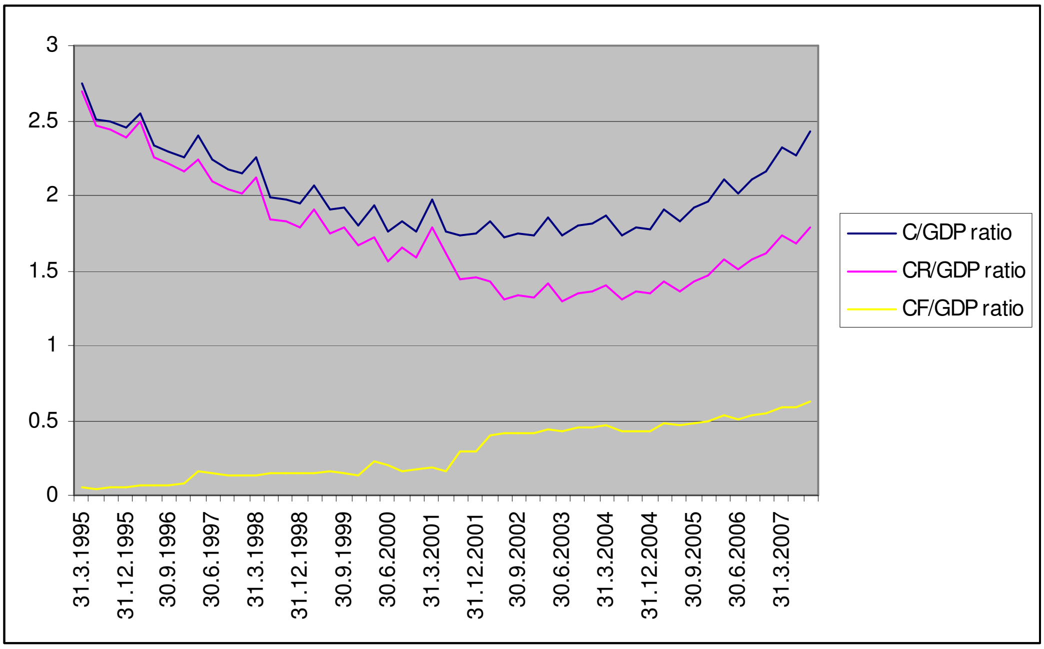
Source: Czech National Bank and authors' calculations

Figure 3: lagged real-sector bank credit constraints and nominal output growth, 1995-2007



Source: Czech National Bank and authors' calculations

Figure 4: Bank-Credit-to-GDP ratios, 1995-2007: total C, real-sector $C_{R,B}$; and financial-sector C_F.



Source: Czech National Bank and authors' calculations

Figure 5: Orthogonalized impulse response function for an (nGDP, $C_{R,B}$, C_F) VAR model: response of nGDP to $C_{R,B}$.

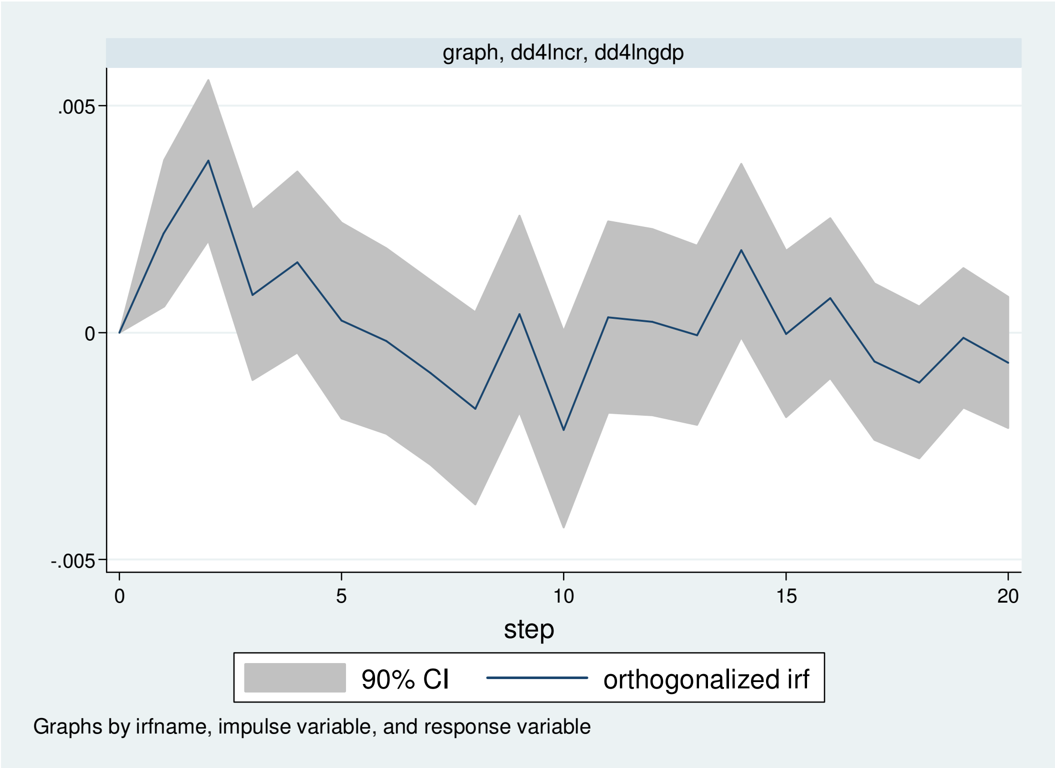


Figure 6: Orthogonalized impulse response function for an (nGDP, $C_{R,B}$, C_F) VAR model: Response of nGDP to $C_{R,F}$.

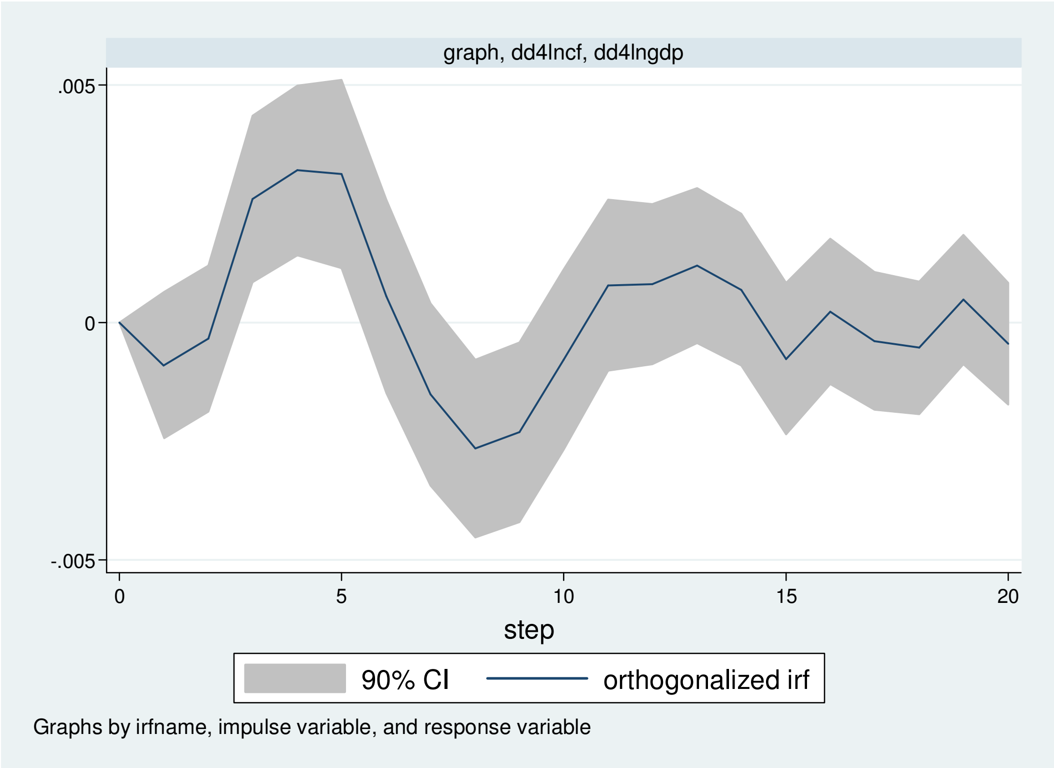


Figure 7: Orthogonalized impulse response function for an (nGDP, C) VAR model: Response of nGDP to C.

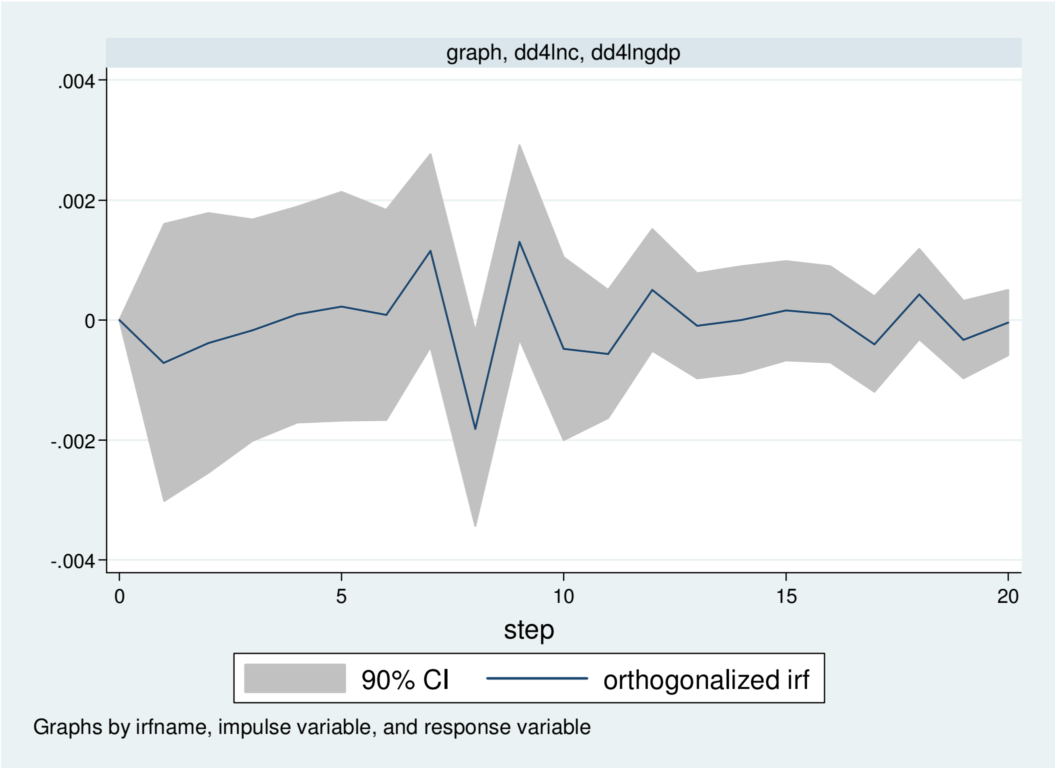
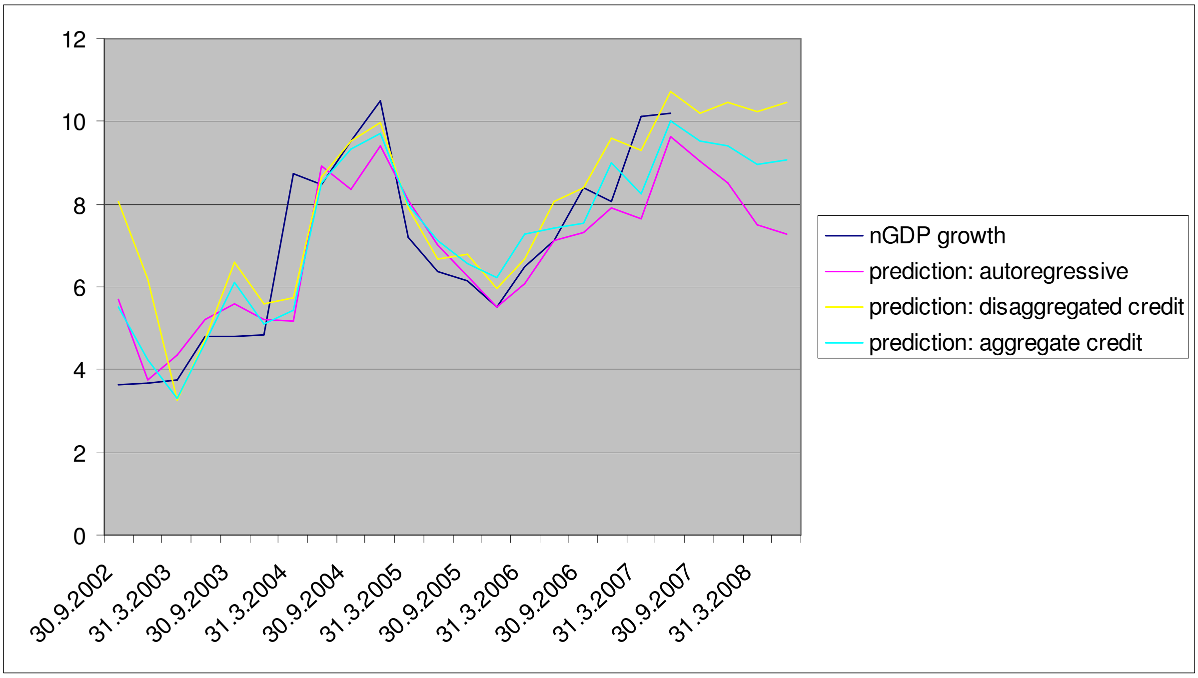
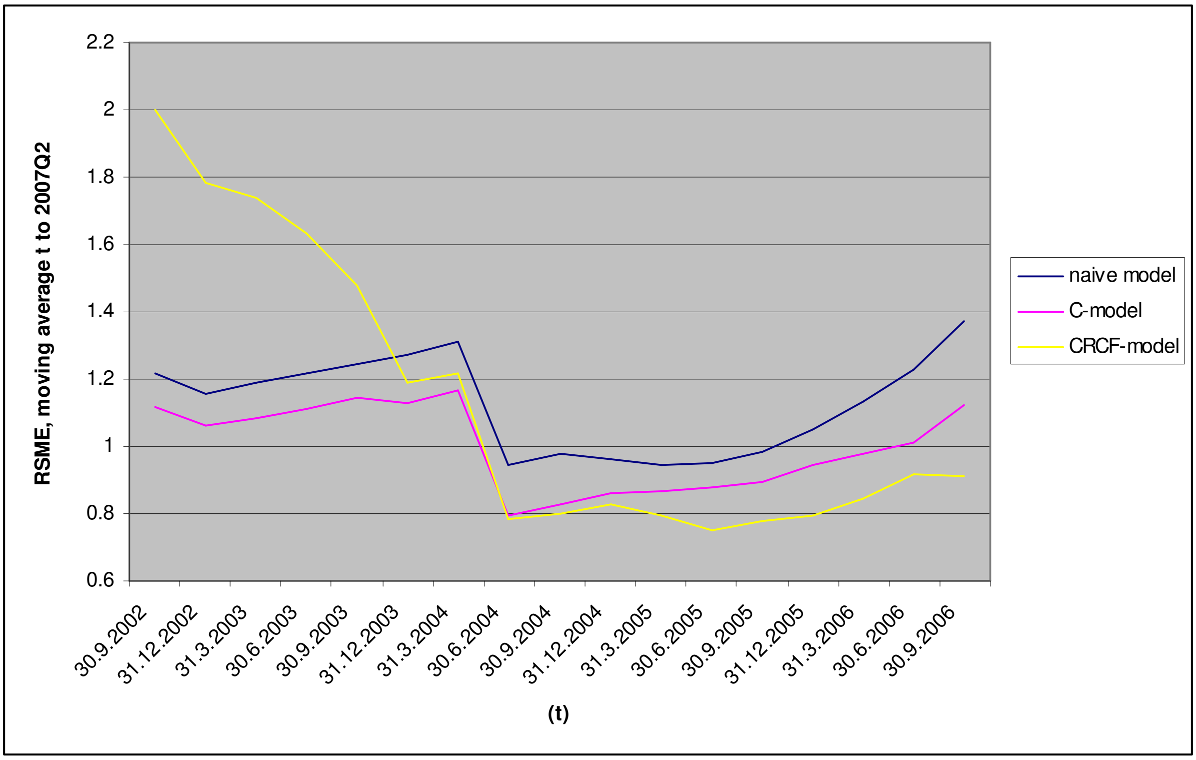


Figure 8: nGDP growth and 4Q-predictions, 2002Q3-2007Q2



Source: Czech National Bank and authors' calculations.

Figure 9: Roots of Mean Square Errors for forward moving averages, t to 2007Q2



Source: Czech National Bank and authors' calculations.

Figure 10: C_RC_F model errors and C_F-to-GDP ratio