The Output Effect of the Funding for Growth Scheme: Empirical Evidence Using the Hungarian Bank Lending Survey

Attila Gyetvai

Central European University
Department of Economics

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Supervisor: Professor Sergey Lychagin

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Abstract

In this thesis I measure the impact of the Central Bank of Hungary's Funding for Growth Scheme (FGS) on output. I use a novel identification strategy that marries micro and macro level techniques: I create an indicator of credit supply using bank level responses in the Hungarian Bank Lending Survey, then use this indicator to put a supply side structure on a system of equilibrium aggregates. Comparing program and no-program scenarios, I find that the output effect of FGS is 0.4 percent until the end of 2013 and 0.2 percent until the end of 2014. These figures lie between previous findings: micro data based results imply a smaller effect while macro data based ones estimate it to be larger.

Acknowledgments

First of all, I am indebted to Professor Sergey Lychagin for his excellent supervision. I am also grateful to Professor Robert Lieli for his invaluable comments.

This thesis was written mainly during my summer internship at the Central Bank of Hungary in 2014.* The idea of using the Bank Lending Survey to identify credit supply shocks was developed in our research project with Nikolett Vágó, to whom I owe a lot. I am also thankful to Ádám Banai for his various useful suggestions, and to my former colleagues. All remaining errors are mine.

Of course, this thesis could not have been written without the help of my beloved friends and the support of my family. Thank you all.

*The views expressed in this thesis are my own and do not necessarily reflect the official view of the Central Bank of Hungary.

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1 Motivation

The spillover of the 2008 financial crisis and the great recession thereafter to Hungary caused an overall economic slowdown. Simultaneously, the rising trend in the amount of outstanding corporate loans at Hungarian banks turned into a decrease. To revert this trend and enhance economic growth, the Central Bank of Hungary initiated its so-called Funding for Growth Scheme (FGS) which provides small and medium size enterprises (SMEs) with low-rate loans through the banking system. In my thesis I assess the success of this program using a novel identification strategy.[1]

In FGS, banks can borrow from the central bank on zero interest and use this interest-free asset to lend to SMEs at a maximum interest rate of 2.5 percent. As of the summer of 2015,[2] FGS has had two stages and there are differences in the permitted use of these loans. In the first stage (June 1, 2013–September 30, 2013), SMEs could take FGS loans to refinance their already existing loans; this use is limited in the second stage (October 1, 2013–December 31, 2015).[3] This difference is clearly shown in the takeup of the program: the total amount loaned was 700 billion Hungarian forints (approx. 3.2 billion US dollars) in the first stage and has been 600 billion Hungarian forints (approx. 2.2 billion US dollars[4]) until the end of 2014, i.e. an almost fourfold period, during the second stage. Out of the 700 billion Hungarian forints in the first stage, 410 billion was spent on refinancing already existing loans; the remaining 290 billion, such as the 600 billion amount in the second stage, financed new long-term investments and working capital, and prefinanced EU funds.

Such a lending scheme by a central bank is not a conventional monetary policy tool. Komlóssy et al. (2014) compare FGS to three similar programs: the Funding for Lending

[1] This thesis complements an ongoing project at the Central Bank of Hungary. Gyetvai and Vágó (unpublished) identify credit supply shocks using changes in Hungarian bank lending standards in the manner of Bassett et al. (2014); I employ this strategy too. The novelty of my thesis lies in using this credit supply indicator to assess the impact of FGS on output.

[2] The data and model assumptions reflect the stance of FGS at the summer of 2014 when I was an intern at the Central Bank of Hungary. At that time, FGS was announced to end at December 31, 2014; it was extended by one year on October 29, 2014.

[3] Loan contracts have to be signed until December 29, 2015. Disbursement takes place until December 31, 2015 or June 31, 2016 in some special cases.

[4] The exchange rate used is 220 Hungarian forints/US dollars in the first stage and 270 Hungarian forints/US dollars in the second stage.

Scheme (FLS) of the Bank of England, the Monetary Easing program of the Bank of Japan, and the Targeted Longer-term Refinancing Operations (TLTRO) of the European Central Bank. They state that FGS is the largest of the four, in terms of GDP, both in terms of disbursement and allocated amount. Since these programs are rare and recent, studies that evaluate their success are limited. The macroeconomic impacts of FGS are assessed by Endrész et al. (2014): using several macro-level identification schemes they find that, from the start of the program until the end of 2014, firm investment increased by 2.4–8.3 percent, consumption by 0.1–0.5 percent, GDP by 0.5–1.1 percent, and employment by 3–9,000 workers. Their strategy is capable of capturing multiplicative effects but it uses macro aggregates, thus results are less reliable. Endrész et al. (2015) show in a firm-level difference-in-differences analysis that FGS generated 3.4 percent extra firm investment until the end of 2013 which roughly translates into a 0.2 percent increase in GDP. Although their analysis uses reliable micro-level data, it neglects multiplicative effects between investment and output; therefore the found output effect is not claimed to be valid.

My identification strategy differs from previous literature. I use *both* micro-level data and macro aggregates in a two-stage setup: first I identify credit supply using bank-level data and then I put a supply side structure on macro aggregates using this supply indicator. Specifically, I employ a structural vector autoregression (SVAR) model similar to those by Endrész et al. (2014) and Tamási and Világi (2011); however, I identify credit supply *outside* the SVAR. Previous models use broad credit supply measures that might be determined simultaneously with demand; I create an indicator of credit supply that is filtered from these demand factors. I use bank level responses from the Bank Lending Survey (BLS) for identification. I include this supply indicator in the SVAR to model the Hungarian economy extended by a detailed loan market setup. Using SVAR results, I forecast the series first without any intervention, then with additional assumed trends of the interest rate and the amount of outstanding corporate loans. Both of these modified variables are market equilibrium measures; the previously identified supply indicator puts a structure on the system, thus modeling the supposed channel of FGS through credit supply. The output effect of the program is displayed by the difference between the two forecasted GDP series. My results indicate that the effect is 0.4 percent until the end of 2013 and 0.2 percent until the end of 2014; that is, my findings lie in between those of Endrész et al. (2014) and Endrész et al. (2015).

The rest of the thesis is structured as follows: In Section 2 I describe the data. In Section 3 I discuss the identification of the credit supply indicator, preceded by a Monte Carlo motivation of the estimator used. In Section 4 I set up the SVAR and assess the impacts of FGS using iterative forecasts. Finally, Section 5 concludes.

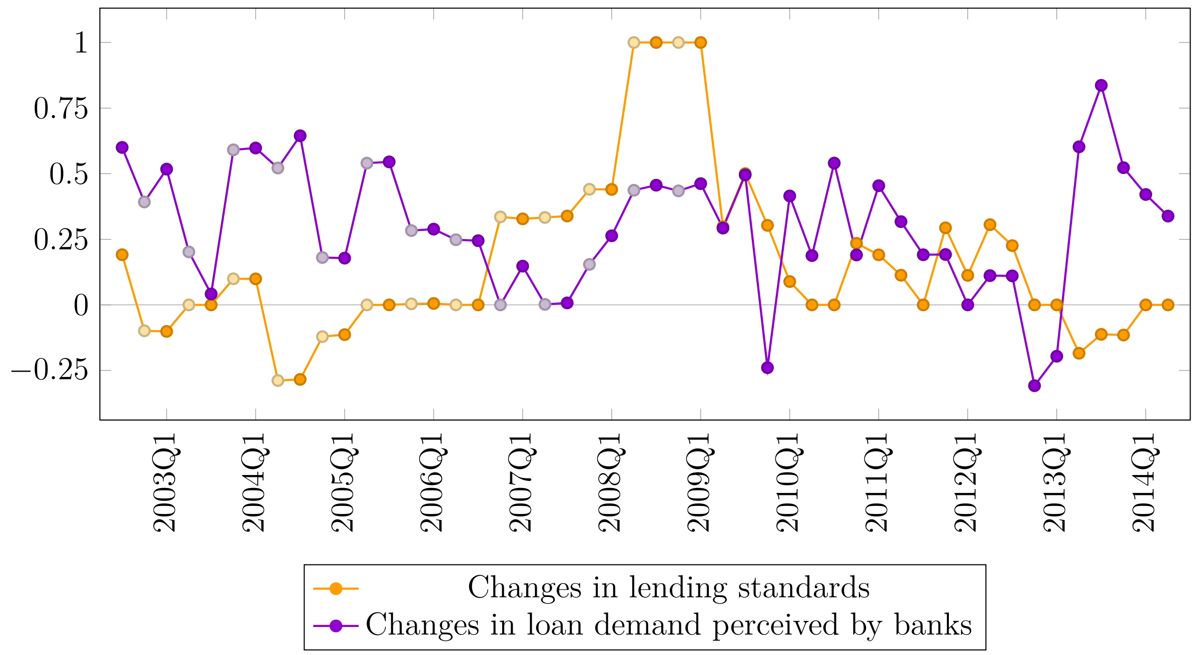
2 Data description and manipulation

Here I describe the data used in the first part in more detail. These data come from a less known source, the Bank Lending Survey (BLS). In the second part of my analysis I set up an SVAR with widely accepted and used variables.

BLS is conducted by the Central Bank of Hungary. In each period, executives of banks handling approx. 90 percent of the total amount of outstanding loans are surveyed. Between the second half of 2002 and 2008 the survey was conducted biannually; since 2009 it has been conducted on a quarterly basis. Bank executives are asked questions about changes in loan demand and lending standards from the previous period, and the change they anticipate for the next one. Each question is asked regarding corporate, real estate and consumer loans; I use responses to the corporate loans segment of the survey only since FGS targets this sector. Unfortunately, there are no responses regarding SMEs separately.

The variables of interest are the survey answers regarding the change in lending standards and in loan demand since the date of the previous survey wave. Both variables are measured as a $\{-1, 0, 1\}$ variable, where -1 means easing standards/declining demand, 0 means stagnation in standards/demand, and 1 means tightening standards/increasing demand. Note that this measurement does not represent the *magnitude* of changes, only their direction. An example: Suppose that the reported change in standards by bank i on loan category k in period t is 1, i.e. $\Delta S_{it}^k = 1$; suppose also that $\Delta S_{i,t+1}^k = -1$. This does

Figure 1: Aggregate changes in lending standards and loan demand



Notes: Light orange data points represent derived changes in lending standards. Light purple data points represent derived changes in loan demand perceived by banks. Series are weighted averages of reported changes in lending standards, where weights are lagged amounts of outstanding corporate loans.

not provide information whether standards overall have tightened, eased, or stagnated from the beginning of period t to the end of period $t+1$; this only shows that tightening preceded easing. Changes in lending standards and loan demand, weighted by the lagged amount of outstanding corporate loans, are shown in Figure 1.

Since data are only biannual in the first part of the sample, I need to derive quarterly measures in the second and fourth quarters of the years 2002–2009. A naive solution would be to assign the half-year answer to both quarters. However, as emphasized above, it might happen that easing standards/declining demand during a certain half-year is the consequence of a small tightening/small increase in demand in its first quarter and a great easing/great decline in demand in the second. To overcome this issue, I assume a smooth backward-looking formation of standards following Sóvágó (2011); assumptions made are summarized in Table 1. Generally, I make the assumption that the reported change in the latter half-year is preceded by the same direction of change in standards. The only exception is when opposite directions of changes are reported in half-year occurrences; in this case I assume a smooth transition. With this derivation, the least amount of variance

Table 1: Derivation of missing quarterly measures for periods with half-yearly observations

		Half-year $t+1$		
		-1	0	1
	-1	-1	0	0
Half-year t	0	-1	0	1
	1	0	0	1

Notes: The table is read as follows: between half-years t and $t+1$, I assume a change in lending standards of the degree in respective cells. I.e. if the reported change in standards is 0 in t and 1 in $t+1$, I assume that the change in the intermediate, unobserved quarter is 1. Quarterly measures are derived for the second and fourth quarters of the years 2003–2008.

is introduced into the system. As a consequence, I might underestimate credit supply.

I consider three model specifications to identify the sought credit supply indicator. The first two are nested in the preferred bank-level specification and serve as robustness checks. In the first, benchmark specification I only include the lagged reported changes in lending standards and loan demand. In the second, macro specification I add yearly changes in log retail sales, yearly changes in the short term interest rate (the interest rate of the two-week bond issued by the Central Bank of Hungary), and quarterly changes in the Economic Sentiment Indicator (ESI), computed by Eurostat as a weighted average of sectoral confidence indicators. This latter variable depicts anticipated changes in the economic outlook, thus having an impact on current lending standards. In the—preferred—third, bank-level specification, in addition to the variables in the former two, I also include quarterly changes in the rate of non-performing corporate loans, log available stable funding (equity, short funds, and short household deposits), and the lagged share of core loans (the ratio of the sum amount of outstanding commercial and industrial, real estate, and consumer loans to all outstanding loans). Data are gathered by the Central Bank of Hungary; BLS survey answers and bank-specific variables in the third specification are confidential and conditionally available upon request.

I incorporate macro aggregates in the second part of my analysis. I include the identified credit supply indicator, log real GDP, log core lending capacity (outstanding corporate loans plus unused loan commitments), average interest rate on corporate loans weighted by the lagged outstanding amount, and the Hungarian forint/euro exchange rate. I also include the EURIBOR rate and log new export orders as exogenous variables to capture external relations.

3 Identifying credit supply

The first step in quantifying the impact of FGS on output is to identify credit supply. This is a difficult task since credit supply and demand are not observable separately. My approach draws from Bassett et al. (2014): I create an indicator of credit supply by cleaning bank-level data on lending standards from factors that simultaneously determine demand. I call this supply indicator the effective supply component of lending standards (ESCLS).

I employ dynamic panel data models for identification. In this section, I first compare the performance of seven possible estimators, then provide regression results from three nested model specifications. Finally I discuss the identified ESCLS series, i.e. the indicator of credit supply.

3.1 Monte Carlo comparison of possible estimators

There are several features of the data which the employed estimation technique should take into account. First, it is of crucial importance to include individual effects in order to control for unobserved bank-level heterogeneity. Second, including the lagged dependent variable on the right hand side is necessary as lending standards are serially correlated. Third, the dependent variable is categorical $\{-1, 0, 1\}$, therefore limited dependent variable techniques might be required.

Unfortunately, there is no estimator available that would be suitable for a dynamic multinomial setup with individual effects. A natural solution is to ignore one of these three features, bearing precision loss in mind. Omitting the first feature, individual effects, is definitely out of the question: even though the dependent variable is in differences, data show bank-level trends which are not vanished by differencing. The presence of such trends might be a result of different ownership structures: the lending behavior of foreign-owned banks might be largely affected by their parents and events at their countries, hence they could display other dynamics than Hungarian ones. For this reason, it is more plausible to assume that individual effects are fixed rather than random. Consequently, the options left are not to take the dynamic or the discrete nature of the data into account.

The two main kinds of estimators I discuss are (i) dynamic and (ii) nonlinear ones. Of the first type, I consider the estimators by Anderson and Hsiao (1982), Arellano and Bond (1991), Blundell and Bond (1998), and Bruno (2005); I denote them by AH, AB, BB, and LSDVc, respectively. This last one needs some introduction as it is not frequently used in the literature. LSDVc is a bias-corrected version of the standard least squares dummy variable (LSDV) estimator. Bruno (2005) provides bias approximation formulas by extending earlier results of Kiviet (1995), Kiviet (1999), and Bun and Kiviet (2003) to unbalanced panels. All these estimators are designed for a dynamic FE setup but they assume a continuous dependent variable.

Of the second type, I discuss the Blow-Up and Cluster (BUC) estimator by Baetschmann et al. (2014) along with standard RE ordered probit and logit estimators. The BUC estimator is an FE ordered logit estimator that collapses the outcome variable to a binary one in the manner of Chamberlain (1980) and estimates the coefficients at each cutoff jointly. These estimators are designed for an ordered multinomial outcome variable but might not perform well in a dynamic setup. Furthermore, only the BUC estimator features fixed effects; the other two assume that the individual effect is random which might be an incorrect assumption as motivated above. To assess the performance of the considered estimators, I conduct the MC simulation in both a nondynamic and a dynamic setup, i.e. I do not or do include the lagged dependent variable in the list of regressors.

It is not clear how banks' decisions to change lending standards should be thought of. On one hand, it is possible that the decision is (partly) determined by the *direction* of the previous change. On the other hand though, there might be an underlying continuous process which is observable to the econometrician only in discrete terms. Such a process could be some indicator of the maximum loan-to-value ratio, the ratio of required install-

Table 2: Monte Carlo comparison of dynamic panel and ordered probit/logit estimators

(a) Iterative discretization

Variable	True value	AH	AB	BB	LSDVc	BUC (ND)	Ord. probit (RE, ND)	Ord. logit (RE, ND)	BUC (D)	Ord. probit (RE, D)	Ord. logit (RE, D)
$y^D_{i,t-1}$	0.5	0.342	0.392	0.383	0.409	–	–	–	2.713	1.615	2.870
x_{it}	0.35	0.067	0.074	0.075	0.074	0.485	0.276	0.486	0.653	0.369	0.656
$\text{corr}(u_{it}, \hat{u}_{it})$	1	0.242	0.328	0.327	0.353	0.237	0.237	0.237	0.216	0.286	0.285

(b) Continuous underlying process

Variable	True value	AH	AB	BB	LSDVc	BUC (ND)	Ord. probit (RE, ND)	Ord. logit (RE, ND)	BUC (D)	Ord. probit (RE, D)	Ord. logit (RE, D)
$y^D_{i,t-1}$	0.5	0.360	0.402	0.394	0.423	–	–	–	1.916	1.166	2.055
x_{it}	0.35	0.062	0.068	0.069	0.068	0.348	0.201	0.349	0.400	0.226	0.399
$\text{corr}(u_{it}, \hat{u}_{it})$	1	0.416	0.566	0.566	0.588	0.429	0.429	0.429	0.406	0.505	0.505

Notes: $N = 7$, $T = 45$. Figures are averages of 1,000 MC repetitions. AH: Anderson-Hsiao. AB: Arellano-Bond. BB: Blundell-Bond. LSDVc: corrected LSDV by Bruno (2005). BUC: Blow-Up and Cluster estimator by Baetschmann et al. (2014); FE ordered logit. RE: random effects. ND: non-dynamic specification. D: dynamic specification. Data are generated by the following processes:

For iterative discretization:

$$y_{it} = \alpha + \gamma y^D_{i,t-1} + \beta x_{it} + c_i + u_{it},$$

$$y^D_{it} = \begin{cases} -1 & \text{if } y_{it} \leq T_1 \\ 0 & \text{if } T_1 < y_{it} \leq T_2 \\ 1 & \text{if } T_2 \leq y_{it} \end{cases},$$

T_1 and T_2 being the 1st and 2nd tertiles.

For the continuous underlying process:

$$y_{it} = \alpha + \gamma y_{i,t-1} + \beta x_{it} + c_i + u_{it},$$

$$y^D_{it} = \begin{cases} -1 & \text{if } y_{it} \leq T_1 \\ 0 & \text{if } T_1 < y_{it} \leq T_2 \\ 1 & \text{if } T_2 \leq y_{it} \end{cases},$$

T_1 and T_2 being the 1st and 2nd tertiles.

x_{it} is serially correlated, i.e. $\text{corr}(x_{it}, x_{i,t-1}) = 0.4$. The disturbance term is normally distributed, i.e. $u_{it} \sim N(0, 1.5)$. c_i is correlated with x_{it}.

ments to income, and the downpayment-to-loan ratio. Since both cases are plausible, I consider both by generating data in an iterative discretization scheme and also assuming a continuous underlying process.

Results are summarized in Table 2. The recovered correlation between the fitted residuals and actual simulated disturbance terms is shown in the last line of both Panels (a) and (b). It is not surprising that all estimators applied on data generated assuming a continuous underlying process perform better than in the iterative discretization case in terms of recovered correlation since discretization is less drastic. It is a more important finding that the dynamic estimators perform better than the ordered ones in both cases. Specifically, the LSDVc estimator recovers the most correlation among the considered alternatives: the correlation between residuals and disturbances is 35.3 percent in the iterative discretization case and 58.8 percent in the continuous underlying process case.

Consequently, I employ the LSDVc estimator in the identification of ESCLS.

The LSDVc estimator recovers 98.7 percent of the correlation on the same size of data where the dependent variable is continuous, which is almost perfect. Therefore the distance of the correlation measures from 1 is solely due to discretization. Consequently, despite noise the LSDVc estimator can be successful in identifying ESCLS if the model is correctly set up (that is, there are neither omitted nor unnecessary variables included and the assumption of fixed effects is valid).

3.2 First stage model

The goal of the first stage model is to create an indicator of credit supply which is free from factors that simultaneously determine demand. Obviously, many of these factors affect demand and supply at the same time; therefore some of the supply variation is also vanished from the identified supply series. As established previously, I estimate the model by the LSDVc estimator.

I consider three nested specifications: the benchmark, macro, and bank-level specifications. Out of these three, I consider the third, widest model the most capable of identifying ESCLS. That is, I specify the following models:

$$\begin{aligned} \Delta S_{it} = {} & \gamma_1 \Delta S_{i,t-1} + \gamma_2 \Delta D_{i,t-1} && \text{(benchmark)} \\ & + \mu_1 \Delta ESI_t + \mu_2 \Delta^4 y_t + \mu_3 \Delta^4 r_t && \text{(macro)} \\ & + \beta_1 \Delta NPL_{it} + \beta_2 ASF_{it} + \beta_3 CL_{it} && \text{(bank-level)} \\ & + \eta_i + \epsilon_{it} \end{aligned}$$

where the benchmark specification is shown in the first line, the macro specification is shown in the first two lines, and the—most appropriate—bank-level specification is the whole equation. ΔS_{it} is the quarterly change in lending standards at bank i, ΔD_{it} is the quarterly change in loan demand perceived by bank i, ESI_t is the Economic Sentiment Indicator, y_t is retail sales, r_t is the base rate of the central bank, NPL_{it} is the rate of nonperforming loans at bank i, ASF_{it} is the available stable funding at bank i, and

CL_{it} is the share of core loans in bank i's loan portfolio; Δ denotes quarterly, and Δ^4 denotes yearly changes. I include bank fixed effects in the model to control for unobserved bank-level trend heterogeneity.

The inclusion of the lagged changes in lending standards is necessary since the series is serially correlated. Changes in loan demand perceived by banks is the main demand factor which I clean lending standards from; bank lending behavior lags behind demand trends, therefore I include one lag. These two explanatory variables constitute to the benchmark specification of the model. In addition to these two, the macro specification features the Economic Sentiment Indicator (ESI), retail sales, and the MP base rate. ESI captures expected changes in the economic outlook, thus it has an impact on loan taking (and also lending) decisions. Past changes in retail sales might shape loan demand and supply: an increase in retail sales gives rise to expectations of its continuation and the promise of higher sales increases the willingness-to-borrow of firms (and also the willingness-to-lend of banks). The MP base rate is a good indicator of the stance of the economy, thus it also correlates with loan demand and supply.

I consider the third, bank-level specification the most appropriate to identify credit supply. In this specification, I include other bank-level variables on top of the macro one. The rate of nonperforming loans in banks' portfolios indicates the quality of clients in terms of default. The available stable funding (i.e. equity, short funds, and short household deposits) and the share of core loans (i.e. the ratio of the sum amount of outstanding commercial and industrial, real estate, and consumer loans to all outstanding loans) indicate the financial health of banks. The NPL rate and stable funding affect lending standards contemporaneously but the impact of the share of core loans is more sluggish, hence I use one lag.

The estimated coefficients are presented in Table 3. In all specifications, the serial correlation in the changes of lending standards is approx. 55-60 percent and a perceived past increase in loan demand eases lending standards. In the macro and the bank-level specifications, an improving economic outlook, increasing retail sales, and a higher base rate also result in the easing of lending standards. In the bank-level specification, an

Table 3: First-stage regression results

	Benchmark	Macro	Bank-level
$\Delta S_{i,t-1}$	0.623***	0.601***	0.556***
	(0.049)	(0.048)	(0.049)
$\Delta D_{i,t-1}$	−0.047	−0.045	−0.045
	(0.034)	(0.033)	(0.034)
ΔESI_t		−0.011***	−0.012***
		(0.004)	(0.004)
$\Delta^4 y_t$		−0.455	−0.525
		(0.658)	(0.656)
$\Delta^4 r_t$		−0.014*	−0.020**
		(0.008)	(0.008)
ΔNPL_{it}			0.003
			(0.012)
ASF_{it}			−0.009***
			(0.003)
$CL_{i,t-1}$			0.004
			(0.005)
N	315	315	315

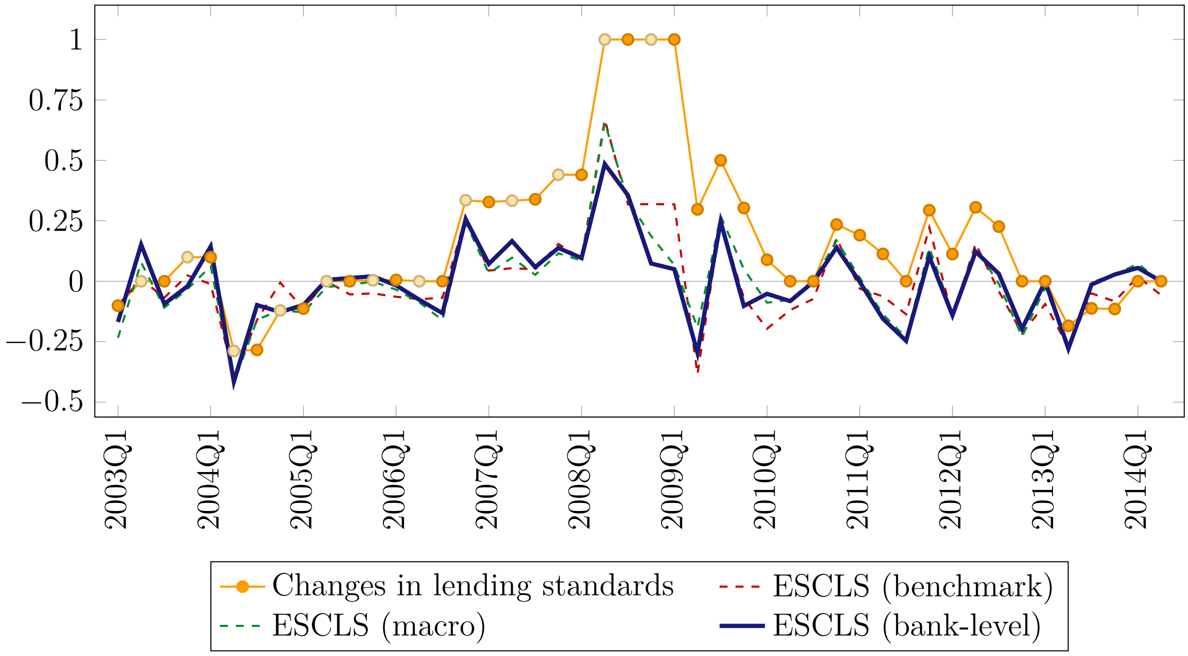
Notes: Bootstrap standard errors in parentheses, 1,000 repetitions. Asterisks denote significance: * 10%, ** 5%, *** 1%. ΔS_{it}: quarterly changes in lending standards at bank i; ΔD_{it}: quarterly changes in loan demand perceived by bank i; ΔESI_i: quarterly changes in the Economic Sentiment Indicator; $\Delta^4 y_t$: yearly changes in retail sales; $\Delta^4 r_t$: yearly changes in base rate; ΔNPL_{it}: quarterly changes in the rate of nonperforming loans at bank i; ASF_{it}: available stable funding at bank i; CL_{it}: share of core loans in bank i's loan portfolio.

increasing NPL rate and an increase in the share of core loans tightens standards while extending stable funds eases them.

After estimating both models, I weight the fitted residuals by the amount of outstanding corporate loans at each bank to create the sought credit supply indicator. I name them the effective supply component of lending standards (ESCLS). This series supposedly captures shocks to credit supply from several possible sources: (i) exogenous foreign shocks since Hungary is a small open economy; (ii) parent banks' regulations; and (iii) random realizations of the anticipated economic outlook like unforeseen fiscal policy shocks.

The fitted ESCLS series, along with the reported changes in lending standards, are shown in Figure 2. The identified ESCLS does not differ from the reported changes from the start of the sample until the end of 2006—that is, loan demand did not affect supply much during this period. In 2007 and 2008 ESCLS is lower than changes in lending standards—during the pre-crisis decline in the Hungarian economic activity standards were higher than banks' decisions of pure supply. This phenomenon is even more appar-

Figure 2: ESCLS series from the benchmark, macro, and bank-level specifications



Notes: Light orange data points represent derived changes in lending standards. Series are weighted averages of reported changes in lending standards and fitted residuals from the models in Table 3, where weights are lagged amounts of outstanding corporate loans.

ent during the crisis. In the second quarter of 2009, ESCLS even displays an easing in standards while the realized changes in lending standards show a continuation of tightening, although it is more modest than in preceding periods. After the crisis ESCLS is persistently below reported changes and its sign alternates between subsequent quarters while standards remain tight. This trend reverts in the second quarter of 2013 when FGS is announced. During FGS, reported changes in standards show easing while ESCLS displays a slight tightening.

The main trends of the series coming from different specifications are similar but there are subtle differences between them. The most apparent difference displays the crisis behavior of banks: controlling for bank-level demand factors results in an ESCLS series that displays a smaller tightening than those from the benchmark and macro specifications. Furthermore, during FGS the bank-level and the macro specifications' ESCLS series are above the one from the benchmark specification, which moves along with reported changes.[5]

[5]Gyetvai and Vágó (unpublished) discuss the ESCLS series identified on a data set containing both

The identification of ESCLS is not without caveats. There are a couple of reasons why it might be problematic to interpret ECSLS as a pure credit supply indicator. First, as I already mentioned, the missing quarterly observations between 2003 and 2009 are derived in such a way that the least amount of variation is added to the series. As a consequence, ESCLS might underestimate credit supply. Second, the changes in perceived loan demand and lending standards are reported regarding the whole corporate credit market, not only the SME sector which FGS targets. Results might be distorted by the loan-taking behavior of larger firms if it differs greatly from that of SMEs. Third, the data set contains the seven largest Hungarian banks that handle approx. 90 percent of total outstanding loans. My estimates might suffer from selection bias if there are structural differences in lending behavior between these seven and other banks not present in the sample. Módos et al. (2014) summarize the characteristics of FGS loans and banks providing them; they claim that in the first stage of FGS large banks lent their already existing clients while smaller banks acquired new loan takers, and the share of medium-sized enterprises in banks' portfolios were higher at large banks; both of these effects vanished in the second stage of FGS though. Fourth, as I already mentioned, factors that determine credit demand might affect supply too simultaneously; therefore a portion of credit supply might be vanished from the identified ESCLS series. Fifth, the reverse also could be true: despite my best effort there might be some demand variation left in the identified credit supply indicator. Sixth, the used LSDVc estimator provides a noisy measure of ESCLS as explained in Subsection 3.1. Nevertheless, I find ESCLS sufficient to capture bank behavior, hence it is capable to put a supply side structure on equilibrium measures in the second stage analysis.

4 The impact of FGS on output

Now that I have identified an indicator of credit supply, I am in the position to assess the output effect of FGS. I use ESCLS to put a supply side structure on credit market

corporate and household loans. The inclusion of the household credit sector results in a different figure. Those series clearly display events on the household credit market such as the early repayment scheme.

equilibrium measures, output and prices. I set up an SVAR model of the Hungarian economy to estimate the relationships between variables; I include output, prices, and a credit market in the model, along with external relations as exogenous variables. I capture output by log real GDP (denoted by Y_t) and prices by the Hungarian forint/euro exchange rate (XR_t); furthermore, I model the credit market by ESCLS ($ESCLS_t$), the average corporate interest rate (IR_t), and core lending capacity (outstanding loans plus unused commitments, CLC_t). I represent external relations by foreign prices, captured by the EURIBOR rate ($EURIBOR_t$), and foreign demand, captured by new export orders (XD_t). I employ a Cholesky orthogonalization to estimate the structural parameters of the model. Then I forecast the series using these estimates; I compare simple forecasts to forecasts from an FGS scenario where I make assumptions on the effect of FGS on the interest rate and outstanding loans. The difference between the two forecasted GDP series is the output effect of the program.

4.1 Second stage model

My SVAR specification draws from Tamási and Világi (2011) and Endrész et al. (2014). I use similar aggregate variables to model the Hungarian economy and the inclusion of external relations is also a common feature. The two main differences are that (i) I put a supply side structure on the model by using credit supply shocks estimated separately while it is done inside the model in previous literature; and (ii) I follow a structural identification approach while they employ Bayesian techniques.

My SVAR model is of the following form:

$$\mathbf{A}\mathbf{y}_t = \mathbf{A}\mathbf{C}_0 + \mathbf{A}\mathbf{C}_1\mathbf{y}_{t-1} + \mathbf{A}\mathbf{C}_2\mathbf{y}_{t-2} + \mathbf{A}\mathbf{C}_x\mathbf{x}_t + \mathbf{B}\mathbf{e}_t \tag{2}$$

where $\mathbf{y}_t = (ESCLS, Y, CLC, IR, XR)'_t$ is a 5×1 vector of endogenous variables, $\mathbf{x}_t = (EURIBOR, XD)'_t$ is a 2×1 vector of exogenous variables, $\mathbf{A}$ and $\mathbf{B}$ are 5×5 matrices of structural parameters, $\mathbf{C}_0$ is a 5×1 vector of constants, $\mathbf{C}_1$ and $\mathbf{C}_2$ are 5×5, and $\mathbf{C}_x$ is a 5×2 matrix of coefficients; $\mathbf{e}_t$ is a 5×1 vector of orthogonalized disturbances, i.e.

$\mathbf{e}_t \sim N(\mathbf{0}, \mathbf{I}_5)$ and $\mathrm{E}(\mathbf{e}_t \mathbf{e}_s') = \mathbf{0}_5$ for all $t \neq s$. I employ a Cholesky orthogonalization, i.e. I restrict the structural parameter matrices such that

$$\mathbf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{pmatrix} \quad \text{and} \quad \mathbf{B} = \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{pmatrix}$$

The Cholesky ordering of the variables needs justification, although I do not conduct an impulse response analysis where it would be crucial. I follow Bassett et al. (2014) in ordering ESCLS first, output second, and core lending capacity third; the remaining two variables, interest rate on corporate loans and the Hungarian forint/euro exchange rate (ordered fourth and fifth, respectively), are not present in their VAR. As they argue, this identification allows ESCLS to have an immediate impact on these variables but not vice versa. This is especially true in the case of Hungary: since ESCLS supposedly captures supply shocks coming from foreign sources and unanticipated policies, it is justifiable to neglect contemporaneous effects of output and prices on credit supply. The remaining four variables affect each other in a recursive manner, from the most sluggish output to the most quickly adjusting exchange rate.

The estimated SVAR coefficients and structural parameters are included in Table A1 in the appendix. The SVAR is stable using both ESCLS series; stability test results are included in Figure A1 in the appendix. I estimate the model on the sample until 2013Q2, i.e. before the start of FGS. Forecasting using these coefficients implicitly assumes that the parameters of the model are unaffected by the implementation of the program. This may or may not be true; however, any such analysis is subject to this Lucas-type critique. To refute it, I show the estimated output effect derived from SVAR parameters that are estimated on the whole sample, i.e. including the period of FGS, in Figure A2 in the appendix. The main trends of the forecasted bank-level series do not differ drastically from their restricted-sample counterpart, hence this issue might be neglected. The apparent differences between forecasts are probably due to another caveat, namely that the SVAR

Table 4: Unit root test statistics of time series in the SVAR specification

	Trend included?	ADF	DF-GLS	PP	Conclusion
$ESCLS_t$	No	-2.921^{**}	-2.391^{**}	-6.014^{***}	$I(0)$
Y_t	Yes	-2.276	-1.626	-1.772	$I(1)$
CLC_t	Yes	-1.052	-0.472	-1.307	$I(1)$
IR_t	Yes	-1.832	-1.878	-3.387^{*}	$I(1)$
XR_t	Yes	-3.474^{*}	-2.316^{**}	-3.805^{**}	$I(0)$
$EURIBOR_t$	Yes	-2.320	-2.596	-1.903	$I(1)$
XD_t	Yes	-1.778	-1.984	-2.746	$I(1)$

Notes: Asterisks denote the absence of a unit root in the corresponding series. ***: 1%, **: 5%, *: 10%. ADF: augmented Dickey-Fuller test statistic; null is unit root. DF-GLS: modified Dickey-Fuller test statistic (critical values by Elliott et al., 1996); null is unit root. PP: Phillips–Perron test statistic; null is unit root. When trend is not included, the asymptotic critical values of the ADF and PP tests are −3.614 (1%), −2.944 (5%), and −2.606 (10%); the asymptotic critical values of the DF-GLS test are −2.626 (1%), −1.950 (5%), and −1.608 (10%). When trend is included, the asymptotic critical values of the ADF and PP tests are −4.148 (1%), −3.499 (5%), and −3.179 (10%); the asymptotic critical values of the DF-GLS test are −3.755 (1%), −3.177 (5%), and −2.878 (10%). All tests include two lagged values of the corresponding series.
$ESCLS_t$: effective supply component of lending standards; Y_t: log real GDP; CLC_t: core lending capacity (outstanding loans plus unused loan commitments); $PREM_t$: credit rate spread; XR_t: Hungarian forint/euro exchange rate; $EURIBOR_t$: EURIBOR; XD_t: external demand.

is overfitted. The model features 80 parameters (10 in $\mathbf{A}$, 5 in $\mathbf{B}$, 5 in $\mathbf{C_0}$, 25–25 in $\mathbf{C_1}$ and $\mathbf{C_2}$, and 10 in $\mathbf{C_x}$); my sample is not sufficiently large to provide precise estimates. This issue could be overcome by using Bayesian techniques; however, it is beyond the scope of this thesis.

As a consequence of overfit, there is no room to model cointegrating relationships between variables that follow a unit root process. It would be desirable though: three of the endogenous variables and both two exogenous ones are $I(1)$; unit root test statistics are shown in Table 4. Consequently I use differences of $I(1)$ variables. Nevertheless, since my goal is to assess the short and medium-term effects of FGS, leaving long-run relationships between variables unmodeled is permissible.

4.2 Forecasts from the model

Given the estimated coefficients and structural parameters in the SVAR, I forecast the anticipated paths of the included variables. Forecasts of the endogenous variables are iterated from the SVAR while the paths of the exogenous variables are estimated in

Table 5: Assumed values for forecasts of the interest rate and the outstanding amount of corporate loans during FGS

Quarter	2013Q3	2013Q4	2014Q1	2014Q2	2014Q3	2014Q4
Int. rate (bp)	400	570	460	410	410	410
Δ Int. rate (bp)	-300	$+170$	-110	-50	0	0
Additional outst. loans (billion HUF)	116	20	20	20	20	20

Notes: Gray figures represent assumptions, black figures represent observations.

separate ARIMA models shown in Table A2 in the appendix. I consider two scenarios: when FGS is not implemented and when it is. To simulate FGS, I make the following two assumptions: (i) the interest rate on corporate loans takes its observed realizations in the first four quarters of the program then it remains unchanged;[6] and (ii) the outstanding amount of corporate loans extends by 116 billion Hungarian forints in the first stage of FGS (the first quarter) then it extends further by 20 billion in the second stage of the program (the subsequent 5 quarters). I summarize these assumptions in Table 5. Both assumptions capture changes on the whole market, not only on FGS loans. The rationale behind the assumption on the first quarter expansion in the amount of outstanding corporate loans relates to the supposed counterfactual scenario: approx. 40 percent of the amount of loans lent to finance new investments (290 billion Hungarian forints) would not have take place without FGS.[7] In the second stage of FGS until the end of 2014,[8] the total amount of provided loans is 600 billion Hungarian forints, and I assume that the share of new loans within this amount is the same as was before, i.e. still 40 percent, and that it is distributed evenly across time periods. In possession of more precise and longer data series, one can rerun the forecasts to estimate the effect of the program even more precisely.

The estimated forecasts of the two scenarios are displayed in Figure 3. I use the ESCLS series from the bank-level specification to put a supply side structure on the system of equilibrium aggregates. Figures A3 and A4 in the appendix show the forecasts using the

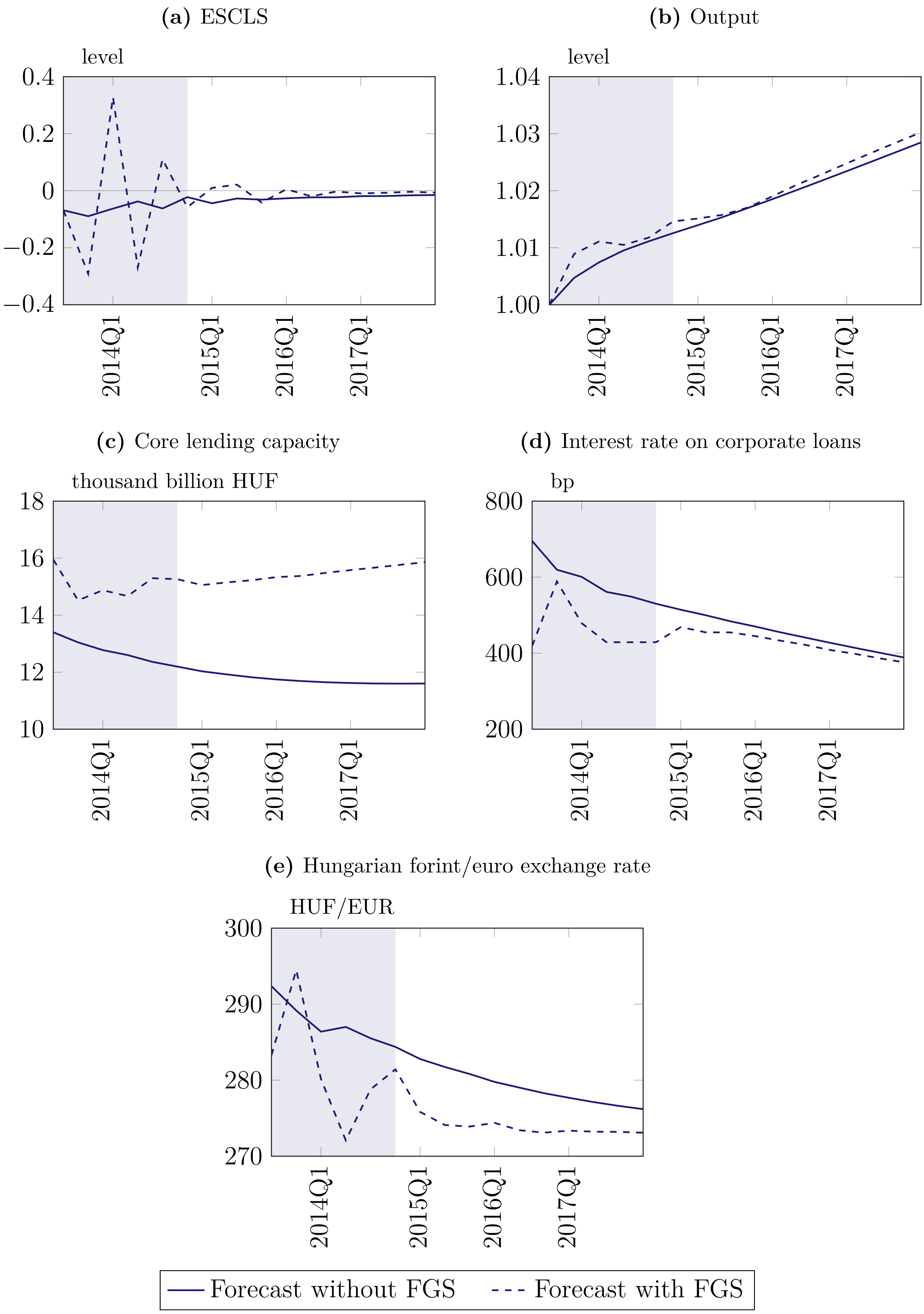
[6]Due to the lack of data, assuming no further changes in the interest rate is the most appropriate.
[7]This rule of thumb of central bankers is strengthened by empirical evidence of Endrész et al. (2015).
[8]I reiterate that the assumptions represent the stance of FGS as of the summer of 2014; that is, I do not assume FGS to continue in the year of 2015, even though this extension was announced in the fall of 2014.

benchmark and the macro ESCLS series, respectively. Differenced variables are cumulated to show levels. According to the figure, the supply channel adjusts through an oscillating decay, starting with a medium easing as an immediate reaction to the implementation of FGS. The immediate output effect is positive during the program but this increase is transitory (with a negligibly small positive difference on the medium run). The core lending capacity turns to a higher and increasing level after the program. The interest rate reverts to its no-progam trend after its exogenous path during FGS. Finally, the Hungarian forint/euro exchange rate reverts to its no-FGS trend as well after a short jump-and-fall trend with a maximum volatility of 20 Hungarian forints/euros.

Comparing the forecasts to alternative ones using other ESCLS series, it is comforting to see no systematic differences. The paths of adjustment through ESCLS, the core lending capacity, and the exchange rate are almost identical in each cases. The output paths differ the most out of the five variables: in the benchmark specification the starting output effect prevails on the medium run too, while in the macro specification it is negative. The interest rate is higher after the program than in the no-program case; the difference is within 150 basis points though. Since the previously identified ESCLS series do not differ substantially, these differences signal the poor fit of the SVAR model. Therefore it is difficult to interpret these results as statistical evidence for the impact of the program. Nevertheless, the found impact of FGS on the system meets intuition and makes economic sense, and the methodology used in this thesis is ready to be rerun on longer data series.

For better understanding, I show the found output effect of FGS separately in Figure 4. Panel (a) displays the output effect from the SVAR that uses the preferred bank-level ESCLS series; I include output effects in Panel (b) with ESCLS series from the benchmark, macro, and bank-level models, and also without the inclusion of ESCLS. According to the figure, output increases by 0.4 percent two periods after the implementation of FGS, i.e. until the end of 2013; the results of Endrész et al. (2015), derived from firm investment without multiplicative effects, imply an increase of 0.2 percent. I find the output effect to be 0.2 percent until the end of 2014; Endrész et al. (2014) find the effect to be 0.5-1.1 percent on the same horizon. Their analysis is based on equilibrium aggregates; therefore

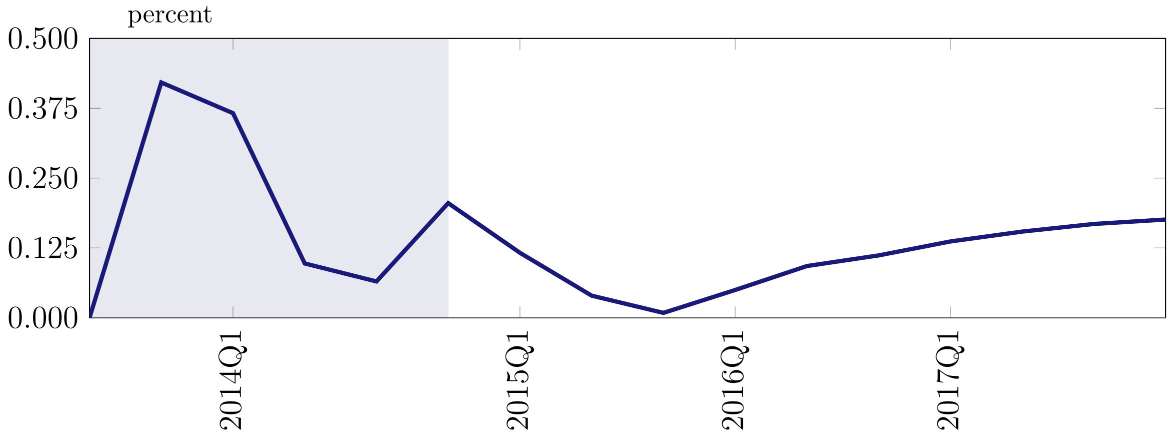
Figure 3: Forecasts with and without FGS



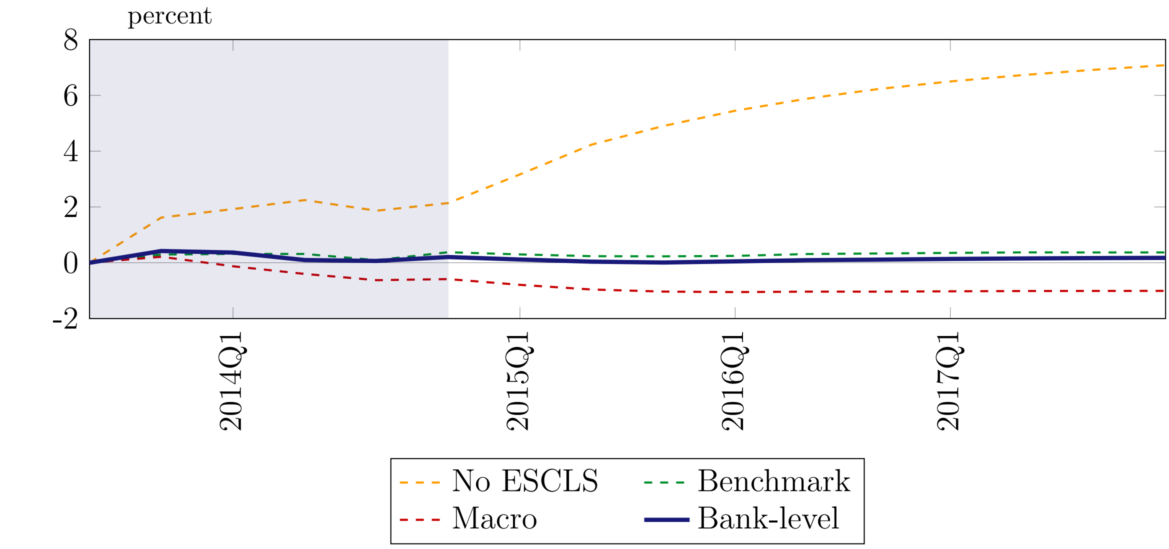
Notes: FGS takes place in periods denoted by the light blue area.

Figure 4: Output effect of FGS

(a) With the preferred bank-level ESCLS series



(b) With alternative ESCLS series



Notes: FGS takes place in periods denoted by the light blue area.

the inclusion of the microfounded supply channel—the supposed mechanism of FGS—*intermediates* previous results. My findings also show a small, 0.15 percent increase in output on the medium run; this longer-term result might be implausible though due to the overfitted hence imprecise SVAR coefficients.

When I exclude the structuring supply channel from the SVAR, the output effect is fourfold and increases even more after FGS. This fact reassures that the more modest output effect I find is indeed the result of the inclusion of the supply channel. Using the ESCLS series from the macro specification results in a negative output effect; this phenomenon is most probably due to the poor precision of estimates.

5 Conclusion

My thesis assessed the success of the Central Bank of Hungary's Funding for Growth Scheme (FGS), i.e. its impact on output. This program has intended to boost post-crisis economic growth by providing small and medium size enterprises with low-interest loans. My contribution is a novel identification strategy: I estimated a structural vector autoregression on equilibrium aggregates by putting a supply side structure to model the supposed mechanism of FGS. This supply side structuring variable was estimated using micro level survey answers from the Bank Lending Survey on changes in lending standards and loan demand perceived by banks. I filtered the reported changes in standards from factors that determine demand and, possibly, supply simultaneously, thus creating an indicator of credit supply called the effective supply component of lending standards (ESCLS). Then I included ESCLS in an otherwise standard SVAR on GDP, core lending capacity (outstanding corporate loans plus unused commitments), average interest rate on corporate loans, and the Hungarian forint/euro exchange rate, and also the EURIBOR rate and net export orders as exogenous variables capturing external relations. Using SVAR estimates, I forecasted the endogenous variables without any intervention, then with an exogenous negative shock to the interest rate and a positive shock to core lending capacity; the difference between the two forecasted series showed the impact of FGS. I found that the output effect is 0.4 percent until the end of 2013 and 0.2 percent until the end of 2014. My findings lie between results from previous micro and macro level analyses.

My results were weakened by several factors. The main issue was that the SVAR in the second stage has been overfitted; therefore estimates were imprecise. Consequently my results are to be interpreted as statistical evidence with caution. Second, the identified ESCLS series that putted a supply side structure on the SVAR could either be overfiltered from supply factors and also have remaining demand variation. Third, the used estimator for the first stage identification might not have been suitable, hence ESCLS was a noisy indicator of credit supply. Nevertheless, the found impact of FGS made economic sense and were in line with previous literature.

An important implication of my findings is that it is crucial to include an uncontaminated credit supply measure in macro models that assess the multiplicative effects of credit boost programs. This is a difficult task since usually credit supply *per se* is not observable. Using bank lending surveys to create a broad indicator of supply proves to be one working solution; without the inclusion of any supply side structure, the output effect is overestimated. Future research should focus though on finding a more precise way to capture credit supply.

Appendix

Table A1: Estimated SVAR coefficients and parameters

(a) VAR coefficients

	$ESCLS_t$	ΔY_t	ΔCLC_t	ΔIR_t	XR_t
$ESCLS_{t-1}$	0.070	-0.020^{***}	-0.099^{***}	1.450^{*}	-19.782^{**}
	(0.166)	(0.007)	(0.024)	(0.783)	(7.868)
$ESCLS_{t-2}$	0.101	-0.011	-0.008	2.192^{**}	5.512
	(0.186)	(0.008)	(0.027)	(0.878)	(8.822)
ΔY_{t-1}	-4.414	0.205	0.712	4.495	-143.317
	(3.779)	(0.159)	(0.547)	(17.821)	(179.095)
ΔY_{t-2}	-1.397	-0.079	0.555	21.095	192.274
	(3.130)	(0.132)	(0.453)	(14.760)	(148.335)
ΔCLC_{t-1}	-0.668	0.014	-0.487^{***}	5.220	14.375
	(1.084)	(0.046)	(0.157)	(5.114)	(51.396)
ΔCLC_{t-2}	0.845	-0.011	-0.231^{**}	2.799	-124.710^{***}
	(0.796)	(0.034)	(0.115)	(3.755)	(37.736)
ΔIR_{t-1}	0.045	-0.001	0.009^{**}	0.196	1.190
	(0.031)	(0.001)	(0.005)	(0.147)	(1.474)
ΔIR_{t-2}	-0.058^{*}	-0.001	0.008^{*}	0.208	-2.405^{*}
	(0.030)	(0.001)	(0.004)	(0.143)	(1.439)
XR_{t-1}	-0.004	-0.000	-0.002^{***}	0.031^{**}	0.922^{***}
	(0.003)	(0.000)	(0.000)	(0.014)	(0.137)
XR_{t-2}	0.002	-0.000	-0.001^{*}	-0.004	-0.283
	(0.005)	(0.000)	(0.001)	(0.022)	(0.221)
$\Delta EURIBOR_t$	0.111	0.012^{***}	-0.015	0.534	-9.787^{***}
	(0.080)	(0.003)	(0.012)	(0.376)	(3.779)
ΔXD_t	-0.305	0.008	0.022	-1.141	-0.628
	(0.252)	(0.011)	(0.036)	(1.187)	(11.928)
Constant	0.623	0.032	0.852^{***}	-7.360	99.030^{**}
	(0.986)	(0.041)	(0.143)	(4.648)	(46.709)
N	39	39	39	39	39
R^2	0.314	0.681	0.769	0.516	0.847

(b) Structural matrix **A**

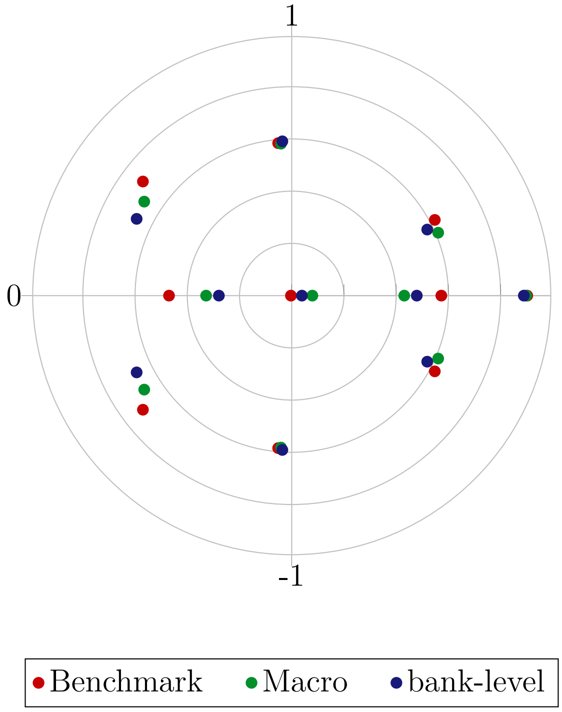
	$ESCLS_t$	ΔY_t	ΔCLC_t	ΔIR_t	XR_t
$ESCLS_t$	1				
ΔY_t	0.002	1			
	(0.007)				
ΔCLC_t	0.025	-0.617	1		
	(0.022)	(0.533)			
ΔIR_t	-1.924^{***}	17.963	-1.734	1	
	(0.691)	(16.437)	(4.857)		
XR_t	17.500^{**}	58.693	-38.164	-5.693^{***}	1
	(6.974)	(153.723)	(44.815)	(1.475)	

(c) Diagonal of structural matrix **B**

$ESCLS_t$	ΔY_t	ΔCLC_t	ΔIR_t	XR_t
0.145^{***}	0.061^{***}	0.020^{***}	0.614^{***}	5.658^{***}
(0.016)	(0.007)	(0.002)	(0.070)	(0.641)

Notes: Standard errors in parentheses. Asterisks denote significance: * 10%, ** 5%, *** 1%.

Figure A1: SVAR stability tests



Benchmark		Macro		bank-level	
Eigenvalue	Modulus	Eigenvalue	Modulus	Eigenvalue	Modulus
0.902	0.902	0.898	0.898	0.889	0.889
$-0.570 \pm 0.437\,i$	0.718	$-0.565 \pm 0.360\,i$	0.670	$-0.594 \pm 0.294\,i$	0.663
$0.548 \pm 0.290\,i$	0.620	$0.561 \pm 0.241\,i$	0.611	$-0.036 \pm 0.591\,i$	0.592
$-0.052 \pm 0.584\,i$	0.587	$-0.041 \pm 0.582\,i$	0.584	$0.519 \pm 0.253\,i$	0.577
0.573	0.573	0.431	0.431	0.479	0.479
-0.470	0.470	-0.328	0.328	-0.279	0.279
-0.003	0.003	0.079	0.079	0.039	0.039

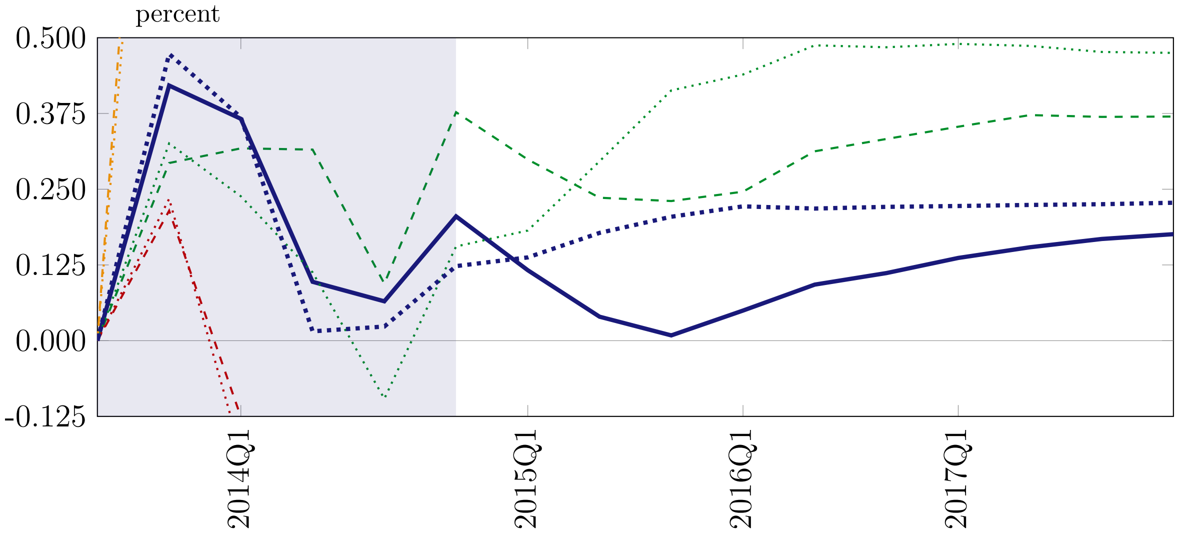
Table A2: ARIMA forecasts of exogenous variables in the SVAR

Variable	φ
$EURIBOR_t$	0.565^{***}
	(0.079)
XD_t	-0.341^{**}
	(0.138)

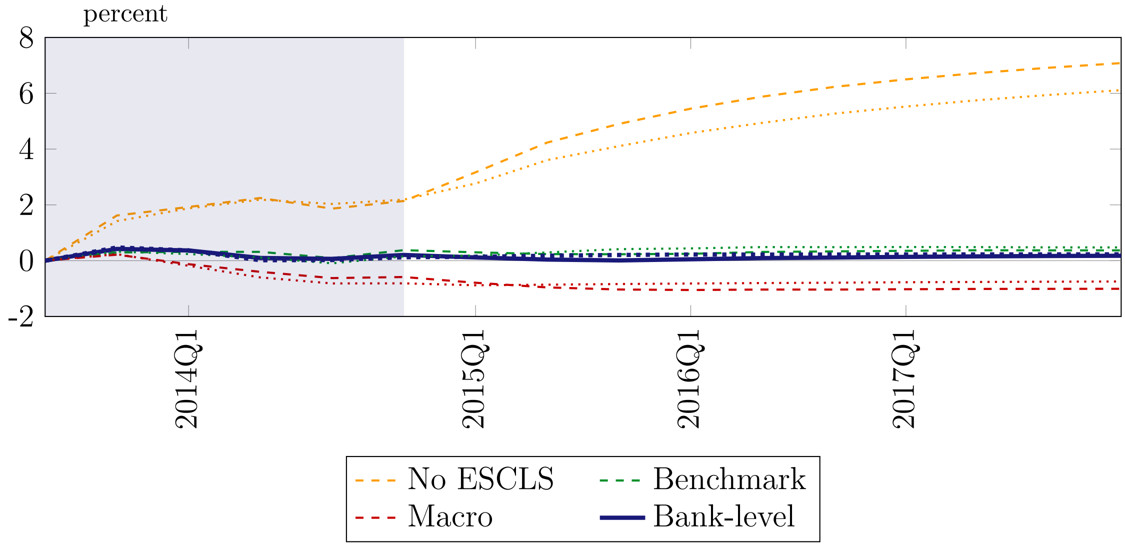
Notes: Standard errors in parentheses. Asterisks denote significance: * 10%, ** 5%, *** 1%.
Both models are ARIMA(1,1,0) selected by the Box-Jenkins method:
$\Delta y_t = \varphi \Delta y_{t-1} + \epsilon_t$, $y_t = \{EURIBOR_t, XD_t\}$.

Figure A2: Output effect of FGS from SVARs estimated on the full sample

(a) Benchmark and bank-level ESCLS



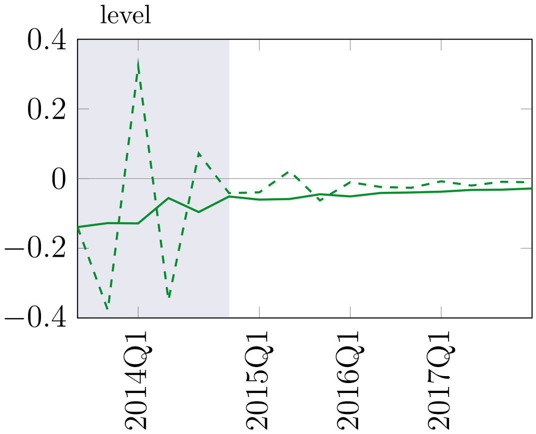
(b) All alternatives



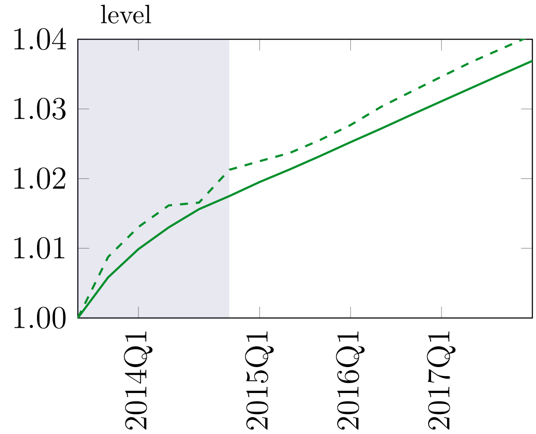
Notes: FGS takes place in periods denoted by the light blue area. Dotted lines represent forecasts from SVARs on the whole sample.

Figure A3: Forecasts with the benchmark ESCLS series

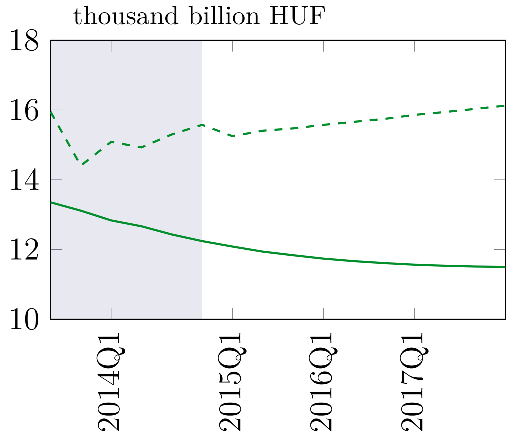
(a) ESCLS (benchmark)



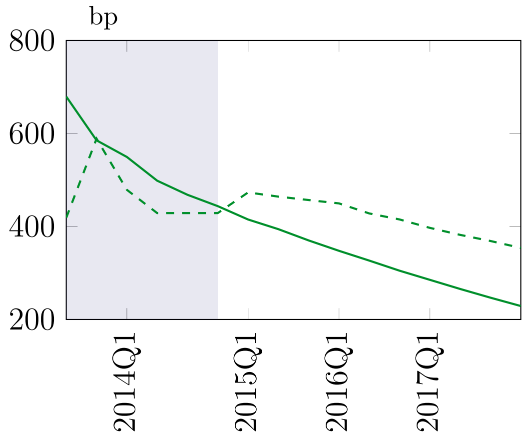
(b) Output



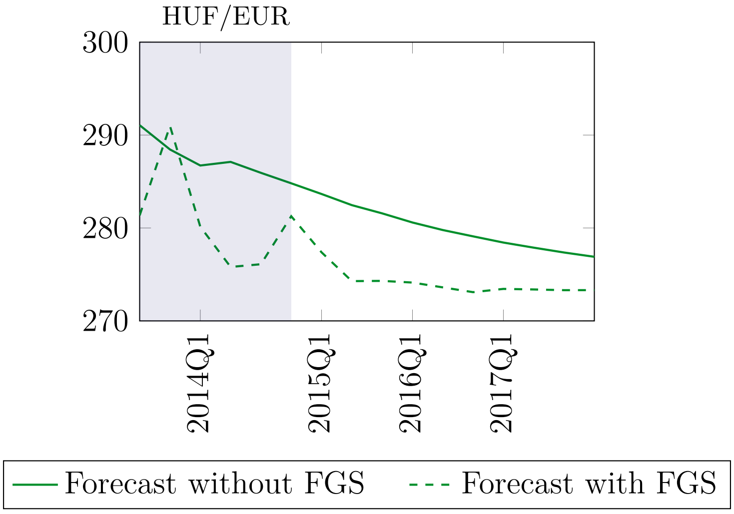
(c) Core lending capacity



(d) Interest rate on corporate loans



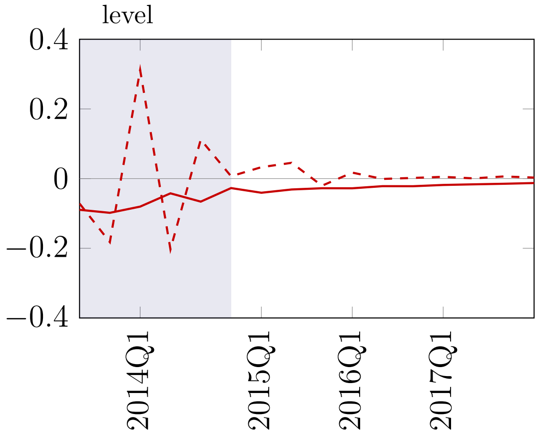
(e) Hungarian forint/euro exchange rate



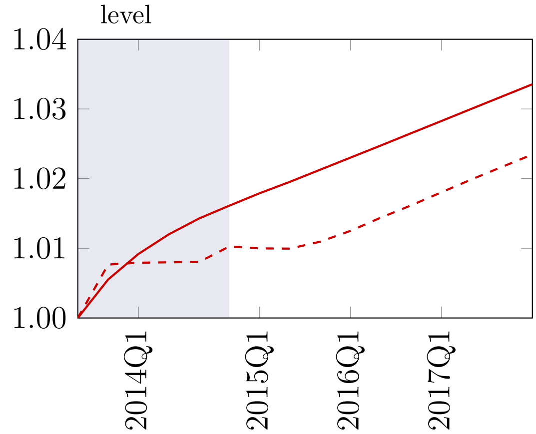
Notes: FGS takes place in periods denoted by the light blue area.

Figure A4: Forecasts with the macro ESCLS series

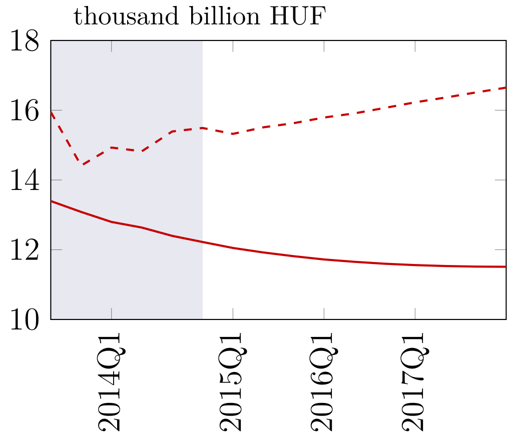
(a) ESCLS (macro)



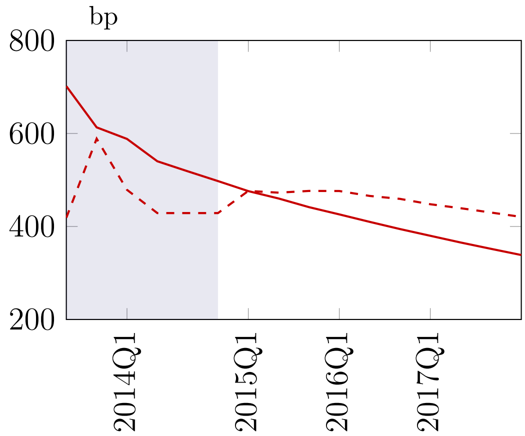
(b) Output



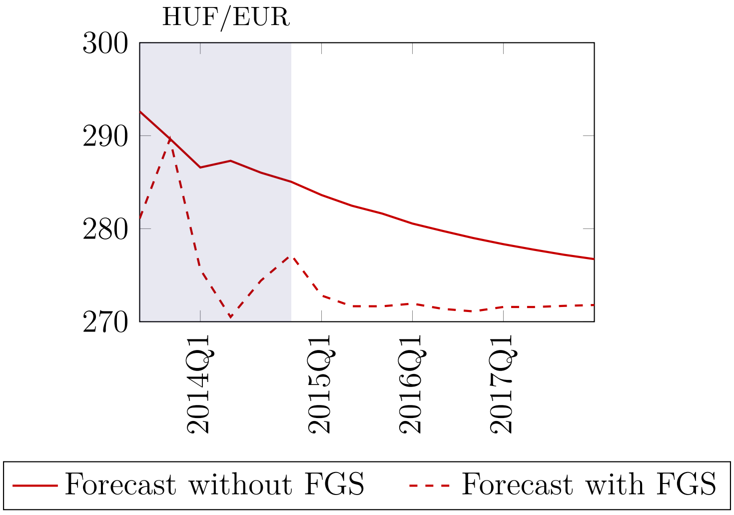
(c) Core lending capacity



(d) Interest rate on corporate loans



(e) Hungarian forint/euro exchange rate



Notes: FGS takes place in periods denoted by the light blue area.

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