BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working Papers)

Forecasting with instabilities: an application to DSGE models with financial frictions

by Roberta Cardani, Alessia Paccagnini and Stefania Villa

October 2019

Number 1234

BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working Papers)

Forecasting with instabilities: an application to DSGE models with financial frictions

by Roberta Cardani, Alessia Paccagnini and Stefania Villa

Number 1234 - October 2019

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

FORECASTING WITH INSTABILITIES:
AN APPLICATION TO DSGE MODELS WITH FINANCIAL FRICTIONS

by Roberta Cardani[*], Alessia Paccagnini[**] and Stefania Villa[***]

Abstract

We assess the importance of parameter instabilities from a forecasting standpoint in a set of medium-scale DSGE models with and without financial frictions using US real-time data. We find that failing to update DSGE model parameter estimates with new data arrival deteriorates point forecasts due to the estimated parameters variation. We also find that the presence of financial frictions helps to better forecast GDP and inflation.

JEL Classification: C11, C13, C32, E37.
Keywords: Bayesian estimation, forecasting, financial frictions, parameter instabilities.

Contents

[*] European Commission – ISPRA, Italy.
[**] University College Dublin – Michael Smurfit Business School, Ireland.
[***] Bank of Italy, Directorate General for Economics, Statistics and Research.

1 Introduction[1]

Recent macroeconometric literature suggests that estimated dynamic stochastic general equilibrium (DSGE) models are suitable for forecasting purposes (see Del Negro and Schorfheide, 2013; Kolasa and Rubaszek, 2015b; Caraiani, 2016, among others). However, the forecasting evaluation of these macroeconomic models is subject to the estimation of the parameters of the model and, as discussed in Giacomini and Rossi (2016), there is ample evidence of instabilities in parameters that might affect their forecasting performance. Gürkaynak et al. (2013) find that the forecasting performance of the medium-scale DSGE model of Smets and Wouters (2007) (hereafter, SW) has been unstable over time. In particular, this model started to fail to produce accurate forecasts when researchers included data following the recent crisis. One of the main reasons of this failure is that the modeling choices of the SW model reflect the properties of the sample data before the Great Recession (see Giacomini and Rossi, 2015).

The DSGE empirical literature offers alternative approaches to deal with the issue of parameters instability (see Fernández-Villaverde et al., 2010; Inoue and Rossi, 2011; Bianchi, 2013; Caldara et al., 2012; Castelnuovo, 2012; Bekiros and Paccagnini, 2013; Hurtado, 2014; Bekiros et al., 2016; Galvao et al., 2016, among others).[2]

A practical way to deal with the parameter instability in a DSGE model forecasting analysis is discussed in Kolasa and Rubaszek (2015b). They observe that central banks are used to re-estimate DSGE models only occasionally but this practice might affect the forecasting performance. Hence, they investigate how frequently models should be re-estimated so that the accuracy of forecasts they generate may be unaffected. They find that updating the model parameters only once a year generally does not lead to a significant deterioration in the accuracy of point forecasts, while increasing the frequency of re-estimation is better in terms of density forecasts.

[1]The opinions and views expressed in this paper are those of the authors and should not be considered as official positions of the European Commission or Banca d'Italia. We are grateful to Fabio Canova, Efrem Castelnuovo, Todd Clark, Francesco Furlanetto, Paolo Gelain, Francesco Ravazzolo, Barbara Rossi, Michał Rubaszek, Tatevik Sekhposyan, Stefano Siviero, Herman van Dijk, Karl Whelan, Emilio Zanetti Chini, Roberta Zizza and to conference and seminar participants at the NBP 2015 Forecasting Workshop in Warsaw, University College Dublin, IAAE 2015 Annual Conference in Thessaloniki, the 2015 ASSA Meetings in Boston, SNDE 2014 conference in New York, CEF 2014 in Oslo, Advances in Applied Macro-Finance and Forecasting 2014 in Istanbul, CFE 2014 in Pisa, 2014 EC2 conference "Advances in Forecasting" in Barcelona for their insightful comments. All remaining errors are ours. Cardani and Paccagnini acknowledge financial support from the RastaNews project funded by the European Community's 7th Framework Program (FP7). A previous version of this paper circulated as "Forecasting in a DSGE Model with Banking Intermediation: Evidence from the US".

[2]It should be noted that the approach of estimating the Markow-switching DSGE via perturbation methods faces the issue of obtaining a well-defined steady state around which we can calculate higher-order approximations to the solutions of the model. See Foerster et al. (2016) and Giacomini and Rossi (2014) on this topic.

We investigate the role of parameters instabilities in forecasting analysis by addressing two main questions: (1) *does failing to update model parameter estimates with new data arrival affect the quality of point forecasts?* and (2) *does a DSGE model featuring financial frictions provide a better forecasting performance compared to a standard medium-scale model?*

We borrow the first research question from Kolasa and Rubaszek (2015b), where they provide evidence about the role of parameters re-estimation only in case of the SW model. In our exercise, we compare the workhorse SW model with two models incorporating the financial sector: a SW economy augmented by a banking sector as in Gertler and Karadi (2011) (hereafter, SWBF); and a SW economy augmented with financial frictions as Bernanke et al. (1999) (hereafter, SWSWBGG). DSGE models with financial frictions have become popular, as financial factors have played a central role in the recent financial crisis by affecting the amount of credit available in the economy. The seminal DSGE model proposed by Bernanke et al. (1999) considers financial frictions at the level of firms. Their model implies that borrowers can obtain funds directly from lenders without any active role for the banking sector. In the wake of the financial turmoil understanding the disruption in financial intermediation has become a priority. This explains why we consider the model by Gertler and Karadi (2011), in which an endogenous leverage constraint on banks effectively links the provision of credit to the real economy.

We estimate, using Bayesian techniques, the three models – SW, SWBF and SWBGG – on US real-time data using rolling windows of 120 observations. The out-of-sample forecasting period is from 2003Q2 to 2018Q1.[3]

Second, we compare the forecasting performance of the three models conducting both point forecast, using Root Mean Square Forecast Error (RMSFE) and Fluctuations test as in Giacomini and Rossi (2010, 2016), as well as density forecast using the average of the log predictive density scores (LPDS). The out-of-sample forecasting period is split into two sub-samples when computing RMSFE and LPDS: (pre-crisis) 2003Q2-2008Q4 and (post-crisis) 2009Q1-2018Q1. In this way we investigate whether the forecasting performance changes across the two sub-samples.

Our main findings are as follows. First, re-estimating every quarter the model parameters leads to a better forecasting performance due to the estimated parameters instabilities, differently from the result in Kolasa and Rubaszek (2015b). It should be noted that Kolasa and Rubaszek (2015b) investigate only the SW model and consider another sample period: their

[3]The forecasting literature has partly assessed the empirical relevance of DSGE models with financial frictions for the US economy (see Villa, 2016; Kolasa and Rubaszek, 2015a). Differently from them, we study the role of parameter instabilities in a forecasting comparison of a set of DSGE models using revised data.

estimation period is 1966Q1-1989Q4, while their forecasting sample is 1990Q1-2011Q4. The different results are driven by these features. In order to rationalize these results, we show the rolling estimation of the main parameters of the three DSGE models and we find a considerable degree of parameters variation. Second, forecasting analysis based on the RMSFE and LPDS suggests that models with financial frictions outperform the SW model in terms of forecasting accuracy particularly in the post-crisis period. A forecasting analysis conducted using the Fluctuations test shows that the prediction performance of the models with financial frictions is statistically different from that of the SW model for GDP growth rate and inflation, except for a few quarters around 2008 where the performance of the SW model is not statistically different from that of the SWBF model for inflation.

The remainder of the paper is organized as follows. Section 2 briefly sketches the three models and describes the Bayesian estimation procedure. Section 3 presents the two forecasting comparisons. Finally, Section 4 concludes.

2 Models and estimation procedure

The economy is composed by households, labor unions, labor packers, a productive sector and a monetary authority. Households consume, accumulate government bonds and supply labor. A labor union differentiates labor and sets wages in a monopolistically competitive market. Competitive labor packers buy labor services from the union, package and sell them to intermediate goods firms. Output is produced in several steps, including a monopolistically competitive sector with producers facing price rigidities. The monetary authority sets the short-term interest rate according to a Taylor rule. In the SWBF model, the presence of an agency problem limits the ability of financial intermediaries to obtain deposits from households. This, in turn, affects the leverage ratio of financial intermediaries. On the contrary, in the SWBGG model firms stipulate a financial contract to obtain funds from the lenders in presence of a costly state verification problem. The equations of the three models are reported in Table 1.

The SW model features seven exogenous disturbances: total factor productivity, price mark-up, wage mark-up, investment-specific technology, risk premium, exogenous spending, and monetary policy shocks. The SWBF and SWBGG models also feature a net worth shock.

The three DSGE models are recursively estimated for the US quarterly real-time data (Edge and Gurkaynak, 2011; Wolters, 2015). To estimate the SW model we use the standard seven observables: GDP, investment, consumption, wages, hours of work, GDP deflator inflation, and the federal funds rate. In the SWBF model we also include net worth of financial intermediaries as a financial observable since the model features a net worth shock.[4] The additional financial observable in the SWBGG model is, instead, the credit spread similarly to Del Negro and Schorfheide (2013).

In particular, we build our variables as described in Kolasa and Rubaszek (2015a).[5] All the models are estimated with a number of shocks equal to the number of observable variables to avoid the stochastic singularity.[6]

Our general calibration and estimation strategy follow the standard procedure proposed by Smets and Wouters (2007) adapted to models augmented with financial frictions. In particular, we calibrate the parameters i) using *a priori* source of information and ii) to match some stylized facts over the period of consideration. The time period in the model corresponds to one quarter in the data. As shown in Table 2, the discount factor, β, is set equal to 0.99, implying a quarterly steady state real interest rate of 1%.[7] The depreciation rate of capital, δ, is set equal to 0.025. The Kimball aggregators in the goods and labor market are equal to 10, and the steady state gross wage mark-up is set to 1.5. The share of government to GDP is equal to 0.18. Similarly to Villa (2016), in the SWBF model ϖ, ϕ and χ are calibrated to target an average working life of bankers of almost a decade, a steady state spread of 150 basis points and a steady state leverage ratio of financial intermediaries equal to 4. In the SWBGG model, the expected working life of firms is almost a decade and the leverage ratio is set equal to 2, as in Bernanke et al. (1999).

The remaining parameters governing the dynamics of the model are estimated using Bayesian techniques. The locations of the prior mean correspond to those in Smets and Wouters (2007). Similarly to De Graeve (2008), we set a Uniform distribution between 0 and 0.3 for the parameter measuring the elasticity of external finance premium with respect to the leverage position of firms in the SWBGG model.

[4]The Appendix contains a detailed discussion of real-time data sources, definitions and transformations.

[5]See Casares and Vázquez (2016) and Galvão (2017) for a discuss about a possible combination of real-time and revised data for estimation of DSGE models.

[6]Equation 2 in the Appendix reports the set of measurement equations linking the observable variables in the dataset with the endogenous variables of the DSGE models.

[7]In the more recent period a different value for the discount factor could have been more appropriate. However, for the sake of simplicity, we set a unique value for β over the whole sample.

3 Evaluating forecast accuracy

This section illustrates the forecasting exercises. In Section 3.1, we compare the forecasting accuracy of the three DSGE models re-estimated by updating the models parameters each quarter versus a fixed scheme in which parameters are estimated only once, at the beginning of the forecast evaluation sample. We investigate the role of instabilities in order to rationalize the results of this first comparison. In Section 3.2, we compare the forecasting accuracy of the three models by evaluating the point and density forecasts. As described in Wolters (2015) and in Kolasa and Rubaszek (2015a), for each parameter a large number of values are drawn from the parameter's posterior distribution. We take each 20th draw from the final 150,000 parameter draws calculated by the Metropolis-Hastings algorithm, which produces 7,500 draws from the posterior distribution. For each of them, we draw seven shock trajectories to generate the predictions for the seven macro-variables of interest. The obtained 52,500 trajectories are draws from the predictive density and hence can be used to evaluate the density forecasts. The point forecasts are calculated as means of these draws (see Wolters, 2015, for technical details).

The forecasting scheme is rolling in any exercise and the evaluation sample spans the period 2003Q2 to 2018Q1. The first set of forecasts is generated for the period 2003Q2-2006Q1, with models estimated on the sample spanning 1973Q2-2003Q1 (120 quarters), the second set of forecasts is for the period 2003Q3-2006Q2, with models estimated on the sample spanning 1973Q3-2003Q2, and so on. As our dataset ends in 2018Q1, we can calculate forecast errors on the basis of between 60 (1-quarter-ahead) and 49 (12-quarter-ahead) forecasts. Our evaluation sample is split into two parts: 2003Q2 - 2008Q4 and 2009Q1 - 2018Q1.[8] In such a way it is possible to distinguish between a pre-crisis period and a post-crisis period. A multi-steps forecasting analysis is implemented with forecasts for the horizon $h \in (1, 2, 4, 8, 12)$.

3.1 Comparison #1: Update or not to update the models parameters?

We compare the accuracy of forecasts generated by the three models (SW, SWBF, and SWBGG), the parameters of which are re-estimated every quarter versus a fixed forecasting scheme with constant parameters. This exercise makes it possible to examine whether parameters instabilities might affect the accuracy of forecasts, evaluated by means of the RMSFE. In particular, Table 3 reports the ratio of the RMSFE of the models with fixed parameters and that of the models

[8] Our results are qualitatively robust if we stop the first sample at 2007 and we include 2008 in the second sample.

updated each quarter for the period 2003Q2-2008Q4. Hence values lower than one indicate that the updated model has a higher RMSFE than the fixed model. For each forecast horizon we report the ratio of RMSFEs for each model for the seven standard observable variables of the SW model. In general, the forecasting accuracy for output growth, inflation, and FFR are always better if parameters are re-estimated instead of taking them fixed. Same findings are in favor of re-estimation for the other variables.

Table 4 reports the ratio of the RMSFE of the models with fixed parameters and that of the models updated each quarter for the period 2009Q1-2018Q1. In the post-crisis sample it is always better to re-estimate the parameters of the three models for all variables. This gain is statistically significant particularly for the SWBGG model and, to a minor extent, for the SW and SWBF models.

Our findings suggest that the re-estimation scheme is always preferred to the fixed parameters scheme. Our results are robust to the model specification. In fact, the superiority of the updating procedure is common to the three models. Second, overall it is better to re-estimate the models parameters, in particular, as expected, in "turbulent" periods such as the second sub-sample. Kolasa and Rubaszek (2015b) evidence that updating the model parameters only once a year does not produce better accuracy of point forecast during the "turbulent" period. However, their sample stops at 2011, meanwhile we include years up to 2018 long after the turbulent period of the Great Recession.

Differently from Kolasa and Rubaszek (2015b), we compare quarterly re-estimated parameters vs fixed parameters forecasting and we do not consider intermediate re-estimation patterns. Our general results have the conclusion that re-estimation is important.

Tables 3 and 4 provide evidence in favor of re-estimated parameters model. For instance, the RMSFE ratio for output growth is always bigger than 1.10, with this value being statistically significant in the SWBF model at horizon 1, in the SW model at horizon 2 for the first sub-sample; and in the SWBGG model at horizons 2 and 12 in the second sub-sample. A similar pattern is found for FFR and inflation, as well for investment. The gain in forecast precision is smaller for wage. These results are broadly similar across the two sub-samples but for consumption and hours for which considerable gains are more evident in the first and second sub-sample, respectively.

3.1.1 Parameters instabilities

In order to rationalize these results, we check for possible instabilities in the time dimension of the structural parameters, which might affect the forecasting analysis.

All parameters and shocks of the DSGE models are hence estimated in a rolling scheme with the first window covering the period 1973Q2-2003Q1 and the last window the period 1988Q1-2018Q2, with real-time data. The evaluation sample 2003Q2-2018Q1 yields 60 different posterior densities of all parameters, each of which is computed with the Metropolis-Hasting algorithm with two chains of 250,000 draws each.[9]

Our chosen methodology has the caveat that the DSGE models do not feature a zero lower bound (ZLB) constraint on the nominal interest rate, which is instead observed in the data starting from December 2008. Hirose and Inoue (2016) investigate how and to what extent parameter estimates can be biased in DSGE models lacking this constraint. They find that the bias becomes large when the probability of hitting the ZLB increases. Given our estimation sample, the bias in parameter estimates could be potentially relevant. Alternatively, we could have used the shadow rate as in De Polis and Pietrunti (2019).

Figure 1 shows the evolution of selected shock processes and parameters of the SW model.[10] The standard deviation of the risk shocks shows a considerable degree of variation. In the Smets and Wouters (2007) model the risk premium shock captures the wedge between different interest rates. Here we consider two measures as proxies for spreads: (i) Moody's BAA corporate bond yield minus ten-year Treasury constant maturity rate, as in Del Negro and Schorfheide (2013); and (ii) the difference between the 3-month bank prime loan rate and the quarterly Treasury bill rate. In the data the volatility of the spreads increased after the 2000Q1 recession. The standard deviations of the other shocks also change over time, similarly to Bekiros et al. (2016) and Giacomini and Rossi (2016). The volatility of the monetary policy shock decreases steadily over time.

The figure also shows that instabilities are particularly evident for the most relevant parameters. The coefficient of relative risk aversion is quite volatile. Hence, the willingness of households to substitute consumption over different periods is changing particularly after the financial crisis. The Taylor rule has become more inertial over time.

[9] We implement the sensitivity analysis and identification test proposed by Ratto (2011) and Ratto and Iskrev (2011) in Dynare. For all the samples, the SW, SWBF, and SWBGG models do not present identification issues.

[10] For the sake of brevity, we do not report charts on the rolling estimates of all shocks and parameters, which are available upon request.

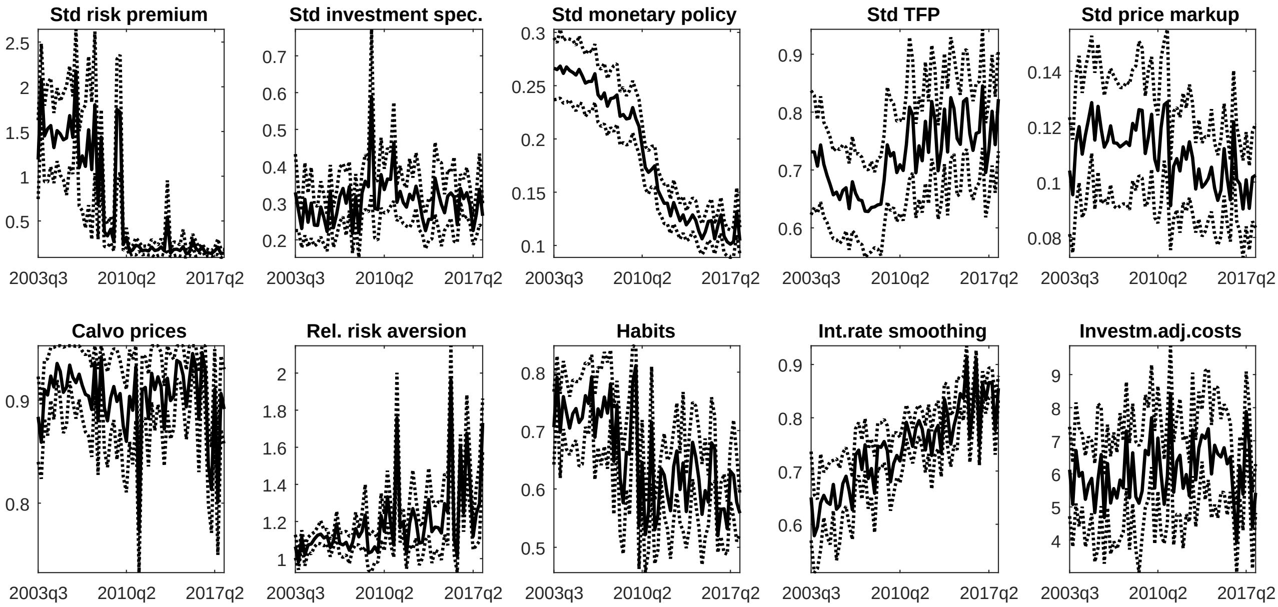


Figure 1: Evolution of selected shock processes and parameters of the SW model. Solid lines represent the posterior mean, while dotted lines 5th and 95th posterior percentiles. Estimates are computed based on a rolling estimation scheme starting from 1973Q2-2003Q1 and ending in 2018Q1.

In the SWBF model the volatility is particularly evident for estimated shocks, as shown by Figure 2.[11] The volatility of the net worth shock seems to be related to the number of bank failures, which peaked in the period 2009-2012 (by looking at Federal Deposit Insurance Corporation data). The number of bank failures in 2002 was higher than those in preceding and subsequent years, while in 2005 there has been a serious concern on the surge in bank credit (Melina and Villa, 2018). The volatility of the monetary policy shock increased in the second part of the sample. The comparison with the SW model reveals that the standard deviation of the risk premium shock is lower. The two peaks in the volatility of the monetary policy shock correspond to the announcement of third round of Quantitative Easing by the FOMC in 2012Q4 and to the end of this program. As far as the parameters are concerned, they all display variation over time.

Figure 3 shows rolling estimates of selected shock processes and of structural parameters in the SWBGG model. The volatility of the risk premium shock and of the investment-specific technology shock has decreased in the most recent sample, whereas the net worth shock is extremely volatile almost over the whole sample.[12] The parameters of the SWBGG model are

[11] Canova et al. (2015) study how parameter variation can affect the decision rules in a DSGE model. Similar to us and to Cardani et al. (2015), they evidence an importance role of time-variation for the identification of DSGE parameters, even if it is not only related to the Gertler and Karadi (2011) set up.

[12] It should be noted that the volatility of the financial variable used in the estimation – the credit spread – has increased from 2008.

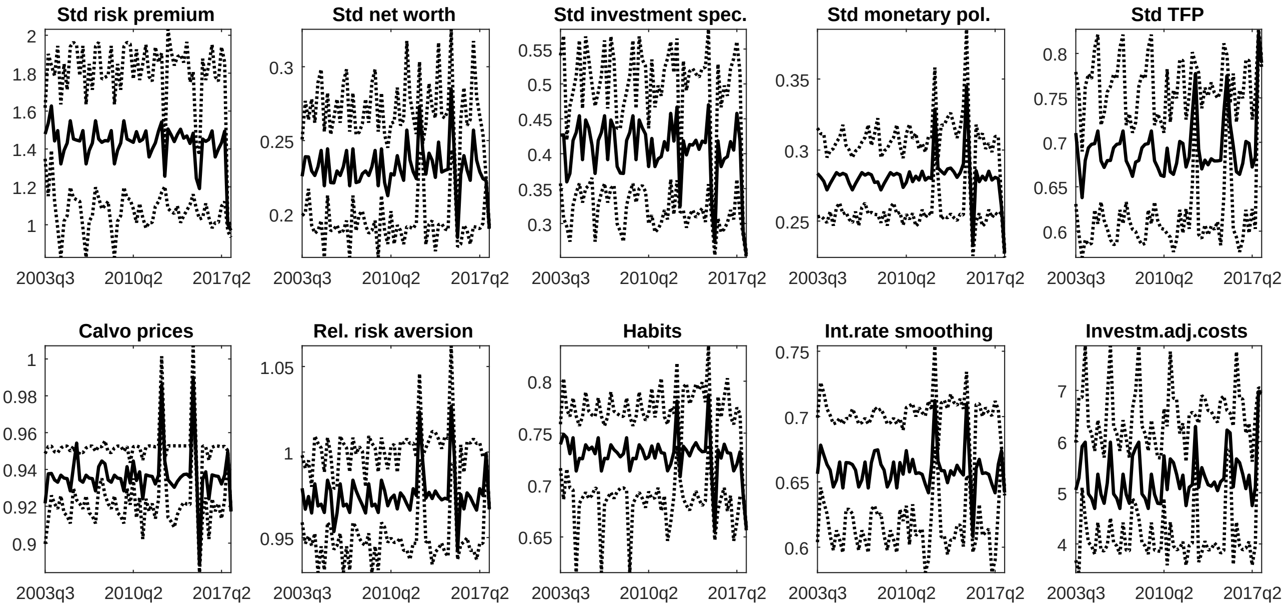


Figure 2: Evolution of selected shock processes and parameters of the SWBF model, where the observable financial variable is net worth. Solid lines represent the posterior mean, while dotted lines 5th and 95th posterior percentiles. Estimates are computed based on a rolling estimation scheme starting from 1973Q2-2003Q1 and ending in 2018Q1.

also changing over time.[13]

Overall, the presence of parameter instabilities in all the three models explains why we find evidence in favour of re-estimating the model parameters from a forecasting viewpoint.

3.2 Comparison #2: Which model forecasts better?

3.2.1 Point Forecast Evaluation

We perform a point forecast comparison among the three models re-estimating the parameters. In particular, we compare the second moments of the forecast errors. Table 5 shows the ratio of the RMSFE of the SWBF and SWBGG models relative to the SW model for the forecasting periods 2003Q1-2008Q4, whereas Table 6 shows the same ratios for the period 2009Q1-2018Q1 Values greater than one denote that the SW model has a lower RMSFE than the alternative model featuring financial frictions. To check the statistical significance of these ratios, we report the Clark and West (2006) test which is suitable for non-nested and nested models. As far as the SWBF model is concerned, in the period 2001-2008 there is not a clear result against the SW model for the three key macro variables (output growth, inflation and FFR). For output

[13]For more details about the implications of real time data, see Bekiros et al. (2016), Galvão (2017) and Masolo and Paccagnini (2019).

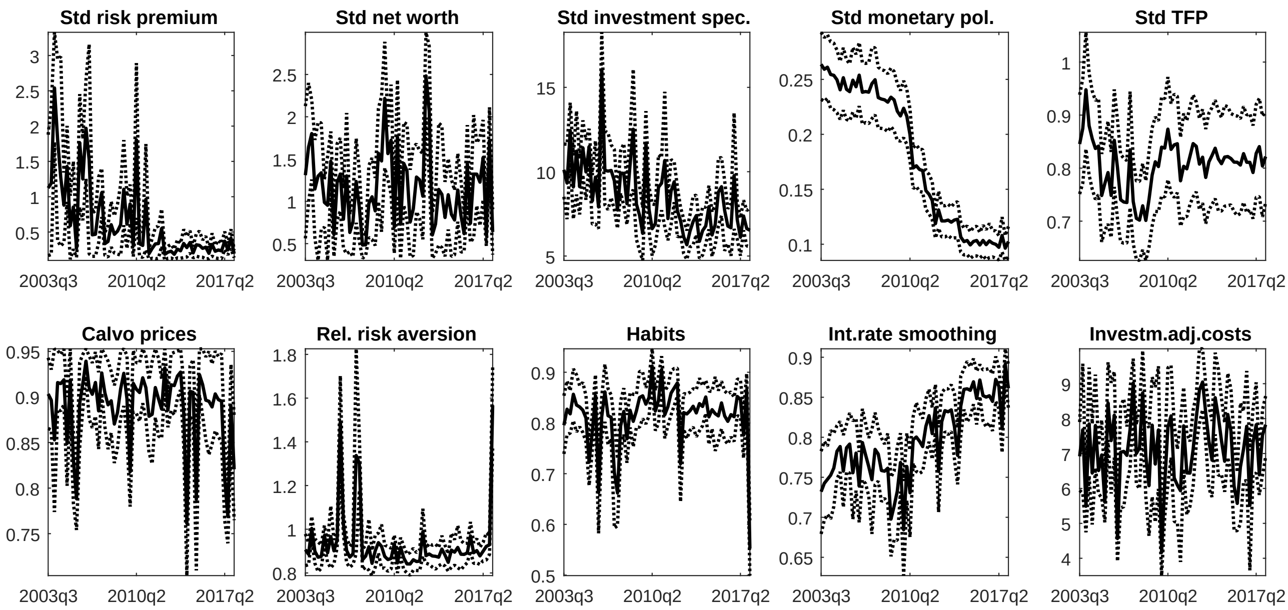


Figure 3: Evolution of selected shock processes and parameters of the SWBGG model, where the observable financial variable is credit spread. Solid lines represent the posterior mean, while dotted lines 5th and 95th posterior percentiles. Estimates are computed based on the recursive estimation sample starting from 1984Q1-2000Q4 and ending in 2016Q1.

growth, the SWBF model outperforms the SW model, except at horizon 1, but results are only statistically significant at horizon 4. Meanwhile, for inflation and for FFR the SWBF model outperforms the SW model respectively at the short and at the medium horizon. For the other variables, in general the SWBF model forecasts better than the SW one, with statistically significant results at horizon 4. The SWBGG model outperforms the SW model in forecasting output growth for almost all horizons, even if it is statistically significant in its favor only in case of horizon 1. In case of inflation and FFR, we report a mixed result but without statistically significance. For the other variables, in general SWBGG model produces better forecasting performance but the Clark-West test does not support the statistical significance.

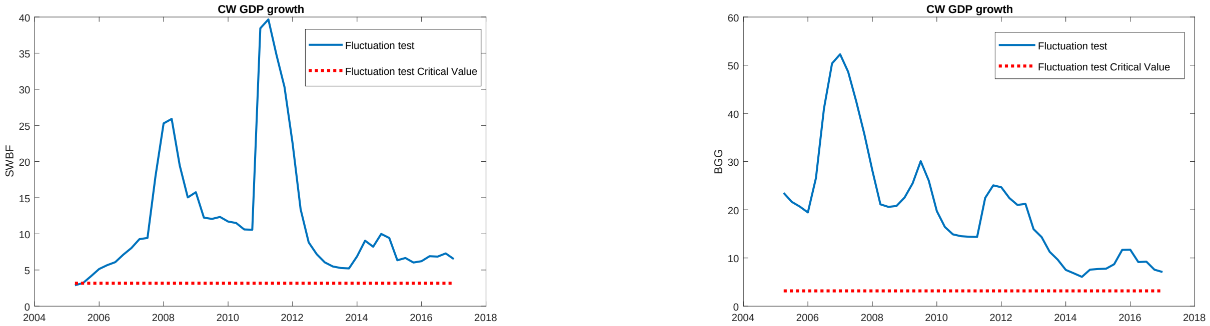
For the period 2009-2016, Table 6 shows that the SWBF model outperforms the SW model for almost all variables, in particular in the short horizon. The results are statistically significant for output growth rate, inflation, and consumption for the medium horizon (2 and 4 quarters) and for FFR and investment for the short horizon. Similarly, the SWBGG model outperforms the SW model for all variables; in particular results are statistically significant for output growth, FFR, and consumption. In general, during the Great Recession and in the aftermath, the models including financial variables outperform the standard new-Keynesian model. This finding is in line with the recent literature which provides evidence of the role of financial variables to improve the forecasting of the business cycle (see Gertler and Gilchrist, 2018; Paccagnini, 2019, among others).

To assess the validity of the point forecast, we employ the Fluctuation test as in Giacomini and Rossi (2010), Giacomini and Rossi (2016) and Fawcett et al. (2015) to assess the predictive ability when there are instabilities over time.[14] As noted by Giacomini and Rossi (2010), in the presence of structural instability, the forecasting performance of two alternative models may itself be time-varying.

Figures 4 and 5 report the Fluctuation tests based on Clark - West test for GDP growth and CPI inflation. The four graphs show the relative performance between the SW model and the SWBF or SWBGG models. There are three possible cases. First, if the statistic drawn in blue is located above the upper bound (the red line) the SWBF or SWBGG model has a superior forecasting performance; second, the statistic is located below the lower bound, then the SW model is preferred.[15] Finally, if a blue line between the two bounds means that the predictably performance is not statistically different between the models. Figure 4 shows that for GDP growth rate the forecasting performance of the SWBF and SWBGG models is always statistically different from the SW model. Figure 5 shows that for CPI inflation the SWBF and SWBGG models produce better predictive performances than that of the SW model except for some quarters during the Great Recession when the forecasting performance of the two models is not statistically different. In general, the Fluctuation test suggests that: (i) the results produced using point forecast analysis are robust; and (ii) both models featuring financial frictions outperform the SW model in forecasting output growth and inflation virtually over the whole period. Three considerations are in order. First, an obvious remark should be made about the information set of the different models. The SW model features seven shocks and seven observable variables, while both models featuring financial frictions include an additional shock and an additional observable variable. Obviously the information set used for the forecasting exercise is richer in the latter models compared to the former one and this clearly goes into the direction of improving forecasting accuracy (Stock and Watson, 1999; Bernanke and Boivin, 2003). In addition, it should be noted that the forecasting horizon 2003-2018 covers a period in which leverage by the corporate sector has increased significantly, with financial factors likely

[14]We implement the Fluctuation test using a rolling window setup as described by Giacomini and Rossi (2010), Algorithm 1. The rolling window scheme allows the test to have a non-time variant critical value. For more details about the test implemented in case of Clark and West (2006), the null hypothesis, as well as the critical values obtained using a Monte Carlo experiment, see Giacomini and Rossi (2010).

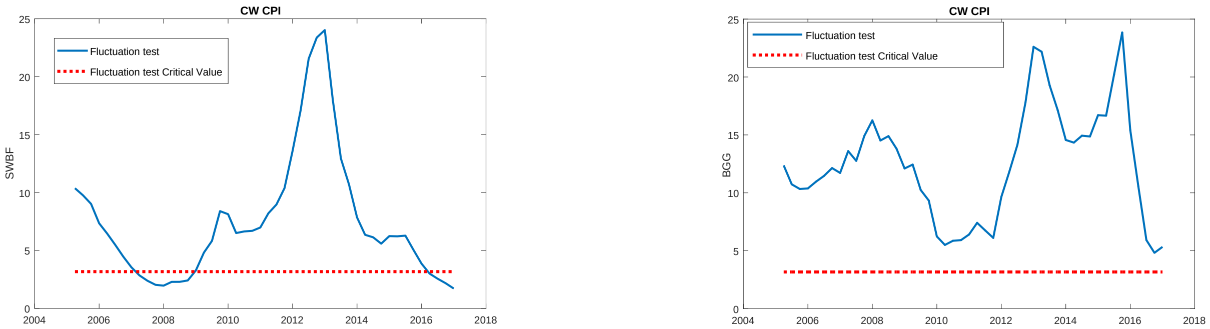
[15]In the figures we report only the upper bound since the statistics never cross the lower bound.



(a) SWBF model

(b) SWBGG model

Figure 4: Fluctuation test for GDP growth



(a) SWBF model

(b) SWBGG model

Figure 5: Fluctuation test for inflation

to affect business cycle fluctuations also in "normal times". Therefore, taking financial variables into account might help the forecasting performance even in the pre-crisis period. Households leverage, instead, has dramatically increased only in the latest financial crisis (Smets and Villa, 2016). The SWBF and SWBGG models do not feature household indebtedness and this might explain why our results differ from the ones in Kolasa and Rubaszek (2015b). Finally, in the SWBGG model the parameter measuring the elasticity of external finance premium with respect to the leverage position of firms, $\varkappa$, is estimated in the range [0.053,0.065] over the sample 2003Q3-2018Q1. Therefore, the presence of financial frictions is always empirically relevant since a model without financial frictions features of value of zero for $\varkappa$. This also helps explaining the results of the Fluctuation test.

3.2.2 Density Forecast Evaluation

The forecast evaluation is completed with an assessment of the density forecasts to provide a realistic pattern of the actual uncertainty. This kind of analysis has recently become popular in forecasting exercises involving DSGE-based models (Herbst and Schorfheide, 2012; Kolasa et al., 2012; Del Negro and Schorfheide, 2013; Wolters, 2015). However, the evaluation of the density forecasts is less straightforward than the evaluation and the comparison of RMSFEs. As discussed in Wolters (2015), the true density is never observed. Notwithstanding this, the researcher can compare the distribution of observed data with density forecasts to investigate whether forecasts explain the actual uncertainty. There are different ways of examining the accuracy of density forecasts for DSGE model forecasting. We evaluate and rank the density forecasts using the log predictive density scores (LPDS) (as in Adolfson et al., 2007; Christoffel et al., 2010; Marcellino and Rychalovska, 2014, among others). We can define $f_{t+h,t,i}$ as a prediction of the density Y_{t+h}, conditional on information up to date t. Meanwhile, y_{t+h} is the realization of Y_{t+h}, and the h-step ahead density forecasts are available from a starting date T^s based on a total number of T observations. The average log score is given by the following formula:

$$AS_{i,h} = \frac{1}{T-h-T^s+1} \sum_{t=T^s}^{T-h} \ln f_{t+h,t,i}(y_{t+h}), \tag{1}$$

A higher value for the LPDS suggests a more accurate density forecast. We implement a nonparametric kernel estimator for the density and distribution function of the forecasts. As discussed in Chiu et al. (2017), this estimator helps the researcher to account for any potential non-linearities in the forecast distribution and, in addition, it is able to allow better performance at the tails of the predictive density, where the Great Recession would reasonably fall.

Table 7 presents the LPDS of the SWBF and SWBGG models relative to SW for the period 2003-2008. A positive number indicates an improvement over the SW model. For output growth, wage, consumption, investment and hours, the SW model is always better than the SWBF and SWBGG models. For inflation, the SWBF/SWBGG models produce the best performance in the longer horizon. The SWBGG model outperforms the SW model also for predicting FFR. Table 8 presents the LPDS of the SWBF and SWBGG models relative to SW for the period 2009-2016. According to the LPDS, for output growth the SWBGG model clearly outperforms the SW model at any horizon, while the SWBF model predicts better at horizons 1, 4, and 12. For inflation, both SWBF and SWBGG models outperform the SW one with the exception of horizon 1. Meanwhile, for FFR, consumption, investment, hours and wage, the SW is always outperformed by the other two models.

This result is in line with the findings of the point forecast reported in Table 6. Our results, especially for inflation, are in line with other findings in forecasting DSGE with financial frictions as shown in Del Negro and Schorfheide (2013), Kolasa and Rubaszek (2015a) and Galvao et al. (2016). In addition, in Tables 9 and 10, we report the log predictive density score for the models estimated with fixed parameters. In both samples, we provide evidence on how the SW model outperforms the models with financial frictions, showing how the models with updated parameters are preferred in a forecasting evaluation since they may produce more reliable forecasting evaluation. These results which also show how density forecasts are worse in case of fixed parameters models are due to the sample used in the estimation analysis. The models are estimated since 1973 including high volatility periods such as the 70s and the 80s, before the Great Moderation. In case of turbulent periods (as it was after the oil price shock or the Great Recession), updating parameters allows the researcher improving forecast accuracy.

4 Conclusion

This paper analyses the forecasting performance of DSGE models with and without financial frictions using US real-time data. It presents two different comparisons. First, it investigates whether updating parameters estimation as new data become available provides better forecast versus a fixed-parameters estimation. This analysis aims at disentangling the role of parameters instabilities in affecting point forecasts in DSGE models. The paper then compares the forecasting performance of two DSGE models with different types of financial frictions versus a standard medium-scale DSGE model *à la* Smets and Wouters (2007).

The forecast analysis based on RMSFE and LPDS shows that updating models parameters yields to lower forecast errors compared to the fixed scheme model. This result can be explained by the fact that the rolling estimation of parameters exhibits a considerable degree of variation in all the three DSGE models over the sample starting from 1973Q2-2003Q1 and ending in 2018Q1. As far as the second comparison is concerned, in the first sample (2003Q2-2008Q4) there is a weak evidence in favor of financial frictions; meanwhile in the second sample (2009Q1-2018Q1) there is a clear evidence in favor of financial frictions in terms of forecasting accuracy. We implement an additional forecast analysis by means of the Fluctuation test as in Giacomini and Rossi (2010), which reveals that for both GDP growth and inflation models with financial frictions outperform the SW model. In particular, adding financial frictions to a standard medium-scale DSGE model helps to improve the forecasting performance of output growth and overall also of inflation.

This exercise turns out to be useful also for policy-making since updating parameter estimates with real-time data is a more appropriate forecasting exercise due to the estimated instabilities in the parameters. In addition, omitting financial variables would severely decrease the forecasting performance of DSGE models. This would lead eventually to the design of appropriate model features which take into account the underlying driving forces of business cycle fluctuations.

	Linearized equations
SW model	
Euler equation	$c_t = \frac{h/\gamma}{1+h/\gamma} c_{t-1} + \left(1 - \frac{h/\gamma}{1+h/\gamma}\right) E_t c_{t+1} + \frac{(\sigma_c - 1)(w_* l_*/c_*)}{\sigma_c(1+h/\gamma)} \left(l_t - E_t l_{t+1}\right)$ $- \frac{1-h/\gamma}{\sigma_c(1+h/\gamma)} \left(r_t - E_t \pi_{t+1} + e_t^b\right)$
Sticky wages	$w_t = \frac{1}{1+\beta\gamma^{1-\sigma_c}} w_{t-1} + \left(1 - \frac{1}{1+\beta\gamma^{1-\sigma_c}}\right)\left(E_t w_{t+1} + E_t \pi_{t+1}\right) - \frac{1+\beta\gamma^{1-\sigma_c}\iota_w}{1+\beta\gamma^{1-\sigma_c}} \pi_t$ $+ \frac{\iota_w}{1+\beta\gamma^{1-\sigma_c}} \pi_{t-1} - \frac{\left(1+\xi_w\beta\gamma^{1-\sigma_c}\right)(1-\xi_w)}{\left(1+\beta\gamma^{1-\sigma_c}\right)\xi_w[(\phi_w - 1)e^w + 1]} \mu_t^w + e_t^w$
Wage mark-up	$\mu_w = w_t - \left[\sigma_l l_t + \frac{1}{1-h}\left(c_t - h c_{t-1}\right)\right]$
Production function	$y_t = \phi_p \left[\alpha\left(k_{t-1} + u_t\right) + (1-\alpha) l_t\right] + e_t^a$
Utilization rate	$u_t = \frac{(1-\psi)}{\psi} z_t^k$
Sticky prices	$\pi_t = \frac{\iota_p}{1+\beta\gamma^{1-\sigma_c}\iota_p} \pi_{t-1} + \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}\iota_p} E_t \pi_{t+1} - \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_p\right)(1-\xi_p)}{\left(1+\beta\gamma^{1-\sigma_c}\iota_p\right)\xi_p[(\phi_p-1)e^p+1]} \mu_t^p + e_t^p$
Price mark-up	$\mu_p = \alpha\left(k_{t-1} + u_t - l_t\right) + e_t^a - w_t$
Marginal product of capital	$z_t^k = -\left(k_{t-1} + u_t - l_t\right) + w_t$
Investment dynamics	$i_t = i_1 i_{t-1} + (1 - i_1) E_t i_{t+1} + i_2 q_t + e_t^x$
Capital accumulation	$k_t = \frac{(1-\delta)}{\gamma} k_{t-1} + \left(1 - \frac{1-\delta}{\gamma}\right) i_t + \left[1 - \frac{(1-\delta)}{\gamma}\right]\left(1 + \beta\gamma^{1-\sigma_c}\right)\gamma^2 \varphi e_t^x$
Taylor rule	$r_t = \rho_r r_{t-1} + (1-\rho_r)\left[\rho_\pi \pi_t + \rho_y\left(y_t - y_t^p\right)\right] + \rho_{\Delta y}\left[\left(y_t - y_t^p\right) - \left(y_{t-1} - y_{t-1}^p\right)\right] + e_t^i$
Resource constraint	$y_t = c_y c_t + i_y i_t + \frac{z_*^k k_*}{y_*} + e_t^g$
Tobin'q	$q_t = q_{1r} E_t q_{t+1} + (1 - q_{1r}) E_t z_{t+1}^k - \left(r_t - E_t \pi_{t+1}\right)$
SWBF model	
Credit spread	$r_t^{ep} = r_{t+1}^k - \left(r_t - E_t \pi_{t+1}\right)$
Balance sheet	$q_t + k_t = lev_t + n_t$
Leverage	$lev_t = \eta_t + \frac{v}{\phi - v} v_t$
Gain of having net worth	$\eta_t = \frac{\varpi\beta}{\gamma^{\sigma_c}} z_* \left(E_t \Lambda_{t+1} - \Lambda_t + z_t + E_t \eta_{t+1}\right)$
Growth rate of net worth	$z_t = \frac{lev_* r_*^k}{z_*} r_t^k + r_*(1 - lev_*)\left(r_{t-1} - \pi_t\right) + lev_*\left(r_*^k - r_*\right) lev_{t-1}$
Gain of expanding assets	$v_t = \frac{\varpi\beta}{\gamma^{\sigma_c}} z_* \left(E_t \Lambda_{t+1} - \Lambda_t + x_t + E_t v_{t+1}\right) + \frac{(1-\varpi)\beta}{\gamma^{\sigma_c}\nu_*}\left[r_*^k r_t^k - r_*\left(r_{t-1} - \pi_t\right)\right]$ $+ \frac{(1-\varpi)\beta}{\gamma^{\sigma_c}\nu_*}\left(r_*^k - r_*\right)\left(E_t \Lambda_{t+1} - \Lambda_t\right)$
Growth rate in assets	$x_t = lev_t - lev_{t-1} + z_t$
Net worth	$n_t = \frac{n_*^e}{n} n_t^e + \frac{n_*^n}{n_*} n_t^n$
Net worth of existing bankers	$n_t^e = n_{t-1}^e + z_t + e_t^n$
Net worth of new bankers	$n_t^n = \xi lev_*(q_t + k_t)$
Price of capital	$r_{t+1}^k = \frac{z_*^k}{r_*^k} z_{t+1}^k + \frac{(1-\delta)}{r_*^k + (1-\delta)} q_{t+1} - q_t$
SWBGG Model	
Spread	$E_t r_{t+1}^k = r_t + EP_t$
External finance premium	$EP_t = \varkappa\left(q_t + k_{t+1} - n_{t+1}\right)$
Net worth	$\frac{1}{\theta r^k} n_{t+1} = \frac{k_*}{n_*} r_t^k - \left(\frac{k_*}{n_*} - 1\right)\left(r_{t-1} - \pi_t\right) - \varkappa\left(\frac{k_*}{n_*} - 1\right)$ $\left(k_t + q_{t-1}\right) + \left[\left(\frac{k_*}{n_*} - 1\right)\varkappa + 1\right] n_t + e_t^n$

Table 1: Linearized equations. All variables are log-linearized around their steady state balanced growth path and starred variables represent steady state values. The parameters are: h the degree of habits in consumption; σ_c the coefficient of relative risk aversion; γ the steady state growth rate; β the discount factor; ξ_w the Calvo probability of not adjusting nominal wages; ι_w the degree of wage indexation; e^w the curvature of the Kimball aggregator in the labor market; α the output elasticity to capital; ψ the elasticity of the capital utilization adjustment cost; ι_p the indexation parameter; ξ_p the degree of price stickiness; e^p the curvature of Kimball aggregator in the goods market; φ the elasticity of investment adjustment costs; δ the depreciation rate of capital; ρ_r, ρ_π, ρ_y and $\rho_{\Delta y}$ the responsiveness of the nominal interest rate to inflation, to the output gap and to changes in the output gap, respectively; c_y and i_y are the steady state share of consumption and investment; ϖ the survival rate of banks; ϕ fraction of capital that can be diverted; and ξ the start-up transfer. The shocks are: e_t^a, TFP; e_t^p, price mark-up; e_t^w, wage mark-up; e_t^x, investment-specific technology; e_t^b, risk premium; e_t^g, exogenous spending; e_t^i, monetary policy; and e_t^n, net worth shock in the SWBF and SWBGG models.

Parameter		Value
Capital depreciation rate	δ	0.025
Kimball aggregator in the goods market	η_p	10
Kimball aggregator in the labor market	η_w	10
Gross mark-up in the labor market	λ_w	1.5
Government share of output	$\frac{G}{Y}$	0.18
Survival rate of financial intermediaries/firms (SWBF/SWBGG)	ϖ	0.9715
Fraction of divertable assets (SWBF)	ϕ	0.515
Fraction of assets given to new bankers (SWBF)	ξ	0.001
Firm's leverage ratio (SWBGG)	k_*/n_*	2

Table 2: Calibration

	Horizon	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
	SW	1.45	0.99	1.23	1.13	1.25	1.21	1.15
1	SWBF	1.2**	1.12	1.09	1.22	1.23**	1.25	1.02
	SWBGG	1.4	1.05*	1.14	1.15*	1.21	1.14	1.05
	SW	1.11*	1.17	1.25	1.08	1.42	1.14	1.1
2	SWBF	1.15	1.13	1.22***	1.1	1.25	1.18	1.07
	SWBGG	1.14	1.15	1.22	1.03	1.31**	1.2	1.01
	SW	1.26	1.17	1.35	1.1	1.29**	1.17	1.05*
4	SWBF	1.23	1.15	1.27	1.06	1.43	1.13	1.12
	SWBGG	1.26	1.18**	1.28	1.07**	1.36	1.15	1.13**
	SW	1.13	1.15	1.2	1.05	1.43	1.18	1.08
8	SWBF	1.15	1.28	1.27	1.11	1.32	1.14	1.06
	SWBGG	1.17	1.11	1.16	1.1	1.35*	1.2	1.12
	SW	1.36	1.32	1.45	1.11	1.54	1.36	1.1
12	SWBF	1.24	1.21	1.36	1.06	1.47	1.24	1.15*
	SWBGG	1.34	1.25	1.39	1.08	1.51	1.37	1.16

Table 3: Relative Root Mean Square Forecast Error (RMSFE), computed as a ratio between the RMSFE of the model with fixed parameters and the RMSFE of the model updated each quarter. Hence values greater than one indicate that the updated model has a lower RMSFE than the one with fixed parameters. Forecasting evaluation period: 2003Q3-2008Q4. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test (one-sided alternative).

	Horizon	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
	SW	1.12	1.08	1.32	1.23	1.42	1.17*	1.9
1	SWBF	1.07	1.05	1.23	1.2	1.35	1.19*	1.55
	SWBGG	1.11	1.11	1.25	1.25	1.21	1.23	1.6
	SW	1.17	1.16	1.2	1.01	1.12	1.26	1.14
2	SWBF	1.15	1.14	1.25	1.12	1.24	1.34	1.23
	SWBGG	1.11**	1.08**	1.15	1.03	1.27	1.15	1.05
	SW	1.14	1.19	1.33	1.11	1.08**	1.15	1.23
4	SWBF	1.12	1.27	1.26**	1.08	1.17	1.18	1.2
	SWBGG	1.12	1.12**	1.35**	1.07	1.2	1.12**	1.12
	SW	1.28	1.33	1.31	1.15	1.16	1.21	1.18
8	SWBF	1.26	1.38	1.27	1.05	1.19	1.23	1.15
	SWBGG	1.27	1.31	1.28	1.12**	1.13	1.23	1.17**
	SW	1.38	1.38	1.43	1.13	1.16	1.19	1.23
12	SWBF	1.29	1.36	1.38	1.14	1.22	1.21	1.24
	SWBGG	1.33*	1.42**	1.35	1.18	1.14	1.16	1.19*

Table 4: Relative Root Mean Square Forecast Error (RMSFE), computed as a ratio between the RMSFE of the model with fixed parameters and the RMSFE of the model updated each quarter. Hence values greater than one indicate that the updated model has a lower RMSFE than the one with fixed parameters. Forecasting evaluation period: 2009Q1-2018Q1. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test (one-sided alternative).

Horizon	Model	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
1	SWBF	1.04	0.98	1.04	0.94	0.98**	0.89	0.98
	SWBGG	0.94*	0.97	1.01	0.91	0.94	0.92	1.04
2	SWBF	0.95	0.95	1.03	0.97**	0.97	0.93	1.01*
	SWBGG	0.97	1.01	0.99	0.99	0.89	0.95	0.96
4	SWBF	0.98**	0.96**	0.97**	1.01	0.98***	0.87**	0.97
	SWBGG	0.97	0.97	0.98	1.02	0.97	0.89	0.99
8	SWBF	0.99	1.01	0.94	0.99	0.96	0.93	0.89***
	SWBGG	1.01*	1.02	1.01*	0.95**	0.98	0.95	0.91
12	SWBF	0.96	1.05*	1.02	0.98	0.89	0.97	1.05
	SWBGG	0.95	1.04	1.01	1.01	0.92	0.89	0.97

Table 5: Root Mean Square Forecast Error (RMSFE) are computed as a ratio between the RMSFE of the SWBF/SWBGG model and the RMSFE of the SW model. Hence values greater than one indicate that the SW model has a lower RMSFE than the alternative model featuring financial frictions. Forecasting evaluation period: 2003Q2-2008Q4. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10%significance levels of the Clark - West test.

Horizon	Model	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
1	SWBF	0.99	0.95	0.95*	0.98**	0.89	0.91	0.94
	SWBGG	0.98	0.87	0.97**	0.94**	0.98	0.92**	0.97
2	SWBF	0.97**	0.89**	0.89	1.01	0.97**	0.95***	0.98
	SWBGG	0.99**	0.93**	0.98	1.01	0.96***	0.99	0.97
4	SWBF	0.89**	0.95	0.97**	0.96	0.91	0.98**	0.96
	SWBGG	0.91**	0.91	0.99**	0.97	0.97**	0.98	0.93**
8	SWBF	0.92***	0.97**	0.97	0.99**	0.99	0.99***	0.95***
	SWBGG	0.93**	0.99*	0.89	0.93**	1.01	0.96**	0.87**
12	SWBF	0.99	1.01	0.87**	0.99	0.98***	0.95	0.89*
	SWBGG	0.98	1.02	0.88***	0.98	0.99**	0.94	0.95

Table 6: Root Mean Square Forecast Error (RMSFE) are computed as a ratio between the RMSFE of the SWBF/SWBGG model and the RMSFE of the SW model. Hence values greater than one indicate that the SW model has a lower RMSFE than the alternative model featuring financial frictions. Forecasting evaluation period: 2009Q1-2018Q1. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test.

Horizon	Model	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
	SWBF	-10.34	-5.43	1.23	-37.23	-8.23	-34.89	-265.34
1	SWBGG	-5.45	-3.76	1.45	-13.01	-10.37	-179.90	-269.23
	SWBF	-2.34*	-0.59*	2.45	1.72	-1.23	-204.76	-335.45
2	SWBGG	-3.47	-0.33*	3.46	-32.02	-2.34*	-240.67*	-405.23
	SWBF	-5.45	-0.11	4.67*	-31.91	-8.79*	-180.67*	-365.78
4	SWBGG	-3.67	0.47	3.21	-8.78***	-9.79*	-190.79	-338.23*
	SWBF	-2.58	-0.22*	4.32	2.09	-10.70*	-204.67	-280.34*
8	SWBGG	-3.32	0.36*	5.56	-31.33**	-11.12	-236.66	-322.76
	SWBF	-1.23	0.89	5.67	-30.91	-11.48	-240.76	-337.54
12	SWBGG	-2.76	1.41	3.45	-7.84	-10.34	-247.23	-314.01

Table 7: Percentage improvement in the log predictive scores (LPS) for the period 2003Q2-2008Q4 of the SWBF/SWBGG model over the SW model with updated parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

Horizon	Model	Output	Inflation	FFR	Wage	Consumption	Investment	Hours
	SWBF	24.55	-2.34	1.23	1.45	12.34	230.45	123.89***
1	SWBGG	6.89	-0.67	1.45	1.34	10.20	256.89	167.56***
	SWBF	-1.56	2.50	2.45*	3.56	9.56*	334.67*	203.98***
2	SWBGG	31.31*	2.76***	3.46*	5.67*	10.34*	370.45*	205.89
	SWBF	29.44*	2.98***	4.67*	3.47*	11.78*	330.89*	145.78
4	SWBGG	8.67*	3.56*	3.21*	4.78	10.78*	325.89	178.45
	SWBF	-1.80*	2.87*	4.32*	5.67	9.87*	279.56	203.89**
8	SWBGG	31.46*	3.45*	5.56***	8.70	9.45	287.98	201.88**
	SWBF	33.66	3.98*	5.67***	7.68	9.09	302.65	205.87**
12	SWBGG	9.58	4.50*	3.45***	9.56	12.09	301.67	234.89**

Table 8: Percentage improvement in the log predictive scores (LPS) for the period 2009Q1-2018Q1 of the SWBF/SWBGG model over the SW model with updated parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

Horizon	Model	Output	Inflation	FFR	Wage	Consump.	Invest.	Hours
1	SWBF	-30.56	-0.43	1.34	-31.55	-41.10	-17.64	-130.84
	SWBGG	-45.45*	-0.41	1.65	-46.42	-55.99*	-32.53	-145.73
2	SWBF	-10.98	-2.43	1.98	-11.97	-21.52*	1.94	-111.26
	SWBGG	-11.97	-3.21	2.35	-12.60*	-22.51	0.95	-112.25
4	SWBF	-12.45	-3.12*	3.78	-13.90	-22.98	0.48	-112.72
	SWBGG	-23.87	-5.64	3.54	-24.86	-36.40	-12.94**	-126.14
8	SWBF	-34.98	-3.67	3.98	-22.44	-45.52	-22.06**	-135.26
	SWBGG	-29.45	-2.65	-4.56**	-41.99	-39.99	-16.53	-129.73
12	SWBF	-34.87**	-4.65	-4.89**	-35.86	-45.41	-21.95	-135.15
	SWBGG	-37.80**	-3.45	-4.23**	-38.79	-48.34	-24.88	-138.08

Table 9: Percentage improvement in the log predictive scores (LPS) for the period 2003Q2-2008Q4 of the SWBF/SWBGG model over the SW model with fixed parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

Horizon	Model	Output	Inflation	FFR	Wage	Consump.	Invest.	Hours
1	SWBF	-8.43	-12.25	-0.68	-17.98	-7.09	1.79	-118.50
	SWBGG	-3.54	-3.54	-0.46	-18.09	-9.23	-13.10	-135.53
2	SWBF	-0.43	-0.43	0.54	-15.87	-9.87	21.37	-101.70
	SWBGG	-1.56	-1.56	1.55*	-13.76*	-9.09	20.38	-101.91*
4	SWBF	-3.54	-3.54	2.76*	-15.96*	-7.65	19.91	-100.94**
	SWBGG	-1.76	-1.76*	1.30	-14.65	-8.65	6.49	-115.36
8	SWBF	-0.67	-0.67	2.41	-13.76	-9.56**	-2.63	-125.39
	SWBGG	-1.41	-1.41	3.65	-10.73	-9.98	2.90	-120.28
12	SWBF	0.68**	0.68	3.76	-11.75	-10.34**	-2.52	-126.06
	SWBGG	-0.85**	-0.85	1.54	-9.87	-7.34	-5.45	-125.99

Table 10: Percentage improvement in the log predictive scores (LPS) for the period 2009Q1-2018Q1 of the SWBF/SWBGG model over the SW model with fixed parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

References

Adolfson, M., Lindé, J., and Villani, M. (2007). Forecasting performance of an open economy DSGE model. *Econometric Reviews*, 26(2-4):289–328.

Amisano, G. and Giacomini, R. (2007). Comparing density forecasts via weighted likelihood ratio tests. *Journal of Business & Economic Statistics*, 25(2):177–190.

Bekiros, S. and Paccagnini, A. (2013). On the predictability of time-varying VAR and DSGE models. *Empirical Economics*, 45(1):635–664.

Bekiros, S. D., Cardani, R., Paccagnini, A., and Villa, S. (2016). Dealing with financial instability under a DSGE modeling approach with banking intermediation: a predictability analysis versus TVP-VARs. *Journal of financial stability*, 26:216–227.

Bernanke, B., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle model. *Handbook of Macroeconomics*, 1:1341–1393.

Bernanke, B. S. and Boivin, J. (2003). Monetary policy in a data-rich environment. *Journal of Monetary Economics*, 50(3):525–546.

Bianchi, F. (2013). Regime switches, agents' beliefs, and post-world war II US macroeconomic dynamics. *The Review of Economic Studies*, 80(2):463–490.

Caldara, D., Fernández-Villaverde, J., Rubio-Ramírez, J. F., and Yao, W. (2012). Computing DSGE models with recursive preferences and stochastic volatility. *Review of Economic Dynamics*, 15(2):188–206.

Canova, F., Ferroni, F., and Matthes, C. (2015). Approximating time varying structural models with time invariant structures. *CEPR Discussion Papers*, 10803.

Caraiani, P. (2016). The role of money in DSGE models: a forecasting perspective. *Journal of Macroeconomics*, 47(Part B):315–330.

Cardani, R., Paccagnini, A., and Villa, S. (2015). Forecasting in a DSGE model with banking intermediation: Evidence from the US. *University of Milano-Bicocca Working Papers*, 292.

Casares, M. and Vázquez, J. (2016). Data revisions in the estimation of DSGE models. *Macroeconomic Dynamics*, pages 1–34.

Castelnuovo, E. (2012). Fitting U.S. Trend Inflation: A Rolling-Window Approach. In Balke, N., Canova, F., Milani, F., and Wynne, M., editors, *Advances in Econometrics: DSGE Models in Macroeconomics - Estimation, Evaluation, and New Developments*, pages 201–252.

Chiu, C.-W., Haroon, M., and Gábor, P. (2017). Forecasting with var models: Fat tails and stochastic volatility. *International Journal of Forecasting*, 33(4):1124 – 1143.

Christoffel, K., Warne, A., and Coenen, G. (2010). Forecasting with DSGE models. *ECB Working Paper Series*, 1185.

Clark, T. E. and West, K. D. (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics*, 135(1):155–186.

De Graeve, F. (2008). The external finance premium and the macroeconomy: US post-WWII evidence. *Journal of Economic Dynamics and Control*, 32(11):3415–3440.

De Polis, A. and Pietrunti, M. (2019). Exchange rate dynamics and unconventional monetary policies: it's all in the shadows. *Temi di discussione (Economic working papers), Bank of Italy*, 1231.

Del Negro, M. and Schorfheide, F. (2013). DSGE model-based forecasting. *Handbook of Economic Forecasting*, 2.

Edge, R. M. and Gurkaynak, R. S. (2011). How useful are estimated DSGE model forecasts? *Finance and Economics Discussion Series*, 2011-11.

Fawcett, N., Korber, L., Masolo, R., and Waldron, M. (2015). Evaluating UK point and density forecasts from an estimated DSGE model: The role of off-model information over the financial crisis. *Bank of England Working Paper*, 538.

Fernández-Villaverde, J., Guerrón-Quintana, P., and Rubio-Ramírez, J. F. (2010). Fortune or virtue: Time-variant volatilities versus parameter drifting in U.S. data. *NBER Working Papers*, 15928.

Foerster, A. T., Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. A. (2016). Perturbation methods for Markov-switching DSGE models. *Quantitative Economics*, 7:637–669.

Galvão, A. B. (2017). Data revisions and DSGE models. *Journal of Econometrics*, 196(1):215–232.

Galvao, A. B., Giraitis, L., Kapetanios, G., and Petrova, K. (2016). A time varying DSGE model with financial frictions. *Journal of Empirical Finance*, 38:690–716.

Gelain, P. and Ilbas, P. (2017). Monetary and macroprudential policies in an estimated model with financial intermediation. *Journal of Economic Dynamics and Control*, 78:164–189.

Gertler, M. and Gilchrist, S. (2018). What happened: Financial factors in the great recession. *Journal of Economic Perspectives*, 32(3):3–30.

Gertler, M. and Karadi, P. (2011). A model of unconventional monetary policy. *Journal of Monetary Economics*, 58(1):17–34.

Giacomini, R. and Rossi, B. (2010). Forecast comparisons in unstable environments. *Journal of Applied Econometrics*, 25(4):595–620.

Giacomini, R. and Rossi, B. (2015). Forecasting in nonstationary environments: what works and what doesn't in reduced-form and structural models. *Annual Review of Economics*, 7(1):207–229.

Giacomini, R. and Rossi, B. (2016). Model comparisons in unstable environments. *International Economic Review*, 57(2):369–392.

Gürkaynak, R. S., Kisacikoglu, B., and Rossi, B. (2013). Do DSGE Models Forecast More Accurately Out-of-Sample than VAR Models? *CEPR Discussion Papers*, (9576).

Herbst, E. and Schorfheide, F. (2012). Evaluating DSGE model forecasts of comovements. *Journal of Econometrics*, 171(2):152–166.

Hirose, Y. and Inoue, A. (2016). The zero lower bound and parameter bias in an estimated DSGE model. *Journal of Applied Econometrics*, 31(4):630–651.

Hurtado, S. (2014). DSGE Models and the Lucas critique. *Economic Modelling*, 44(S1):S12 – S19.

Inoue, A. and Rossi, B. (2011). Identifying the sources of instabilities in macroeconomic fluctuations. *Review of Economics and statistics*, 93(4):1186–1204.

Kolasa, M. and Rubaszek, M. (2015a). Forecasting with DSGE models with financial frictions. *International Journal of Forecasting*, 31(1):1–19.

Kolasa, M. and Rubaszek, M. (2015b). How frequently should we reestimate DSGE models? *International Journal of Central Banking*, 11(4):279–305.

Kolasa, M., Rubaszek, M., and Skrzypczyński, P. (2012). Putting the New Keynesian DSGE model to the real-time forecasting test. *Journal of Money, Credit and Banking*, 44(7):1301–1324.

Marcellino, M. and Rychalovska, Y. (2014). Forecasting with a DSGE model of a small open economy within the monetary union. *Journal of Forecasting*, 33(5):315–338.

Masolo, R. and Paccagnini, A. (2019). Identifying Noise Shocks: A VAR with Data Revisions. *Journal of Money, Credit and Banking*. Forthcoming.

Melina, G. and Villa, S. (2018). Leaning against windy bank lending. *Economic Inquiry*, 56(1):460 – 482.

Paccagnini, A. (2019). Did financial factors matter during the Great Recession? *Economics Letters*, 174:26–30.

Ratto, M. (2011). Analysing DSGE models with global sensitivity analysis. *Computational Economics*, 31(2):115–139.

Ratto, M. and Iskrev, N. (2011). Identification toolbox for DYNARE. Mimeo.

Smets, F. and Villa, S. (2016). Slow recoveries: Any role for corporate leverage? *Journal of Economic Dynamics and Control*, 70:54–85.

Smets, F. and Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review*, 97(3):586–606.

Stock, J. H. and Watson, M. W. (1999). Forecasting inflation. *Journal of Monetary Economics*, 44(2):293–335.

Villa, S. (2016). Financial frictions in the Euro Area and the United States: a Bayesian assessment. *Macroeconomic Dynamics*, 20(05):1313–1340.

Wolters, M. H. (2015). Evaluating point and density forecasts of DSGE models. *Journal of Applied Econometrics*, 30(1):74–96.

Online Appendix

A Data sources and transformations

This section discusses the sources of the observables used in the estimation and their transformation. The source of macroeconomic data, except the short term interest rate, used to estimate the models is the Real-Time Data Set for Macroeconomics (RTDSM) maintained by the Federal Reserve Bank of Philadelphia. GDP is the Real Gross domestic product (ROUTPUT), consumption is the Real personal consumption expenditures (RCON), investment is the Real gross private domestic non-residential investment (RINVBF), hours is the aggregate weekly hours (HOURS), wages is the nominal wage and salary disbursements (WSD), and inflation is calculated using the Price index for gross domestic product (P). The short term interest rate, not subject to revisions, is the Federal Funds Rate downloaded from the ALFRED database of the Federal Reserve Bank of St. Louis. Net worth of banks is downloaded from the FRED database and it is computed as the difference between total assets of all commercial banks (TLAACBW027SBOG) and total liabilities of all commercial banks (TLBACBM027SBOG). The spread in the SWBGG model is computed as the annualized Moody's Seasoned Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield at Constant Maturity, as in Del Negro and Schorfheide (2013). Data are transformed as in Smets and Wouters (2007). In particular, GDP, consumption, investment and net worth are transformed in real per-capita terms by the civilian population. Real wages are computed by dividing compensation per hour by the Price level. As shown in the measurement equations, the observable variables of GDP, consumption, investment, wages and net worth are expressed in first differences. Hours worked are multiplied by civilian employment, expressed in per capita terms and demeaned. The inflation rate is computed as a quarter-on-quarter difference of the log of the GDP deflator. The fed funds rate is expressed in quarterly terms. Remaining variables are expressed in 100 times log. All series are seasonally adjusted. Data on spreads are also extracted from the ALFRED database of the Federal Reserve Bank of St. Louis. Our variables are built as described in Kolasa and Rubaszek (2015a).

The following set of measurement equations shows the link between the observable variables in the dataset and the endogenous variables of the DSGE model:

$$\begin{bmatrix} \Delta Y_t^o \\ \Delta C_t^o \\ \Delta I_t^o \\ \Delta W_t^o \\ L_t^o \\ \pi_t^o \\ r_t^{n,o} \\ \Delta N_t^o \\ EP_t^o \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{l} \\ \bar{\pi} \\ \bar{r}^n \\ \bar{\gamma}^N \\ \bar{EP} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ l_t \\ \pi_t \\ r_t \\ n_t - n_{t-1} \\ EP_t \end{bmatrix}, \tag{2}$$

where $\bar{\gamma} = 100(\gamma - 1)$ is the common quarterly trend growth rate of GDP, consumption, investment and wages; $\bar{l}$ is the steady-state hours of work; $\bar{\pi}$ is the steady-state quarterly inflation rate; and $\bar{r}^n$ is the steady-state quarterly nominal interest rate; $\bar{\gamma}^N = 100(\gamma^N - 1)$ is the quarterly trend growth rate of net worth of financial intermediaries in the SWBF model, as in Gelain and Ilbas (2017); and $\bar{EP}$ is the steady-state quarterly credit spread.

RECENTLY PUBLISHED "TEMI" (*)

N. 1213 – *A regression discontinuity design for categorical ordered running variables with an application to central bank purchases of corporate bonds*, by Fan Li, Andrea Mercatanti, Taneli Mäkinen and Andrea Silvestrini (March 2019).

N. 1214 – *Anything new in town? The local effects of urban regeneration policies in Italy*, by Giuseppe Albanese, Emanuele Ciani and Guido de Blasio (April 2019).

N. 1215 – *Risk premium in the era of shale oil*, by Fabrizio Ferriani, Filippo Natoli, Giovanni Veronese and Federica Zeni (April 2019).

N. 1216 – *Safety traps, liquidity and information-sensitive assets*, by Michele Loberto (April 2019).

N. 1217 – *Does trust among banks matter for bilateral trade? Evidence from shocks in the interbank market*, by Silvia Del Prete and Stefano Federico (April 2019).

N. 1218 – *Monetary policy, firms' inflation expectations and prices: causal evidence from firm-level data*, by Marco Bottone and Alfonso Rosolia (April 2019).

N. 1219 – *Inflation expectations and firms' decisions: new causal evidence*, by Olivier Coibion, Yuriy Gorodnichenko and Tiziano Ropele (April 2019).

N. 1220 – *Credit risk-taking and maturity mismatch: the role of the yield curve*, by Giuseppe Ferrero, Andrea Nobili and Gabriele Sene (April 2019).

N. 1221 – *Big-city life (dis)satisfaction? The effect of living in urban areas on subjective well-being*, by David Loschiavo (June 2019).

N. 1222 – *Urban agglomerations and firm access to credit*, by Amanda Carmignani, Guido de Blasio, Cristina Demma and Alessio D'Ignazio (June 2019).

N. 1223 – *The international transmission of US tax shocks: a proxy-SVAR approach*, by Luca Metelli and Filippo Natoli (June 2019).

N. 1224 – *Forecasting inflation in the euro area: countries matter!*, by Angela Capolongo and Claudia Pacella (June 2019).

N. 1225 – *Domestic and global determinants of inflation: evidence from expectile regression*, by Fabio Busetti, Michele Caivano and Davide Delle Monache (June 2019).

N. 1226 – *Relative price dynamics in the Euro area: where do we stand?*, by Pietro Cova and Lisa Rodano (June 2019).

N. 1227 – *Optimally solving banks' legacy problems*, by Anatoli Segura and Javier Suarez (June 2019).

N. 1228 – *Il mercato degli affitti nelle città italiane: un'analisi basata sugli annunci online*, di Michele Loberto (Luglio 2019).

N. 1229 – *Using credit variables to date business cycle and to estimate the probabilities of recession in real time*, by Valentina Aprigliano and Danilo Liberati (July 2019).

N. 1230 – *Disinflationary shocks and inflation target uncertainty*, by Stefano Neri and Tiziano Ropele (July 2019).

N. 1231 – *Exchange rate dynamics and unconventional monetary policies: it's all in the shadows*, by Andrea De Polis and Mario Pietrunti (July 2019).

N. 1232 – *Risky bank guarantees*, by Taneli Mäkinen, Lucio Sarno and Gabriele Zinna (July 2019).

(*) Requests for copies should be sent to:
Banca d'Italia – Servizio Studi di struttura economica e finanziaria – Divisione Biblioteca e Archivio storico – Via Nazionale, 91 – 00184 Rome – (fax 0039 06 47922059). They are available on the Internet www.bancaditalia.it.

2017

AABERGE, R., F. BOURGUIGNON, A. BRANDOLINI, F. FERREIRA, J. GORNICK, J. HILLS, M. JÄNTTI, S. JENKINS, J. MICKLEWRIGHT, E. MARLIER, B. NOLAN, T. PIKETTY, W. RADERMACHER, T. SMEEDING, N. STERN, J. STIGLITZ, H. SUTHERLAND, *Tony Atkinson and his legacy,* Review of Income and Wealth, v. 63, 3, pp. 411-444, **WP 1138 (September 2017).**

ACCETTURO A., M. BUGAMELLI and A. LAMORGESE, *Law enforcement and political participation: Italy 1861-65,* Journal of Economic Behavior & Organization, v. 140, pp. 224-245, **WP 1124 (July 2017).**

ADAMOPOULOU A. and G.M. TANZI, *Academic dropout and the great recession,* Journal of Human Capital, V. 11, 1, pp. 35–71, **WP 970 (October 2014).**

ALBERTAZZI U., M. BOTTERO and G. SENE, *Information externalities in the credit market and the spell of credit rationing,* Journal of Financial Intermediation, v. 30, pp. 61–70, **WP 980 (November 2014).**

ALESSANDRI P. and H. MUMTAZ, *Financial indicators and density forecasts for US output and inflation,* Review of Economic Dynamics, v. 24, pp. 66-78, **WP 977 (November 2014).**

BARBIERI G., C. ROSSETTI and P. SESTITO, *Teacher motivation and student learning,* Politica economica/Journal of Economic Policy, v. 33, 1, pp.59-72, **WP 761 (June 2010).**

BENTIVOGLI C. and M. LITTERIO, *Foreign ownership and performance: evidence from a panel of Italian firms,* International Journal of the Economics of Business, v. 24, 3, pp. 251-273, **WP 1085 (October 2016).**

BRONZINI R. and A. D'IGNAZIO, *Bank internationalisation and firm exports: evidence from matched firm-bank data,* Review of International Economics, v. 25, 3, pp. 476-499 **WP 1055 (March 2016).**

BRUCHE M. and A. SEGURA, *Debt maturity and the liquidity of secondary debt markets,* Journal of Financial Economics, v. 124, 3, pp. 599-613, **WP 1049 (January 2016).**

BURLON L., *Public expenditure distribution, voting, and growth,* Journal of Public Economic Theory,, v. 19, 4, pp. 789–810, **WP 961 (April 2014).**

BURLON L., A. GERALI, A. NOTARPIETRO and M. PISANI, *Macroeconomic effectiveness of non-standard monetary policy and early exit. a model-based evaluation,* International Finance, v. 20, 2, pp.155-173, **WP 1074 (July 2016).**

BUSETTI F., *Quantile aggregation of density forecasts,* Oxford Bulletin of Economics and Statistics, v. 79, 4, pp. 495-512, **WP 979 (November 2014).**

CESARONI T. and S. IEZZI, *The predictive content of business survey indicators: evidence from SIGE,* Journal of Business Cycle Research, v.13, 1, pp 75–104, **WP 1031 (October 2015).**

CONTI P., D. MARELLA and A. NERI, *Statistical matching and uncertainty analysis in combining household income and expenditure data,* Statistical Methods & Applications, v. 26, 3, pp 485–505, **WP 1018 (July 2015).**

D'AMURI F., *Monitoring and disincentives in containing paid sick leave,* Labour Economics, v. 49, pp. 74-83, **WP 787 (January 2011).**

D'AMURI F. and J. MARCUCCI, *The predictive power of google searches in forecasting unemployment,* International Journal of Forecasting, v. 33, 4, pp. 801-816, **WP 891 (November 2012).**

DE BLASIO G. and S. POY, *The impact of local minimum wages on employment: evidence from Italy in the 1950s,* Journal of Regional Science, v. 57, 1, pp. 48-74, **WP 953 (March 2014).**

DEL GIOVANE P., A. NOBILI and F. M. SIGNORETTI, *Assessing the sources of credit supply tightening: was the sovereign debt crisis different from Lehman?,* International Journal of Central Banking, v. 13, 2, pp. 197-234, **WP 942 (November 2013).**

DEL PRETE S., M. PAGNINI, P. ROSSI and V. VACCA, *Lending organization and credit supply during the 2008–2009 crisis,* Economic Notes, v. 46, 2, pp. 207–236, **WP 1108 (April 2017).**

DELLE MONACHE D. and I. PETRELLA, *Adaptive models and heavy tails with an application to inflation forecasting,* International Journal of Forecasting, v. 33, 2, pp. 482-501, **WP 1052 (March 2016).**

FEDERICO S. and E. TOSTI, *Exporters and importers of services: firm-level evidence on Italy,* The World Economy, v. 40, 10, pp. 2078-2096, **WP 877 (September 2012).**

GIACOMELLI S. and C. MENON, *Does weak contract enforcement affect firm size? Evidence from the neighbour's court,* Journal of Economic Geography, v. 17, 6, pp. 1251-1282, **WP 898 (January 2013).**

LOBERTO M. and C. PERRICONE, *Does trend inflation make a difference?,* Economic Modelling, v. 61, pp. 351–375, **WP 1033 (October 2015).**

MANCINI A.L., C. MONFARDINI and S. PASQUA, *Is a good example the best sermon? Children's imitation of parental reading,* Review of Economics of the Household, v. 15, 3, pp 965–993, **WP No. 958 (April 2014).**

MEEKS R., B. NELSON and P. ALESSANDRI, *Shadow banks and macroeconomic instability,* Journal of Money, Credit and Banking, v. 49, 7, pp. 1483–1516, **WP 939 (November 2013).**

MICUCCI G. and P. ROSSI, *Debt restructuring and the role of banks' organizational structure and lending technologies,* Journal of Financial Services Research, v. 51, 3, pp 339–361, **WP 763 (June 2010).**

MOCETTI S., M. PAGNINI and E. SETTE, *Information technology and banking organization,* Journal of Journal of Financial Services Research, v. 51, pp. 313-338, **WP 752 (March 2010).**

MOCETTI S. and E. VIVIANO, *Looking behind mortgage delinquencies,* Journal of Banking & Finance, v. 75, pp. 53-63, **WP 999 (January 2015).**

NOBILI A. and F. ZOLLINO, *A structural model for the housing and credit market in Italy,* Journal of Housing Economics, v. 36, pp. 73-87, **WP 887 (October 2012).**

PALAZZO F., *Search costs and the severity of adverse selection,* Research in Economics, v. 71, 1, pp. 171-197, **WP 1073 (July 2016).**

PATACCHINI E. and E. RAINONE, *Social ties and the demand for financial services,* Journal of Financial Services Research, v. 52, 1–2, pp 35–88, **WP 1115 (June 2017).**

PATACCHINI E., E. RAINONE and Y. ZENOU, *Heterogeneous peer effects in education,* Journal of Economic Behavior & Organization, v. 134, pp. 190–227, **WP 1048 (January 2016).**

SBRANA G., A. SILVESTRINI and F. VENDITTI, *Short-term inflation forecasting: the M.E.T.A. approach,* International Journal of Forecasting, v. 33, 4, pp. 1065-1081, **WP 1016 (June 2015).**

SEGURA A. and J. SUAREZ, *How excessive is banks' maturity transformation?,* Review of Financial Studies, v. 30, 10, pp. 3538–3580, **WP 1065 (April 2016).**

VACCA V., *An unexpected crisis? Looking at pricing effectiveness of heterogeneous banks,* Economic Notes, v. 46, 2, pp. 171–206, **WP 814 (July 2011).**

VERGARA CAFFARELI F., *One-way flow networks with decreasing returns to linking,* Dynamic Games and Applications, v. 7, 2, pp. 323-345, **WP 734 (November 2009).**

ZAGHINI A., *A Tale of fragmentation: corporate funding in the euro-area bond market,* International Review of Financial Analysis, v. 49, pp. 59-68, **WP 1104 (February 2017).**

2018

ACCETTURO A., V. DI GIACINTO, G. MICUCCI and M. PAGNINI, *Geography, productivity and trade: does selection explain why some locations are more productive than others?,* Journal of Regional Science, v. 58, 5, pp. 949-979, **WP 910 (April 2013).**

ADAMOPOULOU A. and E. KAYA, *Young adults living with their parents and the influence of peers,* Oxford Bulletin of Economics and Statistics,v. 80, pp. 689-713, **WP 1038 (November 2015).**

ANDINI M., E. CIANI, G. DE BLASIO, A. D'IGNAZIO and V. SILVESTRINI, *Targeting with machine learning: an application to a tax rebate program in Italy,* Journal of Economic Behavior & Organization, v. 156, pp. 86-102, **WP 1158 (December 2017).**

BARONE G., G. DE BLASIO and S. MOCETTI, *The real effects of credit crunch in the great recession: evidence from Italian provinces,* Regional Science and Urban Economics, v. 70, pp. 352-59, **WP 1057 (March 2016).**

BELOTTI F. and G. ILARDI *Consistent inference in fixed-effects stochastic frontier models,* Journal of Econometrics, v. 202, 2, pp. 161-177, **WP 1147 (October 2017).**

BERTON F., S. MOCETTI, A. PRESBITERO and M. RICHIARDI, *Banks, firms, and jobs,* Review of Financial Studies, v.31, 6, pp. 2113-2156, **WP 1097 (February 2017).**

BOFONDI M., L. CARPINELLI and E. SETTE, *Credit supply during a sovereign debt crisis,* Journal of the European Economic Association, v.16, 3, pp. 696-729, **WP 909 (April 2013).**

BOKAN N., A. GERALI, S. GOMES, P. JACQUINOT and M. PISANI, *EAGLE-FLI: a macroeconomic model of banking and financial interdependence in the euro area,* Economic Modelling, v. 69, C, pp. 249-280, **WP 1064 (April 2016).**

BRILLI Y. and M. TONELLO, *Does increasing compulsory education reduce or displace adolescent crime? New evidence from administrative and victimization data,* CESifo Economic Studies, v. 64, 1, pp. 15–4, **WP 1008 (April 2015).**

BUONO I. and S. FORMAI *The heterogeneous response of domestic sales and exports to bank credit shocks,* Journal of International Economics, v. 113, pp. 55-73, **WP 1066 (March 2018).**

BURLON L., A. GERALI, A. NOTARPIETRO and M. PISANI, *Non-standard monetary policy, asset prices and macroprudential policy in a monetary union,* Journal of International Money and Finance, v. 88, pp. 25-53, **WP 1089 (October 2016).**

CARTA F. and M. DE PHLIPPIS, *You've Come a long way, baby. Husbands' commuting time and family labour supply,* Regional Science and Urban Economics, v. 69, pp. 25-37, **WP 1003 (March 2015).**

CARTA F. and L. RIZZICA, *Early kindergarten, maternal labor supply and children's outcomes: evidence from Italy,* Journal of Public Economics, v. 158, pp. 79-102, **WP 1030 (October 2015).**

CASIRAGHI M., E. GAIOTTI, L. RODANO and A. SECCHI, *A "Reverse Robin Hood"? The distributional implications of non-standard monetary policy for Italian households,* Journal of International Money and Finance, v. 85, pp. 215-235, **WP 1077 (July 2016).**

CECCHETTI S., F. NATOLI and L. SIGALOTTI, *Tail co-movement in inflation expectations as an indicator of anchoring,* International Journal of Central Banking, v. 14, 1, pp. 35-71, **WP 1025 (July 2015).**

CIANI E. and C. DEIANA, *No Free lunch, buddy: housing transfers and informal care later in life,* Review of Economics of the Household, v.16, 4, pp. 971-1001, **WP 1117 (June 2017).**

CIPRIANI M., A. GUARINO, G. GUAZZAROTTI, F. TAGLIATI and S. FISHER, *Informational contagion in the laboratory,* Review of Finance, v. 22, 3, pp. 877-904, **WP 1063 (April 2016).**

DE BLASIO G, S. DE MITRI, S. D'IGNAZIO, P. FINALDI RUSSO and L. STOPPANI, *Public guarantees to SME borrowing. A RDD evaluation,* Journal of Banking & Finance, v. 96, pp. 73-86, **WP 1111 (April 2017).**

GERALI A., A. LOCARNO, A. NOTARPIETRO and M. PISANI, *The sovereign crisis and Italy's potential output,* Journal of Policy Modeling, v. 40, 2, pp. 418-433, **WP 1010 (June 2015).**

LIBERATI D., *An estimated DSGE model with search and matching frictions in the credit market,* International Journal of Monetary Economics and Finance (IJMEF), v. 11, 6, pp. 567-617, **WP 986 (November 2014).**

LINARELLO A., *Direct and indirect effects of trade liberalization: evidence from Chile,* Journal of Development Economics, v. 134, pp. 160-175, **WP 994 (December 2014).**

NUCCI F. and M. RIGGI, *Labor force participation, wage rigidities, and inflation,* Journal of Macroeconomics, v. 55, 3 pp. 274-292, **WP 1054 (March 2016).**

RIGON M. and F. ZANETTI, *Optimal monetary policy and fiscal policy interaction in a non_ricardian economy,* International Journal of Central Banking, v. 14 3, pp. 389-436, **WP 1155 (December 2017).**

SEGURA A., *Why did sponsor banks rescue their SIVs?,* Review of Finance, v. 22, 2, pp. 661-697, **WP 1100 (February 2017).**

2019

ALBANESE G., M. CIOFFI and P. TOMMASINO, *Legislators' behaviour and electoral rules: evidence from an Italian reform,* European Journal of Political Economy, v. 59, pp. 423-444, **WP 1135 (September 2017).**

ARNAUDO D., G. MICUCCI, M. RIGON and P. ROSSI, *Should I stay or should I go? Firms' mobility across banks in the aftermath of the financial crisis,* Italian Economic Journal / Rivista italiana degli economisti, v. 5, 1, pp. 17-37, **WP 1086 (October 2016).**

BASSO G., F. D'AMURI and G. PERI, *Immigrants, labor market dynamics and adjustment to shocks in the euro area,* IMF Economic Review, v. 67, 3, pp. 528-572, **WP 1195 (November 2018).**

BUSETTI F. and M. CAIVANO, *Low frequency drivers of the real interest rate: empirical evidence for advanced economies,* International Finance, v. 22, 2, pp. 171-185, **WP 1132 (September 2017).**

CAPPELLETTI G., G. GUAZZAROTTI and P. TOMMASINO, *Tax deferral and mutual fund inflows: evidence from a quasi-natural experiment,* Fiscal Studies, v. 40, 2, pp. 211-237, **WP 938 (November 2013).**

CARDANI R., A. PACCAGNINI and S. VILLA, *Forecasting with instabilities: an application to DSGE models with financial frictions,* Journal of Macroeconomics, v. 61, **WP 1234 (September 2019).**

CIANI E., F. DAVID and G. DE BLASIO, *Local responses to labor demand shocks: a re-assessment of the case of Italy,* Regional Science and Urban Economics, v. 75, pp. 1-21, **WP 1112 (April 2017).**

CIANI E. and P. FISHER, *Dif-in-dif estimators of multiplicative treatment effects,* Journal of Econometric Methods, v. 8. 1, pp. 1-10, **WP 985 (November 2014).**

CHIADES P., L. GRECO, V. MENGOTTO, L. MORETTI and P. VALBONESI, *Fiscal consolidation by intergovernmental transfers cuts? The unpleasant effect on expenditure arrears,* Economic Modelling, v. 77, pp. 266-275, **WP 985 (July 2016).**

COLETTA M., R. DE BONIS and S. PIERMATTEI, *Household debt in OECD countries: the role of supply-side and demand-side factors,* Social Indicators Research, v. 143, 3, pp. 1185–1217, **WP 989 (November 2014).**

COVA P., P. PAGANO and M. PISANI, *Domestic and international effects of the Eurosystem Expanded Asset Purchase Programme,* IMF Economic Review, v. 67, 2, pp. 315-348, **WP 1036 (October 2015).**

GIORDANO C., M. MARINUCCI and A. SILVESTRINI, *The macro determinants of firms' and households' investment: evidence from Italy,* Economic Modelling, v. 78, pp. 118-133, **WP 1167 (March 2018).**

GOMELLINI M., D. PELLEGRINO and F. GIFFONI, *Human capital and urban growth in Italy,1981-2001,* Review of Urban & Regional Development Studies, v. 31, 2, pp. 77-101, **WP 1127 (July 2017).**

MAGRI S, *Are lenders using risk-based pricing in the Italian consumer loan market? The effect of the 2008 crisis,* Journal of Credit Risk, v. 15, 1, pp. 27-65, **WP 1164 (January 2018).**

MIGLIETTA A, C. PICILLO and M. PIETRUNTI, *The impact of margin policies on the Italian repo market,* The North American Journal of Economics and Finance, v. 50, **WP 1028 (October 2015).**

MONTEFORTE L. and V. RAPONI, *Short-term forecasts of economic activity: are fortnightly factors useful?,* Journal of Forecasting, v. 38, 3, pp. 207-221, **WP 1177 (June 2018).**

MERCATANTI A., T. MAKINEN and A. SILVESTRINI, *The role of financial factors for european corporate investment,* Journal of International Money and Finance, v. 96, pp. 246-258, **WP 1148 (October 2017).**

NERI S. and A. NOTARPIETRO, *Collateral constraints, the zero lower bound, and the debt–deflation mechanism,* Economics Letters, v. 174, pp. 144-148, **WP 1040 (November 2015).**

RIGGI M., *Capital destruction, jobless recoveries, and the discipline device role of unemployment,* Macroeconomic Dynamics, v. 23, 2, pp. 590-624, **WP 871 (July 2012).**

FORTHCOMING

ALBANESE G., G. DE BLASIO and P. SESTITO, *Trust, risk and time preferences: evidence from survey data,* International Review of Economics, **WP 911 (April 2013).**

APRIGLIANO V., G. ARDIZZI and L. MONTEFORTE, *Using the payment system data to forecast the economic activity,* International Journal of Central Banking, **WP 1098 (February 2017).**

ARDUINI T., E. PATACCHINI and E. RAINONE, *Treatment effects with heterogeneous externalities,* Journal of Business & Economic Statistics, **WP 974 (October 2014).**

BRONZINI R., G. CARAMELLINO and S. MAGRI, *Venture capitalists at work: a Diff-in-Diff approach at late-stages of the screening process,* Journal of Business Venturing, **WP 1131 (September 2017).**

BELOTTI F. and G. ILARDI, *Consistent inference in fixed-effects stochastic frontier models,* Journal of Econometrics, **WP 1147 (October 2017).**

CIANI E. and G. DE BLASIO, *European structural funds during the crisis: evidence from Southern Italy,* IZA Journal of Labor Policy, **WP 1029 (October 2015).**

COIBION O., Y. GORODNICHENKO and T. ROPELE, *Inflation expectations and firms' decisions: new causal evidence,* Quarterly Journal of Economics, **WP 1219 (April 2019).**

CORSELLO F. and V. NISPI LANDI, *Labor market and financial shocks: a time-varying analysis,* Journal of Money, Credit and Banking, **WP 1179 (June 2018).**

COVA P., P. PAGANO, A. NOTARPIETRO and M. PISANI, *Secular stagnation, R&D, public investment and monetary policy: a global-model perspective,* Macroeconomic Dynamics, **WP 1156 (December 2017).**

D'AMURI F., *Monitoring and disincentives in containing paid sick leave,* Labour Economics, **WP 787 (January 2011).**

D'IGNAZIO A. and C. MENON, *The causal effect of credit Guarantees for SMEs: evidence from Italy,* Scandinavian Journal of Economics, **WP 900 (February 2013).**

ERCOLANI V. and J. VALLE E AZEVEDO, *How can the government spending multiplier be small at the zero lower bound?,* Macroeconomic Dynamics, **WP 1174 (April 2018).**

FEDERICO S. and E. TOSTI, *Exporters and importers of services: firm-level evidence on Italy,* The World Economy, **WP 877 (September 2012).**

FERRERO G., M. GROSS and S. NERI, *On secular stagnation and low interest rates: demography matters,* International Finance, **WP 1137 (September 2017).**

GERALI A. and S. NERI, *Natural rates across the Atlantic,* Journal of Macroeconomics, **WP 1140 (September 2017).**

GIACOMELLI S. and C. MENON, *Does weak contract enforcement affect firm size? Evidence from the neighbour's court,* Journal of Economic Geography, **WP 898 (January 2013).**

LIBERATI D. and M. LOBERTO, *Taxation and housing markets with search frictions,* Journal of Housing Economics, **WP 1105 (March 2017).**

LOSCHIAVO D., *Household debt and income inequality: evidence from italian survey data,* Review of Income and Wealth, **WP 1095 (January 2017).**

NATOLI F. and L. SIGALOTTI, *Tail co-movement in inflation expectations as an indicator of anchoring,* International Journal of Central Banking, **WP 1025 (July 2015).**

PANCRAZI R. and M. PIETRUNTI, *Natural expectations and home equity extraction,* Journal of Housing Economics, **WP 984 (November 2014).**

PEREDA FERNANDEZ S., *Teachers and cheaters. Just an anagram?,* Journal of Human Capital, **WP 1047 (January 2016).**

RAINONE E., *The network nature of otc interest rates,* Journal of Financial Markets, **WP 1022 (July 2015).**

RIZZICA L., *Raising aspirations and higher education. evidence from the UK's widening participation policy,* Journal of Labor Economics, **WP 1188 (September 2018).**

SEGURA A., *Why did sponsor banks rescue their SIVs?,* Review of Finance, **WP 1100 (February 2017).**