Income inequality, consumption, credit and credit risk in a data-driven agent-based model☆

Georgios Papadopoulos

Analysis and Research Centre, Bank of Slovenia, Ljubljana, Slovenia

ARTICLE INFO

ABSTRACT

The issue of income inequality occupies a prominent position in the research agenda of academic and policy circles alike, especially after the crisis of 2008, due to its potential causal link with the development of credit bubbles and therefore the emergence of financial crises. This paper examines the long-run effect of income inequality on consumption, consumer credit and non-performing loans through the means of a data-driven agent-based model. The data-driven nature of the model enhances its ability to match historical series and thus makes it suitable for policy simulations tailored for specific economies. The analysis indicates that higher income inequality has a detrimental impact on consumption and is associated with lower volumes of consumer credit. However, the ratio of non-performing loans as a share of total loans seems to be independent of income inequality.

1. Introduction

The central theme of this paper is the effect of inequality in the distribution of income on aggregate macroeconomic and financial variables. At its core is essentially a thought experiment attempting to answer the question: *How would the initial level of income inequality affect aggregate consumption, consumer credit and non-performing loans of an economic system which would otherwise follow a specific historical scenario?*

The issue of inequality and the effects of its various manifestations -such as income, wealth or consumption- on both developing and developed countries has attracted the attention of academia and policy makers alike, especially after the financial crisis of 2008, with several studies documenting significant increases in the skewness and kurtosis of income and wealth distributions over the past three decades (e.g. Atkinson and Morelli, 2011; Piketty and Saez, 2003; Piketty and Saez, 2006) and highlighting its persistent nature even after the implementation of financial reforms (Christopoulos and

McAdam, 2017a; 2017b). More recently, research from policy making institutions contributed to the debate by examining the relationship between central bank policies and inequality (Amaral, 2017; Ampudia et al., 2018; Colciago et al., 2018). However, this topic might not have risen to such prominent position within the economics profession if it weren't for the potential causal links between rising inequality and financial crises.

The rationale behind this cause and effect relationship begins with households with insufficient financial resources resorting to borrowing in order to maintain their living standards. In turn, the excess leverage creates unsustainable credit growth which subsequently ends with a credit bubble bust. One of the consequences of the latter is the amplification of pre-existing inequalities thus resulting in a positive feedback loop between inequality and crises. For a review of the recent literature on the complex interconnections between inequality, leverage and crises the reader is referred to the excellent work of Bazillier and Héricourt (2017) and references therein.

Interestingly, empirical literature on the first, fundamental element of the hypothesized underlying mechanism linking higher inequality with increased volumes of credit is not conclusive. Results range from suggesting a positive (Christen and Morgan, 2005; Perugini et al., 2015), negative (Coibion et al., 2014) or even insignificant (Bordo and Meissner, 2012) relationship. On the contrary, theoretical works display a higher consensus regarding the sign and the direction of the aforementioned relationship. Contributions from the DSGE literature (Iacoviello, 2008; Kumhof et al., 2015) show how increased inequality can create highly indebted, low-income households which eventually results in a fragile economy, prone to financial and real crises.

Another strand of literature employs agent-based models (ABM)[1] to explore the economic effects of various inequality forms such as income (Cardaci and Saraceno, 2015; Dosi et al., 2013; 2015; 2016; Palagi et al., 2017), wealth (Russo et al., 2016) or both (Caiani et al., 2017) and indeed finds that higher inequality has detrimental macroeconomic effects, impeding growth and increasing the probability of a crisis occurring.

The bottom-up nature of ABM makes this approach flexible and appropriate to examine distributional questions, hence it will be followed in this study. However, contrary to the aforementioned works where fully-fledged models are developed with all interactions among agents being endogenously determined, in this paper certain agents are not explicitly modelled. Instead, for simplicity, their interactions with the other agents enter the model exogenously, as input from historical data[2] (Hassan et al., 2010). This approach shares some similarities with the literature of microsimulation which -as regards income inequality- is most frequently used to evaluate the effects redistribution policies, such as taxes and benefits, on household income and its distribution. For an early example the reader is referred to the work of Basu et al. (1998), while for an extensive, recent survey the work of Figari et al. (2015) is an excellent reference.

This modelling choice allows to simplify the interaction structure among agents to a large extent by forcing them to follow as closely as possible the actual evolution of several key variables. This specific approach has two benefits. Firstly, it enables the targeted examination of the effect of a single parameter, namely income inequality, on the variables under study. Secondly, it permits to bring the model closer to the data than the current standard in the ABM literature in economics which is the replication of empirical regularities.[3] By doing so, the empirical validation of the model extends beyond matching stylized facts between simulated and actual data, to directly comparing the evolution of the historical with the artificially generated time series. This enables to use the model for policy simulations referring to specific economies, in addition to answering the core question on the impact of the initial level of income inequality on macro-financial variables.

The remainder of the paper is organized as follows. In Section 2 the model's structure is described in detail. Agents' behavioural rules and interactions in the various markets are elaborated, including a crucial element which is their expectations formation mechanism. Section 3 initially describes the input data used and presents the outcome of model's validation before proceeding with the presentation and discussion of the simulation results. Finally, Section 4 concludes exploring potential uses and extensions of the model.

2. The model

This section provides a description of the modelling properties which characterise the agent-based, macroeconomic model under development. The most elaborate agents of the economic system are households ($h = 1, 2, \ldots, H$) and banks, represented as an all-encompassing banking sector agent. For the remaining agents such as firms, the central bank and the government historical data are used to determine the evolution of their interactions with the former agents in the respective markets.

The economic system evolves over $t = 1, 2, \ldots, T$ time periods, with T being determined by the time range of the historical data used. As follows from the focus of agents' development, the most detailed market in which they interact is the credit market. All other markets are passive and their evolution is governed by that of the historical series.

---

[1] For an elaborate exposition of this modelling approach in macroeconomics see Dawid and Delli Gatti (2018) while for its differences with DSGE models see Fagiolo and Roventini (2017) and references therein.

[2] Thus, it is closely related to the "history-friendly" approach to calibration identified by Fagiolo et al. (2007).

[3] The vast majority of the respective literature has focused on the adequate replication of empirical stylized facts and regularities (Fagiolo et al., 2017). Two of the most successful attempts so far showing a good fit between artificial time series from an ABM and the actual ones have been by Geanakoplos et al. (2012) and Delli Gatti et al. (2011). In the former the authors use data from 2.2 million households to model the housing market of the greater Washington, DC area while in the latter the authors use data for 25,000 Italian firms to validate their macroeconomic ABM.

Households are boundedly rational and simple heuristics control their behaviour. If their financial position allows them, they consume a proportion of their expected income and past deposits in each period and save any remaining resources. Otherwise, in case they are in financial distress, they consume a minimum amount or they ask for credit if their financial position is sound. A key role in credit demand is played by the households' income expectations formation mechanism. Based on the heuristics switching model (HSM) of Anufriev and Hommes (2012a,b), households follow simple linear, adaptive and trend extracting rules to form their expectations. In addition, their chosen rule is not fixed but they update their selection from a small pool of expectation heuristics according to their past performance. As pointed out by De Grauwe and Macchiarelli (2015) it is indeed rational to utilize simple forecasting heuristics and monitor their performance given one's limited cognitive capabilities.

On the supply-side of credit, the bank bases its decision to provide credit on its available deposits and a time-variant measure proxying its risk tolerance, namely the debt service to income ratio (DSTI).

Finally, the labour market is entirely data-driven. The monthly evolution of households' income and their employment status enter the model as input from historical data. Households' income, there being no explicitly modelled government agent and thus no taxes, corresponds to their disposable income. For brevity, in the remainder of the paper *income* will be used to refer to disposable income. Unemployed households receive an unemployment benefit from the government which is assumed to coincide with the subsistence consumption level. It should be noted that the only interaction between the implicit government agent and households is through the unemployment benefit.

In the following subsections are described the initialization of the simulation, the timeline of events taking place at each period and subsequently the agents and their interactions in the respective markets.

2.1. Initialization

One of the prerequisites for a micro-founded ABM is that agents' initial conditions should be initialized with actual data (Delli Gatti et al., 2011). At the beginning of the simulation each household is endowed with a monthly income[4] drawn from a gamma distribution, $\Gamma(\alpha, 1/\lambda)$ with α and λ the shape and scale parameters respectively.[5] By adjusting the shape and scale one can specify the distribution so that it has the same average and minimum values as well as the same degree of inequality as the historical distribution. It should be noted that, for a given α, the smaller the λ the less skewed the distribution, i.e. the lower the inequality.

The initialization of the unemployment rate is also based on its historical figures at the start of the simulation. According to these, a number of households is chosen randomly and their income is fixed at the level of the unemployment dole which permits them to maintain the minimum consumption level required to survive.

After the initialization of income and unemployment all growth rates are set to zero and the simulation is executed for a burn-in period of *N* time steps, after which the system is assumed to have reached its equilibrium. After that period the historical data enter into the model and its output is recorded. To identify when the system has reached its equilibrium the following property is exploited. At the stationary (or equilibrium) state households have reached their target level of wealth and make no additional savings. Thus, by monitoring the evolution of deposits and determining when their growth first becomes zero ($\Delta D = 0$) allows to identify the equilibrium reaching moment, *N*.

2.2. Sequence of events

The sequence of events in every period of the simulation is the following:

1. Historical series for income and unemployment growth as well as loan and deposit interest rates are updated.
2. The bank sets its DSTI level.
3. Households collect the interest from any deposits they have placed at the bank.
4. Employed households receive their monthly income based on the aforementioned historical growth rates.
5. The historical evolution of unemployment determines households' employment status.
6. Households update their income expectations.
7. Households address their financial obligations and determine their desired consumption.
8. Households with insufficient own financial resources to meet their desired consumption ask for credit.
9. The bank calculates and offers the maximum amount of credit it can to a household given its DSTI and the income of the latter.
10. Households meet their desired consumption or a fraction of it in case they are financially constrained and deposit any remaining income.

---

[4] Computationally, the algorithm described in Hamill and Gilbert (2015) is used to allocate households' income.

[5] Empirical studies show that from the family of two-parameter distributions, gamma distribution fits income data reasonably well in a variety of countries and different periods in time (Bandourian et al., 2002).

2.3. Agent and market description

This subsection provides a detailed description of the agents, their behavioural rules and interactions in the various markets.

2.3.1. Households

Households' consumption decisions crucially depend on their financial position and in particular their ability to consume the minimum amount which ensures their survival. This is summarized in the following rule:

$$C_{h,t}^d = \begin{cases} C_{min,t}, & I_{h,t} + D_{h,t-1} < LP_{h,t} + C_{min,t} \\ max\{\alpha_y \cdot I_{h,t+1}^e + \alpha_w \cdot D_{h,t-1}, C_{min,t}\}, & I_{h,t} + D_{h,t-1} \geq LP_{h,t} + C_{min,t} \end{cases} \quad (1)$$

with $0 < \alpha_w < \alpha_y < 1$ the marginal propensities to consume out of wealth and income respectively.

Those households whose sum of current income ($I_{h,t}$) and past deposits ($D_{h,t-1}$) does not suffice for them to consume the minimum amount ($C_{min,t}$) and meet their monthly loan payment ($LP_{h,t}$), set their desired consumption ($C_{h,t}^d$) to that of the subsistence level. It follows that they don't service any loans they might have for as long as these conditions remain. On the contrary, households who can afford minimum consumption and service their loan they do so and set their desired consumption as the largest element between a percentage of their expected income ($I_{h,t+1}^e$) and past deposits and $C_{min,t}$.

The specific Modigliani and Brumberg (1954) consumption function of the financially sound households in Equation (1) is thoroughly discussed in Godley and Lavoie (2016) and is widely used by the respective ABM literature (Assenza et al., 2015; Caiani et al., 2016; Delli Gatti and Desiderio, 2015; Gualdi et al., 2015; Gurgone et al., 2018; Meijers et al., 2018; Riccetti et al., 2013; 2015; Russo et al., 2016, among others).[6] Although such rule may seem overly simple, Allen and Carroll (2001) argue that linear, rule-of-thumb consumption functions can indeed provide a good approximation of consumption functions -such as the one from buffer stock theory- derived as solutions to utility maximization problems. One interesting implication of the linear consumption function of Eq. (1) is that households have a target wealth to income ratio of $(1 - \alpha_y)/\alpha_w$. Therefore, in an attempt to reach it, they save when their target level of wealth is higher than the realized one (Godley and Lavoie, 2016).

In case a household's remaining income and deposits (i.e. after servicing its loan) is enough to meet its desired level of consumption, it uses its own financial resources (withdrawing from its deposits if need be) to satisfy it. Otherwise it asks for consumer credit from the bank. A household asking for credit is assumed to spend any amount granted along with all of its income plus deposits to satisfy its desired consumption. Thus, it may consume less or more than desired depending on the supplied credit.

Finally, after consumption plans are executed, any income remaining is deposited at the bank at the given overnight deposit interest rate.

2.3.2. Expectations formation

Due to the pivotal role expectations play in credit demand in the model, their formation mechanism merits an elaborate description.

Research on expectations formation has identified three key facts regarding individuals' behaviour:

- Expectations are heterogeneous among individuals.
- Individuals use simple linear (adaptive and trend extrapolating) heuristics to form their expectations.
- Individuals switch among heuristics.

These findings are supported by a large number of studies using both survey data (Branch, 2004; Mankiw et al., 2003; Pfajfar and Santoro, 2010) and in controlled experiments (Assenza et al., 2011; Haruvy et al., 2007; Hommes et al., 2004; 2008; Pfajfar and Žakelj, 2016).

Following the seminal papers by Brock and Hommes (1997, 1998), the works of Anufriev and Hommes (2012a,b) have established that individual and aggregate experimental data can be adequately described by a heuristics switching model (HSM).

In particular, the HSM rests on four simple heuristics, evaluated on the basis of their performance and selected according to a discrete choice model with asynchronous updating (Diks and Van Der Weide, 2005; Hommes et al., 2005).

The expectations heuristics, following the naming conventions used in the original papers (Anufriev and Hommes, 2012a,b), for a generic variable y_t are the following:

Weak trend following rule (WTR):

$$y_{wtr,t}^e = y_{t-1} + \omega_{wtr} \cdot (y_{t-1} - y_{t-2}) \quad (2)$$

Strong trend following rule (STR):

$$y_{str,t}^e = y_{t-1} + \omega_{str} \cdot (y_{t-1} - y_{t-2}) \quad (3)$$

---

[6] For more examples of consumption functions used in various macroeconomic ABMs the reader is referred to the works of Haldane and Turrell (2018) and Dawid and Delli Gatti (2018) and references therein.

Adaptive expectations rule (ADA):

$$y^e_{ada,t} = y^e_{t-1} + \omega_{ada} \cdot (y_{t-1} - y^e_{t-1}) \tag{4}$$

Learning anchoring and adjustment rule (LAA):

$$y^e_{laa,t} = \frac{y^{av}_{t-1} + y_{t-1}}{2} + (y_{t-1} - y_{t-2}), \tag{5}$$

where $y^{av}_{t-1} = \frac{1}{t} \sum_{j=0}^{j=t-1} y_j$

The first two heuristics (WTR and STR) represent a trend-following rule which extrapolates the latest change from the most recent observation of y. Their difference is in how strong the reaction to past changes is with $\omega_{str} > \omega_{wtr}$. Expectations under the adaptive rule (ADA) are formed as a weighted average of the current observation and its expected value and, finally, the LAA heuristic is a slightly more complicated trend-following rule which extrapolates the last observed change from an *anchor* (hence its name). The latter is the average between the last observed value of y and the mean of its past values (Anufriev and Hommes, 2012a,b).

The performance measure of heuristic i is:

$$U_{i,t-1} = -(y_{t-1} - y^e_{i,t-1})^2 + \eta U_{i,t-2} \tag{6}$$

The parameter $\eta \in [0, 1]$ denotes the strength of households' memory, or put differently, the relative weight they assign to past errors. In the case of $\eta = 0$, past performance is completely forgotten and only current one matters. For every other value of $\eta \in (0, 1]$ all past prediction errors are taken into account.

Households employ a specific expectations heuristic with probability $n_{i,t}$, which is updated in every period accordingly:

$$n_{i,t} = \delta n_{i,t-1} + (1 - \delta) \frac{exp(\beta U_{i,t-1})}{\sum_{i=1}^{4} exp(\beta U_{i,t-1})} \tag{7}$$

The parameter $\delta \in [0, 1]$ captures households' willingness to switch among heuristics (i.e. their persistence) and the parameter $\beta \geq 0$ measures the intensity of choice representing households' sensitivity to differences in heuristic performance.

In the model, the values of every parameter associated with the HSM are set according to the ones identified by Anufriev and Hommes (2012a,b) and are reported in Table 4.

2.3.3. Bank

The banking sector is represented by a single agent who supplies credit to households at a monthly interest rate of $r^L_t\%$ and accepts their deposits paying them an interest of $r^D_t\%$ per month. Instead of modelling the evolution of interest rates explicitly (e.g. reacting to a central bank's policy rate and borrowers' risk for the former and deposit demand for the latter), they are both set according to the actual figures of the applied historical scenario.

The key parameter that determines credit supply is DSTI ratio, defined as the sum of interest payments plus amortisations divided by the borrower's monthly income. Given that accurate data on the applied level of DSTI ratio by the banking sector for consumer loans are not publicly available, its values are calibrated based on a combination of data approximating its evolution and the resulting match of simulated to the realized series of credit growth following the procedure described in detail in Appendix B. It should be noted that DSTI ratio reflects the effect of every constraint (e.g. regulatory requirements) that the bank might face and has an impact on credit supply, but is not explicitly incorporated in the model. Thus, it can be regarded as *effective* DSTI. However, given that the volume of consumer credit is, in general, significantly lower compared to other assets (i.e. mortgages) the effect of regulatory constraints is expected to play a minor part,[7] while bank's risk tolerance is expected to be the major factor shaping the applied DSTI ratio.

2.3.4. Credit market

Solvent households (i.e. those who do service their loans) whose own income and deposits do not allow them to satisfy their desired consumption ask for consumer credit:

$$L^{ask}_{h,t} = C^d_{h,t} - (I_{h,t} + D_{h,t-1}) \tag{8}$$

When considering granting a consumer loan the bank calculates the highest affordable monthly payment by the potential borrower based on their income and its own risk tolerance proxied by DSTI as follows:

$$LP^{max}_{h,t} = DSTI_t \cdot I_{h,t} \tag{9}$$

Therefore, the maximum amount of credit that the bank will offer is:

$$L^{max}_{h,t} = \frac{LP^{max}_{h,t} \cdot [1 - (1 + r^L_t)^{-m}]}{r^L_t} - B_{h,t} \tag{10}$$

---

[7] Indeed, the earliest regulatory application of DSTI limits is in late 2011 in few EU jurisdictions, while in the majority of the cases where they are applied refer only to housing credit (European Systemic Risk Board, 2018).

where m is the maturity of the loan, measured in months, which is assumed to be the same for all consumer loans.

As can be seen from Eq. (10), the bank takes into account in its calculation any outstanding debt ($B_{h,t}$) that the household might have. In which case the bank consolidates the new with the pre-existing credit by extending the latter's maturity and charging the current interest rate, r_t^L, to the sum of the two.

Based on the figures of desired and offered credit, a household decides on the loan size it will obtain according to the following rule:

$$L_{h,t} = \begin{cases} L_{h,t}^{max}, & L_{h,t}^{ask} \geq L_{h,t}^{max} \\ U(L_{h,t}^{ask}, L_{h,t}^{max}), & L_{h,t}^{ask} < L_{h,t}^{max} \end{cases} \tag{11}$$

Thus, if the credit offered by the bank is less than what is asked, the household borrows as much as possible. Alternatively, it borrows a random amount from a uniform distribution between $L_{h,t}^{ask}$ and $L_{h,t}^{max}$. The stochastic part in the credit assumption mechanism aims to model the outcome of the interaction between households' credit demand and bank's profit maximizing behaviour. Thus, when a household asks for credit and the bank not only can satisfy its demand but also exceed it (subject to its DSTI and the potential borrowers income), it decides to offer that larger amount. Presented with more credit available, allowing it to consume more, the household assumes a random figure ranging between the asked and supplied volumes. The suitability of this mechanism to approximate the evolution of credit is shown in the validation exercise described in Section 3.2. In addition to the empirical validation and in order to test the mechanism's effect on the results, the analysis is re-executed with the stochastic credit assumption mechanism deactivated. The respective results are presented and discussed in Appendix D.

Based on the mechanism described above, a household's outstanding debt evolves as:

$$B_{h,t} = B_{h,t-1} + L_{h,t} \tag{12}$$

with the associated monthly payment being:

$$LP_{h,t} = \frac{B_{h,t} \cdot r_t^L}{1 - (1 + r_t^L)^{-m}} \tag{13}$$

It should be noted that all loans are of the fixed-payment type.

2.3.5. Labour market

The labour market is completely data-driven. Households' income growth follows the specific path of the historical scenario applied. As a simplifying assumption and in the absence of more specific data on income evolution, the scenario implied growth rate is assumed to affect all households uniformly, regardless of their position in the income distribution.[8] In case unemployment rises by x%, a randomly chosen set -of the appropriate size- of employed households becomes unemployed and instead of its monthly income, receives an unemployment dole from the government. If unemployment declines by x%, a randomly chosen set -of the appropriate size- of unemployed households returns to employment receiving a random monthly income between the unemployment benefit and the median income of that period. It should be noted that the stochastic selection mechanism in unemployment's evolution implicitly ties the latter to households' income. Since income is non-uniformly distributed and positively skewed, then it is more probable that a randomly chosen household will belong to the more populated part of income's distribution; i.e. the bottom part. Thus, although not explicitly modeled, the impact of unemployment is inversely linked to households' income resulting in a stronger effect for lower income households than for higher income ones.

3. Simulation results

3.1. Input data

The injection of historical data into the ABM helps simplifying its structure by fixing the effect of non-modelled agents to the actual scenario,[9] while at the same time allows to isolate and study the impact of few, selected variables. An extra benefit of keeping the simulation close to real data is that model validation goes beyond matching stylized facts to assessing how well the artificial time series fit the historical ones. Thus, in the baseline specification where all parameters are set to match the actual scenario, validating the model provides a clear-cut test of the suitability of the implemented rules and interactions to reproduce real-world phenomena.

Input data can be divided in two categories. The first includes those which are updated at every time step during the simulation and represent the historical scenario that the artificial economy follows. The second contains data which are used to calibrate the ABM and are mainly used to initialize it, such as income distribution parameters and the level of unemployment benefit. A special case which traverses both categories is DSTI. Its evolution enters the simulation exogenously but its initial values are calibrated to match the actual consumer credit series.

---

[8] Therefore the results of this study can be seen as a benchmark in case income evolves homogeneously across its distribution. Of course differential growth among income percentiles is expected to reinforce (reduce) inequality and its effects, i.e. in case lower (upper) percentiles' income declines faster or upper (lower) percentiles' income increases more rapidly than their distributional counterparts.

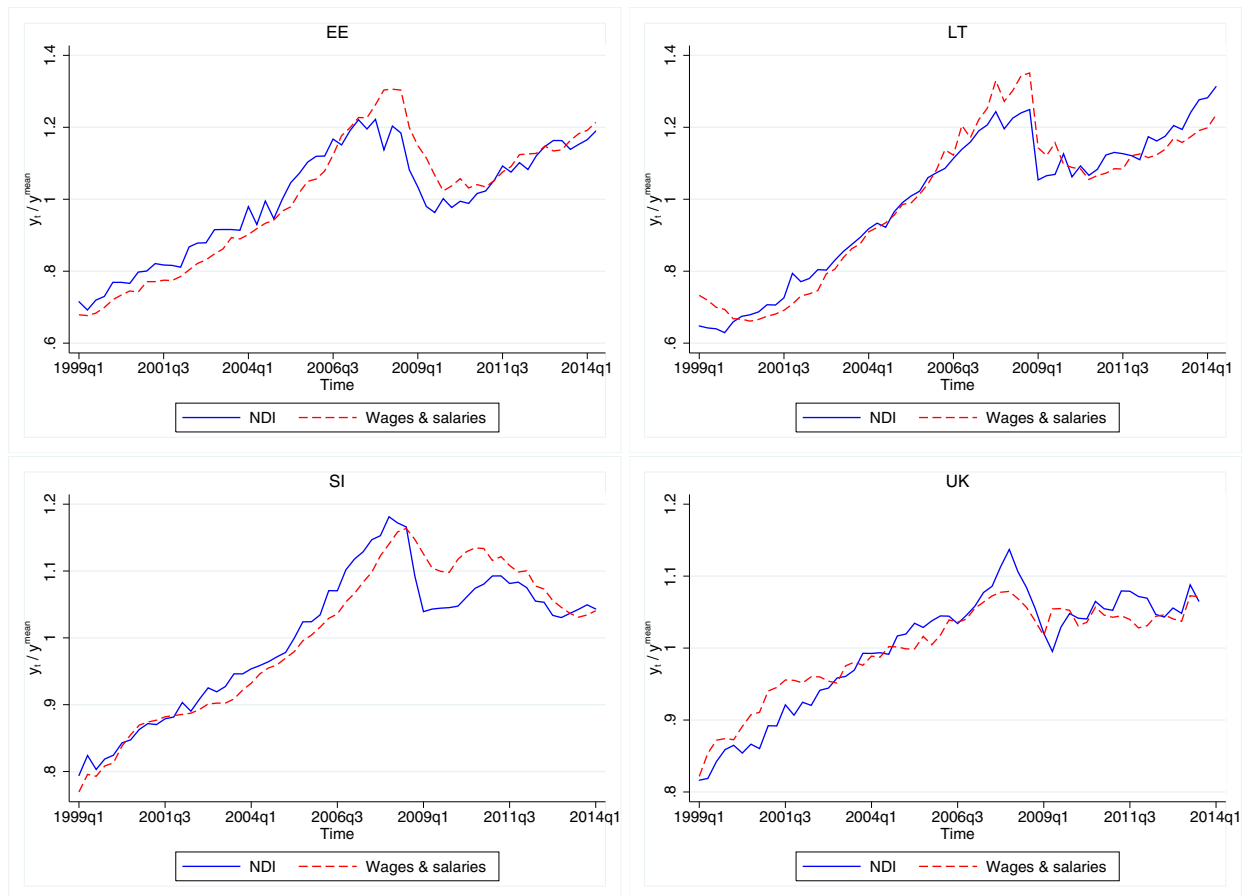[9] To the extent possible, conditional on data availability.

Fig. 1. Comparison between the levels of NDI and wages & salaries for the 4 countries considered in the analysis.

3.1.1. Scenario data

The time step of the simulation corresponds to one month, hence monthly historical data are used wherever possible. In case data at the desired frequency are missing, the closest available (i.e. quarterly) is transformed to monthly by cubic natural spline interpolation and used instead.

The primary input in the simulation is the evolution of households' income which, ideally, should be that of net disposable income, encompassing all sources of income. The first major challenge encountered is the absence of publicly available, monthly data on household net disposable income (NDI) for EU countries. Although the quarterly series provided by Eurostat could be converted to monthly through interpolation, a more serious issue is the unavailability of recent data. In fact, the NDI series which extends sufficiently back in the past (as early as 2001q1 for almost all EU countries and even since 1995q1 for the majority of them) is discontinued with the last recorded observation being in 2014q1.[10] Therefore, another series should be used in order to extend the simulation to the present. That series must follow closely the evolution of NDI so that it will be a good proxy of the latter and thus a meaningful input for the model.

The most obvious candidate series is that of wages & salaries. Since the evolution of the two series may not necessarily coincide, only the cases where they exhibit a high degree of similarity are used as input in the subsequent simulation.[11] The comparison between available data on real NDI[12] and real wages & salaries below, reveals that the two series exhibit sufficiently similar patterns only in four EU countries; Estonia, Lithuania, Slovenia and the UK.

Figs. 1 and 2 display their evolution in levels and annual growth rates respectively. It should be mentioned that nominal series are converted to real ones using the GDP deflator.

---

[10] The respective series could be found in Eurostat's dataset under the code *ei_naia_q*. It has been discontinued and removed from dissemination as it was part of the old data collection according to ESA95.

[11] The comparison is performed for each of the 15 EU countries for which there are available data on NDI. However, in the paper are only shown the cases where the degree of similarity with the series for wages & salaries is high.

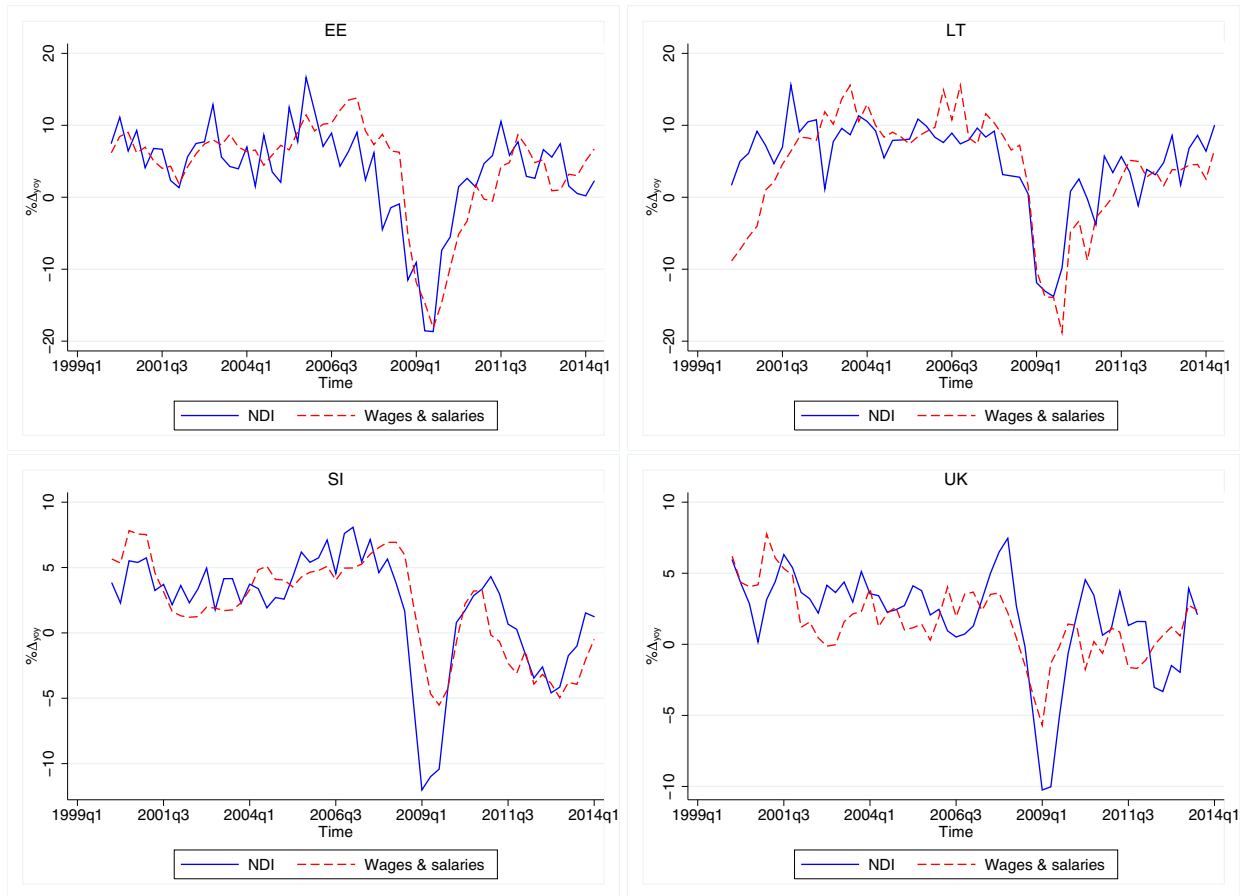[12] The discontinued dataset on NDI covers 15 EU countries.

Fig. 2. Comparison between annual growth rates of NDI and wages & salaries for the 4 countries considered in the analysis.

In order to facilitate comparison, original level data in Fig. 1 are divided by their sample means (y_t/y^{mean}). As is evident, the series in all four countries are adequately close. Some occasional mismatches are mostly associated with the global financial crisis of 2008 and its aftermath. In particular, in Slovenia (SI) and Great Britain (UK) NDI dropped more sharply than wages & salaries, while the opposite is true for Lithuania (LT). In Estonia (EE), the two series move in a highly synchronized manner. These differences are expected to have little impact on the results.

The annual growth ($\%\Delta_{yoy}$) of NDI and wages & salaries in Fig. 2 offers a complementary view on the findings of Fig. 1. Estonian data almost overlap over the whole period whereas for Slovenia and Great Britain NDI's decline during the crisis was almost twice as deep compared to that of wages & salaries. On the contrary, in Lithuania the latter decreased more than the former in 2009q1. A general pattern is that, apart from a short period after the crisis, the two series undergo similar changes within every country. From an intra-country perspective, Estonian and Lithuanian data (first row in both Figs. 1 and 2) exhibit a single dip located in late 2008–early 2009 and recover or at least stabilize after 2011, whereas Slovenian and British data display a second period of negative growth around 2013. In Table 1 are reported three measures which provide a quantitative assessment of the distance and the co-movement between NDI and wages & salaries.

Table 1
Distance and similarity measures between NDI and wages & salaries.

Country	Transformation	MAE	RMSE	Correlation
EE	y_t/y^{mean}	0.045	0.056	0.948
	$\%\Delta_{yoy}$	3.783	4.541	0.528
LT	y_t/y^{mean}	0.040	0.050	0.948
	$\%\Delta_{yoy}$	3.955	5.179	0.639
SI	y_t/y^{mean}	0.026	0.033	0.926
	$\%\Delta_{yoy}$	2.089	2.837	0.767
UK	y_t/y^{mean}	0.022	0.027	0.925
	$\%\Delta_{yoy}$	2.333	2.872	0.474

The measures used to estimate the distance between the two series are the frequently employed Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Moreover, their synchronicity is estimated using the (zero lag) cross-correlation. Results indicate that, on average, the two series exhibit small differences. Both in growth rates and levels (as a ratio of their historical average) their difference ranges from about 2% to 4%. In addition, they display a high degree of synchronization. In levels, correlation is above 90% for every country, while in growth rates the lower bound is around 50% for Estonia and UK and above 75% for the case of Slovenia with Lithuania being in between. Therefore, it is assumed that in these 4 countries; (a) the evolution of wages & salaries is a good approximation for the evolution of disposable income before 2014 and (b) the two series will share the same similarity after 2014.

Data for the average monthly unemployment rate, measured as a percentage of active population, are collected from Eurostat and directly used in the simulation.

Interest rate related data are available from the European Central Bank's Statistical Data Warehouse (SDW) and in particular its Monetary & Financial Institutions Interest Rate Statistics database. Consumer credit interest rates are extracted from the respective series of credit for consumption and other lending, with maturity over 1 and up to 5 years, while for deposits is used the overnight interest rate for deposits from households and NPISH. Both series are recorded as the average interest rate through each month and are reported in percent per annum. Thus, the appropriate transformation is applied to convert them to monthly interest rates.

3.1.2. Calibration data

The data used for calibration are mostly associated with the initial distribution of income. These include minimum and average income as well as the Gini coefficient of income distribution at the beginning of the simulation period. For the latter, the UNU-WIDER World Income Inequality Database (WIID3.4) is an excellent source with detailed information from a variety of providers and with sufficient coverage both in time and from a cross-country perspective.

For the former two series are used proxies, both by Eurostat. As a proxy for minimum income are used monthly minimum wages,[13] while average income is approximated by mean monthly earnings extracted from the Structure of Earnings Survey.[14]

3.1.3. DSTI data

The case of DSTI ratio is special because there is no precise information available for its level neither in micro nor in aggregate data. However, an alternative is the BIS's debt service ratios statistics database. This source provides internationally consistent, country-specific quarterly data which "*should correctly capture how the [DSTI] in a particular country changes over time, even if it does not necessarily accurately measure its level relative to what one could obtain from the correct micro data*" (Drehmann et al., 2015, p. 91). Although this is an aggregate measure and likely different from the bank-level one based on borrower basis as already recognized, in this study is assumed that the evolution of the two is roughly similar and thus the former can be used to provide an adequate approximation of the latter.

Fig. 3 shows the evolution of DSTI ratio for households and NPISHs for a sample of EU countries and the US.

Fig. 3 shows that the aggregate DSTI ratios in the plotted countries share a common evolution. A rapid growth roughly until the end of 2008, followed by a decline with diverse degrees of severity.

Apart from the UK for which there are available data on DSTI, the selection of the remaining DSTI series to calibrate and match with the Estonian, Lithuanian and Slovenian historical macroeconomic scenario is based on the assumption that economic conditions in these countries resembled those in their larger European counterparts. Therefore, this should be reflected on an approximately comparable evolution of DSTI ratios.[15] Data for the US are also included because, as can be seen in Fig. 3, its DSTI shares a similar pattern with that of several European economies.

The calibration procedure is described in detail in Appendix B and consists of a grid-search to find which pair of {initial DSTI, DSTI path} minimizes the distance between the artificial and actual series of consumption and credit.

3.2. Empirical validation

In the empirical validation of the model its output is examined under a baseline setup where all variables and their paths are set according to a country-specific, historical scenario. The ultimate goal is to test its ability to produce close to real-world patterns and thus establish confidence in its results and use for policy simulations.

It should be emphasized that the degree of similarity between the implemented country-specific scenario and the real-world one is of paramount importance for the validation exercise. In that respect, the applied macroeconomic scenario for income and unemployment's evolution can be regarded to replicate the realized one in a sufficient manner, even under the assumption of that evolution being uniform across income distribution as described in Section 2.3.5. However, the results from the DSTI calibration procedure described in Appendix B indicate that only in two countries (SI and UK) the calibrated

---

[13] Eurostat dataset code: *earn_mw_cur*.

[14] Eurostat dataset code: *earn_ses_monthly*.

[15] Of course country-specific factors are expected to affect the actual path of DSTI. Another source of divergence is the different evolution between consumer credit and mortgage DSTIs (see discussion in Appendix B for a detailed example). Thus, the final outcome depends on the degree of similarity between the actual and available data.
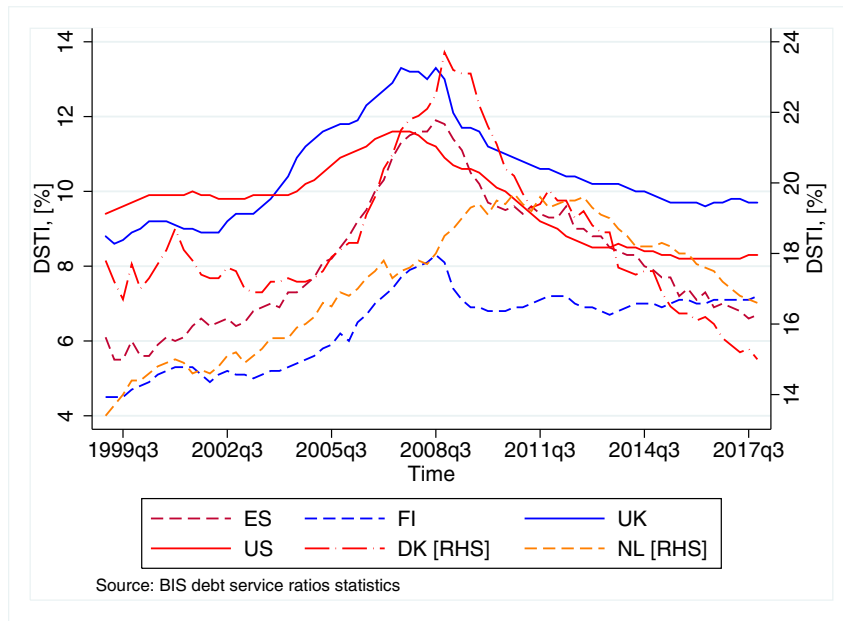
Fig. 3. Evolution of DSTI ratio for households and NPISHs in a sample of countries.

Table 2
Initial setup of the simulation for SI and UK.

Description	Country	
	SI	UK
Average income	1000	2430
Minimum income	350	950
Gini coefficient of income distribution (%)	23	35
Income distribution shape parameter (α)	3.095	0.822
Income distribution scale parameter (λ)	210	1800
Unemployment rate (%)	7.1	5.8
Consumer credit interest rate (%)	5.257	9.904
Overnight deposit interest rate (%)	0.348	2.621
DSTI (%)	50	56

Table 3
The range of the variables used in SI and UK historical scenarios.

Variable	SI	UK
Wages & salaries	2000q1–2018q1	2000q1–2018q1
Unemployment rate	2000m1–2018m3	2000m1–2018m3
Consumer credit interest rate	2005m5–2018m3	2004m1–2018m3
Overnight deposit interest rate	2005m5–2018m3	2004m1–2018m3
DSTI path	US	UK

DSTIs can satisfactorily reproduce the historical evolution of consumer credit. This suggests that the identified DSTI paths for these two cases are, potentially, a decent match of the actual ones. Therefore, for the validation exercise and the subsequent simulation experiments where DSTI is evolving through time the focus will be only on these two countries (SI and UK). The validation results for the other cases are reported in Appendix C, while for the simulations where DSTI is held fixed at a certain value, every country scenario is considered.

Income distribution parameters and scenario related variables are initialized according to the historical data as of January 2000[16] which is the chosen origin of the simulation. The initial setup of the simulations is provided in Tables 2 and 7.

After a burn-in period of $N = 170$ time steps, the country-specific historical scenario is input to the model. A description of the series used and their time periods is provided in Tables 3 and 8.

The quarterly series for wages & salaries are deflated using the GDP deflator and are converted to monthly frequency by spline interpolation. The processed wage series as well as unemployment rate are transformed into monthly growth rates.

---

[16] Or the closest date available.

Table 4
Fixed parameter values.

Description	Parameter	Value
Number of households	H	1000
Burn-in period	N	170
Propensity to consume out of income	α_y	0.65
Propensity to consume out of deposits	α_w	0.05
WTR expectations extrapolation factor	ω_{wtr}	0.4
STR expectations extrapolation factor	ω_{str}	1.3
ADA expectations parameter	ω_{ada}	0.65
Households' memory strength	η	0.7
Households' expectations rule persistence	δ	0.9
Households' intensity of choice	β	0.4
Loan maturity (in months)	m	60

The missing data for interest rates for the first 3 to 5 years depending on country, are approximated with the average of the first 12 non-missing observations of each series. Finally, the DSTI path associated with each macroeconomic scenario is identified through the calibration process described in Appendix B.

Besides scenario and initialization data which are country-specific, a set of parameters associated with agents' behaviour as well as to the model's setup is fixed across simulations and reported in Table 4.

Propensities to consume (α_y and α_w) are set to values commonly used by the literature (Assenza et al., 2015; Godley and Lavoie, 2016; Meijers et al., 2018, among others), while the HSM-related parameters are specified according to the figures identified by Anufriev and Hommes (2012a,b). The unemployment dole, coinciding with the subsistence consumption level, is assumed to be 80% of minimum income at each step of the simulation.

Each simulation is executed 100 times and the final results are summarized by the median over all runs. Median is preferred instead of average in order to avoid outlying values, especially when examining credit growth rates since they may initially assume very small values, thus yielding extraordinarily large growth rates. It should be mentioned that the comparison between artificial and historical data is performed against the original frequency and range of the latter. Hence, simulated data for consumption are summed over each quarter and observations from the simulated series for credit that lie outside the range of the actual data are discarded.

3.2.1. Validation with the Slovenian scenario

The results for the Slovenian scenario, plotted in Fig. 4, exhibit a decent match between artificial and historical data.

Firstly, simulated consumption displays a remarkable degree of similarity in terms of distance and synchronicity with the historical series. Moreover, simulated consumer credit data exhibit a high degree of resemblance to the evolution and magnitude of the historical series. This is indicated by the fact that, in addition to the median simulation being fairly close to the actual data, the latter lie between the first and third quartile (P25/P75) bands of the former for a large part of the simulation horizon. The divergence originates in 2013 when the artificial series begin to rise (Fig. 4, bottom left pane), while the historical ones continue to decline up to 2016. This is associated with the financial difficulties faced by the domestic banking system at the time (Bank of Slovenia, 2013) resulting in a negative growth of consumer loans which only "*moved into positive territory after six years [in 2016].*" (Bank of Slovenia, 2016, p.44). Therefore, during this period, the assumed DSTI path used in the model is most likely more benign from what occurred in reality. However, after early 2017 the two series resume their co-movement indicating that from then on the assumed DSTI path is again an adequate approximation of the actual one.

The quantitative measures reported in Table 5 provide additional information on the findings of Fig. 4.

The distance between artificial and observed consumption is around 2% in growth rates and about 4% in rescaled levels. At the same time, correlation is high and ranges from 70% to almost 90%. An important finding is that simulated consumer credit growth exhibits an average distance of 6% to 7% from the historical one while correlation remains at sufficiently high levels of about 70%.

Table 5
Distance and similarity measures between simulated and historical data for SI.

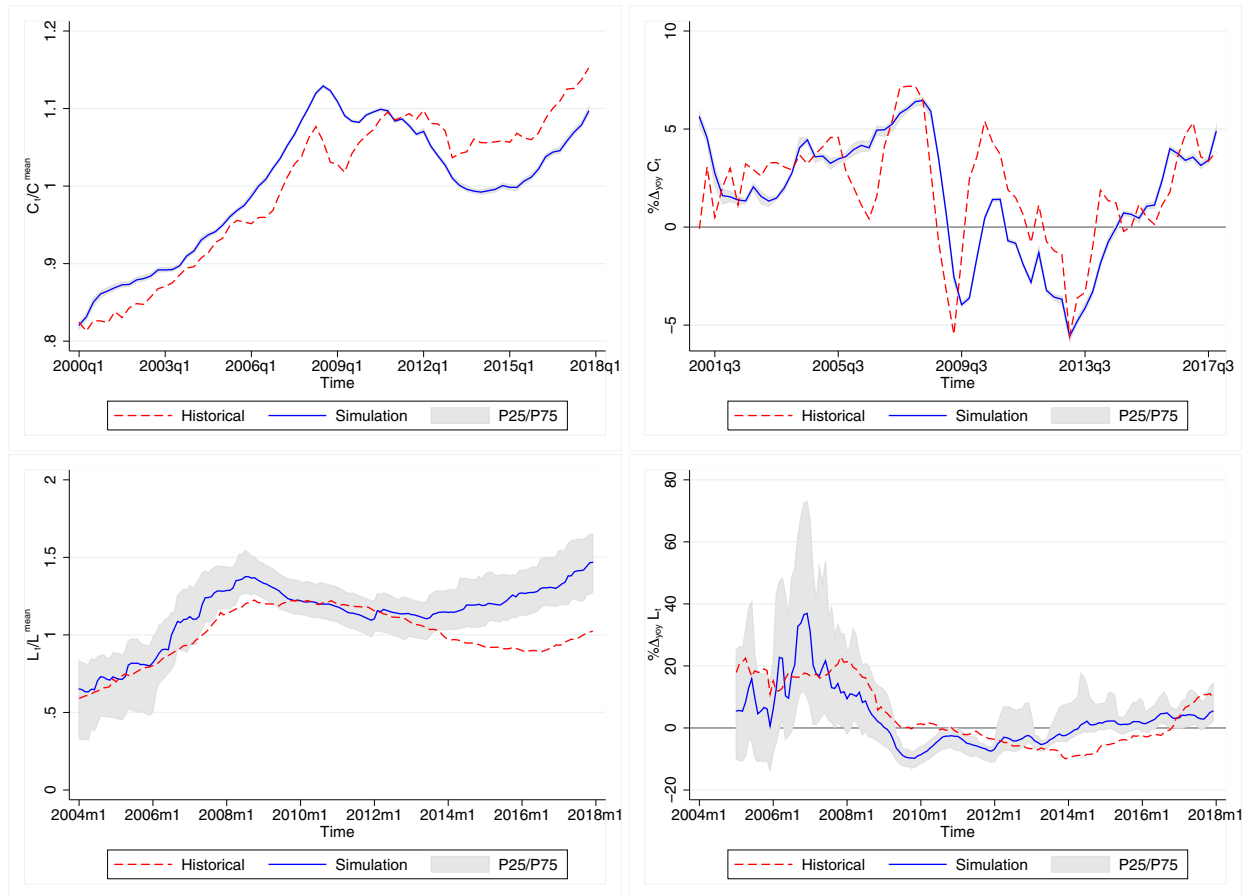| Variable	Transformation	MAE	RMSE	Correlation
Consumption	y_t/y^{mean}	0.038	0.043	0.898
	$\%\Delta_{yoy}$	1.801	2.270	0.710
Credit	y_t/y^{mean}	0.148	0.200	0.711
	$\%\Delta_{yoy}$	6.222	7.375	0.708

Fig. 4. Model validation results for the SI-specific scenario under the baseline settings.

Table 6
Distance and similarity measures between simulated and historical data for UK.

Variable	Transformation	MAE	RMSE	Correlation
Consumption	y_t/y^{mean}	0.034	0.037	0.901
	$\%\Delta_{yoy}$	1.191	1.621	0.606
Credit	y_t/y^{mean}	0.167	0.193	0.918
	$\%\Delta_{yoy}$	4.774	5.929	0.538

3.2.2. Validation with the UK scenario

The next scenario considered for validation purposes is the UK-specific one. Data for DSTI's path are available for this country,[17] which results in the closest emulation of consumer credit evolution generated by the model. The output is presented in Fig. 5.

As seen in Fig. 5, apart from simulated consumption series which show the, common among all scenarios (see also results in Appendix C), noteworthy similarity to the actual ones, simulated consumer credit exhibits the highest degree of closeness to the historical series from all scenarios examined. First and third quartile bands envelop the actual data for almost the entire simulation horizon both in levels and in growth rates. An obvious exception is observed towards the end of the simulation, approximately after early 2016, when simulated series begin to flatten and growth rates to decline whereas the actual ones show an upward trend (with the respective growth rates being on positive ground). It should be mentioned that to avoid distortions related to very low figures in the beginning of the simulation horizon, observations prior to December 2002 are discarded from the analysis.

Table 6 shows in a quantitative way the good fit between the artificial and historical series.

---

[17] Given the caveats discussed before, such as the essentially unknown levels of DSTI and potential differences between overall and consumer credit DSTI.
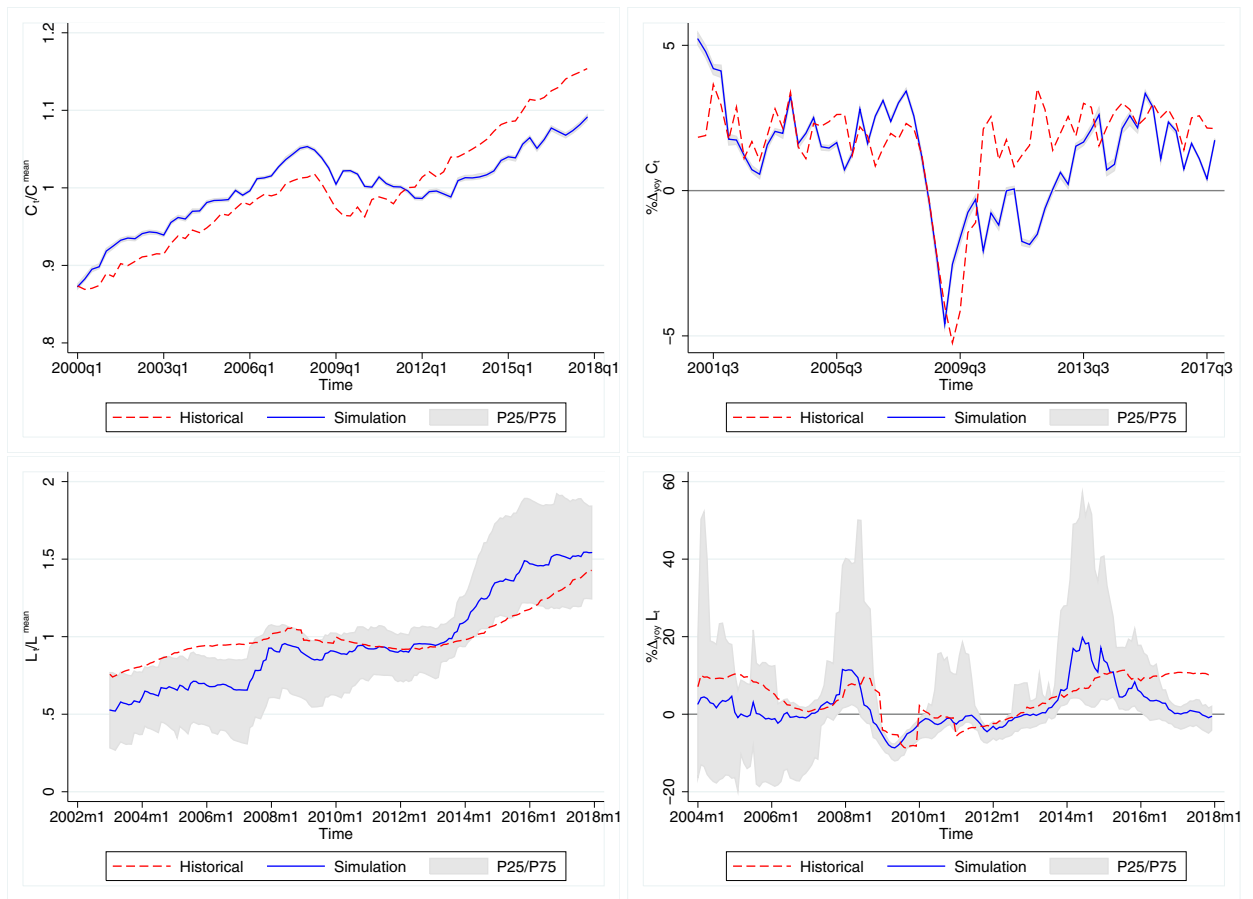
Fig. 5. Model validation results for the UK-specific scenario under the baseline settings.

Table 7
Initial setup of the simulation for EE and LT.

Description	Country	
	EE	LT
Average income	282	265
Minimum income	90	110
Gini coefficient of income distribution (%)	36	35.5
Income distribution shape parameter (α)	1.280	0.816
Income distribution scale parameter (λ)	150	190
Unemployment rate (%)	12.9	15.9
Consumer credit interest rate (%)	6.738	4.948
Overnight deposit interest rate (%)	0.699	0.368
DSTI (%)	50	52

Table 8
The range of the variables used in EE and LT historical scenarios.

Variable	EE	LT
Wages & salaries	2000q1–2018q1	2000q1–2018q1
Unemployment rate	2000m1–2018m3	2000m1–2018m3
Consumer credit interest rate	2005m1–2018m3	2005m3–2018m3
Overnight deposit interest rate	2003m3–2018m3	2005m3–2018m3
DSTI path	DK	DK

As expected, the results in Table 6 are the best among all scenarios examined. Simulated consumption displays the minimum distance and high correlation with actual data. Despite the fact that correlation between artificial and observed growth rates is relatively low compared to the other cases, it is still at the satisfactory level of about 60% while at the same time both MAE and RMSE are below 2%. Results on consumer credit show a similar pattern; an average correlation accompanied by the lowest distance in growth rates and the highest correlation with comparable distance measures in rescaled levels.

Overall the validation exercise revealed three common patterns among all scenarios; first, there is a remarkably good fit between artificial and actual data on consumption. This indicates that the implemented consumption rule combined with data on disposable income can provide an appropriate approximation of aggregate consumption. Second, first and third quartile bands around the median simulated consumption are very narrow. Since the stochastic element associated with consumption comes from consumer credit, this indicates that the latter is a small fraction of consumption. Finally, simulated consumer credit is adequately close to the observed data where available data for DSTI are a good approximation of the realized series. This enhances trust in the validity of the model to appropriately capture the underlying credit supply mechanism and reproduce its dynamics once reliable data are used as input.

3.3. The role of expectations on the evolution of credit

A key element of the ABM under development is the implementation of the HSM for agents' expectations. The vast majority of macroeconomic ABMs is mainly endowing their agents with a single or, in some cases, two expectations heuristics. The most frequently used choices include naive expectations ($y_t^e = y_{t-1}$), an adaptive rule similar to that in Eq. (4) or some form of trend-extrapolating rule analogous to Eq. (2). Other choices range from regressive techniques to rational expectations. The interested reader is referred to the excellent work of Franke and Westerhoff (2017) and references therein for a survey of modelling of animal spirits.

The only, to the best of the author's knowledge, macroeconomic ABM where the HSM is used, is by Dosi et al. (2017) where the authors find that expectations do not have a large effect on the dynamics of the economy.

However, credit demand in the present model depends heavily on income expectations and is essentially determined by households' forecast errors; optimistic households whose actual income is less than expected will likely ask for credit; on the contrary, pessimistic households will consume less, save more and deleverage. Therefore, given the central role that expectations play in the model, their effect on credit dynamics will be further examined.

All initialization parameters are set at their baseline figures, as reported in Table 2.[18] Using each individual expectations heuristic alone, plus all four of them with the switching mechanism of the HSM, the evolution of credit for each macroeconomic scenario is examined and presented in Fig. 6.

In Fig. 6 is plotted the mean outstanding credit in every time step over 100 simulations by expectations heuristic per macroeconomic scenario. The first observation is that, although credit growth rates are close for every heuristic -for a given country scenario- as demonstrated by the roughly similar patterns, the levels are markedly different. As one would anticipate, STR (red, solid line) is associated with more optimistic forecasts resulting in higher credit levels. The LAA rule (green, dash-dotted line), being a trend extrapolation one, also generates increased credit demand but not as high as the STR rule. Interestingly, mean[19] outstanding credit is absent in the cases of WTR and ADA rules. This indicates that under these rules income expectations are very close to the realized figures or they are downwards biased. In the former case, the desired consumption demand from any small, optimistic income forecast can be met by deposit withdrawal. In case expectations are downwards biased, the actual income suffices to satisfy desired consumption therefore credit is not needed. Finally, the HSM being a changing mixture of all four rules, results in levels of credit which are influenced by the dominating heuristic and in any case lie between the polar cases of STR and WTR (or ADA). This is more evident in the case of the UK scenario[20] where the simulation indicates that the LAA rule is heavily dominating, hence the results of the HSM are very close to the LAA's.

The differential effect of expectations heuristics on the level of credit raises the question whether this could also affect the size and evolution of non-performing loans ratio (NPL).[21] The results for NPLs are extracted from the previous simulations for the heuristics that did lead to credit growth (STR, LAA and the HSM) and are plotted in Fig. 7.

Fig. 7 shows that average NPL evolution and size is almost identical among heuristics in three out of four cases. The exception is the UK-specific scenario where, during the crisis period, average NPLs under the HSM are are about 2% higher compared to the STR rule and approximately 1% higher relative to the LAA rule. Apart from this discrepancy, the size as well as the evolution is comparable among all expectations heuristics.

The previous analysis suggests that expectations heuristics have differential and significant impact on the levels of provided credit, with some even resulting in its complete absence. Nevertheless, differences among those which do result in

---

[18] As a robustness check, the same analysis is conducted while keeping DSTI fixed to 100% in order to remove any constraints related to credit supply. The results are presented and discussed in Appendix F.

[19] Results are the same even up to the 75th percentile of all simulation runs.

[20] Including initialization parameters. This is due to the fact that forecast errors for variables with sizable values in absolute terms (such as the average and minimum income related to the UK scenario) will be also large, thus influencing heuristic selection.

[21] NPL ratio is defined as the share of loans which are past due by 6 or more consecutive months to total outstanding credit.
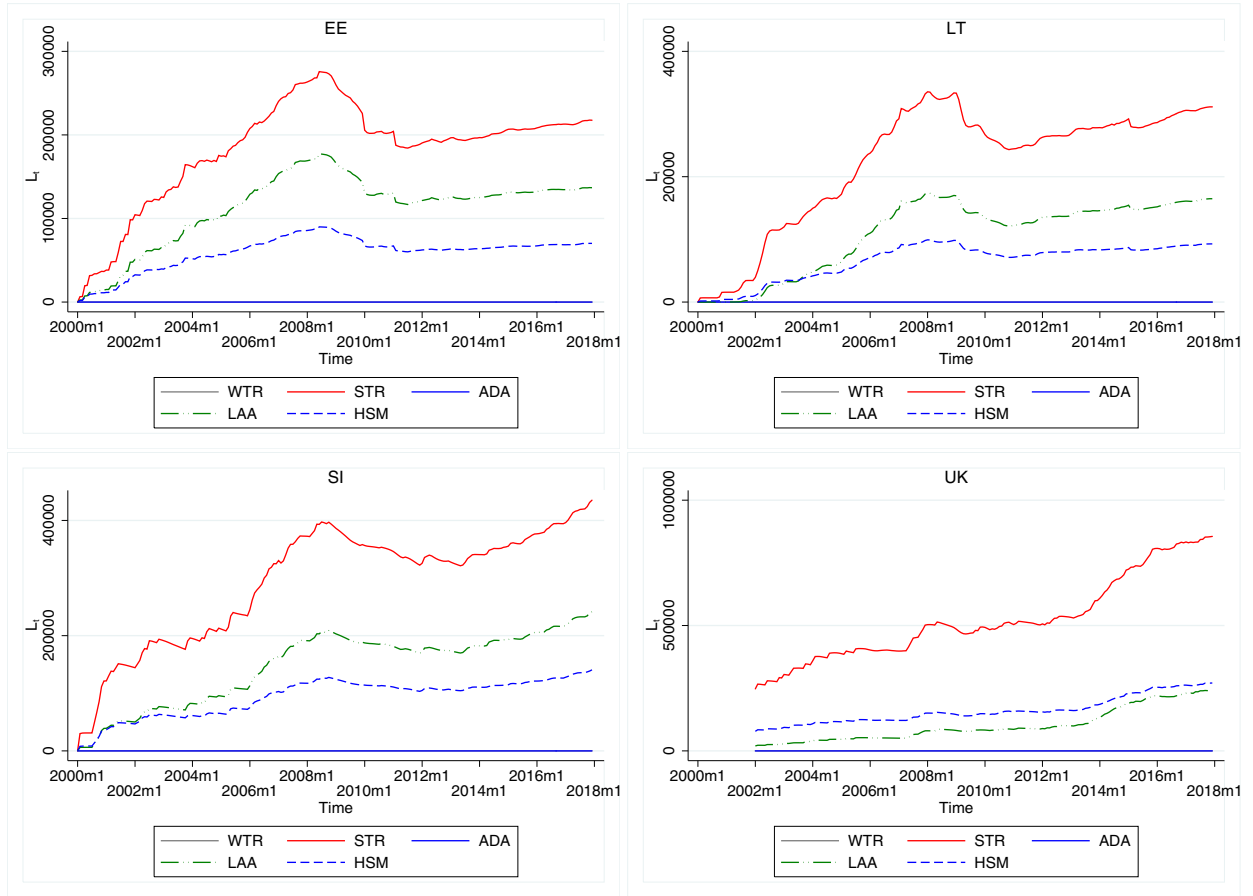
Fig. 6. Outstanding credit evolution for different expectations heuristics under the baseline country-specific scenario.

credit demand are not substantial neither in its growth rate nor in the size and evolution of NPLs. Consequently, taking also into account the experimental evidence by the respective literature, the HSM will be used throughout this study.

3.4. Inequality, credit supply and macro-financial developments

In this part of the study the model is used to conduct several experiments to examine the impact of income inequality and credit supply -proxied by DSTI- on aggregate consumption, outstanding credit and bank NPLs. To do that two modifications on the baseline scenario are applied; the first leaves DSTI at it's original setup and examines the effect of different initial inequality levels; the second fixes DSTI at certain values throughout the simulation and analyzes the impact of different initial levels of income inequality. The results from the experiments are discussed below.

3.4.1. Evolving DSTI

In the first experiment is examined the effect of initial income inequality on consumption, credit and NPLs. The simulation is executed with the only difference from the baseline settings being in the initial level of income inequality. For various income distribution Gini coefficients spanning from approximately 22% to about 38% the model is run 100 times using two of the scenarios examined (SI and UK) and the results over the whole simulation horizon are averaged[22] and reported in Figs. 8–10. The rationale for using these two country scenarios for this experiment is that for these cases every input series, including that of DSTI, is a good approximation of the historical ones. Therefore, the outcome should be clean from any potential complications arising from possible mismatches between actual and injected data.[23]

To facilitate comparison, results are benchmarked against the figure at the highest level of inequality. Hence, the vertical axis corresponds[24] to $\%\Delta y_\lambda^* = 100\left(\frac{y_\lambda}{y_*} - 1\right)$, where $y = \{C, L\}$, y_λ the value of variable y at scale λ and y_* is the bench-

---

[22] Specifically, it's the whole period average of the average over the 100 runs.

[23] The qualitative agreement between the results from the first and the second experiment where DSTI is kept fixed throughout the simulation enhances trust in this study's findings.

[24] In the case of NPLs, the latter being already expressed as a ratio, the distance from the benchmark is simply $\Delta y_\lambda^* = y_\lambda - y_*$.
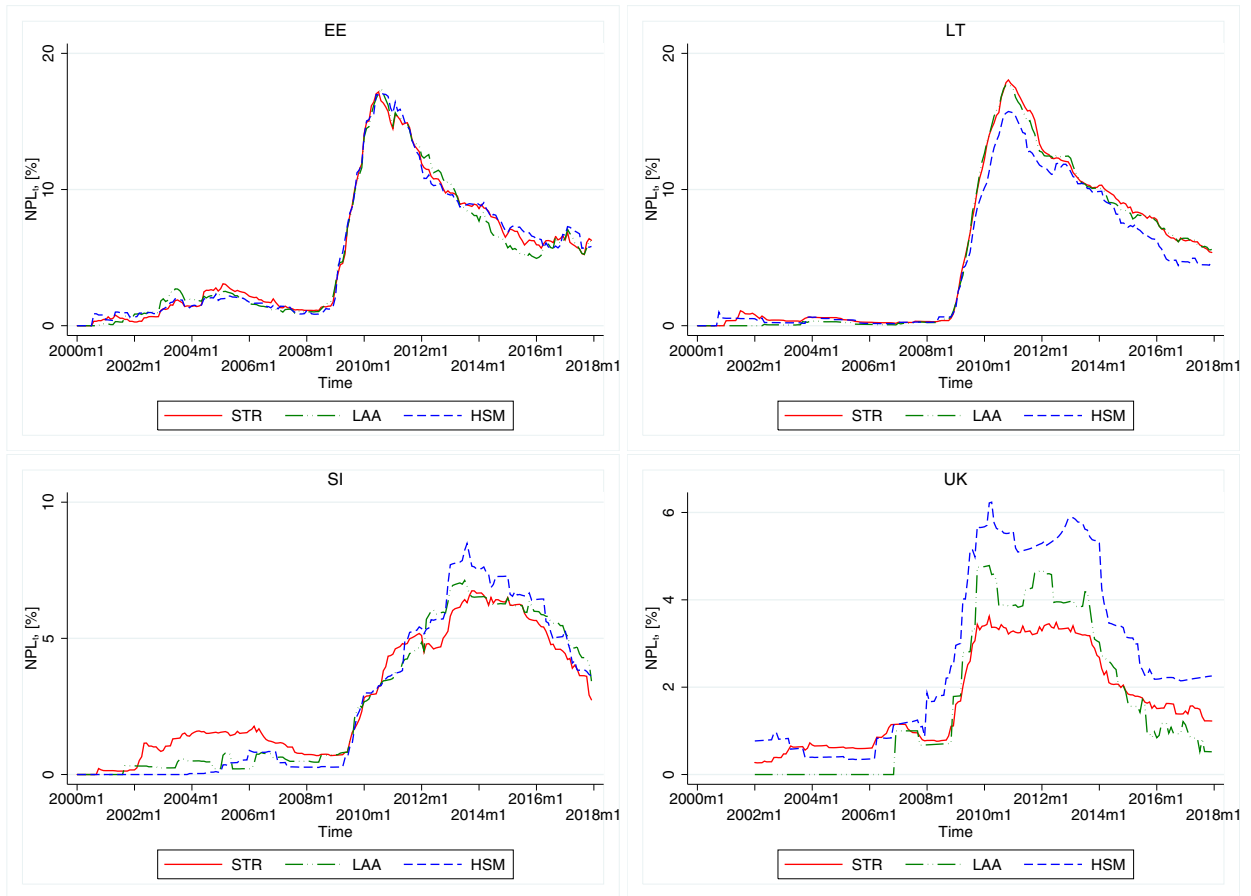
Fig. 7. Non-performing loans ($\geq$ 180 days past due) ratio evolution for different expectations heuristics under the baseline country-specific scenario.
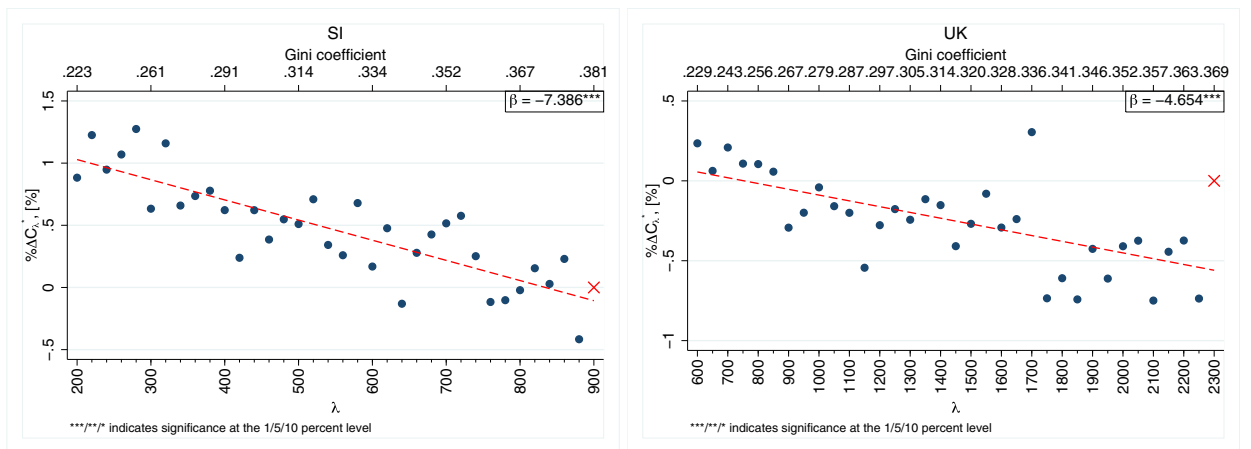

Fig. 8. The relationship between income inequality and average consumption. The red $\times$ denotes the benchmark value.

mark value of variable y. The two horizontal axes in the respective graphs denote the initial scale parameter, λ, of the $\Gamma(\alpha, 1/\lambda)$ income distribution (bottom) or, equivalently, the corresponding Gini coefficient (top). In addition, the regression lines $\%\Delta y_\lambda^* = \beta_y \cdot Gini + constant_y$ are drawn and the estimated β_y coefficients with the corresponding statistical significance levels are reported.
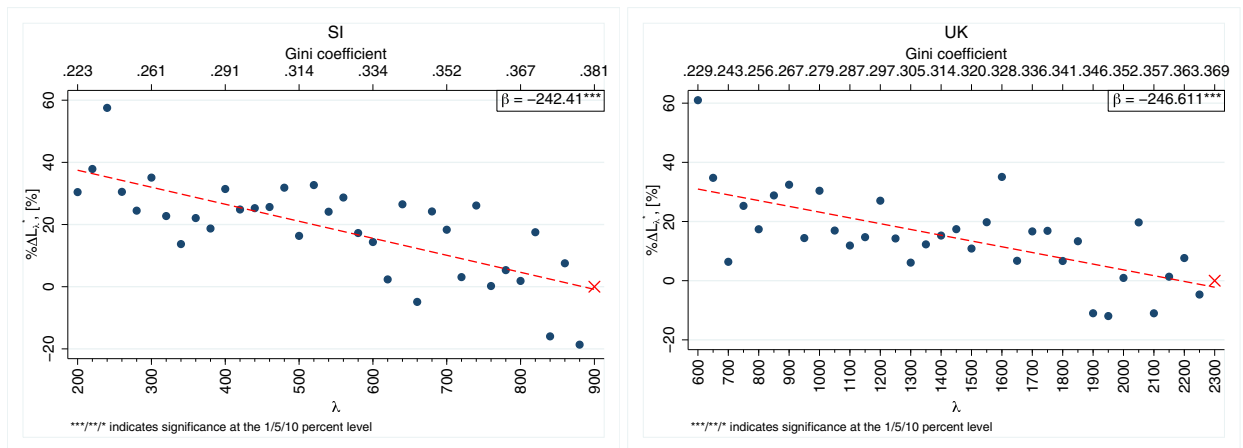
The results for consumption are presented in Fig. 8.

Fig. 9. The relationship between income inequality and average consumer credit. The red × denotes the benchmark value.
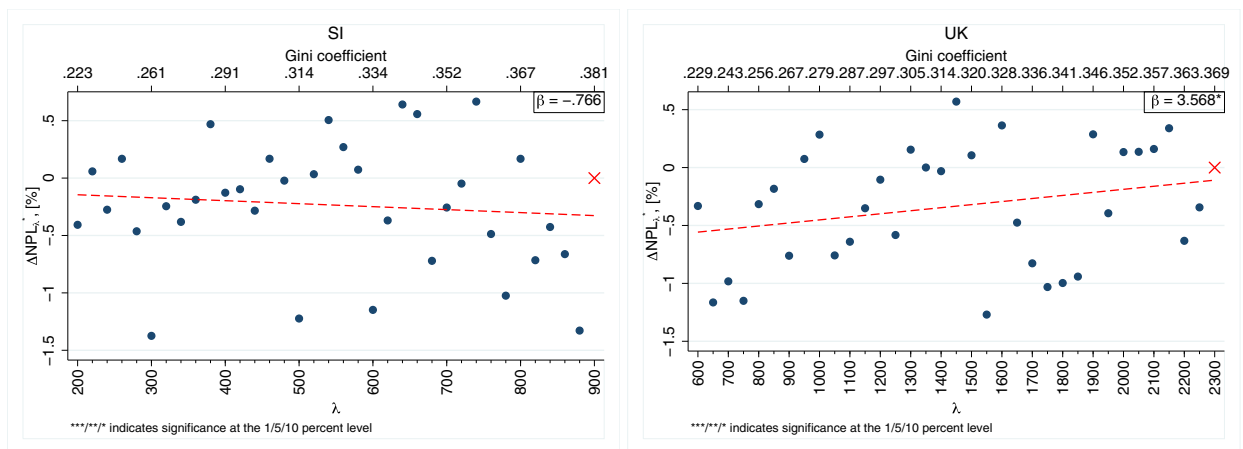

Fig. 10. The relationship between income inequality and average NPLs. The red × denotes the benchmark value.

Fig. 8 exhibits a clear, negative relationship between income inequality and average consumption for both scenarios. This is also manifested in the statistically significant coefficients of the respective regression lines which indicate that a 1% decrease in Gini coefficient of income distribution results in an approximate 0.04% to 0.07% increase in average consumption, depending on the scenario examined. The sign of the relationship is as expected. When income is more equally distributed, then a larger number of households have more funds available thus resulting in higher levels of consumption. On the contrary, when income is more concentrated, consumption cannot be supported by the few at the top of the distribution and therefore settles in lower average values. In the next subsection is examined whether considerably looser credit supply can mitigate the detrimental effect of inequality on consumption. Moving to consumer credit, Fig. 9 reveals an interesting pattern.

As seen in Fig. 9, income inequality does affect the average volume of consumer credit. In particular, a 1% increase in the former (more precisely in income distribution's initial Gini coefficient) results in an approximate decrease of the latter by 2.4% as suggested by the respective regressions.

This result deserves further discussion given that various studies suggest a positive relationship between the two variables. The underlying rationale is associated with credit demand triggered by households' desire to keep their consumption close to some external ("keeping up with the Joneses") or internal reference (own past consumption or "habit formation") level. Several, closely related, theories have been proposed to explain this behaviour such as the relevant income hypothesis (Duesenberry, 1967), the theory of expenditure cascades (Frank et al., 2014) or the need to sustain living standards by households at the bottom part of income distribution (Atkinson and Morelli, 2011). The work of Bazillier and Héricourt (2017) provides a very comprehensive survey of the recent literature on the links between inequality, leverage and crises. Something that should be kept in mind is, however, that the aforementioned theories assume that households' access to credit is unrestricted by their income or risk.
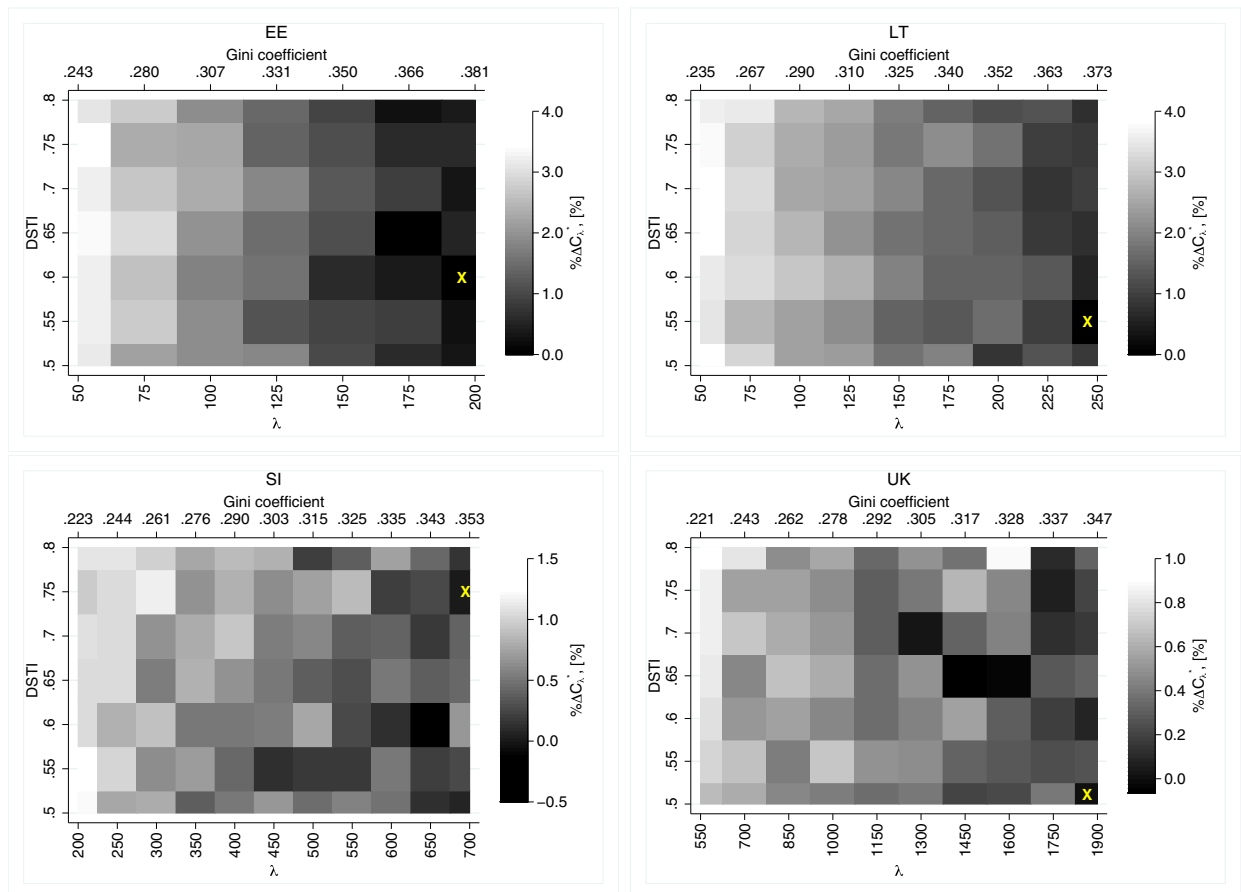
Fig. 11. Average consumption per DSTI and initial income inequality level. The yellow × denotes the benchmark value.

An additional challenge is posed by the empirical study of the relationship between inequality and household leverage. While the measure of credit implied by the theories above is household credit -and in particular consumer credit- the majority of empirical studies use some aggregate measure of credit in the economy, including that to firms, which might be unrelated to inequality. This could affect the results, obscuring the potential underlying causal relationship. Even in the best case where household credit comprising of mortgages and consumer loans is considered, the different dynamics of the two components might have substantial impact on the results obtained and their interpretation. Indeed, data from Jordà et al. (2015) show that the trends and levels of the two types of credit are noticeably different in 17 countries,[25] resulting in a 20% difference as a share of GDP around 2012. The possibly different mechanism associated with housing credit as opposed to consumer credit might imply a different explanation for credit growth than the need of low income households supporting their living standards (Bazillier and Héricourt, 2014). In fact, Coibion et al. (2014) using household-level data reject the "keeping up with the Joneses" hypothesis, i.e. the demand-side explanation of credit growth and find a negative relation between inequality and household debt.

The pattern observed in Fig. 9 is also associated with the supply-side of credit. The mechanism works through the adequately high income being held by a large number of households. This configuration results in more credit being considered as affordable by the banking sector (i.e. supported by the potential borrowers' income) for a given DSTI[26] and therefore being granted once it is asked for, assuming that demand remains roughly the same under different inequality regimes.[27] Another key driver of this result is households' assumed consumption function in Eq. (1). Since habit formation or comparison with some external reference level are not explicitly considered, desired consumption -and by extension consumer credit demand- is driven by income expectations. Nevertheless, once credit demand is expressed it is for the bank to decide

---

[25] Especially in the period after early 2000s, which is the focus of the present study.

[26] And other supply-side related properties such as loan interest rates and maturities.

[27] Results from simulations which are available upon request suggest that indeed consumer credit demand is invariable across different initial income inequality levels.
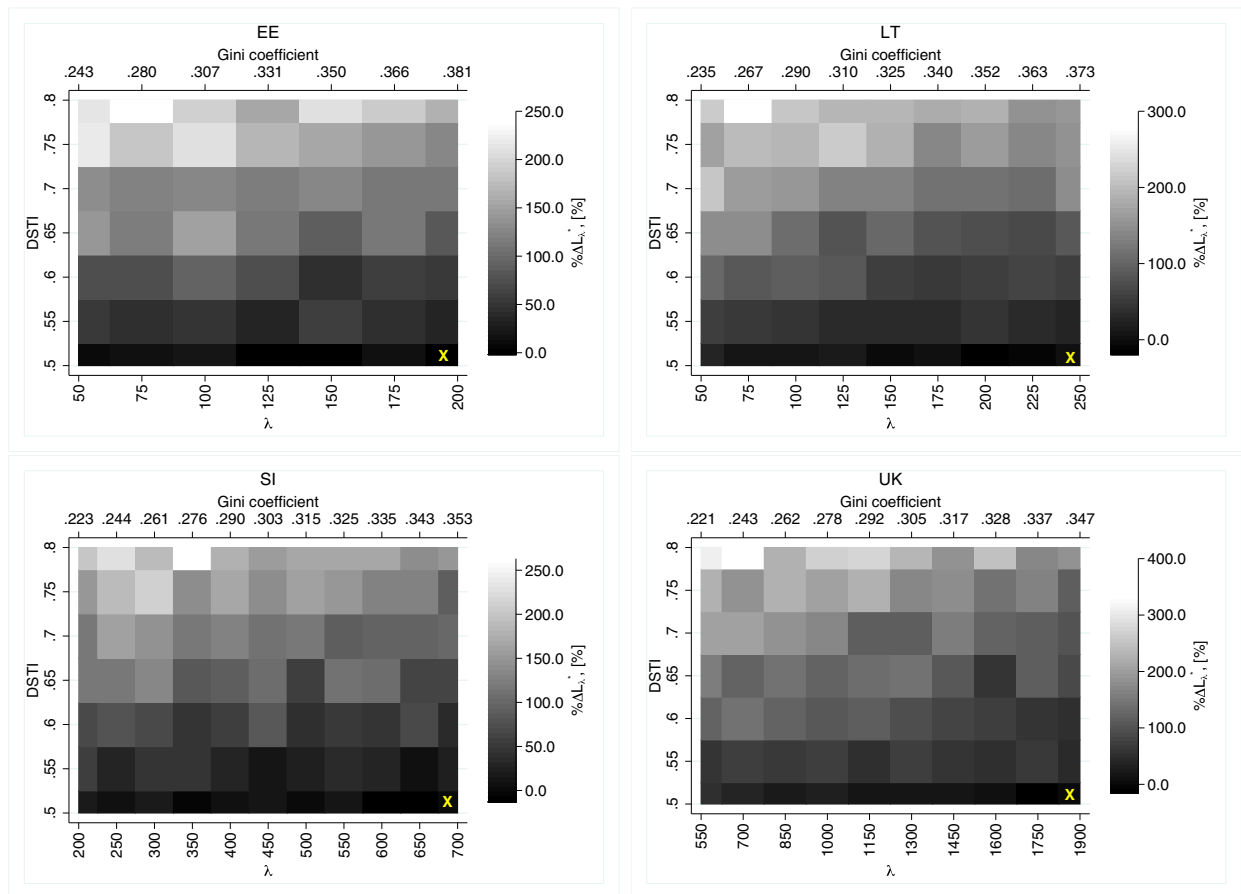
Fig. 12. Average consumer credit per DSTI and initial income inequality level. The yellow × denotes the benchmark value.

how much to lend according to its DSTI level. Hence, households exceeding the bank's risk tolerance will be rationed and credit supply effectively limited. Finally, results for NPLs are shown in Fig. 10.

Fig. 10 suggests that the relationship between income inequality and average NPLs is weak at best or possibly non-existent. In the UK-specific scenario (right graph in Fig. 10), higher inequality is associated with higher NPLs, although the magnitude of the relationship is small and its statistical significance low. On the contrary, in the case of the SI-specific scenario NPLs seem to be independent from the level of income inequality, something which is reflected on the statistically insignificant (i.e. indistinguishable from zero) slope of the respective regression line. The main reason behind this result is the volume of consumer credit.

The volume of credit provided is primarily controlled by the interaction between the expectations-based demand and the DSTI-constrained supply. In general, the amount of consumer credit asked is small since income expectations are never that extraordinarily far from the realized values to render households' available financial resources inadequate to cover an important part of desired consumption. In addition, DSTI limits the *maximum* monthly loan installment of an indebted household at the level of 50% to 60% of its income, depending on the scenario applied (see Table 3). Finally, the debt assumed by a household stochastically ranges between the demanded and the maximum amount offered (see Eq. (11)). Thus, it is more probable that it will be lower than the upper value permitted by DSTI at any point in time. The interplay of these mechanisms results in the respective monthly installments being a small fraction of households' income, hence facilitating loan servicing even if income declines considerably. Therefore, the main driver of NPLs is unemployment, the latter being the reason for substantial income reduction, rendering debt unserviceable.

The scarcity of exact data on unemployment's evolution by income percentile does not allow for the development of a more accurate historical scenario,[28] thus the baseline assumption of a stochastic impact of unemployment is applied.

---

[28] Data from the International Labour Organization on the distribution of unemployment by education level indicate that for Slovenia and the UK the largest share of unemployed persons have an intermediate level of education. This pattern holds since 2000 in the former and 2005 in the latter. Although education level might give an indication about the distribution of unemployment by income, the three levels (basic, intermediate, advanced) considered make for a quite coarse distributional division with no clearly defined boundaries.
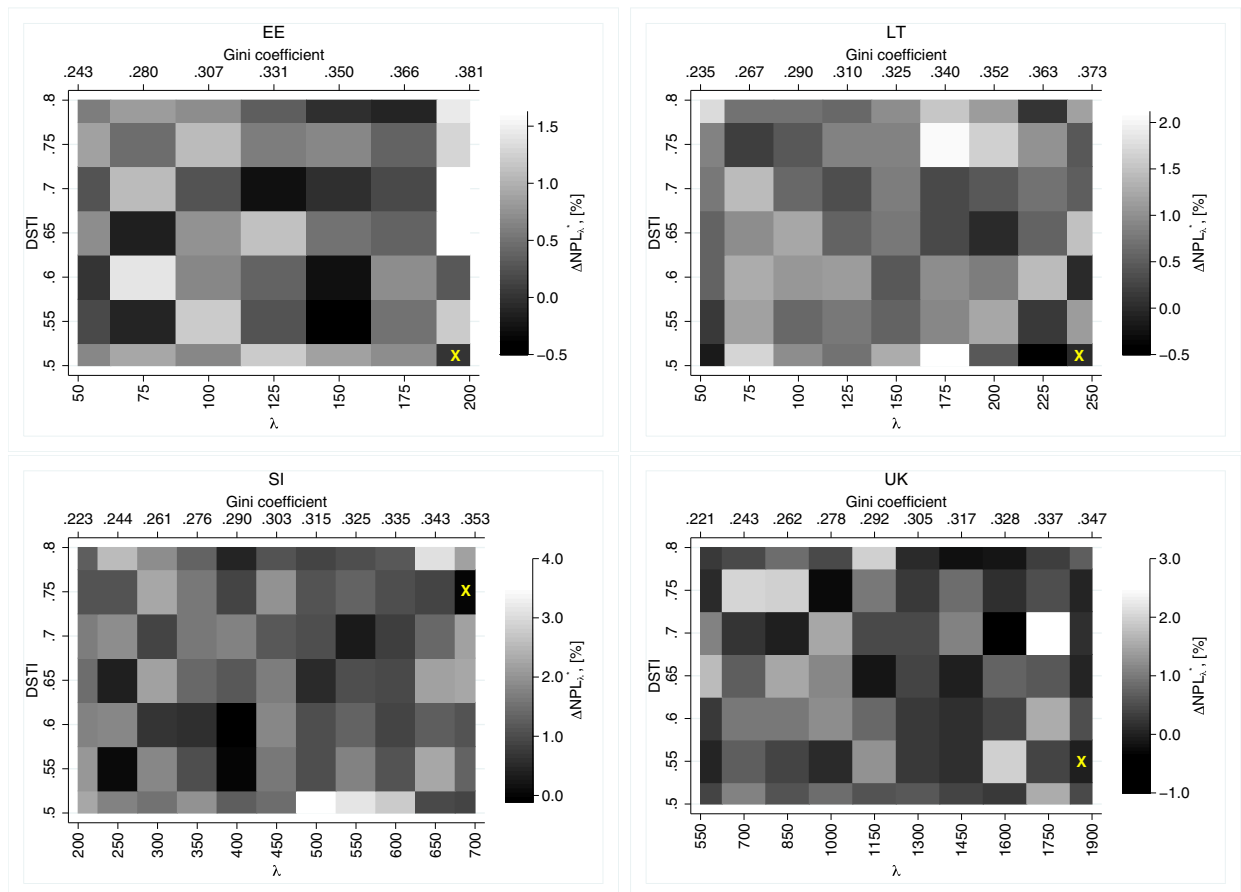
Fig. 13. Average NPLs per DSTI and initial income inequality level. The yellow × denotes the benchmark value.

However, as described in Section 2.3.5, the stochastic nature of unemployment shocks implicitly links them with the inverse of households' income; i.e. households at the lower parts of income's distribution are more likely to be unemployed. Then, since NPL's main driver is associated with income's distribution, why this is not reflected in a relationship between NPLs and income inequality? The main reason is that consumer credit is very sparsely spread across households. Thus, even though unemployment affects more frequently low income households than their distributional counterparts, it only occasionally impacts an indebted household.

It is possible that differential unemployment growth across the distribution of income might influence the result. However, the outcome depends on the distributional "focal point" and severity of unemployment's impact. If the impact of unemployment is stronger among households who, in general, do not or cannot resort to borrowing to meet their consumption needs (i.e. those at the very bottom and top of the distribution) the relationship between NPLs and inequality is expected to be weak at best. Similarly, if unemployment mostly affects median income households (see discussion in Appendix E on which income class commonly holds credit), then again NPLs will not be associated with income inequality. On the contrary, if unemployment's impact is concentrated around the average of income's distribution, then a negative link between NPLs and income inequality is expected.[29]

It should be reminded that NPLs are defined as the share of loans past due 6 months to total loans. Obviously, if instead of the ratio is considered the level of non-performing loans the sign of the relationship is clearly negative. Lower income inequality and its associated larger volumes of credit are more likely to result in higher amounts of non-performing obligations. In that respect, NPLs expressed as ratio is a more meaningful metric.

---

[29] This is due to the fact that the average is closer to the median for low than for high inequality distributions. Combined with the results described in Appendix E showing that consumer credit is most commonly held by median-income households, it follows that in such unemployment scenario the relationship between NPLs and income inequality will be negative.

3.4.2. Fixed DSTI

In this experiment, besides the effect of initial income inequality, is also studied the effect of different DSTIs on consumption, credit and NPLs. In particular, DSTI ranges from 50% up to 80% and remains fixed throughout the simulation. Moreover, for each DSTI level the model is run 100 times with different initial income distribution Gini coefficients which span from about 22% to 38%. The rest of the macroeconomic scenario remains at its baseline setup.

The average of every variable over the whole simulation per {DSTI, initial Gini coefficient} pair is plotted in Figs. 11–13. The benchmark against which the comparison is made, as well as the horizontal axes follow the same conventions as in the previous experiment. The vertical axis represents the various DSTI levels while the colour of each cell indicates their distance from the associated zero-level.

Results in Fig. 11 display an interesting pattern. For low levels of income inequality (Gini $\leq$ 25% to 27% approximately) average consumption is larger than the benchmark even for low levels of DSTI. This difference is more sizable in economies with lower absolute levels of minimum and average income, fluctuating around 4% as shown in the first row of Fig. 11. As these distributional parameters increase, the magnitude of the effect declines to 1%–1.5% although the general pattern remains the same. As one moves to higher levels of inequality, consumption does not seem to be substantially supported by looser credit supply and settles to lower values. Finally, at the high inequality regions of the graphs consumption is evidently lower for any DSTI level as indicated by the more frequent dark-coloured patches in Fig. 11.

Results for consumer credit are presented in Fig. 12 and display a rather expected structure.

In general, for any level of initial income inequality, an increase in DSTI levels is followed by an increase in the average volume of consumer credit. However, results indicate that income inequality does affect credit provision, with the sign of the relationship corroborating the findings of the previous experiment. For a given DSTI, average consumer credit is higher for smaller Gini coefficients and drops as the latter increases. It should be noted here that the considerably wide range of results is due to the small value of the benchmark, generated under the minimum DSTI examined.

Finally, the outcome of the experiment for NPLs is shown in Fig. 13.

In line with the results of the experiment with evolving DSTI, Fig. 13 suggests that there is no apparent link between the average level of NPLs and income inequality for any DSTI level. Dark and bright-coloured patches are alternating with no clear structure emerging within the range of DSTIs and Gini coefficients examined.

4. Conclusions

This study examined the effect of income inequality on consumption, credit and non-performing loans by the means of a simple, data-driven agent-based model.

For its development are used standard elements from the respective macroeconomic ABM literature, augmented with a heuristics switching model based on the findings from experimental studies on expectations formation. Overall, its structure is kept simple by replacing the actions of and interactions among some agents with the historical evolution of the associated series. This simplicity allows the model's output to be a markedly close replication of the actual data when input is accurate enough.

The good agreement of model's validation output with historical data suggests that, apart from studying the effects of income inequality, the model is suitable for policy simulation purposes. Under the baseline specification it can be readily used to provide scenario analyses examining the impact of macroprudential regulations (e.g. DSTI or consumer loan maturity limits) on consumption and credit growth, conditional on income and unemployment's evolution. Moreover, the associated flexibility and granular nature of the agent-based modelling approach allows for a more focused analysis compared to standard, structural macro models. Such framework enables the examination of the effects of policy actions on specific parts of the economy, thus contributing in a better understanding of their impact and a more targeted calibration of the applied policies.

The experimental simulations performed with the model indicate that, in the long run, income inequality is negatively associated with both consumption and the volume of consumer credit. The former result is as expected. A more equal distribution of income implies that a larger number of households have more purchasing power available thus being able to maintain higher consumption levels. The latter result corroborates the findings of recent empirical studies which find a negative relationship between inequality and household debt. An interesting result is that the ratio of non-performing obligations as a share of total consumer credit seems to be independent of inequality. This is the outcome of the interplay between two mechanisms governing the volume of consumer credit; an expectations-based demand and a DSTI-constrained supply. These mechanisms result in serviceable debt levels even under significant income decreases for any inequality level. Obviously, this result should not be linked with the large volume of mortgages observed in many countries since the early 2000s and the associated non-performing obligations which cannot be studied under the current implementation of the model.

Future research aims at extending the model in several dimensions, while maintaining its close link with the actual data. A first step will be to include agents which in the current version are assumed to be exogenous such as firms or a more elaborate banking sector reacting to central bank's actions. Equipping the model with more active agents will also permit a more detailed description of various markets such as the labour market or the incorporation of additional ones such as the housing market. These extensions will allow to study the effect of implementing and the interactions among various economic policies thus assisting policy makers in supporting and promoting societies' well-being.
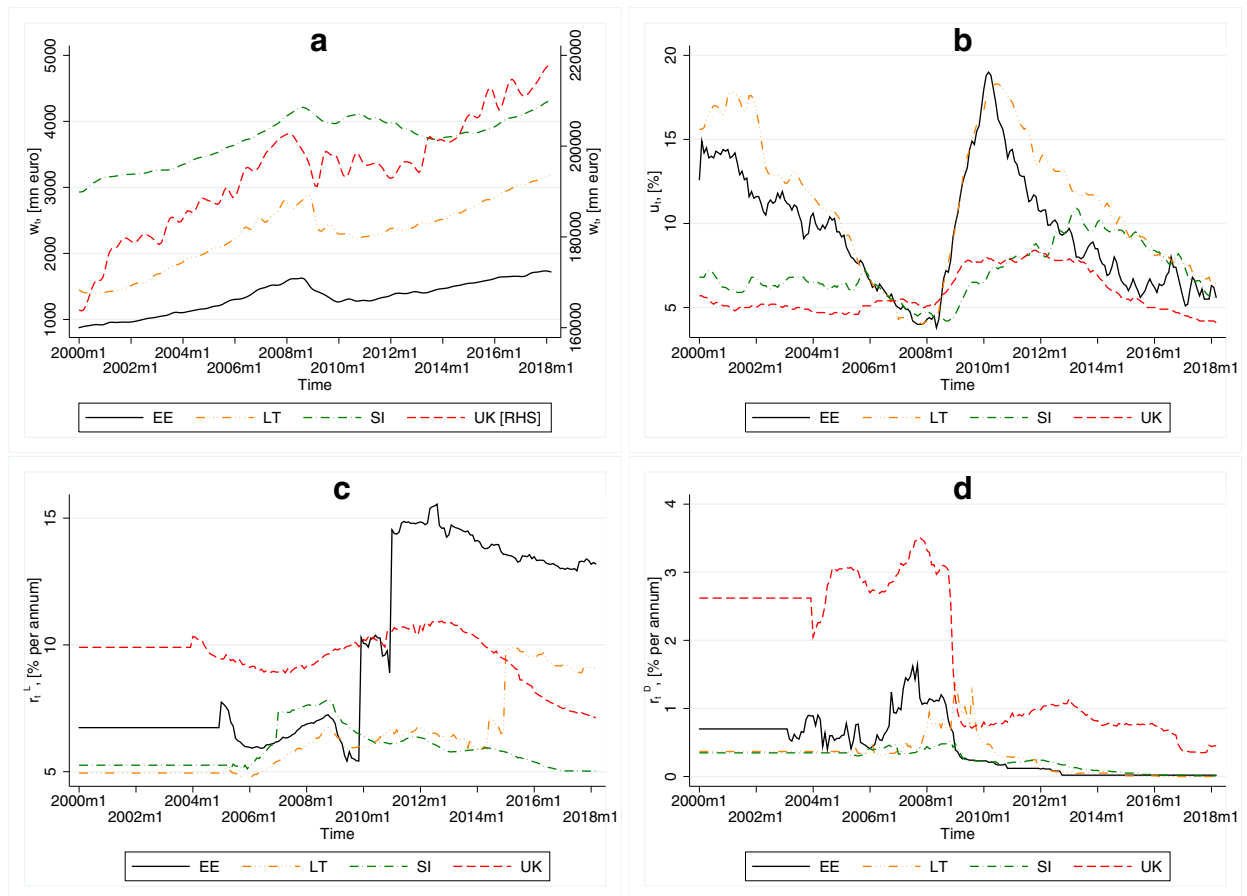
Fig. A1. The evolution of input series per country-specific scenario. Subplot (a) shows the evolution of wages & salaries and Subplot (b) that of unemployment's rate. Consumer credit and overnight deposit interest rates are plotted in Subplots (c) and (d) respectively.

Appendix A. The evolution of input series in the historical scenarios

While the direction of the relationship between income inequality holds for every historical scenario examined, the dynamics of the output series exhibit some country-specific patterns. This can be seen, for example, in the validation exercise in Section 3.2 for the case of consumption and consumer credit or in Fig. 7 for NPLs. The main driver of behind this diversity lies in the applied historical scenarios. In Fig. A1 is plotted the evolution of the input series for each historical scenario.

From Fig. A1 one can see that the most important drivers of the output variables' dynamics are the series for wages & salaries in subplot (a) and unemployment rate in subplot (b). In particular, income -proxied by wages & salaries- is the main determinant of consumption as is evident from the comparison between its dynamics and the respective ones for consumption found in the top-left subplots of every validation exercise (in Figs. 4,5,C1 and C2). Income is also a significant determinant of consumer credit, in conjunction with DSTI. The former drives expectations formation which are manifested in credit demand. The latter, in turn, interacts with credit supply governed by DSTI to result in the provision of credit. Interest rates also play a role, although not a major one compared to that of the previous series. Finally, the comparison between the evolution of NPLs in Fig. 7 and that of unemployment's in Fig. A1 reveals their strong link as discussed in the respective part of Section 3.4.1.

Appendix B. Calibration of initial DSTI and its evolution

The fact that exact information about the level of DSTI and its path is not available poses a major challenge given the data-driven nature of the ABM under development. Although consumption is not significantly affected (as suggested by the narrow bands around simulated consumption series in Figs. 4 and 5), consumer credit strongly depends on DSTI levels (see e.g. Fig. 12) and its evolution through time. In this section is described an attempt to overcome this issue by calibrating the level and path of DSTI using publicly available information.
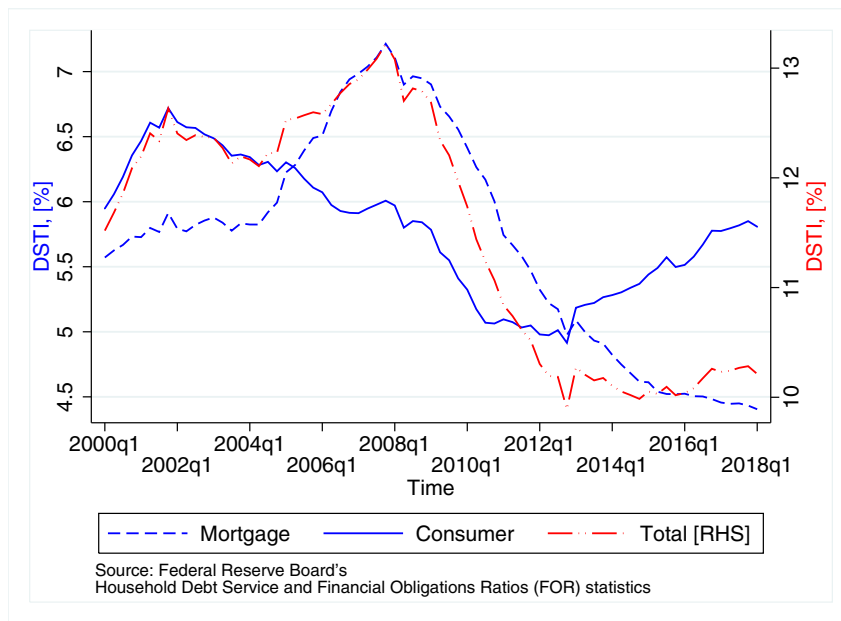
Fig. B1. Household debt service payments and financial obligations as a percentage of disposable personal income for the US (seasonally adjusted).

The only source which provides internationally consistent, country-specific data on DSTI is the BIS's debt service ratios statistics database. This dataset has two desirable properties; its quarterly frequency is adequately high for transforming it to a satisfactorily realistic monthly interpolation and there are separate series by borrower type, including households and NPISHs. One caveat associated with the last property is that, even though the data refer to DSTI for credit provided to households and NPISHs, there could be significant differences by credit type; i.e. housing and consumer credit. Indeed, the case of the US where more detailed data exist from the Federal Reserve Board's Financial Obligations Ratios database presented in Fig. B1 is illuminating.

As can be seen in Fig. B1, up to approximately early-2002 the two components of total DSTI share a roughly common evolution. However, from then until 2008 their paths are strongly divergent with consumer credit DSTI declining while mortgage DSTI showing a sharp upward trend. Since 2008 and the emergence of the subprime crisis, mortgage DSTI decreases at a faster rate compared to consumer credit's and it currently seems to have stabilized around it's lowest figures reached in 2013. On the contrary, the latter shows a solid recovery from its 2013 bottom and now is close to its 2000 levels. Another important observation is that, for the most part, total DSTI's pattern (plotted in red, dash-dotted line in Fig. B1) resembles more closely that of mortgage DSTI's. Thus, since in the BIS's database DSTI refers to total credit, this might result in discrepancies between simulated and historical data on consumer credit when inserted into the model.

Apart from the specific path, another important missing element is the level of DSTI. Data from the BIS "*should correctly capture how the DSTI in a particular country changes over time, even if it does not necessarily accurately measure its level relative to what one could obtain from the correct micro data*" (Drehmann et al., 2015, p. 91). Since the issue of disentangling the two DSTI components cannot be addressed, the subsequent procedure focuses on at least approximating the level and path of DSTI and associate it with the country-specific macroeconomic scenarios examined.

The calibration process consists of a grid-search over a range of initial DSTI values combined with several growth rate paths for DSTI in order to find which combination yields the minimum distance and maximum similarity between simulated and actual series of consumer credit.

The choice of initial DSTI range over which the grid-search is performed, is guided by the figures applied by the respective authorities as regulatory constraints on European banks. A recent report by the European Systemic Risk Board (European Systemic Risk Board, 2018) indicates that DSTI limits range between 40% to 80% of households' disposable income. These constraints mostly apply for housing credit but there are several occasions where similar values are considered for consumer credit. Therefore, a reasonable search range for initial DSTI values is between 40% to 60% considering that almost every DSTI path applied increases from 2000 until 2008. A step of 2% is used since it is fine enough to allow for a sufficiently dense examination while it is as coarse as needed to keep computational burden manageable.

The DSTI growth rate paths are calculated from the BIS series, after transforming them from quarterly into monthly frequency through cubic spline interpolation. Apart from the case of UK where country-specific data are available, the choice for the rest countries is based on the assumption that they should broadly exhibit a comparable evolution of DSTIs with their larger European counterparts due to roughly similar economic conditions. Thus, the DSTI growth rate paths examined are
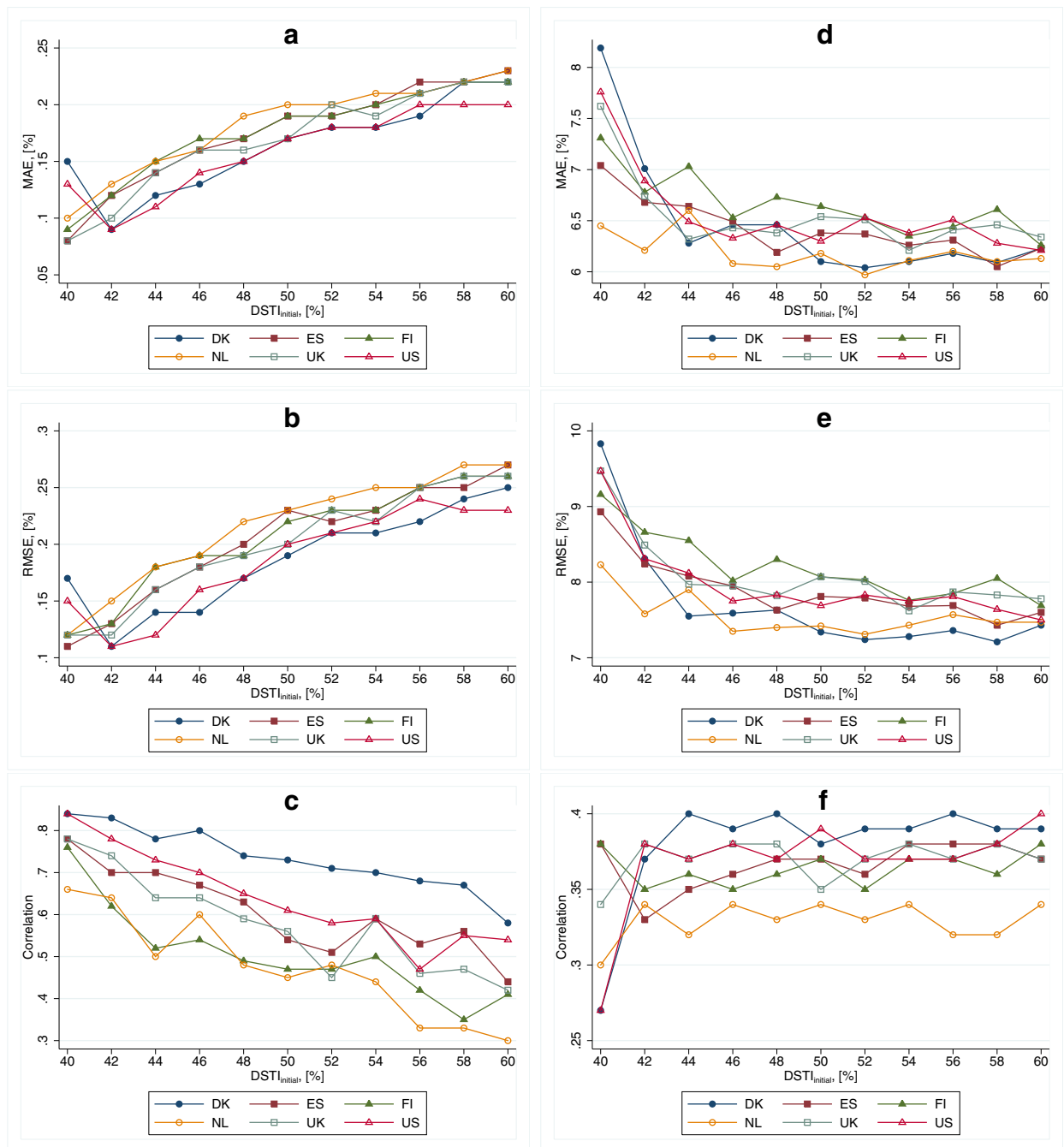
Fig. B2. Calibration of initial DSTI and DSTI growth rate path for EE. Subplots (a) to (c) correspond to the distance between simulated and historical consumer credit series in rescaled levels and (d) to (f) to annual growth rates.

those from Denmark (DK), Spain (ES), Finland (FI), the Netherlands (NL), the UK (UK) and the US (US) plotted in Fig. 3. The last one is included because it shares a similar pattern with that of many European economies.

The simulation is executed 100 times under the baseline parameter setup for each pair of {initial DSTI, DSTI growth rate path} resulting in 66 pairs per country. Next, the median of the rescaled levels and annual growth rates of consumer credit over all runs per pair is compared with the respective historical series. The measures for comparing the simulated with the observed data are the commonly used Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)[30] and zero-lag

---

[30] Also known as Manhattan and Euclidean distances respectively.
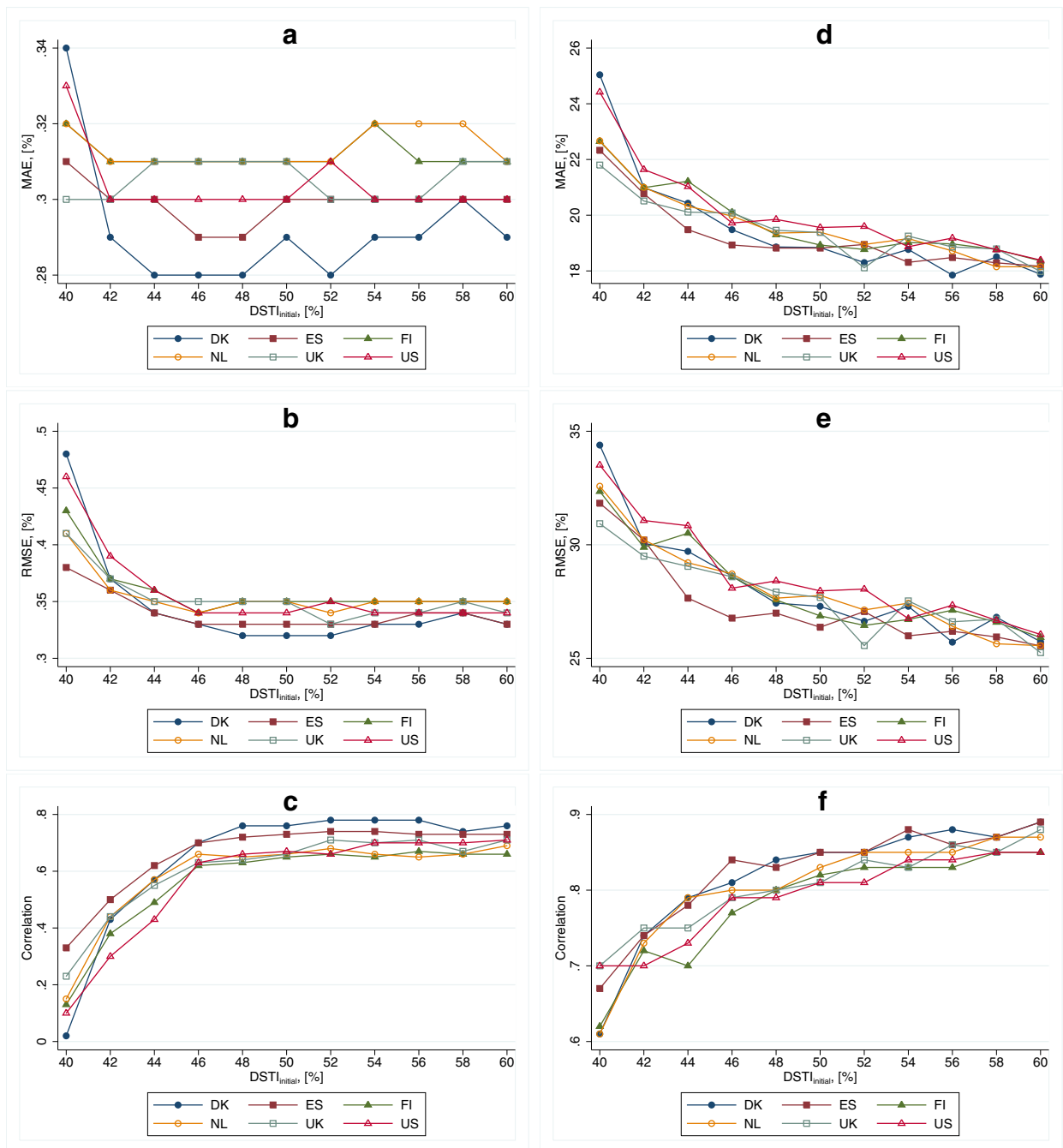
Fig. B3. Calibration of initial DSTI and DSTI growth rate path for LT. Subplots (a) to (c) correspond to the distance between simulated and historical consumer credit series in rescaled levels and (d) to (f) to annual growth rates.

cross-correlation (Stonedahl and Rand, 2014). Finally, the combination resulting in the minimum distance and maximum correlation is selected and added to the respective country's baseline macroeconomic scenario. In case results are not conclusive, a balanced choice is made taking into account performance in both rescaled levels and annual growth rates. In Figs. B2–B5 are plotted the distance and correlation measures following from the described grid-search procedure.

The results for case of EE in Fig. B2 indicate that possibly none of the DSTI paths examined is a good approximation of what actually occurred. On the one hand the best fit in rescaled series is observed for low initial DSTI levels, while the opposite holds for annual growth rates. One common feature seems to be that the DK scenario exhibits the best performance in both cases. Therefore, this is selected with the initial value set to 50% as trade-off between the two transformations.
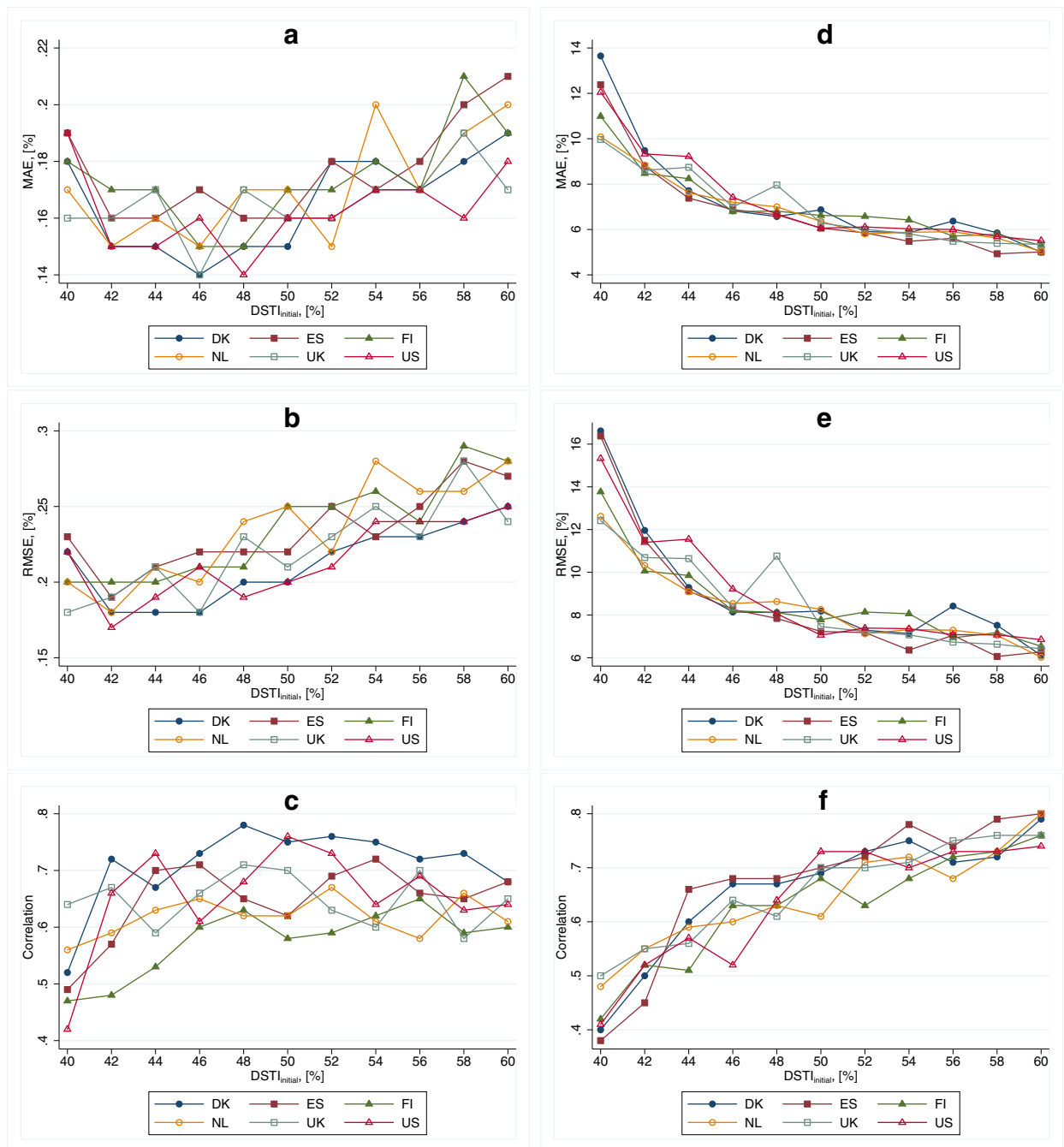
Fig. B4. Calibration of initial DSTI and DSTI growth rate path for SI. Subplots (a) to (c) correspond to the distance between simulated and historical consumer credit series in rescaled levels and (d) to (f) to annual growth rates.

In the case of LT the calibration results exhibit a uniform pattern; in both rescaled levels and annual growth rates distance is smaller for higher initial DSTIs and stabilizes for $DSTI_{initial} \geq 50\%$. While all DSTI paths display comparable performances, the DK one seems to perform slightly better. For the choice of initial DSTI, the value of 52% is selected since results after that do not substantially improve. One noticeable fact is that distance measures are significantly larger in LT compared to other countries, especially in annual growth rates (around 3 to 4 times higher). This suggests that, as in EE, also in this case the applied DSTI paths are likely not a good approximation of the realized series.

Results for SI in Fig. B4 display two patterns. In rescaled levels performance improves roughly up to $DSTI_{initial} = 50\%$ and then deteriorates, while in growth rates it continues monotonically as initial DSTI increases (albeit at a declining rate). The
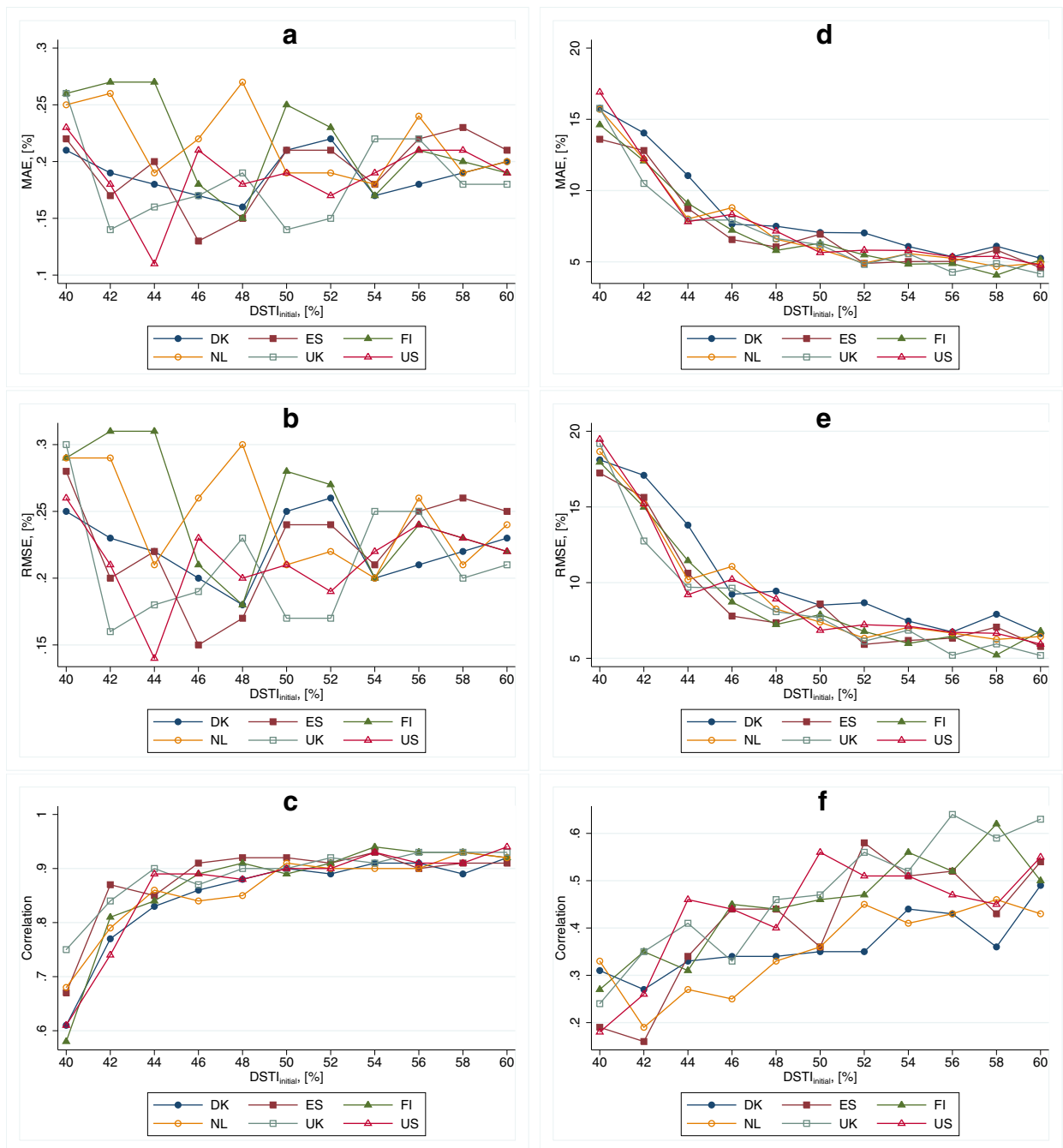
Fig. B5. Calibration of initial DSTI and DSTI growth rate path for UK. Subplots (a) to (c) correspond to the distance between simulated and historical consumer credit series in rescaled levels and (d) to (f) to annual growth rates.

scenarios which seem to outperform the rest are the DK and the US one with the latter being marginally better. Hence the initial level of DSTI is set to 50% and the selected scenario is the US-specific. It should be mentioned that anecdotal discussions with supervisors suggest that indeed the path of the Slovenian banking system's DSTI has an inverted U shape and currently its levels are considerably lower compared to the pre-crisis status.

Finally, results for the UK indicate that indeed the country-specific DSTI path from the BIS database provides the best fit, followed closely by the ES and US scenarios with which it shares a quite similar pattern (see Fig. 3). Since the direction of improvement is the same for both rescaled and growth rate series, the selected value for initial DSTI's level is set to 56%.

Appendix C. Validation with inadequate approximation of DSTI

The results presented in Section 3.2 demonstrated the ability of the model to reproduce historical series once input data used are a good approximation of the realized ones. In this section is examined the model's performance when some of the utilized data diverge from the actual figures. In particular, are presented the cases of EE and LT where the implemented DSTI is not a good approximation of the historical one as discussed in Appendix B. This mainly affects the results as regards consumer credit's evolution whereas the simulated consumption series show a good match to the observed ones, similar to the case for SI- and UK-specific scenarios. That being said, the artificial series for consumer credit do not show extraordinary deviations from the historical ones, which indicates that a more accurate input for DSTI will improve the fit.

The initial values of the Estonian and Lithuanian simulation parameters are presented in Table 7.

A description of the series used and their time periods is provided in Table 8.

C1. Validation with the Estonian scenario

The results for the EE-specific scenario are plotted in Fig. C1. The first row presents the results for consumption and the second those for consumer credit. Column-wise, the first column shows the results in levels (rescaled by their sample means), while the last one in annual growth rates.

As one can see in Fig. C1, the simulated series for consumption are in very good agreement with the historical ones both in levels, and in growth rates. On the contrary, results for consumer credit are not as satisfactory. In Table 9 are reported three quantitative measures of the distance between the artificial and actual observations.

The quantitative measures in Table 9 corroborate the findings in Fig. C1. They reveal a distance of approximately 3% to 4% on average and high correlation (above 75% in growth rates and above 90% in levels) between the actual and artificial series of consumption. For the case of credit though, results are less encouraging with higher error measures but also substantially lower correlation.
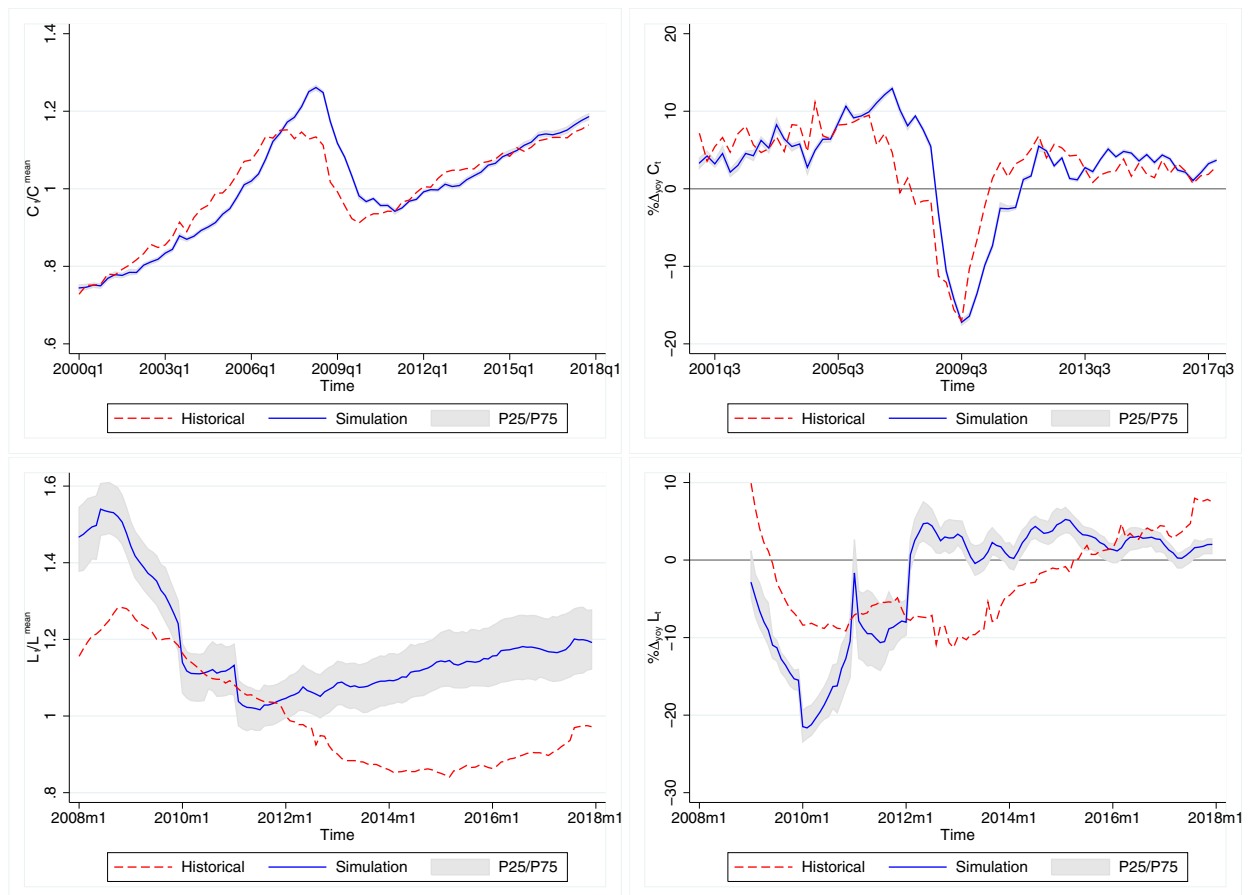

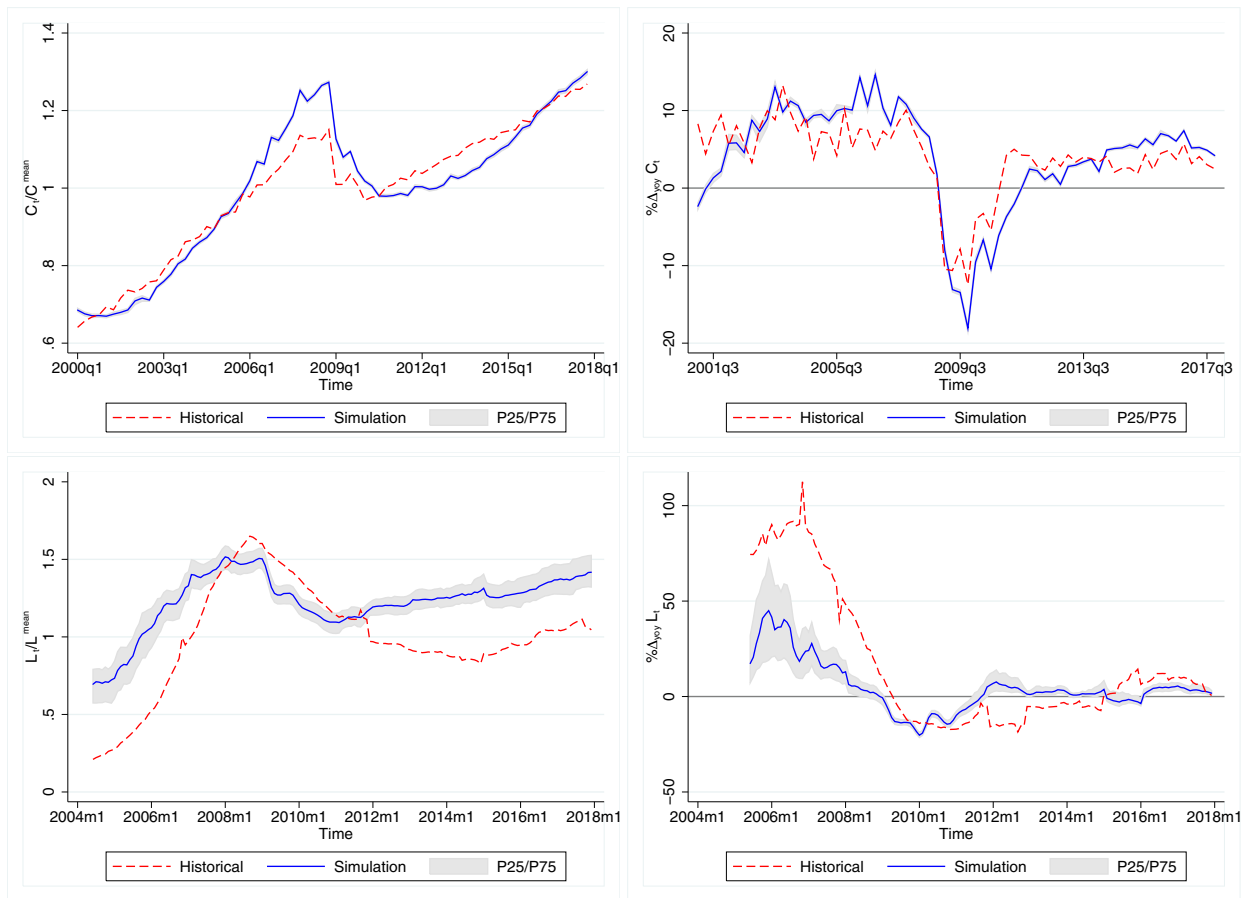**Fig. C1.** Baseline simulation results for the EE-specific scenario.

Fig. C2. Baseline simulation results for the LT-specific scenario.

Table 9
Distance and similarity measures between simulated and historical data for EE.

Variable	Transformation	MAE	RMSE	Correlation
Consumption	y_t/y^{mean}	0.037	0.052	0.932
	$\%\Delta_{yoy}$	3.012	4.101	0.767
Credit	y_t/y^{mean}	0.182	0.208	0.684
	$\%\Delta_{yoy}$	6.233	7.418	0.389

Table 10
Distance and similarity measures between simulated and historical data for LT.

Variable	Transformation	MAE	RMSE	Correlation
Consumption	y_t/y^{mean}	0.042	0.053	0.960
	$\%\Delta_{yoy}$	3.066	3.830	0.829
Credit	y_t/y^{mean}	0.285	0.322	0.784
	$\%\Delta_{yoy}$	18.645	27.015	0.862

C2. Validation with the Lithuanian scenario

The results for the Lithuanian scenario are more promising and are presented in Fig. C2.

As in the case of EE, simulated data for consumption (first row of Fig. C2) are almost indiscernible from the observed ones. Credit related series in the second row of Fig. C2 show that there is some degree of similarity in distance and synchronicity between artificial and historical data. The patterns both in levels and growth rates are comparable while in the latter even magnitudes are close after 2010. In Table 10 are reported the quantitative measures of distance and similarity between the two series.

Regarding consumption, the figures in Table 10 demonstrate that indeed there is a very good agreement between the two series both in magnitude (their average distance is around 4%)as well as in co-movement (correlation ranges between

80% and 96%). Results for credit series show a mixed picture. On the one hand distance measures (MAE and RMSE) reveal large discrepancies which are mainly driven by the period up to 2010. On the other hand, high correlation indicates that the two series move in a strongly synchronized manner.

Appendix D. The effect of the stochastic credit assumption mechanism

A crucial assumption in households' credit demand is the stochastic credit assumption mechanism described in Eq. (11). As demonstrated in Section 3.2, this mechanism is able to replicate the observed credit dynamics in a satisfactory way, when input data are good proxies of the historical ones.
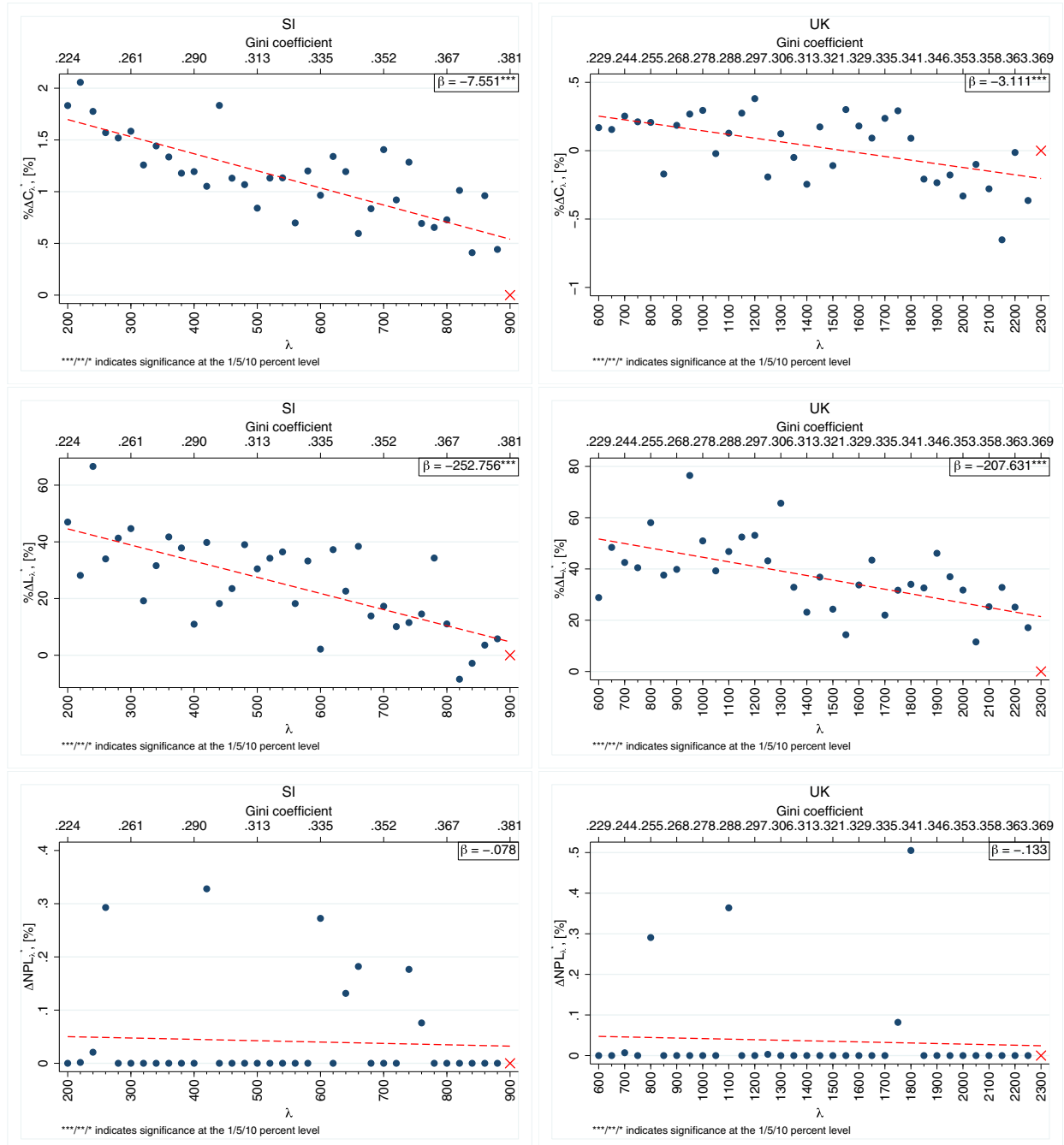

Fig. D1. The effect of initial income inequality on consumption, consumer credit and the associated NPLs for SI and UK scenarios. Potential borrowers receive, at most, the exact amount of credit they asked according to Eq. (14).
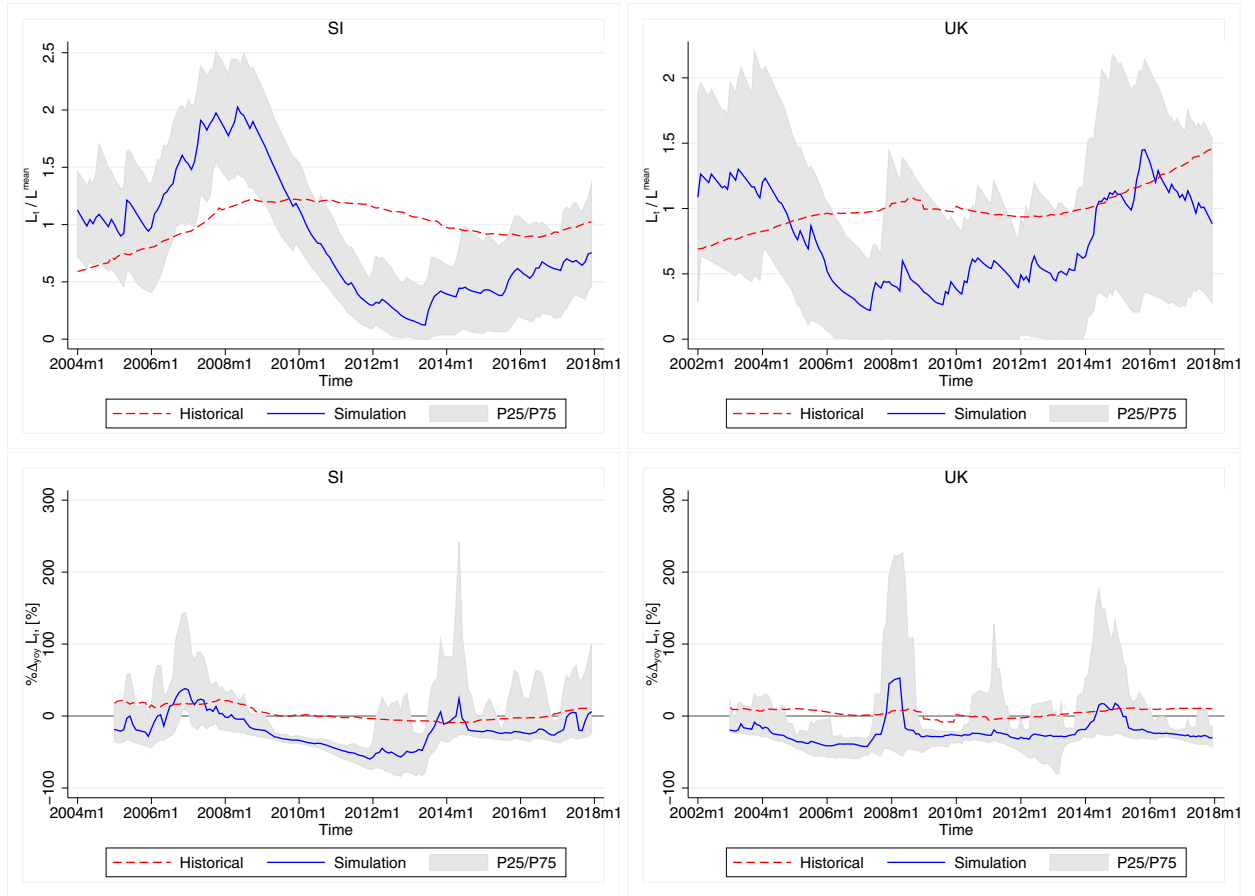
Fig. D2. Comparison between historical and simulated evolution of consumer credit under the exact credit assumption mechanism described in Eq. (14).

In order to study the impact of the assumed mechanism on the obtained results the stochastic part is switched off and replaced by the standard mechanism used in the literature (Cardaci, 2018; Russo et al., 2016); even if offered with more credit than asked, a household will receive the exact difference between desired consumption and available resources. Therefore, the rule in Eq. (11) is changed as follows:

$$L_{h,t} = \begin{cases} L_{h,t}^{max}, & L_{h,t}^{ask} \geq L_{h,t}^{max} \\ L_{h,t}^{ask}, & L_{h,t}^{ask} < L_{h,t}^{max} \end{cases} \tag{14}$$

The configuration is the same as in the experiment described in Section 3.4.1. Every input is set to its baseline values with the exception of initial income distribution's Gini coefficient which varies between about 22% and 38%. The average simulation results over 100 runs per initial Gini coefficient are presented in Fig. D1 for the same country scenarios studied previously.

The left column in Fig. D1 shows the results for the Slovenian scenario, while the right column the ones from the UK-specific one. Row-wise, from top to bottom, the subplots in Fig. D1 correspond to consumption, consumer credit and NPLs respectively. As is evident, the relationship structure between income inequality and the respective variables remains unaffected by the credit assumption mechanism change. Consumption and consumer credit exhibit a negative link with income inequality, whereas NPLs seem to be independent from it. Quantitatively, the results are very close to those obtained in Section 3.4.1 where the stochastic credit assumption mechanism is used as can be seen from the associated linear regression coefficients. A noticeable difference is observed in the results for NPLs, in the last row of Fig. D1. Although qualitatively the relationship is the same as before, one can see that most data points lie on the zero level. This is not only because their difference from the benchmark is zero. It is due to the fact that the benchmark, along with most of the observations are in fact zero. This is the result from the very low volumes of credit generated by the exact credit assumption mechanism. Since the size of the loan received by a household is small it is, consequently, very easy to service.

Apart from the credit assumption's mechanism effect on the underlying relationship between income inequality and the variables under study, it is examined its ability to replicate observed patterns. Similarly to the validation exercise in Section 3.2 the simulation is executed 100 times keeping every parameter to its baseline figures and every scenario to
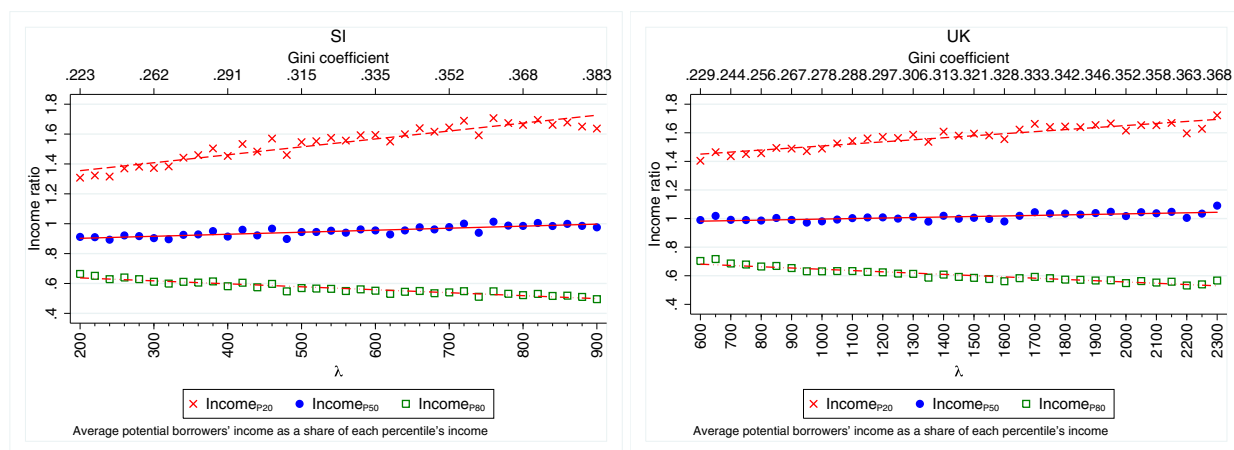
Fig. E1. Average potential borrowers' income as a share of 20th, 50th and 80th income percentiles for various initial income inequality levels.

its country-specific path. Since results for consumption are very similar to the ones obtained under the stochastic credit assumption mechanism, only those for consumer credit are presented in Fig. D2.

The top row in Fig. D2 shows the results for the rescaled series, while the bottom row shows the results in growth rates. The subplots on the left correspond to the SI-specific scenario, and the ones on the right to the UK-specific one. Clearly the match between simulated and historical data is worse compared to the case of stochastic credit assumption mechanism. As discussed previously, the exact credit assumption mechanism results in very low volumes of credit which is reflected in extremely large growth rates. Even the rescaled series exhibit a poor fit not only in terms of size, but also in the dynamics.Therefore, it can be considered that the stochastic credit assumption mechanism can approximate households' behavior in a more satisfactory way than the alternative.

Appendix E. Who is holding consumer credit

An interesting feature of the agent-based modelling approach is that it allows monitoring and collecting data at the individual agent level. This can be very useful to clarify the workings of the rules applied and the interactions among agents. An interesting question both from a modelling and an economic policy point of view is to examine which income class more commonly holds consumer credit in the model.

In order to analyze borrowers' income is performed an experiment similar to the one described in Section 3.4.1 with the only difference being in the collected data from the simulation. Thus, the model is ran with all of its parameters and input series set to their baseline values, apart from the initial level of income inequality which is varied between approximately 22 % to 38 % for the SI- and UK-specific scenarios. For every initial income inequality level the simulation is executed 100 times and the ratios of $\frac{\bar{I}_t^B}{I_t^{P20}}$, $\frac{\bar{I}_t^B}{I_t^{P50}}$ and $\frac{\bar{I}_t^B}{I_t^{P80}}$ are collected. Here, $\bar{I}_t^B$ is the average income of households asking for credit at time t, whereas I_t^{P20}, I_t^{P50} and I_t^{P80} denote the 20th percentile, the median and the 80th percentile of income's distribution at time t. The average over the whole simulation and over all runs is presented in Fig. E1

As can be seen in Fig. E1, the average income of credit demanding households is very close to the median of income's distribution and always far from the bottom as well as the top 20th percentiles. Interestingly, a recent analysis conducted by the Bank of England and the Financial Conduct Authority[31] shows that households with average/above average credit scores hold the majority of consumer credit in Britain. Therefore, assuming that income is positively associated with credit score, the stylized fact captured by the model is in line with the findings of the aforementioned analysis.

Appendix F. A robustness check on the role of expectations on the evolution of credit

In Section 3.3 is examined the effect of the expectations heuristic on the evolution of credit under the baseline scenario. As a robustness check, the same analysis is carried out with the exception of DSTI which is kept fixed at 100% over the whole simulation. This large value is chosen in order to enable the bank to accommodate practically any credit request, even if the associated monthly payment equals the borrower's income. In that manner, any effects arising from constraints related to credit supply will be minimized. In Fig. F1 are shown the results of credit's evolution.

The results for consumer credit in Fig. F1 exhibit a similar pattern to that shown in the case with evolving DSTI, albeit at higher levels. This is an expected outcome due to the more relaxed credit supply compared to the baseline case where

---

[31] https://www.fca.org.uk/insight/whos-driving-consumer-credit-growth [accessed: February 2019].
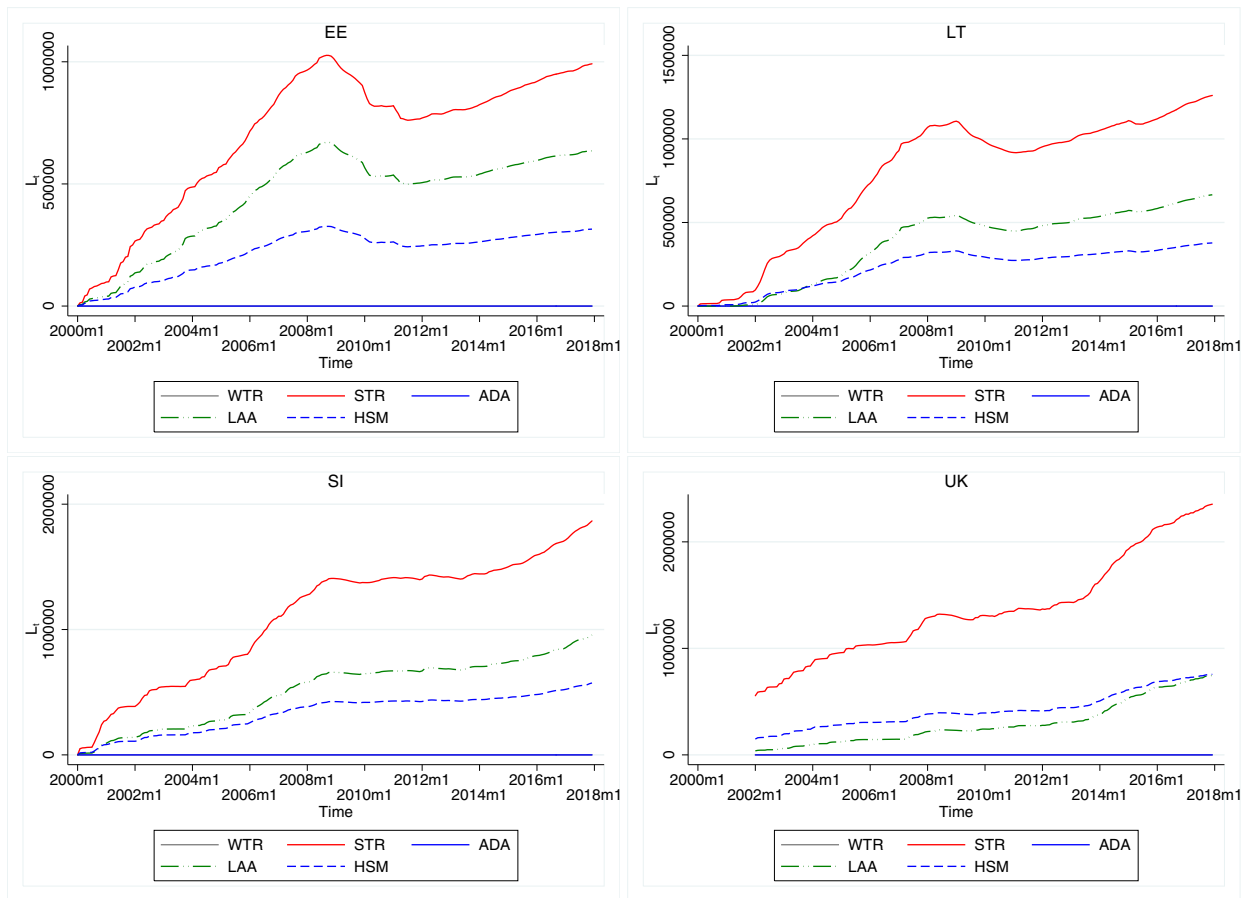
Fig. F1. Outstanding credit evolution for different expectations heuristics. DSTI is kept fixed at 100% throughout the simulation.

maximum DSTI during the simulation is about 60%. Moreover, the same heuristics (ADA, WTR) which did not lead in any credit growth in Section 3.3 show the same behaviour in this case as well. In Fig. F2 are presented the results for NPLs.

In Fig. F2 the evolution non-performing loans under the fixed DSTI scenario is comparable to the evolving-DSTI one both in evolution and in levels. This result is expected since in both cases they are expressed as a share of total loans. Consequently, as the increase in the volume of consumer credit is followed by an increase in non-performing loans their ratio remains unchanged. Overall, the robustness check corroborates the findings discussed in Section 3.3.
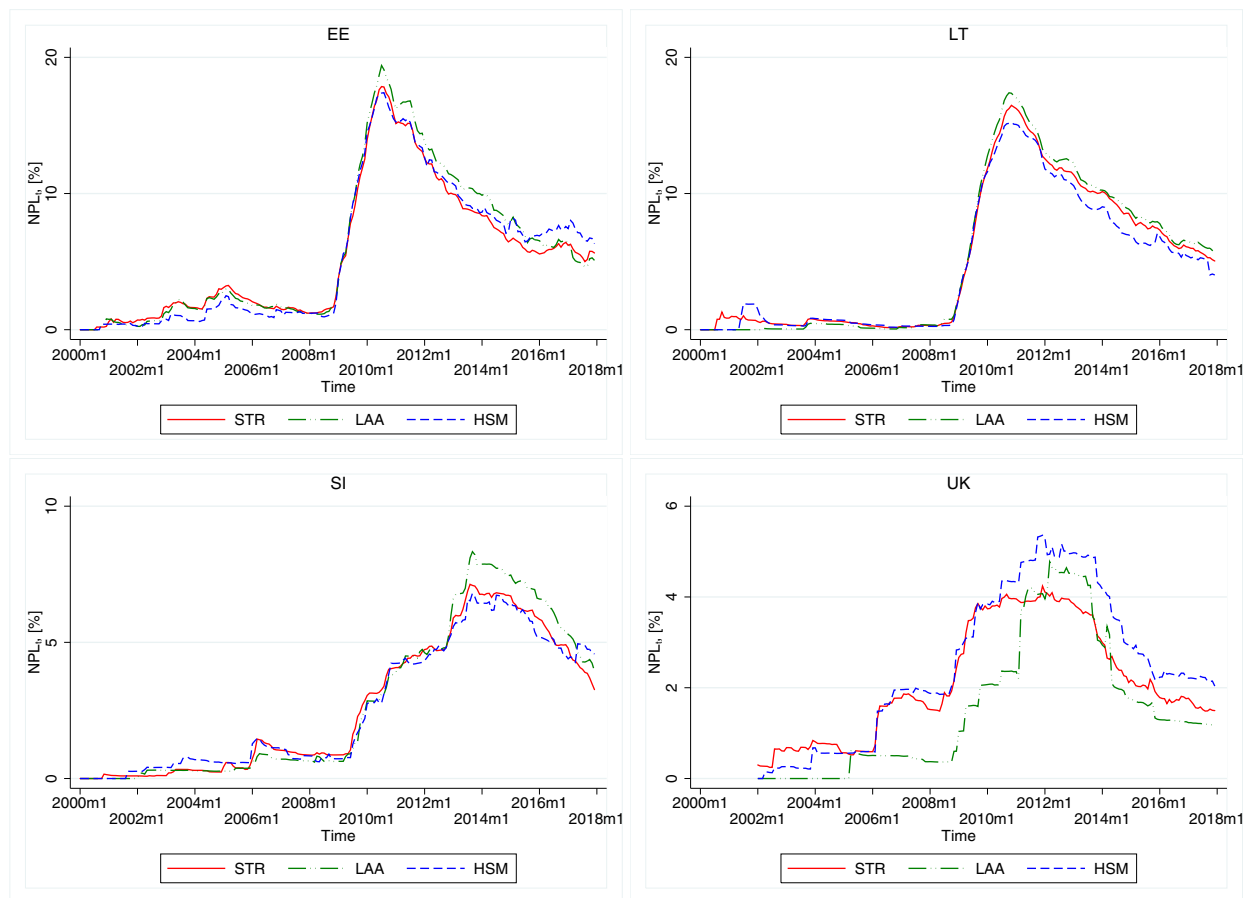
Fig. F2. Non-performing loans (≥ 180 days past due) ratio evolution for different expectations heuristics. DSTI is kept fixed at 100% throughout the simulation.

References

Allen, T.W., Carroll, C.D., 2001. Individual learning about consumption. Macroecon. Dyn. 5 (02), 255–271.

Amaral, P., 2017. Monetary policy and inequality. In: Federal Reserve Bank of Cleveland Economic Commentary 2017-01.

Ampudia, M., Georgarakos, D., Slacalek, J., Tristani, O., Vermeulen, P., Violante, G., 2018. Monetary Policy and Household Inequality. ECB Working Paper, No. 2170.

Anufriev, M., Hommes, C., 2018a. Evolution of market heuristics. Knowl. Eng. Rev. 27 (2), 255–271.

Anufriev, M., Hommes, C., 2018b. Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments. Am. Econ. J. 4 (4), 35–64.

Assenza, T., Delli Gatti, D., Grazzini, J., 2015. Emergent dynamics of a macroeconomic agent based model with capital and credit. J. Econ. Dyn. Control 50, 5–28.

Assenza, T., Heemeijer, P., Hommes, C.H., Massaro, D., 2011. Individual Expectations and Aggregate Macro Behavior. De Nederlandsche Bank Working Paper No. 298.

Atkinson, A.B., Morelli, S., 2011. Economic Crises and Inequality. Human Development Report Office (HDRO), No. HDRP 2011-06.

Bandourian, R., McDonald, J., Turley, R., 2002. A Comparison of Parametric Models of Income Distribution Across Countries and Over Time. LIS Working Paper Series, No. 305.

Bank of Slovenia, 2013. Annual Report. Technical Report. Bank of Slovenia.

Bank of Slovenia, 2016. Economic and Financial Developments, October. Technical Report. Bank of Slovenia.

Basu, N., Pryor, R., Quint, T., 1998. Aspen: a microsimulation model of the economy. Comput. Econ. 12 (3), 223–241.

Bazillier, R., Héricourt, J., 2014. The Circular Relationship Between Inequality, Leverage, and Financial Crises: Intertwined Mechanisms and Competing Evidence, 1. Document de travail du CEPII.

Bazillier, R., Héricourt, J., 2017. The circular relationship between inequality, leverage, and financial crises. J. Econ. Surv. 31 (2), 463–496.

Bordo, M.D., Meissner, C.M., 2012. Does inequality lead to a financial crisis? J. Int. Money Finance 31 (8), 2147–2161.

Branch, W.A., 2004. The theory of rationally heterogeneous expectations: Evidence from survey data on inflation expectations. Econ. J. 114 (497), 592–621.

Brock, W.A., Hommes, C.H., 1997. A rational route to randomness. Econometrica 1059–1095.

Brock, W.A., Hommes, C.H., 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model. J. Econ. Dyn. Control 22 (8–9), 1235–1274.

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., Stiglitz, J.E., 2016. Agent based-stock flow consistent macroeconomics: towards a benchmark model. J. Econ. Dyn. Control 69, 375–408.

Caiani, A., Russo, A., Gallegati, M., 2017. Does inequality hamper innovation and growth? An AB-SFC analysis. J. Evol. Econ. 1–52.

Cardaci, A., 2018. Inequality, household debt and financial instability: an agent-based perspective. J. Econ. Behav. Organ. 149, 434–458.

Cardaci, A., Saraceno, F., 2015. Inequality, financialisation and economic crisis: an agent-based model. Observatoire Francais des Conjonctures Economiques (OFCE).

Christen, M., Morgan, R.M., 2005. Keeping up with the Joneses: analyzing the effect of income inequality on consumer borrowing. Quant. Market. Econ. 3 (2), 145–173.

Christopoulos, D., McAdam, P., 2017a. Do financial reforms help stabilize inequality? J. Int. Money Finance 70, 45–61.

Christopoulos, D., McAdam, P., 2017b. On the persistence of cross-country inequality measures. J. Money Credit Bank. 49, 255–266. doi:10.1111/jmcb.12374.

Coibion, O., Gorodnichenko, Y., Kudlyak, M., Mondragon, J., 2014. Does Greater Inequality Lead to More Household Borrowing? New Evidence from Household Data. Technical Report. National Bureau of Economic Research (No. w19850).

Colciago, A., Samarina, A., de Haan, J., 2018. Central Bank Policies and Income and Wealth Inequality: A Survey. De Nederlandsche Bank Working Paper No. 594.

Dawid, H., Delli Gatti, D., 2018. Agent-based macroeconomics. Handbook of Computational Economics, vol. 4, pp. 63–156.

De Grauwe, P., Macchiarelli, C., 2015. Animal spirits and credit cycles. J. Econ. Dyn. Control 59, 95–117.

Delli Gatti, D., Desiderio, S., 2015. Monetary policy experiments in an agent-based model with financial frictions. J. Econ. Interact. Coord. 10 (2), 265–286.

Delli Gatti, D., Desiderio, S., Gaffeo, E., Cirillo, P., Gallegati, M., 2011. Macroeconomics From the Bottom-Up, vol. 1. Springer Science & Business Media.

Diks, C., Van Der Weide, R., 2005. Herding, a-synchronous updating and heterogeneity in memory in a CBS. J. Econ. Dyn. Control 29 (4), 741–763.

Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., 2013. Income distribution, credit and fiscal policies in an agent-based Keynesian model. J. Econ. Dyn. Control 37 (8), 1598–1625.

Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., Treibich, T., 2015. Fiscal and monetary policies in complex evolving economies. J. Econ. Dyn. Control 52, 166–189.

Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J.E., Treibich, T., 2017. Rational Heuristics? Expectations and Behaviors in Evolving Economies with Heterogeneous Interacting Agents. LEM Working Paper Series 2017/31, Sant'Anna School of Advanced Studies.

Dosi, G., Pereira, M.C., Roventini, A., Virgillito, M.E., 2016. The effects of labour market reforms upon unemployment and income inequalities: an agent-based model. Socio-Econ. Rev.

Drehmann, M., Illes, A., Juselius, M., Santos, M., 2015. How much income is used for debt payments? A new database for debt service ratios. BIS Quart. Rev. 89.

Duesenberry, J.S., 1967. Income, Saving, and the Theory of Consumer Behavior, vol. 180. Oxford University Press.

European Systemic Risk Board, 2018. A Review of Macroprudential Policy in the EU in 2017. Technical Report. European Systemic Risk Board.

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A., Roventini, A., 2017. Validation of Agent-Based Models in Economics and Finance. LEM Working Paper Series.

Fagiolo, G., Moneta, A., Windrum, P., 2007. A critical guide to empirical validation of agent-based models in economics: methodologies, procedures, and open problems. Comput. Econ. 30 (3), 195–226.

Fagiolo, G., Roventini, A., 2017. Macroeconomic policy in dSGE and agent-based models redux: new developments and challenges ahead. J. Artif. Soc. Social Simul. 20 (1).

Figari, F., Paulus, A., Sutherland, H., 2015. Microsimulation and policy analysis. In: Handbook of Income Distribution, vol. 2. Elsevier, pp. 2141–2221.

Frank, R.H., Levine, A.S., Dijk, O., 2014. Expenditure cascades. Rev. Behav. Econ. 1 (1–2), 55–73.

Franke, R., Westerhoff, F., 2017. Taking stock: a rigorous modelling of animal spirits in macroeconomics. J. Econ. Surv. 31 (5), 1152–1182.

Geanakoplos, J., Axtell, R., Farmer, D.J., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Palmer, N.M., Yang, C.-Y., 2012. Getting at systemic risk via an agent-based model of the housing market. Am. Econ. Rev. 102 (3), 53–58. doi:10.1257/aer.102.3.53.

Godley, W., Lavoie, M., 2016. Monetary Economics: An Integrated Approach to Credit, Money, Income, Production and Wealth. Springer.

Gualdi, S., Tarzia, M., Zamponi, F., Bouchaud, J.-P., 2015. Tipping points in macroeconomic agent-based models. J. Econ. Dyn. Control 50, 29–61.

Gurgone, A., Iori, G., Jafarey, S., 2018. The effects of interbank networks on efficiency and stability in a macroeconomic agent-based model. J. Econ. Dyn. Control.

Haldane, A.G., Turrell, A.E., 2018. Drawing on different disciplines: Macroeconomic agent-based models. J. Evol. Econ. 1–28.

Hamill, L., Gilbert, N., 2015. Agent-Based Modelling in Economics. John Wiley & Sons.

Haruvy, E., Lahav, Y., Noussair, C.N., 2007. Traders' expectations in asset markets: experimental evidence. Am. Econ. Rev. 97 (5), 1901–1920.

Hassan, S., Pavón, J., Antunes, L., Gilbert, N., 2010. Injecting data into agent-based simulation. In: Simulating Interacting Agents and Social Phenomena. Springer, pp. 177–191.

Hommes, C., Huang, H., Wang, D., 2005. A robust rational route to randomness in a simple asset pricing model. J. Econ. Dyn. Control 29 (6), 1043–1072.

Hommes, C., Sonnemans, J., Tuinstra, J., van de Velden, H., 2004. Coordination of expectations in asset pricing experiments. Rev. Financ. Stud. 18 (3), 955–980.

Hommes, C., Sonnemans, J., Tuinstra, J., van de Velden, H., 2008. Expectations and bubbles in asset pricing experiments. J. Econ. Behav. Organ. 67 (1), 116–133.

Iacoviello, M., 2008. Household debt and income inequality, 1963–2003. J. Money Credit Bank. 40 (5), 929–965.

Jordà, Ò., Schularick, M., Taylor, A.M., 2015. Betting the house. J. Int. Econ. 96, S2–S18.

Kumhof, M., Rancière, R., Winant, P., 2015. Inequality, leverage, and crises. Am. Econ. Rev. 105 (3), 1217–1245.

Mankiw, N.G., Reis, R., Wolfers, J., 2003. Disagreement about inflation expectations. NBER Macroecon. Ann. 18, 209–248.

Meijers, H., Nomaler, Ö., Verspagen, B., 2018. Demand, credit and macroeconomic dynamics. A micro simulation model. J. Evol. Econ. 1–28.

Modigliani, F., Brumberg, R., 1954. Utility analysis and the consumption function: an interpretation of cross-section data. Franco Modigliani 1, 388–436.

Palagi, E., Napoletano, M., Roventini, A., Gaffard, J.-L., 2017. Inequality, redistributive policies and multiplier dynamics in an agent-based model with credit rationing. Ital. Econ. J. 3 (3), 367–387.

Perugini, C., Hölscher, J., Collie, S., 2015. Inequality, credit and financial crises. Camb. J. Econ. 40 (1), 227–257.

Pfajfar, D., Santoro, E., 2010. Heterogeneity learning and information stickiness in inflation expectations. J. Econ. Behav. Organ. 75 (3), 426–444.

Pfajfar, D., Žakelj, B., 2016. Inflation expectations and monetary policy design: evidence from the laboratory. Macroecon. Dyn. 22 (04), 1035–1075.

Piketty, T., Saez, E., 2003. Income inequality in the United States, 1913–1998. Quart. J. Econ. 118 (1), 1–41.

Piketty, T., Saez, E., 2006. The evolution of top incomes: a historical and international perspective. Am. Econ. Rev. 96 (2), 200–205.

Riccetti, L., Russo, A., Gallegati, M., 2013. Unemployment benefits and financial leverage in an agent based macroeconomic model. Economics 7 (2013-42), 1–44.

Riccetti, L., Russo, A., Gallegati, M., 2015. An agent based decentralized matching macroeconomic model. J. Econ. Interact. Coord. 10 (2), 305–332.

Russo, A., Riccetti, L., Gallegati, M., 2016. Increasing inequality, consumer credit and financial fragility in an agent based macroeconomic model. J. Evol. Econ. 26 (1), 25–47.

Stonedahl, F., Rand, W., 2014. When does simulated data match real data? In: Advances in Computational Social Science. Springer, pp. 297–313.