

# Employment and income distribution turbulence due to Artificial Intelligence: a stock-flow consistent model approach

Lida Vrisiida Vandorou

National and Kapodistrian University of Athens, PhD Candidate

## **Abstract**

Technological advancements through Machine Learning (ML) and Artificial Intelligent (AI) have been accelerated in the last two decades. While it is difficult to make precise predictions regarding employment and wages in the future there is a growing literature that attempts theoretical and empirical to make estimations regarding the trends of the labor demand under the new technologies. In this paper we will attempt using of a Stock Flow Consistent (SFC) model to evaluate the consequences of the new technologies in the economy and specifically in the income distributions. SFC modeling could describe the functions of a complete macroeconomic system and could be ideal to make predictions regarding the effects of new technologies. In order to consider the dynamics of income inequality through different positions in the labour market we will distinguished the households into categories: manual routine , manual non-routine , cognitive routine , cognitive non-routine and also households of entrepreneurs. The differentiation of the workers allows examining the changes in income distribution during the transformation of the production process.

# 1 Introduction

Technological advancements through Machine Learning (ML) and Artificial Intelligent (AI) have been accelerated in the last two decades. These developments have concerned scientists regarding the future of work. While it is difficult to make precise predictions regarding employment and wages in the future there is a growing literature that attempts theoretical and empirical to make estimations regarding the trends of the labor demand under the new technologies.

In this paper we will attempt with a use of a Stock Flow Consistent (SFC) model to evaluate the consequences of the new technologies in the economy and specifically in the income distributions. SFC modeling could describe the functions of a complete macroeconomic system and could be ideal to make predictions regarding the effects of new technologies. However, there are only few attempts that have researched the effects of new technology on the economy. Caiani et al. (2012) constructed two SFM, one that is based on the Schumpeterian description of the business cycles through technological change and another that describes a multi-sectoral economy that analyzes the dynamics of the economy through the rise of innovations with a focus n financial innovations. Also, Kinsella et al. (2010) construct a SFC model that takes into account from one point the education and the ability of households and from the other the investment and innovation of firms. Moreover, Dafermos and Papatheodorou (2015) construct a SFC model and distinguished four types of households (high-skilled employed, high-skilled unemployed, low-skilled employed, high-skilled unemployed) to linking functional with personal income distribution and to indicate income inequality.

While the previous papers modeled the effects of the technology and abilities of each worker group on the employment they did not emphasize on the new technological advances such as AI and ML and the effects that will bring an extent automatization of the work process. In this paper we will incorporate

this literature that contains different workers' categories, a dynamic process of labor demand for these categories and the release of new tasks in the production process.

We will proceed with a brief literature review in section 2 and then in section 3 we will present the model. In section 4 we will present our next steps of experiments. In section 5 we will conclude

## **2 Literature review**

### **2.1 The ALM hypothesis and its consequences**

During the '80s an extensive use of computers and technology in the work process changed not only the required task of each job but also the allocation of labor demanded jobs. Katz and Murphy (1992) explain these changes in labor market with an implementation of a canonical model of the skill-biased technical change (SBTC) in which the workers are separated into two categories: skilled and unskilled workers. SBTC explained the rising wage inequalities in the USA with the increasing demand for high skilled workers. Katz and Murphy (1992) use a simple supply and demand framework in which different groups that distinguished by sex, education and experience are considered as different labour inputs. The use of dispersion of relative wage examines that the wage changes can be explained through substantial changes in demand either within industries (changes in intensity in the factor of production within industries at fixed relative wages) or between industries (different allocation of total labor demand in industries).

Within industry changes occur because of increased non-neutral technological change in prices of non-labor inputs (use of ICT) and extensive use of outsourcing (move part of production process in another country with low

labor cost). On the other hand, the changes in demand in between industries are imposed due to changes in international trade and changes in product demand across industries. The combination of the above is, according to Katz and Murphy (1992), the main reasons for the substantial wage changes and the increase of wage inequality within and between demographical groups in the USA between 1863 and 1987. However, the SBTC hypothesis failed to explain the mechanism that drives technology to raise labor demand for skilled workers (Autor et. al 2003, Susskind 2017).

Later on, while this theoretical gap on technological impact in labour market existed, Autor et. al (2003) did consistent research regarding the effects of computer technology on the job concept and job skill demands. Since the path of knowledge and intelligence is not fully clear yet, the substitutability of workers happens in tasks that are performed with a clear order sequence and a desired end. They distinguished the tasks on the job into two pairs: routine and non-routine, manual and cognitive, then they state that the intensive computerization of work is correlated to the routine or non-routine tasks that a job description includes. This main proposition that may refer to ‘routinization’ or ‘Autor Levy Murname (ALM)’ hypothesis inspired to an extent ‘task-based’ literature.

The approach that not all the tasks could perform into a step processing base has been previously analyzed by Michael Polanyi in his remarkable book ”Tacit dimension ” (1966) with the quote “we can know more than we can tell” (p.4). The basic issue of tacit knowledge is that there are two terms of the knowledge: the ”knowing what”, propositional or factual knowledge, and “knowing how” practical knowledge (Ryle, 1945). These two terms of knowledge have a similar structure and in the process of knowledge are present together. When we refer to knowing we shall include both theoretical and practical knowledge. Moreover, knowing a certain task could elaborate if we include in the picture the use of certain tools, and certain pointing such as languages (verbal pointing).

A precise description of the difference between practical expertise and routine was given by Annas (2011). While sometimes the two aspects are thought to be identical this is misleading (Annas 2011). In the case of practical expertise, the expertise cannot decompose from the person’s ability to behave and act consciously during the process of action. Habituation in the case of routine tasks is different from the habituation of practical expertise that is a dynamic and complex process and contains intelligent and elective response (Annas, 2011). The practical expertise that the workers gain through the learning process in a working environment gives them the ability to perform non-routine tasks when this is required. These follow that, jobs that contain a considerable amount of non-routine tasks, cognitive or manually, are less likely to be automatized.

Goos and Manning (2003) went a step further using the concept that new technology has affected the routine manual and the routine cognitive workers and this has caused a phenomenon called ”job polarization” in labor market of advanced economies.

## **2.2 Extensions of ALM hypothesis**

However, since computer science is fasting developed, Polany’s statement as long as the ALM hypothesis may underestimate the tasks that the robots could perform. For example, as Susskind (2017) emphasize, Polany (1966) considered driving as a major example of tacit knowledge: “The skill of a driver cannot be replaced by a thorough schooling in the theory of the motorcar.” (pg. 20) In the same manner Autor et.al (2003) consider driving as non-routine task: “Navigating a car through city trac or deciphering the scrawled handwriting on a personal check – minor undertakings for most adults – are not routine tasks by our definition. The reason is that these tasks require visual and motor processing capabilities that cannot at present be described in terms of a set of programmable rules.” (pg. 1283). However, as we all know, the previous passages do not reflect reality since driverless cars have been pilot for some years

and through continuing, Deep Reinforcement learning may be the majority of vehicles in streets in some years (Abdur et. al. 2018).

From the above we can understand that the ALM hypothesis does not work always well and since computer science is proceeding continuous tasks that consider non-routine will be able to translate into steps and then could be considered as a non-routine task that can be automatized. The above could better summarize with the Sysskind hypothesis: “(1) that machines substitute for workers in carrying out a set of tasks and activities that are ‘routinisable’; and (2) that machines complement workers in carrying out a set of tasks that are ‘unroutinisable’. The set of tasks and activities that are routinisable changes over time.” (Sysskind 2017 p.13). The last sentence extends the traditional ALM hypothesis and made the future of labour demand less optimistic. Computers with the use of data science and machine learning could overcome a non-routine task without decomposing each and every step of the process for this task. The dynamical nature of routine and non-routine tasks will be considered for the modeling process.

One other but still quite abstract approach was given by Acemoglu and Restrepo (2018) which named the debate regarding the effect of automatization in employment and wages as ”false dichotomy” and they propose that the use of new technology create a displacement effect in the labor market that tend to reduce the labor share and the level of wages in the economy. Therefore there are four countervailing effects against this: 1) the productivity effect that raise the demand for labor on the non-automated tasks, 2) the increased capital accumulation due to the automatization will act as countervailing effect to the wages and employment that would be downscale due to the substitution, 3) deepening of automation in tasks that have already been automated will not cause reduction in employment and will enhance the productivity effect and the labor demand, 4)the most important argument that Acemoglu and Restrepo (2018) against the ”phobia” of automation is that new, labor intensive, tasks

will be created and will bring a reinstatement effect.

While they developed a quite optimistic view about new technology they put some counterforce such as, that inequality could be enlarged. Second, it is very possible to be a mismatching of "new" skills and the skills that the workers possessed. Third Acemoglu and Restrepo (2018) is expressed the fear that governments and labor institutions will hinder automation due to their fear of losing jobs. While Acemoglu and Restrepo (2018) made strong arguments with a historic perspective regarding the demand for new tasks that will arise due to automation, this is still very general and we cannot support that the demand for new tasks will be more or equal as the annulment of the old tasks.

### **2.3 Further empirical research**

The continuing advances and uses of technology, mainly robotics and artificial intelligent, in labor market have risen concern regarding the employment and wages in the near future. Moreover, researchers using different economic models come with different results. Frey and Osborne (2013) fueled the discussion with their estimates that about 47 percent of US employment is at risk due to computerization of the work process. Moreover they argue that wages and education have negative relationship with risk of job loss due to automation. However this research received extended critique because it is considered that Frey and Osborne (2013) might overestimated the tasks that automation could handle. Occupations that are labelled as high-risk occupations may contain numerous tasks that are hard to automate because are consider non-routine (Arntz et al, 2016) .In many cases, the substitution of workers with robots will not be easy due to legal and ethical obstacles (Arntz et al, 2016). Regarding the level of wages, Manning and Caselli (2019) support that the wages will not decrease due to new technology and even will increase if the prices of investment products fallen more than the prices of consumer products could increase.

### 3 The Model of stock flow: Are the skills affect inequality?

Evidence using a stock flow model

In this paper we will attempt to research the impact of automatization in the economy with the use of a stock-flow consistent model. We will extend the model of Papachristou and Dafermos (2015) in order to consider the dynamics of income inequality through different positions in the labour market. The researched economy includes households, firms and commercial banks. Following the ALM hypothesis the household is distinguished the workers into 5 categories: 1) Household headed by manual routine worker (mr): Their income consists of their wage. They do not save from their income 2) Households headed by manual non-routine worker (mnr): their income consisted of their wage. They do not save from their income. 3) Households headed by cognitive routine worker(cr): their income consists of their wage and the interest rate from their accumulated deposit. The wage is higher than the wage of manual workers, routine and non-routine. They continue to save and such as to accumulate deposits. 4) Households headed by cognitive non-routine worker(cnr): their income consisted from their wage, that is higher than the wage of cognitive routine worker and the interest rate from their past accumulation 5) Households headed by entrepreneurs(e): their income come from the profits obtained from their business as long as from the interest that receive from their accumulated deposits. They continue to save and accumulate deposits. The differentiation of the workers allow examining the changes in income distribution during the transformation of production process because of automatization. Moreover extending the model for lots of time period we can follow the Susskind hypothesis and transfer workers from non-routine categories to routine. We will make several scenarios to show the effects of the creation of new tasks through time periods, the “reinstatement effect” (Acemoglu and Restrepo, 2018).

### 3.1 Households of manual routine workers

$$Y_{mr} = w_{mr} * N_{mr}(1)$$

$$C_{mr} = Y_{mr}(2)$$

$$YH_{mr} = Y_{mr}/N_{mr}(3)$$

Equation (1) shows the disposable income of manual routine employed workers and equals their wage ( $w_{mr}$ ) times the number of the manual routine workers. Equation (2) shows the consumption of the manual workers that is equal to their disposable income. Equation (3) is equal to the income per household of manual routine workers.

### 3.2 Households of manual non routine workers

$$Y_{mnr} = w_{mnr} * N_{mnr}(4)$$

$$C_{mnr} = Y_{mnr}(5)$$

$$YH_{mnr} = Y_{mnr}/N_{mnr}(6)$$

The disposable income of one household of manual non-routine workers (equation 4) is equal to the wage of manual non-routine times the number of the manual non routine workers. The consumption of the manual non-routine workers is equal to their disposable income because a state before the manual workers does not save. Moreover equation (6) shows the disposal income per household.

### 3.3 Household of cognitive routine workers

$$Y_{cr} = w_{cr} * N_{cr} + rd * M_{cr-1}(7)$$

$$Ccr = Ncr * (ccr_1 * YHcr_{-1} + ccr_2 * Mcr_{-1}/Ncr_{-1})(8)$$

$$Mcr = Ycr - Ccr + Mcr_{-1}(9)$$

$$YHcr = Ycr/Ncr(10)$$

Equation (7) shows the income of cognitive routine workers and equation (8) shows their consumption while equation (9) shows their deposits. Equation (10) shows the disposal income of each household.

### 3.4 Households of cognitive non routine workers

$$Ycnr = wcnr * Ncnr + rd * Mcnr_{-1}(11)$$

$$Ccnr = Ncnr * (ccr_1 * YHcnr_{-1} + ccr_2 * Mcnr_{-1}/Ncnr_{-1})(12)$$

$$Mcnr = Ycnr - Ccnr + Mcnr_{-1}(13)$$

$$YHcnr = Ycnr/Ncnr(14)$$

Equation (11) shows the income of cognitive non routine workers while equation (12) shows their consumption. Equation (13) shows their deposits and equation (14) the income per household of cognitive non routine workers.

### 3.5 Household of entrepreneurs

$$Ye = DP + BP + rm * Me_{-1}(15)$$

$$Ce = ce_1 * Ye_{-1} + ce_2 * Ve_{-1}(16)$$

$$Ve = Ye - Ce + Ve_{-1}(17)$$

$$Me = Ve(18)$$

$$YHe = Ye/Ne(19)$$

Equation (15) shows the income of entrepreneurs that consist of distributed profits, bank profits and the gains from their deposits. The consumption function of entrepreneurs is shown in equation (16), while in equation (17). Since we do not have include equity market in the model the wealth of entrepreneurs is equal with their deposits equation (18). Equation (19) shows the income per household of entrepreneurs.

### 3.6 Firms

$$Y = C + I(20)$$

$$C = Cmr + Cmnr + Ccr + Ccnr + Ce(21)$$

$$W = wmr * Nmr + wmnr * Nmnr + wcr * Ncr + wcnr * Ncnr(22)$$

$$TP = Y - W - rl * L_{-1}(23)$$

$$RP = sf * TP(24)$$

$$DP = TP - RP(25)$$

$$lmr = lmr[-1] * (1 + gmr)(26)$$

$$lmnr = lmnr_{-1} * (1 + gmnr)(27)$$

$$lcr = lcr_{-1} * (1 + gcr)(28)$$

$$lcnr = lcnr_{-1} * (1 + gnr)(29)$$

$$Ystar = v * K(30)$$

$$u = Y/Ystar(31)$$

$$wmr = smr * lmr(32)$$

$$wmnr = smr * lmnr(33)$$

$$smr = wo(34)$$

$$wcr = wmr + smr * lmr(35)$$

$$wcnr = wmnr + smr * lmnr(36)$$

$$I = grk * K_{-1}(37)$$

$$K = I + K_{-1}(38)$$

$$L = I - RP + L_{-1}(39)$$

Equation (20) shows the total output, equation (21) shows the total consumption and equation (22) the wage count. Equation (23) the Total profits of the firms and equation (24) the retained profits while equation (25) the distributed profits. Equations (26), (27), (28),(29) describe the productivity rate for each group (l<sub>mr</sub>, l<sub>mnr</sub>, l<sub>cr</sub>, l<sub>cnr</sub>) that grows for an exogenous rate that its different for each group g<sub>mr</sub>, g<sub>mnr</sub>, g<sub>cr</sub>, g<sub>cnr</sub> respectively. Equation (30) show the full-capacity output while equation (31) show the rate of capacity utilization. Another part of interest in this model is the determination of the wage for each category of worker. The wage of manual routine workers (equation 32 and 33) is determined as a proportion of manual routine workers' productivity, this proportion denoted with *smr* (Equation 34), and is exogenous determines. The wage determination of cognitive non-routine workers that presenting here is not constant with the perception of the compensation of high skills workers as a wage rate plus a part of the profits that are described in the baseline model (Dafermos and Papatheodorou 2015). This baseline model is anchored in the paper of nglander and Kaufman(2004) and Bebhuk and Grinstein( 2005) which shows that the managers are mainly taking premium compensation from the expansion of the firm even if this is suboptimal for the profits. However, no all the cognitive non-routine workers refer to managers. For this reason, we will not consider the part that considers the wage of cognitive non-routine workers as a wage base plus a premium from profits , rather we will consider that the wage of cognitive workers have a premium from the manual workers plus a correspondence to their productivity. Equation (37) shows the investment of the firms while (38) is the capital equation. Equation (39) shows the loans that the firm receive.

### 3.7 Commercial Banks

$$BP = rl * L_{-1} - rm * M_{-1}(40)$$

$$M = M_{cr} + M_{cnr} + M_e(41)$$

$$rl = spr + rm(42)$$

We have keep the bank system quite simple in this model. Equation (40) shows the bank profits and equation (41) shows the deposits of the banks, while equation (42) define the interest rate of loans and is equal with the interest rate on deposits plus a fixed spread.

### 3.8 Number of workers for each category

$$N_{mr} = Y/lmr(43)$$

$$N_{mnr} = Y/lmnr(44)$$

$$N_{cr} = Y_{star}/lcr(45)$$

$$N_{cnr} = Y_{star}/lcnr(46)$$

The number of workers in each category is depend on the demand for the labour force with the specific characteristics that each category have. This is depend with the productivity of each category.

## 4 Data and Simulation

In order to simulate the model we have first to find the exogenous variable that correspond for each household's category. For this reason we follow the distinction of Autor and Dorn (2013) through the databases that have thoroughly

uploaded. The database follows the OCC1990 and categorize each occupation for three characteristics of the occupations: abstract, routine and manual task content. We use the routine and manual content and we named "manual routine" if an occupation is more than the average manual and routine "manual non-routine" if it is more than the average manual and less than the average routine, "cognitive routine" if it is less than the average manual and more than the average routine, "cognitive non-routine" if it is less than the average manual and less than the average routine. With the use of IPUMS-USA microdata from 2000 to 2020 we found the number of workers that belong to each category and the corresponding wage share and we use that for the calibration of the model. The initial idea was to include also the unemployment workers in the model following (Dafermos and Papatheodorou, 2015), however there were difficulties to calibrate the model due to the singularity of the matrix, for this reason we have to follow a much more simple approach. However we still keep the idea that the workers with cognitive occupations could have deposits while the manual workers not. We run the model for 100 periods in order to calibrate it. The time frame is fictitious, hat is usual or these type of models Godley and Lavoie (2007), Dafermos and Papatheodorou (2015). The package of R, sfer has solved the models numerically and found a set of the steady state parameter values.

#### **4.1 Does the technology affect income distribution ?**

In this sections we impose a shock to the baseline model to the productivity of each workers' category that simulate the effects of AI technology to the labour demand. With this methodology we attempt to estimate the effect that will have the stimulation of Machine Learning and Artificial Intelligence in the production process. Since in our baseline model we have tight the productivity with both the wage rate and the employed workers of each category the effect will be apparent. We impose a positive shock to the productivity of cognitive and manual non routine workers from the year 50 to 100. Then we evaluate the comparative

results on the income per household of the other two categories: manual routine and cognitive routine that their productivity remains unchanged. As we can see in Figure 1 the comparative income of routine workers is falling in comparison with the income of cognitive non routine workers.

Figure 1 insert here

In the next figures we show the evolution of disposable income and household consumption of each workers category

Figure 2 insert here

Figure 3 insert here

Figure 4 insert here

Figure 5 insert here

From these figures we can point first that there is a substantial positive effect to the disposable income and consumption of all the categories. This is happening because we have a substantial increase to productivity of the biggest part of the workers. Also before the increase of productivity the consumption of manual workers was negative and this correspond first to the absent of unemployment and second to the absent of dept to the households.

## 5 Conclusion and Remarks

With this preliminary model we show that since the productivity of the biggest part of the workers is increased this fact could be positive for all the categories of the workers. However it is undeniable that the income of routine workers is growing less than those of non routine workers. There are some key addition that should be done to this model in order to study the effects of Universal Base Income and minimum wage to the situation of the technology in the labour

market. First the insert of unemployment in all the categories. Second the insert of loans and debts to the households. Third the ability of the workers to change category through the education that will be correspond to some student loans.

## 6 References

Abdul, A., Vermeulen, J., Wang, D., Lim, B. Y., Kankanhalli, M. (2018, April). Trends and trajectories for explainable, accountable and intelligible systems: An CHI research agenda. In Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-18).

Acemoglu, D., Restrepo, P. (2018). Artificial intelligence, automation and work (No. w24196). National Bureau of Economic Research.

Annas, J. (2011). Practical expertise. Knowing how: Essays on knowledge, mind, and action, 101-112.

Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris.

Autor, D. H., Levy, F., Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly journal of economics, 118(4), 1279-1333.

Bebchuk, L., Grinstein, Y. (2005). The growth of executive pay. Oxford review of economic policy, 21(2), 283-303.

Caiani, Alessandro; Godin, Antoine; Lucarelli, Stefano (2012) : Schumpeter in a matrix: a Stock Flow Consistent analysis of technological change, Quaderni di Dipartimento, No. 175, Università degli Studi di Pavia, Diparti-

mento di Economia Politica e Metodi Quantitativi (EPMQ), Pavia

Caselli, F., Manning, A. (2019). Robot arithmetic: new technology and wages. *American Economic Review: Insights*, 1(1), 1-12.

Dafermos, Y., Papatheodorou, C. (2015). Linking functional with personal income distribution: a stock-flow consistent approach. *International Review of Applied Economics*, 29(6), 787-815.

Englander, E., Kaufman, A. (2004). The end of managerial ideology: From corporate social responsibility to corporate social indifference. *Enterprise Society*, 404-450.

Frey, C. B., Osborne, M. (2013). The Future of Employment. Working Paper Oxford Martin Programme on Technology and Employment. Oxford Martin School. University of Oxford

Goos, M., Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics*, 89(1), 118-133.

Katz, L. F., Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, 107(1), 35-78.

Kinsella, S., Greiff, M., Nell, E. J. (2011). Income distribution in a stock-flow consistent model with education and technological change. *Eastern Economic Journal*, 37(1), 134-149.

Polanyi, M. (2009). *The tacit dimension*. University of Chicago press.

Ryle, G. (1945, January). Knowing how and knowing that: The presidential address. In *Proceedings of the Aristotelian society* (Vol. 46, pp. 1-16). Aristotelian Society, Wiley.

Susskind, D. (2017). Re-Thinking the Capabilities of Machines in Economics. Department of Economics Discussion Paper Series, Oxford: University of Oxford.

## 7 Appendix A

### 7.1 Exogenous and values

$$rd = 0.021$$

$$ce1 = 0.6$$

$$ce2 = 0.04$$

$$v = 0.125$$

$$ccr1 = 0.8$$

$$ccr2 = 0.08$$

$$lo = 0.56$$

$$la = 0.4$$

$$lb = 0.05$$

$$lc = 0.08$$

$$grk = 0.17$$

$$sf = 0.36$$

$$spr = 0.05$$

$$gmr = .01$$

$$gmr = 0.03$$

$$gcr = 0.04$$

$$gnr = 0.05$$

$$wo = 0.24$$

$$N = 1000000$$

$$Ne = 50000$$

$$rm = 0.01$$

$$Ymr = 30000000$$

$$Ymnr = 35000000$$

$$Ycr = 45000000$$

$$Ycnr = 60000000$$

$$Ye = 90000000$$

$$I = 30000000$$

$$lmr = 35000$$

$$lmnr = 40000$$

$$lcr = 50000$$

$$lcnr = 70000$$

$$Ncnr = 300000$$

$$Ncr = 200000$$

$$Nmnr = 200000$$

$$Nmr = 100000$$

## Figures and Tables

Table 1. Balance Matrix

	Households of				Firms	Commercial banks	Total
	Manual routine workers	Manual nonroutine workers	Cognitive routine workers	Cognitive nonroutine workers	Entrepren. -capital owners		
Deposit			+M <sub>cr</sub>	+M <sub>cnr</sub>	+M <sub>E</sub>	-M	0
Loans						+L	0
Capital						+K	+K
Total (net worth)	0	0	+M <sub>cr</sub>	+M <sub>cnr</sub>	+V <sub>E</sub>	+V <sub>F</sub>	+K

Table 2. Transition Matrix

	Households of Manual routine employed workers	Households of manual nonroutine employed workers	Households of cognitive routine employed workers	Households of cognitive nonroutine employed workers	Entrepreneurs	Firms current	Firms capital	Commercial Banks Current	Commercial Banks Capital	$\Sigma$
Consumption	-C <sub>mr</sub>	-C <sub>mnr</sub>	-C <sub>cr</sub>	-C <sub>cnr</sub>	-C <sub>e</sub>	+C				0
Investment						+I	-I			0
Wages	+w <sub>mr</sub> · N <sub>mr</sub>	+w <sub>mnr</sub> · N <sub>mnr</sub>	+w <sub>cr</sub> · N <sub>cr</sub>	+w <sub>cnr</sub> · N <sub>cnr</sub>		-W				0
Firms' Profits					+DP	-TP	+RP			0
Commercial banks profits					+BP			-BP		0
Interest on deposits			+r <sub>m</sub> · (M <sub>cr-1</sub> )	+r <sub>m</sub> · (M <sub>cnr-1</sub> )	+r <sub>m</sub> · M <sub>e-1</sub>			-r <sub>m</sub> · (M <sub>-1</sub> )		0
Interest on loans						-r <sub>l</sub> · L <sub>-1</sub>		+r <sub>l</sub> · L <sub>-1</sub>		0
Ddeposits			-(DM <sub>cr</sub> )	-(DM <sub>cnr</sub> )	-(DM <sub>e</sub> )					+(DM) 0
Dloans								+(DL)	-(DL)	0

Figure 1.

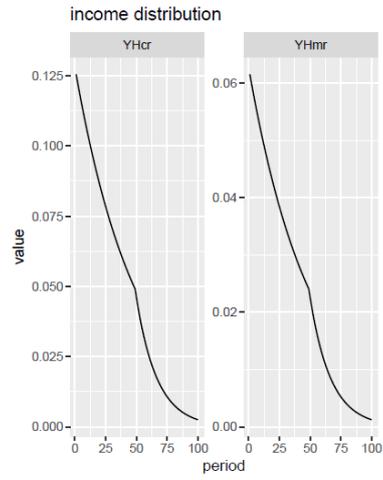


Figure 2.

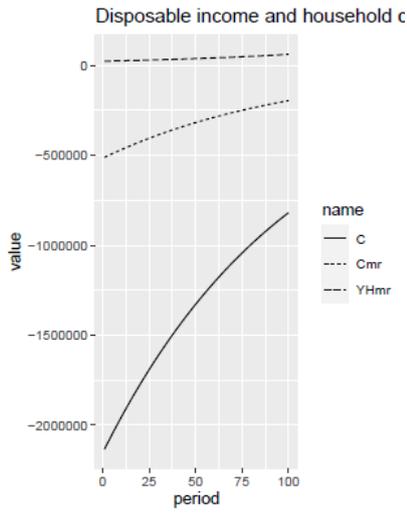


Figure 3.

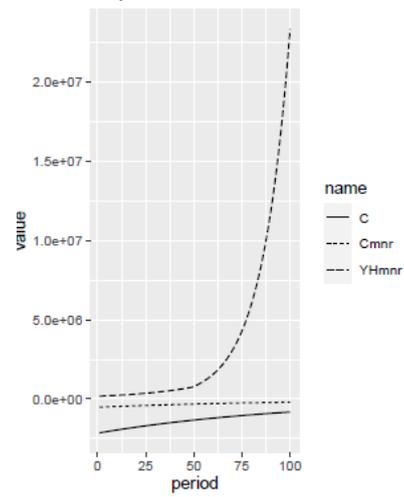


Figure 4.

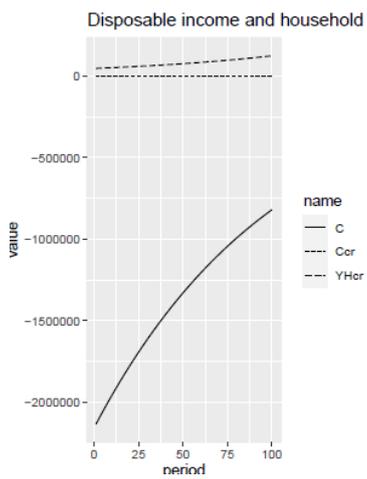


Figure 5.

