IWH Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers

No. 28
November 2022

Automation with Heterogeneous Agents: The Effect on Consumption Inequality

Tommaso Santini

Author

Tommaso Santini
Halle Institute for Economic Research – Member of the Leibniz Association, Department of Structural Change and Productivity
E-mail: tommaso.santini@iwh-halle.de
Tel +49 345 7753 784

Editor

Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Automation with Heterogeneous Agents: The Effect on Consumption Inequality*

Abstract

This version: November 3, 2022
Click here for the latest version.

In this paper, I study technological change as a candidate for the observed increase in consumption inequality in the United States. I build an incomplete market model with educational choice combined with a task-based model on the production side. I consider two channels through which technology affects inequality: the skill that an agent can supply in the labor market and the level of capital she owns. In a quantitative analysis, I show that (i) the model replicates the increase in consumption inequality between 1981 and 2008 in the US (ii) educational choice and the return to wealth are quantitatively important in explaining the increase in consumption inequality.

Keywords: automation, factor shares, inequality, productivity, tasks, technological change

JEL classification: D63, J23, J24, O14, O31, O33

* I thank Javier Fernandez-Blanco, Jordi Caballé, Árpád Ábrahám, Christopher Bush, Alexander Ludwig, Philipp Kircher, Francesc Obiols-Homs, Luis Rojas, Alessandro Ruggeri, Raul Santaeulalia-Llopis and Eugenia Vella. Website: www.santinit.com.

1 Introduction

Since the beginning of the eighties, consumption inequality in the United States has risen.[1] The increase ranges, between 1982 and 2005, from around 30% to 95%, depending on the adopted measure.[2] In this paper, I evaluate the role played by technological change and, in particular, by the automation of tasks, in the observed increase in consumption inequality.

To this end, I build a general equilibrium model combining two theoretical frameworks. On the household side, I use an Ayiagari incomplete market model with educational choice while, on the production side, I use a task-based model borrowed from Acemoglu and Restrepo (2018b). Agents face skill-specific uninsurable idiosyncratic risk and choose how much to save and consume. When they die, they are replaced by their offspring who can decide whether to go to college or not. A unique final good is produced by aggregating a unit measure of tasks. Three inputs of production, capital, unskilled labor, and skilled labor are endogenously allocated to perform tasks, given their productivities and endogenous factor prices.

Automation directly displaces low-skill workers from the performance of some tasks and increases aggregate productivity. The net effect on the wage of the low-skill workers depends on the trade-off between the displacement and the productivity effect. Moreover, as high-skill workers perform tasks that cannot be performed by machines, automation increases the relative demand for skilled relative to unskilled workers (Acemoglu and Autor (2011)). I consider the effect of the introduction of new tasks in which labor has a comparative advantage, which has been argued to be one of the most important forces countervailing the displacement effect of automation.[3] In my model, the introduction of new tasks increases productivity and the demand for high-skill relative to low skill workers. The assumption that new tasks increase the relative labor demand of more educated workers receives support from the data.[4]

[1] See Aguiar and Bils (2015), Attanasio, Battistin, and Ichimura (2004), Attanasio and Pistaferri (2014), Attanasio and Pistaferri (2016), and Heathcote, Perri, and Violante (2010).

[2] Attanasio and Pistaferri (2016) show that consumption inequality, measured as the variance of log-consumption, varies between 30% to 95%. The variation in this result depends on the different ways in which consumption is computed in the data.

[3] Automation technologies might need labor in order to be operated and this, directly, can create demand for new jobs (or new tasks for existing jobs). Moreover, by decreasing the relative price of labor with respect to capital, automation incentivizes the development of new, labor-intensive technologies. Acemoglu and Restrepo (2019) show that the introduction of new tasks can account for around 50% of the employment growth in the US between 1980 and 2010. Over the same period, a 10 log points increase in labor demand is attributed to the introduction of new tasks.

[4] Acemoglu and Restrepo (2018b) show that occupations with a greater number of new job titles employ,

Technological change affects labor demand and wages, but also the return to capital. In particular, the adoption of automation technology increases capital demand and, therefore, the return to wealth for the agents who lend capital to the firms. As wealth is unequally distributed among the agents, the increase in the price of capital has distributional implications. In this model, automation increases *total income* inequality for two different but interconnected reasons. First, because it increases labor income inequality due to differential ways in which technology impacts skill demands. Second, because it increases capital income inequality by raising the return to wealth. As agents who earn a higher salary are also able to accumulate more wealth, the rise in the return to wealth *increases* total income inequality.

The spread in the income distribution translates into increased consumption inequality. The mapping between these two depends on the aggregation of individual saving decisions of the agents. This, in turn, depends on the amount of risk agents face. I assume that labor income risk fluctuations depend on education, as this is the case in the data (Guvenen (2009)).

Crucially, I model educational choice to allow agents to react to prices changes by adjusting their skill supplies. To ignore this fact, the effect of automation on the education premium would be overestimated. Indeed, as the education premium reacts to scarcity, the education decision buffers the increase in the premium implied by technological change.

I calibrate the model to the US economy over the period between 1978 and 1981. With the calibrated model, I compute transitional dynamics to a new steady-state with different levels of technology. In particular, I show that, after an automation shock, the wage of workers without education decreases in the short run and recovers along with the transition. Despite the short-run decrease in the low-skill labor income, total income does not decline for every agent without education. Indeed, richer low-skill agents who had a positive series of labor income shocks can experience a rise in total income, as the increase in the return of capital compensates for the decline in labor income.

Thereafter, I estimate from the data measures of task automation and task introduction spanning from 1981 - the initial steady-state - to 2008. I plug these series in the model and compute the implied transitional dynamics. I show that the estimated technological change explains the increase in consumption inequality observed in the US in the years under study. Moreover, the model explains around 35% of the increase in the college premium and around 53% of the increase in the share of workers with a college

on average, workers with more years of schooling.

degree in the US. Finally, I estimate the role of various components in the model in explaining the increase in inequality. In particular, I show that both the return to wealth channel and the endogenous education decision are quantitatively important. To estimate the role played by the increase in the return to wealth, I compute the transition between steady-states with the interest rate fixed to its initial steady-state value. In this case, the effect of technological change on inequality is 4% lower as it increases only the education premium and it does not directly increase inequality in capital income. To quantify the role of endogenous educational choice, I compute the transition with the probability of dying equal to zero. In this way, the shares of educated and uneducated workers remain fixed to the initial steady-state value. With this decomposition, I show that without allowing the agents to adjust their skill supplies as the demand changes, the overall effect of technology on inequality is twice as large.

Literature Review

First, this paper contributes to the literature that focuses on the determinants of income and consumption inequality. There are several papers that use the Aiyagari (1994), Bewley (1986), and Huggett (1993) framework to study the role of technology on inequality as, for instance, Heckman, Lochner, and Taber (1998), Hubmer, Krusell, and Smith Jr (2016), and Kaymak and Poschke (2016). The most important differences with respect to these studies are the way in which I conceptualize technological change - a combination of automation and creation of new tasks - and that I consider the effect of the return to wealth on inequality. Methodologically, my paper is similar to Kaymak and Poschke (2016) in the way I decompose the effect on consumption inequality of various channels in the model. Another paper that underlines the importance of the return to wealth is Moll, Rachel, and Restrepo (2019). They combine a task-based model with a perpetual youth structure with imperfect dynasties, which is another way to get a determinate wealth distribution and study the implication of the return to wealth on inequality. Using instead an incomplete market model, I can account for differences in labor income risk between education groups (Guvenen (2009)). Another key difference with respect to that paper is that I do model educational choice, and I show that it is crucial in the observed increase in inequality. Finally, I also consider the effect of new tasks introduction.

Second, this paper contributes to the literature that studies the effect of automation, spurred by recent advances in technological capabilities. Like the majority of papers in this literature, I use a task-based model of production (Zeira (1998), Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018b)). Most of the papers studying the effect of automation using general equilibrium models either focus on aggregate labor demand (as Acemoglu and Restrepo (2018b)) or consider labor income inequality (Hémous and Olsen (2014)). But as automation increases the demand for capital, I show that the channel through the increase in the return of wealth is quantitatively important. I extend the conceptual models used in previous research by including heterogeneous capital accumulation that depends on the labor income and individual risk. In a representative household model (e.g. Acemoglu and Restrepo (2018b)) automation always increases total income and consumption. That is because automation always increases output; hence, even if wages are reduced, the household is compensated with a higher capital income. This is not true for all the agents in a model with endogenous wealth distribution.

The rest of the paper is organized as follows: In Section 2 I explain the structure of the model. In Section 3.1 I take the model to the data. In Section 3.2 I discuss the mechanisms of the model. In Section 3.3 I explain the estimation of the shocks that I use in Section 3.4 to contrast the model with the data. In Section 3.5 I quantify the role of various elements of the model. Section 4 concludes.

2 Model

The model combines two theoretical frameworks. The consumption side borrows the basic features of the Aiyagari (1994) incomplete market model combined with endogenous educational choice. The production process, instead, is modeled with a particular task-based production function borrowed from Acemoglu and Restrepo (2018b).

The population is normalized to one and time is discrete and indexed by t. I make the dependence of time explicit to underline non-stationarity in the model. An agent is born with a level of assets and chooses whether or not to become high skill by paying a cost $\theta(a)$ which is a function of asset holdings. This decision is permanent for an agent. Then, during her life, the agent chooses how much to save and how much to consume; she cannot borrow, and her labor supply is exogenous. In every period there is a probability of dying d; when an agent dies, her offspring inherits the level of asset holdings the agent had in her last period of life.

Productivity differs between skill groups but is identical within each skill group. Consequently, wages differ between skills but are identical within skills. On top of this, agents face a not insurable idiosyncratic shock and this creates heterogeneity within each skill group.

Consumption Side:
The initial problem of an agent is the following:

$$v_t^n(a) = \max\left\{\mathbb{E}_{\varepsilon^h}\left\{v_t^h(a,\varepsilon^h)\right\} - \theta(a),\quad \mathbb{E}_{\varepsilon^\ell}\left\{v_t^\ell(a,\varepsilon^\ell)\right\}\right\}, \tag{1}$$

where $v_t^n(a)$ is the value function of new-born agents, $v_t^h(a,\varepsilon^h)$ is the value function of a high skill agent that depends on the asset holdings and on the realization of the labor endowment shock ε^h.[5] $v_t^\ell(a,\varepsilon^\ell)$ is, similarly, the value function of a low-skill agent. The value of becoming a high-skill is reduced by a fixed cost, $\theta(a)$, which decreases with the level of capital. The expectations are formed using the stationary Markov distributions which are type-specific.
Once the decision regarding the type is taken, the agent i solves the following problem, with $j = \{\ell, h\}$:

$$v_t^j(a_{i,t},\varepsilon_{i,t}^j) = \max_{c_t, a_{t+1}}\left\{u(c_{i,t}) + \beta(1-d)\sum_{\varepsilon_{t+1}^j}\pi\left(\varepsilon_{t+1}^j \mid \varepsilon_{i,t}^j\right)v_{t+1}^j\left(a_{i,t+1},\varepsilon_{i,t+1}^j\right)\right\}, \tag{2}$$

$$\text{subject to}\quad c_{i,t} + a_{i,t+1} = (1 + r_t - \delta)a_{i,t} + w_t^j\cdot\varepsilon_{i,t}^j,\quad \text{and}\quad a_t > 0.$$

Where w_t^j is the type-specific wage rate and $\varepsilon_{i,t}^j$ is the idiosyncratic shock, which follows a type-specific Markov process. r_t is the interest rate and δ is capital depreciation.

Production Side:
As mentioned, the production side borrows from Acemoglu and Restrepo (2018b). In that paper, they build a representative agent model combined with task-based production with capital and labor. Then, in an extension (see page 1519), they propose a way to model heterogeneous skills in their task-based production and characterize balance growth path wage inequality depending on the difference between productivities between high and low-skill labor. They do this exercise with fixed shares of labor skill types. In this paper, I use the framework developed in that extension.

[5] I refer to the shock as "labor endowment" as in Aiyagari (1994). In the literatiure is maybe more common to use "productivity shocks", however, in this model the shock does not change the productivity of the agents which is a very precise thing in the production side (see below). The productivity of the agent determines her wage rate, while, the shock, together with the wage rate determines the total labor income.

There is a unique final good produced with a continuum of tasks:

$$lnY = \int_{N-1}^{N} ln[y(x)]dx,$$

where Y is the output of the final good and $y(x)$ is the quantity of task x produced. The final good is produced with a unit measure of tasks that ranges from $N-1$ to N. An increase in N, which corresponds to the introduction of new tasks, does not alter the total measure of tasks in the economy. Each task is produced with a linear production function as in Equation (3). Where, for instance, $m(x)$ is the amount of capital (machines) used in the production of task x and $\gamma_m(x)$ is the productivity of capital in the production of task x. $\gamma_m(x)$ is, therefore, the productivity schedule of capital: a function that for every task gives the productivity of capital in that task. Similarly for the other factors of production.

$$y(x) = \gamma_m(x)m(x) + \gamma_\ell(x)l(x) + \gamma_h(x)h(x). \tag{3}$$

The relationship between the productivity schedules of capital and the two productivity schedules of labor determines, together with factor prices, how the production of tasks is split between capital and labor. I assume the following:

Assumption 1

$$\frac{d}{dx}\left(\frac{\gamma_\ell(x)}{\gamma_m(x)}\right) > 0 \quad \text{and} \quad \frac{d}{dx}\left(\frac{\gamma_h(x)}{\gamma_m(x)}\right) > 0. \tag{A1}$$

This implies that labor has a comparative advantage in higher indexed tasks. And,

Assumption 2

$$\gamma_l(x) = \begin{cases} \gamma_h(x) & x \leq \bar{N} \\ \gamma_h(x) \cdot \Gamma & x > \bar{N} \end{cases} \tag{A2}$$

Where $\Gamma < 1$. High-skill labor has a comparative advantage in higher index task with respect to low-skills. $\bar{N}$ can be thought of as a division between old and new tasks, or complex and non-complex tasks.

The highest indexed task produced with capital, $\tilde{I}$, is given by solving the following equation,

$$\tilde{I} : \frac{r}{\gamma_m(\tilde{I})} = \frac{w_\ell}{\gamma_\ell(\tilde{I})}.$$

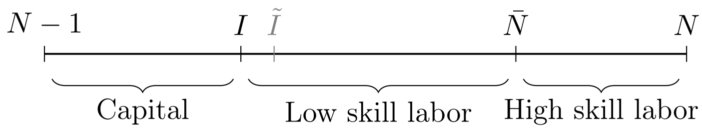

FIGURE 1: Allocation of factors of production in the unit measure of tasks.

Hence, $\tilde{I}$ is the task in which the effective costs - price over productivity - of capital and labor are equal. The division between high and low-skills in the labor area follows a similar logic. However, given the discontinuity in the productivity of the low-skills, there is not one clear equation that pins down the separation threshold, as we have for the division capital-labor. Therefore, for simplicity, I restrict the attention to the case in which the following condition is verified [6]:

Assumption 3

$$\Gamma < \frac{w_\ell}{w_h} < 1. \tag{A3}$$

This in turn implies the following:

$$\frac{w_\ell}{\gamma_\ell(x)} < \frac{w_h}{\gamma_h(x)} \quad \text{if} \quad x < \bar{N},$$
$$\frac{w_\ell}{\gamma_\ell(x)} > \frac{w_h}{\gamma_h(x)} \quad \text{if} \quad x > \bar{N}.$$

The left hand side of both equations is the effective cost of producing tasks with low-skill labor while, the right hand side is the same variable for high-skills. These equations tell us that when assumptions A2 and A3 are satisfied, only high-skills are employed in *new* tasks and only low-skills are employed in *old* tasks. The separation threshold between the two types of labor is equal to $\bar{N}$. Assumptions A1, A2 and A3 imply that the unit measure of tasks is divided into three areas: tasks performed by capital, tasks performed by low-skill labor, and tasks performed by high skill labor (see Figure 1).

Automation is modeled in the following way. As said, $\tilde{I}$ is the highest indexed task that is optimal to automate given productivity schedules and factor prices. I now define I as the highest indexed task that is *feasible* to automate. This means that for $x > I$ simply does not exist the technology that allows producers to use machines to perform these tasks. In general, then, the highest indexed task automated in equilibrium, I^*, is equal to

$$I^* = \min\{I, \tilde{I}\}.$$

[6] This assumption is made on endogenous objects and must be verified ex-post in equilibrium.

For some combinations of the parameters in the model, the profit maximization problem of the firm is constrained in the equilibrium, that is $I^* = I$. In these cases, automation is a *relaxation* of this constraint, an increase in I. For the rest of the paper, I focus on this case because is the only one which allows me to study the implication of an invention in automation technology. Indeed, when some automation technologies are not adopted ($\tilde{I} < I$), an increase in I has absolutely no effects on the equilibrium in this model.
The total output, Y, can be rewritten as a Cobb Douglas in the three factors of production, in which, crucially, factors' shares are endogenous and depend on technology.[7]

$$Y = G\left(\frac{K}{I-N+1}\right)^{I-N+1}\left(\frac{L}{\bar{N}-I}\right)^{\bar{N}-I}\left(\frac{H}{N-\bar{N}}\right)^{N-\bar{N}}. \tag{4}$$

The expressions of factors' prices take the usual form,

$$r = Y \cdot \frac{I-N+1}{K}, \tag{5}$$

$$w_\ell = Y \cdot \frac{\bar{N}-I}{L}, \tag{6}$$

$$w_h = Y \cdot \frac{N-\bar{N}}{H}. \tag{7}$$

The price of each factor is proportional to total output and to the share of the factor in aggregate production, and inversely proportional to the supply of the factor.

Before turning to the definition of equilibrium, it is useful to describe the transition of the distribution between a generic period t and $t+1$. In every period t, each agent is characterized by three variables, the level of assets she owns, $a_{i,t}$, the Markov state $\varepsilon^j_{i,t}$ and, her education level, e_i. λ_t is the asset distribution of agents over states at time t. At the end of the period, a random sample of size d - which corresponds to the probability of dying in t - is drawn from λ_t. Before the beginning of the next period, the deceased agents are replaced by their offspring who inherit their level of capital. First, they decide their level of education based on (1). Second, their Markov state realizes based on the education-specific stationary Markov distribution. The transition of the agents who do not die in period t into a new position in state space in $t+1$ depends on the solution of the value function (2) - that depends on their level of asset holdings, Markov state, and

[7] With

$$G = \exp\left(\int_{N-1}^{I} \ln(\gamma_m)\,dx + \int_{I}^{\bar{N}} \ln(\gamma_\ell(x))\,dx + \int_{\bar{N}}^{N} \ln(\gamma_h(x))\,dx\right)$$

education type - and on the realization of the idiosyncratic shock in $t+1$.

Equilibrium:
Given a sequence of technological parameters $\{I_t\}_{t=0}^{\infty}$ and $\{N_t\}_{t=0}^{\infty}$, a recursive competitive equilibrium are sequences of value functions $\left\{v_t^h\right\}_{t=0}^{\infty}$ and $\left\{v_t^\ell\right\}_{t=0}^{\infty}$, policy functions $\left\{c_t^h, a_{t+1}^h\right\}_{t=0}^{\infty}$ and $\left\{c_t^\ell, a_{t+1}^\ell\right\}_{t=0}^{\infty}$, firm's choices $\{L_t, H_t, K_t\}_{t=0}^{\infty}$, prices $\left\{w_t^\ell, w_t^h, r_t\right\}_{t=0}^{\infty}$ and ditributions $\{\lambda_t\}_{t=0}^{\infty}$ such that, for all t:

- Given prices, the policy functions solve the agents' problems and the associated value functions are $\left\{v_t^h\right\}_{t=0}^{\infty}$ and $\left\{v_t^\ell\right\}_{t=0}^{\infty}$.
- Given prices and technology, firms choose optimally labor inputs and capital.
- The labor markets clear,

$$H_t = \left[\left(\Pi^{*,h}\right)^T \cdot \boldsymbol{\varepsilon}^h\right] S_t^h,$$

$$L_t = \left[\left(\Pi^{*,\ell}\right)^T \cdot \boldsymbol{\varepsilon}^\ell\right] S_t^\ell,$$

  where $\Pi^{*,j}$ is the stationary distribution associated with the Markov process of type j; ε^j is a vector containing the values of the shock corresponding with the stationary distribution and S_t^j is the number of agents that belong to type j.

- The asset market clears,

$$K_t = \int_{A\times E} a_{t+1}(a_t, \varepsilon_t) d\lambda_t,$$

  where E is the space of labor endowment shocks ε.

3 Quantitative Results

I now turn to the quantitative analysis of the model. First, I explain how I calibrate the model parameters. Then, with the calibrated model, I discuss the mechanism at play in the model. To do so, I report, separately, the transitional dynamics between steady-states for two different shocks: an increase in automation and an introduction of new tasks in which labor has a comparative advantage. For the sake of clarity, I assume that these shock are instantaneous, that is, the final steady-state value of the shock is reached immediately. In this way, it is easier to understand the reaction of the model economy with respect to a case in which the shock happens gradually. This strong assumption is relaxed in the main result of the paper, in which I compute the transitional dynamics implied by sequences of technological parameters estimated from the data. Finally, with a decomposition exercise, I quantitatively evaluate the contribution of various components of the model in determining the increase in inequality.

3.1 Bringing the model to the data

The composition adjusted college premium is reported in Figure 2. The data is taken from the March CPS database; I restrict the sample to include only full-time full-year workers with age between 16 and 64. This measure of the college premium, taken from Acemoglu and Autor (2011), ensures that this statistic is not "mechanically affected by shift in experience, gender composition, or average level of completed schooling within the broader categories of college and high-school graduates".
I assume that the economy is in a steady state from year 1978 to 1981 - red dashed horizontal line in the graph - because in this period the college premium displays more stability relative to the whole period.

In Table II I report the calibrated parameters and the relative targets or sources used in the calibration. The table is divided into two parts: preferences and technology. The result of the calibration of the labor income risk parameters is excluded from the Table but is also discussed in this section. I now explain the reasoning behind the calibration strategy for each parameter.

Regarding the parameters that enter the preferences of the agents, I set the dying probability equal to 3% to imply an average working life of 33 years. To estimate the cost of education, I use as a target the average share of workers with a college degree in the US between 1963 and 1981, which is equal to 14%. The remaining parameters relative to the preferences of the agents have standard values taken from the literature. All the parameters relative to the labor income risk that the agents face are calibrated using the estimates from Guvenen (2009). Using data from the Panel Study of Income Dynamics (PSID) covering 1968 to 1993, he estimates an AR(1) income process separately for college and non-college graduates [8]. The values he estimates for the persistence and

[8] Using Guvenen words, his sample consist of "*[...] male head of households between the ages of 20 and 64. I include an individual into the sample if he satisfies the following conditions for twenty (not necessarily consecutive) years: the individual has (1) reported positive labor earnings and hours; (2)*

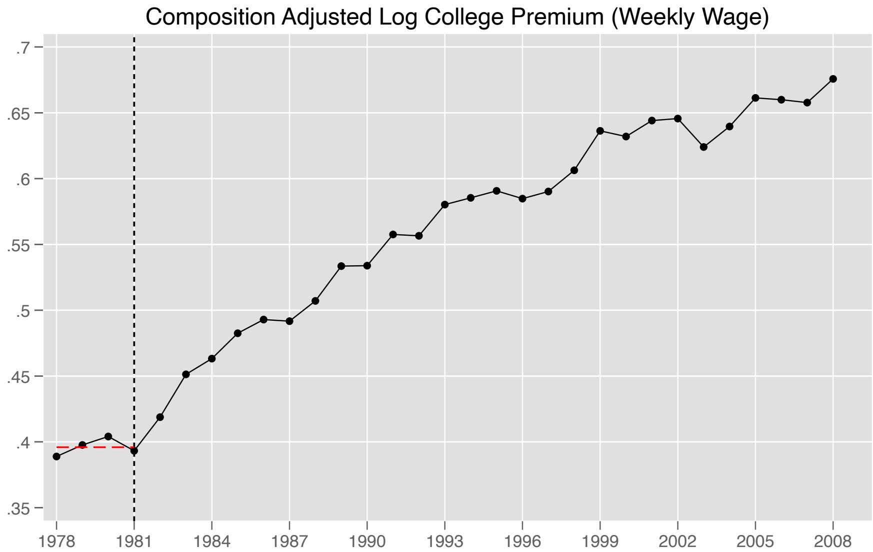

FIGURE 2: Composition-adjusted log college premium from 1978 to 2008 in the United States. Data from March CPS, full-time, full-year workers. The steady state value - red dashed line in the graph - is equal to 0.39. I use the estimation technique of Acemoglu and Autor (2011).

the variance of the innovation are reported in table I.

Parameters	Values
ρ_ℓ	.829
σ^2_ℓ	.022
ρ_h	.805
σ^2_h	.025

TABLE I: Values from Guvenen (2009).

I compute the associated Markov process using the Tauchen's method. When doing this, I have to set the number of Markov states, S, and the maximum number of standard deviation from the mean, i.e. the dispersion of the Markov's state space. I set $S = 9$ and $max(SD) = 1$. From the discretization, I obtain the conditional probabilities of the Markov matrix, Π^i, and the vector of Markov states, ε^i. Given that Guvenen uses log labor earnings to estimate the labor income risk parameters, I have to normalize the

worked between 520 and 5110 hours in a given year; (3) had an average hourly earnings between a preset minimum and a maximum wage rate (to filter out extreme observations). I also exclude individuals who belong to the poverty (SEO) subsample in 1968".

values of the Markov process to have $\mathbb{E}(\exp(\varepsilon_i^j)) = 1$. To do this, I symmetrically shift the values found with the Tauchen method.

I now turn to the discussion of the parameters of the production side of the economy. I normalize the highest-indexed task in the economy $N_0 = 1$ (the sub-index "0" indicates the initial steady-state). To compute the highest indexed task automated in equilibrium I use the following relationship that holds in the model:[9]

$$I_t = N_t - (\text{LABOR SHARE})_t.$$

The series of the Labor Share (LS) is a crucial object for the result of this paper, as this is used to impute the level of automation in the initial steady-state and, as will be explained in the following section, to estimate the sequences of the technology parameters.

FIGURE 3: Labor share. Data from the Bureau of Economic Analysis. The average value of the labor share in the initial steady-state is 0.64.

The remaining four parameters ($\tilde{\gamma}$, q_y, m, $\bar{N}$) in Table II determine the shape of the

[9]From the definition of the labor share,

$$LS = \frac{w_h H + w_\ell L}{Y},$$

substitute the expressions for the wages, (6) and (7), to obtain,

$$LS = \frac{Y(N - \bar{N}) + Y(\bar{N} - I)}{Y} = N - I.$$

DESCRIPTION		VALUE	TARGET/SOURCE
PREFERENCES			
σ	Risk Aversion	2	Standard
β	Discount	0.95	Standard
δ	Depreciation	6%	Standard
d	Death probability	3%	33 years average working life
$\tilde{\theta}$	Education Cost	15.04	Share of workers with col. degree
TECHNOLOGY			
N	Highest-indexed task	1	Normalization
I	Highest-indexed automated task	0.35	Labor share $= 0.66$
$\tilde{\gamma}$	Productivity	0.12	$K/Y = 3$
q_y	Productivity of labor 1	0.7	Cost saving $= 30\%$
m	Productivity of labor 2	1.66	$\hat{z} = 1.67$
$\bar{N}$	Highest-indexed task non-college	0.84	Log college premium $= 0.43$

TABLE II: Calibrated parameters of the model.

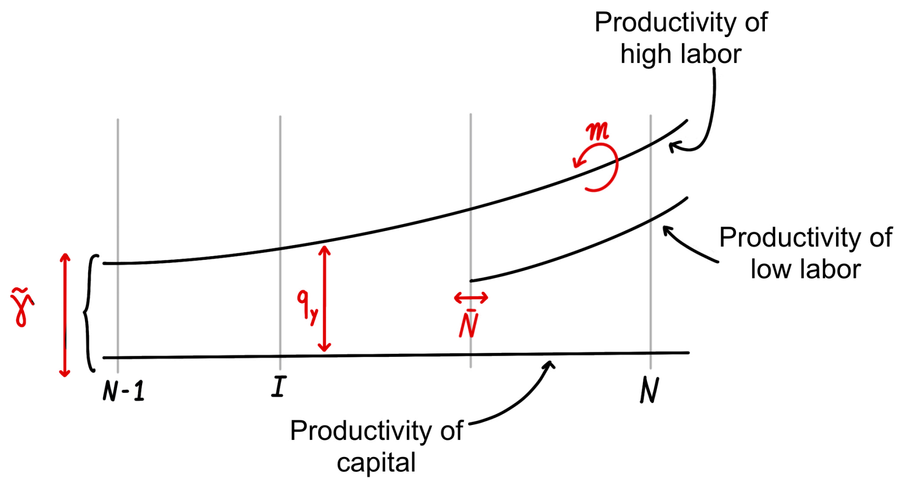

FIGURE 4: Productivity schedules of inputs of production. In red, the parameters to calibrate.

productivity schedules of the factors of production. The functional forms chosen for the productivity schedules are the following:

$$\gamma_h(x) = \tilde{\gamma} \cdot q_y \cdot e^{m(x - \frac{I+N}{2})} \tag{8}$$

$$\gamma_\ell(x) = \begin{cases} \gamma_h(x) & x \leq \bar{N} \\ \gamma_h(x) \cdot \Gamma & x > \bar{N} \end{cases} \tag{9}$$

$$\gamma_m(x) = \tilde{\gamma} \tag{10}$$

To have a sense of how the to-be-calibrated parameters affect the shapes of the productivity schedules, take a look at Figure 4. $\tilde{\gamma}$ determines the aggregate productivity as an increase in this parameter shifts up all productivity schedules. q_y determines the difference between the productivity of capital and that of labor. $\bar{N}$ controls the difference between the productivity schedule of unskilled and skilled labor while m regulates the slope of the productivity schedule of labor.

As will be more precisely explained in the following section, the effect of task automation on the economy crucially depends on the trade-off between the displacement and the productivity effect. The displacement effect depends on how tasks automation changes the relative demand for factors, as an increase in I decreases the size of the set of tasks performed by low-skills and increases the size of the set of tasks performed by capital. However, automation also increases productivity and this tends to increase all factor prices. I specify the productivity schedule in (8) so that the parameter m determines precisely this trade-off. As m increases, for a given productivity of capital and a given displacement effect, the cost-saving (and therefore the productivity effect) implied by automation is greater. The chosen specification for the productivity schedule in (8) implies that, in the initial steady-state, a change in the parameter m within a range of values, does not change the equilibrium of the model economy. This is because it does not change the aggregate productivity G and does not change the relative demand for factors[10]. In this way, m is directly linked with the previously mentioned trade-off. m reflects also the difference between the average productivity of workers with a college degree and the average productivity of workers without a college degree. Indeed, as m increases, the average productivity of college workers increases relative to non-college workers. This is perfectly consistent with the relationship between m and the trade-off. As the productivity of the workers who will be automated increases, the cost-saving coming from automation decreases, and the impact of automation on the economy changes. To calibrate this parameter, I use, therefore, the following statistics:

$$\hat{z} = \frac{\text{Average workplace productivity of workers with a college degree}}{\text{Average workplace productivity of workers without a college degree}}$$

[10] Wages in this model change because of two reasons (i) the aggregate productivity G changes (ii) the relative demand for factors change. The aggregate productivity does not change with m because, thanks to the specific chosen functional form, as, for instance, m increases, the productivity of skilled workers increases but the productivity of low-skills decreases in a way that perfectly offsets the effect on aggregate productivity. Moreover, the change in productivity does not change the relative demand of labor because, on one side, there is the technological constraint (I) and, on the other side - the threshold that separates the two types of labor - there is the discontinuity of the productivity schedule of the low-skill workers.

I take the estimate for $\hat{z}$ from Hellerstein et al. (1999): $\hat{z} = 1.67$. In this paper, the authors estimate precisely the difference in productivity between workers with and without college education. To build the counterpart of this statistic in the model, I use the implication of assumption A2 and A3 about the labor productivity schedule. In the initial steady-state, low-skill workers perform tasks between I and $\bar{N}$ and skilled workers between $\bar{N}$ and N. The average productivity of a low-skill worker is

$$\bar{\ell} = \frac{\int_I^{\bar{N}} \gamma_\ell(x) \cdot \frac{L}{\bar{N}-I} dx}{L}$$

While for high-skill workers,

$$\bar{h} = \frac{\int_{\bar{N}}^{\bar{N}} \gamma_h(x) \cdot \frac{H}{N-\bar{N}} dx}{H}$$

Finally, the moment condition I sue to calibrate m is,

$$\frac{\bar{h}(m)}{\bar{\ell}(m)} = \hat{z}.$$

Which, after plugging the expressions for $\bar{\ell}$ and $\bar{h}$ becomes,

$$\frac{\exp(mN) - \exp(m\bar{N})}{\exp(m\bar{N}) - \exp(mI)} \cdot \frac{\bar{N} - I}{N - \bar{N}} = \hat{z}. \tag{11}$$

To calibrate q_y I use the estimate from Acemoglu and Restrepo (2017) of the cost-saving associated with the adoption of automation technology. To pin down $\tilde{\gamma}$ I use the capital-output ratio. Finally, for $\bar{N}$, I use the adjusted log college premium, $\widehat{CP}$ (average value over the period 1963-1981, see Figure 2). Given that $\widehat{CP}$ is the difference between the average log wages for the two education groups, the moment condition is not simply $log\left(w_h/w_\ell\right) = \widehat{CP}$. To explain the derivation of this moment condition, I use the example of a three state Markov process. The average log wage for low-skills is

$$\begin{gathered} \pi_1^{*,\ell} \log\left(w_\ell \varepsilon_1^\ell\right) + \pi_2^{*,\ell} \log\left(w_\ell \varepsilon_2^\ell\right) + \pi_3^{*,\ell} \log\left(w_\ell \varepsilon_3^\ell\right) = \\ \log\left(w_\ell\right) \underbrace{\left(\pi_1^* + \pi_2^* + \pi_3^*\right)}_{1} + \left(\Pi^{*,\ell}\right)^T \log\left(\varepsilon^\ell\right) = \\ \log\left(w_\ell\right) + \left(\Pi^{*,\ell}\right)^T \log\left(\varepsilon^\ell\right) \end{gathered} \tag{12}$$

Where $\Pi^{*,j}$ is the stationary distribution associated with the type-specific Markov

Expressions		Data/Targets	Model
$log\left(w_h/w_\ell\right)$	Log coll. premium	0.39	0.39
$\hat{z}$	prod. ratio	1.67	1.67
K/Y	Capital/output	3	2.58
$\frac{w_\ell}{\gamma_\ell(I)}/\frac{r}{\gamma_m}$	Cost saving autom.	30%	30%
S_h	college share	18%	18%

Table III: Calibration results, targeted moment.

Gini coefficients	Data	Model
Consumption	0.24	0.15
Wealth	0.77	0.44

Table IV: Untargeted moments. Source: Kuhn et al 2018 and Krueger and Perry 2006.

process. Hence, the moment condition is

$$\overline{\log\left(w_h\right)} - \overline{\log\left(w_\ell\right)} = \log\left(w_h\right) - \log\left(w_\ell\right) + \\ + \left(\Pi^{*,h}\right)^T \log\left(\varepsilon^h\right) - \left(\Pi^{*,\ell}\right)^T \log\left(\varepsilon^\ell\right) = \widehat{CP} \quad (13)$$

Which, given the model expression of the wage ratio,

$$\frac{w_h}{w_\ell} = \frac{N - \bar{N}}{\bar{N} - I} \cdot \frac{L}{H} \quad (14)$$

becomes,

$$\log\left(\frac{N - \bar{N}}{\bar{N} - I} \cdot \frac{L}{H}\right) + \left(\Pi^{*,h}\right)^T \log\left(\varepsilon^h\right) - \left(\Pi^{*,\ell}\right)^T \log\left(\varepsilon^\ell\right) = \widehat{CP} \quad (15)$$

In Tables III I report the model generated moments used in the calibration and their data counterparts. In Table IV I report the Gini's coefficients of the wealth and consumption distribution of the simulated economy. These moment were not targeted directly. The model generates 57% of the wealth inequality observed in the data and 62% of the consumption inequality.

3.2 Mechanisms' Discussion

To analyze the effect of task automation and new task introduction, I now report, separately, one transition for each shock. First, look at Figure 5. In these graphs I show the transitional dynamics after a permanent and instantaneous increase in the tasks performed with machines (a 5% increase of I). To understand the reaction of the interest rate, capital and output, it is convenient to recall equation (5),

$$r = Y \cdot \frac{\uparrow I - N + 1}{K}$$

In the first period after the shock, the increase in I implies an instantaneous increase in the interest rate. Indeed, the reaction of the aggregate capital stock is sluggish and the supply of capital takes time and does not compensate immediately the increase in demand. As time goes by, agents start to accumulate more capital and the interest rate decreases until the final steady-state value. As more capital is accumulated, the output increases.

In the short run, the effect of automation on the wage of educated workers is unambiguously positive, as automation increases productivity and does not decrease the demand for educated labor. Instead, in the short run, the effect on the wage of workers without college education depends on the trade-off between the increase in productivity and the decrease in the number of tasks in which they are demanded by the firms, or, in other words, the fact that they are reallocated in a different set of tasks. This trade-off can be analyzed by taking the following derivative:

$$\frac{d \ln w_\ell}{dI} = \underbrace{\frac{d \ln(Y/L)}{dI}}_{\text{Productivity Effect}} + \underbrace{\frac{d \ln(\bar{N} - I)}{dI}}_{\text{Reallocation Effect}}$$

The productivity effect can be expressed in terms of productivities and prices,

$$\frac{d \ln w_\ell}{dI} = \underbrace{\ln\left(\frac{w_\ell}{\gamma_L(I)}\right) - \ln\left(\frac{r}{\gamma_m(I)}\right)}_{\text{Productivity Effect}} - \underbrace{\frac{1}{\bar{N} - I}}_{\text{Reallocation Effect}} \tag{16}$$

Thanks to this manipulation, we can see that the productivity effect is greater the greater is the difference between the cost of producing task I with low-skill labor and with capital. In other words, the greater is the cost saved thanks to the automation adoption, the greater is the increase in productivity. Thus, whether the low-skill wage decreases

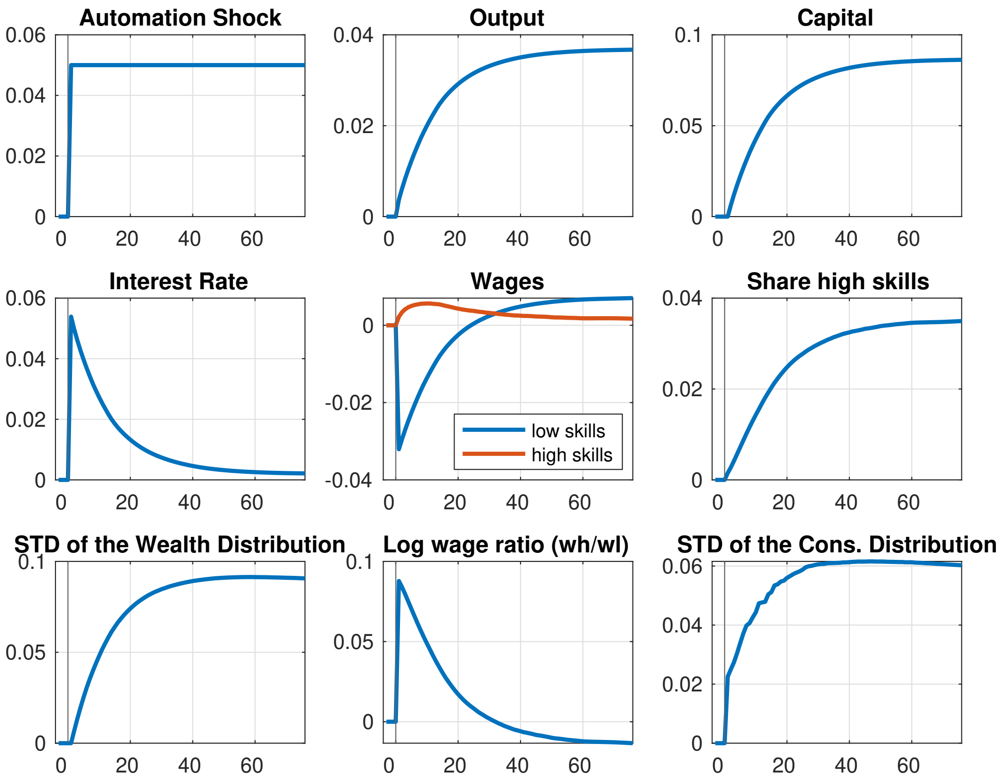

FIGURE 5: Transitional dynamics between the initial, calibrated steady-state and a final steady state in which the size of the set of tasks performed by capital has increased by 5%. All reported variables are normalized to zero in the initial steady-state.

in the short-run depends on which of the two effects is bigger, which in turn depends on the comparative advantage structure and on the magnitude of the shock. With the chosen calibration for this model, the reallocation effect is stronger than the productivity effect in the short run. In the long-run, the accumulation of capital and the increase in the share of agents with a college education affect the transition of wages. The increase in capital tends to increase output and therefore both wages, while the increase in the number of educated workers decreases the wage of high-skill labor and increases the wage of the low-skills. To understand the difference between the short and the long-run, it is important to notice that while the reallocation effect is instantaneous, the implications of the productivity effect change over time as more and more capital is accumulated. For this reason, the reallocation effect can be greater than the productivity effect in the short-run, but the opposite can be true in the long-run. Hence, for a fixed reallocation of factor, the greater the productivity effect, the greater is the difference between the short- and the long-run effects.

To analyze the transition of the college premium and the share of educated workers, it is useful to report the expression of the wage ratio,

$$\frac{w_h}{w_\ell} \propto \frac{N - \bar{N}}{\bar{N} - \uparrow I} \cdot \frac{(1 - S_h)}{S_h},$$

and the problem of a new-born worker,

$$v_t^n(k) = \max\left\{\uparrow \mathbb{E}_\varepsilon \left\{v_t^h\left(k, \varepsilon^h\right)\right\} - \theta(k), \quad \mathbb{E}_\varepsilon \left\{v_t^\ell\left(k, \varepsilon^\ell\right)\right\}\right\}.$$

Right after the shock, the immediate increase in the college premium implies an increase in the expected lifetime utility of high-skills relative to low-skills. For this reason, more agents decide to get education (increase in S_h) thus implying a decline in the college premium. However, there is another force that tends to increase the share of high-skill agents: as aggregate capital and per capita capital increase, also the average new-born worker becomes richer. As the cost of education is constant in the model, *more* agents can afford to get education. This last point explains why, in the final steady-state, the share of high-skills is higher than its value in the initial steady-state despite the college premium being lower. The increase in the interest rate increases wealth inequality, as the agents who own more capital benefit more from this increase. Also, the sudden jump in the college premium, allows college-educated workers to accumulate more capital. This boost in wealth inequality, combined with the increase in wage inequality implies a permanent increase in the spread of the consumption distribution, measured with the standard deviation.

In Figure 6 I further focus on the effect of automation on inequality. To show how the total income and consumption distribution react to the sudden substitution between low-skill labor and capital in production, I report, for each distribution, the relative change with respect to the initial steady-state value of each percentile. In these graphs, each line represents the percentiles changes in a *given period* after the shock. The blue line depicts the change at $t = 3$, which is almost immediately after the shock. To understand what happens, recall that the wage of the uneducated workers decreases immediately but the interest rate increases. As a consequence, about half of the population in the model economy experience a decrease in total income when tasks are automated. This, despite the fact that the fraction of agents without a college degree is 82% in the initial steady-state (see Table III). The reason is that uneducated workers who had a lucky series of shocks and managed to accumulate a relative big wealth, do not see their total

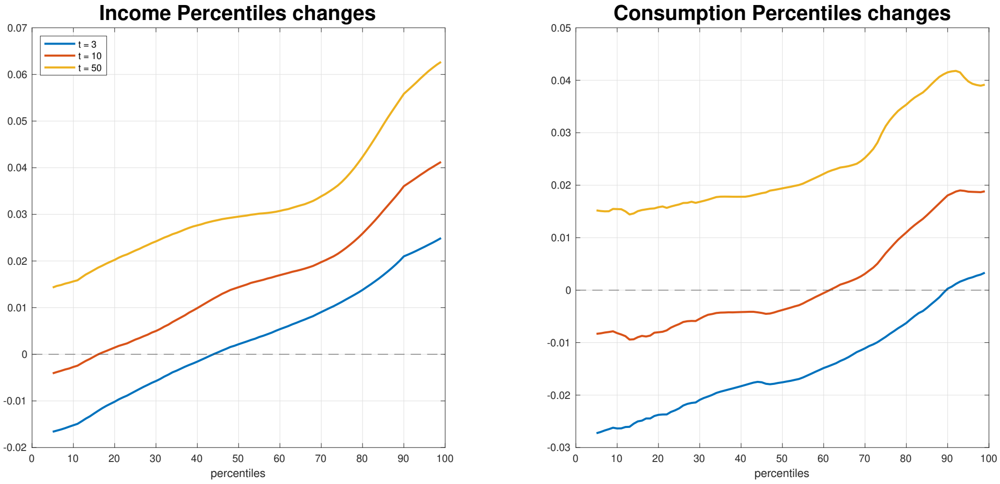

FIGURE 6: Percent variation of percentiles with respect to the initial steady-state value. Each line represents the variation a given number of years after the shock hits the economy. Left panel, total income distribution. Right panel, consumption distribution.

income decrease, as the increase in the capital income *compensates* the decline in their return from the labor market. This highlights the importance of departing from the representative household model when studying the effect of technology on total income and consumption. In that model, as automation increases output, even if the labor income declines, the household is compensated with the increase in capital income. As a consequence, consumption and welfare necessarily increase. This is not true anymore with heterogeneous agents: only a small fraction of the agents who see their labor income drop benefit from greater capital income. The implication for consumption distribution can be seen in the right panel of the same figure. Right after the shock (blue line) percentiles up to the 85th decrease with respect to initial steady-state value. The decrease in consumption is greater than the one in the income distribution because agents are taking advantage of the high interest rate therefore postponing their consumption. As time goes by both distribution "shift to the right" and approximately after 50 years every percentile of both distribution is at a higher value.

In Figure 7 I show the transition after an introduction of tasks in which labor has a comparative advantage with respect to capital. In the short run, the introduction of new tasks increases productivity, and, consequently output increases. However, the production of the final good becomes more labor-intensive and the relative demand for capital decreases. The effect on the absolute demand for capital depends on the interaction between the boost in productivity and the decrease in the relative demand for capital;

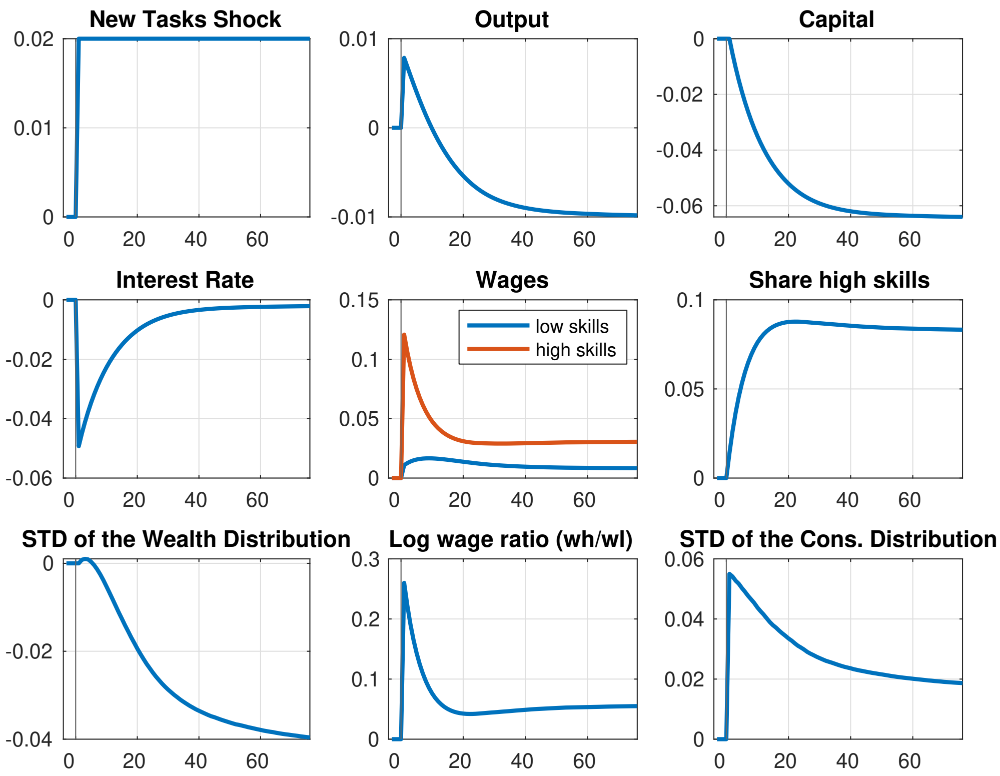

FIGURE 7: Transitional dynamics between the initial, calibrated steady-state and a final steady state in which the highest-indexed task in the economy, N, increases by 2%. All reported variables are normalized to zero in the initial steady-state.

with the chosen calibration the demand for capital decreases, as can be observed in the transition of the interest rate. The decrease in the interest rate implies that the aggregate level of capital starts decreasing, in turn implying a decrease in the production of the final good. Both wages increase because of the increase in productivity; however, the wage of educated workers increases more, as they also benefit from the increase in the relative demand for skilled labor. By looking at the following equation,

$$\frac{w_h}{w_\ell} \propto \frac{\uparrow N - \bar{N}}{\bar{N} - I} \cdot \frac{(1 - S_h)}{S_h}$$

it is clear why the college premium increases in the short run. Along with the transition, as more agents choose to get education given the increased premium, the gap between the wage of high- and low-skill workers declines until its final steady-state value. The effect on wealth inequality depends, as before, on the interaction between the effect on the return of capital and wage inequality. The increase in wage inequality dominates in the short-run, implying an increase in wealth inequality which, however, decreases along with the transition because of the lower interest rate and the decreasing college premium. For similar reasons, the standard deviation of the consumption distribution increases when new tasks are introduced and reaches its maximum right after the shock. After that, it starts to decline.

3.3 Estimation of the Shock

In the two transitions I showed in the previous subsection, the shocks are instantaneous and their magnitudes are chosen ad hoc to have the clearest possible dynamics. In this section, instead, I explain how I estimate from the data the sequences of the two technology variables $\{I_t, N_t\}$. In the following section, I use these estimated sequences to compute the transition that I then compare with the data. For the estimation of I_t and N_t, I use the series of the labor share as reported by the BEA (see Figure 3) and the expression that links, in the model, these two variables with the labor share, $I_t = N_t - (\text{LABOR SHARE})_t$. Given the initial values for I_0 and N_0 I adopt a similar technique as in Acemoglu and Restrepo (2019) which in turn relies on the theory developed in **(alias?)**: in a model with endogenous technological change, in a given period, is either profitable to develop technologies which are labor-intensive or automation technologies with the purpose of substituting labor in a given set of tasks. With this reasoning in mind, I assume that in a given period there are three possibilities: an increase in I, an increase in N, or no technological change. Following this logic, if the labor share increases I impute this increase to the introduction of new tasks, if it decreases, to the automation of tasks. This computation results in the sequences reported in Figure 8.

3.4 Transitional dynamics of the calibrated economy

In this section, I compute the transition of the model economy using the estimated sequences and compare the transition with real data in the period from 1981 to 2008. To simulate a balanced growth path, I extend the estimated sequences with linear trends until 50 years after the initial steady state. After this period, the technology parameters remain constant. As the agents discount the future and also have a probability of dying in every period, what happens in the first 30 years after the initial steady-state - which is the period under study - is not affected by what happens in a so remote future.

In Figure 9 I contrast the model generated series of consumption inequality with the data. For completeness, I report both the Gini's coefficient and the standard deviation

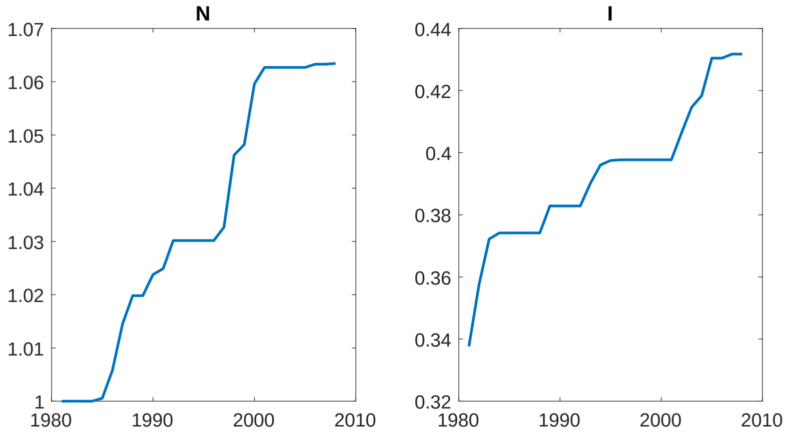

FIGURE 8: Estimated sequences of the technology parameters N - left panel - and I - right panel.

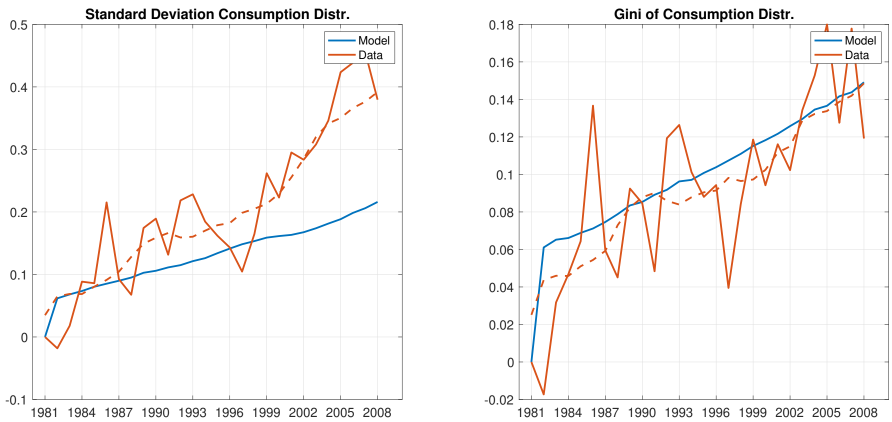

FIGURE 9: Evolution over time of the standard deviation and the Gini's coefficient of the consumption distribution. The model generated series are contrasted with the data counterparts. All values are normalized to zero in 1981. For illustrative purposes, I also report the 10-year moving average for the data series.

of the distribution. The standard deviation implied by the model follows closely the increase in the spread of the distribution measured in the data until 1999. At that point, the inequality measured in the data increases relatively to the model. The Gini's coefficients are pretty close along the period under study: the model is able to generate the 14% increase in the Gini's coefficient. Consumption inequality depends on the college premium and on the fraction of workers with a college degree, for this reason, in Figure 10 I also contrast the evolution of these variables with the data. The model is able to explain around 35% of the increase in the college premium and around 63% of the increase in the share of educated workers.

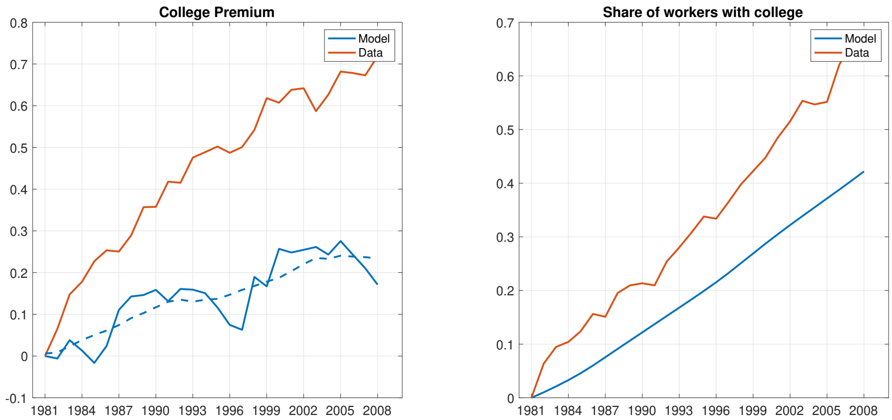

FIGURE 10: Evolution over time of the college premium and the share of workers with a college degree. The model generated series are contrasted with the data counterparts. All values are normalized to zero in 1981. For illustrative purposes, I also report the 10-year moving average for model generate college premium.

3.5 Effect Decomposition

In this section, I analyze the role played by task automation, the introduction of new tasks, the return of wealth, and endogenous education decision in the transition showed in the previous section. To understand the role of these components I compute the transition keeping the component fixed to the initial steady-state value. In Figure 11 I report the transition in which I fix the capital intensity to the initial steady-state value, the transition with no introduction of new tasks, and the benchmark transition for comparison. From this figure, we see how task automation contributes to the increase in inequality. The college premium increases *less* when no tasks are automated and, as consequence, the share of college workers is also smaller along with the transition. Task automation also contributes to the increase in the return of wealth. The lower

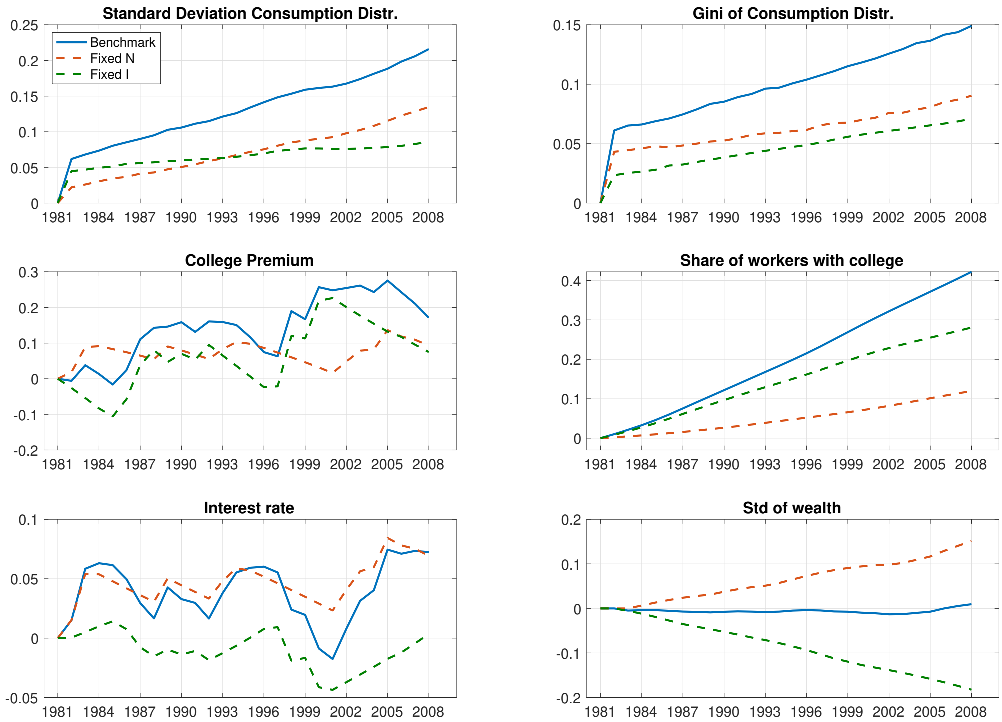

FIGURE 11: This figure compares the benchmark transition with two transitions in which I fix the automation of tasks and the introduction of new tasks.

return to wealth combined with the lower college premium implies that both measures of consumption inequality are lower in every year under study when no tasks are automated.

In the same figure, we see how also the new task introduction contributes to the increase in consumption inequality. First, the introduction of new tasks increases the college premium. Second, as the relative demand of capital decreases because production becomes more labor-intensive, tasks introduction decreases the value of the return to wealth. This has the effect of decreasing wealth inequality. However, the increase in the college premium dominates and, according to the model, the introduction of new tasks has contributed to the observed increase in consumption inequality between 1981 and 2008.

In Figure 12 I report the transition with a fixed return to wealth and fixed education shares. Similarly to the previous exercises, I fix the interest rate to the initial steady-state value. As the interest rate is an endogenous variable in the model, fixing it implies that, along with the transition and in the final steady-state the capital supply does not equal the capital demand. This exercise shows the importance of taking into account heterogeneous capital accumulation when studying the implication of technological change

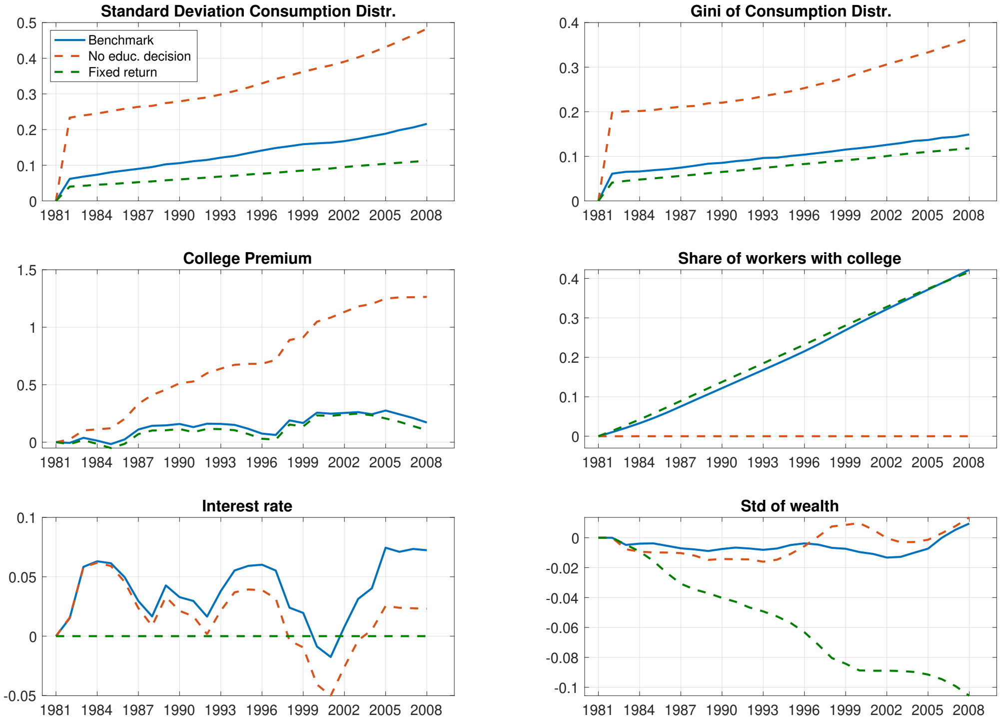

FIGURE 12: This figure compares the benchmark transition with two transitions in which I shut down the educational choice decision and the increase in the return to wealth.

on inequality. Indeed, the increase in the interest rate contributes to the growth of consumption inequality by almost 4%.

In the same figure, I report the transition in which agents do not have the opportunity to choose their education. The way I do this in practice is to set to zero the probability of dying, d, in the household optimization problem. In this way, the shares of college and non-college-educated agents remain fixed to the initial steady-state level. When the labor force does not adjust the skill supply, the level of inequality is much higher. The college premium increases dramatically more with respect to the benchmark transition. As the college premium increases, both measures of consumption inequality increase *more* as well. The role of educational choice is therefore to buffer the increase in inequality implied by technological change.

4 Conclusion

I study the relationship between automation and consumption inequality by combining two theoretical frameworks. I use an incomplete market model à la Ayiagari with endogenous educational choice with a task-based model borrowed from **(alias?)**. After calibrating the model to the US economy between 1978 and 1980 I first show what are the effects of a sudden adoption of automation technology and a sudden introduction of new tasks. I do that by computing the transitional dynamics from the initial steady-state. In particular, I show that automation decreases the labor income of uneducated workers and that the implied increase in the return to wealth counteracts that drop only for the uneducated rich. As the high-skill workers earn more and have, on average, higher wealth, the increase in the return to wealth widens the gap between the total income of high- and low-skills.

After estimating the series of automation and new tasks creation from the data, I compute the model implied transition and contrast this with the data. The model is able to replicate the increase in consumption inequality that took place in the US between 1981 and 2007. Finally, I decompose the effects of various components of the model along with the transition. I find that both educational choice and the return to wealth channel are quantitatively important in accounting for the increase in consumption inequality.

A natural use of the calibrated model developed in this paper is to use it for policy analysis. Regarding the possible effect of massive adoption of automation technology, a tax on robots has been proposed and evaluated by economists [11]. This is left for future research.

References

Daron Acemoglu and David Autor. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier, 2011.

Daron Acemoglu and Pascual Restrepo. Robots and jobs: Evidence from us labor markets. 2017.

Daron Acemoglu and Pascual Restrepo. Artificial intelligence, automation and work. Technical report, National Bureau of Economic Research, 2018a.

Daron Acemoglu and Pascual Restrepo. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542, 2018b.

[11] For example, Guerreiro et al. (2017).

Daron Acemoglu and Pascual Restrepo. Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30, 2019.

Daron Acemoglu, Gino Gancia, and Fabrizio Zilibotti. Competing engines of growth: Innovation and standardization. *Journal of Economic Theory*, 147(2):570–601, 2012.

Daron Acemoglu, Claire LeLarge, and Pascual Restrepo. Competing with robots: Firm-level evidence from france. Technical report, National Bureau of Economic Research, 2020.

Mark Aguiar and Mark Bils. Has consumption inequality mirrored income inequality? *American Economic Review*, 105(9):2725–56, 2015.

S Rao Aiyagari. Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, 109(3):659–684, 1994.

Melanie Arntz, Terry Gregory, and Ulrich Zierahn. The risk of automation for jobs in oecd countries: A comparative analysis. *OECD Social, Employment, and Migration Working Papers*, (189):0_1, 2016.

Orazio Attanasio and Luigi Pistaferri. Consumption inequality over the last half century: some evidence using the new psid consumption measure. *American Economic Review*, 104(5):122–26, 2014.

Orazio Attanasio, Erich Battistin, and Hidehiko Ichimura. What really happened to consumption inequality in the us? Technical report, National Bureau of Economic Research, 2004.

Orazio P Attanasio and Luigi Pistaferri. Consumption inequality. *Journal of Economic Perspectives*, 30(2):3–28, 2016.

David Autor. The" task approach" to labor markets: an overview. Technical report, National Bureau of Economic Research, 2013.

David H Autor, Frank Levy, and Richard J Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118 (4):1279–1333, 2003.

Truman Bewley. Stationary monetary equilibrium with a continuum of independently fluctuating consumers. *Contributions to mathematical economics in honor of Gérard Debreu*, 79, 1986.

Benjamin Bridgman. Is labor's loss capital's gain? gross versus net labor shares. *Macroeconomic Dynamics*, 22(8):2070–2087, 2018.

Erik Brynjolfsson and Andrew McAfee. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company, 2014.

Wolfgang Dauth, Sebastian Findeisen, Jens Suedekum, Nicole Woessner, et al. Adjusting to robots: Worker-level evidence. Technical report, 2018.

Carl Benedikt Frey and Michael A Osborne. The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280, 2017.

Katja Grace, John Salvatier, Allan Dafoe, Baobao Zhang, and Owain Evans. When will ai exceed human performance? evidence from ai experts. *arXiv preprint arXiv:1705.08807*, 2017.

Joao Guerreiro, Sergio Rebelo, and Pedro Teles. Should robots be taxed? Technical report, National Bureau of Economic Research, 2017.

Fatih Guvenen. An empirical investigation of labor income processes. *Review of Economic dynamics*, 12(1):58–79, 2009.

Nigar Hashimzade and Michael A Thornton. *Handbook of research methods and applications in empirical macroeconomics*. Edward Elgar Publishing, 2013.

Jonathan Heathcote, Fabrizio Perri, and Giovanni L Violante. Unequal we stand: An empirical analysis of economic inequality in the united states, 1967–2006. *Review of Economic dynamics*, 13(1):15–51, 2010.

James J Heckman, Lance Lochner, and Christopher Taber. Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of economic dynamics*, 1(1):1–58, 1998.

Judith K Hellerstein, David Neumark, and Kenneth R Troske. Wages, productivity, and worker characteristics: Evidence from plant-level production functions and wage equations. *Journal of labor economics*, 17(3):409–446, 1999.

David Hémous and Morten Olsen. Dp10244 the rise of the machines: Automation, horizontal innovation and income inequality. 2014.

Joachim Hubmer, Per Krusell, and Anthony A Smith Jr. The historical evolution of the wealth distribution: A quantitative-theoretic investigation. Technical report, National Bureau of Economic Research, 2016.

Mark Huggett. The risk-free rate in heterogeneous-agent incomplete-insurance economies. *Journal of economic Dynamics and Control*, 17(5-6):953–969, 1993.

Barış Kaymak and Markus Poschke. The evolution of wealth inequality over half a century: The role of taxes, transfers and technology. *Journal of Monetary Economics*, 77:1–25, 2016.

John Maynard Keynes. Economic possibilities for our grandchildren. In *Essays in persuasion*, pages 321–332. Springer, 2010.

Dongya Koh, Raül Santaeulalia-Llopis, and Yu Zheng. Labor share decline and intellectual property products capital. *Available at SSRN 2546974*, 2016.

Frank Levy and Richard J Murnane. *The new division of labor: How computers are creating the next job market*. Princeton University Press, 2005.

Jeffrey Lin. Technological adaptation, cities, and new work. *Review of Economics and Statistics*, 93(2):554–574, 2011.

Alan Manning. We can work it out: the impact of technological change on the demand for low-skill workers. *Scottish Journal of Political Economy*, 51(5):581–608, 2004.

James Manyika, Susan Lund, Michael Chui, Jacques Bughin, Jonathan Woetzel, Parul Batra, Ryan Ko, and Saurabh Sanghvi. Jobs lost, jobs gained: Workforce transitions in a time of automation. *McKinsey Global Institute*, 150, 2017.

Benjamin Moll, Lukasz Rachel, and Pascual Restrepo. Uneven growth: automation's impact on income and wealth inequality. *Manuscript, Princeton University*, 2019.

Daniel Susskind et al. A model of technological unemployment. *University of Oxford, Department of Economics Discussion Paper. https://www. economics. ox. ac. uk/materials/papers/15126/819-susskind-a-model-of-technological-unemploymentjuly-2017. pd f*, 2017.

Joseph Zeira. Workers, machines, and economic growth. *The Quarterly Journal of Economics*, 113(4):1091–1117, 1998.

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188