Automation and the Fall and Rise of the Servant Economy

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Abstract. We develop a macroeconomic theory of the division of household tasks between servants and own work and how it is affected by automation in households and firms. We calibrate the model for the U.S. and apply it to explain the historical development of household time use and the distribution of household tasks from 1900 to 2020. The economy is populated by high-skilled and low-skilled households and household tasks are performed by own work, machines, or servants. For the period 1900–1960, innovations in household automation motivate the decline of the servant economy and the creation of new household tasks motivates an almost constant division of household time between wage work and domestic work. For the period 1960-2020, innovations in firm automation and the implied increase of the skill premium explain the return of the servant economy. We show the robustness of results to the introduction of time trends in skilled-labor supply and the consideration of endogenous demand for leisure. With counterfactual experiments we address the effects of task-dependent disutility of work and of innovations in servant efficiency (the Gig economy). We provide supporting evidence for inequality as a driver of the return of the servant economy in a regional panel of U.S. metropolitan statistical areas for the period 2005 – 2020.

Keywords: Automation, Robots, Home production, Inequality, Servants, Maids, Gig economy

JEL: D13, E24, J22, J24, O11, O30.

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For centuries, a woman's social status was clear-cut:
Either she had a maid or she was one.

(Ester Bloom, 2015)

Merry Maids strives to take the stress out of your day so you can do life your way. With more than 40 years of experience and an advanced, time-tested cleaning process, we can help you reclaim time with your loved ones.
(Internet advertisement, 2020)

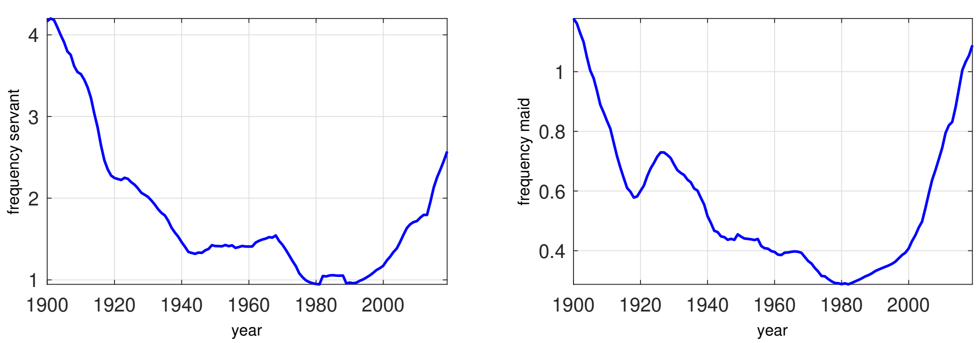
1. Introduction

In this paper, we develop a theory of the servant economy, i.e. the delegation of household tasks to hired labor and how its historical decline and later return can be explained by the state of automation in households and firms (the use of new machines and robots). In a general equilibrium framework, we adapt to the household sector the task-based production theory of Acemoglu and Autor (2010). Household tasks are either produced by own work, hired help, or machines. The economy is populated by high-skilled workers and low-skilled workers. For the production of market goods, we adapt the automation theory developed by Krenz et al. (2021). Final goods are produced by high-skilled workers and intermediate goods are assembled by low-skilled workers or machines (robots). Low-skilled workers are thus either employed in the production of goods or take on tasks in households of high-skilled workers.

The first half of the 20th century was characterized by a series of innovations in household appliances that substantially reduced the time needed to perform tasks such as washing, ironing, or food conservation (Greenwood et al., 2005). It may thus appear surprising that the 'electrification of households' had only a small impact on the average time spent on domestic work and wage work. According to Ramey and Francis (2009), the average weekly time that prime-aged individuals (age 25-54) devoted to domestic work changed from 26 hours in 1900 to 27.2 hours in 1960 while weekly hours in wage work changed from 29.6 to 27.0. In our model, these developments are explained by (i) a gradual substitution of servant work by machines and the transition of the former maids and servants to the manufacturing sector and (ii) the creation of new households tasks (motivated by new standards in sanitation and nutrition, Mokyr, 2000). The automation of household tasks by electric appliances (such as the washing machine) thus explains why the number of servants per household declined from almost 12 percent in 1900 to 3.5 percent in 1950 (Kornrich, 2012).

The historical evolution of the domestic service sector over the first half of the century is consistent with modernization theory in sociology, which predicts that in the process of development, employment of servants and maids should decline and eventually disappear (e.g. Coser, 1978). Against this background, it may appear surprising that the domestic service sector returned in the second half of the century. Measurement is more difficult in the second period because now domestic services are less frequently carried out "en bloc" by a servant or maid attached to a specific household. Instead, single tasks are outsourced to workers specialized in tasks such as cleaning, cooking, food delivery, or walking the dog, a process that was facilitated by the innovation of the internet and the smartphone app. Thompson (2019) investigates recent trends in outsourcing of domestic tasks in the U.S. and documents that, for example, the number of jobs for cooks in private households increased by about 25 percent from 2000-2017, while jobs for non-farm animal caretakers increased by about 40 percent. Autor and Salomons (2019) investigate categories of new jobs that emerged from 1980 to 2010 and found the largest category (52 percent of all new jobs) to be characterized as "wealth work", i.e. jobs that provide labor-intensive, in-person services to affluent households.

Figure 1: Relative Frequency of 'Servant' and 'Maid' in Google Books: 1900–2019



The figure shows the relative frequency per 100000 words in Google Books by year of publication, normalized by the number of books published in each year. Based on Google Books (2021).

The creation of new jobs in wealth work, however, does not capture the return of traditional domestic services. As an alternative indicator, we consider the mentioning of traditional domestic service jobs in the literature. Figure 1 shows the relative frequency of the words 'servant' and 'maid' in books by year of publication, normalized by the total number of publications in the year of publication. Both frequencies trace the decline of the servant economy in the first half of the 20th century quite well. In the second half of the century, the decline first continues and then, around 1980, the trend is reversed and servants and maids are on the rise again.

In order to explain the return of the servant economy, we propose to consider growing income inequality instead of indicators of development such as average household income. With a rising skill-premium, the opportunity cost of home-production increases for high-skilled workers who 'transform wealth into happiness' by outsourcing household chores to low-skilled workers (Whillans et al., 2017). The saved time from household chores can be spent on wage work, leisure, or new time-intensive tasks of home production such as caring for elderly children and their entry into prestigious colleges (Ramey and Ramey, 2010). The model predictions are in line with evidence provided by Milkman et al. (1998) who found that, across American metropolitan areas, household income inequality is significantly associated with the share of the female labor force employed in domestic labor.

According to our model, the trend towards outsourcing domestic tasks was initiated and propelled by skill-biased technological progress at the workplace. Increasing automation in manufacturing increased productivity and wages for high-skilled workers but not for low-skilled workers (Autor et al., 2003; Acemoglu and Restrepo, 2020). Increasing wage inequality then motivated high-skilled workers to gradually delegate more domestic tasks to low-skilled workers. Moreover, technological innovations in the domestic service sector (such as the internet and the smartphone) improved the matching of household tasks and worker talents and helped to save transaction costs. We model the gig economy as increasing efficiency of domestic service work and show that it contributed to further increasing demand for low-skilled domestic workers and that increasing demand prevented a substantial decline of low-skilled wages.

In an extension of the model, we consider endogenous leisure choice. We show that long-run trends of average leisure are consistent with a standard macroeconomic utility function (King et al., 1988). The average, however, hides that the model cannot explain the trend of rising leisure among the low-skilled. Standard extensions of the utility function suggested in the literature (MaCurdy, 1981; Boppart and Krusell, 2020) address the income-dependence of household time use. They have limited explanatory power for leisure trends of low-skilled workers whose income stayed almost constant. Here, we propose a simple refinement of the utility function by allowing households to experience greater disutility from work when they work in domestic services. The transition from work in manufacturing (building cars) to domestic services (cleaning toilets of other people) is then accompanied by declining labor supply and increasing leisure. However, these leisure trends are not utility-enhancing. Contrary to textbook predictions, the model with task-dependent utility suggests that increasing leisure is associated with declining welfare when it is caused by a transition from preferred work in manufacturing to less preferred work in domestic services.[1]

Our theory is related to a series of papers that explores the role of home production in a general equilibrium context, see, for example, Benhabib et al. (1991) Greenwood et al. (2005), Albanesi and Olivetti (2009), and Doepke and Tertilt (2016). While the available literature focusses on the division of domestic chores between husband and wife, we investigate, to the best of our knowledge for the first time, the division of tasks between servants, machines, and household members. Applying Occam's razor, we neglect the subdivision of tasks between the spouses as a problem that has been extensively discussed in the literature. Our approach is supported by Ramey and Francis (2009) whose time-use data we employ for the calibration of the model and who argue that the best way to view the data may be that of a representative household.

In order to adapt Acemoglu and Autor's (2010) task-based production function to the household, we apply a broad definition of automation and servant work that extends the original meaning of these terms. Regarding dinner preparation, for example, we conceptualize the heating of processed food in the microwave as automation and the on-demand delivery of food as servant work. The division of tasks could go further. For example, the groceries needed for for dinner could be delivered while the actual cooking is done by household members, or household members provide the ingredients, which are then assembled by a hired cook. Children are not explicitly modeled. Child rearing and education are conceptualized to be included as abstract tasks, in which machines, servants, or the parents have a comparative advantage. For example, looking after small children, may be delegated to nannies, some entertaining of children may be automated (delegated to the TV set), and some parenting tasks (chauffeuring, preparation for college) may be taken over by the parents. To acknowledge household appliances as automation requires a fine subdivision of tasks. A washing machine, for example, automates several but not all washing tasks. Putting clothes in the machine and adding detergent are tasks left for the household or the servant.

[1]Case and Deaton (2017) argue that deteriorating happiness of low-skilled workers is rooted in the labor market and may be even so strong to cause drug use and suicide. Grossmann and Strulik (2021) investigate these trends in a general equilibrium framework in which utility declines with a worker's transition of performing traditional middle class tasks to performing low-skilled tasks.

Our paper is also related to a series of papers on automation in manufacturing, e.g. Acemglu and Restrepo (2018, 2019, 2020), Prettner and Strulik (2020), and (Hemous and Olson, 2021). Here, we follow the modeling of automation by Krenz et al. (2021) where intermediate goods producing firms face a constant trend in improving productivity of robots, which gradually motivates more firms to replace low-skilled labor by robots and which generates a trend of increasing income inequality. In contrast to the available literature, we focus on automation-induced structural change, i.e. on the decline of manufacturing and the rise of the domestic service sector.

The paper is organized as follows. In Section 2, we set up the model and derive its analytical implications. In Section 3, we calibrate the model with U.S. data and apply it to explain the decline of the servant economy in the period 1900-1960. In Section 4, we apply the model to the period 1960-2020 and the return of the servant economy. In Section 5, we provide supporting evidence for inequality as a driver of the the return of the servant economy in a panel of U.S. metropolitan statistical areas for the period 2005 – 2020. Section 6 concludes the paper.

2. The Model

2.1. **Society.** The economy is populated by a continuum of size 1 of adults. Individuals can be imagined as non-aging or as members of non-overlapping generations. A fraction $\bar{L}_H$ of individuals has a high level of education, implying that $\bar{L}_L = 1 - \bar{L}_H$ individuals have a low level of education. $\bar{L}_H$ is given parametrically but allowed to change exogenously. Low-skilled individuals may take on tasks in high-skilled household production. We then call them servants. In the basic model, all labor not used in household production (in one's own or another individual's household) is supplied to firms in market goods production. In an extension, we also consider leisure as a third activity. We explore how the impact of automation in household production and market goods production affects the division of labor between own household work and servant work. Because of this focus we neglect a further subdivision of own household work between husband and wife (and perhaps other household members). The household is thus represented as a unitary agent. All variables can be time-dependent but, for notational convenience, a time-index is omitted whenever not needed for understanding. Constants are represented by Greek symbols or bars (as in $\bar{x}$).

2.2. **Firms.** Because the main innovation of our paper is at the households' side, we introduce automation at the firm level in a deliberately straightforward way, similar as in Krenz et al. (2021). Firms produce manufactured goods using homogenous high-skilled labor L_H and a set of intermediate goods y of measure 1 produced by low-skilled labor or machines (robots). Specifically, the production function for final output Y is given by

$$Y = AL_H^{1-\epsilon} \int_Q^{Q+1} y(q)^\epsilon \mathrm{d}q, \tag{1}$$

in which A is aggregate productivity and goods are indexed by the potential productivity of robots in producing the specific good. The gradual automation of manufacturing is represented by an increase of Q over time. Specifically, good $y(q)$ is produced according to $y(q) = \ell_L(q) + qx(q)$, in which ℓ_L is low-skilled labor input and x is machine input. Machines are produced using final goods. For simplicity, we assume that machines for manufacturing are produced at unit cost ϕ and machines for home production are produced at unit cost ψ. The price of the final good is normalized to 1. Workers receive a wage w_L per unit of low-skilled labor and a wage w_H per unit of high-skilled labor.

The first order conditions of profit maximization with respect to L_H, ℓ_L, and x require:

$$(1-\epsilon)AL_H^{-\epsilon} \int_Q^{Q+1} y(q)^\epsilon \mathrm{d}q - w_H = 0 \tag{2}$$

$$\left[\epsilon AL_H^{1-\epsilon}(\ell + qx)^{\epsilon-1} - w_L\right] \ell_L = 0 \tag{3}$$

$$\left[\epsilon q AL_H^{1-\epsilon}(\ell + qx)^{\epsilon-1} - \phi\right] x = 0. \tag{4}$$

Equation (2) is the indirect demand function for high-skilled labor. Inspecting the Kuhn-Tucker conditions (3) and (4) shows that machines and labor are efficiently employed together only at the threshold where $q = q_L \equiv \phi/w_L$. For lower automation productivity q, firms prefer to produce the good with low-skilled labor and for higher q machines are preferred. We thus obtain the demand functions:

$$\ell_L(q) = \left(\frac{w_L}{\epsilon AL_H^{1-\epsilon}}\right)^{\frac{1}{1-\epsilon}} \qquad \text{for } q < \phi/w_L \text{ and 0 otherwise,} \tag{5}$$

$$x(q) = \left(\frac{\phi}{\epsilon AL_H^{1-\epsilon} q}\right)^{\frac{1}{1-\epsilon}} \frac{1}{q} \qquad \text{for } q > \phi/w_L \text{ and 0 otherwise.} \tag{6}$$

Focussing on parameter values that ensure employment of low-skilled labor, we obtain aggregate demand for low-skilled labor:

$$L_L \equiv \int_Q^{\min\{q_L, Q+1\}} \ell_L(q)\mathrm{d}q = \min\left\{\frac{\phi}{w_L} - Q,\ 1\right\} \cdot \left(\frac{\epsilon A L_H^{1-\epsilon}}{w_L}\right)^{\frac{1}{1-\epsilon}}. \tag{7}$$

A corner solution without automation applies for $q_L > Q+1$. If the solution is interior, increasing efficiency in automation Q reduces the number of intermediate goods produced with low-skilled labor. For given labor supply this implies the following result.

Proposition 1. *For given labor supply, increasing efficiency of automation Q leads to lower low-skilled wages w_L.*

This intuitive result is proven by implicitly differentiating (7). In the following, however, we consider variable labor supply due to changing conditions of household production.

2.3. **Households.** In this unisex model, a representative household is best imagined as a homogenous couple with unitary utility function. We thus ignore issues of gender-specific preferences, matching of partners etc. and focus on the household work to be done. Households face a measure $(0, \bar{I})$ of distinct household tasks per unit of time. Each task is required θ_j times, $j = H, L$. With $\theta_H \geq \theta_L$ we implement the feature that high-skilled individuals live in larger houses and have larger floors to clean, larger gardens to maintain etc. Tasks are performed with own labor ℓ_O, by household machines z, or by servants s. We adapt to the household sector the task-based production function proposed by Acemoglu and Autor (2010) for market goods production. Specifically, the production function of task i by household type $j = H, L$ is given by:

$$\theta_j = a_o(i)\ell_j(i) + A_s a_s(i) s_j(i) + A_z a_z(i) z_j(i), \tag{8}$$

in which A_s and A_z capture the general productivity of servants and machines in household production, and $a_o(i)$, $a_s(i)$, $a_z(i)$, are task-specific productivities. We assume that high- and low-skilled households have access to the same household technology and that the ratios $a_s(i)/a_o(i)$ and $a_z(i)/a_s(i)$ are strictly decreasing in i. This means that comparative advantage ensures a unique sorting of input use such that tasks with the highest index are performed by households themselves, tasks with intermediate index are potentially outsourced to servants, and the lowest tasks are potentially performed by machines. It is technologically feasible that $\bar{I}_z \leq \bar{I}$ tasks are performed by machines. It should be mentioned that the infinite elasticity of substitution of inputs at the task level translates into an "ordinary" production function with finite elasticity of substitution at the level of factor inputs (Acemoglu and Autor, 2010).

If households perform task i themselves, the required labor input is $\theta_j/a_o(i)$ and costs are $\theta_j w_j/a_o(i)$. If the task is done by servants, costs are $\theta_j w_L/(A_s a_s(i))$ and if the task is done by machines, costs are $\theta_j \psi/(A_z a_z(i))$ since ψ is the unit price of a machine. In order to facilitate an analytical solution of task allocation, we assume that $a_o(i) = 1$, $a_s(i) = 1/(1+i)$, and $a_z(i) = 1/(1+\alpha \cdot i)$, with $\alpha > 1$ such that the above assumptions on comparative advantage are fulfilled. In order to limit case differentiation, we assume that $A_s \leq 1$, which ensures that low-skilled households do not employ servants.

Cost comparison between servants and machines provides the threshold:

$$I_{zH} = \max\left\{0,\ \min\left\{\frac{A_z(w_L/\psi) - A_s}{\alpha A_s - A_z(w_L/\psi)},\ \bar{I}_z\right\}\right\}. \tag{9}$$

Tasks with index $i < I_{zH}$ are produced by machines. It is most intuitive for the later analysis to discuss the automation-servant threshold as a function of the ratio between low-skilled wages and the price of automated household goods (the wage–price ration, w_L/ψ).

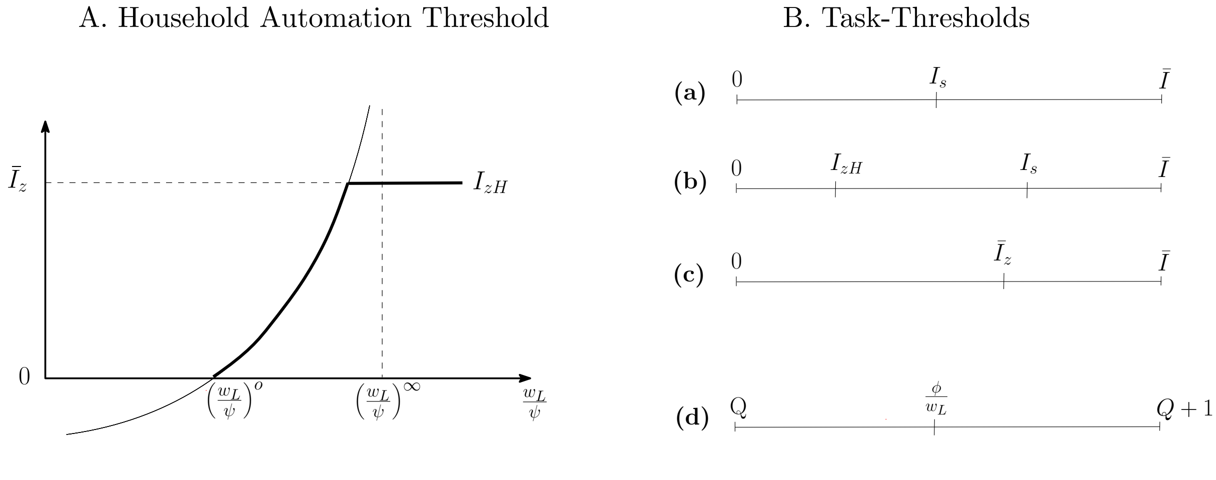
Proposition 2. *If the wage-price ratio w_L/ψ is equal or smaller than $(w_L/\psi)^o \equiv (A_s/A_z)$, then there is no automation of household tasks.*

The proof follows from comparison of the interior and corner solution of (9). Automation is induced if the price of household machines becomes sufficiently low (compared to servant wages) and/or if the productivity of household machines A_z becomes sufficiently high (compared to servant productivity A_s).

Proposition 3. *If the wage-price ratio w_L/ψ is equal or greater than $(w_L/\psi)^\infty \equiv \alpha(A_s/A_z)$, then there is no servant labor in household production.*

The proof follows from the observation that the interior solution of (9) exhibits a pole at $(w_L/\psi)^\infty$. Servant work is abandoned if the price of household machines becomes sufficiently low (compared to servant wages) and/or if the productivity of household machines A_z becomes sufficiently high (compared to servant productivity A_s). Comparison shows that $(w_L/\psi)^o < (w_L/\psi)^\infty$ since $1 < \alpha$. The threshold is shown in the diagram on the left-hand side of Figure 2. The interior solution is represented by the convex curve. The interior solution is feasible within the limits zero and $\bar{I}_z$. The pole implies:

Figure 2: Division of Tasks



PROPOSITION 4. *With continually rising wage-price ratio, the maximum of automation in rich households is reached before servant work is completely abandoned.*

The proof is obvious from inspection of Figure 2.

Comparison of (opportunity-) costs of servant work and own work provides the threshold:

$$I_s = \max\left\{0,\ \min\left\{\left[A_s\left(\frac{w_H}{w_L}\right) - 1\right],\ \bar{I}\right\}\right\}. \tag{10}$$

Tasks with index $i > I_s$ are performed by the rich households themselves. Tasks with index $I_{zH} < i < I_s$ are performed by servants when there are servants. For $(w_L/\psi) > (w_L/\psi)^\infty$ the threshold I_s disappears and servant work is abandoned. Recalling Proposition 4, we notice that this happens after automation has reached its technically feasible maximum, implying a threshold at $\bar{I}_z$ that separates automated tasks from own tasks. Tasks with index $i < \bar{I}_z$ are performed by machines and tasks with index $i > \bar{I}_z$ are performed by own work.

The thresholds are depicted in the panel on the right-hand side of Figure 2. The figure can be used to describe the evolution of the servant economy in partial equilibrium. Initially, the productivity of household machines is too low or their price too high, so that household tasks are divided between servants and own work (case a). With improving productivity and/or declining price of machines and/or rising low skilled wages, a part of household tasks becomes automated (case b). With further ongoing automation and/or rising low-skilled wages, the household becomes fully automated and servant work becomes eventually abandoned (case c).

If low-skilled wages decline and/or the productivity of servant work (A_s) increases, servant work will become re-introduced. Reading Figure 2 backwards, we see that for mildly declining w_L/ψ, automation stays at its technologically feasible maximum. Servants replace solely own work. With further declining w_L/ψ, servant work replaces previously automated tasks. For example, rich households employ cooks instead of eating ready-made meals from the microwave.

Low-skilled households compare costs of automated tasks and own work, which provides the threshold

$$I_{zL} = \max\left\{0, \ \min\left\{(w_L/\psi)A_z - 1, \ \bar{I}_z\right\}\right\}. \tag{11}$$

In low-skilled households, tasks with an index below I_{zL} are produced by machines and tasks with a higher index are produced with the household's own work. Notice from inspection of (10) and (11) that both types of households are more inclined to use machines when the real price of machines in terms of low-skilled wages (given by ψ/w_L) declines. Demand for tasks performed by servants, in contrast, increases in inequalty, i.e. the wage premium w_H/w_L, see (9). The model thus predicts that, ceteris paribus, servant work is more prevalent in unequal societies.

Integrating ℓ_H over all tasks, we obtain household hours worked by rich households:

$$h_H = \int_{\min\{I_{zH}, I_s\}}^{\bar{I}} \theta_H \mathrm{d}i = \theta_H \left(\bar{I} - \min\left\{I_{zH}, I_s\right\}\right). \tag{12}$$

Hours worked in home production increase in the size of the house θ_H, and the number of tasks $\bar{I}$, and they decline in the number of tasks outsourced to servants and machines. Likewise, we obtain household demand for servant work s and machines z_H:

$$s = \theta_H \int_{\max\{I_{zH}, I_s\}}^{I_s} \frac{1}{A_s a_s(i)} \mathrm{d}i = \frac{\theta_H}{A_S} \left| \frac{i^2}{2} + i \right|_{\max\{I_{zH}, I_s\}}^{I_s}, \tag{13}$$

$$z_H = \theta_H \int_0^{I_{zH}} \frac{1}{A_z a_z(i)} \mathrm{d}i = \frac{\theta_H}{A_z} \left[\frac{\alpha}{2}\left(I_{zH}\right)^2 + I_{zH}\right]. \tag{14}$$

Reiterating the computation for the low-skilled household, we obtain hours worked in (own) home production h_L and machine demand z_L:

$$h_L = \theta_L \int_{I_{zL}}^{\bar{I}} \mathrm{d}i = \theta_L \left(\bar{I} - I_{zL}\right). \tag{15}$$

$$z_L = \theta_L \int_0^{I_{zL}} \frac{1}{A_z a_z(i)} \mathrm{d}i = \frac{\theta_L}{A_z} \left[\frac{\alpha}{2}\left(I_{zL}\right)^2 - I_{zL}\right]. \tag{16}$$

2.4. **Labor Supply and Market Equilibrium.** High-skilled households supply $m^H = 1 - h_H$ units of time for wage work in goods production. Aggregate labor supply is thus

$$L_H = (1 - h_H)\bar{L}_H. \tag{17}$$

Low-skilled households work h_L units of time for themselves and $s_L \equiv s\bar{L}_H/\bar{L}_L$ units of time as servants in rich households such that hours supplied in goods production are given by $m_L = 1 - h_L - s_L$ and aggregate labor supply for goods production is

$$L_L = (1 - h_L - s_L)\,\bar{L}_L. \tag{18}$$

The basic model is fully described by (1)–(18). In general equilibrium w_L and w_H adjust such that the markets for high- and low skilled labor (in home and goods production) clear. Inserting everything in (2) and (7), the model is in reduced-form given by 2 equations in 2 unknowns, w_L and w_H, and can be solved for equilibrium. From there we obtain recursively the goods market equilibrium and the structure of intermediate goods production, the aggregate input of machines, and aggregate output. Unfortunately, the model is not accessible to an analytical solution such that results will be discussed numerically.

2.5. **Leisure.** The focus of our paper is on the division of work. Related empirical studies, however, usually consider the household's division of time in which leisure is considered as a third potential use of non-sleeping time aside from household work and wage work. It is thus interesting to investigate in an extension how, according to the model, automation in households and firms affects the leisure decision and how the model needs to be refined in order to approximate the stylized facts. As a benchmark, we use the iso-elastic utility function employed in conventional macroeconomics (KPR preferences, King et al., 1988), $u_j = \log c_j - \eta x_j^{1+1/\nu}/(1+\nu)$, in which x_j are the time units worked. High-skilled households work $x_h = m_H + h_h$ units of time and low-skilled household work $x_L = m_L + h_L + s_L$. This function will be sufficient to explain most stylized facts of the evolution of time use.

Additionally, we consider a refinement of the utility function, in which servant work generates greater disutility than working in the industrial sector, such that $x_L \equiv m_L + h_L + \gamma s_L$ with $\gamma > 1$. This feature may represent a direct utility effect stemming from the unpleasant nature of tasks assigned to servants and maids. For example, the negative utility experienced from cleaning other people's toilets may be greater than that experienced from building things in the manufacturing sector. The feature may also represent in reduced form that work in the servant sector, in particular in the modern on-demand economy, is more likely to be associated with unpredictable hours, unpaid overtime, less job security, no retirement plans, and no employer-provided health insurance (Ehrenreich, 2003).

The budget constraint requires $c_H = w_H m_H - \psi z_H - w_L s$ for high-skilled households and $c_L = w_L(m_L + s_L) - \psi z_L$ for low-skilled households. The first order conditions for optimal work are thus obtained as:

$$w_H = (w_H m_H - \psi z_H - w_L s)\, \eta(m_H + h_H)^{1/\nu}, \tag{19}$$

$$w_L = (w_L(m_L + s_L) - \psi z_L)\, \eta(m_L + \gamma s_L + h_L)^{1/\nu}. \tag{20}$$

with $\gamma = 1$ in the benchmark case. These two equations are added as additional constraints to the general equilibrium described above. Leisure time is inferred from the time budget constraints as $v_H = 1 - m_H - h_H$ and $v_L = 1 - m_L - h_L - s_L$. In a world without household work, ν would be the constant Frisch elasticity of labor supply. The log-form for utility from consumption is supported by studies suggesting that the intertemporal elasticity of substitution is close to unity (Chetty, 2006; Layard et al., 2008).

3. Household Automation and The Fall of the Servant Economy: 1900–1960

3.1. Introduction. We apply the model in order to explain the historical evolution of household and wage work over the 20th century and beyond. We focus on developments in the U.S. Other developed countries followed similar trajectories. In a stylized way, we can divide the 20th century in two periods: automation in the household from 1900 to 1960 and automation in the workplace from 1960 to 2020 and beyond. Almost all technical appliances that facilitate household work, the great 'engines of liberation' (Greenwood et al., 2005), were invented in the first half of the 20th century and then improved quickly and continuously: the vacuum cleaner (1901), the electric iron (1903), the electric washing machine (1904) the refrigerator (1913), the dishwasher (1903), the completely automatic washing machine including dryer (mid 1930s), and the microwave oven (1945). Aside from the microwave, the innovations quickly diffused and were in widespread use in 1960 (Greenwood et al., 2005).

We relate the predictions of the calibrated model to Ramey and Francis (2009) estimates of times that U.S. Americans spent in home production, market work, and leisure during the last century. Since the model neglects periods of life in education and retirement, households are best approximated by Ramey and Francis' time series for prime-aged adults (age 25 to 54). A perhaps surprising result from Ramey and Francis is that the time that these individuals spent on leisure is virtually the same in the year 2005 as it was in 1900. In our benchmark model we thus ignore leisure in order to facilitate the explanation of the main mechanisms of the model.[2]

Ramey and Francis document that weekly hours worked declined by only 3 hours from 1900 to 1950 after which they increased by about 5 hours, and that weekly leisure increased by only 4 hours from 1900 to 1950 after which it returned to its 1900 level. An obvious question that arises from these observations is: what happened to all of the time saved by automating the housework? The answer offered by our model analysis below is that it has been used to abandon servant work and to create new household tasks.

3.2. **Benchmark Model: Calibration.** In the benchmark model, households divide one unit of time between wage work and home production. In order to relate its predictions to the data, we compute from the Ramey and Francis (2009) data the time that prime-aged households spend on either work or home production as a fraction of the total time spent on work and home production. Kornich (2012) provides historical data on the number of servants per household. Since the number of households increased during the observation period, we deflated the denominator by the growth rate of households, which we computed from Hobbs and Stoops (2002). We used data from Greenwood et al. (2005) on the adoption rates of electrical household appliances to build an index of household automation by computing the average adoption rate of six appliances, the refrigerator, the vacuum cleaner, the washer, the dryer, the dishwasher, and the microwave. Technological progress is exogenous. In the benchmark model, we assume that there is only technological progress in the efficiency of household machines A_z. Alternatively, we could assume a continuous decline in the cost of producing household machines ψ. These mechanisms are equivalent, as can be seen from (9) and (11).

In the course of the 20th century, the notion of a high level of education has changed substantially. At the beginning of the century, a high school degree was a rare achievement, while at the end of the century high-school graduation was standard and college education was widespread. We address this problem by assuming that high school graduation is viewed as the high-skill

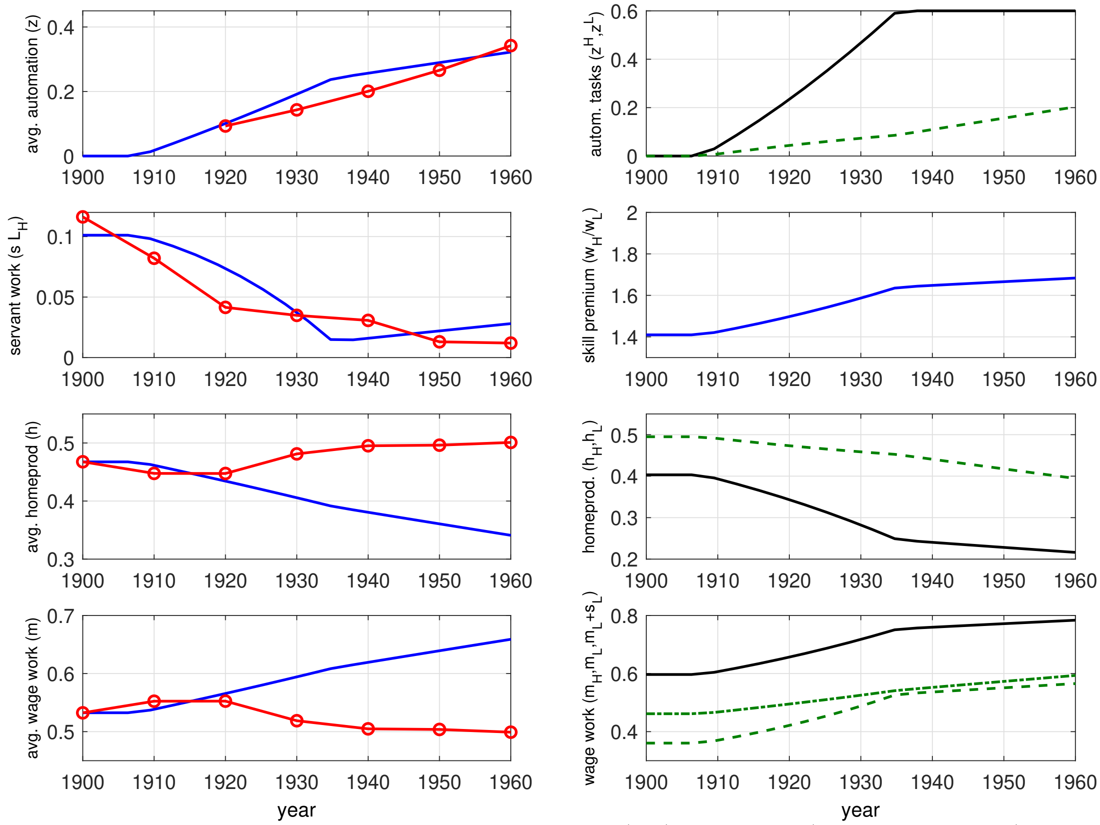
[2]The question why households prefer to spend almost all of their extra lifetime generated by improving health and longevity in retirement and why the age of entry into retirement has hardly changed in the long-run is addressed in Dalgaard and Strulik (2017) and Strulik and Werner (2018).

qualification for the period 1900–1960 and that college graduation is the high-skill qualification for the period 1960–2020. In the benchmark model, we assume that the proportion of qualifications in the population is constant. This assumption makes sense in order to focus the analysis on the labor market effects of household automation. It creates a controlled computational experiment that eliminates other confounding trends. Approximating the period average, we set $\bar{L}_H = 0.3$.

In order to compare the model predictions with data, we compute population averages, $z = z_H \bar{L}_H + z_L \bar{L}_L$ for average household automation, $m = m_h L_H + (m_L + s_L) L_L$ for average time spent on wage work, and $h = h_H L_L + h_L L_L$ for average home production. We normalize the measure of tasks $\bar{I}$ and the productivity of servants A_s to unity. We arbitrarily set $\psi = \phi = \theta_L = 1/2$. We set $Q = 0.1$ with no time trend, which eliminates the use of robots in firms during the period 1900-1960. We calibrate the remaining parameters and the (arithmetic) growth rate of A_z in order to approximate the diffusion of household automation and the decline of the servant sector 1900-1960, an average high-skill premium of 1.5, and the initial division of household tasks in 1900. This leads to the estimates $\alpha = 1.3$, $\epsilon = 0.5$, $\bar{I}_z = 0.6$, $A = 0.8$, $A_z(1900) = 1.4$, $A_z(1960) = 2.1$, and $\theta_H = 0.7$, implying that high-skilled households are 40 percent bigger than low-skilled households in terms of magnitude of household tasks.

Results are shown in Figure 3. The panels on the left hand side of the Figure show predicted averages (blue solid lines) and targeted data (red circled lines). The panels on the right hand side show the division of the average between high-skilled (solid black lines) and low-skilled (greed dashed lines) households. The second panel on the right hand side shows the predicted skill-premium. The prediction of average household automation z fits the actual diffusion of household appliances and the prediction of servant work per household $sL_H/(L_H + L_L)$ traces the actual decline of servant work reasonably well. An increase of 50 percent in the efficiency of household machines is sufficient to explain these trends. The model predicts that new or improved household appliances are taken up more quickly by high-skilled households where they reach the fixed upper limit in the mid 1930s. New appliances do not only substitute for servants but also for own home production in both high- and low-skilled households and thus labor supply of both household increases. Due to the declining servant sector, low-skilled labor supply in manufacturing increases (by more than that of high-skilled workers), which causes an increasing skill premium. While the prediction is intuitive from applying general equilibrium

Figure 3: Household Automation and the Decline of the Servant Economy: 1900–1960

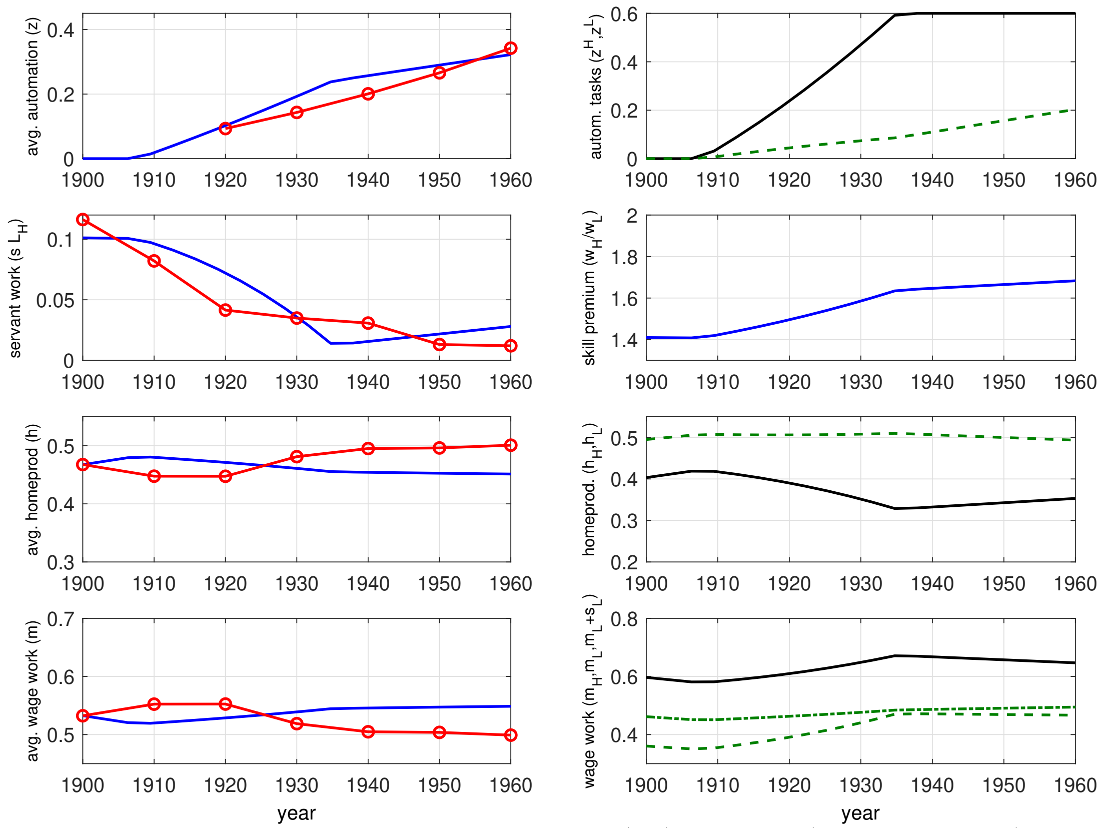


Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

considerations it is also counterfactual since the skill premium (both the high school premium as well as the college premium) declined during the period of investigation (Goldin and Katz, 2007). Another counterfactual prediction is the substantial decline in average home production mirroring the substantial increase in average wage work. The benchmark model is too simple to explain all targeted outcomes.

3.3. **New Household Tasks.** We first address the problem of the benchmark model to overestimate the impact of household automation on labor supply. Inspired by similar considerations at the level of firms (Acemolgu and Restrepo, 2019), we assume that the automation of household tasks is accompanied by the creation of new tasks. Applying this mechanism to households takes up the idea of Mokyr (2000) that the era of innovations in household automation coincided with the development of new standards in hygiene and nutrition that created new tasks in home cleaning and meal preparation (see also Ramey, 2009).

Figure 4: Household Automation and New Tasks: 1900–1960

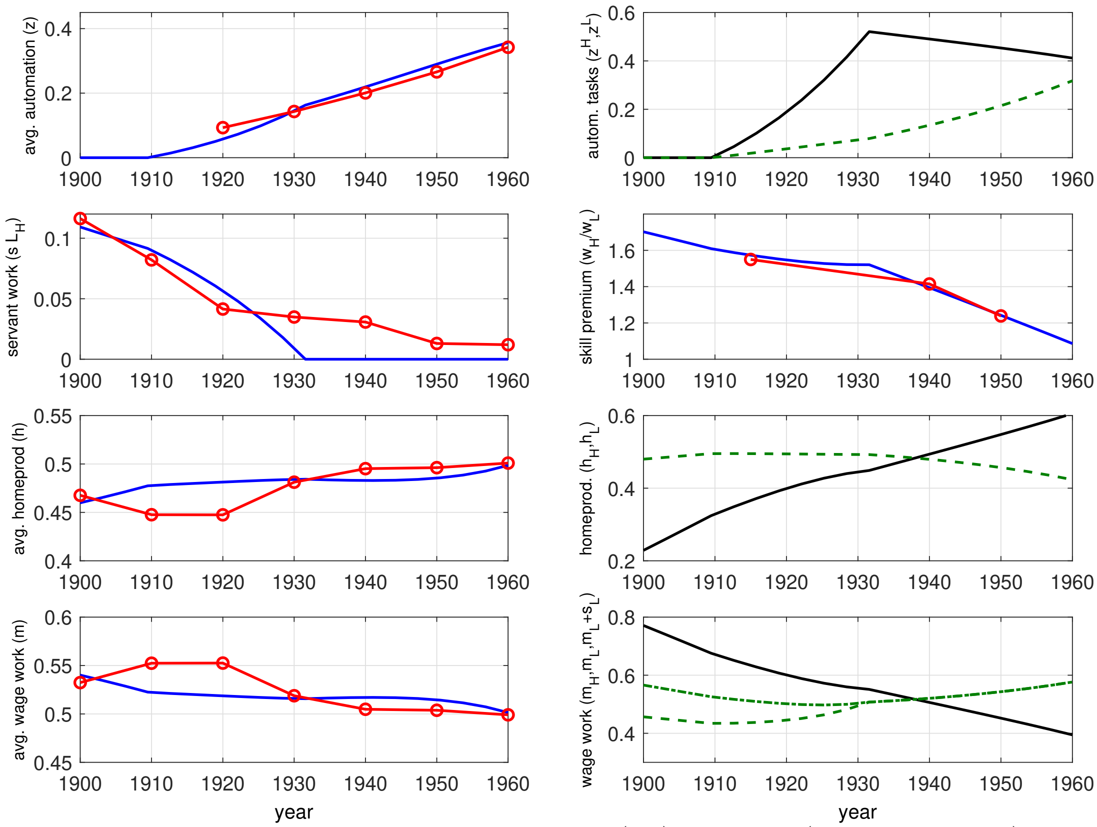


Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

Figure 4 shows results when the benchmark model is refined by assuming that the measure of household tasks increases linearly from 1 to 1.2 in the period 1900-1960. As can be seen from the third and fourth panel on the left, the 20 percent increase in household tasks is sufficient to explain a virtually constant time spent in home production and a virtually constant labor supply. The almost constant supply of low skilled workers (dash-dotted lines in the lower right panel) is accompanied by drastic structural change. Low-skilled individuals made redundant by automation leave servant work and find new employment in the manufacturing sector.

3.4. **Trends in Education.** We address the historical evolution of the skill premium by giving up the assumption of a constant stratification of the workforce. Implementing the facts documented in Katz and Goldin (2009) and Census Bureau (2021), we assume that the share of high school graduates in the labor force (L_H) increased gradually from 8 percent in 1900 to 45 percent in 1960. Naturally, the changing supply of high-skilled labor needs an adjustment of the factor share ϵ. If we kept the factor shares constant, the initial skill premium and its change over time would be hugely overestimated. As a further robustness check we introduce steady TFP growth in manufacturing. In the first half of the twentieth century TFP growth increased by about one percent (Gordon, 1999). However, for labor allocation, according to the model, relative sectoral productivity growth is decisive and productivity of servants in domestic work may have also increased due to the new technologies, a feature that is only indirectly and partially implemented by the upward shift of I_s induced by household automation. We thus assume an excess growth rate of TFP in manufacturing (above productivity of servant work) of 0.5 percent.

Figure 5: Household Automation and Trends in Education: 1900–1960



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

Given the trends of education shares and TFP, we re-calibrate the model and the trend of ϵ in order to fit the stylized facts of household automation and time division and additionally aim to fit the historical evolution of the skill premium. Data for the skill premium was taken from

Katz and Goldin (2009). The calibration provides $\theta_H = 0.8$, a decline of ϵ from 0.8 to 0.6 (at an annual rate of 0.3 percent), and an increase of A_z from 1.1 to 1.3. All other parameters are taken from the benchmark model.

Results are shown in Figure 5. The skill premium now fits the declining trend observed by Katz and Goldin (2009). The fit of the targeted time paths remains good. Comparison with the experiment from Figure 4 (where the skill premium increases) shows that automated appliances are now predicted to diffuse slower among high-skilled households and quicker among low-skilled households. This is so because low-skilled households are absolutely and relatively richer compared to the benchmark. Due to increasing wages of low-skilled households, a lower rate of technical progress in household appliances is sufficient to abolish servant work.[3]

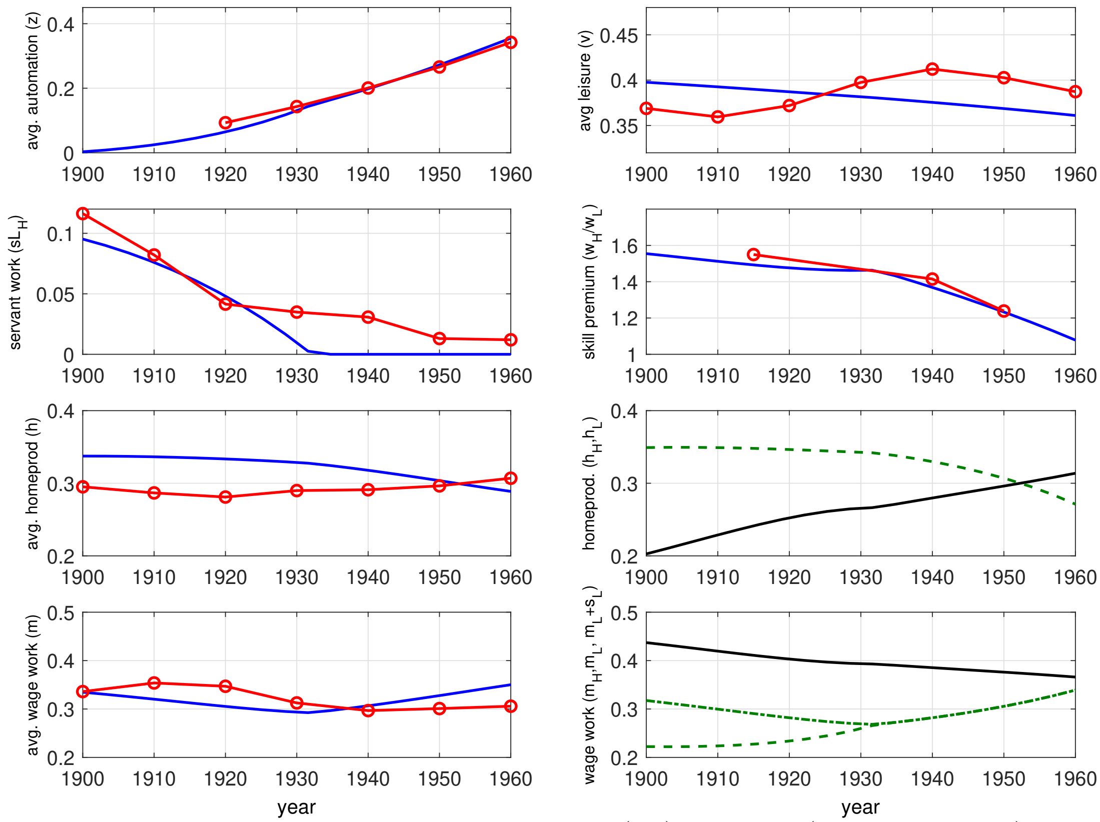
Home production of high-skilled households is predicted to increase over time, partly due to the increasing number of tasks and partly because high-skilled households increasingly perform tasks previously done by servants (due to the declining skill premium). As a result, high-skilled wage work per household is predicted to decline steeply while low-skilled wage work is trendless and u-shaped. Low-skilled work in manufacturing, however, is predicted to increase over the whole time period due to the shift of low-skill workers out of servant work. Increasing productivity of low-skilled labor additionally contributed to the decline of servant work. This channel can best be seen by comparing Figure 5 with Figure 3 and the feature that, in case of increasing productivity in manufacturing (rising A), servant work starts declining before the diffusion of household automation sets in.

3.5. **Leisure.** We next extend the model by a choice of leisure time as described in Section 2.5. This requires a re-scaling of the Ramey and Francis (2009) data, which is now measured as the fraction of wage work, home production, and leisure relative to total time spent on the three activities. We consider the benchmark utility function with $\gamma = 1$ and set $\nu = 0.82$, according to the Frisch elasticity of labor supply estimated by Chetty et al. (2011). We calibrate η and the other parameters of the model in order to fit the previous stylized facts as well as the average leisure level in the period 1900-1960. This leads to $\eta = 7.5$, $\theta_L = 0.3$, and $\theta_H = 0.45$. Both types of households are now estimated to be smaller since, in relative terms, less time is spent in home production. The other parameters are kept from the benchmark model with some small changes

[3]The model's two-class stratification of society is too coarse to capture the feature that, actually, servant work was never fully abolished during the 20th century.

in the time trends: A_z is estimated to increase from 1.1 to 1.4, $\bar{I}$ is estimated to increase from 1 to 1.1 (smaller increase of domestic tasks than for benchmark), and ϵ is estimated to decline from 0.8 to 0.55 as the high-skilled labor force increases from 0.08 to 0.45.

Figure 6: Household Automation and Leisure: 1900–1960



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

Results are shown in Figure 6, where the upper right panel has been replaced to show the evolution of leisure. While the model gets the level of leisure about right, it fails to predict the slight upward trend 1910-1940. A constant profile of leisure could be generated by abolishing the creation of new tasks with the side effect of predicting a more strongly falling level of home production. An increasing time series of leisure, on the other hand, could easily be generated by imposing a faster growth in the efficiency of automation and a faster diffusion of household appliances. It would entail a counterfactual prediction of steeply declining home production. Comparing Figure 5 with Figure 6, we see that the introduction of leisure led to less steeply declining labor supply of high-skilled households (lower left panel) and that otherwise results from the simpler model are robust to the consideration of leisure. The main takeaway is thus that automation of household technology explains the demise of servant work (amplified by increasing low-skilled productivity in manufacturing) and that the creation of new household tasks (and the partial substitution of servant work by own home-production due to a declining skill premium) explains why home production did not decline and leisure did not rise during the first half of the 20th century.

4. Automation in Goods Production and the Rise of the Servant Economy: 1960–2020

4.1. **Benchmark Model.** At the beginning of our second 60-year period of observation, all major innovations in household automation had already been made. For this period, the focus is on automation in firms, introduced by an exogenous trend in the productivity of industrial robots Q. Automation by robots appeared first in the 1980s and took off in the 1990s (IFR, 2015). We compare the model predictions with data on U.S. robots per 1000 workers as used in Acemoglu and Restrepo (2020). As explained above, we redefine high-skilled workers, which are now considered to be college graduates. We start again with a benchmark model by assuming a constant population share L_H at a level of 0.22, which is the population share of individuals with 4 years or more of college education in 1990, i.e. at the onset of the rise of the robots. For the benchmark model we also omit the leisure decision.

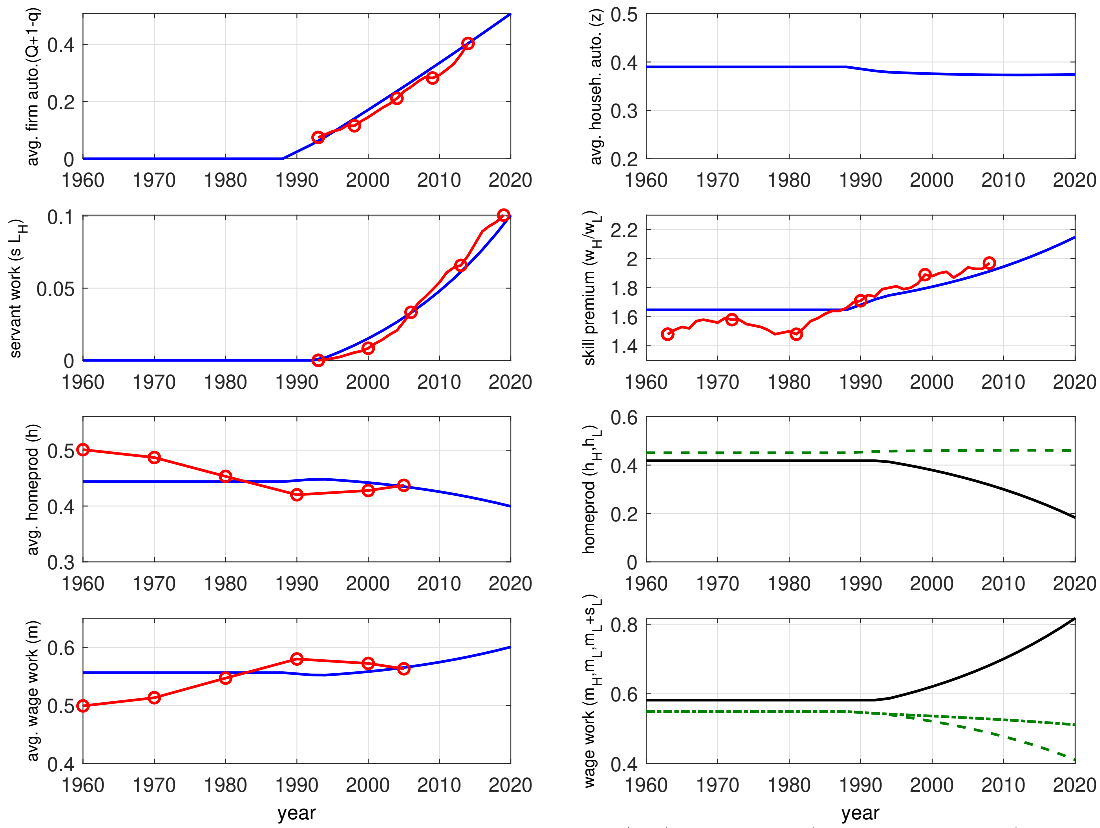
The rise in Q implies that technological progress is strongly skill-biased. It boosts high-skilled wages due to the complementarity of robots and high-skilled work and it reduces low-skilled wages due to increasing competition of the low-skilled for declining employment opportunities. The model thus predicts that low-skilled wages are basically flat before the rise of the robots in the late 1980s and then decline afterwards. Aside from a period of increasing low-skilled wages during the 1960, these predictions are in line with the stylized facts (Acemoglu and Autor, 2010) such that we do not consider skill-neutral technological progress (which would boost also low-skilled wages).

We calibrate the model by assuming that Q reaches in the year 1988 a level at which automation sets in and then continues to grow linearly such that the predicted growth of automated firms approximates the actual growth in U.S. robots according to Acemoglu and Restrepo (2020). The number (and share) of automated firms is given by $Q + 1 - q$ with threshold $q = \phi/w_L$ (see panel (d) of Figure 2). The calibration also targets the evolution of the skill premium, for which we use the data from Autor (2010). We aim again to fit the levels and trends of average time spent on wage work and home production. To do this, we re-scale the Ramey and Francis (2009) data, as described above. We take the frequency of "maid" in publications, discussed in the Introduction, as a yardstick to compare the model's prediction on the division of domestic work. This leads to the estimates $\epsilon = 0.67$, $\theta_H = 0.63$, $\alpha = 2.2$, $A = 0.85$, $A_z = 2.4$, $A_s = 0.92$ and Q growing linearly from 0.38 to 0.94 over the period 1990-2020.

Results are shown in Figure 7. The upper left panel shows the evolution of automation measured by the share of firms that use robots. In order to compare the robots data from Acemoglu and Restrepo (2020) with the predictions, we normalized its final level in 2019 such that it coincides with the predicted level. The automation induced by the linear increase of robot efficiency fits the data quite well. The model correctly predicts that the timing of the take-off of automation coincides with that of an increasing skill premium. The model somewhat overestimates the skill premium in the early period but traces the path of increasing inequality quite well.

Because of rising inequality in society, it becomes efficient again to delegate household tasks to servants and in the year 1992 the servant economy emerges again. Automation in rich households has reached its technologically feasible maximum and servants replace the homeowner's own work. In order to compare with the 'maid frequency' in publications we subtract the frequency at the year 1992 (i.e. we control for the frequency before the onset of the servant economy) and normalize its value such that the final value coincides with the predicted series. We thus compare slopes not levels. The prediction traces the take-off of 'maid frequency' reasonably well. Importantly, the rising servant economy absorbs the low-skill workers dismissed in industrial production. Industrial employment of low-skilled households declines by about 30 percent (dashed lines in the lower right panel) while predicted total hours in wage work stay almost constant. These trends reflects the prediction that low-skilled wages decline only mildly, by 5 percent from 1990 to 2020. The rising skill-premium is mainly caused by rising high-skilled wages, which increase by 25 percent over the same period. In order to investigate an interesting counterfactual, we set $A_z = 0$ and prevent the rise of the servant economy. In this case, the increasing obsolescence of low-skilled workers in manufacturing would have led to a fall in low-skilled wages by 12 percent from 1990 to 2020. The return of the servant economy thus prevents a drastic decline of low-skilled wages.

Figure 7: Automation and the Rise of the Servant Economy: 1960–2020

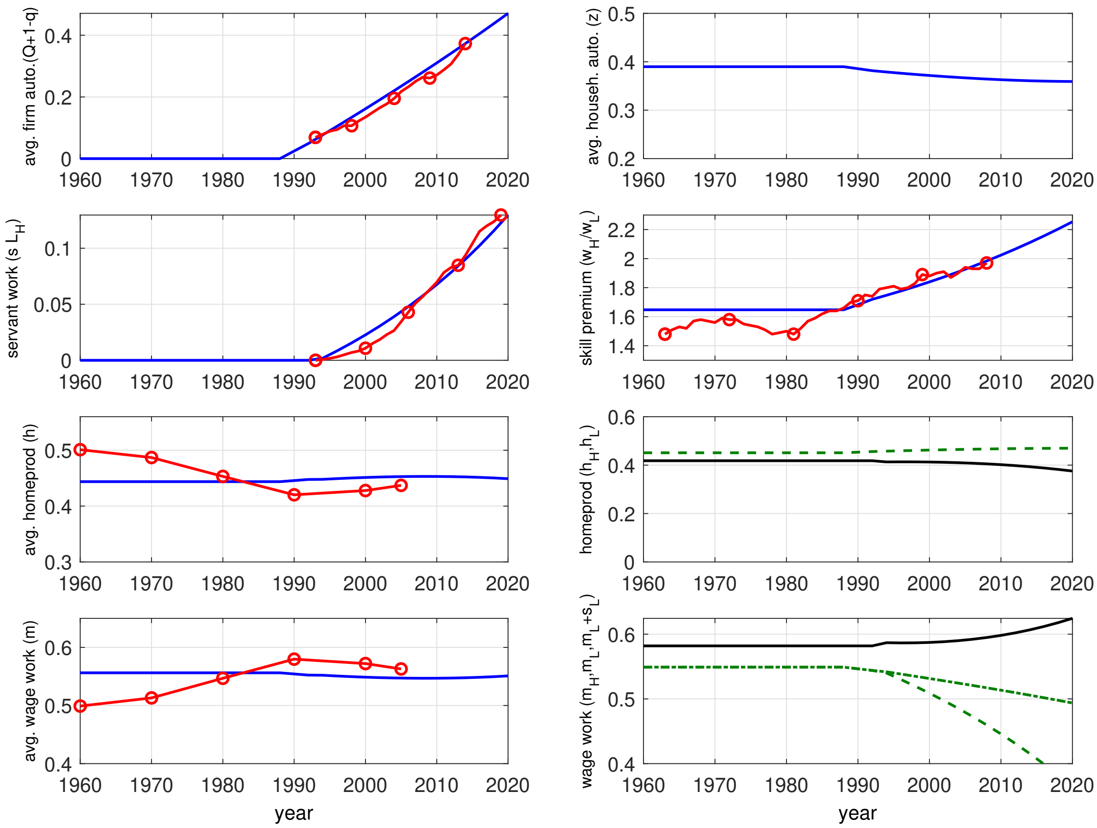


Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

4.2. **New Household Tasks.** While the benchmark model gets the average time spent on wage work and home production about right, it predicts for high-skilled households a counterfactually large decline of home production mirrored by a large increase of wage work. In order to address this problem we introduce again the formation of new tasks but this time new tasks are only created by high-skilled households. The creation of new tasks can be seen as a result of increasing competition of high-skilled households for access to (prestigious) college education for their children, which generates such tasks as homework supervision and chauffeuring for the 'helicopter' parents (Doepke and Zilibotti, 2017). While time spent on older children increased also in low-skilled households, it increased much more in high-skilled households (Ramey and Ramey, 2010).

Figure 8 shows results when the tasks for high-skilled households increase by one percent annually from 1998 to 2020. Home production then stays virtually constant over the 1960–2020

Figure 8: Automation and the Rise of the Servant Economy: New Household Tasks



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

period. These predictions are consistent with the observation that the time spent on household tasks other than care for elderly children has decreased since the 1990, freeing up the time spent on 'helicopter tasks' while total time devoted to home production remained roughly constant (Ramey and Ramey, 2010). This means that the increasing competition for access to college has been facilitated by the rise of the servant economy.

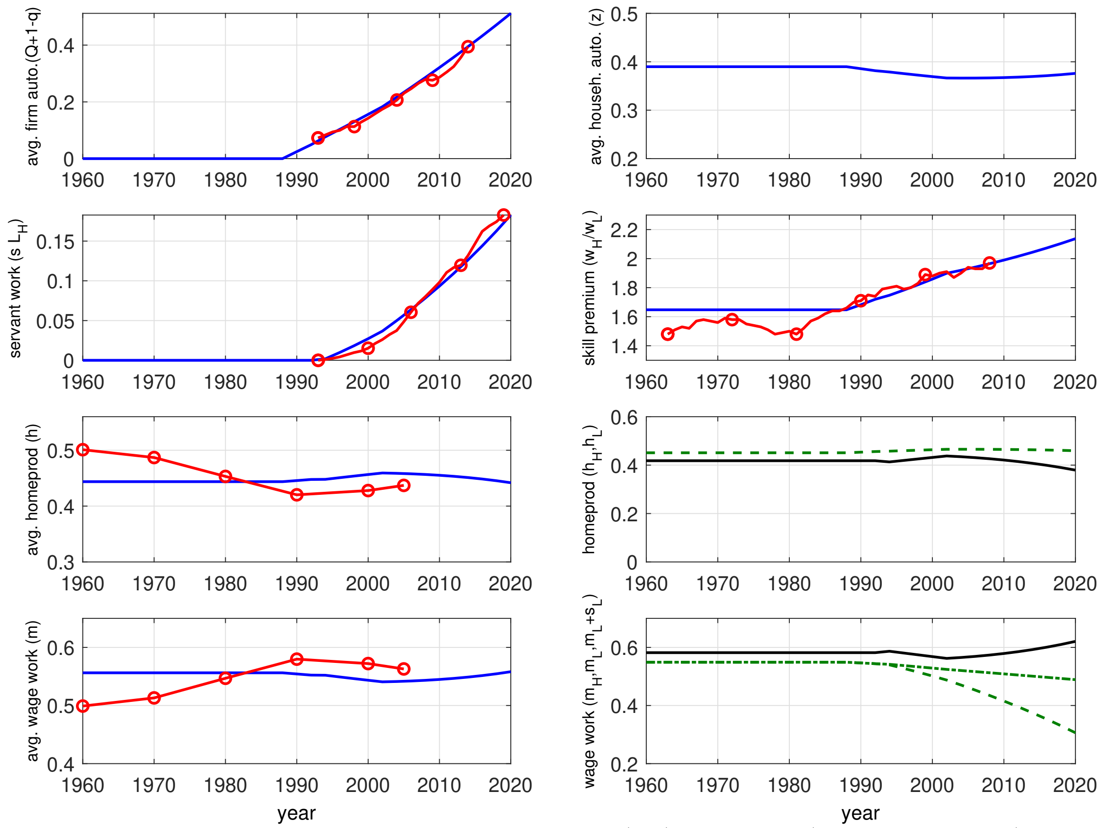
In Appendix A.1 we show robustness of these results to the consideration of a variable share of high-skilled households that grows from 10 percent in 1960 to 36 percent in 2019. As for the extended model from the last section, the education trend needs to be counterbalanced by an increasing factor input share ϵ in order to trace the actual evolution of the skill premium. Since there are otherwise no additional insights from the extension, we henceforth keep the education share and ϵ constant as in the theoretical model. This allows for an easier interpretation of the model's predictions since all changes in inequality can be attributed to automation and other innovations.

4.3. **The Gig Economy.** As discussed in the Introduction, the rise of the 'Gig Economy' is another technology trend that potentially contributed to the rise of the servant sector. Smartphone apps such as MerryMaids, Instacart, MyTable, and Rover help households to outsource tasks such as home cleaning, cooking, grocery shopping, or dog walking. In contrast to the old days when servants and maids were attached to specific households and performed an extended list of tasks, the gig economy allows to find for any household task the most efficient helper. It raises efficiency, reduces transaction costs, and the piecemeal assignment of tasks potentially induces outsourcing of tasks by households that would not have considered hiring a maid or a chauffeur in the 20th century. In the model, the gig economy can be captured by an exogenous increase of servant productivity A_z. It is reasonable to assume that the efficiency gains from outsourcing via apps started to rise with the launch of the iPhone (which coincided with the financial crisis, which many observers associate with the rise of the gig economy).

In order to investigate how the gig economy affects the predictions, we recalibrate the model assuming that after the year 2005, servant productivity rises at an annual rate of one percent and compare results with the counterfactual (no iPhone) by setting A_z constant. The benchmark model is extended by A_z growing at one percent from 2005 to 2020. In order to fit the targeted trajectories, we recalibrated $\epsilon = 0.65$, $A = 0.85$, and the measure of tasks for high-skilled households, which increases at a rate of two percent from the year 1998 onwards. Figure 9 shows the model predictions along with the fitted trajectories, which look basically as before.

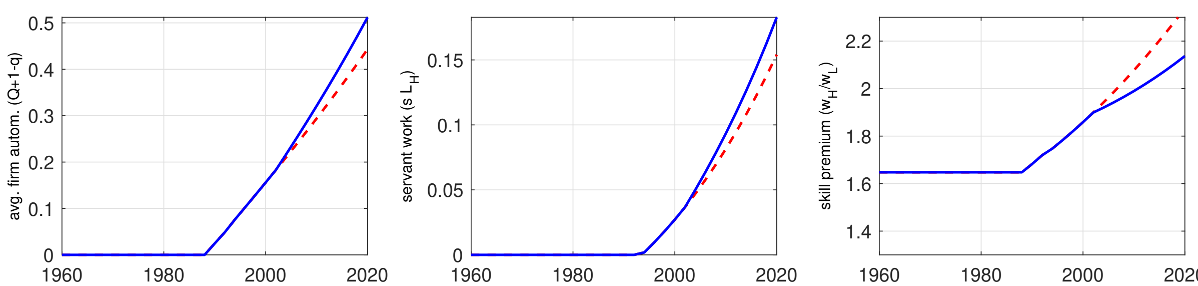
Figure 10 shows results for automation in firms, servant tasks, and the skill premium. Here, the trajectories are also shown for the counterfactual prediction of no improvement in servant productivity. The model predicts that without the rise of the gig economy, the increase in household services would have been smaller and the increase in inequality would have been greater (dashed lines in Figure 10). Automation in firms would have happened at a slower pace. The gig economy increases the demand for low-skilled workers and, as a result, low-skilled wages remain basically constant. Without the gig economy, low-skilled wages would have fallen by 7 percent from 1990 to 2020. Due to the relatively higher low-skilled wages, the gig economy accelerates automation in firms but this does not lead to increasing inequality as workers laid off in manufacturing (due to increasing automation) are absorbed into additional servant work.

Figure 9: Automation and Rise of the Servant Economy: Gig Economy



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

Figure 10: Automation and the Rise of the Servant Economy: Gig Economy



Solid blue lines: predictions for the calibrated model with an annual one percent increase of A_z from 2005 to 2020. Dashed (red) lines: counterfactual prediction: no improvement in servant productivity.

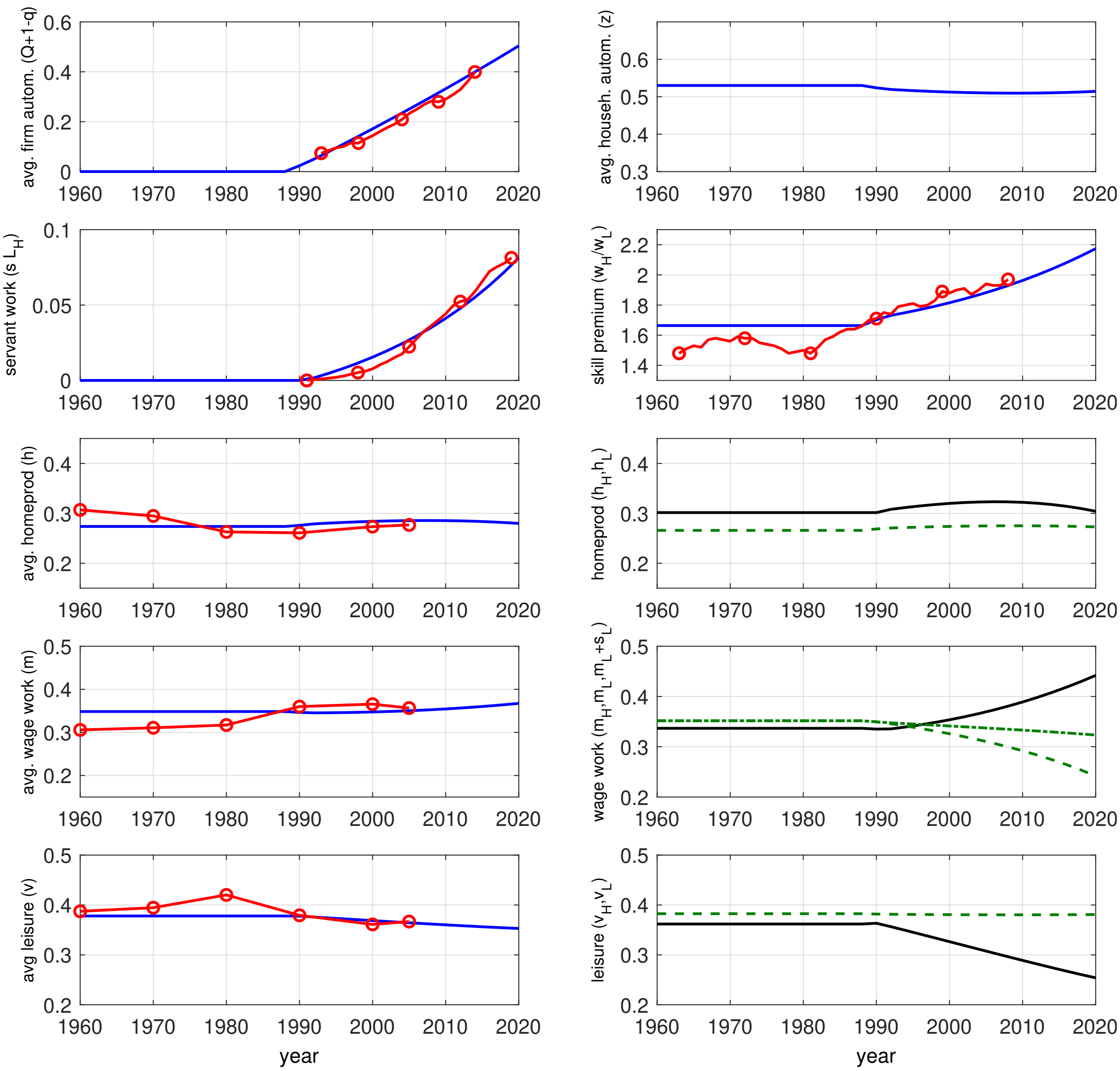
4.4. **Endogenous Leisure.** We next extend the model with endogenous leisure choices. The time use data from Ramey and Francis (2009) is re-scaled as described in Section 3. We begin with the textbook utility function by setting $\gamma = 1$. We calibrate the remaining parameters in order to fit the trajectories for average time use, automation, and the skill premium. This leads to the estimates α_z, $\epsilon = 0.69$, $\eta = 8.4$, $\theta_L = 0.35$, $\theta_H = 0.45$, and the remaining parameter values as for the benchmark case.

Figure 11 shows the predicted evolution of the economy. Additionally to the stylized facts traced by the benchmark economy, the model predicts a reversal of the association of wages and hours works, in line with the evidence presented in Bick et al. (2018). In a less advanced state of the economy, low-skilled individuals (who earn low wages) supply more labor. With the onset of automation, labor supply of high-skilled individuals becomes larger and rising. The standard result implied by KPR preferences that labor supply is independent from wages does no longer hold. With the consideration of home production, increasing wages elicit more labor supply because they increase the opportunity cost of domestic work (formally, this can be seen by implicitly differentiating (19)). With rising wages, high-skilled households are motivated to automate more tasks (e.g. heating industrial processed food in the microwave) or to delegate them to servants (hiring a cook or catering service). Additional wage work is thus "financed" by a re-allocation of tasks in the household. These effects alone would have led to less home-production. However, we have also assumed that there are more 'helicopter tasks' for high-skilled households. This effect keeps their home production constant and reduces their leisure.

Labor supply of low-skilled households, in contrast, stays almost constant. Due to automation in manufacturing there is a large shift of employment to services but only a small decline of aggregate low-skilled employment. Low-skilled households receive somewhat lower wages due to automation and are thus motivated to spend a little more time in home production and to replace previously automated tasks (e.g. more meals are home-made again instead of delivered).

While the model gets the slightly falling trend of aggregate leisure about right, it mispredicts the evolution of low-skilled leisure, which increased over the observation period and, in particular, since the late 1980s (Boppart and Ngai, 2021). Standard amendments of the utility function that associate labor supply with wages (MaCurdy, 1981; Boppart and Krusell, 2020) are not helpful in explaining this phenomenon since there is so little variation over time in low-skilled wages. Boppart and Ngai (2021) propose a general equilibrium model of time use with heterogeneity in wealth and factor productivity to explain the phenomenon of rising leisure inequality and conclude that the "less privileged" households partly reverse the welfare implications of rising income inequality by enjoying more leisure. We next consider an alternative explanation of low-skilled leisure trends, which leads to a less favorable conclusion.

Figure 11: Automation and the Rise of the Servant Economy: Endogenous Leisure



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households.

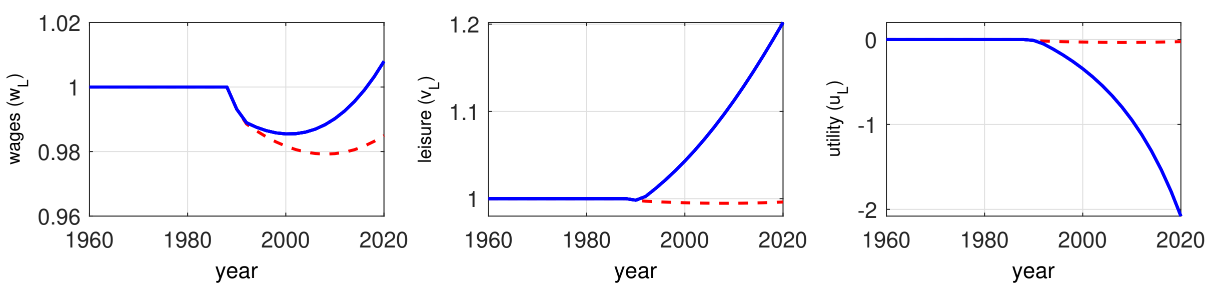
4.5. **Welfare-Reducing 'Leisure Time'.** An alternative view on low-skilled leisure trends could be that they capture, at least partly, rising involuntary unemployment.[4] Here, we propose a mechanism according to which the trend of increasing leisure is voluntary, as in Boppart and

[4] Prettner and Strulik (2020) implemented Akerlof and Yellen's (1990) fair wage theory in a model of automation and showed how the desire of low-skilled individuals to participate in the gains from skill-biased technological progress creates rising technological unemployment. In a statistical sense, leisure would thus be biased by measurement error. The time spent searching for a job would account for as leisure. Likewise, leisure would increase due to increasing work in exploitive conditions with unpaid overtime, denied breaks etc., arrangements that are common in domestic services (Ehrenreich, 2003).

Ngai (2021), but nevertheless welfare-reducing. The offered explanation is that the negative utility experienced from work is task-dependent and larger in the servant sector.

As a calibration target for the utility weight of servant work γ, we use the feature that leisure of individuals with only a high school degree increased by 15 percent from the 1960s to 2013 (Boppart and Ngai, 2021). This leads to the estimate of $\gamma = 5.4$ and a re-adjustment of the growth rate of new tasks to 0.7 percent. The rest of the model is calibrated as before. Results are shown in Appendix A.2. The release of low-skilled workers from the manufacturing sector reduces labor supply because working in the servant sector causes greater disutility from work. As a result, low-skilled wages decline by less, inequality increases less steeply, and high-skilled households outsource fewer tasks to servants. This in turn means that high-skilled labor supply increases less steeply than in the previous case.

Figure 12: Welfare-Reducing 'Leisure Time'



Solid blue lines: predictions for the calibrated model with task-depending disutility from work ($\gamma = 5.4$). Red dashed lines: counterfactual prediction: no task-depending disutility from work ($\gamma = 1$). Wages and leisure are expressed relative to their initial value in 1960; utility is expressed as deviation from the initial value, $u(year) - u(1960)$.

In Figure 12 we focus on the implied trajectories for wages, leisure, and utility of low-skilled households. Due to task-dependent disutility from work, automation in manufacturing causes only a temporary decline in low-skilled wages and a large increase in leisure, compared to the case of task-independent utility where wages drop by two percent and leisure stays virtually constant. Nevertheless, the welfare loss is greater for the task-dependent case due to the increased disutility from servant work. Relatively higher wages and more leisure do not compensate fully for the increased disutility when tasks are shifted from manufacturing to the servant sector.

Our unisex model does not distinguish between genders but it stands to reason that comparatively higher gains in leisure (losses of employment) for men are explained by a greater task-dependent disutility from work, which leads to stronger responses of men when tasks shift from manufacturing (car building) to servant work (house cleaning). A gender-specific γ-value would capture, in reduced-form, evolved work ethics and norms about ‘appropriate’ work for men.

5. Inequality and Servant Work: Empirical Evidence

5.1. **Data and Methodology.** In this section, we provide empirical evidence in support of a central prediction of the model, namely that increasing inequality is associated with more servant work. To this end, we extracted data on occupation-specific employment, mean wages, and the distribution of wages along percentiles from the Occupational Employment and Wage Statistics (OEWS) of the U.S. Bureau of Labor Statistics (2021). The data, which were sourced from annual surveys on establishments in the U.S., are available at the level of metropolitan statistical areas (MSA), which allowed us to construct a panel across MSA regions and years ranging from 2005 to 2020.[5] We collected data for three typical occupations of the servant economy: maids, animal caretakers, and couriers and messengers. We also considered aggregate employment of these three occupations (servant aggregate).

We obtained further data on population and real GDP at the level of MSAs over time from the U.S. Bureau of Economic Analysis (2021). In the benchmark regression, we considered all MSAs populated by more than 200,000 people over time. The focus on larger MSAs is motivated by the expectation that the servant economy is mainly a city-phenomenon and not visible in predominantly rural areas. We measure area- and year-specific GDP and employment in the servant occupations in per capita terms. To deflate wage measures, we extracted CPI data from the World Bank World Development Indicators (2021). In the benchmark regression, we measure inequality by the ratio of the 90th percentile to the median of wages in all occupations (also obtained from the U.S. Bureau of Labor Statistics, 2021). The 90-50 ratio provides a reliable measure of inequality and at the same time avoids biased results due to a direct effect of servant wages on servant employment, as the level of wages in servant occupations is around or below the 25th percentile. Table A.5 in the Appendix contains the descriptive statistics.

For employment, we estimate the following equation:

$$\log employment_{rt} = \beta_0 + \beta_1 \log inequality_{rt} + \beta_2 \log GDP_{rt} + \theta_r + \tau_t + \epsilon_{rt}, \tag{21}$$

[5] In the OEWS, occupational employment data is given by the estimate of total wage and salary employment in an occupation. The wages are given by gross pay, exclusive of premium pay. Self-employed individuals are not included. This means that trends in self-employed servant work promoted by the gig economy are not visible in the data.

in which $employment_{rt}$ is, alternatively, per capita employment of maids, animal caretakers, couriers and messengers, and the servant aggregate in region r and year t; GDP_{rt} is measured per capita; $inequality_{rt}$ is the 90-50 percentile wage ratio for all occupations; ϵ_{rt} is an idiosyncratic error term; θ_r are metropolitan area fixed effects and τ_t are time fixed effects, i.e. we focus on the within-region impact of inequality on servant employment.

Given our model predictions, we expect increasing demand for servants not only to be reflected by increasing employment of servants but also by higher wages in servant occupations. In order to estimate whether increasing inequality in a region is associated with higher servant wages, we set up the following regression:

$$wage_{rt} = \gamma_0 + \gamma_1 \log inequality_{rt} + \gamma_2 \log GDP_{rt} + \lambda_r + \mu_t + \nu_{rt}, \tag{22}$$

in which $wage_{rt}$ is the mean annual wage of, alternatively, maids, animal caretakers, and couriers and messengers in region r and year t. Alternatively, we also consider hourly wages instead of annual wages in the regressions.

5.2. **Results.** Table 1 shows the results for the employment regressions (21). For each occupation we report results without and with income (GDP per capita) in the regression. When income is included, it is positively associated with servant employment, but significantly only for maids and the servant aggregate. These results contradict the modernization hypotheses of the servant economy arguing that the employment of servants should vanish with economic growth. More importantly, the coefficient for inequality is hardly affected by the inclusion of income in the regression. Inequality is found to be significantly positively associated with all servant occupations and the servant aggregate with elasticities ranging from 0.30 (maids) to 0.84 (couriers). This means that the inequality nexus is also economically significant. A 10 percent increase in inequality is associated with an increase in the employment of maids by 3 percent, couriers by more than 8 percent, and the servant aggregate and animal caretakers by about 5 percent. Table A.1 in the Appendix shows that the results remain basically unchanged when the inequality measure is constructed from hourly wages.

Results from regression (22) are shown in Table 2. The dependent variable is mean annual wages which are measured in thousand \$. The results indicate a significantly positive association between inequality and the mean wages of maids. For couriers and messengers, and animal caretakers the coefficients are not significant, but also hint to a positive association between

Table 1. Servant Employment and Inequality

Dependent variable: Log employment of	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Servants aggregate		Maids		Couriers, messengers		Animal caretakers	
Log inequality	0.5113	0.5049	0.2916	0.3031	0.8364	0.8374	0.4950	0.5010
	(0.001)	(0.001)	(0.077)	(0.065)	(0.019)	(0.018)	(0.069)	(0.066)
Log GDP per capita		0.1302		0.1228		0.186		0.1649
		(0.027)		(0.045)		(0.169)		(0.123)
Metropolitan Statistical Area FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Obs.	2,547	2,547	3,185	3,185	2,672	2,672	3,016	3,016
R^2	0.848	0.849	0.810	0.811	0.613	0.614	0.705	0.706

Notes: The analysis is based on the level of metropolitan statistical areas with population size above 200,000 for the years 2005 to 2020. The dependent variable is the log of employment per capita of different occupational groups. The servants aggregate comprises the sum of employment of animal caretakers, couriers and messengers, and maids. The inequality measure is the ratio between the 90th percentile of annual wages for all occupations and the median of annual wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021).

inequality and wages. According to the point estimates, a 10 percent increase in inequality is associated with an increase of annual wages by about \$ 217 for maids, \$ 8 for couriers and messengers, and \$ 212 for animal caretakers. Regional GDP is also significantly positively associated with servant wages. These results are unsurprising since regional GDP controls for trends in the average regional level of wages. Table A.2 in the Appendix shows that similar results are obtained for hourly wages of servants and inequality constructed from hourly wages. The results suggest that increasing demand for servant work was mainly reflected increasing employment for animal caretakers and couriers and messengers.

In the Appendix, we present further results. In Table A.3, we show results for the servant employment regression (21) when all MSAs (including those with population below 200,000) are considered. Results for animal caretakers, couriers and messengers, and the servant aggregates are somewhat weaker but altogether similar to those from the benchmark regression. The positive association between inequality and maids employment, however, is lost, presumably because maids are predominantly hired in larger urban areas rather than in smaller or rural regions. In Table A.4, we consider a different inequality measure, namely the 90-10 percentile of the ratio of annual or hourly wages. Here, we find no support for a significantly positive relationship between inequality and employment of servants. As discussed above, a potential reason for this observation is that wages of servants are included in the denominator of the

Table 2. Servant Annual Wages and Inequality

Dependent variable: Mean annual wage of	(1)	(2)	(3)	(4)	(5)	(6)
	Maids		Couriers, messengers		Animal caretakers	
Log inequality	1.7946	2.1713	0.0489	0.0825	1.8964	2.1165
	(0.096)	(0.036)	(0.980)	(0.966)	(0.254)	(0.199)
Log GDP per capita		3.7580		3.9476		3.5023
		(0.000)		(0.000)		(0.000)
Metropolitan Statistical Area FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
Obs.	3,190	3,190	2,839	2,839	3,109	3,109
R^2	0.874	0.879	0.675	0.679	0.611	0.616

Notes: The analysis is based on the level of metropolitan statistical areas with population size above 200,000 for the years 2005 to 2020. The dependent variable is the mean annual wage (in thousand $) of different occupational groups. The inequality measure is the ratio between the 90th percentile of annual wages for all occupations and the median of annual wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021), World Bank (2021).

inequality measure. Since more demand for servants leads to higher wages of servants and thus lower inequality, inequality and servant employment would be negatively associated through this channel, a feature that could counterbalance the positive impact of rising wages of the rich on the demand of servants.

6. Conclusion

We proposed a new theory of task-based home production and explored how the division of household tasks depends on the level of automation in households and firms. We applied the theory to explain the historical evolution of the servant economy, i.e. the secular decline of outsourced household tasks over the first half of the 20th century and their return in the late 20th century. In contrast to earlier sociological approaches to the servant economy, our theory proposes that the extent of servant work is not based on modernization or other trends of aggregate development, but on two cost-efficiency ratios. Using a model calibrated for the U.S., we showed that increasing efficiency of household appliances explains the initial decline of the servant economy, whereas increasing wage inequality, caused by automation in manufacturing, explains the return of the servant economy. We provided supporting evidence for the inequality mechanism using data for a panel of U.S. metropolitan areas in 2005 – 2020. Controlling for year- and regional fixed effects, we found that higher inequality (measured by the 90-50 percentile ratio of wages) is associated with more employment and higher wages of maids, animal caretakers, and couriers and messengers, i.e. typical occupations in the new servant economy.

According to the model, the creation of new household tasks explains why home production and leisure of high-skilled households remained virtually unaffected by trends of the servant economy and the consideration of task-dependent disutility of work explains recent leisure trends for low-skilled workers. Increasing servant productivity generated by innovations of on-demand internet platforms and smartphone apps (the Gig economy) further amplified the demand for servant work and prevented the decline of low skilled wages. The return of the servant economy facilitated the creation of new tasks for high-skilled households and it can be argued that it enabled the increasing competition of 'helicopter parents' for their children's access to college.

While the linear task production function appears to be simplistic, the model is actually quite general and flexible at the factor input level. As shown by Acemoglu and Autor (2010), the implied aggregate production function displays constant returns to scale and an elasticity of substitution equal to or larger than one and embeds the conventional production function. In principle, the task-based production function could also be employed in the manufacturing sector. Here, we decided to follow the analytically more straightforward approach to automation in firms developed in Krenz et al. (2021).

While the theory is ready for further policy experiments such as the impact of taxes or subsidies on the division of household tasks, other applications would require a refinement of the model. Formally, the theory is easily extended towards a subdivision of tasks between husband and wife or other household members. Conceptually, however, it might be difficult to assign comparative advantages in home production. Galor and Weil (1996) argue that men have a comparative advantage in brawn-intensive market activities while both spouses are equally good in home production (child rearing). If gender differences originate solely from wage work, the task-based model will probably not lead to further insights beyond the available literature on home production (cited in the Introduction). It may be more promising to investigate evolved norms of home production which could be, in first approximation, represented by gender- and task-specific disutility from domestic work. Other forms of discrimination could be implemented at the demand side for servant work in a model variant that considers a subdivision of servant tasks by ethnicity or migrant status. The explicit integration of agencies (platforms) that intermediate demand and supply of domestic tasks could be another future application of our theory of task-based home production.

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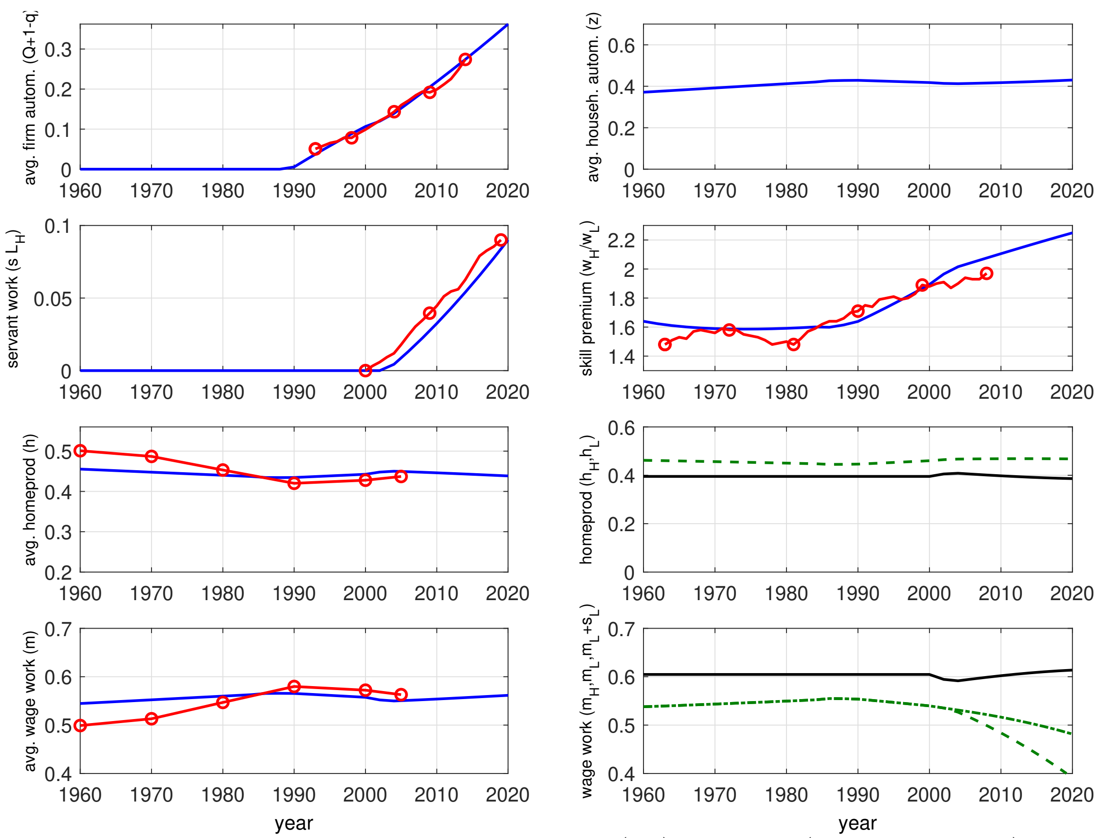
Appendix

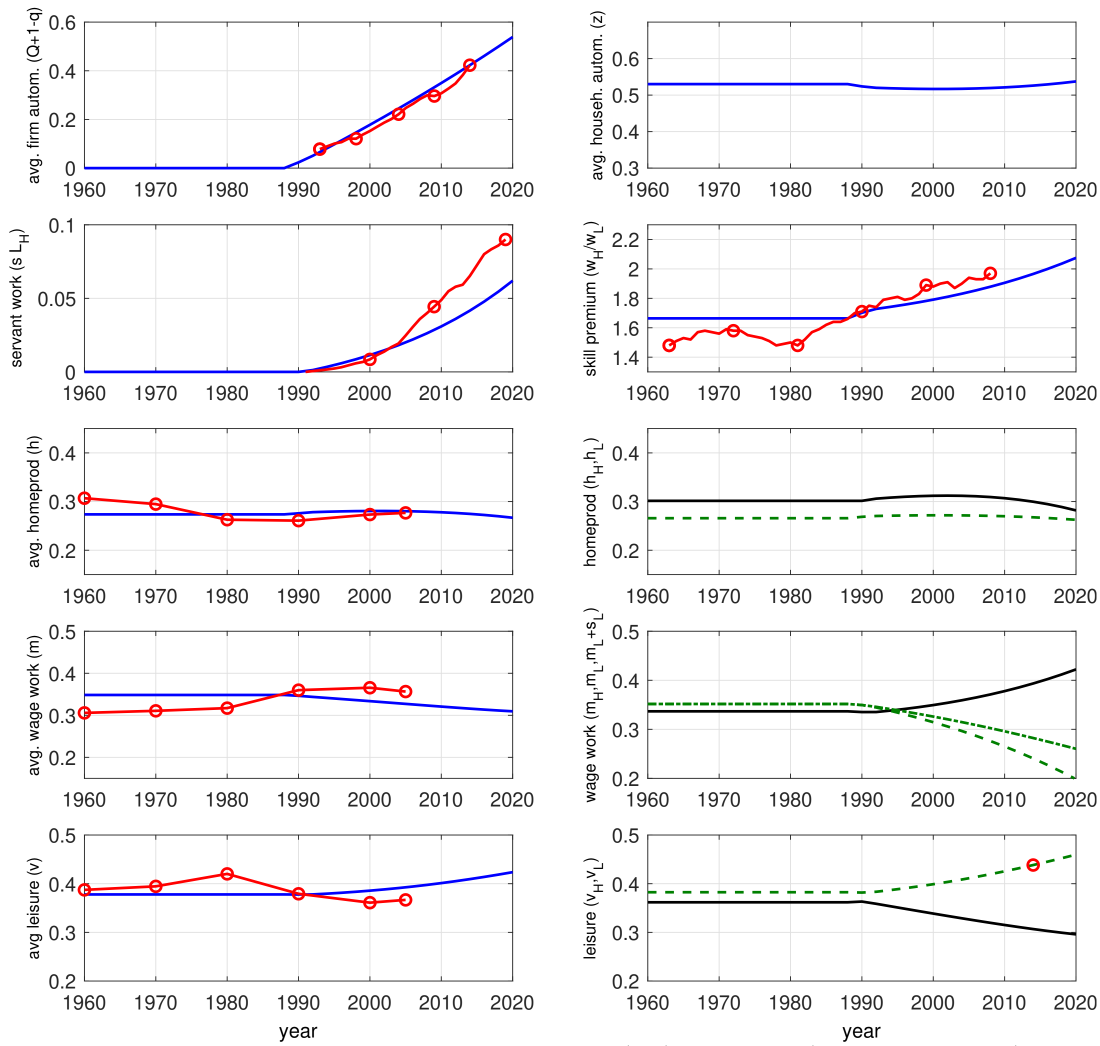
A.1 Growing College Education. We recalibrate the model by feeding in an increasing population share of college educated households, which grows from 0.1 in 1960 to 0.36 in 2020 (Census, 2021). In order to fit the actual evolution of the skill premium, ϵ is adjusted to decline from 0.86 in 1960 to 0.45 in 2020. The other parameters of the model that are re-calibrated are $A = 1.0$, $A_S = 0.8$, $A_z = 2.1$, and $\theta_H = 0.6$. Results are shown in Figure A.1.

Figure A.1: Automation and Rise of the Servant Economy - Growing College Education



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

Figure A.2: Automation and Rise of the Servant Economy: Leisure



Solid blue lines: model predictions for averages. Circled (red) lines: data (see text for details). Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households.

Table A.1. Servant Employment and Inequality – Hourly Wages

Dependent variable: Log employment of	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Servants aggregate		Maids		Couriers, messengers		Animal caretakers	
Log inequality	0.511	0.5046	0.2908	0.3024	0.8379	0.8391	0.4941	0.5002
	(0.001)	(0.001)	(0.078)	(0.066)	(0.018)	(0.018)	(0.070)	(0.066)
Log GDP per capita		0.1302		0.1229		0.1861		0.165
		(0.027)		(0.045)		(0.169)		(0.123)
Metropolitan Statistical Area FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Obs.	2,547	2,547	3,185	3,185	2,672	2,672	3,016	3,016
R^2	0.848	0.849	0.810	0.811	0.613	0.614	0.705	0.706

Notes: The analysis is based on the level of metropolitan statistical areas with population size above 200,000 for the years 2005 to 2020. The dependent variable is the log of employment per capita of different occupational groups. The servants aggregate comprises the sum of employment of animal caretakers, couriers and messengers, and maids. The inequality measure is the ratio between the 90th percentile of hourly wages for all occupations and the median of hourly wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021).

Table A.2. Servant Hourly Wages and Inequality

Dependent variable: Mean hourly wages of	(1)	(2)	(3)	(4)	(5)	(6)
	Maids		Couriers, messengers		Animal caretakers	
Log inequality	0.8549	1.0367	0.0219	0.0390	0.9009	1.0077
	(0.099)	(0.038)	(0.981)	(0.966)	(0.259)	(0.203)
Log GDP per capita		1.8062		1.8963		1.6854
		(0.000)		(0.000)		(0.000)
Metropolitan Statistical Area FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
Obs.	3,190	3,190	2,839	2,839	3,109	3,109
R^2	0.874	0.879	0.675	0.679	0.611	0.616

Notes: The analysis is based on the level of metropolitan statistical areas with population size above 200,000 for the years 2005 to 2020. The dependent variable is the mean hourly wages of different occupational groups. The inequality measure is the ratio between the 90th percentile of hourly wages for all occupations and the median of hourly wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021), World Bank (2021).

Table A.3. Servant Employment and Inequality – Annual Wages – All MSAs

Dependent variable: Log employment of	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Servants aggregate		Maids		Couriers, messengers		Animal caretakers	
Log inequality	0.3953	0.3940	-0.0445	-0.0012	0.6703	0.6893	0.2846	0.2805
	(0.007)	(0.007)	(0.718)	(0.992)	(0.032)	(0.027)	(0.135)	(0.141)
Log GDP per capita		0.0656		0.2608		0.1605		-0.09
		(0.223)		(0.000)		(0.181)		(0.269)
Metropolitan Statistical Area FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Obs.	2,947	2,947	5,505	5,505	3,230	3,230	4,649	4,649
R^2	0.843	0.843	0.800	0.801	0.613	0.613	0.66	0.660

Notes: The analysis is based on the level of metropolitan statistical areas in the USA for the years 2005 to 2020. The dependent variable is the log of employment per capita of different occupational groups. The servants aggregate comprises the sum of employment of animal caretakers, couriers and messengers, and maids. The inequality measure is the relation of the 90th percentile of annual wages for all occupations and the median of annual wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021).

Table A.4. Servant Employment and Inequality – Annual wages – Inequality as 90-10 Ratio

Dependent variable: Log employment of	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Servants aggregate		Maids		Couriers, messengers		Animal caretakers	
Log inequality 90-10 pct	-0.0283	-0.0189	-0.5226	-0.5109	-0.1114	-0.0985	0.0948	0.1203
	(0.723)	(0.812)	(0.000)	(0.000)	(0.554)	(0.601)	(0.485)	(0.380)
Log GDP per capita		0.1338		0.0750		0.1814		0.1720
		(0.021)		(0.207)		(0.181)		(0.110)
Metropolitan Statistical Area FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Obs.	2,547	2,547	3,185	3,185	2,672	2,672	3,016	3,016
R^2	0.847	0.848	0.813	0.813	0.612	0.613	0.705	0.705

Notes: The analysis is based on the level of metropolitan statistical areas with population size above 200,000 for the years 2005 to 2020. The dependent variable is the log of employment per capita of different occupational groups. The servants aggregate comprises the sum of employment of animal caretakers, couriers and messengers, and maids. The inequality measure is the relation of the 90th percentile of annual wages for all occupations and the 10th percentile of annual wages for all occupations. p-values in parentheses. Robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021).

Table A.5 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Log maids per 1000 pop	0.982	0.392	-0.628	2.651	3,186
Maids per 1000 pop	2.899	1.374	0.534	14.167	3,186
Log animal caretakers per 1000 pop	-0.762	0.498	-2.685	1.166	3,018
Animal caretakers per 1000 pop	0.523	0.264	0.068	3.209	3,018
Log couriers per 1000 pop	-1.368	0.516	-3.072	0.332	2,678
Couriers per 1000 pop	0.291	0.158	0.046	1.394	2,678
Log sum empl maids, animal caretakers, couriers per 1000 pop	1.267	0.318	0.204	2.623	2,553
Sum empl maids, animal caretakers, couriers per 1000 pop	3.748	1.396	1.226	13.774	2,553
Log inequality hourly wage 90-50 pct	0.844	0.070	0.599	1.082	4,267
Inequality hourly wage 90-50 pct	2.331	0.166	1.820	2.950	4,267
Log inequality annual wage 90-50 pct	0.844	0.070	0.599	1.082	4,267
Inequality annual wage 90-50 pct	2.331	0.166	1.820	2.950	4,267
Log inequality hourly wage 90-10 pct	1.460	0.150	0.761	1.972	4,267
Inequality hourly wage 90-10 pct	4.355	0.636	2.140	7.188	4,267
Log inequality annual wage 90-10 pct	1.460	0.150	0.761	1.972	4,267
Inequality annual wage 90-10 pct	4.355	0.636	2.140	7.186	4,267
Mean annual wage maids in thousands	20.305	3.090	13.566	37.610	4,233
Mean annual wage couriers in thousands	25.118	3.779	14.732	42.725	3,609
Mean annual wage animal caretakers in thousands	21.631	2.788	15.096	37.092	4,030
Mean hourly wage maids	9.762	1.485	6.521	18.081	4,233
Mean hourly wage couriers	12.076	1.817	7.085	20.541	3,609
Mean hourly wage animal caretakers	10.400	1.341	7.258	17.832	4,030
Log GDP per capita	3.848	0.245	3.067	5.157	3,470
GDP per capita	48.339	12.593	21.479	173.589	3,470

Notes: This Table shows descriptive statistics for MSAs with population size >200000 from 2005 – 2020. Source: Based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021), World Bank (2021).