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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 use counterfactual historical experiments to assess the role of automation, the creation of new household tasks, and the gig economy for the division of household time and tasks. We provide supporting evidence for the relation between automation and inequality, and 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.

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 function of Acemoglu and Autor (2011). Household tasks are either produced by own work, hired help, or machines. The economy is populated by high-skilled

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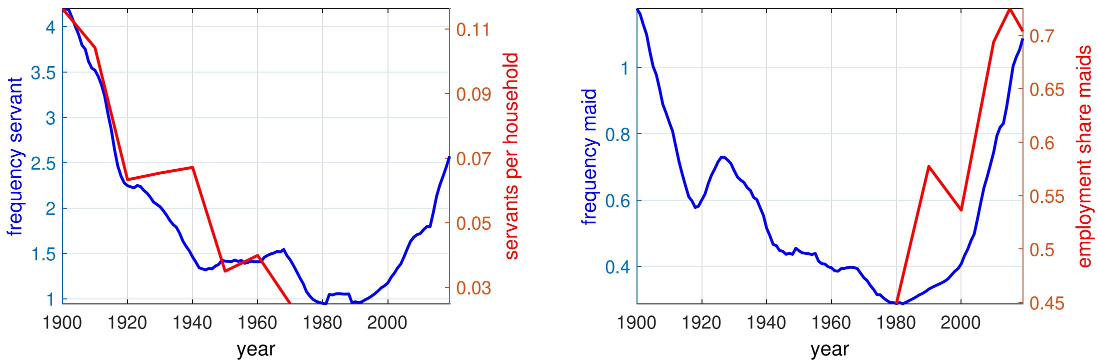

Fig. 1. Servants and maids: 1900–2019. Blue lines show the relative frequency per 100 000 words in Google Books by year of publication, normalized by the number of books published in each year; based on Google Books (2021). Red lines show the number of servants per household (left) and the share of maids and housekeeping cleaners in the employed population (right). Data from Kornrich (2012) and U.S. Census (various years), see text for details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 h in 1900 to 27.2 h 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). 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, 1973). 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 smartphone apps. 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 to be characterized as "wealth work", i.e. jobs that provide labor-intensive, in-person services to affluent households.

Since the nature of domestic services changed so much over the 20th century, it is hard to capture its evolution in one statistic. As an alternative indicator, we consider the mentioning of traditional domestic service jobs in the literature. Fig. 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.

The panel on the left-hand side of Fig. 1 shows also the actual number of servants per household in the U.S. (taken from Kornrich (2012)).[1] The mentioning of servants in books and the actual number of servants per household follow similar trends. By the 1970s, traditional domestic servants practically disappeared (Kornrich, 2012), which however, does not mean that domestic work was no longer outsourced. Instead of hiring full-time employees, households increasingly outsourced certain tasks on an hourly basis. Maids, for example, increasingly worked for 'maid services' covering several households. The panel of the right-hand side shows the employment share of 'maids and housekeeping cleaners' from 1980 to 2019 computed from U.S. Census data (U.S. Census, 1984, 1992, 2000, 2022). The employment share and the mentioning of maids in books follow similar trends.

[1] A similar decline in servants has been reported by Stigler (1946): from 9.4 percent per family in 1900 to 6.0 percent in 1940, the year of the last observation. Stigler reports also similar trends for Great Britain and Germany.

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). These model predictions are in line with evidence provided by Milkman et al. (1998). Milkman et al. showed that, across American metropolitan areas, household income inequality is positively 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 (Acemoglu and Restrepo, 2020). Increasing wage inequality then motivated high-skilled workers to gradually delegate more domestic tasks to low-skilled workers. This view is supported by Autor and Dorn (2013) who showed that, across American commuting zones, the change in service employment over the period 1980–2005 was positively associated with the average initial share of (more easily automated) routine employment. We argue that, additionally, 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 increasing demand for low-skilled domestic workers and a slowdown in rising inequality.

In our general equilibrium model, we also consider the time spent on leisure. We show that the long-run trends of income, automation, and inequality are consistent with a nearly unchanged leisure time for average Americans over the period 1900–2020. The average, however, hides distinct trends by skill group. The model predicts that leisure time declined over the whole century for high-skilled households and increased for low-skilled households since the 1990s, in line with the actually observed trends (Boppart and Ngai, 2021).

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), 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 unitary household.

So far, the task-based production function has been used to investigate how technological progress expands the range of tasks in which machines can be used instead of labor in manufacturing (Champernowne, 1963; Zeira, 1998; Acemoglu and Autor, 2011). In order to adapt it 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 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.

Our paper is also related to a series of papers on automation in manufacturing, e.g. Acemoglu and Restrepo, Prettner and Strulik (2020), and Hemous and Olsen (2022). Here, we follow the stylized modeling of automation by Krenz et al. (2021) where a productivity time-trend determines the share of production processes that can be automated, i.e. where low-skilled workers can be replaced by machines. In contrast to the available literature, we focus on the automation-induced rise of the domestic service sector. The influence of technological progress in manufacturing on inequality and the outsourcing of household tasks has also been investigated in Cozzi and Impullitti (2016). Their study focusses on endogenous R&D in an international context and the influence of technological competition on high and low-skilled wages in the technological leader country. Their study examines complementary mechanisms for why low-skilled workers leaving manufacturing enter the domestic production of high-skilled workers with a focus on comparative steady-state analysis of the role of globalization in wage polarization. In contrast, we focus on long-term trends of automation in households and firms and their impact on the division of household tasks between machines, servants, and own work and on the division of household time between wage work, housework, and leisure.

We provide supporting evidence for the link between automation and inequality, and between inequality and the outsourcing of domestic tasks using data for a panel of U.S. metropolitan areas in 2005–2020. The results show that an increase in the total number of industrial robots is associated with an increase of inequality, as measured by the 90–50 percentile ratio of wages. Controlling for year- and regional fixed effects, we find that higher inequality 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. Wages in these occupations are also increasing in response to rising inequality.

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 the link between automation and inequality and for inequality as a driver of 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 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. Individuals have a unit of time at their disposal, which they spend on wage labor, work in their own households, and leisure time. All individuals can earn a wage in goods production. Additionally, low-skilled individuals can take on tasks in high-skilled household production. We then call them servants.

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 considered as a unitary agent, represented by a single utility function. We therefore ignore issues of gender-specific preferences, matching of partners etc. and focus on the division of household tasks between household members, servants, and machines. 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. Firms produce manufactured goods using homogenous high-skilled labor L_H and a measure of intermediate goods $x(i)$ produced by low-skilled labor or machines (robots). The hybrid CES production function for final output Y is given by

$$Y = \left[\left(A_H L_H \right)^{\frac{\epsilon-1}{\epsilon}} + A_L^{\frac{\epsilon-1}{\epsilon}} \int_0^1 x(i)^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}i \right]^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

with $x(i) = \ell_L(i) + \tilde{\lambda}(i) q(i)$ where $\ell_L(i)$ are low-skilled workers and $q(i)$ are machines employed in the production of intermediate goods i. The indicator variable $\tilde{\lambda}(i) \in \{0, 1\}$ is zero if production of the intermediate i is not (yet) automatable and one otherwise. The elasticity of substitution between high-skilled labor and intermediate goods is given by ϵ. Without automation, the production function thus collapses to the conventional CES production function with skill-biased technological progress. The skill-bias is determined by the elasticity of substitution and the evolution of the ratio of factor productivities $(A_H/A_L)^{\frac{\epsilon-1}{\epsilon}}$. A second pathway of technological progress operates through the share of intermediates that can be produced by robots. Automation is characterized by an infinitely large elasticity of substitution between low-skilled workers and machines in the production of intermediates. The key difference between both pathways is that high-skilled biased technological progress also benefits low-skilled workers in terms of rising wages (only high-skilled workers benefit more) whereas automation replaces low-skilled workers and benefits only the high-skilled workers. The hybrid CES production function is a convenient way to implement the two pathways of technological progress that have affected the history of industrial production to varying degrees.

Workers receive a wage w_L per unit of low-skilled labor and a wage w_H per unit of high-skilled labor. Machines for manufacturing are produced at unit cost ϕ. The first order conditions of profit maximization with respect to $L_H, \ell_L(i)$, and x require:

$$A_H^{\frac{\epsilon-1}{\epsilon}} L_H^{\frac{\epsilon-1}{\epsilon}-1} [\cdot]^{\frac{\epsilon}{\epsilon-1}-1} - w_H = 0 \tag{2}$$

$$\left\{ A_L^{\frac{\epsilon-1}{\epsilon}} \left[\ell_L(i) + \tilde{\lambda}(i) q(i) \right]^{\frac{\epsilon-1}{\epsilon}-1} [\cdot]^{\frac{\epsilon}{\epsilon-1}-1} - w_L \right\} \ell_L(i) = 0 \tag{3}$$

$$\left\{ A_L^{\frac{\epsilon-1}{\epsilon}} \left[\ell_L(i) + \tilde{\lambda}(i) q(i) \right]^{\frac{\epsilon-1}{\epsilon}-1} [\cdot]^{\frac{\epsilon}{\epsilon-1}-1} - \phi \right\} q(i) = 0. \tag{4}$$

In order to avoid unnecessary case differentiation, we assume that $\phi < w_L$ such that production is automated whenever this is technically feasible. Let λ denote the share of production processes that are not yet automated. We then have aggregate low-skilled labor demand from manufacturing $L_L = \int_0^\lambda \ell_L(i) \mathrm{d}i$ and, due to symmetry of the production processes, every non-automated production of intermediates requires the labor input $\ell_L(i) = L_L/\lambda$. Using this information, we obtain from (2) and (3) the skill premium as

$$\frac{w_H}{w_L} = \left(\frac{A_H}{A_L} \right)^{\frac{\epsilon-1}{\epsilon}} \left(\frac{L_H}{L_L/\lambda} \right)^{-\frac{1}{\epsilon}}. \tag{5}$$

Automation (i.e. a declining share λ of not yet automated processes) thus acts like an increase of the low-skilled work force on the skill premium. This is so because the workers laid off by automation increase the competition for the remaining low-skilled jobs.

2.3. Households

Households experience disutility from work and utility from the consumption of market goods and a composite household good, which consists of a measure of household tasks. Specifically, utility of household j, $j = H, L$, is given by

$$u_j = \log c_j - \frac{\eta b_j^{1+1/\nu_j}}{1 + 1/\nu_j} + \Theta_j \tag{6}$$

in which c_j are market goods, b_j are the time units worked, and Θ_j is the composite household good. With respect to c_j and b_j the utility function is of the conventional iso-elastic utility type (also known as KPR preferences in macroeconomics, King et al. (1988)). High-skilled households work $b_h = m_H + h_h$ units of time and low-skilled household work $b_L = m_L + h_L + s_L$ time units, in which m_j is household j's time supplied to work in goods production. 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). In a world without household work, ν_j would be the constant Frisch elasticity of labor supply. We allow ν_j to depend on the household-type in order to better match the association between income and labor supply of high and low-skilled workers. We assume that the composite household good enters the utility function linearly such that it will not depend on income but on prices and productivities of task provision. Households are endowed with one unit of time, which they can use to do wage work for firms or other households, work in their own household, or leisure.

2.4. Household tasks

The composite household good is defined as $\Theta_j \equiv \theta_j \int_0^{\bar{I}} \mathrm{d}i$. It consists of a measure $\left(0, \bar{I}\right)$ of distinct household tasks of which each task is performed θ_j times per unit of time, $j = H, L$. 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. Any task i can be performed by own labor $\ell_j(i)$, by household machines $z_j(i)$, or by servants $s_j(i)$. We adapt to the household sector the task-based production function proposed by Acemoglu and Autor (2011) for market goods production. Specifically, the production function of task i by household type $j = H, L$ is given by:

$$\theta_j = a_o(i)\ell_j(i) + A_s a_s(i) s_j(i) + A_z a_z(i) z_j(i). \tag{7}$$

In Eq. (7), A_s and A_z capture the general productivity of servants and machines in household production. An increase of A_z boosts the productivity of all tasks that are potentially delegated to machines. A prime example is the increase of A_z promoted by electricity. The invention and diffusion of electricity as a general purpose technology increased the productivity of many if not all household machines. Similarly, the invention of the internet and smartphone app can be seen as a general-purpose technology that increased A_s, making it easier to outsource household tasks to specialists who could perform them more efficiently or at lower cost (e.g., animal caretakers, cooks, or nannies).

The parameters $a_o(i)$, $a_s(i)$, $a_z(i)$, are task-specific productivities. They state how productive a particular task i is performed by own labor, servants, or machines. For example, a technical improvement in the washing machine increases the productivity of machines for the task of washing. 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 tasks with the lowest index are potentially performed by machines. It is technologically feasible that $\bar{I}_z \leq \bar{I}$ tasks are performed by machines. Household machines are produced from final goods and available at unit cost ψ.[2]

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 is a sufficient condition for households with low qualifications not to employ servants.

Cost comparison between servants and machines provides the threshold:

$$I_{zs} = \begin{cases} \max\left\{0,\ \min\left\{\frac{A_z(w_L/\psi)-A_s}{\alpha A_s - A_z(w_L/\psi)},\ \bar{I}_z\right\}\right\} & \text{for } w_L/\psi < \alpha A_s/A_z \\ \bar{I}_z & \text{otherwise}. \end{cases} \tag{8}$$

Households prefer machines to servants for tasks below the threshold and vice versa above the threshold. 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 ratio, w_L/ψ). The threshold is depicted in Fig. 2 as the upward sloping curve that reaches its upper bound at $\bar{I}_z$.

[2] 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, 2011).

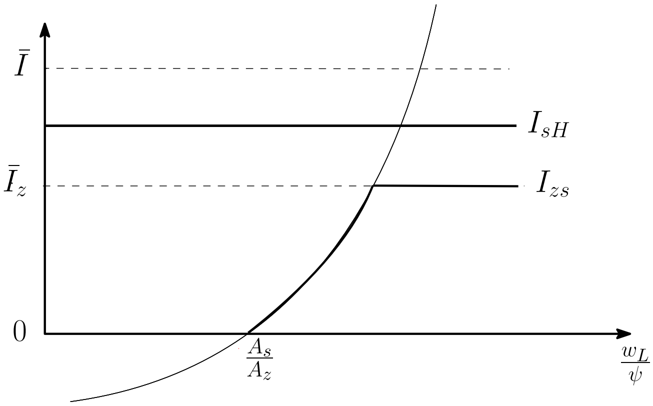

Fig. 2. Division of tasks in rich households.

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

$$I_{sH} = \max\left\{0,\ \min\left\{\left[A_s\left(\frac{w_H}{w_L}\right) - 1\right],\ \bar{I}\right\}\right\}. \tag{9}$$

Households prefer servants to own work for tasks below the threshold and vice versa above the threshold. The threshold is shown for a constant skill premium w_H/w_L as a horizontal line in Fig. 2. The prevalence of servant work obviously requires that the I_{sH}–threshold lies above the I_{zs}–threshold, an observation that leads to the proposition:

Proposition 1. *If $I_{zs} < I_{sH}$, then tasks $i < I_{zs}$ are produced by machines, tasks $I_{zs} \le i < I_{sH}$ are produced by servants and tasks $i \ge I_{sH}$ are produced by high-skilled households' own work. For constant inequality (skill premium) w_H/w_L and constant servant productivity A_s, higher income w_L, lower prices for appliances ψ, or greater productivity of appliances A_z leads to a replacement of servants by machines without affecting the time spent in home work of rich households. Increasing inequality w_H/w_L or increasing productivity of servants A_s leads to a replacement of households' own work by servant work without changing the use of household machines.*

The proof is obvious from Fig. 2.

If the I_{sH}–threshold lies below the I_{zs}–threshold, servant work disappears and high-skilled households compare costs of automated tasks and own work, which provides the threshold

$$I_{zH} = \max\left\{0,\ \min\left\{\frac{1}{\alpha}\left(\frac{w_H}{\psi}A_z - 1\right),\ \bar{I}_z\right\}\right\}. \tag{10}$$

Proposition 2. *If $I_{zs} \ge I_{sH}$, then tasks $i < I_{zH}$ are produced by machines and tasks $i \ge I_{zH}$ are produced by high-skilled households' own work. The division of household work is independent from low-skilled wages and productivity of servants. Higher income w_H, lower prices for appliances ψ, or greater productivity of appliances A_z leads to a replacement of households own work by machines until automation reaches an upper bound $\bar{I}_z$.*

The proof is obvious from inspection of (10). As a corollary from these propositions, we conclude that with perpetually rising w_L/ψ ratio, servant work is eventually abandoned if w_H/w_L is sufficiently low such that $A_s(w_H/wL) - 1 \le \bar{I}_z$. Otherwise servant work persists.

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

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

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 (9) 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 inequality, 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 over tasks, we obtain total household hours worked. If $I_{zs} < I_{sH}$, all modes of household production are active and we obtain rich households own work h_H, machine work z_H, and servant work s in high-skilled households as

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

$$z_H = \theta_H \int_0^{I_{zs}} \frac{1}{A_z a_z(i)}\mathrm{d}i = \frac{\theta_H}{A_z}\left[\frac{\alpha}{2}\left(I_{zs}\right)^2 + I_{zs}\right] \tag{13}$$

$$s = \theta_H \int_{I_{zs}}^{I_{sH}} \frac{1}{A_s a_s(i)} \mathrm{d}i = \frac{\theta_H}{A_S} \left| \frac{i^2}{2} + i \right|_{I_{zs}}^{I_{sH}}. \tag{14}$$

Since only high-skilled households employ servants, average servant work (number of servants per household) in the society is given by $s\bar{L}_H$. Notice that servant work can increase because more tasks in rich households are taken on by servants or because there are more rich households. Average servant work supplied by low-skilled households is given by $s_L \equiv s\bar{L}_H/\bar{L}_L$.

If $I_{zs} \geq I_{sH}$, there are no servants and total work in high-skilled households is obtained as

$$h_H = \theta_H \int_{I_{zH}}^{\bar{I}} \mathrm{d}i = \theta_H \left(\bar{I} - I_{zH}\right) \tag{15}$$

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

Likewise, hours worked in low-skilled households are:

$$h_L = \theta_L \int_{I_{zL}}^{\bar{I}} \mathrm{d}i = \theta_L \left(\bar{I} - I_{zL}\right) \tag{17}$$

$$z_L = \theta_L \int_0^{I_{zL}} \frac{1}{A_z a_z(i)} \mathrm{d}i = \frac{\theta_L}{A_z} \left[\frac{\alpha}{2} \left(I_{zL}\right)^2 - I_{zL}\right]. \tag{18}$$

2.5. Market equilibrium

The budget constraints of households are given by $w_H m_H = c_H + \psi z_H + w_L s$ for high-skilled households and $w_L(m_L + s_L) = c_L - \psi z_L$ for low-skilled households. Maximizing (6) with respect to optimal supply of wage work and subject to the budget constraint provides the first order conditions:

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

$$w_L = \left(w_L(m_L + s_L) - \psi z_L\right) \eta (m_L + s_L + h_L)^{1/\nu_L}. \tag{20}$$

Leisure time is inferred from the time budget constraints as $v_H = 1 - m_H - h_H$ and $v_L = 1 - m_L - h_L - s_L$.

High-skilled households supply $m^H = 1 - h_H - v_H$ units of time for wage work in goods production. Labor market equilibrium for high-skilled labor thus requires that

$$L_H = (1 - h_H - v_H)\bar{L}_H. \tag{21}$$

Low-skilled households work h_L units of time for themselves and s_L units of time as servants in rich households such that hours supplied in goods production are given by $m_L = 1 - h_L - s_L - v_L$ and labor market equilibrium requires that

$$L_L = \left(1 - h_L - s_L - v_L\right) \bar{L}_L. \tag{22}$$

The basic model is fully described by (1)–(22). 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. Since the model is not accessible analytically and our main focus is the quantitative exploration of the impact of automation in household and firms, and their impact on servant labor and the household division of tasks and time, we proceed with a numerical calibration of the model.

3. Household automation and the fall of the servant economy: 1900–1960

3.1. Remarks on the general calibration procedure

We apply the model in order to explain the historical evolution of U.S. American household and wage work over the 20th century and beyond. As shown in the Introduction, we need such a long time horizon in order to capture the phenomenon of the fall and rise of servant work. The time frame means that we need to take into account that the composition of the American society, as reflected in the share of high-skilled workers, has changed enormously over the last century. At the dawn of the 20th century, a small elite of less than 10 percent of the American population had a high school degree such that high school graduation clearly defined a high-skilled worker (Goldin and Katz, 2007). In the year 2020, high-school graduation was almost universal at 91 percent (U.S. Census Bureau, 2021) and being 'high skill' is now associated with college education.

Since the model society is stratified by education, we used consistently over the whole time period the skill premium as the calibration target for inequality. However, in order to account for the changing concept of high-skilled labor and to apply the model in a meaningful way, we divide the last 120 years in two equally sized periods. The period 1900–1960 reflects the rise of high-school education (as high-skilled labor) and the decline of servant work while the period 1960–2020 reflects the rise of college education (as high-skilled labor) and the return of servant work. In the calibration of the model for the two periods, we aim for cross-century stability of parameters (in particular for those capturing preferences) but naturally some parameters capturing technology need to change to adapt to the changing notion of high-skilled work.

The calibration of the model in this and the next section proceeds according to the following steps. We feed into the model the time series for the share of high-skilled labor. We calibrate the series of productivities A_L, A_H, and λ such that the model predictions align with the path of the skill-premium and (in the later period) the diffusion of robots as well as the average growth rate of income per capita over the period. We calibrate a linear trend for the creation of new tasks $\bar{I}$ and a linear trend for the price of household machines (in the early period) or the productivity of servant work (in the later period) along with the values of all constant parameters such that the model prediction fits the observed paths in the allocation of time to household work, market work, and leisure, as well as average servant work per household.[3]

3.2. Calibration and benchmark results

In this section, we focus on the period 1900–1960, in which workers with high school diploma or more are considered highly skilled. We obtained the share of these workers from Goldin and Katz (2007) and the U.S. Census Bureau (2021) and fed them into the model as time series of $\bar{L}_H$. Missing values were obtained by extrapolation of the data. From 1900 to 1960, the share of high school graduates increased from 8 to 45 percent while the share of workers with 4 or more years of college increased from 2.1 to 8.3 percent. To account for the fact that some workers earn more than the high-school wage premium, we compute an average wage premium as the weighted average of the high-school wage premium and the college wage premium where the weights are calculated as the share of workers with only high-school diploma and of workers with college education among the workers with at least a high school diploma. The underlying data were again obtained from Goldin and Katz (2007) and the U.S. Census Bureau (2021).

We use historical data on the number of servants per household provided in Kornrich (2012) to calibrate the average demand for servant services per household ($s\bar{L}_H$). We use the estimates provided in Ramey and Francis (2009) on the time use of U.S. American households to calibrate the average time use for home production, market work, and leisure. 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). Ramey and Francis document that weekly hours worked declined by only 3 h from 1900 to 1950 after which they increased by about 5 h, and that weekly leisure increased by only 4 h from 1900 to 1950 after which it returned to its 1900 level.

In order to compare the model predictions with the Ramey–Francis data, we compute population averages, $m = m_h\bar{L}_H + (m_L + s_L)\bar{L}_L$ for average time spent on wage work, $h = h_H\bar{L}_H + h_L\bar{L}_L$ for average home production, and $v = v_H\bar{L}_H + v_L\bar{L}_L$ for average leisure. We set the initial measure of different household tasks to one ($\bar{I}(0) = 1$) and calibrate the household sizes θ_H and θ_L in order to match the average level of household work. We set $\nu_L = 0.82$, according to the Frisch elasticity of labor supply estimated by Chetty et al. (2011), and calibrate η and ν_H to match the time path for leisure in the Ramey-Francis data.

Almost all technical appliances that facilitate household work, the great 'engines of liberation' (Greenwood et al., 2005), were invented in the early 20th century: 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. We computed a time series of the average adoption rate of these six appliances, taken from Greenwood et al. (2005). In the calibration, we use the time series of the average adoption rate as target for the average number of tasks in households performed by machines. We normalize $A_z = A_s = 1$ and calibrate a linear time path of the price ψ such that the predicted path of average automation $I_z = I_{zH}\bar{L}_H + I_{zL}\bar{L}_L$ matches the diffusion path of household machines.

We assume that robots played no role in the early period by setting $\lambda = 1$. We calibrate the elasticity of substitution ϵ, initial technology levels $A_H(1900)$ and $A_L(1900)$ and a constant growth rate g in $A_H(t) = (1+g)^t A_H(1900)$ to fit the observed time path of the skill premium and an average growth of income of 1.3 percent per year. The growth rate matches the average annual growth rate of U.S. income per capita in 1900–1960 period, computed from the Maddison data (Bolt and Van Zanden, 2020).

Finally, we allow for a trend in the creation of new household tasks. This feature improves not only the predictive power of the model, but it also captures the observation that the early 20th century was a period in which the development of new standards in hygiene and nutrition created new tasks in home cleaning and meal preparation (Ramey, 2009). We demonstrate the contribution of the trend by removing it in counterfactual analyses.

Summarizing, we jointly calibrate the following set of parameters α, ϵ, η, ν_H, θ_H, θ_L, $\bar{I}_z$, $A_H(1900)$, $A_L(1900)$, and constant time trends for A_H, ψ, and $\bar{I}$ in order to fit the time paths of household automation and the skill premium, the share of time allocated to household work, market work, and leisure, and average servant work per household. The predicted trajectories are shown by blue lines in Fig. 3. The targeted data series are shown by red circled lines.

The calibrated elasticity of substitution between high and low-skilled workers ϵ is 1.5, a value that agrees well with empirical estimates of the canonical CES production function (e.g. Goldin and Katz, 2007; Acemoglu, 2012). The calibrated time path of A_H implies an annual growth rate of high-skilled technology of 1.8 percent. Despite the large skill-biased technological progress, the skill premium declines in the 1900–1960 period due to the massive increase of the share of high-skilled workers (cf. Eq. (5)), as shown in the center-right panel of Fig. 3. During the 1900–1960 period, low-skilled wages increased by an annualized rate of 0.7 percent, implying that a great part of growth of income per capita is explained by the changing skill composition, i.e. upward mobility of the American workforce. The combined series of w_L and ψ implies that the real price of household appliances declined by 40 percent for low-skilled workers. The calibrated value of ν_H implies that high-skilled labor supply responds more weakly to changes in wages than low-skilled labor (as observed e.g. in Kydland, 1984). The calibrated values of θ_H and θ_L imply that high-skilled households

[3] The skill-premium and servant employment are treated as fully endogenous variables. While they are indirectly affected by the calibrated productivity trends, they are not directly subject to exogenous time trends.

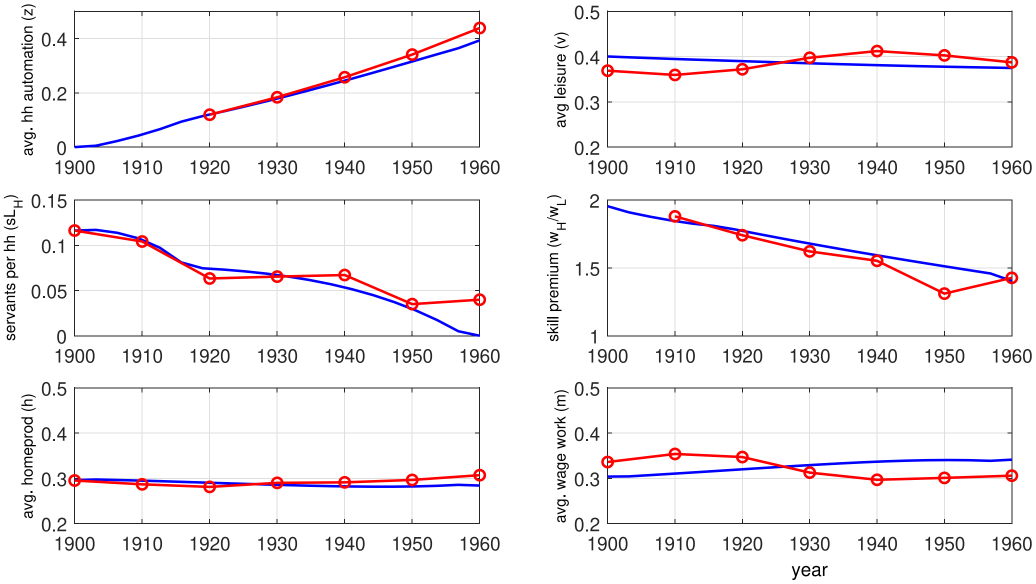

Fig. 3. Household automation and the decline of the servant economy: 1900–1960. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

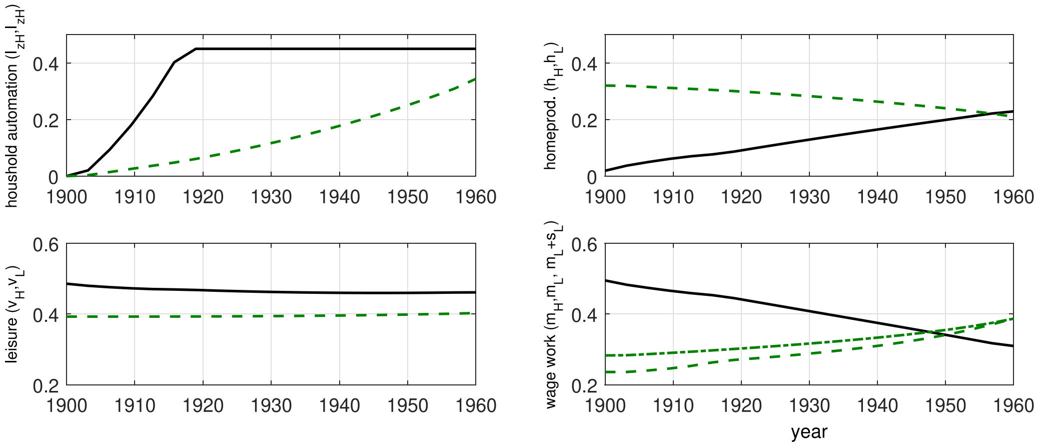

Fig. 4. Household automation and household time allocation by skill group: 1900–1960. Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

are by 20 percent larger than low-skilled households. This relatively low difference could mean that the frequency or scale of many tasks is insignificantly influenced by household size or that the effect of a larger house of high-skilled households (more floors to clean) is partly offset by a greater number of children in low-skilled households (more meals to cook).

The prediction of average household automation fits the actual diffusion of household appliances (as shown in the upper left panel of Fig. 3) and the prediction of servant work per household sL_H traces the actual decline of servant work reasonably well (center left panel). The model also correctly predicts the almost trendless paths for household time spent on leisure (upper right panel), home production (lower left panel), and wage work (lower right panel).

The aggregate time series obscure the (non-targeted) model predictions by skill group. These trajectories are shown in Fig. 4 where high-skilled households are represented by solid black lines and low-skilled household by green dashed lines. Household appliances are quickly adopted by high-skilled households and more slowly by low-skilled workers (upper left panel of Fig. 4). High-skilled households apparently use the new appliances as a substitute for servant work. Home production increases among the high-skilled households while it declines for low-skilled workers such that at the end of the period both groups spend about the same time on housework (upper right panel). This behavior is incentivized by the declining wage premium. As shown in the lower right panel, market work declines for high-skilled households while it increases for low-skilled households. Low-skilled workers do not only increase their aggregate labor supply they also move from servant work to goods production, visible by the converging dashed

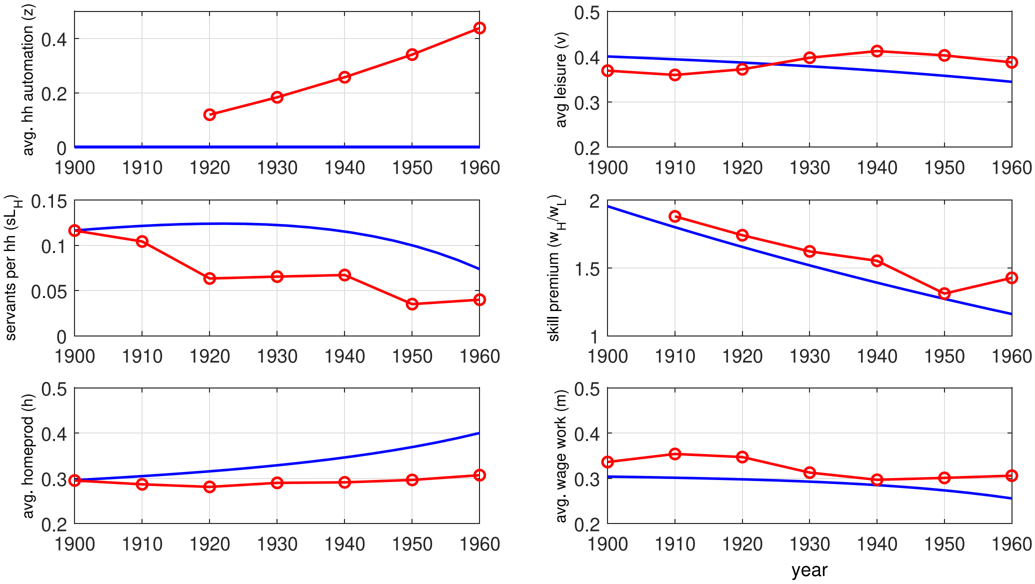

Fig. 5. Counterfactual experiment: No household automation. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

trajectory for goods production and the dotted trajectory for all wage work. The aggregation at the household level cannot capture the feature that the sectoral movements are largely attributable to women who switch from the profession of maid to industrial work. High-skilled households spend more time in leisure but leisure showed no trend for both groups, implying that low-skilled households used the time saved by household automation for extending their wage work.

3.3. Counterfactual experiment: No household automation

We next use the model for counterfactual historical experiments (in the spirit of Fogel, 1964) in order to assess the role of household automation and the creation of new tasks for servant employment and the allocation of household time. We begin with the experiment of eliminating household automation. To that end, we set the productivity of household appliances A_z to a value close to zero, implying a scenario were the 'engines of liberation' were not invented. Everything else is kept from the calibrated model.

Fig. 5 shows the predicted trajectories. Without household automation, servant work is predicted to stay at the high initial level until about 1940 and decline mildly thereafter (center left panel in Fig. 5). This outcome is explained by two opposing trends. On the one hand, the skill premium decreases, which makes servants more expensive and reduces the number of servant tasks per rich household (s). On the other hand, the number of rich households that employ servant work $\bar{L}_H$ increases. In the early 20th century the scale effect offsets the price effect and in the 1940–1960 period the price effect becomes mildly dominating.

In the counterfactual scenario, inequality (the skill premium) is predicted to decline more steeply than with household automation (center right panel). The sustained demand for servants reduces the labor supply for the industrial sector and thus increases the wage for low-skilled work compared to the benchmark scenario.

Not all previously automated tasks are taken over by servants. Home production also increases (lower left panel in Fig. 5) and leisure declines (upper right panel). These counterfactual trends are mainly driven by the expansion of housework in high-skilled households. Low skilled households are less affected by missing automation because the diffusion rate of appliances was anyway lower for them in the benchmark scenario. The main effect of missing automation on low-skilled households is the missing rise in time allocation to industrial production (maids remain maids and do not enter factory employment).

3.4. Counterfactual experiment: No new tasks

In the next counterfactual experiment, we assume that there were no developments of new standards in hygiene and nutrition in the early 20th century or that these cultural changes did not create new tasks in home cleaning and meal preparation. Fig. 6 shows the predicted trajectories for constant $\bar{I}$ (instead of a gradual increase by altogether 20 percent). The model now predicts a substantial decline in home production (lower left panel) and a mild increase in leisure (upper right panel) and wage work (lower right panel). These shifts in time allocation are made by both high and low-skilled workers and have thus insignificant impact on the skill premium and servant employment.

The counterfactual experiments suggest a solution to the conundrum of the almost constant time spent on leisure and wage work over the period 1900–1960 and what happened to all the time saved by automating domestic chores. The time was used to abandon

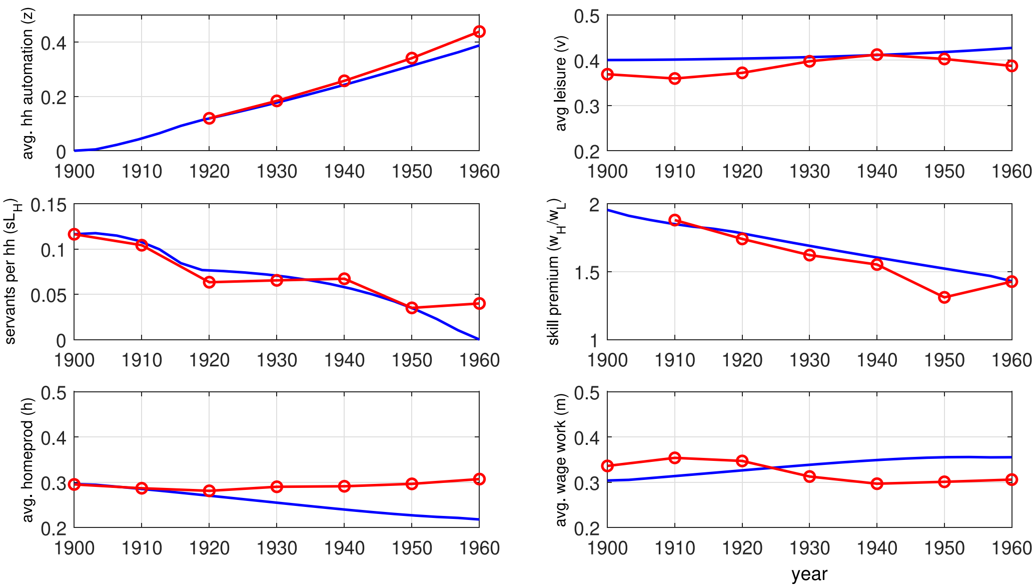

Fig. 6. No creation of new tasks. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

servant work and to create new household tasks. The results also suggests that the decline of servant work was causally driven by two distinct forces. Automation of household chores in rich households has been the main driver in the 1900–1920 period while declining inequality due to increased high-skill education has been the main driver in the 1940–1960 period.

4. Automation in goods production and the rise of the servant economy: 1960–2020

4.1. Calibration and benchmark results

We next consider the 1960–2020 period, which is characterized by the rise of college education, automation in firms, and the return of the servant economy. As explained above, being highly skilled is now associated with college education and we used the time series of individuals with four or more years of college education from the U.S. Census (2021) as the $\bar{L}_H$ series in the model. We used the wage premium of college graduates vs. high school graduates from Autor (2010). The Autor series basically coincides with the Goldin and Katz (2007) series until the year 2000. Because the Autor series ends in 2008, we added additional data points for 2010, 2015, and 2020, which were obtained from the Bureau of Labor Statistics (2021), and calculated the ratio of average earnings with a bachelor's degree or more to a high school degree.

For the 1960–2020 period, all major innovations in household automation had already been made. We therefore focussed on automation in firms. We re-calibrated the elasticity of substitution ϵ, the cost of robots ϕ, and the time paths for the share of automatable processes λ and high-skilled productivity A_H in order to fit the evolution of the skill premium and the robot intensity of production. We matched the time series of λ with the time series for U.S. robots per 1000 workers as used in Acemoglu and Restrepo (2020). We also targeted an average annual growth rate of income per capita of 1.9 percent (again computed from Bolt and van Zanden, 2020, for the 1960–2019 period).

In order to improve the fit of the model, we introduced two additional trends. First, we implemented an increase of servant productivity. We conceptualize this trend as the rise of the 'Gig Economy', which 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. 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). We obtained the best fit of the model when A_S increases by one percent per year from 2007 onwards (from level 0.8 to 0.9).[4]

[4] While it was reasonable to assume that low-skilled households did not employ servants in the earlier period, it is plausible that the gig economy also allows low-skilled households to outsource some tasks (such as on-demand delivery of low-quality food). Including servant tasks in low-skilled households would increase the overall demand for servant work and, consequently, raise aggregate demand for low-skilled labor. On its own, this would push up low-skilled wages,

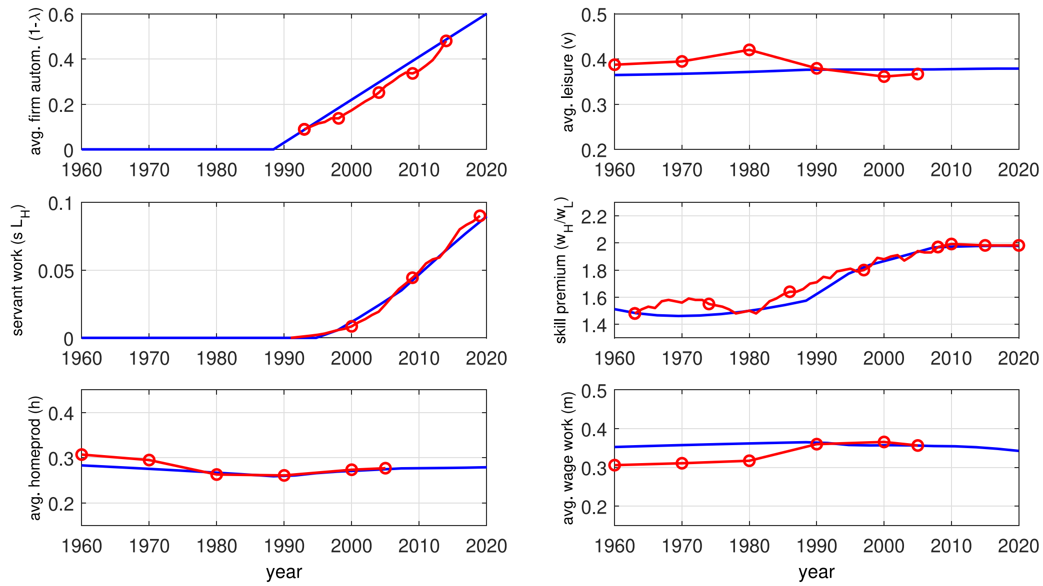

Fig. 7. Automation and the rise of the servant economy: 1960–2020. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

Secondly, we introduced a trend in the formation of new tasks for high-skilled households. We conceptualize this trend 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). We obtained the best fit of the model when $\bar{I}$ increases from 1985 onwards by one percent per year (from level 1.2 to level 1.6).

We demonstrate the contribution of the trends in servant productivity and household tasks by removing them in counterfactual analysis. The calibration led to an estimated elasticity of substitution ϵ of 2.0. The elasticity of substitution is higher than for the earlier period (1.5), in line with the observation of increasing substitutability of skills in Goldin and Katz (2007) and Acemoglu (2012). The calibrated technology A_H increases by 3.3 percent per year (from level 0.09 to level 0.57) and the calibrated λ declines linearly from 1 in 1985 to 0.4 in 2020. All other parameter values are kept from the calibration for the earlier period.

Results are shown in Fig. 7. Again the model's predictions are shown by blue solid lines and the targeted data are shown by red circled lines. The upper left panel shows the time path of the share of automated tasks in manufacturing $(1-\lambda)$ and the employment of U.S. robots per worker from Acemoglu and Restrepo (2020). In order to compare the robots data with the predictions, we normalized its final level in 2019 such that it coincides with the predicted share of automated tasks. This means that the calibration targets the speed of automation, and the model's prediction agrees quite well with the actual increase of robot employment in manufacturing.

The center right panel in Fig. 7 shows the evolution of the skill premium, which remained largely stationary from 1960–1980 and then took off roughly at the same time as automation in firms. With a delay of about a decade, increasing inequality triggers the return of the servant economy, as shown in the center left panel. The predicted time path of average servant tasks per household is shown together with the frequency of "maid" in publications (red lines, replicated from Fig. 1 of the Introduction). Again, we do not compare levels but slopes and for that purpose we subtracted maid frequency in the year 1992 (i.e. we control for the frequency before the onset of the servant economy) and normalize the series such that the final value coincides with that of the predicted servant series. This means that the calibration targets the speed at which tasks are outsourced to hired help.

As shown in the remaining panels, the model predicts that the average time allocation to leisure, home production, and wage work stayed roughly constant over the 1960–2020 period, in line with the time allocation paths estimated by Ramey and Francis (2009).

The constancy of average time use in employment hides that there are substantial changes at the group level. These changes are revealed in Fig. 8, which shows the predicted (but non-targeted) trajectories of time use for high and low-skilled households. As shown in the lower two panels of Fig. 8, leisure of high-skilled households is predicted to decline and wage work to increase while the opposite is true for low-skilled workers. The model thus predicts a new trend in behavior, starting with automation: rich and high-skilled individuals supply more labor as the wage increases and eventually they supply more labor than poor and low-skilled

creating a second-order effect that, in turn, reduces the demand for servant work by low-skilled households. Rising low-skilled wages would also exert a negative (second-order) effect on servant demand by high-skilled households. Overall, the rise of the servant economy would be less strongly linked to rising inequality, and the expansion of the gig economy would account for a larger share of it.

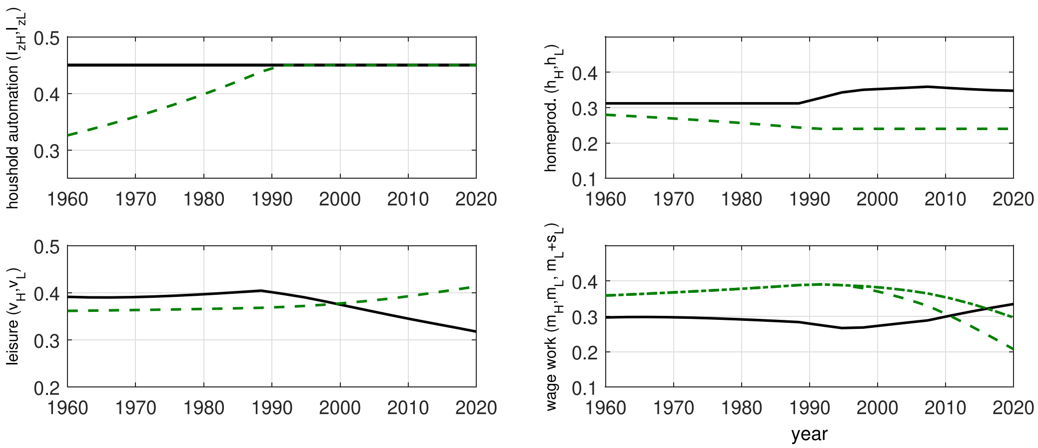

Fig. 8. Firm automation and household time allocation by skill group: 1960–2020. Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms (m_L) and the dashed-dotted lines shows work at firms plus servant work ($m_L + s_L$).

individuals. This prediction is consistent with a reversal of the association of wages and hours worked in rich economies (Bick et al., 2018).

The mirror image of labor supply behavior is predicted for leisure. With the takeoff of automation in the late 1980s, a new trend is emerging: high-skilled individuals reduce their leisure time while low-skilled individuals increase it, in agreement with observed trends in education-specific time use (Boppart and Ngai, 2021).

4.2. Counterfactual experiment: No firm automation

In analogy to the main counterfactual experiment of the 1900–1960 period, we next investigate the counterfactual outcome when there is no automation in firms, i.e. λ is kept constant at one. Results are shown in Fig. 9. Without the replacement of low-skilled workers in goods production, inequality is predicted to increase much slower (center right panel) and it does not trigger the rise of the servant economy. Instead, servant employment emerges with the takeoff of the gig economy, i.e. the increase in servant efficacy, after the year 2007. Since the gig economy creates new demand for low-skill work, inequality is counterfactually predicted to decline from 2007 to 2020. Due to rising demand for low-skilled work and rising wages for low-skilled labor there is no decline in low-skill labor and no reversal of the wage–labor supply nexus (the figure showing group-specific time allocations is omitted for brevity). Summarizing, the model causally attributes the rise of the servant economy since the 1980s to firm automation and the implied increase in the skill premium.

Notice that automation is not the sole driver of inequality. According to the calibration, the trend in λ operates alongside a trend in general skill-biased technological change, with (A_H/A_L) increasing by 3.3 percent per year. This explains why the skill-premium continues to rise in the 1980–2005 period even after the upward pressure from automation has been eliminated. Skill-biased technological change captures in reduced-form all other drivers of the skill-premium. In contrast to automation (decline of λ), general skill-biased technological change (increase A_H/A_L) improves the productivity of both low-skilled and high-skilled workers, though the increase is much greater for high-skilled workers. This explains why rising inequality does not trigger the servant economy in Fig. 9: the effect of rising inequality on increasing demand for servants is offset by the decreasing demand due to the (moderately) rising wages of low-skilled workers. The demand for servant tasks only takes off when servant productivity improves with the rise of the gig economy.[5]

4.3. Counterfactual experiment: No new tasks for high-skilled households

In the next experiment, we counterfactually assume that there was no increasing college competition among the high-skilled households or that the competition did not create additional household tasks (no additional household time spent on older children). Results are shown in Fig. 10. Average time spent on household production is now predicted to decline and leisure to increase. These trends are entirely driven by a change in behavior of rich households due to the time saved from the outsourcing of tasks to servants. This means that the reversal in leisure trends from the benchmark case is no longer observed. Instead, the counterfactual scenario predicts that high-skilled leisure remains higher than low-skilled leisure and continues to rise with increasing income and inequality.

[5] However, not all factors influencing the skill premium, aside from automation, are fully explained by skill-biased technological change. For instance, outsourcing or reductions in the social welfare state put downward pressure on low-skilled wages, functioning more like automation than skill-biased technological change in this regard.

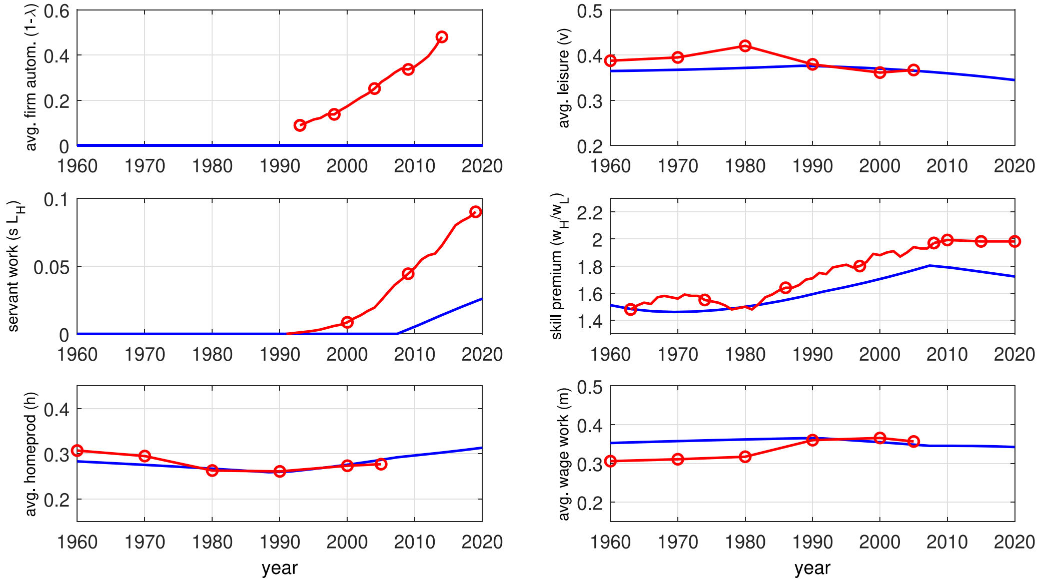

Fig. 9. No automation in firms. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

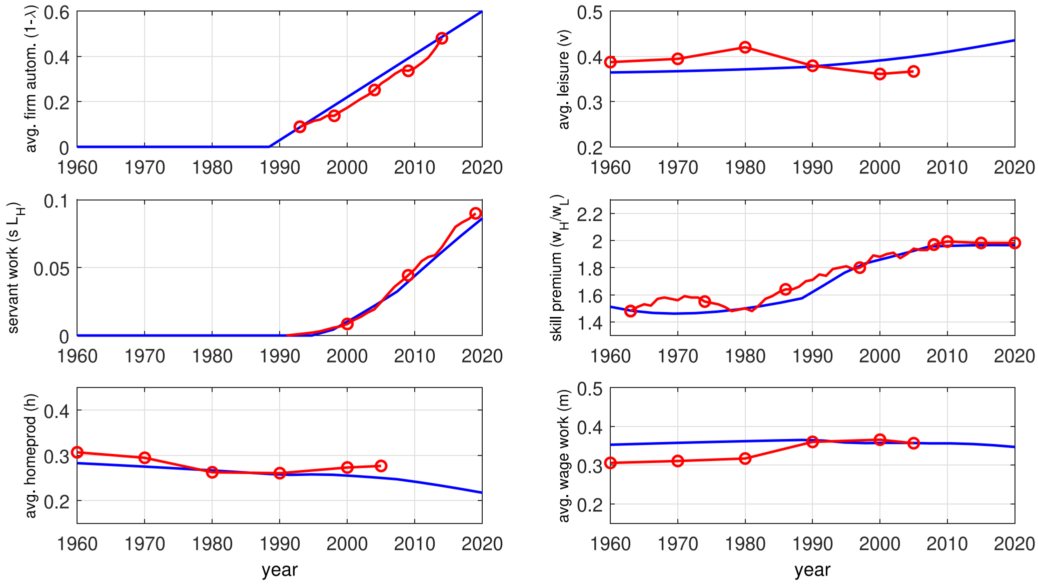

Fig. 10. No new household tasks. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

4.4. Counterfactual experiment: No gig economy

Finally, we counterfactually assume that there is no gig economy, i.e. no trend in the efficiency of servant work. Results for constant A_S are shown in Fig. 11. The predicted increase in servant work is now less steep and the path of increasing inequality does not flatten in the 2005–2020 period. The model therefore attributes the recent slowdown in skill premium growth to rising demand for low-skilled labor due to the burgeoning gig economy.

Summarizing, the almost stationary average time allocation of households is explained by the offsetting trends of the rising servant economy caused by increasing inequality due to firm automation (and further amplified by the gig economy) and the rising

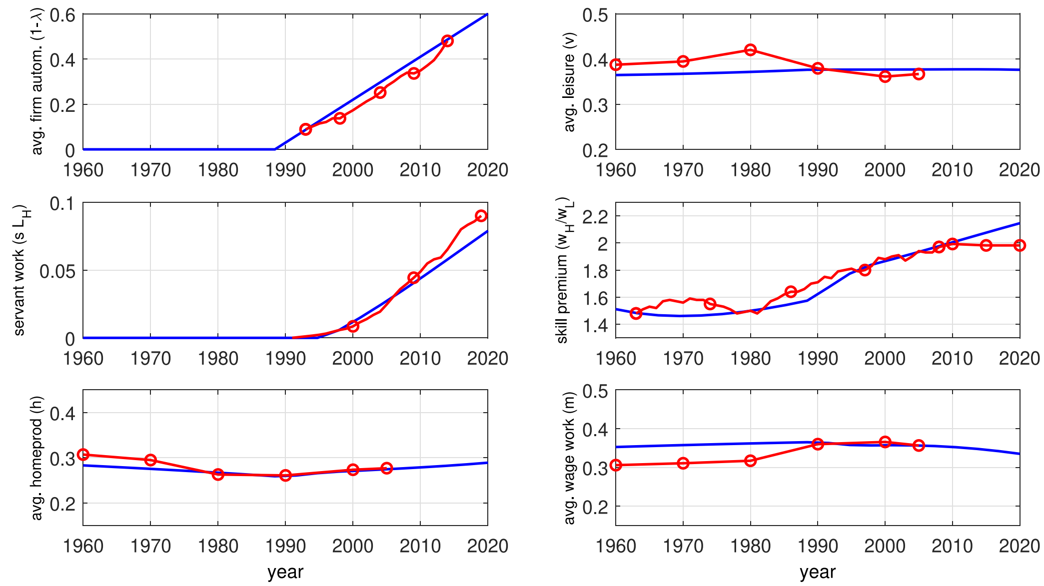

Fig. 11. No gig economy. Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

trend of new tasks in high-skilled households. This explanation is consistent with a reversal of the wage-labor supply association and a reversal of leisure trends for low and high-skilled households.

5. Automation, inequality and servant work: Empirical evidence

5.1. Data and methodology

In this section, we provide empirical evidence in support of central predictions of the model, namely between increasing automation and inequality, and for increasing inequality to be associated with more servant work (mechanisms in Section 2.2 and in Section 2.4). To this end, we collected data for robots exposure at the level of U.S. metropolitan statistical areas (MSA) from Brookings (2017). Brookings' data are built on statistics from the International Federation of Robotics and measure the total number of industrial robots for the year 2010 and 2015.

Furthermore, 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 MSAs, which allowed us to construct a panel across MSA regions and years ranging from 2005 to 2020. In contrast to previous studies (e.g., Milkman et al., 1998) that focussed on variation across MSAs, we focus on inequality and employments trends within MSAs. Using a panel fixed effects model with MSA-fixed-effects, we control for potential confounders such as local labor market conditions and the composition of the workforce by age and education.[6] 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. 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). 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 reverse causality. Since the level of wages in servant occupations is around or below the 25th percentile, the 90–50 percentile ratio is unaffected by the wages of servants and maids. This removes any concern about servant wages causing inequality. Summary statistics are provided in Table A.4.

In a first step - due to data availability - we estimate the relation between inequality and robots at the metropolitan area level for the cross-section of the year 2015:

[6] 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. Maids and housekeeping cleaners as well as couriers and messengers may take on tasks for private households or for firms. 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.

Table 1
Robots exposure and inequality.
Source: Computations based on data from the Bureau of Labor Statistics (2021) and Brookings (2017).

Dependent variable: Log inequality	(1)	(2)	(3)
Robots exposure - 2015	0.0131 (0.003)		
Robots exposure - 2010		0.0344 (0.001)	
IV Robots exposure			0.0498 (0.000)
First Stage			0.3323 (0.020)
F-Stat			24.211
Obs	365	365	359
R^2	0.042	0.047	0.2394

Notes: The analysis is based on the level of metropolitan statistical areas for the year 2015. The dependent variable is the inequality measure, given by the ratio between the 90th percentile of annual wages for all occupations and the median of annual wages for all occupations. The independent variable in the three regressions is the total number of robots (in thousands) in 2015, in 2010, and an instrumental variable of robots for the year 2015, respectively. *p*-values in parentheses. Robust standard errors were computed.

$$\log inequality_{r,2015} = \alpha_0 + \alpha_1 robots_{r,2015} + \epsilon_{r,2015}, \tag{23}$$

in which $inequality_r$ is the 90–50 percentile wage ratio for all occupations in region r, $robots_r$ is the total number of industrial robots in an MSA, and ϵ_r is an idiosyncratic error term.

For employment, we estimate the following equation:

$$\log employment_{rt} = \beta_0 + \beta_1 \log inequality_{rt} + \beta_2 \log GDP_{rt} + \theta_r + \tau_t + \xi_{rt}, \tag{24}$$

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; ξ_{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:

$$wage_{rt} = \gamma_0 + \gamma_1 \log inequality_{rt} + \gamma_2 \log GDP_{rt} + \lambda_r + \mu_t + \nu_{rt}, \tag{25}$$

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 regressions of inequality (based on annual wages) on regional robots exposure (measured in thousands). The coefficient from Column 1 in Table 1 shows that an increase of 1000 industrial robots is associated with an increase of inequality by 1.3 percent. We further investigate the link between inequality and automation, using a lagged measure of robots from the year 2010. The coefficient from Column 2 shows that the inequality measure increases by 3.5 percent. In a further step, we consider an instrument for robots exposure. For the construction of the instrument, we selected for each MSA the three MSAs that are closest with respect to the level of employment (over all occupations) each from below and from above, and took their average of the number of robots (thus dividing the sum by six). The idea for the instrument is that other regions with similar employment levels have similar levels of automation while there is no direct effect of other MSAs' automation on inequality. Column 3 from Table 1 displays that an increase of the total number of industrial robots by 1000 leads to an increase of inequality by 5.1 percent. The first stage regression and the F-statistic support the instrument.

Table 2 shows the results for the employment regressions (24). 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. A 10 percent increase in inequality is associated with an increase in the employment of maids by 2.9 percent, couriers

Table 2
Servant employment and inequality.
Source: Computations based on data from the Bureau of Labor Statistics (2021) and Bureau of Economic Analysis (2021).

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.	2547	2547	3185	3185	2672	2672	3016	3016
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 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. Cluster-robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions.

Table 3
Servant annual wages and inequality.
Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021) and World Bank (2021).

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.	3190	3190	2839	2839	3109	3109
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. Cluster-robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions.

by 8.3 percent, and animal caretakers and the servant aggregate by about 5 percent. This means that the inequality nexus is also economically significant. Table A.1 in the Appendix A shows that the results remain basically unchanged when the inequality measure is constructed from hourly wages.

Results from regression (25) are shown in Table 3. 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 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. This result is unsurprising since regional GDP controls for trends in the average regional level of wages. Table A.2 in the Appendix A shows that similar results are obtained for hourly wages of servants and inequality constructed from hourly wages. The results suggest that for animal caretakers and couriers and messengers increasing demand for servant work was mainly reflected by increasing employment.

In the Appendix A, we present further results. In Table A.3, we show results for the servant employment regression (24) 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.

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 and declining inequality, caused by the rise of mass education, explain the initial decline of the servant economy, whereas increasing inequality, caused by automation in manufacturing, explains the return of the servant economy.

We provided supporting evidence for the relation between automation and inequality, and for inequality as a driver of the rise of the servant economy using data for a panel of U.S. metropolitan areas in 2005–2020. We found that an increase in the number of industrial robots by 1000 leads to an increase of inequality by 5.1 percent. 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 of maids, animal caretakers, and couriers and messengers, i.e. typical occupations in the new servant economy. We found that a 10 percent increase in inequality is associated with an increase in the employment of maids by 2.9 percent, couriers by 8.3 percent, and animal caretakers and the servant aggregate by about 5 percent. Furthermore, inequality is positively associated with maid wages. Interestingly, if we look at inequality statistics throughout the 20th century and beyond, we see that inequality follows a similar U-shaped pattern as the employment of servants and maids, with a nadir in the 1980s.

We also used counterfactual computational experiments to assess the role of new households tasks (in hygiene and food provision in the earlier period and in care for older children in the later period) and the gig economy for the division of household time. We found that the creation of new household tasks can explain why home production and leisure of high-skilled households remained virtually unaffected by trends of the servant economy. We found that increasing servant productivity generated by innovations of on-demand internet platforms and smartphone apps further amplified the demand for servant work and slowed down the increase of the wage premium. The return of the servant economy facilitated the creation of new tasks for high-skilled households and it can be argued that the servant economy enabled the increased competition of 'helicopter parents' for their children's access to college.

Improving access to education is often proposed as a policy measure to address rising inequality driven by automation. Our model, consistent with the canonical model of the skill premium, also suggests that an increasing proportion of college graduates always reduces inequality. The response of servant work to a greater share of high-skilled households is generally ambiguous. On the one hand, servant demand per household declines because of increasing relative wages of low-skilled workers. On the other hand, there are more high-skilled households that delegate tasks to servants. In counterfactual simulations we confirmed that the price effect dominates such that a greater supply of high-skilled labor reduces aggregate employment in servant tasks. However, if the demand for higher education is modeled as an endogenous response to automation among individuals with varying abilities, it will become increasingly difficult, and ultimately impossible, to reduce rising inequality due to automation solely through an increase in high-skilled education (Prettner and Strulik, 2020).

Our study focussed on the fall and rise of the servant economy in the U.S. and we make no claims to external validity. Workers in Germany and Japan, for example, have experienced greater increases in robot exposure than those in the U.S. but the college wage premium today is about the same as in the 1980s. For Japan, the stability of the wage premium has been largely attributed to a much higher increase in college education compared to the U.S. (Kawaguchi and Mori, 2016) while for Germany it has been attributed to employment protection and on-the-job skill investments (Doepke and Gaetani, 2024). A trendless wage premium eliminates inequality as the major driver of the rise of the servant economy in our model. However, outsourcing to servants may still increase due to rising servant productivity (the gig economy) or factors not considered in our model. For example, in Germany and Japan, aging populations lead to an increase in household tasks related to elderly care, thereby boosting the demand for servant work. The present model cannot address this phenomenon since it focusses on prime age adults. Expanding our theory within an overlapping generations framework could explore population aging as an additional factor driving the servant economy.

The theory is ready for 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.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Astrid Krenz reports financial support was provided by UK Economic and Social Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A.1
Servant employment and inequality – Hourly wages measure.
Source: Computations based on data from the Bureau of Labor Statistics (2021) and Bureau of Economic Analysis (2021).

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.	2547	2547	3185	3185	2672	2672	3016	3016
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 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. Cluster-robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions.

Table A.2
Servant hourly wages and inequality – Hourly wages measure.
Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021) and World Bank (2021).

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.	3190	3190	2839	2839	3109	3109
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. Cluster-robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions.

Table A.3
Servant employment and inequality – Annual wages measure – All MSAs.
Source: Computations based on data from the Bureau of Labor Statistics (2021) and Bureau of Economic Analysis (2021).

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.	2947	2947	5505	5505	3230	3230	4649	4649
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 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. Cluster-robust standard errors were computed. Metropolitan Statistical Area fixed effects and year fixed effects are included in the regressions.

Table A.4
Descriptive statistics.
Source: Based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021), World Bank (2021) and Brookings (2017).

Variable	Mean	Std. Dev.	Min	Max	Obs
Maids per 1000 pop	2.8988	1.3743	0.5336	14.167	3186
Couriers per 1000 pop	0.2905	0.1582	0.0463	1.3943	2678
Animal caretakers per 1000 pop	0.5233	0.2637	0.0682	3.2085	3018
Sum empl maids, animal caretakers, couriers per 1000 pop	3.7477	1.3958	1.2259	13.7744	2553
Inequality annual wage 90-50 pct	2.3306	0.1656	1.8201	2.9504	4267
Inequality hourly wage 90-50 pct	2.3306	0.1656	1.8197	2.9495	4267
Mean annual wage maids in thousands	20.3055	3.0896	13.5662	37.6104	4233
Mean annual wage couriers in thousands	25.1183	3.7787	14.7323	42.7246	3609
Mean annual wage animal caretakers in thousands	21.6313	2.7883	15.0959	37.0922	4030
Mean hourly wage maids	9.7624	1.4854	6.5207	18.0806	4233
Mean hourly wage couriers	12.0764	1.8166	7.0849	20.5408	3609
Mean hourly wage animal caretakers	10.4000	1.3406	7.2577	17.8315	4030
GDP per capita	48.3386	12.5930	21.4790	173.5892	3470
Robots exposure, 2015, in thousands	0.4774	1.1008	0.0028	15.1151	382
Robots exposure, 2010, in thousands	0.1995	0.4441	0.0009	5.7529	382
IV robots exposure, 2015, in thousands	0.4528	0.7005	0.0241	4.4969	359

Notes: This Table shows descriptive statistics for MSAs with population size >200 000 from 2005–2020, for robots exposure for 2015, 2010 over all MSAs.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2024.104926.

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