

# 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.

*Keywords:* Automation, 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 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 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.

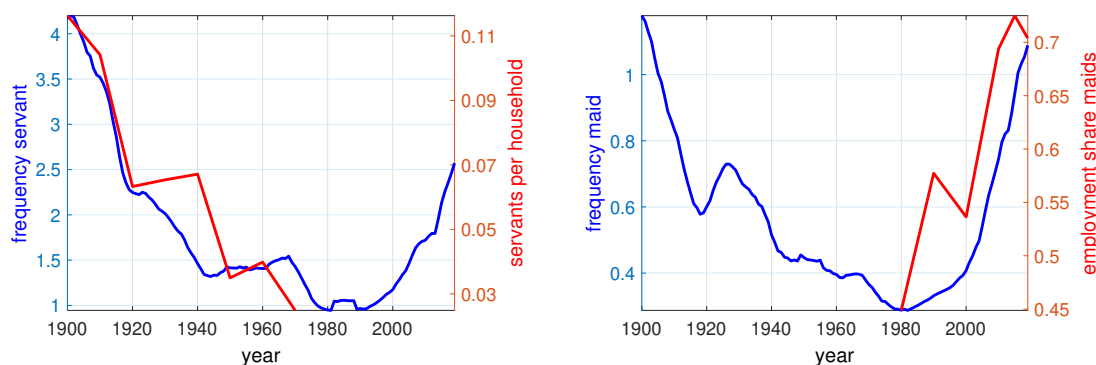
The first half of the 20th century was characterized by a series of innovations in household appliances that substantially reduced the time needed to perform tasks such as washing, ironing, or food conservation (Greenwood et al., 2005). It may thus appear surprising that the ‘electrification of households’ 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 household 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, 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 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. 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.

Figure 1: Servants and Maids: 1900–2019



Blue lines show 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). 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.

The panel on the left-hand side of Figure 1 shows also the actual number of servants per household in the U.S. (taken from Kornrich, 2012).<sup>1</sup> 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 (Konrich, 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

<sup>1</sup>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.

(U.S. Census, 1984, 1992, 2000, 2022). The employment share and the mentioning of maids in books follow similar trends.

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 (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. 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 technical 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 (chauffeur, 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 (2018, 2019, 2020), Prettner and Strulik (2020), and (Hemous and Olson, 2021). Here, we follow the stylized modeling of automation by Krenz et al. (2021) where a productivity time-trend determines the share of production process 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 (2019). 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 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. Individuals have a unit of time at their disposal, which they spend on wage labor, work in their own household 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

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

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  $\epsilon$ . 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  $\phi$ . The first order conditions of profit maximization with respect to  $L_H, \ell_L(i)$ , and  $x$  require:

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

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

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

In order to avoid unnecessary case differentiation, we assume that  $\phi < w_L$  such that production is automated whenever this is technically feasible. Let  $\lambda$  denote the share of production processes that are not yet automated. We then have aggregate low-skilled labor demand from manufacturing  $L_L = \int_0^\lambda \ell_L(i) di$  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

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

Automation (i.e. a declining share  $\lambda$  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 face a measure  $(0, \bar{I})$  of distinct household tasks per unit of time. Each task is required  $\theta_j$  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. 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:

$$\theta_j = a_o(i)\ell_j(i) + A_s a_s(i)s_j(i) + A_z a_z(i)z_j(i), \quad (6)$$

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  $a_z(i)/a_o(i)$  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. Household machines are produced from final goods and available at unit cost  $\psi$ . 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, 2011).

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  $\psi$  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:

$$I_{zs} = \begin{cases} \max \left\{ 0, \min \left\{ \frac{A_z(w_L/\psi) - A_s}{\alpha A_s - A_z(w_L/\psi)}, \bar{I}_z \right\} \right\} & \text{for } w_L/\psi < \alpha A_s/A_z \\ \bar{I}_z & \text{otherwise .} \end{cases} \quad (7)$$

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,  $w_L/\psi$ ). The threshold is depicted in Figure 2 as the upward sloping curve that reaches its upper bound at  $\bar{I}_z$ .

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

$$I_{sH} = \max \left\{ 0, \min \left\{ \left[ A_s \left( \frac{w_H}{w_L} \right) - 1 \right], \bar{I} \right\} \right\}. \quad (8)$$

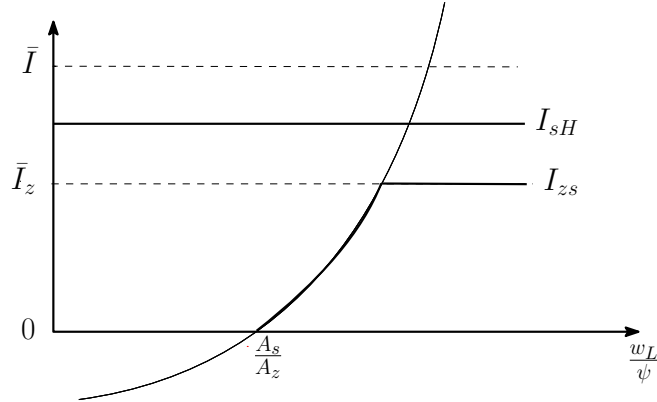
Households prefer servants to own work for tasks below the threshold and vice versa above the threshold. The threshold is shown for a constant skill premium  $w_H/w_L$  as a horizontal line in Figure 2. The prevalence of servant work obviously requires that the  $I_{sH}$ –threshold lies above the  $I_{zs}$ –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  $I_{zs} \leq i < I_{sH}$  are produced by servants and tasks  $i \geq I_{sH}$  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  $\psi$ , 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 Figure 2.



Figure 2: Division of Tasks in Rich Households



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

$$I_{zH} = \max \left\{ 0, \min \left\{ \frac{1}{\alpha} \left( \frac{w_H}{\psi} A_z - 1 \right), \bar{I}_z \right\} \right\}. \quad (9)$$

**PROPOSITION 2.** *If  $I_{zs} \geq I_{sH}$ , then tasks  $i < I_{zH}$  are produced by machines and tasks  $i \geq I_{sH}$  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  $\psi$ , 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 (9). As a corollary from these proposition we conclude that with perpetually rising  $w_L/\psi$  ratio, servant work is eventually abandoned if  $w_H/w_L$  is sufficiently low such that  $A_s(w_H/w_L) - 1 \leq \bar{I}_z$ . Otherwise servant work persists.

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

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

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 (8) and (10) 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  $\psi/w_L$ ) declines. Demand for tasks performed by servants, in contrast, increases in inequality, i.e. the wage premium  $w_H/w_L$ , see (8). 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

$$h_H = \int_{I_{sH}}^{\bar{I}} \theta_H di = \theta_H (\bar{I} - I_{sH}). \quad (11)$$

$$z_H = \theta_H \int_0^{I_{zs}} \frac{1}{A_z a_z(i)} di = \frac{\theta_H}{A_z} \left[ \frac{\alpha}{2} (I_{zs})^2 + I_{zs} \right] \quad (12)$$

$$s = \theta_H \int_{I_{zs}}^{I_{sH}} \frac{1}{A_s a_s(i)} di = \frac{\theta_H}{A_s} \left[ \frac{i^2}{2} + i \right]_{I_{zs}}^{I_{sH}}, \quad (13)$$

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

$$h_H = \theta_H \int_{I_{zH}}^{\bar{I}} di = \theta_H (\bar{I} - I_{zH}) \quad (14)$$

$$z_H = \theta_H \int_0^{I_{zH}} \frac{1}{A_z a_z(i)} di = \frac{\theta_H}{A_z} \left[ \frac{\alpha}{2} (I_{zH})^2 - I_{zH} \right]. \quad (15)$$

Likewise, hours worked in low-skilled households are:

$$h_L = \theta_L \int_{I_{zL}}^{\bar{I}} di = \theta_L (\bar{I} - I_{zL}) \quad (16)$$

$$z_L = \theta_L \int_0^{I_{zL}} \frac{1}{A_z a_z(i)} di = \frac{\theta_L}{A_z} \left[ \frac{\alpha}{2} (I_{zL})^2 - I_{zL} \right]. \quad (17)$$

**2.4. Leisure and Utility Maximization.** Households face a conventional iso-elastic utility function (also know as KPR preferences in macroeconomics, King et al., 1988). Utility of household  $j$ ,  $j = H, L$ , is given by  $u_j = \log c_j - \eta x_j^{1+1/\nu_j} / (1 + 1/\nu_j)$ , in which  $c_j$  is consumption and  $x_j$  are the time units worked. High-skilled households work  $x_h = m_H + h_h$  units of time and low-skilled household work  $x_L = m_L + h_L + s_L$  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,  $\nu_j$  would be the constant Frisch elasticity of labor supply. We allow  $\nu_j$  to depend on the household-type in order to better match the association between income and labor supply of high and low skilled workers.

The budget constraints 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. The first order conditions for optimal work are thus obtained as:

$$w_H = (w_H m_H - \psi z_H - w_L s) \eta (m_H + h_H)^{1/\nu}, \quad (18)$$

$$w_L = (w_L (m_L + s_L) - \psi z_L) \eta (m_L + s_L + h_L)^{1/\nu}. \quad (19)$$

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

**2.5. Labor Supply and Market Equilibrium.** 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

$$L_H = (1 - h_H - v_H)\bar{L}_H. \quad (20)$$

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

$$L_L = (1 - h_L - s_L - v_L)\bar{L}_L. \quad (21)$$

The basic model is fully described by (1)–(21). 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. Education Trends and Split of the Observation Period.** 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 and the skill premium, 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.<sup>2</sup>

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.

**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

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<sup>2</sup>We focus on developments in the U.S. Other developed countries followed similar trajectories for servant work, household automation, high-skilled education, and economic growth.

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 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.

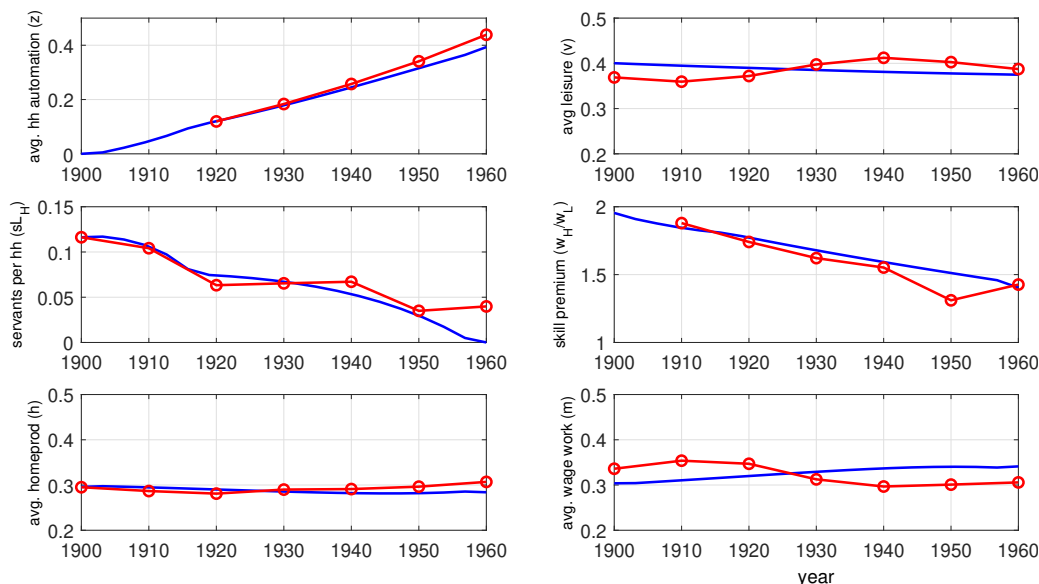
In order to compare the model predictions with the Ramey–Francis data, we compute population averages,  $m = m_h\bar{L}_H + (m_L + s_L)\bar{L}_L$  for average time spent on wage work,  $h = h_H\bar{L}_H + h_L\bar{L}_L$  for average home production, and  $v = v_H\bar{L}_H + v_L\bar{L}_L$  for average leisure. We set the initial measure of different household tasks to one ( $\bar{I}(0) = 1$ ) and calibrate the household sizes  $\theta_H$  and  $\theta_L$  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  $\eta$  and  $\nu_H$  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  $\psi$  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  $\epsilon$ , 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).

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).

Finally, we allow for a trend in the creation of new household tasks. This feature improves not only the predictive power of the model 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 analysis.

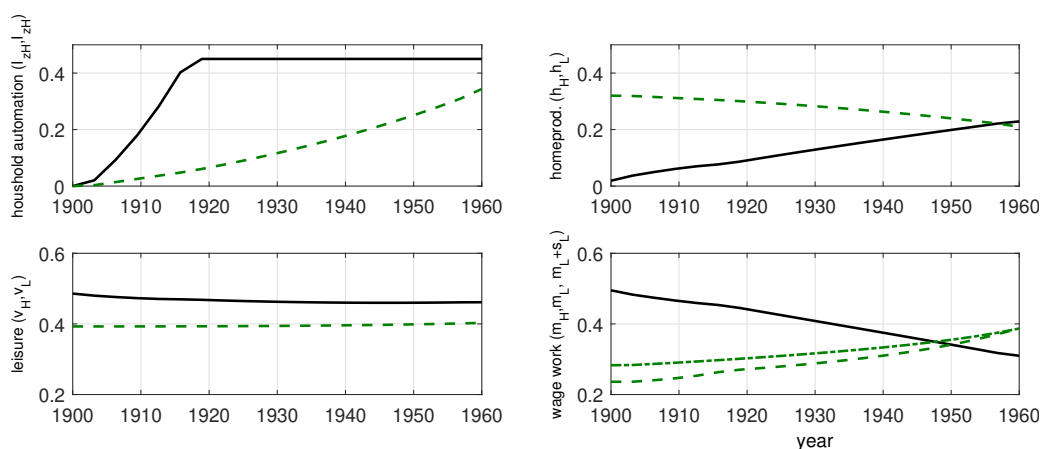
Summarizing, we jointly calibrate the following set of parameters  $\alpha$ ,  $\epsilon$ ,  $\eta$ ,  $\nu_H$ ,  $\theta_H$ ,  $\theta_L$ ,  $\bar{I}_z$ ,  $A_H(1900)$ ,  $A_L(1900)$ , and constant time trends for  $A_H$ ,  $\psi$ , and  $\bar{I}$  in order to fit the time paths of household automation 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 Figure 3. The targeted data series are shown by red circled lines.

The calibrated elasticity of substitution between high and low-skilled workers  $\epsilon$  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. equation (5)), as shown in the center-right panel of Figure 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  $\psi$  implies that the real price of household appliances declined by 40 percent for low-skilled workers. The calibrated value of  $\nu_H$  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  $\theta_H$  and  $\theta_L$

imply that high-skilled households 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).

As shown in the upper left panel of Figure 3, the prediction of average household automation fits the actual diffusion of household appliances 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).

Figure 4: Household Automation and Household Time Allocation by Skill Group: 1900–1960

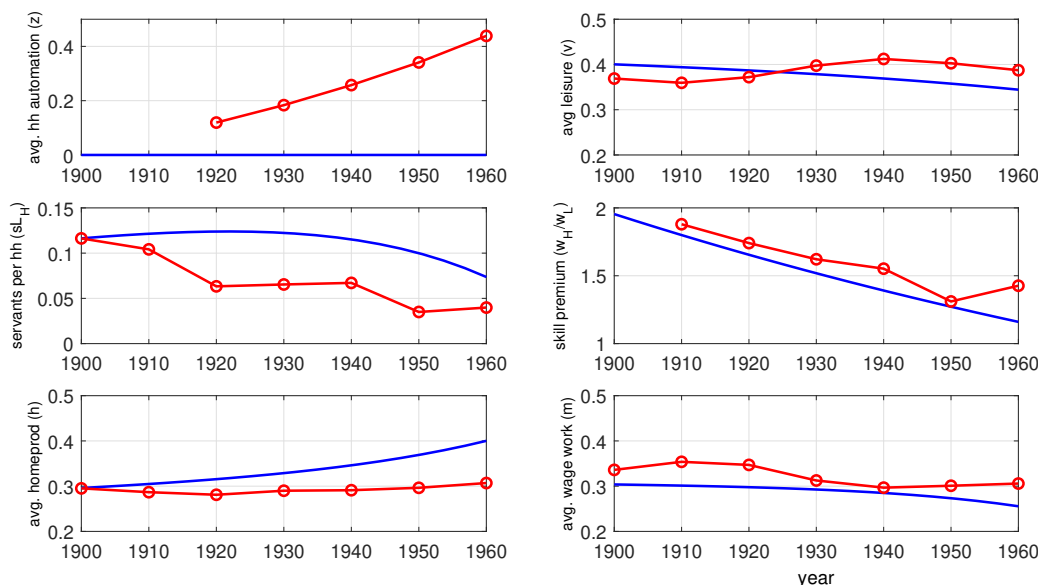


Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms ( $m_L$ ) and the dashed-dotted lines shows work at firms plus servant work ( $m_L + s_L$ ).

The aggregate time series hide the (non-targeted) model predictions by skill group. These trajectories are shown in Figure 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 Figure 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. 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 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 where the ‘engines of liberation’ were not invented. Everything else is kept from the calibrated model.

Figure 5: Counterfactual Experiment: No Household Automation



Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

Figure 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 Figure 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.

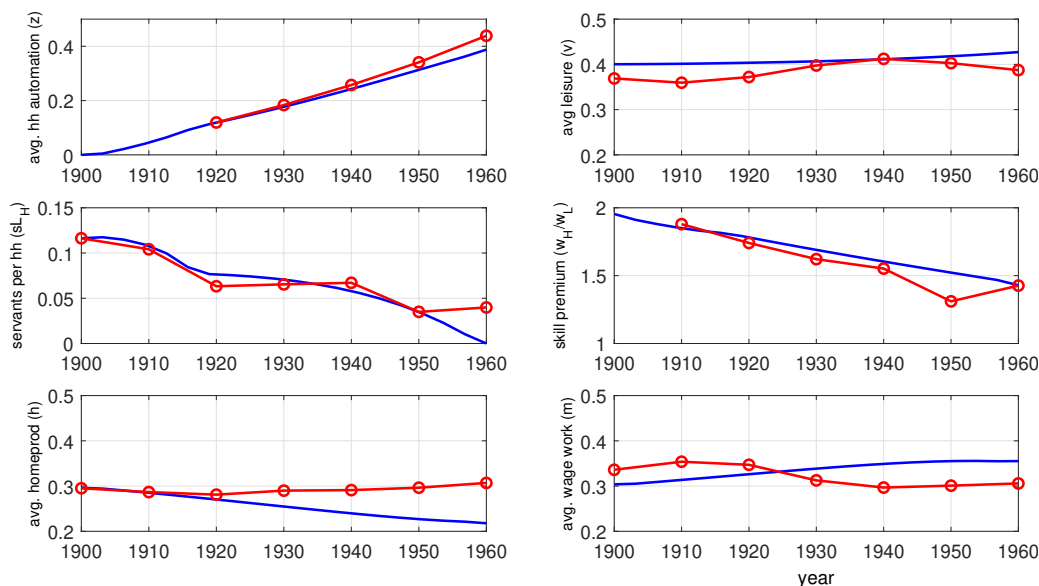
In the counterfactual scenario, inequality (the skill premium) is predicted to decline more steeply than with household automation (center right panel). The sustained demand for servants reduces the labor supply for the industrial sector and thus increases the wage for low-skilled work compared to the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

Not all previously automated tasks are taken over by servants. Home production also increases (lower left panel in Figure 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. Figure 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.

Figure 6: No Creation of New Tasks



Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

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 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-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  $\epsilon$ , the cost of robots  $\phi$ , and the time paths for the share of automatable processes  $\lambda$  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  $\lambda$  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).

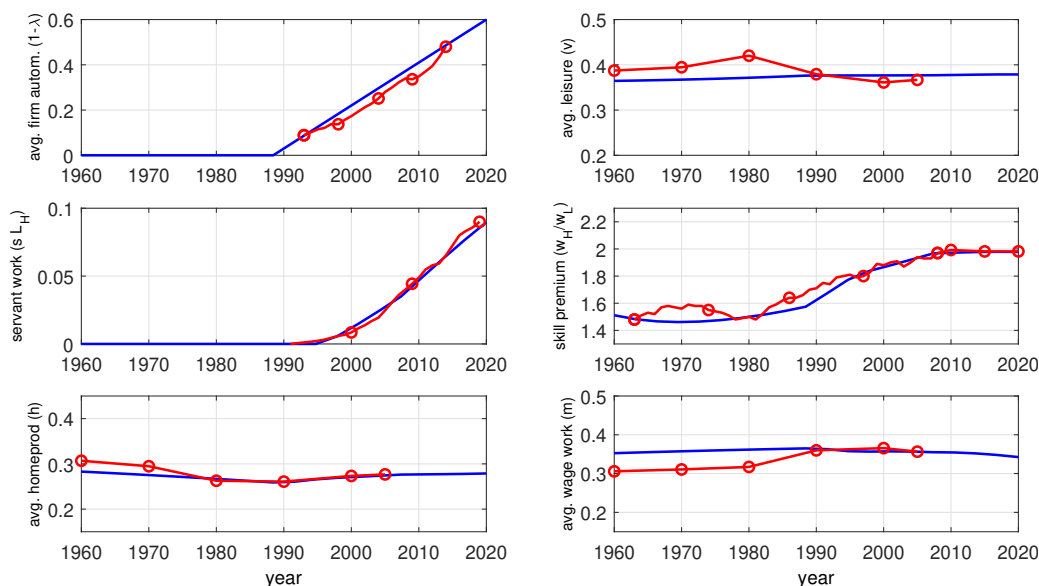
Secondly, we introduced a trend in the formation of new tasks for high-skilled households. We conceptualize this trend as a result of increasing competition of high-skilled households for access to (prestigious) college education for their children, which generates such tasks as homework supervision 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 1.20 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  $\epsilon$  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  $\lambda$  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 Figure 7. Again the model’s predictions are shown by blue solid lines and the targeted data is shown by red circled lines. The upper left panel shows the time path of the share of automated industrial tasks ( $1 - \lambda$ ) 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.

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

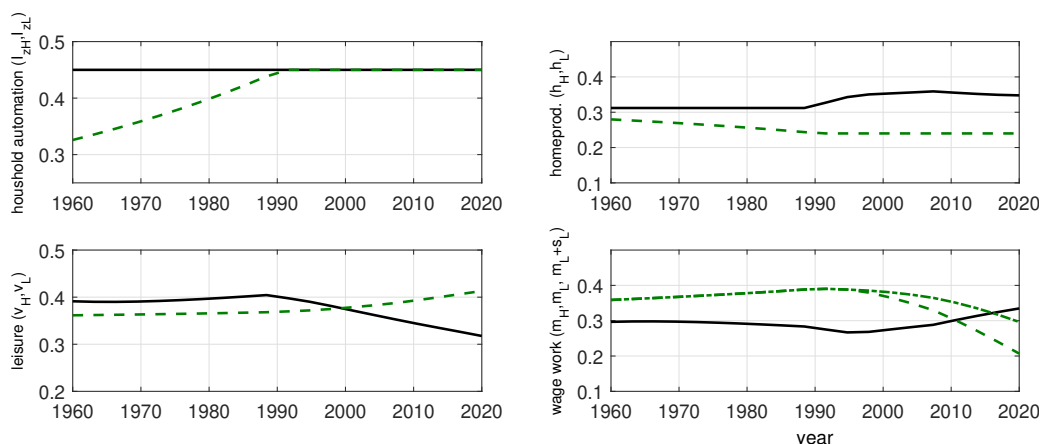


Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

The center right panel in Figure 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 from Figure 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).

Figure 8: Firm Automation and Household Time Allocation by Skill Group: 1960–2020



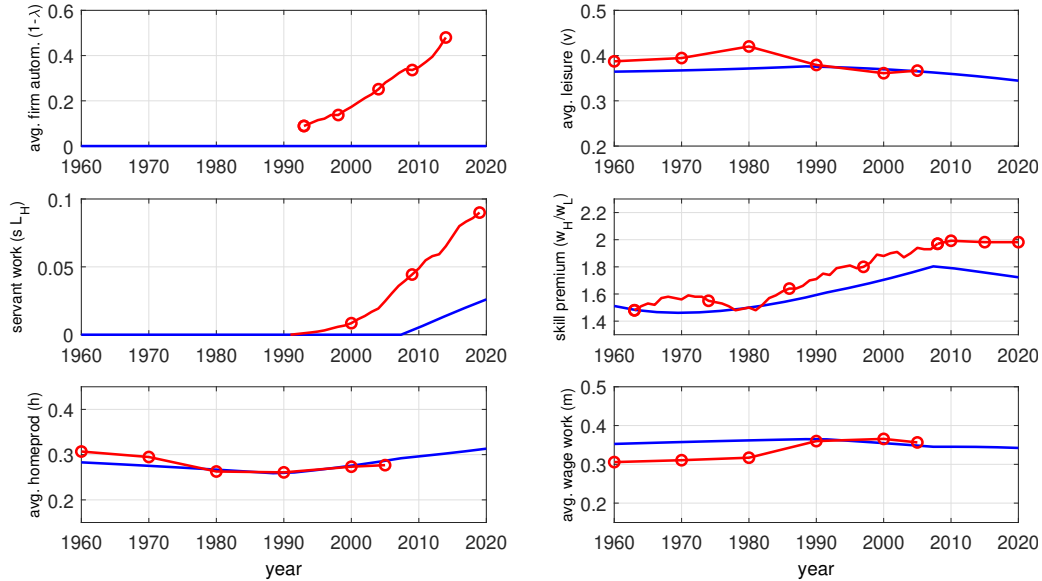
Solid black lines: model predictions for high-skilled households. Dashed (green) lines: model predictions for low-skilled households. In the bottom right panel the dashed line shows work at firms ( $m_L$ ) and the dashed-dotted lines shows work at firms plus servant work ( $m_L + s_L$ ).

The constancy of average time use in employment hides that there are substantial changes at the group level. These changes are revealed in Figure 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 Figure 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 individuals. This prediction is consistent with a reversal of the association of wages and hours works 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.  $\lambda$  is kept constant at one. Results are shown in Figure 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 associated increase in the skill premium.

Figure 9: No Automation in Firms



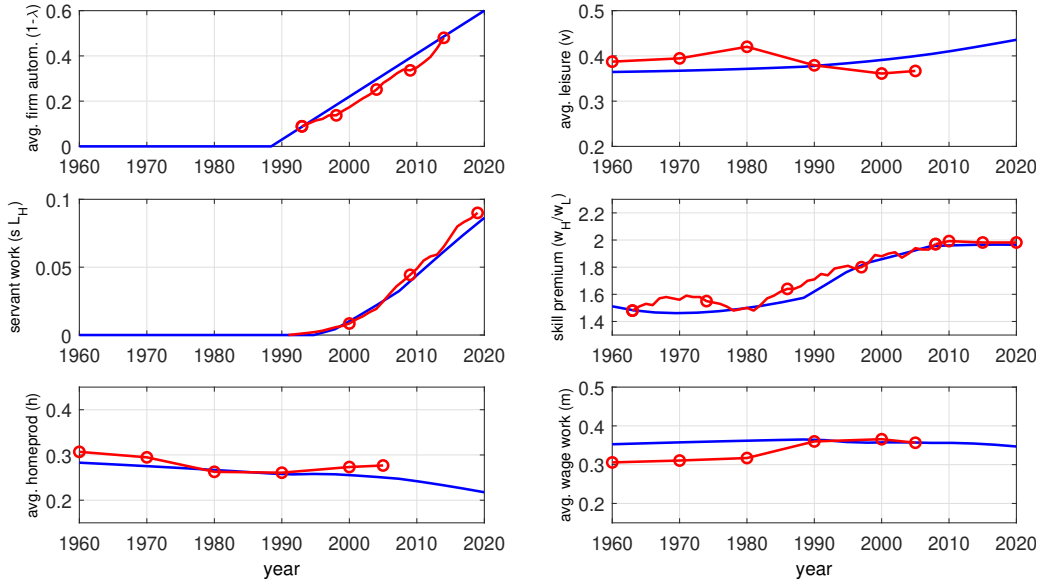
Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

**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 Figure 10. Average time spent on household production is now predicted to decline and 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.

**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 Figure 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.

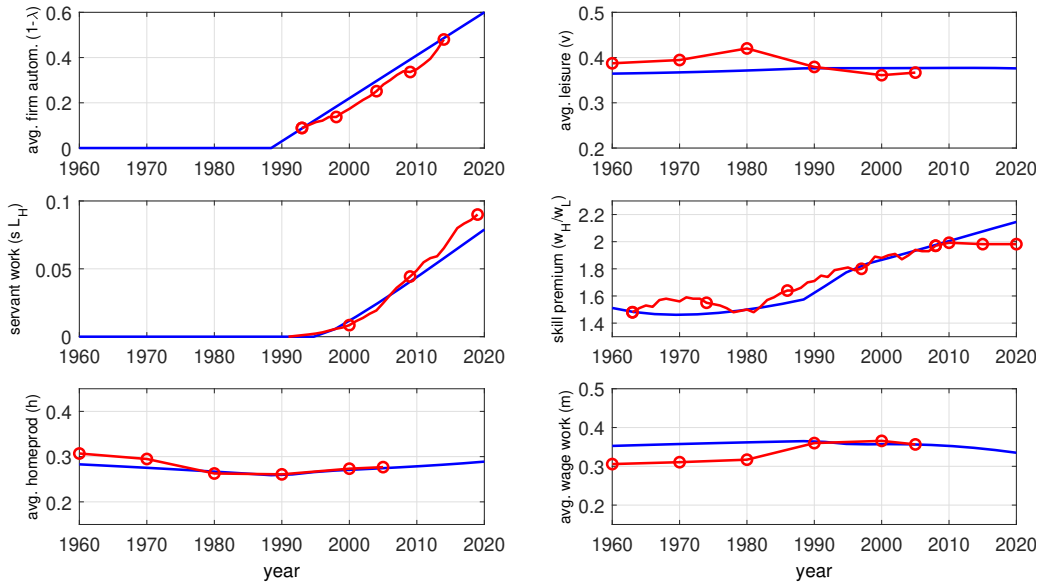
Summarizing, the almost stationary average time allocation of households is explained by the offsetting trends of the rising servant economy caused by increasing inequality due to firm automation (and further amplified by the Gig economy) and the rising trend of new tasks in high skilled households. 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.

Figure 10: No New Household Tasks



Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

Figure 11: No Gig Economy



Solid blue lines: model predictions for averages. Circled red lines: data (see text for details).

## 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 2.3). 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 (FE) 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.<sup>3</sup> 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). 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.4 in the Appendix contains the descriptive statistics.

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:

$$\log inequality_{r,2015} = \alpha_0 + \alpha_1 robots_{r,2015} + \epsilon_{r,2015}, \quad (22)$$

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  $\epsilon_r$  is an idiosyncratic error term.

For employment, we estimate the following equation:

$$\log employment_{rt} = \beta_0 + \beta_1 \log inequality_{rt} + \beta_2 \log GDP_{rt} + \theta_r + \tau_t + \xi_{rt}, \quad (23)$$

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;  $\xi_{rt}$  is an idiosyncratic

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<sup>3</sup>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.

error term;  $\theta_r$  are metropolitan area fixed effects and  $\tau_t$  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:

$$wage_{rt} = \gamma_0 + \gamma_1 \log inequality_{rt} + \gamma_2 \log GDP_{rt} + \lambda_r + \mu_t + \nu_{rt}, \quad (24)$$

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 ( $\exp(\beta) - 1$  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 (23). 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 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 shows that the results remain basically unchanged when the inequality measure is constructed from hourly wages.

Results from regression (24) 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

Table 1. Robots exposure and Inequality

Dependent variable:	(1)	(2)	(3)
Log inequality			
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. Source: Computations based on data from the Bureau of Labor Statistics (2021), Brookings (2017).

Table 2. Servant Employment and Inequality

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment of								
	Servants aggregate		Maids	Couriers, messengers			Animal caretakers	
Log inequality	0.5113 (0.001)	0.5049 (0.001)	0.2916 (0.077)	0.3031 (0.065)	0.8364 (0.019)	0.8374 (0.018)	0.4950 (0.069)	0.5010 (0.066)
Log GDP per capita		0.1302 (0.027)		0.1228 (0.045)		0.186 (0.169)		0.1649 (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 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. 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. This result is 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.



Table 3. Servant Annual Wages and Inequality

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Mean annual wage of	Maids		Couriers, messengers		Animal caretakers	
Log inequality	1.7946 (0.096)	2.1713 (0.036)	0.0489 (0.980)	0.0825 (0.966)	1.8964 (0.254)	2.1165 (0.199)
Log GDP per capita		3.7580 (0.000)		3.9476 (0.000)		3.5023 (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. Cluster-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).

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, we present further results. In Table A.3, we show results for the servant employment regression (23) 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 and higher wages 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. Moreover, a 10 percent increase in inequality is associated with an increase of annual wages by about \$ 217 for maids and \$ 212 for animal caretakers. 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 experiments with the model to assess the role of new household 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.

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 (2011), 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.

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.

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APPENDIX

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

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment of	Servants aggregate		Maids	Couriers, messengers		Animal caretakers		
Log inequality	0.511 (0.001)	0.5046 (0.001)	0.2908 (0.078)	0.3024 (0.066)	0.8379 (0.018)	0.8391 (0.018)	0.4941 (0.070)	0.5002 (0.066)
Log GDP per capita		0.1302 (0.027)		0.1229 (0.045)		0.1861 (0.169)		0.165 (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 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. 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 – Hourly Wages Measure

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Mean hourly wages of	Maids		Couriers, messengers		Animal caretakers	
Log inequality	0.8549 (0.099)	1.0367 (0.038)	0.0219 (0.981)	0.0390 (0.966)	0.9009 (0.259)	1.0077 (0.203)
Log GDP per capita		1.8062 (0.000)		1.8963 (0.000)		1.6854 (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. Cluster-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 Measure – All MSAs

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment of	Servants aggregate		Maids	Couriers, messengers			Animal caretakers	
Log inequality	0.3953 (0.007)	0.3940 (0.007)	-0.0445 (0.718)	-0.0012 (0.992)	0.6703 (0.032)	0.6893 (0.027)	0.2846 (0.135)	0.2805 (0.141)
Log GDP per capita		0.0656 (0.223)		0.2608 (0.000)		0.1605 (0.181)		-0.09 (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 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. Source: Computations based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021).

Table A.4 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
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
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 >200000 from 2005 – 2020, for robots exposure for 2015, 2010 over all MSAs. Source: Based on data from the Bureau of Labor Statistics (2021), Bureau of Economic Analysis (2021), World Bank (2021), Brookings (2017).