Automation and occupational mobility: A data-driven network model

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Many existing jobs are prone to automation, but since new technologies also create new jobs it is crucial to understand job transitions. Based on empirical data we construct an occupational mobility network where nodes are occupations and edges represent the likelihood of job transitions. To study the effects of automation we develop a labour market model. At the macro level our model reproduces the Beveridge curve. At the micro level we analyze occupation-specific unemployment in response to an automation-related reallocation of labour demand. The network structure plays an important role: workers in occupations with a similar automation level often face different outcomes, both in the short term and in the long term, due to the fact that some occupations offer little opportunity for transition. Our work underscores the importance of directing retraining schemes towards workers in occupations with limited transition possibilities.

Introduction

Recent studies have raised concerns about job displacement due to automation [21, 13]. However, history suggests that while some jobs are automated, new jobs are created, making it essential to understand job transitions. Here we study how automation affects employment through a model that focuses on the process of *labor reallocation*. Consider, for example, employment security faced by a statistical assistant vs. a childcare worker. Forecasts suggest that the statistical assistant is more likely to be replaced by software technology than the childcare worker [21]. However, the statistical assistant's current skills allow her to transition into occupations with low risk of automation and growing demand. In contrast, as automation displaces workers, many of them may have the skills required for childcare jobs, and may consequently threaten the job security of existing childcare workers. Thus, even though the direct replacement effect of automation is larger for statistical assistants, when we account for possible occupational transitions and labor demand reallocation, the negative impact of automation is worse for childcare workers.

The model that we develop here captures these important but often overlooked indirect displacement effects. We study the effect of labor market frictions caused by the mismatch of skills, and show how they can prevent unemployed workers from finding jobs even when there are job vacancies. Our key finding is that network effects can concentrate unemployment in specific areas of the occupational mobility network. This suggests that policies could be more effective by strategically targeting workers in these areas.

Labour market disruptions caused by automation have been a topic of intense interest in the last few years [28, 2, 13, 20, 8]. Recent technical developments in machine learning and artificial intelligence led researchers to develop predictions for a new wave of automation. Based on experts' opinions on the automatability of specific occupations, Frey and Osborne [21] estimate that approximately half of the jobs in the U.S. are at risk of automation. While related studies have nuanced these numbers by arguing that jobs will evolve rather than disappear [5, 13], there is general agreement that the biggest challenge lies in the reallocation of workers and the development of new skills [7, 14, 5]. It is particularly worrying that several studies estimate that low-wage and low-skill occupations are most at risk of automation [5, 21].

Automation affects occupations differently. For example, in the 2000s, digital technologies affected middle-wage occupations disproportionately. This was because computerization replaced not only manual labor but also cognitive routine occupations such as clerical work [7]. Today digital technologies are undergoing significant progress that has allowed machines to achieve human-level performance in tasks that have previously been out of reach. A classic example is driving cars, which in 2003 was not considered automatable [9]. Today, self-driving vehicles are thought to be close to commercial distribution, with the potential to replace 2 million truck and taxi drivers in the U.S. alone [15].

Fears of technological unemployment are neither new, nor unfounded, but they are sometimes misplaced. While it is clear that automation will replace a large number of workers, this is an old process that has so far not caused persistent large unemployment rates. Instead, the average length of the work week has declined substantially and work has shifted to new occupations. Without taking a position on the likelihood of automation, our model makes it possible to study job transitions under any given automation scenario. We consider the two automation scenarios based on Frey and Osborne [21] and Brynjolfsson et al. [14] and study how the resulting job transitions affect unemployment.

To understand how jobs will be affected by automation we distinguish three types of direct effects of automation on labor markets. i) Some skills may become obsolete, causing jobs to disappear. ii) Upcoming technologies will require new skills to operate, creating new jobs. iii) Automation will generate productivity improvements and raise aggregate income, thus increasing labor demand in sectors where consumer demand is high. These three effects will lead to a significant reallocation of labor demand, with some occupations increasing and others decreasing their labor demand. As the labor market converges to a new configuration with reallocated demand, there will be adverse effects, with workers being displaced and firms failing to find workers with the appropriate skills.

Building on recent contributions that have demonstrated the importance of modeling labor flows using networks [35, 31, 24, 10, 26, 27, 11, 18, 29], we construct an *occupational mobility network* where nodes are occupations and edges correspond to the probability that workers transition between occupations. We model the labor market as a stochastic process with discrete time steps. During each time step occupations open vacancies and separate (fire) workers, unemployed workers search for a new job, and vacancies and job applications are matched. A key restriction is that the last occupation in which a worker is employed determines the possible jobs that she can apply for.

We analyze the dynamics using master equations. In the limit where the number of jobs and workers are large this can be reduced to a deterministic dynamical system, which dramatically speeds up the analysis with little loss of accuracy. We use empirical data both to create the occupational mobility network and to calibrate the parameters of the model.

The model we develop here is quite general and can potentially be used to study network-induced labor frictions in any setting. We calibrate the model by fitting it to the empirical Beveridge curve, which relates vacancies and unemployment rates. The model's key prediction is the heterogeneous distribution of unemployment and long-term unemployment rates at the occupation level. We show that the effects of network structure on aggregate unemployment are substantial, increasing unemployment by roughly 25%, and that changes in the distribution of the labor demand across the network can cause significant shifts in the aggregate unemployment rate even when the total supply and demand of jobs is held constant.

To understand the effect of automation we impose a time-dependent shock, which lowers the demand for some occupations while raising the demand for others, and study the dynamics of unemployment as a function of time. We find that the effect on aggregate employment depends on the nature of the shock: The predictions of Frey and Osborne for automation cause a substantial increase in aggregate unemployment for a period of about a decade. These effects are felt in both short term and long-term unemployment. While occupations that are at high risk of automation tend to be affected most, network position is also important and causes substantial deviations in the levels of unemployment. Surprisingly, in the long-term this shock also shifts the steady-state aggregate employment to a lower level. In contrast, the automation predictions of Brynjolfsson et al. have surprisingly little effect on unemployment.

Results

The occupational mobility network

We first construct an occupational mobility network representing the ease with which a worker can transition between occupations. To do this we follow the work of Mealy et. al. [27] and construct the network based on empirical data on occupational transitions in the United States between 2010–2017. In this network nodes are occupations and the weights of the edges are proportional to the probability that a worker transitions between occupations. The resulting network is weighted and directed (see Fig. 1). The network also has self-loops, since workers often remain in the same occupation when they change jobs. We represent the network by its adjacency matrix A, with elements

$$A_{ij} = \begin{cases} r & \text{if } i = j \\ (1-r)P_{ij} & \text{if } i \neq j, \end{cases} \tag{1}$$

where the indices i and j label the n possible occupations. r is the weight of the self-loops, and is the probability that a worker who is changing jobs applies to a job vacancy in her original occupation. P_{ij} is the empirical probability that a worker transitioning out of occupation i moves to occupation j. For details on how we compute P_{ij} we refer the reader to the *Methods* section. For the purposes of this paper we assume that A_{ij} is fixed in time – edges do not change and no nodes are removed or added.

As shown in Fig 1, the set of possible job transitions has a rich network structure [27]. This reinforces recent studies that have shown that occupational mobility is significantly more restricted than is commonly assumed in most labor-market models [6, 32]. Fig. 1 also shows how estimates of the automatability of occupations are distributed across the occupational mobility network assuming estimates by Frey and Osborne and Brynjolfsson et al.

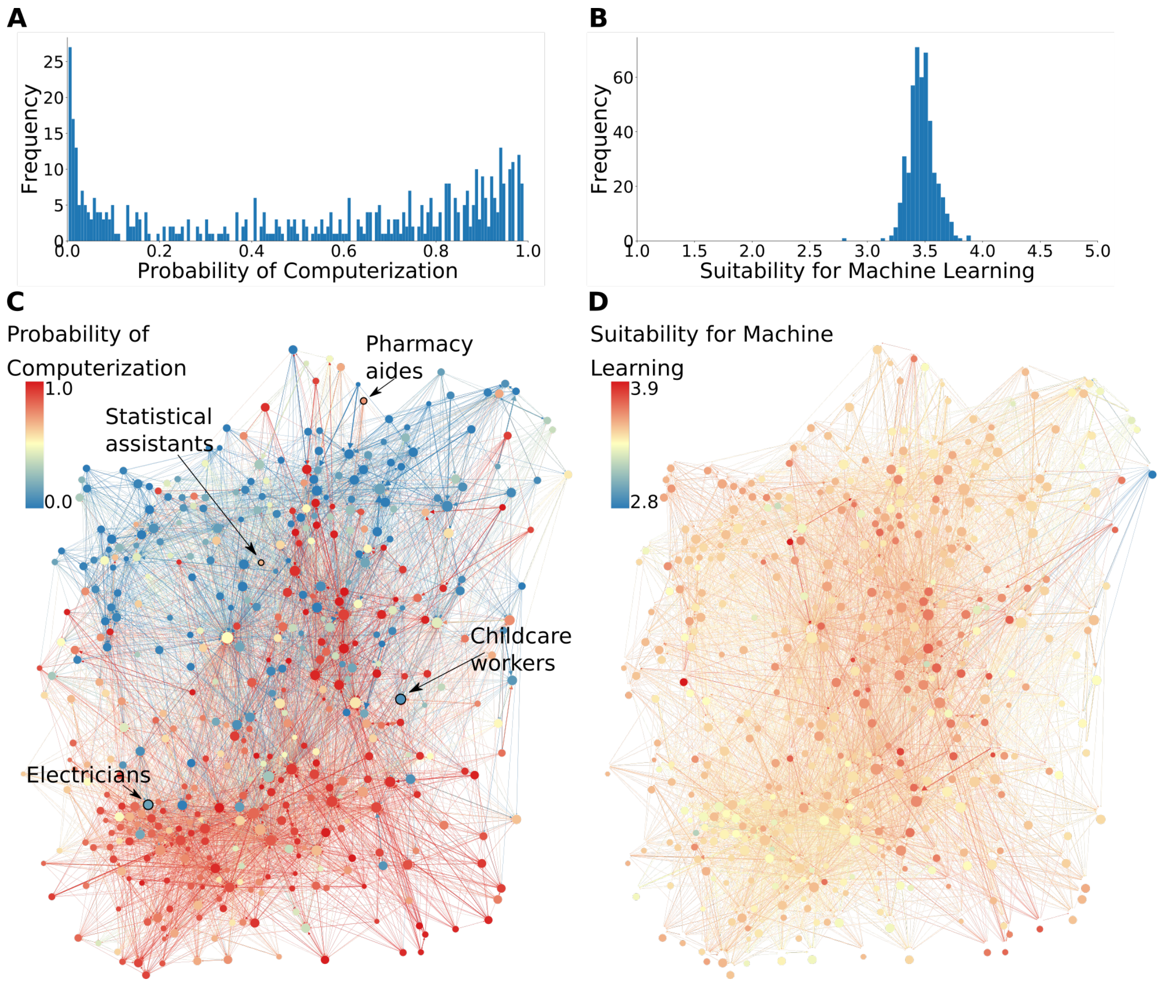

Figure 1: **Estimates of automatability in the occupational mobility network.** Panel (**A**) is a histogram of the probability of computerization for different occupations as estimated by Frey and Osborne [21] and panel (**B**) is a similar histogram for the suitability for machine learning as estimated by Brynjolfsson et al. [14]. The probability of computerization has a bimodal distribution, while the suitability for machine learning has a unimodal distribution. The bottom panels show the occupational mobility network, where nodes represent occupations and links represent possible worker transitions between occupations. The color of the nodes indicates the estimated automatability for (**C**) the probability of computerization and (**D**) the suitability for machine learning. Red nodes have high automatability and blue nodes have low automatability. The size of the nodes indicates the number of employees in each occupation.

A network model of the labor market.

Our model is designed to understand the dynamics of unemployment at the occupation level. The network labor flow is described by a set of discrete time stochastic processes for employment, unemployment and vacancies in each occupation i. We assume that workers are perfectly geographically mobile and we neglect wage pressure. The set of possible occupations is fixed and the occupation of a worker is defined as the last occupation in which she was last employed. At any given time t the number of workers employed in occupation i is $e_{i,t}$, the number of unemployed workers is $u_{i,t}$, and the number of job vacancies is $v_{i,t}$. The number of workers that are separated (i.e. fired) is $\omega_{i,t}$ and the number of vacancies is $\nu_{i,t}$. The labor flow $f_{ij,t+1}$ is the number of workers hired in occupation j who were previously unemployed in occupation i. The resulting set of stochastic processes can be described by equations,

$$\text{employment} \qquad e_{i,t+1} = e_{i,t} - \underbrace{\omega_{i,t+1}}_{\text{separated workers}} + \underbrace{\sum_j f_{ji,t+1}}_{\text{hired workers}} \tag{2}$$

$$\text{unemployment} \qquad u_{i,t+1} = u_{i,t} + \underbrace{\omega_{i,t+1}}_{\text{separated workers}} - \underbrace{\sum_j f_{ij,t+1}}_{\text{transitioning workers}} \tag{3}$$

$$\text{vacancies} \qquad v_{i,t+1} = v_{i,t} + \underbrace{\nu_{i,t+1}}_{\text{opened vacancies}} - \underbrace{\sum_j f_{ji,t+1}}_{\text{hired workers}} . \tag{4}$$

These equations express conservation laws stating that the change in each variable is equal to the difference between inflow and outflow. Eq. (2) states that the change in employment is equal to the number of workers that are hired minus the number of workers that are separated. Similarly, Eq. (3) states that the change in unemployment is equal to the number of workers who are fired minus the number who are hired. Finally, Eq. (4) states that the number of vacancies is equal to the number of vacancies created minus the number of workers who are hired to fill them. Fig. 2 is a flow chart that makes the transitions explicit from the perspective of a worker and from the perspective of a job vacancy.

We denote occupation specific variables by lower-case letters and aggregate quantities by upper-case letters (e.g., total unemployment is $U_t = \sum_i u_{i,t}$) and use bold font for vectors (i.e., the ith element of $\mathbf{u}_t$ is $u_{i,t}$). The time steps are chosen so that their duration is long enough for workers to transition between occupations, but too short for workers to change their employment status more than once. That is, a worker is not allowed to switch her status from employed to unemployed and then back to employed in a single time step. Likewise, a vacancy cannot be opened and filled within the same time step.

We assume that the number of separated workers $\omega_{i,t+1}$ and the number of job openings $\nu_{i,t+1}$ follow binomial processes of the form,

$$\omega_{i,t+1} \sim \mathrm{Bin}(e_{i,t}, \pi_{u,i,t}), \tag{5}$$

$$\nu_{i,t+1} \sim \mathrm{Bin}(e_{i,t}, \pi_{v,i,t}), \tag{6}$$

where $\mathrm{Bin}(m, p)$ denotes a binomial distribution with m trials and success probability p. The success probabilities $\pi_{u,i,t}$ and $\pi_{v,i,t}$ depend on the imbalance of supply and demand for labor and play a key role in the dynamics. Because this is a bit complicated, we will first complete our overview of the model and return in a moment to specify $\pi_{u,i,t}$ and $\pi_{v,i,t}$.

The labor flow $f_{ij,t+1}$ depends on the structure of the occupational mobility network, the number of vacancies and unemployed workers, and the processes of job search and job matching. The search and matching process can be thought of as an urn problem. Imagine each worker has a ball with her name on it and each job vacancy is an urn. With probability A_{ij} each worker in occupation i picks an urn corresponding to occupation j and places her ball in it. After all workers have placed their balls, a ball is drawn from each urn with uniform probability and the corresponding worker is hired. If a vacancy does not receive job applicants it remains open on the next time step.

The labor flow $f_{ij,t+1}$ is thus a stochastic variable that can be computed based on the fact that the probability that a worker makes a transition from occupation i to occupation j is equal to the probability $q_{ij,t+1}$ that she applies to j, times the probability $p_{ij,t+1}$ that her application is accepted. The probability $q_{ij,t+1}$ that an unemployed worker in occupation i applies to a vacancy in occupation j is

$$q_{ij,t+1} = \frac{v_{j,t} A_{ij}}{\sum_l v_{l,t} A_{il}}. \tag{7}$$

This means the expected number of applications submitted from occupation i to occupation j is

$$\mathrm{E}[s_{ij,t+1} | u_{i,t}] = u_{i,t} q_{ij,t+1}. \tag{8}$$

Since each unemployed worker sends one job application, for fixed i the random variables $s_{ij,t+1}$ follow a multinomial distribution with $u_{i,t}$ trials and probabilities $q_{ij,t+1}$ for $j = 1, ..., n$. All vacancies that have applications hire one worker, but some vacancies may lack applications, in which case no one is hired and the job vacancy remains open. As we will make explicit later, the probability $p_{ij,t+1}$ that an application is successful follows from the urn model [36].

Supply and demand for labor Workers move across the occupational mobility network in response to shifts in labor supply and demand. This is determined by the success probability $\pi_{u,i,t}$ of the binomial process for separating workers in Eq. (5) and the success probability

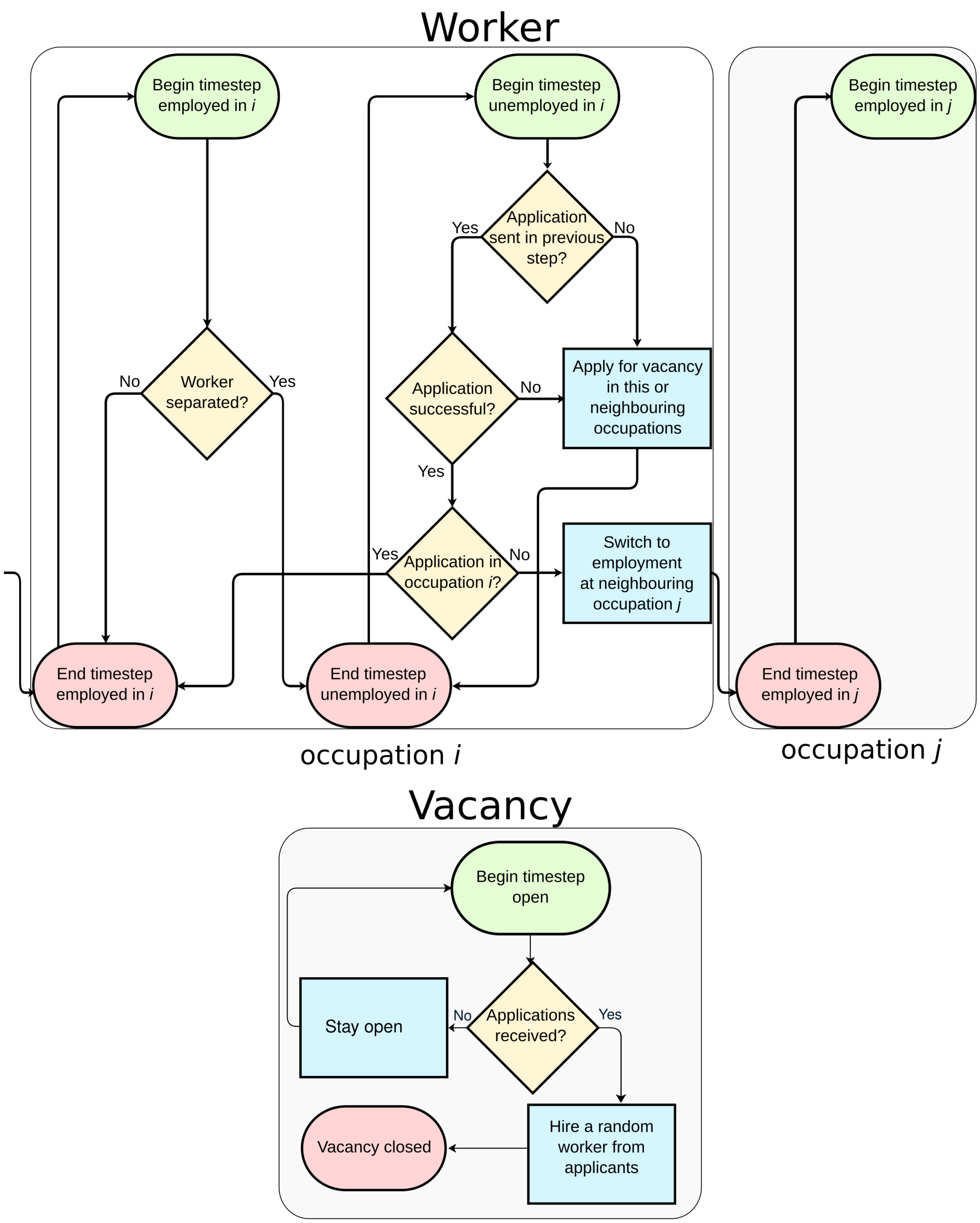

Figure 2: **Flow chart illustrating the possible transitions of workers and job vacancies during a given time step.** *Top*: transitions of a worker. *Bottom*: The transitions of a job vacancy. Note that vacancies created in the current time step do not accept job applications until the following time step.

$\pi_{v,i,t}$ for the binomial process for creating vacancies in Eq. (6). We break each of these into two separate random processes. The first is a *spontaneous process* and the second is a *state-dependent process*.

In the spontaneous process workers are separated and vacancies are opened at random, independent of the state of the system. For simplicity here we assume that the separation and opening rates are the same for all occupations. For any given occupation, the spontaneous probability that a given worker is separated at any given time is δ_u and the spontaneous probability that a vacancy opens is δ_v times the number of workers in that occupation.

The state-dependent process accounts for imbalances in supply and demand. This is done by adding an additional occupation-specific probability $\alpha_{u,i,t}$ that a worker from occupation i is separated at time t and an additional occupation-specific probability $\alpha_{v,i,t}$ that a vacancy in occupation i opens. Both of these probabilities are functions of time, constructed to equilibrate supply and demand. The *target* labor demand $d^{\dagger}_{i,t}$ is the desired quantity of labor for occupation i at time t. This is imposed externally, and allows us to impose automation shocks as a function of time. The *realized* labor demand, in contrast, is a time dependent variable corresponding to the sum of the number of employed workers plus the number of job vacancies in a given occupation, i.e.

$$d_{i,t} = e_{i,t} + v_{i,t}.$$

$\alpha_{u,i,t}$ and $\alpha_{v,i,t}$ satisfy the following conditions:

1. If the realized labor demand of an occupation equals the target labor demand, i.e., $d_{i,t} - d^{\dagger}_{i,t} = 0$, then no adjustments are made, i.e. $\alpha_{u,i,t} = \alpha_{v,i,t} = 0$.

2. $\alpha_{u,i,t}$ is an increasing function of $d_{i,t} - d^{\dagger}_{i,t}$. This condition guarantees that when the realized demand of an occupation is greater than the target demand, the occupation is more likely to separate workers and thus decrease its realized demand. Likewise, $\alpha_{v,i,t}$ is an increasing function of $d^{\dagger}_{i,t} - d_{i,t}$, so that when the realized demand is less than the target demand, the occupation is more likely to open vacancies and thus increase its realized demand.

3. $\alpha_{u,i,t}$ and $\alpha_{v,i,t}$ are probabilities and lie in the interval $[0, 1]$.

For the purposes of this paper we assume that supply and demand equilibrate at a linear rate with respect to the difference between the realized labor demand and the target labor demand, and require that this relationship be non-negative. This leads to the functional forms

$$\alpha_{u,i,t} = \gamma_u \frac{\max\left\{0, d_{i,t} - d^{\dagger}_{i,t}\right\}}{e_{i,t}}, \tag{9}$$

$$\alpha_{v,i,t} = \gamma_v \frac{\max\left\{0, d^{\dagger}_{i,t} - d_{i,t}\right\}}{e_{i,t}}, \tag{10}$$

where γ_u and γ_v are parameters that determine the speed of adjustment. They are in the interval $[0, 1]$: $\gamma_u = \gamma_v = 1$ corresponds to immediate full adjustment and $\gamma_u = \gamma_v = 0$ corresponds to no adjustment at all. The α's are probabilities, and so must satisfy $0 \leq \alpha_{u,i,t} \leq 1$ and $0 \leq \alpha_{v,i,t} \leq 1$. Although this condition is normally satisfied automatically, there are exceptional circumstances where it would exceed the upper interval, in which case we set $\alpha = 1$. For simplicity, for the purposes of this paper we let the rates for separations and vacancies be the same, i.e. $\gamma_u = \gamma_v = \gamma$. For a description of how we calibrated parameters and set initial conditions see the *Methods* section.

All of the processes corresponding to δ_u, δ_v, $\alpha_{u,i,t}$ and $\alpha_{v,i,t}$ are independent. Thus the probability that a worker in occupation i is *not* separated from her job is $(1 - \delta_u)(1 - \alpha_{u,i,t})$. This means that the probability that a worker *is* separated is given by

$$\pi_{u,i,t} = 1 - (1 - \delta_u)(1 - \alpha_{u,i,t}) = \delta_u + \alpha_{u,i,t} - \delta_u \alpha_{u,i,t}, \tag{11}$$

where the negative term on the right hand side avoids counting a worker as separated twice. Similarly, for each employed worker in occupation i, the probability that a vacancy opens is

$$\pi_{v,i,t} = \delta_v + \alpha_{v,i,t} - \delta_v \alpha_{v,i,t}. \tag{12}$$

Automation shocks. We assume that automation reallocates labor demand across occupations, decreasing the number of jobs available in some professions and increasing them in others. Since the set of occupations is fixed, we base the creation of new jobs on the thought experiment that each non-automated job reduces work hours so that the total number of jobs in the economy stays constant. This assumption is motivated by the long-run evidence that unemployment rates have no trend but hours worked have decreased [34]. We assume that automation reduces the target demand for occupations with a high automation level and correspondingly increases the target demand for occupations with a lower automation level, so that the number of jobs destroyed equals the number of jobs created (see *Methods*). Here we also assume that the total labor force L is fixed, so that $D^{\dagger}_t = D_0 = L$. In the Supplementary Material we relax this assumption and investigate the behavior under changes in aggregate demand.

This completes our specification of the model. Table S1 of the Supplementary Materials gives a summary of the variables and parameters and the Materials and Methods section gives the calibration procedure and Table 1 contains fitted values for all the parameters.

Deterministic approximation for large populations

When the number of workers L is large we can take advantage of the law of large numbers to approximate the system's behavior in terms of expected values. This provides a good approximation for most purposes and is faster to simulate and easier to analyze, which is very useful for exploring the parameter space when calibrating the model. When the target labor demand is constant we show that there exists a computable steady-state value for the unemployment and vacancy rates.

We compute expectations for Eqs. (2 - 4) in the limit of a large number of agents and conditional on the state of the system at the previous time step. To keep the notation compact, we often denote expected values by a bar above the variable, e.g.,

$$\bar{u}_{i,t+1} \equiv E\left[u_{i,t+1}|\mathbf{u}_{i,t}, \mathbf{v}_{i,t}, \mathbf{e}_{i,t}\right].$$

All expected values are dependent on the state $(\mathbf{u}_{i,t}, \mathbf{v}_{i,t}, \mathbf{e}_{i,t})$.

The expectation of a binomial process is its success rate. Thus, from Eqs. (5), (9) and (11) we can compute the expected number of separations conditioned on the unemployment, and similarly, from Eqs. (6), (10) and (12) we can compute the expected number of vacancies. This gives

$$\bar{\omega}_{i,t+1} = \pi_{u,i,t}\bar{e}_{i,t} = \delta_u \bar{e}_{i,t} + (1-\delta_u)\gamma \max\left\{0, \bar{d}_{i,t} - d^{\dagger}_{i,t}\right\}, \tag{13}$$

$$\bar{\nu}_{i,t+1} = \pi_{v,i,t}\bar{e}_{i,t} = \delta_v \bar{e}_{i,t} + (1-\delta_v)\gamma \max\left\{0, d^{\dagger}_{i,t} - \bar{d}_{i,t}\right\}. \tag{14}$$

The labor flow $f_{ij,t+1}$ is equal to the number of workers from occupation i applying to occupation j, $s_{ij,t+1}$, multiplied by the probability $p_{j,t+1}$ that each application is successful. (All applications are accepted with uniform probability, so p does not depend on i). The expected value is

$$\bar{f}_{ij,t+1} = E\left[s_{ij,t+1}p_{j,t+1}|\mathbf{u}_{i,t}, \mathbf{v}_{i,t}, \mathbf{e}_{i,t}\right]. \tag{15}$$

Letting the total number of applications $s_{j,t+1}$ to occupation j be

$$s_{j,t+1} = \sum_k s_{kj,t+1}, \tag{16}$$

the fraction $p_{j,t+1}$ of successful applications is the ratio of the number of vacancies $m_{j,t+1}$ that successfully match to the total number of applications, i.e.

$$p_{j,t+1} = m_{j,t+1}/s_{j,t+1}. \tag{17}$$

The variables $s_{ij,t+1}$, $m_{j,t+1}$ and $s_{j,t+1}$ are not independent. Nonetheless, in the Supplementary Material we show that in the large L limit we can approximate $\bar{f}_{ij,t+1}$ as

$$\bar{f}_{ij,t+1} \approx \bar{s}_{ij,t+1}\bar{v}_{j,t}\frac{(1 - e^{-\bar{s}_{j,t+1}/\bar{v}_{j,t}})}{\bar{s}_{j,t+1}}. \tag{18}$$

The relative error of approximation is

$$\left|\frac{\mathrm{E}[f_{ij,t+1}|\mathbf{u}_t,\mathbf{v}_t;A]-\bar{f}_{ij,t+1}}{\mathrm{E}[f_{ij,t+1}|\mathbf{u}_t,\mathbf{v}_t;A]}\right| < \frac{c}{L+c},$$

where c is a constant, here $\mathrm{E}[f_{ij,t+1}|\mathbf{u}_t,\mathbf{v}_t;A]$ denotes the expected value and $\bar{f}_{ij,t+1}$ the expected value in the limit of a large number of agents.

Substituting Eqs. (7) and (8) into Eq. (18), we can write $\bar{f}_{ij,t+1}$ in terms of the adjacency matrix and the expected values of the state variables as

$$\bar{f}_{ij,t+1} = \frac{\bar{u}_{i,t}\bar{v}_{j,t}^2 A_{ij}(1-e^{-\bar{s}_{j,t+1}/\bar{v}_{j,t}})}{\bar{s}_{j,t+1}\sum_k \bar{v}_{k,t}A_{ik}}, \tag{19}$$

where

$$\bar{s}_{j,t+1} = \sum_i \frac{\bar{u}_{i,t}\bar{v}_{j,t}A_{ij}}{\sum_k \bar{v}_{k,t}A_{ik}}. \tag{20}$$

We have now reduced the master equations to a $3n$ dimensional deterministic dynamical system, of the form

$$\bar{e}_{i,t+1} = \bar{e}_{i,t} - \underbrace{\left(\delta_u\bar{e}_{i,t}+(1-\delta_u)\gamma_u\max\left\{0,\bar{d}_{i,t}-d^\dagger_{i,t}\right\}\right)}_{\text{separated workers}} + \underbrace{\sum_j \bar{f}_{ji,t+1}}_{\text{hired workers}}, \tag{21}$$

$$\bar{u}_{i,t+1} = \bar{u}_{i,t} + \underbrace{\left(\delta_u\bar{e}_{i,t}+(1-\delta_u)\gamma_u\max\left\{0,\bar{d}_{i,t}-d^\dagger_{i,t}\right\}\right)}_{\text{separated workers}} - \underbrace{\sum_j \bar{f}_{ij,t+1}}_{\text{transitioning workers}}, \tag{22}$$

$$\bar{v}_{i,t+1} = \bar{v}_{i,t} + \underbrace{\left(\delta_v\bar{e}_{i,t}+(1-\delta_v)\gamma_v\max\left\{0,d^\dagger_{i,t}-\bar{d}_{i,t}\right\}\right)}_{\text{opened vacancies}} - \underbrace{\sum_j \bar{f}_{ji,t+1}}_{\text{hired workers}}, \tag{23}$$

where $\bar{f}_{ij,t+1}$ is given by Eq. (19) and $\bar{d}_{i,t} = \bar{e}_{i,t}+\bar{v}_{i,t}$. Given a set of time series for the target labor demand $d^\dagger_{i,t}$ and a set of initial conditions, Eqs. (21 – 23) determine the expected employment, unemployment and vacancies as a function of time.

All of our results here are based on the U.S. occupational mobility network, which classifies jobs into 464 occupational categories. In the Supplementary Material we show that the deterministic approximation derived above provides a good approximation when using the U.S. occupational mobility network as long as each occupation has a target demand of at least 50 workers. If we assume a labor force of 1.5 million, almost all occupations satisfy this. Thus for most occupations the deterministic approximation is valid for any labor pool bigger than that of a medium sized city. Our results can thus be thought of as applying to city of at least this size, under the assumption of perfect job mobility within the city. We will also assume that the occupational mobility network A for this "typical city" is that of the U.S. as a whole. Because we will later calibrate the model based on national occupational unemployment levels we implicitly assume that these reflect the national average.

Steady-state

The system approaches a steady-state when the target demand is constant. We denote the constant value of the target demand by $d_i^\dagger$ and the steady-state values of the steady state values of the state variables as $\bar{e}_i^*$, $\bar{u}_i^*$ and $\bar{v}_i^*$. Setting $\bar{e}_{i,t} = \bar{e}_{i,t+1} = \bar{e}_i^*$, and so on for the other state variables, Eqs. (21–23) imply that at the steady state

$$\bar{v}_i^* = d_i^\dagger - \left(1 - \frac{\delta_u - \delta_v}{\gamma_v(1-\delta_v)}\right)\bar{e}_i^*. \tag{24}$$

and

$$\bar{e}_i^* = \frac{1}{\delta_u}\sum_j \bar{f}_{ji}^*, \tag{25}$$

where $f_{ij}^* = f_{ij}[\bar{\mathbf{u}}^*, \bar{\mathbf{e}}^*, \bar{\mathbf{v}}^*]$. Except for the simple case of a complete network, with $A_{ij} = 1/n$, we cannot derive a closed form solution for the occupational unemployment $\bar{u}_i^*$. Nonetheless, the numerical solution is relatively easy given that $\bar{f}_{ij}^*$ satisfies

$$\sum_j \bar{f}_{ji}^* = \sum_j \bar{f}_{ij}^*. \tag{26}$$

Eqs. (24 – 26) make it clear that the steady-state values depend on the network structure as well as the target labor demand. Thus the network structure can have a substantial influence on the steady state unemployment at both the occupational and the aggregate level.

The Beveridge curve

The Beveridge curve is one of the most well-known macroeconomic stylized facts [17, 12]. It states the relation between vacancies and unemployment: When unemployment goes up, vacancies go down. The intuition is that when many workers are unemployed, vacancies are filled faster, resulting in a lower vacancy rate. Similarly, when there are many vacancies, unemployed workers are more likely to find jobs, reducing the unemployment rate.

In panel A of Fig. 3 we plot the Beveridge curve for the USA between January 2001 and September 2018. We observe that in recession periods, and particularly from December 2007 to June 2009, the unemployment and vacancy rates move downward along the curve. In contrast, from July 2009 onward the economy recovers and the unemployment and vacancy rates move upward along the curve. While the slope is negative for almost all periods, the curve itself also shifts as the cycle unfolds. After the 2009 financial crisis the Beveridge curve shifted away from the origin, with unemployment increasing for all vacancy rates.

There are several theories for the dynamics of the Beveridge curve (see [19] for a review). The most prominent is the work of Diamond, Mortensen and Pissarides, which proposes that movements along the curve are caused by the different stages of the business cycle [33, 16]. During booms more vacancies open and unemployment decreases, while in recessions fewer vacancies open and more workers are separated. Their theory correctly predicts that points on the upper left of the curve correspond to booms and points on the lower right correspond to recessions (see panel A of Fig. 3).

We test our model by imposing a simulated business cycle. For simplicity, we assume that the aggregate target labor demand D_t oscillates according to a sine wave. We then calibrate the amplitude of the sine wave and the parameters δ_u, δ_v and τ to match the empirical Beveridge curve during the most recent U.S. business cycle, from 2008 to 2018. We set the initial target labor demand of each occupation equal to the observed average employment in 2016 (see calibration in the *Methods* section for details). As the sine wave varies, the target demand for each occupation remains fixed relative to the aggregate demand. This means that the target demand of all occupations moves in tandem according to the same sine wave. Thus while there are aggregate dynamics, there are no structural changes.

As seen in Fig. 3C, the behavior of the simulation closely resembles the empirically observed Beveridge curve. Consistent with the empirically observed behavior, the simulated vacancy rates move upwards during booms and downwards in recessions. The principal difference is that, since the sine wave is smooth, the simulation is also smooth. This is in contrast to the much rougher empirical curve, which is presumably due to the noisy behavior of the target demand during a real business cycle.

The Diamond-Mortensen-Pissarides model predicts that the shifts of the Beveridge curve are caused by structural changes in the labor market, including changes in the efficiency of labor market matching and changes in job search activity. The former can be caused by changes in the mismatch of skills, meaning that job applicants have a difficult time finding jobs because they do not have the right skills for new jobs that are created. The latter can be associated with changes in the enthusiasm with which workers search for jobs. For example, long-term unemployment may discourage workers and makes their job search less efficient. Increasing labor market friction should shift the Beveridge curve to the right, making unemployment higher for the same vacancy rate.

To demonstrate that our model matches this prediction, we now hold the target aggregate demand D_t constant, and instead vary the structure of the network by replacing the empirical

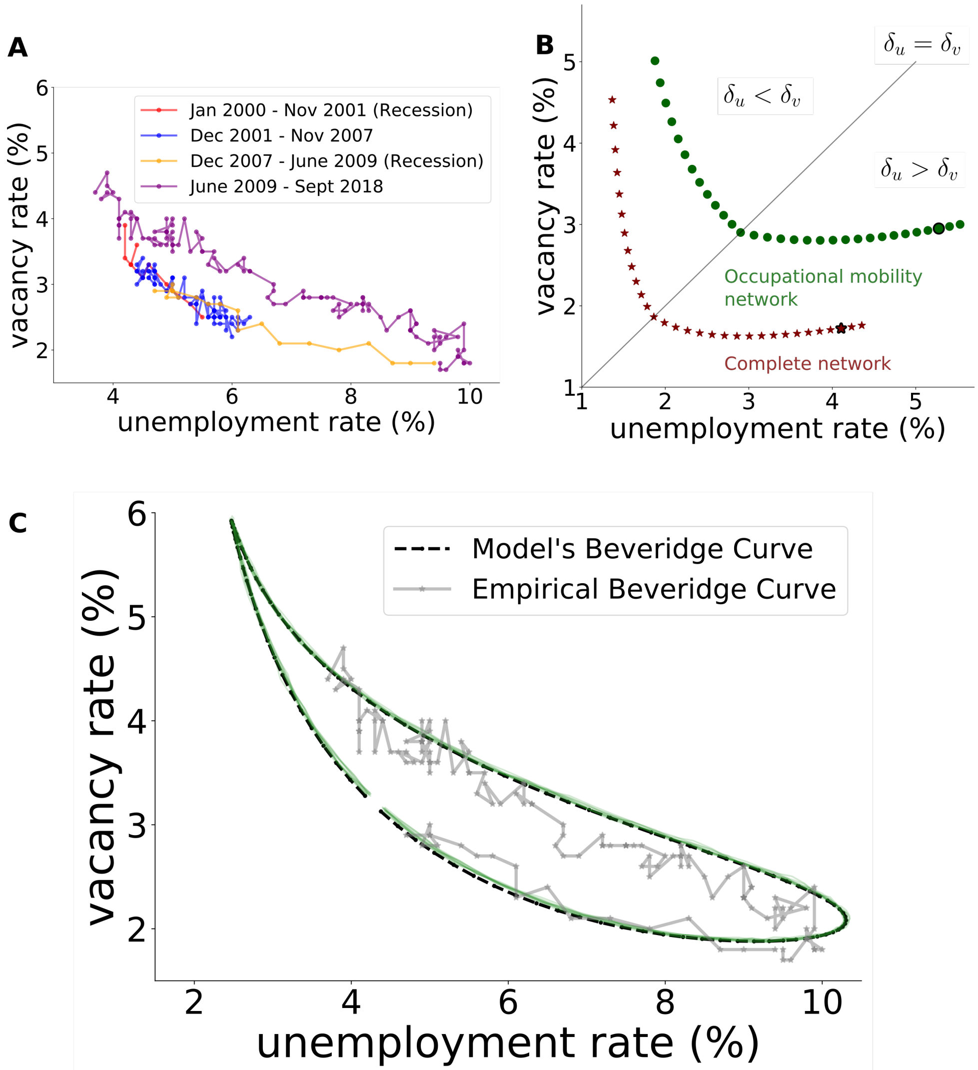

Figure 3: **The Beveridge curve.** In each panel we plot the unemployment and vacancy rate. (**A**) The historical Beveridge curve for the United States, 2000-2018. Different periods are highlighted with different colors. (**B**) Movement of the Beveridge curve due to changes in labor market frictions. In particular, we plot the difference between a complete network, with no skill mismatch frictions, vs. the empirical occupational mobility network. Each dot corresponds to the steady-state unemployment and vacancy rate for different values of δ_u and δ_v. The highlighted points correspond to the unemployment and vacancy rate of the model using the calibrated parameters. (**C**) The Beveridge curve generated by our model. The parameters of the model are calibrated to match the empirical Beveridge curve between December 2007 and December 2018. The dashed lines correspond to the deterministic approximation of Eqs. (21 - 23) and solid green lines to the full stochastic model simulation of Eqs. (2 - 4). The transparent grey line shows the empirical Beveridge curve between December 2007 and December 2018.

network A by a complete network $A_{ij} = 1/n$, in which each node is linked to every other node with equal weights. This corresponds to the null hypothesis of no skill restrictions. We do this for different values of δ_u and δ_v and trace the *steady-state* behavior in Fig. 3B. As expected, when we remove the network structure, the Beveridge curve shifts downwards towards the origin. When we consider parameters calibrated to actual data, (highlighted with a bold border), removing the network structure corresponds to an increase in unemployment from 4.1% to 5.3%. This effect is substantial, representing more than a 25% increase.Our model thus suggests that a fifth of the unemployment is caused by occupational mobility constraints. This prediction agrees with the qualitative prediction of the Diamond-Mortensen-Pissarides model, but it goes beyond it by quantifying the labor frictions imposed by the network.

In addition, we predict an effect that is not present in the Diamond-Mortensen-Pissarides model. Their model predicts that shifts in the Beveridge curve are caused entirely by structural displacements. In contrast, in the experiment shown in Fig. 3C we observe shifts in the Beveridge curve even though we assume no structural displacements. This is because in our model we capture the dynamics of the out of equilibrium behavior of unemployment, which becomes a bigger factor during periods of rapid change.

The impact of automation on employment

We now use the model to assess the impact of automation shocks on employment. We study two automation scenarios, one based on a study by Frey and Osborne [21] and the other based on a study of Brynjolfsson et al. [14]. We refer to these automation scenarios as the *Frey and Osborne shock* and as the *Brynjolfsson et al. shock*.

Estimates of the automation shock

Frey and Osborne estimated the probability that each of 702 occupations in the O*NET 6-digit classification system could be computerized soon [21]. To do this they gave experts a description of tasks performed by workers in a restricted sample of 70 occupations and asked them whether the occupations could be automated within the next two decades. Based on the experts' answers and using nine O*NET variables that describe occupations as inputs, they trained a supervised machine learning algorithm and estimated what they called the the *probability of computerization* for the remaining occupations. They found that approximately half of the jobs in the U.S. would be at risk for some degree of automation.

Brynjolfsson et al. took a different approach, taking advantage of the 8-digit level O*NET classification of occupations based on work activities [13]. (This has 974 occupations). They asked workers from a crowd sourcing platform to rate what they called the *suitability for machine learning* for each work activity. They then used the breakdown of work activities for each occupation to estimate the suitability for machine learning for each occupation, broken down into a five point scale [14]. We normalize this measure by dividing it by 5, so that it is in a range from zero to one. Most occupations have at least some tasks that are suitable for machine learning, but few, if any, have all tasks suitable for machine learning. This suggests that many jobs will be re-designed rather than destroyed.

Both of these studies estimate the probability that an occupation will be *technically automatable*. This is not the probability that an occupation will be automated, which also depends on cost, institutions, etc., and it is not an estimate of the share of jobs in an occupation that will be automated. Nonetheless, for simplicity we interpret these as automation levels, directly determining the share of jobs in an occupation that will be automated. We map the 6 and 8 digit O-NET classifications used in these studies into the the U.S. occupational mobility network (which is based on the 4 digit American Community Survey classification) using the 2016 National Employment Matrix Crosswalk (see [27]).

These two studies yielded substantially different results. First, they differ in their correlation to wages. Several authors have argued that automation has caused wage polarization [8]. The Frey and Osborne estimates are strongly anti-correlated with wages, whereas the Brynjolfsson et al. estimates have a low correlation with wages. Second, as we see in Fig. 1, the distribution of the Frey and Osborne estimates is wide, whereas the Brynjolfsson et al. distribution has a narrow peak. Since the Frey and Osborne estimates vary substantially between occupations and the Brynjolfsson et al. estimates do not, the corresponding changes in the target labor demand are large for the Frey and Osborne shock but small for the Brynjolfsson et al. shock. (See the top panels of Fig. 4 for examples of how the target labor demand changes for different occupations under the two shocks). As already mentioned, we assume that the aggregate demand share remains constant during the shocks; occupations with a high automation level decrease their target labor demand share, whereas occupations with a low automation level correspondingly increase it (see *Methods* section for details).

Impact on employment and long-term unemployment

Before the automation shock, we assume the system is in a steady-state where the target demand $d_i^\dagger$ matches the employment distribution in 2016 (see *Methods*). We then introduce an automation shock by making the target demand $d_{i,t}^\dagger$ follow a sigmoid function, which begins at zero and converges to the post-automation target demand (see top panels of Fig. 4 for examples). We choose the adoption rate so that the total shock is spread across a 30 year period, though most of the change happens within about 10 years. See *Methods* for details, and the Supplementary Material, where we show that the results are fairly robust for reasonable adoption rates.

Aggregate level outcomes. As seen in Fig. 4, even though the aggregate target demand is held constant, the Frey and Osborne shock increases both the aggregate unemployment rate and the aggregate long-term unemployment rate during the period of automation. In contrast, the Brynjolfsson et al. shock causes no noticeable change in the aggregate unemployment rates. This difference is caused by the different distributions of the two shocks. The Frey and Osborne shock is very heterogeneous across occupations, affecting some occupations a great deal and others very little, so that the changes in target demand at the occupation level are substantial (see panel A). In contrast, the Brynjolfsson et al. shock affects most occupations similarly, so that the changes in the target demand are smaller and the network effects are small (see panel B).

We compare the behavior with the empirical occupational mobility network to the hypothetical behavior assuming a complete network, in which any worker can transition equally well to any occupation. We use the same parameters for both networks (see calibrated parameter values in Table 1 in Methods section). The aggregate unemployment rate is initially about 5.3% for the empirical network and 4.1% for the complete network. When we apply the Frey and Osborne shock, the aggregate unemployment rate for the empirical network rises to 6.7% at its peak and then decays. In contrast, for the complete network the aggregate unemployment rises to only 4.7% before it decays. Thus the total change in unemployment with the empirical network is more than a factor of two larger, demonstrating the importance of the network structure.

We also study the behavior of the long-term unemployment as a function of time. For the same simulation, the long-term unemployment rate for the empirical network is about 2.0%, substantially smaller than the (short-term) unemployment. When we apply the Frey and Osborne shock the aggregate long-term unemployment rate rises to 2.6% at its peak and then decays. The relative change from the initial value to the peak value is about 29%, which is similar to the relative change of 27% for the unemployment rate. However, the behavior for the complete network is quite different: First, the initial level of long-term unemployment for the complete network is only 1.0%, more than a factor of two smaller than for the empirical network. Second, when we apply the shock, long-term unemployment for the complete network remains nearly flat.

Another surprising result is that the steady-state value of the aggregate unemployment shifts after the shock. The aggregate unemployment rate changes from 5.27% to 5.11%, for a net change of about -0.15%. While this is small, bear in mind that we have kept the both the total aggregate target demand and all the parameters of the model constant. This is consistent with our result in Eqs. (24 – 26), where we showed that the steady-state explicitly depends on the network structure and the target demand in each occupation, but the fact that we see this shift when we change the target demand demonstrates the key role that the network structure plays in determining the steady-state as well as the transient behavior. Note that there is no noticeable

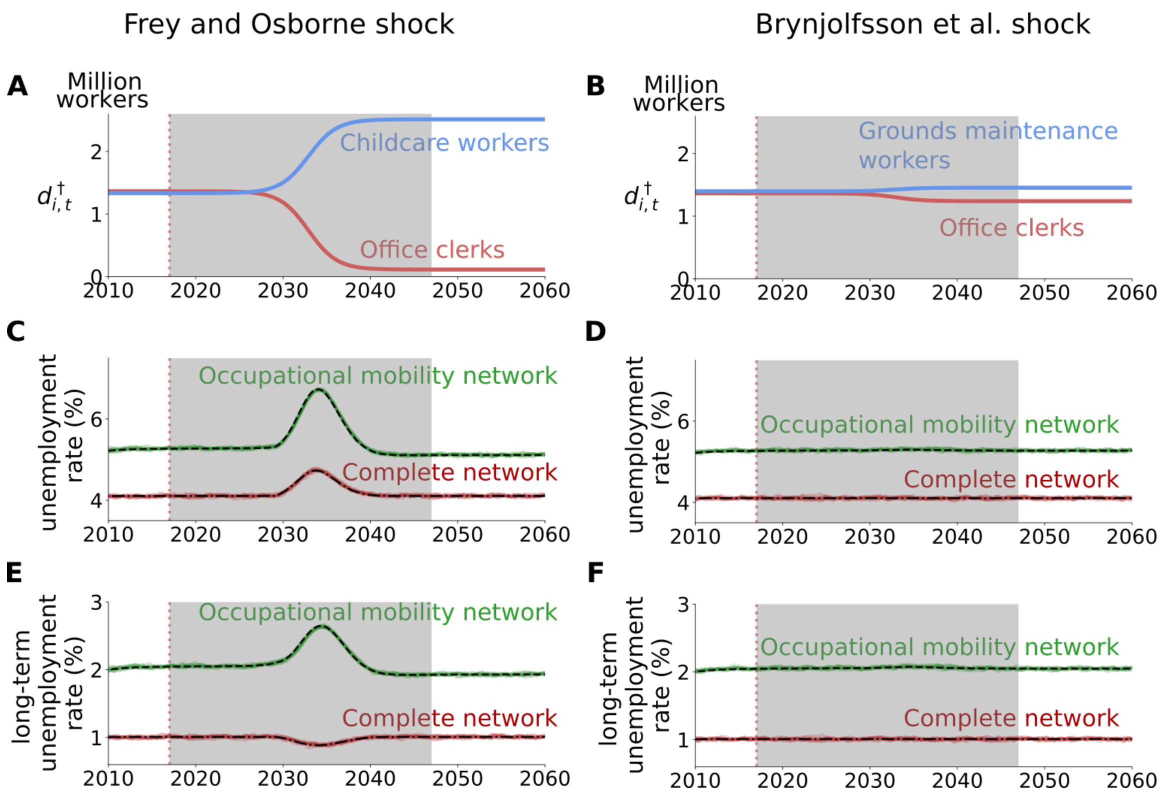

Figure 4: **Aggregate labor market outcomes under automation shocks.** The left panels correspond to the Frey and Osborne shock and the right panels to the Brynjolfsson et al. shock. The grey area denotes the 30 years during which the automation shock takes place. Panels (**A**) and (**B**) show the evolution of the target labor demand for two example occupations. The occupations colored in blue have a low automation level and the occupations colored in red have a high level. Because it is more heterogeneous across occupations, the Frey and Osborne shock implies a larger change in the target labor demand of most occupations. Panels (**C**) and (**D**) show the unemployment rate as a function of time. Dashed lines are our approximations of the expected value (solved numerically) and the solid lines are 10 simulations with 1.5 M agents. Panels (**E**) and (**F**) show the long-term unemployment rate as a function of time. As before, dashed lines correspond to the deterministic approximation of Eqs. (21 - 23) and solid lines to the full stochastic model simulation of Eqs. (2 - 4).

shift in the steady state for the complete network.

We conjecture that the Frey and Osborne shock causes such persistent effects due to the fact that automation levels of neighboring occupations tend to be similar. This has two effects: It means that there are some regions of the network where workers easily find new jobs, and others where workers get trapped because there are no good alternatives, causing a substantial boost to long-term unemployment. The shift in the steady state occurs because the post-automation distribution of the target labor demand across occupations is more concentrated on fewer occupations that are more densely connected between each other, reducing worker-vacancy matching frictions.

To test our conjecture, we create a surrogate Frey and Osborne shock that randomizes the automation levels of occupations. We do this by randomly shuffling the automation level of each of the 464 occupations, i.e. randomly reassigning each automation level to a new occupation (without replacement). This preserves the distribution of automation levels but removes any correlation between neighboring occupations. When we do this the aggregate unemployment rate does not decrease, while the long-term unemployment tends to increase slightly. Thus the most persistent effects disappear when the correlation inherent in the network structure is removed.

To demonstrate that the network correlation structure is indeed the cause, we create another surrogate shock where we randomize relative to the Frey and Osborne shock while intentionally creating a correlation between neighbors. Since occupations of the same O*NET classification typically have high connectivity, we redistribute the probabilities of computerization so that occupations with similar classifications have a similar automation level. We do this by ordering the probabilities of computerization in ascending order and ordering the occupations in ascending order with respect to their occupation code. We then match these to create a surrogate shock with the desired property. When we impose this shock the post-automation aggregate unemployment and long-term unemployment rate both decrease, confirming our conjecture.

These results demonstrate how the structure of the occupational mobility network can cause substantial and long-lasting dislocations of the labor force. When the target demand for labor is altered by the automation shock, old jobs are closed in some occupations and new jobs are opened in others. Under the Frey and Osborne shock, which has strong network structure, we see a large transient effect that causes a substantial rise in aggregate unemployment over the decade during which the dislocation takes place. This is also felt in aggregate long-term unemployment and even causes a permanent shift in aggregate unemployment.

Finally, in the Supplementary Material we explore what happens when we relax the assumption that the aggregate target labor demand remains constant.

Occupation level outcomes. We now show how automation affects the occupation-specific unemployment rates, where the network plays a crucial role. To avoid problems with small denominators, and to ensure that each unemployed worker contributes equally to the average unemployment rate during the automation period, we measure the *average unemployment rate* and *average long-term unemployment rate* during the shock as

$$u_{i,\text{average}}(T) = \frac{\sum_{t\in T} u_{i,t}}{\sum_{t\in T}(u_{i,t} + e_{i,t})},$$

and

$$u^{(\geq\tau)}_{i,\text{average}}(T) = \frac{\sum_{t\in T} u^{(\geq\tau)}_{i,t}}{\sum_{t\in T'}(u_{i,t} + e_{i,t})},$$

where T is the set of time steps that correspond to the automation shock. (We discuss an alternative way of defining the average unemployment rate in the Supplementary Material). For simplicity, from here onward, we refer to the average unemployment rate and the average long-term unemployment rate during the automation period simply as the unemployment rate and the long-term unemployment rate.

In Fig. 5 we compare the percentage changes in unemployment and long-term unemployment with the automation level of each occupation. To highlight the role of the network, we do this both for the occupational mobility network, which includes market frictions due to skill mismatch, and for the complete network, where workers can apply to any job vacancy regardless of their occupation. For the complete network, the automation level of an occupation uniquely determines the impact of automation, i.e. occupations with the same automation level have the same percentage change in their unemployment and long-term unemployment rates. In contrast, for the occupational mobility network, due to network effects, there is considerable scatter around the mean behavior – unlike the complete network, the automation level is *not* a perfect predictor of the occupation-level outcome. The scatter is substantial both for the Frey and Osborne shock and for the Brynjolfsson et al. shock. (See also Tables S2 and S3 of the Supplementary Material).

To make the size of these effects clear it is useful to highlight some specific cases. Both dispatchers and pharmacy aides have a high probability of computerization of 0.72, but the automation shock causes a 19% increase in the dispatchers' long-term unemployment, while the pharmacy aides' long-term unemployment *decreases* by roughly by the same ratio. Similarly, both machinists and avionic technicians have a high 0.70 suitability for machine learning score, but long-term unemployment for machinists only slightly increases, while avionic technicians *decrease* their long-term unemployment by more than 20%. Some occupations experience the opposite change that one would expect. For the Frey and Osborne shock, statistical assistants and pharmacy aides are likely to be automated (with probability of computerization above 0.6)

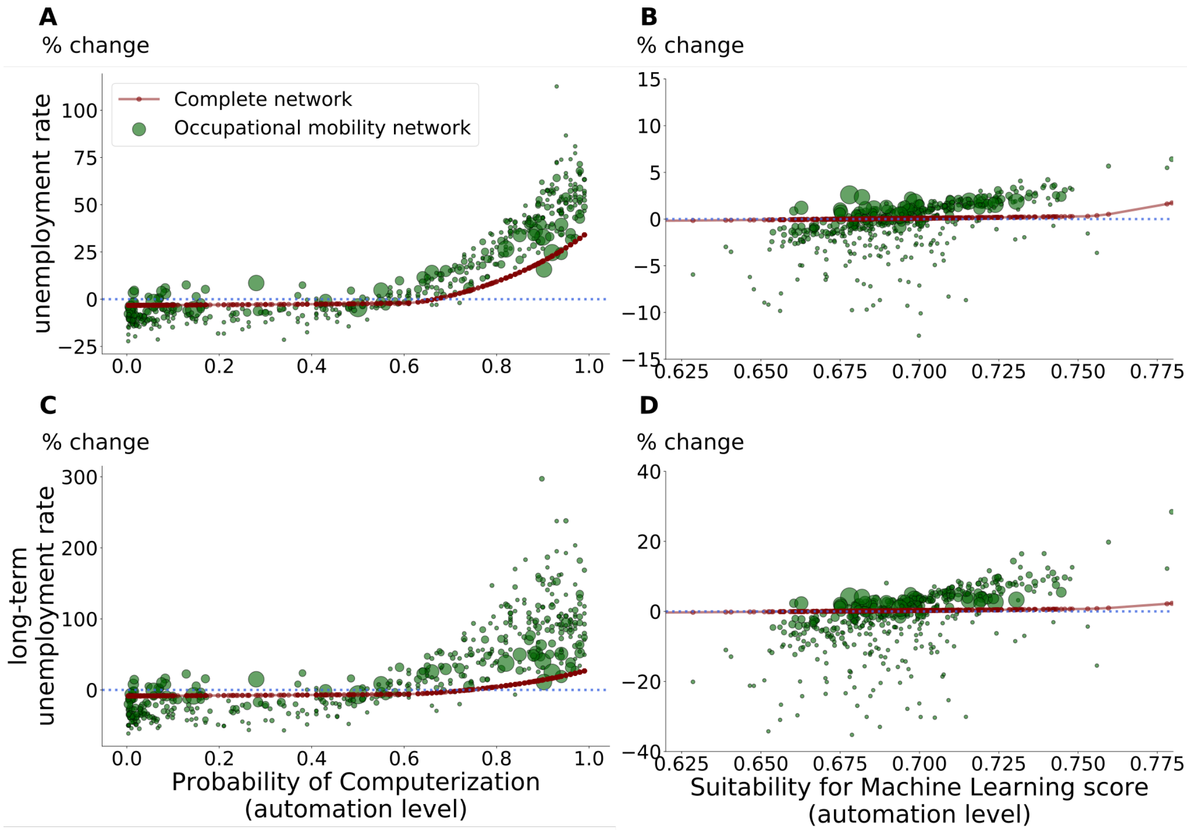

Figure 5: **Impact of automation shocks on unemployment and long-term unemployment at the occupation level.** The left panels correspond to the Frey and Osborne shock and the right panels to the Brynjolfsson et al. shock. The green dots are for the occupational mobility network and the red dots are for the complete network. The size of the green dots is proportional to the employment of the occupation they represent. Panels **(A)** and **B)** show the percentage change in the unemployment rate vs the automation level for each occupation, while panels **(C)** and **(D)** show the same thing for the long-term unemployment rate. The scatter in the results demonstrates that, due to network effects, the automation level only partially explains occupational unemployment.

while childcare workers and electricians are not (with probability of computerization below 0.1). However, statistical assistants and pharmacy aides *decrease* their long-term unemployment, while childcare workers and electricians increase theirs. This is due to the fact that it is relatively easy for statistical assistants and pharmacy aides to transfer to jobs in other occupations with an increasing demand, whereas it is easier for others to transfer to childcare workers or electricians, thereby increasing the supply of workers relative to the demand. This illustrates the importance of network effects.

The differences in wage correlation for the two automation shocks are more or less reproduced in their effect on unemployment, i.e. the correlation between occupational wages and unemployment is similar to the correlation between wages and the shocks themselves.

Discussion

Caveats and further work. The main goal of this study is to show that to assess the impact of automation on employment at the occupation level it is essential to develop models that acknowledge restrictions on occupational mobility. To perfectly calibrate these types of models, we need fine-grained data at the occupation level, which is not always available. For our model, we used as much fine-grained data as possible and, in the spirit of keeping things simple, we filled in the gaps by making assumptions. For example, we assumed that the network is constant in time and that the weights of the self-loops r in the occupational mobility network are homogeneous across occupations. With more data available on job transitions, we could do this more accurately. Our model suggests that automation can strongly affect the long-term unemployment of occupations. However, in a more realistic setting, when people cannot find a job close to their skills they look for alternative options and possibly learn new skills. Thus, our results are prone to exaggerate the effects on long-term unemployment. With a time dependent network we could capture these effects more appropriately. Another potential area of improvement is the calibration method for δ_u, δ_v and γ, where we used data on a single business cycle. Finally, we assumed that estimates of the automatability of occupations would translate directly into levels of automation, with labor being replaced. However, historically, technological change has complemented labor in some occupations and created new entire occupations.

There is plenty of room for further research. As better estimates of the automatability of occupations become available, we can incorporate them into our model to produce more realistic predictions. Our model is tailored to understand the impact of any demand shock on employment, and can be used to study other effects such as off-shoring or unemployment caused by the transition to a sustainable economy. Furthermore, recent work has highlighted how intersectoral and interregional mobility determines regional resilience to shocks.Our work could be further extended to account for the important role geography plays in labour market dynamics. Finally, it would be interesting to embed our occupational mobility model in a macroeconomic model with endogenous business cycles, where consumption choices determine occupation-specific target labor demand.

Summary of the results. We build upon search and matching models, complex networks and agent-based modeling techniques to design a mathematical model of occupational mobility. We use the model to estimate the effects of automation on unemployment, using recent estimates of the potential for automation at the occupation level. At the macro level, our model reproduces the dynamics of the Beveridge curve and suggests that the labor market frictions imposed by the occupational mobility network can account for a substantial amount of the unemployment rate. Furthermore, our model shows that the distribution of the labor demand across occupations in the network can affect the steady-state unemployment, as we saw for the Frey and Osborne automation shock. At the micro level, we show that, although occupation-specific automation levels are a significant driver of the changes in employment of an occupation during the shock, the network's structure also plays an important role. Workers in occupations with the same automation level can be impacted positively or negatively by automation, depending on their position in the network. We also obtain counter-intuitive results where, due to the network's structure, workers in certain highly automated occupations can benefit from automation, while workers in certain occupations with a low level of automation can suffer adverse consequences. Even when the total number of jobs remains constant, automation can increase long-term unemployment due to the mismatch between the skills of unemployed workers and job vacancies.

Contribution to the literature. Search theory acknowledges that it takes time and resources for a worker to find a job. This theory has been successful in explaining why there can simultaneously exist unemployed workers and unfilled vacancies [32]. We contribute to the search theory literature by designing a data-driven network model of labor market frictions at the fine-grained occupational level.

Our work is also related to the *task approach* [6, 1]. In these models, workers are classified according to their skills into two or three groups, where the less skilled workers can only perform a subset of the tasks the more highly skilled workers can do. By assuming that automation increases the tasks capital can produce, these models show displacement of workers due to capital and higher skilled workers [3, 1]. Similarly, in our model workers are displaced by both automation technologies and other workers. However, our model is data-driven in terms of the classification of workers, the occupational mobility network, and the automation shocks.

Macroeconomic models play a crucial role in evaluating policies for labor markets. As reviewed in reference [30], several agent-based models have been proposed. For example, see reference [22], which tests labor policies in France. Our work contributes to this by introducing labor frictions in a data-driven manner

Our model reproduces the movement of the Beveridge curve during business cycles and shows that structural changes shift the Beveridge curve. Most strikingly, our model suggests that the business cycle alone, without any structural change, shifts the Beveridge curve. In our model this is caused by the simple fact that target demand causes non-equlibrium dynamics and long transients due to network effects, which make it difficult for workers to find new jobs. This prediction is in agreement with empirical observations – the Beveridge curve has (almost) always shifted outwards after recessions [17]. Therefore, our model also contributes to the literature on the asymmetric effects of business cycles, where the outward shifts of the Beveridge curve are explained by business cycles rather than structural changes [25].

We also contribute to the literature on applied network science. Networks have been used to study the job mobility response to local and global demand shocks to the labor market [31]. Others have studied the effect of the topology of labor flow networks on "firm-specific unemployment" [24, 10]. Another set of studies has focused on the structure of occupation networks, showing that they capture the skill heterogeneity of workers and that routine, manual and cognitive/abstract skills are clustered in specific parts of the networks [27, 4]. Our work shows how the network of occupation mobility constrains labor reallocation, shaping the reaction of the labor market to structural changes and automation shocks.

In summary, our model is novel in several aspects. First, it has a search and matching process with skills mismatch at the occupation level using a network of occupational mobility. Second, it predicts outward shifts of the Beveridge curve during business cycles. Third, it derives occupation-specific steady-state unemployment and long-term unemployment rates. Finally, allows us to estimate the effects of structural changes on occupation-specific employment during the out-of-equilibrium dynamics.

Policy implications. While what happens in specific examples of occupations is somewhat sensitive to the choice shock and parameters, our work underscores that to create effective retraining programs one needs to properly understand the bottlenecks to occupational mobility. For example, according to Frey and Osborne, statistical assistants are more vulnerable to automation than childcare workers. However, since a statistical assistant can transition into occupations with growing demand, our results suggest that the long-term unemployment for this occupation is more likely to decrease. In contrast, since many occupations with decreasing demand can transition into childcare worker jobs, the long-term unemployment of childcare workers is likely to increase. Thus, support and retraining efforts might be better directed at childcare workers. A model that neglects network structure would not reach this conclusion.

Materials and Methods

Building the occupational mobility network

Following Mealy et. al., we construct the occupational mobility network using empirical data on occupational transitions [27]. The classification is based on the 4-digit occupation codes, which yields 464 distinct occupations. We used monthly panel data from the US Current Population Survey (CPS) to count the number of workers T_{ij} who transitioned from occupation i to occupation j during the period from January 2010 to January 2017. Letting $T_i = \sum_j T_{ij}$, we assume that if a worker changes occupation, the probability of transitioning from occupation i to occupation j is

$$P_{ij} = \frac{T_{ij}}{T_i}. \tag{27}$$

Unfortunately the US Current Population Survey does not record the probability that a worker who switches jobs remains in the same occupation. Due to lack of data, for simplicity we assume here that this is independent of occupation. Letting r be the probability that a worker who changes jobs stays in the same occupation, we write the adjacency matrix of the occupational mobility network in the form

$$A_{ij} = \begin{cases} r & \text{if } i = j, \\ (1-r)P_{ij} & \text{if } i \neq j. \end{cases} \tag{28}$$

As described in more detail in the next section, we estimate r based on aggregate data [23].

In the model, the entry of the adjacency matrix A_{ij} reflects the relative preference or likelihood with which a worker from occupation i chooses to apply to a vacancy of occupation j, rather than any other occupation j (see Eq.(7)). However, this preference is not directly observable from data. To overcome this issue, we use the empirical network of occupational mobility, where A_{ij} is the probability that a worker from occupation i is hired in occupation j, conditional on the worker switching jobs (note this implies the worker was hired).

While the empirical mobility network allows us to calibrate the heterogeneity in occupational mobility at a detailed level, the concepts are different; the relative preference with which a worker from occupation i applies to a job vacancy in j is different from the probability that a worker from occupation i, who is switching jobs, transitions to occupation j. However, the former is not directly observable from data. To overcome this issue, we use the empirical network of occupational mobility as indicative of the preference with which a worker from occupation i applies to a job vacancy in j. A caveat is that since the odds of a worker being hired do not uniquely depend on the preference with which workers apply to job vacancies, the transitions of workers observed in our model do not perfectly match the empirically observed transitions.

Though the matching between the transitions in our model and the empirical ones is not perfect, they are significantly similar – the Pearson correlation between them is 0.97.

Long-term unemployment

We are interested in long-term unemployment. The expected number of workers with an unemployment spell of k steps for occupation i at time t is the expected number of workers with an unemployment spell of $k-1$ steps at the previous time step times the probability that a worker of occupation i is not hired. Thus the expected number of unemployed workers of occupation i with an unemployment spell of k time steps $u_{i,t+1}^{(k)}$ is given by the recursive equation

$$\bar{u}_{i,t+1}^{(k)} = \bar{u}_{i,t}^{(k-1)}\left(1 - \frac{\sum_j \bar{f}_{ji,t}}{\bar{u}_{i,t}}\right), \tag{29}$$

with $\bar{u}_{i,1}^{(1)} = \bar{\omega}_{i,1} = \bar{e}_{i,0}\pi_{u,i,t}$.

The U.S. Bureau of Labor Statistics defines long-term unemployed workers as those who have an unemployment spell of 27 or more weeks. Similarly, in our model the long-term unemployed workers are those who have been unemployed for τ or more time steps. Using Eq. (29), we compute the expected number of long-term unemployed workers ($\bar{u}_{i,t+1}^{(\geq\tau)}$) by summing over all workers with an unemployment spell of τ or more time steps

$$\bar{u}_{i,t+1}^{(\geq\tau)} = \sum_{k=\tau}^{\infty} \bar{u}_{i,t+1}^{(k)}. \tag{30}$$

Calibration

To calibrate the model we use fine-grained data when possible and aggregate data when this is not possible. To calibrate the target labor demand when the shock begins we assume that the labor market is initially in steady state, so that the target labor demand in each occupation is equal to the total employment in that occupation. We thus assume that $d_{i,0}^{\dagger} = e_{i,0}$, where $e_{i,0}$ is the average employment in 2016. We assume that the aggregate target labor demand before the shock. The measured values of the initial target demand for each occupation are given in Table S2 of the Supplementary Material. Throughout the shock we preserve the condition that the aggregate demand $\sum_i d_{i,t}^{\dagger}$ remains constant in time.

To calibrate the parameters δ_u, δ_v, and Δt (the duration of the time step) we simulate an idealized business cycle and adjust these three parameters to find the best match to the empirical U.S. Beveridge curve from December 2007 to December 2018. To create the artificial business cycle we assume the aggregate target demand D_t follows a sine wave of the form $D_t = D_0 + a\sin(t/2\pi T)$, where D_0 is the initial demand and T is the period of the business cycle. Based on visual inspection, we assume that the empirical curve has traversed about three quarters of a business cycle between December 2007 and December 2018. Thus December 2007 is about a quarter of a cycle past the previous peak and December 2018 is the new peak. This gives a period of the oscillation $T = 14.6$ years. (The assumptions about phase do not influence the fit, they only explain our reasoning in choosing T).

We assume the model is at its steady state at the beginning of the simulation, with the initial target demand $d_0^\dagger$ of each occupation matching employment in 2016 (which is the most recent year where we have data for individual occupations). We then let the target demand $d_{i,t}^\dagger$ of individual occupations move in tandem according to the sine wave, so that each occupation makes a pro-rata change tracking D_t, i.e. $d_t^\dagger = d_0^\dagger + asin(t/2\pi T)$ and simulate the model.

We run an exhaustive search over possible values of the amplitude a of the sine function that determines the amplitude of the business cycle and the parameters δ_u, δ_v, and Δt. The objective of the search is to minimize the discrepancy between the model and the empirical Beveridge curve. As the criterion for goodness of fit we compare the intersection of the enclosed areas. The objective function is

$$\min_{a,\delta_u,\delta_v,\Delta t} \frac{A_m \cap A_e}{A_m \cup A_e}, \tag{31}$$

where A_m is the area enclosed by the Beveridge curve of the model, A_e is the area enclosed by the empirical Beveridge curve, $A_m \cap A_e$ is the intersection of their areas and $A_m \cup A_e$ is the union of their areas. (To define the area of the empirical Beveridge curve we close it by connecting the starting and endpoints). The optimal parameters are $a = 0.065$, $\Delta t = 6.75$ weeks, $\delta_u = 0.016$ and $\delta_v = 0.012$. The optimal parameters of the model are reasonably stable with respect to the optimal choice $a = 0.065$. For example, when we increase a by 10%, Δt remains constant while δ_u and δ_v increase roughly by 6%, and when we decrease a by 10%, Δt and δ_u remain constant while δ_v increases by less than 5%.

We now calibrate the parameter r, which is the probability that a worker changing jobs remains within the same occupation. We are handicapped by the fact that this is not directly recorded, but we can use data on the annual occupational mobility rate, which is the percentage of workers that change occupations within a year, to infer this indirectly. Previous studies estimated that 19% of workers in the USA changed occupations in a year, i.e. that 81% did not change occupations in a year. A more recent study shows that in the Danish economy the annual occupational mobility rate is 20% [23]. Therefore, we assume that each year 81% of workers remain in their current occupation and use this to estimate r, using the following approach.

In the previous section, we explained that we use the empirical occupational transitions to incorporate the relative preference with which a worker from occupation i applies to a job vacancy in j (for $i \neq j$). Consistently with this approach (and acknowledging the same caveats), here we use the fact that every year 81% of workers remain in their current occupation to calibrate the preference r with which workers chose to apply to job vacancies in their current occupation.

For simplicity, we consider the following abstraction. We assume that the probability that a worker does not change occupation in one time step is time-invariant and constant across occupations. Then, we observe that in the model, only workers who are unemployed change occupation. Thus, the probability that a randomly chosen worker *does not* change occupation in one time step is the probability $1-u$ that she is employed plus the probability u that she is unemployed times the probability r that she does not change occupation, that is $((1-u)+ur)$. Then, the probability x that a worker does not change occupations in y time steps is $x = ((1-u)+ur)^y$. Solving for r implies

$$r = \frac{x^{1/y} + u - 1}{u}. \tag{32}$$

Our model makes roughly $y = 52/6.75 = 7.7$ time steps in one year. Assuming $x = 0.81$, $\delta_u = 0.016$ and $u = 0.06$ (the average U.S. unemployment rate since the year 2000) gives the estimate $r = 0.55$.

We have no empirical data to calibrate γ, which is the rate at which the realized demand adjusts towards the target demand. However, as we demonstrate in the Supplementary Material, we have the good fortune that the behavior of the model is insensitive to γ across a wide range of reasonable parameters. We choose $\gamma = 10\delta_u$.

Parameter	**Value**	**Description**
δ_u	0.0160	Rate at which employed workers are separated due to the spontaneous process.
δ_v	0.0120	Rate at which employed vacancies are opened due to the spontaneous process.
γ	0.160	Rate at employed workers and vacancies are separated or opened due to market adjustment towards the target demand.
Δt	6.75 weeks	Duration of a time step in units of weeks.
r	0.55	Probability that a worker stays in the same occupation

Table 1: Calibrated parameter values

Labor reallocation due to labor automation.

We now explain how we use the the probability of computerization scores of Frey and Osborne and the suitability for machine learning scores of Brynjolfsson et al. to set the post-shock reallocated demand $\mathbf{d}^\dagger$ of each of the two shocks. The post-shock reallocated demand is the value to which the target labor demand converges after the shock. We discuss the convergence time and functional form of the target labor demand in the next section. We denote the time at which the target labor demand has reached the post-shock level by t^*.

We use the probability of computerization and the suitability for machine learning scores, which are bounded by 0 and 1, as the level of automation in each occupation. We assume that the level of automation is the fraction of total hours worked in an occupation that are no longer needed post-shock. Furthermore, working hours are reduced for all workers in the economy, so that the total number of jobs stays constant. We denote the labor force, which is the number of workers, by L and assume that it remains constant. Let x_0 be the current number of hours of labor for the average worker in a given period of time (say a year). The hours of work each occupation demands is given by the components of the vector

$$\mathbf{h}_0 = x_0 \mathbf{e}_0.$$

Letting $\mathbf{p}$ be the vector with the automation level of each occupation, the new number of hours of work $\mathbf{h}_{t^*}$ after automation is

$$\mathbf{h}_{t^*} = \mathbf{h}_0 \odot (\mathbf{1} - \mathbf{p}),$$

where $\odot$ denotes the element-wise multiplication of vectors and $\mathbf{1}$ the vector of ones. We split the aggregate hours of work equally among workers, thus the number of hours of work per week is

$$x_{t^*} = \frac{\sum_i^n h_{i,t^*}}{L}.$$

Finally, assuming that automation has no impact on the aggregate labor demand unemployment, we split the hours of labor demanded by occupations equally among workers.

$$\mathbf{d}^\dagger_{t^*} \equiv \mathbf{d}^\dagger = \mathbf{h}_{t^*} \frac{1}{x_{t^*}}. \tag{33}$$

where t^* is the time at which the target labor demand reached the post-shock target. Here we have assumed that the aggregate number of jobs remains constant. In the Supplementary Material we explore the behavior under an aggregate increase or decrease in the number of jobs.

Formulating a time dependent automation shock.

We follow the innovation literature, which suggests that the adoption of technologies follows a sigmoid function or S-curve over time [37]. Frey and Osborne say that their estimates are over "some unspecified number of years, perhaps a decade or two." [21]. We assume that the automation happens within 30 years, but mostly happens within 10 years, and explore different alternatives in the Supplementary Material.

We assume that the target demand initial value is the steady-state demand and over time it reaches the post-shock reallocated demand (defined in the previous subsection). Within 15 years, the target demand is at the mid-point between the initial steady-state demand and the post-shock reallocated demand. We use a sigmoid function for the target demand

$$d^{\dagger}_{i,t} = \begin{cases} d_{i,0} & \text{if } t < t_s \\ d_{i,0} + \frac{d^{\dagger}_i - d_{i,0}}{1+e^{k(t-t_0)}} & \text{if } t \geq t_s. \end{cases} \tag{34}$$

where t_s is the time at which the automation shock starts and t_0 is 15 years after t_s. Furthermore $k = 0.79$, which guarantees that the target demand equals the post-shock reallocate demand up to a 0.0001 tolerance.

Before introducing the automation shock, we first initialize the model so that it converges to the steady-state unemployment rate and to the employment distribution of occupations of 2016. After it reaches the steady-state, we introduce the target demand $d^{\dagger}_{i,t}$ as explained above. In the Supplementary Material we demonstrate the robustness of the results under variations in the time span of the automation shock.

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Supplementary Material. Automation and occupational mobility: A data-driven network model

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S1 Mathematical derivations and approximations

In this section we derive the mathematical approximations presented in the Results.

S1.1 Matching

$m_{j,t+1}$ is the number of vacancies that successfully match with a job applicant. Since employees hire a worker unifomly at random from the pool of applicants, then $m_{j,t+1}$ is equal to the number of job applications that receive at least one job application. We estimate $\bar{m}_{j,t+1}$ following the derivations done by [36]. An unemployed worker who applies for a job in occupation j with $v_{j,t}$ vacancies, will apply to a particular vacancy with probability $\frac{1}{v_{j,t}}$.Thus the probability that the worker does *not* send her application to that vacancy is $1 - \frac{1}{v_{j,t}}$. For $s_{j,t}$ unemployed workers sending applications to occupation j, the probability that a particular vacancy does not receive an application is $(1 - \frac{1}{v_{j,t}})^{s_{j,t}}$. Since each vacancy receiving an application hires one worker, the expected number $\bar{m}_{j,t+1}$ of successful job applications is

$$\bar{m}_{j,t+1} = v_{j,t}\left(1 - \frac{1}{v_{j,t}}\right)^{s_{j,t}}.$$

Using the approximation that $(1-x)^y \approx (1 - e^{-xy})$ for large x and y we obtain

$$\bar{m}_{j,t+1} = v_{j,t}(1 - e^{-s_{j,t+1}/v_{j,t}}). \tag{S35}$$

S1.2 Flow of workers

Recall that $f_{ij,t+1}$, the flow of workers, is equal to the number of workers from occupation i applying to occupation j, $s_{ij,t+1}$, multiplied by the probability $p_{ij,t+1}$ that each job application is successful. To compute $\bar{f}_{ij,t+1}$ it is useful to define

$$s_{j\setminus i,t+1} \equiv \sum_{k \neq i} s_{kj,t+1}, \tag{S36}$$

which is the number of applications occupation j receives from all unemployed workers except those from occupation i. Note that $s_{j,t+1} = s_{j\setminus i,t+1} + s_{ij,t+1}$. Using this fact, and Eq. (15) we define the following multivariate form of the flow of workers

$$\bar{f}_{ij,t+1} = h(s_{ij,t+1}, s_{j\setminus i,t+1}) \equiv s_{ij,t+1} v_{j,t} \frac{(1 - e^{-(s_{ij,t+1}+s_{j\setminus i,t+1})/v_{j,t}})}{s_{ij,t+1} + s_{j\setminus i,t+1}}. \tag{S37}$$

This definition will allow us to do a multivariate Taylor expansion of the function h around the expected value of $s_{ij,t+1}$ and $s_{j\setminus i,t+1}$). Recall that, for fixed i, the random variables $s_{ij,t+1}$ follow a multinomial distribution with $u_{i,t}$ trials and probabilities $q_{ij,t+1}$ for $j = 1, ..., n$. This means that $s_{ij,t+1}$ and $s_{il,t+1}$ are drawn from the same realization of the multinomial distribution, and are therefore correlated. However, $s_{ij,t+1}$ and $s_{kj,t+1}$ are drawn from different realizations (and distributions); thus they are independent.

In other words, the number of workers from occupation i that apply to occupation j is correlated with the number of workers from occupation i that apply to occupation l – if all $u_{i,t}$ workers apply to occupation j it means that no workers from i applied to occupation l. However, since workers do not coordinate when sending applications, the fact that many or few workers from occupation i apply to occupation j says noting about the number of workers from occupation k that applied to occupation j. Of course, this is conditional on $v_{j,t}$, the number of vacancies in occupation j at the previous time step.

It follows from the fact that $s_{ij,t+1}$ and $s_{kj,t+1}$ are independent and from Eq. (S36), that $s_{ij,t+1}$ is independent from $s_{j\setminus i,t+1}$. Furthermore, in the limit of a large number of agents, $u_{i,t}$ is large, and the standard deviation of $s_{ij,t+1}$ is small in comparison to the average. The same is true for $s_{j\setminus i,t+1}$; we can therefore expand $\bar{h}(s_{ij,t+1}, s_{j\setminus i,t+1})$ in a Taylor series around the expected value of $s_{j,t+1}$ and $s_{j\setminus i,t+1}$ as follows,

$$\begin{aligned}
\bar{h}(s_{ij,t+1}, s_{j\setminus i,t+1}) &= h(\bar{s}_{ij,t+1}, \bar{s}_{j\setminus i,t+1}) \\
&+ \frac{1}{2}\frac{\partial^2}{\partial s^2_{ij,t+1}} \big(h(\bar{s}_{ij,t+1}, \bar{s}_{j\setminus i,t+1})\big) \,\mathrm{Var}[s_{ij,t+1}] \\
&+ \frac{1}{2}\frac{\partial^2}{\partial s^2_{j\setminus i,t+1}} \big(h\bar{s}_{ij,t+1}, \bar{s}_{j\setminus i,t+1}]\big) \,\mathrm{Var}[s_{j\setminus i,t+1}] + \dots
\end{aligned} \tag{S38}$$

Next, we now show that, in the limit of a large number of agents, the second and third terms are negligible in comparison to the first term. Exclusively for this derivation, we introduce the notation $v \equiv v_{ij,t}$, $x \equiv s_{ij,t+1}$ and $y \equiv s_{j\setminus i,t+1}$. Furthermore, we denote the expected value of a variable x by μ_x and the variance by σ^2_x. Using this notation and taking the partial derivatives from Eq. (S37), we obtain

$$
\begin{aligned}
\bar{h}(x,y) &= h(\mu_x,\mu_y) + \sigma_x^2\left[\left(\frac{v\mu_x}{(\mu_y+\mu_x)^3} - \frac{v}{(\mu_y+\mu_x)^2}\right)\left(1-e^{-(\mu_x+\mu_y)/v}\right)\right. \\
&+ \left.\left(\frac{1}{\mu_y+\mu_x} - \frac{\mu_x}{(\mu_y+\mu_x)^2}\right)e^{-(\mu_x+\mu_y)/v} - \frac{1}{2}\frac{\mu_x}{v(\mu_y+\mu_x)}e^{-(\mu_x+\mu_y)/v}\right] \\
&+ \sigma_y^2\left[\frac{v\mu_x(1-e^{-(\mu_x+\mu_y)/v})}{(\mu_x+\mu_y)^3} - \frac{\mu_x}{(\mu_x+\mu_y)^2}e^{-(\mu_x+\mu_y)/v}\right. \\
&- \left.\frac{1}{2}\frac{\mu_x}{v(\mu_y+\mu_x)}e^{-(\mu_x+\mu_y)/v}\right], \qquad \text{(S39)}
\end{aligned}
$$

where we have neglected second order terms in the expansion.

Since μ_x, μ_y, σ_x^2, σ_y^2 and v scale linearly with the number of agents L, in the limit of a large number of agents these five variables are of the same order of magnitude. It follows from this observation and from Eqs. (S37) and (S39) that, in the limit of large number of agents, the first term of Eq. (S39) scales with L, while the other terms are of the order of a constant c. In other words, in the limit of a large number of agents, we can approximate

$$\bar{f}_{ij,t+1} = \bar{s}_{ij,t+1}\frac{\bar{v}_{j,t}^2(1-e^{-\bar{s}_{j,t+1}/\bar{v}_{j,t}})}{\bar{s}_{j,t+1}}, \qquad \text{(S40)}$$

where we have recovered our original notation. The relative error of this approximation is inversely proportional to the number of agents i.e., the relative error of our approximation is

$$\left|\frac{\mathrm{E}[f_{ij,t+1}|\mathbf{u}_t,\mathbf{v}_t;A] - \bar{f}_{ij,t+1}}{\mathrm{E}[f_{ij,t+1}|\mathbf{u}_t,\mathbf{v}_t;A]}\right| = \frac{c}{L+c},$$

Since c is a constant, when $L\to\infty$, the relative error tends to zero.

Finally, we substitute the expected value of $s_{ij,t+1}$ to obtain,

$$\bar{f}_{ij,t+1} \equiv \frac{\bar{u}_{i,t}\bar{v}_{j,t}^2 A_{ij}(1-e^{-\bar{s}_{j,t+1}/\bar{v}_{j,t}})}{\bar{s}_{j,t+1}\sum_k \bar{v}_{k,t}A_{ik}}, \qquad \text{(S41)}$$

which is the equation we present in the main text. We further check the quality of our approximations in section S2.1, where we compare the simulated unemployment and long-term unemployment rate with our analytic solutions at the occupation level.

S1.3 Steady-state

Steady-state

We derive the master equation for the expected value of the realized demand $\bar{d}_{i,t}$ and we discuss that, when the target demand is constant, the master equation of $\bar{d}_{i,t}$ has a fixed point solution.

Once $\bar{d}_{i,t}$ reaches the fixed point value, $d_{i,t}$ fluctuates around this value, and we say that the system is at the steady-state (see section S1.3.1). At the end of this section we use the steady-state solution of $\bar{d}_{i,t}$ to show that, under constant target labor demand, $\bar{e}_{i,t}$, $\bar{u}_{i,t}$ and $\bar{v}_{i,t}$ also have a steady-state solution. Throughout this section we assume the case $\delta_u > \delta_v$; the other case can be solved analogously.

The realized labor demand is, by definition, the sum of employment and vacancies. Thus, from Eqs. (21 – 23)

$$\bar{d}_{i,t+1} = \bar{d}_{i,t} + (\delta_v - \delta_u)e_{i,t} + \begin{cases} \gamma_u(1-\delta_u)(d^\dagger_{i,t} - \bar{d}_{i,t}) & \text{if } \bar{d}_{i,t} \geq d^\dagger_{i,t} \\ \gamma_v(1-\delta_v)(d^\dagger_{i,t} - \bar{d}_{i,t}) & \text{if } \bar{d}_{i,t} < d^\dagger_{i,t}. \end{cases}$$

We simplify this expression by defining $\gamma'_u = \gamma_u(1-\delta_u)$ and $\gamma'_v = \gamma_v(1-\delta_v)$ as follows,

$$\bar{d}_{i,t+1} = \bar{d}_{i,t} + (\delta_v - \delta_u)\bar{e}_{i,t} + \gamma'_u(d^\dagger_{i,t} - \bar{d}_{i,t}) + (\gamma'_v - \gamma'_u)\max\left\{0, d^\dagger_{i,t} - \bar{d}_{i,t}\right\} \tag{S42}$$

Since the target labor demand has constant value $d^\dagger_i$ and at the steady state $\bar{d}_{i,t+1} = \bar{d}_{i,t}$, then

$$(\delta_u - \delta_v)e_{i,t} = \gamma'_u(d^\dagger_i - d^*_i) + (\gamma'_u - \gamma'_v)\max\left\{0, d^\dagger_i - \bar{d}^*_i\right\}. \tag{S43}$$

where we have assumed that the number of employed workers has reached a steady-state and has expected value $\bar{e}^*_i$. To determine the term within the maximum function, we must determine if $d^\dagger_i < d^*_i$ or $d^\dagger_i > d^*_i$. If we assume $d^\dagger_i < d^*_i$, we obtain that

$$d^\dagger_i - d_* = \frac{\delta_u - \delta_v}{\gamma'_u}e_{i,t}.$$

This is a contradiction since the right hand side is positive, but the left hand side negative (since $\delta_u > \delta_v$). In the case when $d^\dagger_i > d^*_i$, we find the correct steady-state solution

$$d_* = d^\dagger_i - \frac{\delta_u - \delta_v}{\gamma'_v}e_{i,t}.$$

Doing an analogous analysis for the case $\delta_u < \delta_v$ we obtain the following solution for the steady-state of the realized demand,

$$\bar{d}^*_i = \begin{cases} d^\dagger_i - \frac{\delta_u - \delta_v}{\gamma'_v}\bar{e}^*_i & \text{if } \delta_u \geq \delta_v \\ d^\dagger_i - \frac{\delta_u - \delta_v}{\gamma'_u}\bar{e}^*_i & \text{if } \delta_u < \delta_v. \end{cases} \tag{S44}$$

In other words, when $\delta_u > \delta_v$ the realized demand is lower than the target demand. This happens because when $\delta_u > \delta_v$ (i.e., the probability of separation is higher than the probability of opening a vacancy at random) the adjustment towards the target demand does not fully compensate for asymmetry between the opening and separation rates; thus the steady-state value of the realized demand is lower than the target demand. Similarly, when $\delta_u < \delta_v$, the steady-state value of the realized demand is higher than the target demand. In both cases, the difference between the realized and the target demand at the steady-state is proportional to $|\delta_u - \delta_v|$ and inversely proportional to the adjustment rate γ.

Next, we show that under constant target labor demand $\bar{e}_{i,t}$, $\bar{u}_{i,t}$ and $\bar{v}_{i,t}$ also have a steady-state solution. Again, we solve the case $\delta_u \geq \delta_v$; the other case can be solved analogously. We assume that the realized demand has reached its steady-state value d_i^*. Then, since the realized demand is the sum of the employment and vacancies, and using Eq. (S44), we obtain the steady-state equation for the number of vacancies,

$$\bar{v}_i^* = d_i^\dagger - \left(1 - \frac{\delta_u - \delta_v}{\gamma_v'}\right) \bar{e}_i^*. \tag{S45}$$

From the employment equation (Eq. (21), it follows that

$$\bar{e}_i^* = \frac{1}{\delta_u} \sum_j \bar{f}_{ji}^*, \tag{S46}$$

where we have used the fact that $\delta_u > \delta_v$ and the steady-state value of the realized demand from Eq. (S44). We can also obtain Eq. (S46) from the vacancy equation Eq. (24)

Finally, from the unemployment master equation Eq. (23), for a steady-state to exist the unemployment of each occupation, encoded in the vector $\mathbf{u}^*$, must satisfy the following equation,

$$\sum_j \bar{f}_{ji}^* = \sum_j \bar{f}_{ij}^*. \tag{S47}$$

In other words, at the steady-state the total inflow of workers into an occupation equals the total outflow of workers of that same occupation.

S1.3.1 Dynamics of the realized demand

We showed that when the target demand is constant there exists a steady-state solution for $\bar{d}_{i,t}$. In this section we discuss the dynamics of $d_{i,t}$ and show that $d_{i,t}$ fluctuates around d_i^*.

First, we note that $\omega_{i,t}$ and $\nu_{i,t}$ are binomial random variables of $e_{i,t}$ draws and success probability $\pi_{u,i,t}$ and $\pi_{u,i,t}$ respectively. Therefore, in the limit fo a large number of agents their distributions are the normals,

$$\omega_{i,t} \sim \mathcal{N}(e_{i,t}\pi_{u,i,t}, \pi_{u,i,t}(1 - \pi_{u,i,t})e_{i,t}) \tag{S48}$$

$$\nu_{i,t} \sim \mathcal{N}(e_{i,t}\pi_{v,i,t}, \pi_{v,i,t}(1 - \pi_{v,i,t})e_{i,t}). \tag{S49}$$

Their difference is distributed as follows

$$\nu_{i,t} - \omega_{i,t} = e_{i,t}(\pi_{v,i,t} - \pi_{u,i,t}) + \phi_{i,t} \tag{S50}$$

where

$$\phi_{i,t} \sim \mathcal{N}\left(0, \left(\pi_{u,i,t}(1-\pi_{u,i,t}) + \pi_{v,i,t}(1-\pi_{v,i,t})\right) e_{i,t}\right). \tag{S51}$$

Then, from Eqs. (6–8) we obtain that

$$d_{i,t+1} = d_{i,t} + (\delta_v - \delta_u)\bar{e}_{i,t} + \gamma'_u(d^{\dagger}_{i,t} - \bar{d}_{i,t}) + (\gamma'_v - \gamma'_u)\max\left\{0, d^{\dagger}_{i,t} - \bar{d}_{i,t}\right\} + \phi_{i,t} \tag{S52}$$

When $\delta_u > \delta v$, it follows from Eq. (S44) that

$$d^{\dagger}_i = d^*_i + \frac{\delta_u - \delta_v}{\gamma'_v} e_{i,t}.$$

We introduce this expression in Eq. S52 and obtain that

$$d_{i,t+1} = \begin{cases} (1-\gamma'_u)d_{i,t} - \gamma'_u d^*_i - (\delta_u - \delta_v)(1 - \frac{\gamma'_u}{\gamma'_v})e_{i,t} + \phi_{i,t+1} & \text{if } \bar{d}_{i,t} \geq d^{\dagger}_{i,t} \\ (1-\gamma'_v)d_{i,t} - \gamma'_v d^*_i + \phi_{i,t+1} & \text{if } \bar{d}_{i,t} < d^{\dagger}_{i,t}. \end{cases} \tag{S53}$$

In the second case, $d_{i,t+1}$ follows AR(1) process with coefficient γ'_v. On the first case, $d_{i,t+1}$ follows an AR(1) process with and additional negative term that makes $d_{i,t+1}$ get closer to the value of d^*_i. Therefore, $d_{i,t}$ fluctuates around d^*_i. In the particular case when $\delta_u = \delta_v = \delta$ and $\gamma_u = \gamma_v = \gamma$ we obtain the canonical AR(1) process equation

$$d_{i,t+1} = (1-\gamma)d_{i,t} + \gamma d^*_i + \phi_{i,t+1}.$$

S1.3.2 Zero steady-state for the Agent-Based model

Eqs (2–4) accept a trivial steady-state $e^*_i = u^*_i = v^*_i = d^{\dagger}_i = 0$. We neglect this steady-state since it is uninteresting for our analysis. However, when running the agent simulation there is a non-zero probability that the employment of an occupation is zero, i.e., $e_{i,t} = v_{i,t} = 0$. At this point, even if $d^{\dagger}_{i,t} > 0$, no vacancies would open and therefore employment would be zero for the rest of the simulation. Therefore, we introduce the additional rule that if $e_{i,t} = v_{i,t} = 0$ but $d^{\dagger}_{i,t} > 0$, then a vacancy is opened with probability 1. When running the simulation with a large number of agents (which is the case of the labor market) the probability that $e_{i,t} = v_{i,t} = 0$ is negligible and this additional rule is not used.

S1.3.3 Steady-state for the complete network

We now show that our model has an analytically computable steady-state under the following assumptions. First, we assume a complete network of n nodes. Second, we assume that $\delta_u = \delta_v = \delta$ and that $\gamma_u = \gamma_v = \gamma$. Third, as before, we assume that the target labor demand equals the labor supply (*i.e.* $D^\dagger = L$) and that the target labor demand is the same for all occupations (*i.e.* $d_i^\dagger = \frac{L}{n} \quad \forall i$). We now take a deductive approach to show that there is a steady-state under this conditions.

We start with an equal number of unemployed workers and job vacancies for all occupations,

$$u_0 \equiv u_{i,0} = v_{i,0} = \frac{U}{n} \quad \forall i$$

and show that the master equations lead to a steady-state and compute the unemployment and vacancy rate.

It follows from Eq. (S44) and from our second and third assumptions that at the steady-state $d_i^* = d_i^\dagger = \frac{L}{n} \quad \forall i$. Then, given that we started with $\frac{U}{n}$ vacancies and because the labor force is constant, it follows that

$$e_0 \equiv e_{i,0} = \frac{L}{n} - \frac{U}{n} \quad \forall i.$$

Then, from Eq. (23) we obtain

$$u_i \equiv u_{i,1} = \delta(e_0 - u_0) + \sum_j f_{ij}. \tag{S54}$$

Since all occupations have the same number of vacancies and unemployed workers (u_0), the probability that an unemployed worker from occupation i applies to a job vacancy in j at time 1 is

$$q_{ij,1} = \frac{A_{ij}}{n} = \frac{1}{n} \quad \forall i$$

where we have used that we have a complete network. Likewise, the number of applicants (supply) an occupation j receives is

$$s_{j,1} = u_0 \quad \forall j$$

Therefore the flow of workers from occupation i to j is

$$f_{ij,1} = \frac{u_{i,0} q_{ij,1}}{s_{j,1}} v_{j,0} m_{j,1} = \frac{u_0}{n u_0} v_0 (1 - e^{-u_0/v_0})$$

since $v_0 = u_0$ then,

$$f_{ij,1} = \frac{u_0}{n}(1 - e^{-1}).$$

Substituting the flow of workers in Eqs. 21 – 23 , and using that $e_0 = \frac{L}{n} - u$ we obtain

$$u_{i,1} - u_{i,0} = \delta \left(\frac{L}{n} - u_0 \right) + u_0 \left(1 - exp(-1)\right) \quad \forall i. \tag{S55}$$

In other words, the change in the unemployment is equal for all occupations. Similarly, one can derive that the change in employment and vacancies is the same for all occupations at the next time step. Since we started with equal employment, unemployment and vacancies for all occupations, it follows that $u_{i,t} = v_{i,t} = u_t \forall t$ and that $e_{i,t} = e_t \forall t$. Furthermore, since $e_t = \frac{L}{n} - u_n$ our system is determined by the following master equation

$$u_{t+1} = u_t + \delta \left(\frac{L}{n} - u_0 \right) + u_0 \left(1 - exp(-1)\right).$$

The steady-state solution leads to

$$u^* = \frac{\delta}{\delta + 1 - exp(-1)} \left(\frac{L}{n} \right).$$

we compute the aggregate unemployment rate by summing over all occupations and thus

$$\frac{U}{L} = \frac{\delta}{(1 - exp(-1)) + \delta}.$$

S1.3.4 Long-term unemployment at the steady-state

We note that Eq. (31) gives the number of long-term unemployed workers for time t. A special case is that of the steady-state when the unemployment rate of each occupation is u_i^*. Then, the approximate expected number of unemployed workers with a job spell of k time steps is

$$\bar{u}_i^{*(k)} = \delta \bar{e}_i^* \left(1 - \frac{\sum_j \bar{f}_{ij}(\bar{\mathbf{u}}^*, \bar{\mathbf{v}}^*; A)}{\bar{u}_i^*} \right)^k.$$

and decays exponentially with k.

S2 Robustness

In this section we discuss the robustness of our results. For simplicity we show the robustness test for the Probability of Computerization shock. The robustness tests we make are as follows. First, we explore how well our approximations perform with respect to the simulation of the model. Second, we discuss different forms in which we can measure the change in unemployment and long-term unemployment. Third, we show how our model behaves when we include a change in the aggregate demand instead of just a reallocation. Fourth, we explore how different assumptions on the duration of the automation shock and measuring period affect our results. Fifth we explore how different values of γ affect our results. Finally, we discuss how the steady-state unemployment changes depending on the shock distribution across occupations. In particular, we conjecture that when the shock is assortative – meaning that the occupations' automation shock is similar to the one of adjacent occupations – the steady-state unemployment after the automation shock decreases.

S2.1 Simulations vs approximation at the occupation level

We show how our approximations compare with simulations at the occupation. Additionally, we discuss the different reaction to the automation shock different occupations have. In particular, we focus on four occupations that we use as examples: sales representatives, lawyers and judges, and electricians. For each, we compare the average of 10 simulations with our numerical solution. As shown in Fig. S2.1 our approximate solution closely matches the average for all occupations. Because of computational constraints, we run the simulation with 1.5 Million agents which corresponds to one hundredth of the labor force. If we were to run the simulations with the full labor force is (150 Million workers) our approximation would improve further.

We focus on four occupations, the sales representatives, lawyers and judges, electricians, and aircraft assembles, whose real employment is $792,000$, $652,000$, 1.1 million, and 6609 respectively. We note that aircraft assembles is the second occupation with the smallest employment. Since we run the numerical simulations with a hundredth of the real labor force, in our simulations the target demand for each occupation is $7,920$, $6,520$, $11,000$ thousands, and 66 respectively. As shown in Fig. S2.1 our approximations match the average unemployment and long-term unemployment rate of each occupation. Noticeably, the fluctuations are much large for aircraft assemblers, the occupation that has smallest target demand. When we run the simulations with 1.5 million agents all occupations (except Motion picture projectionists) have a target demand above 50 and most occupations continue a target demand above 50, therefore we can conclude that our approximations work well for cities with a labor pool above 1.5 million. Furthermore, if we ran the simulations with the full labor force, we expect that our approximations would closely match the average behaviour of the unemployment rates for all occupations

We also comment the different behaviour of the occupations. The sales representatives, that are likely to be automated, increase their unemployment rate during the shock. Then, the unemployment rate returns to a steady-state with a similar value to the previous one. Instead, lawyers and judges, who are unlikely to be automated, decrease their unemployment rates during the shock. However, after the shock the steady-state unemployment is higher than it was before the shock. Finally, the electricians who are unlikely to be automated initially decrease their unemployment rate but then increase it during the automation shock. We explain this behaviour as follows. During the first part of the automation shock more electrician vacancies open decreasing unemployment. Nevertheless, the automation shock also causes workers of nearby occupations to become unemployed. As the automation shock continues to separate workers of neighboring occupation, many of these unemployed workers apply for the electrician vacancies causing the electrician's unemployment rate to increase.

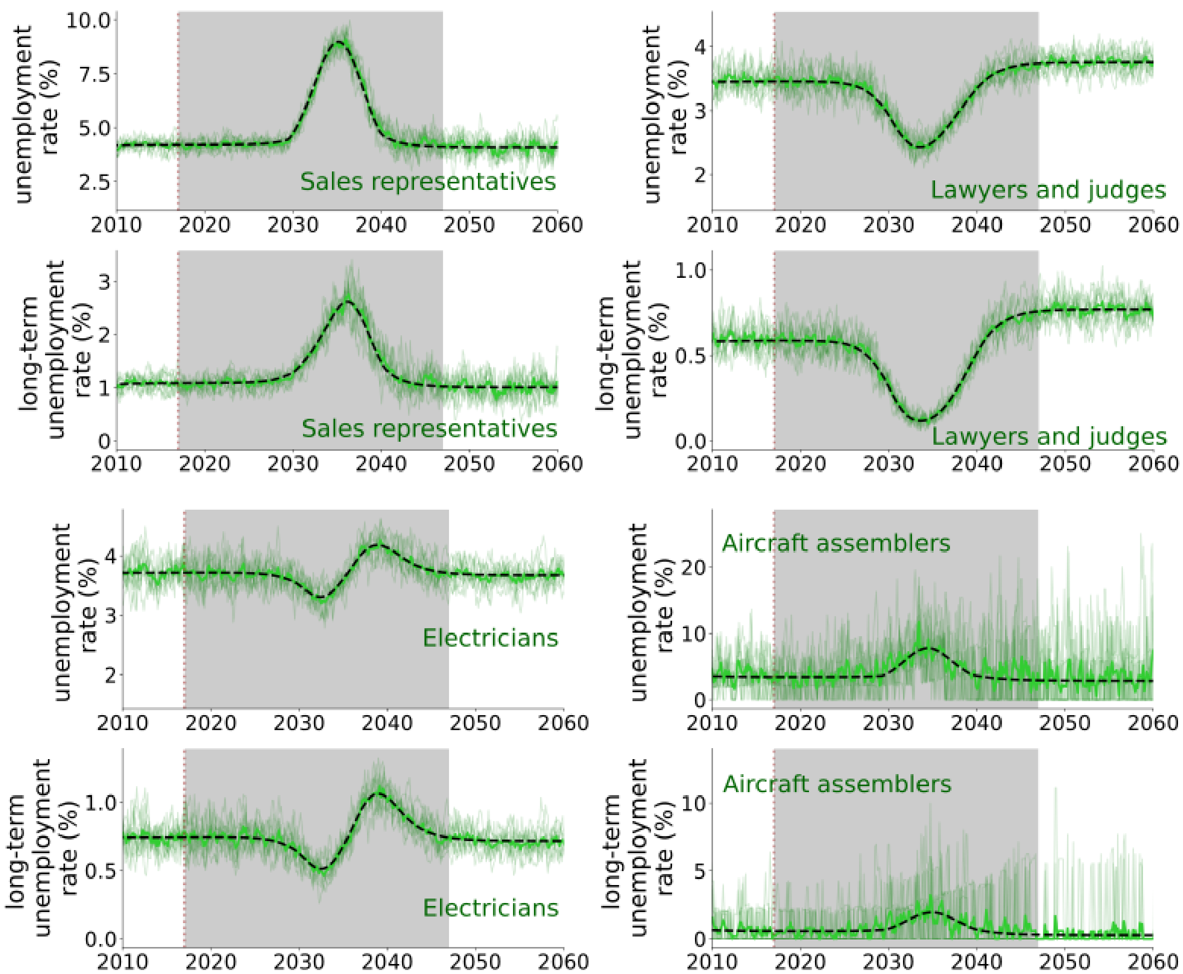

Figure S6: **Unemployment rate at the occupation level simulations and numerical solution** We compare the unemployment and long-term unemployment from the average of the simulations (solid line) and the numerical solution (dashed line). We also show in transparent lines the 10 simulations. Each simulation uses 1.5 Million agents and we average over 10 simulations.

S2.2 Measuring the impact of automation

In the main text, we define the occupation-specific average unemployment and average long-term unemployment as follows:

$$u_{i,\text{average}}(T) = \frac{100}{T} \frac{\sum_{t \in T} u_{i,t}}{\sum_{t \in T} (u_{i,t} + e_{i,t})}$$

and

$$u^{(\geq \tau)}_{i,\text{average}}(T) = \frac{100}{T} \frac{\sum_{t \in T} u^{(\geq \tau)}_{i,t}}{\sum_{t \in T} (u_{i,t} + e_{i,t})}.$$

However, there are other measurements of unemployment and long-term unemployment one can compute. For example, we can compute the unemployment rate at each time step of the automation period and then take the average. Thus, we define the alternative unemployment rate and the alternative long-term unemployment rate by

$$u_{i,\text{alternative}}(T) = \sum_{t \in T} \frac{u_{i,t}}{(u_{i,t} + e_{i,t})}$$

and

$$u^{(\geq \tau)}_{i,\text{alternative}}(T) = \sum_{t \in T} \frac{u^{(\geq \tau)}_{i,t}}{(u_{i,t} + e_{i,t})}.$$

In Fig. S11 we compare the change in the average unemployment and long-term unemployment rate with the change in the alternative unemployment and long-term unemployment rate. On the top and right we show the change in the average unemployment rate in green and the change in the alternative unemployment rate in cyan. On the bottom and right we do the same for the long-term unemployment rate. Both these plots show that there is a strong overlap between the average change and the alternative change.

For a better visualization we plot the change in the average unemployment rate vs the alternative unemployment rate on the top left panel. On the bottom left we plot the change in the average long-term unemployment rate vs the alternative long-term unemployment rate. We observe that almost all occupations lie close to the identity line with the exception of occupations that have low employment (small circles) and are highly likely to be automated (red color). The reason behind this discrepancy is that occupations that are highly likely to be automated and have low employment both increase the number of unemployed workers and also decrease the share of employment (due to the structural change). Thus, the ratio between the two, which is considered by the alternative unemployment rates, the increases considerably. Contrarily, when we measure the average unemployment rate, the initial share of employment prevents the sharp increase. However, both measurements exhibit the network effects – occupations with similar automation probabilities have different percentage change in their unemployment and long-term unemployment rates.

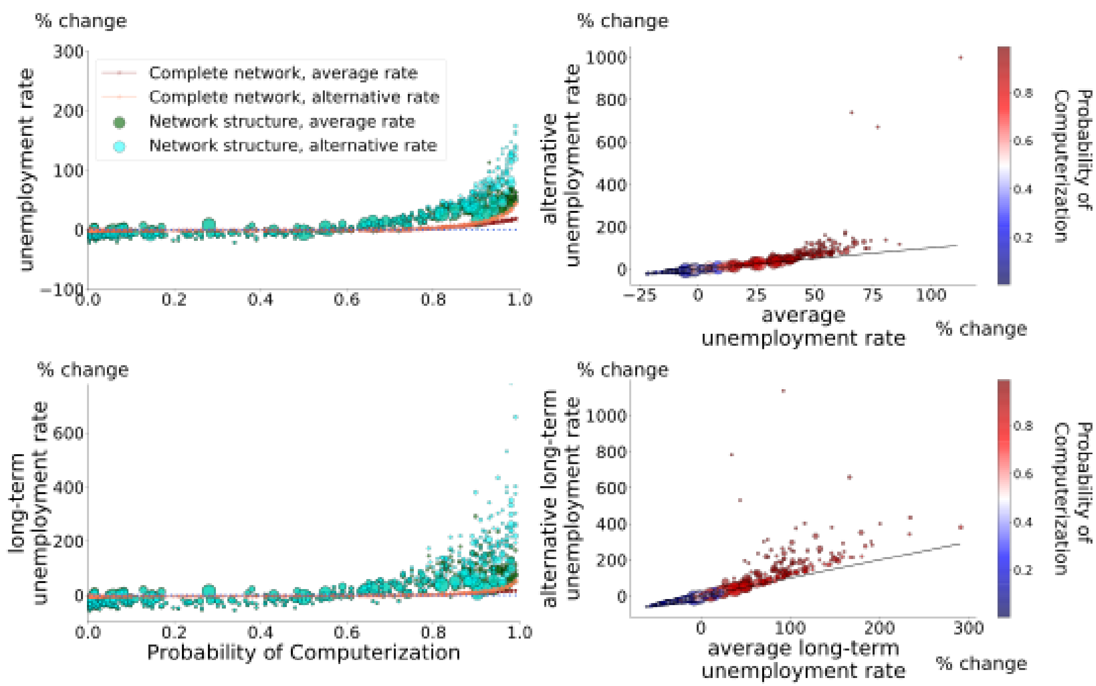

Figure S7: **average and alternative unemployment and long-term unemployment rates Left.** We show the percentage change in the average unemployment and long term unemployment rates in green and the percentage change in the alternative unemployment and long term unemployment rates in cyan. **Right.** We plot the percentage change of the average unemployment and long-term unemployment rate vs the percentage change of the alternative unemployment and long-term unemployment rate

S2.3 Automation that increased/decreases the overall demand

We assumed that the aggregate demand remains constant after the shock. In this section, we break this assumption and we run our model for an increasing and decreasing aggregate demand of 5%. We study the Frey and Osborne automation shock. In Fig. S8 we plot the change in the period unemployment and long-term unemployment rate when the demand changes for each occupations vs the change in the period unemployment and long-term unemployment rate when the demand remains constant. As expected when the aggregate demand increases the percentage change in unemployment and long-term unemployment is lower and the points lie below the identity line. When the aggregate demand decreases, the percentage change in unemployment and long-term unemployment is higher and the points lie above the identity line. While there is a strong correlation between the changes in the unemployment rates when the demand changes and when the demand remains constant, occupations with low automation probabilities (blue dots) lie further away from the identity line. This result means that the structural part of the automation shock mostly affects the occupations with high estimates of automation. When we include a change in the aggregate labor demand then occupations with low automation estimates are also affected considerably.

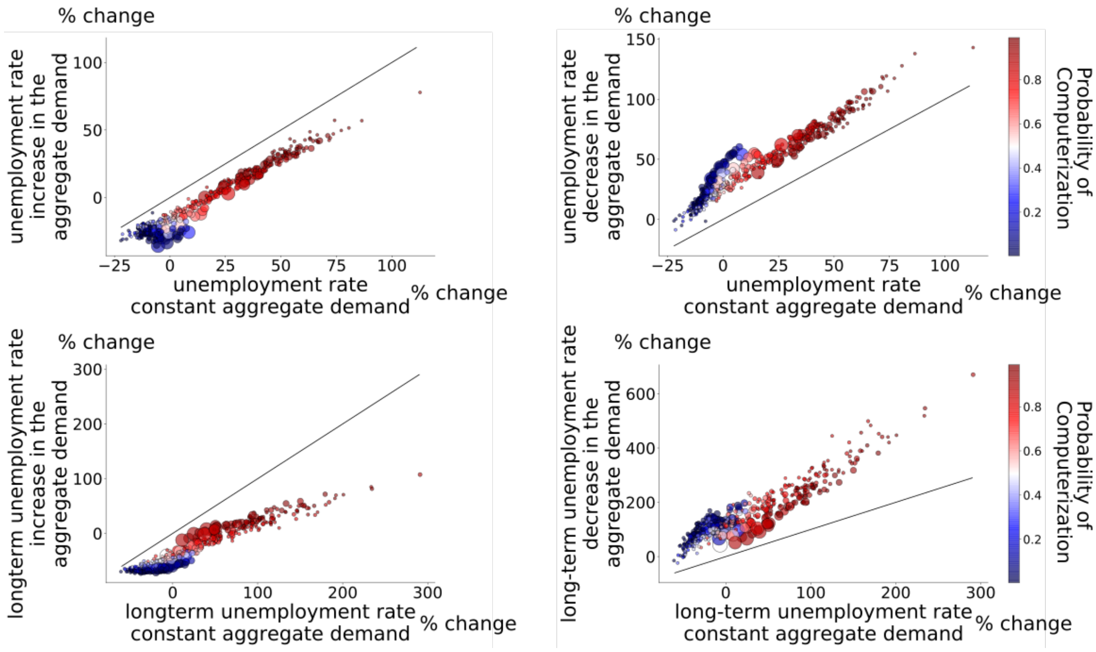

Figure S8: **Frey and Osborne shock with different post-automation target demand scenarios**. In each panel we plot on the x-axis the percentage change in the period unemployment rates when the aggregate demand does not change and on the y-axis the percentage change in the period unemployment rate when the aggregate demand does change. On the left panels we assume the aggregate demand increases by 5% and on the right we assume it decreases by 5%.

S2.4 Automation time and adoption rate

In this section we discuss how our results change when we assume a different duration of the automation shock. We assume that automation happens within 20 and 40 years, instead of 30. We measure the change in unemployment during the whole automation period and during the *steep* transition period. We define the steep transition period as the middle part of the automation period when of the sigmoid is steepest. In Fig. S9 we highlight the whole automation period with a grey area coloring and the steep automation period by a coral shadowing.

As expected, the shorter the automation period is, the larger the increase in the aggregate unemployment and long-term unemployment rates (see top panels of Fig. S9). On the bottom panels of Fig. S9 we plot the percentage change in the unemployment and long-term unemployment rates of each occupation during the whole automation period vs the percentage change of the unemployment rates of each occupations during the steep automation period. There is a strong correlation between the change in unemployment during the whole transition period and during the steep transition period. However, during the steep automation period the percentage change in the unemployment rate is more extreme than during the whole automation period. Namely, occupations with high automation level have a higher percentage change in the unemployment and long-term unemployment rate during the steep automation period than during the whole automation period. Likewise, occupations with low automation level tend to decrease their unemployment and long-term unemployment rate more during the steep automation period than during the whole automation period

S2.5 Results for different values of γ

Here, we check the robustness of our results with respect to different values of the γ parameter. As explained in the main text, γ represents the rate at which the market adjust towards the target demand. In our model δ_u and δ_v represent the probability that workers (vacancies) and separated (open) due to random events; and γ is a adjustment rate. Therefore, we expect that $\gamma \geq \delta_u$ and $\gamma \geq \delta_v$. In the main text we use $\gamma = 10\delta_u$ as a reference point. In this section we explore how our results change for different values. In particular we test for $\gamma = 5\delta_u$ and $\gamma = 20\delta_u$. We chose these ranges since there is little change in the results for larger values of γ and for lower values, we obtain unreasonably high values of the unemployment rate at the aggregate level (more than 15%).

In Fig. S11 we plot the percentage change in the unemployment rate using $\gamma = 10\delta_u$ (our benchmark) vs the percentage change in unemployment rate when $\gamma = 5\delta_u$ and $\gamma = 20\delta_u$ respectively. Our results show that the changes are very similar although as γ increases so does the increase in unemployment and long-term unemployment for occupations that are likely to be automated. These results are not surprising, since the larger γ is the faster the adjustment towards the target demand and thus sharper the shock.

S2.6 Random automation shocks

In the main text we show that the steady-state unemployment rate after the Probability of Computerization shock is lower than the steady-state unemployment rate before the shock. We conjecture that this behaviour is most likely caused by the assortativity of the Probabilities of Computerization. That is, in general, the Probability of Computerization of an occupation is similar to the Probability of Computerization of its neighbors in the network. When the system converges to the new steady the majority of the workers are in the occupations that have low Probability of Computerization. Therefore, workers are in occupations that are close by in the network reducing labor market frictions.

To test this hypothesis we use reshuffled versions of the Probability of Computerization shock. That is, we keep the same distribution of the Probabilities of Computerization but assign them to different occupations. We reshuffle the probabilities in two ways: a simple randomized

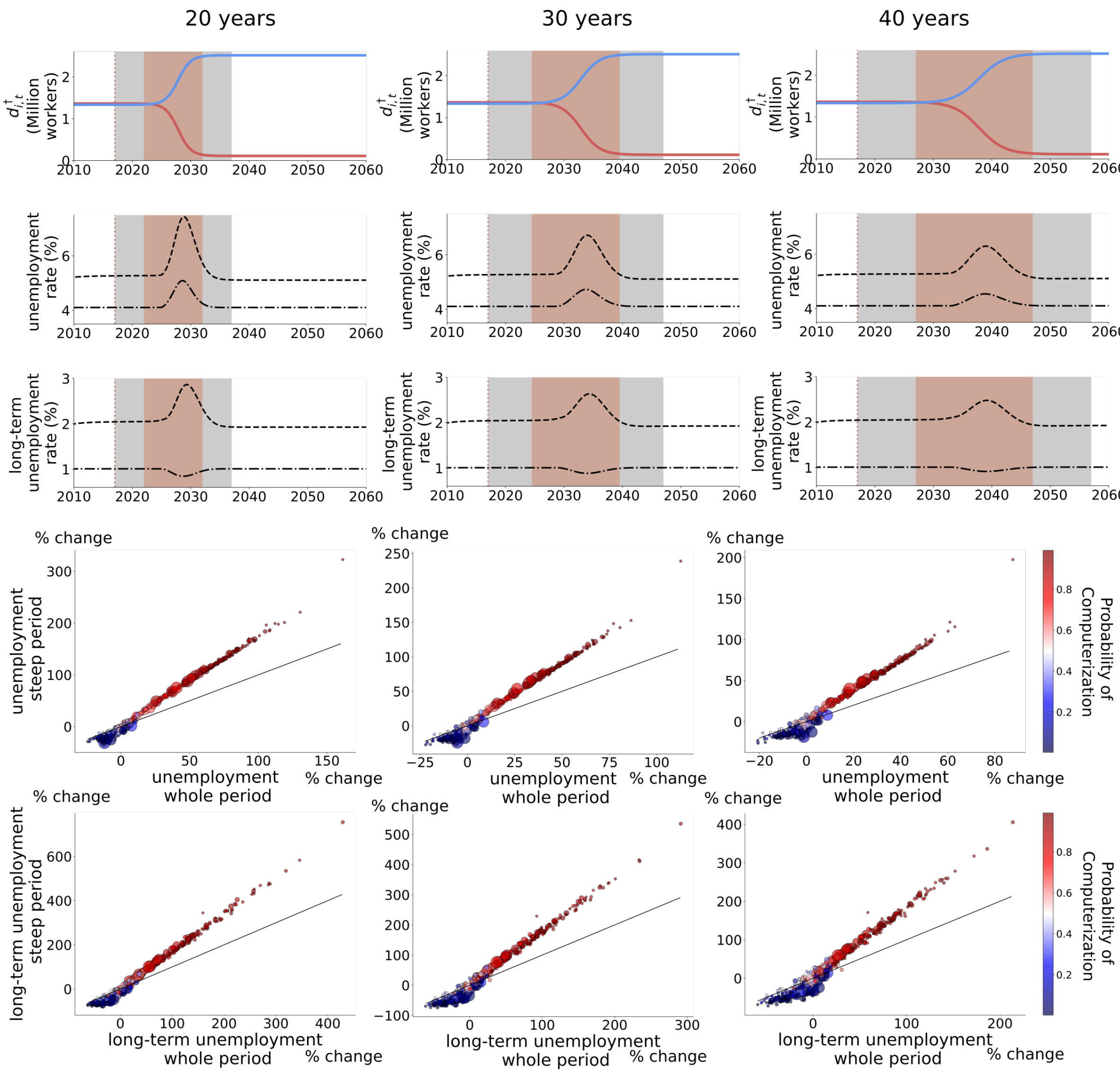

Figure S9: **Shock duration and measuring windows effect on the measurements on unemployment rates Top.** For different durations of the automation shock (20, 30 and 40 years) we show target demand of two occupations, the unemployment, and long-term unemployment rates. The grey area denotes the whole period of automation, meaning that the target demand has reached the automation level within a 1×10^{-4} tolerance. The coral area denotes the sharp transition period which is middle steepest part of the Sigmoid shock. **Bottom.** For each occupation we plot the percentage change during the whole transition period vs the percentage change during the sharp transition period. Occupations are colored by their automation probability.

Figure S10: Expected change in unemployment and long-term unemployment with different γ parameters.

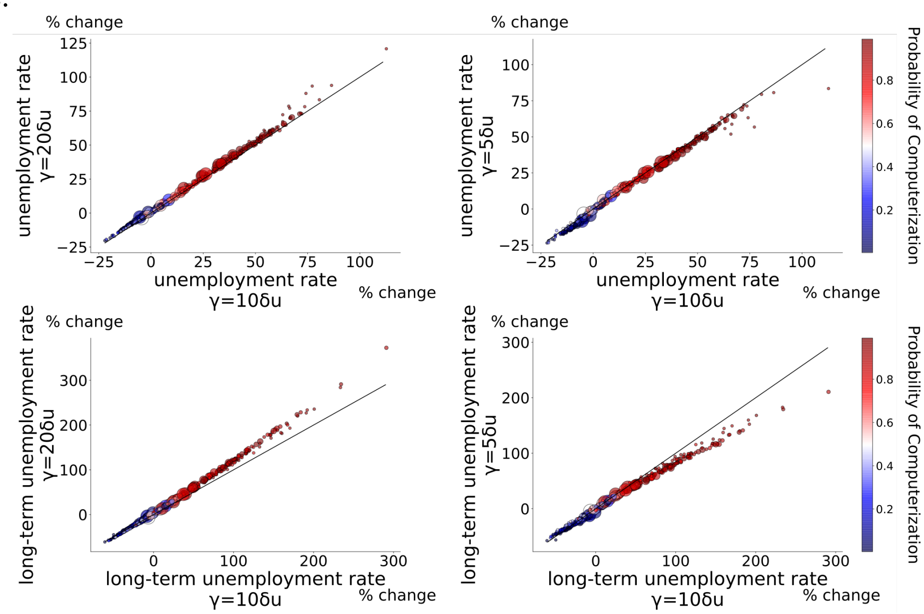

Figure S11: **Change in unemployment and long-term unemployment with different values of gamma** Top panels show the change in unemployment rates vs the automation probability. The bottom panels show the change when $\gamma = 5\delta_u$ and $\gamma = 20\delta_u$ on the y axis and on the x-axis when $\gamma = 10\delta_u$.

shuffling and an assortative shuffling. For the latter, we redistribute the probabilities of computerization so that occupations of the same classification have a similar automation level. In particular, we sort the probabilities of computerization and match them with the occupations sorted by their classification. This ordering is meaningful since the classification system is designed to have similar occupations close.

In Fig. S12 we show our results for the original Probability of Computerization shock, an assortative reordering and five different randomized reshuffling. We observe that all random reshufflings have a higher unemployment rate at the steady-state, while the original and the assortative versions have a lower unemployment rate at the post-automation steady-state. The same is true for the long-term unemployment.

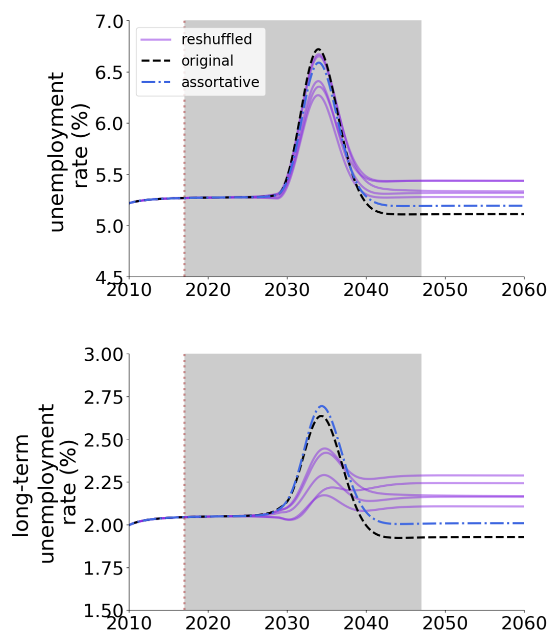

Figure S12: **Randomized and assortative versions of the Probability of Computerization shock.** On the top the unemployment rate. On the bottom the long-term unemployment rate.

S3 Additional tables

Main variables	**Description**
$e_{i,t}$	Number of employed workers at time t on occupation i.
$u_{i,t}$	Number of unemployed workers at time t which were last employed in occupation i
$v_{i,t}$	Number of job vacancies at time t of occupation i
Other variables	
$d_{i,t}$	Realized labor demand at time t of occupation i. ($d_{i,t} = e_{i,t} + v_{i,t}$)
$q_{ij,t}$	The probability that an unemployed worker from occupation i applies to a job vacancy of occupation j at time t.
$p_{j,t}$	The probability that a job application sent to a vacancy of occupation j is successful.
$s_{ij,t}$	The number of job applicants occupation j receives from workers of occupation i at time t.
$s_{j,t}$	The number of job applicants occupation j receives at time t.
$f_{ij,t}$	Flow of unemployed workers of i to be employed at occupation j
$u_{i,t}^{(k)}$	The number of unemployed workers of occupation i that have spent exactly k time steps unemployed at time t.
$\pi_{u,i,t}$	Occupation-specific probability that a worker of occupation i. Though not noted explicitly, this probability is time dependent.
$\pi_{v,i,t}$	Occupation-specific probability that a vacancy of occupation i opens, per worker employed in occupation i. Though not noted explicitly, this probability is time dependent.
$\omega_{i,t}$	Number of workers from occupation i that separated from their jobs at time t. Drawn from Binomial distribution $Bin(e_{i,t}, \pi_{u,i,t})$.
$\nu_{i,t}$	Number of vacancies of occupation i opened at time t. Drawn from Binomial distribution $Bin(e_{i,t}, \pi_{v,i,t})$
Parameters	
δ_u	Rate at which employed workers are separated due to the spontaneous process.
δ_v	Rate at which employed vacancies are opened due to spontaneous process.

γ	Rate at employed workers and vacancies are separated or opened due to the market adjusting towards the target demand.
τ	Number of time steps after which an unemployed workers if considered long-term unemployed
r	weights of the self-loops of the occupational mobility network.
A	Adjacency matrix of the occupational mobility network
$d_i^\dagger$	Post-automation target labor demand. Number of workers needed at occupation i after the automation shock is complete.
$d_{i,t}^\dagger$	Target labor demand of occupation i at time t
Δt	Duration of a time step in units of weeks.

Table S2: Variables and parameters

Table S2: Results for all occupations for the Frey and Osborne shock

Occupation	Probability of computerization	Percentage change in the average unemployment rate	Percentage change in the average long-term unemployment rate	Unemployment rate before shock	Target demand before shock
machine tool cutting setters, operators, and t...	0.90	62	297	2.8	154172
postal service clerks	0.95	65	238	2.8	114948
extruding, forming, pressing, and compacting m...	0.93	73	237	3.2	33072
woodworking machine setters, operators, and te...	0.97	81	203	3.5	18782
machine feeders and offbearers	0.93	72	195	3.6	27175
adhesive bonding machine operators and tenders	0.95	87	192	3.7	8809
automotive body and related repairers	0.91	58	186	3.2	136839
model makers, patternmakers, and molding machi...	0.86	49	183	3.0	43390
packaging and filling machine operators and te...	0.98	71	182	3.5	273293
extruding and drawing machine setters, operato...	0.91	57	172	2.8	12126
tool and die makers	0.84	38	170	2.6	59042
insurance underwriters	0.99	63	168	2.9	109663
tire builders	0.94	74	162	3.6	14930
locomotive engineers and operators	0.94	52	161	2.7	48869
sewing machine operators	0.89	50	160	3.1	185332
cabinetmakers and bench carpenters	0.92	61	157	3.6	57002
miscellaneous metal workers and plastic worker...	0.89	53	156	3.4	407934
roofers	0.90	57	154	3.6	206655
industrial truck and tractor operators	0.93	64	152	4.0	608737
crushing, grinding, polishing, mixing, and ble...	0.92	56	150	3.4	85752
tailors, dressmakers, and sewers	0.92	56	148	3.4	76453
crane and tower operators	0.90	50	148	3.1	60690
prepress technicians and workers	0.97	61	148	2.9	25786
postal service mail sorters, processors, and p...	0.79	34	147	2.8	63159
painting workers	0.84	41	144	3.0	143925
cement masons, concrete finishers, and terrazz...	0.91	58	140	3.8	59051
shipping, receiving, and traffic clerks	0.98	68	135	4.2	606014
print binding and finishing workers	0.95	67	134	3.8	19764
fence erectors	0.92	57	134	3.6	31708
insurance claims and policy processing clerks	0.98	59	129	3.4	388822
sawing machine setters, operators, and tenders...	0.86	44	127	3.3	32983
subway, streetcar, and other rail transportati...	0.84	35	126	2.5	20806
refuse and recyclable material collectors	0.93	59	124	4.1	98068
parts salespersons	0.98	67	121	4.7	114849
maintenance workers, machinery	0.86	41	121	3.0	27694
carpet, floor, and tile installers and finishers	0.82	41	120	3.6	166216
office machine operators, except computer	0.92	49	120	3.2	47109
butchers and other meat, poultry, and fish pro...	0.82	41	118	3.6	271549
bakers	0.89	50	118	3.8	235791
pressers, textile, garment, and related materials	0.81	35	117	3.1	40274
library technicians	0.99	56	117	2.7	45887
combined food preparation and serving workers,...	0.92	57	117	4.5	412026

appraisers and assessors of real estate	0.90	43	116	3.0	93101
transportation inspectors	0.90	43	116	2.9	42943
rolling machine setters, operators, and tender...	0.83	42	116	3.2	8607
ushers, lobby attendants, and ticket takers	0.96	60	112	4.2	45805
hosts and hostesses, restaurant, lounge, and c...	0.97	59	112	4.0	314557
plasterers and stucco masons	0.84	41	111	3.4	33364
rail-track laying and maintenance equipment op...	0.89	51	111	3.4	10864
printing press operators	0.83	36	108	3.2	186104
brickmasons, blockmasons, stonemasons, and rei...	0.87	43	108	3.6	147447
coin, vending, and amusement machine servicers...	0.94	54	107	3.8	38224
miscellaneous construction workers, including ...	0.83	36	107	3.2	82579
cargo and freight agents	0.99	63	107	3.5	23548
telephone operators	0.97	58	105	3.8	37960
weighers, measurers, checkers, and samplers, r...	0.95	51	104	3.4	76815
bill and account collectors	0.95	51	104	3.6	149134
gaming services workers	0.94	47	103	3.2	98722
small engine mechanics	0.79	30	103	3.0	44990
miscellaneous woodworkers, including model mak...	0.94	51	103	3.5	32936
credit authorizers, checkers, and clerks	0.97	54	103	3.3	32740
claims adjusters, appraisers, examiners, and i...	0.98	52	103	3.3	293733
parking lot attendants	0.87	41	102	3.4	89396
railroad conductors and yardmasters	0.83	33	102	2.9	50138
mail clerks and mail machine operators, except...	0.94	48	100	3.3	79211
metal furnace operators, tenders, pourers, and...	0.88	39	99	2.8	24609
structural iron and steel workers	0.83	35	99	3.2	61207
textile winding, twisting, and drawing out mac...	0.96	74	99	3.3	10411
miscellaneous food preparation and serving rel...	0.91	49	99	4.2	349631
counter attendants, cafeteria, food concession...	0.96	57	97	4.9	200340
construction equipment operators except paving...	0.88	43	97	3.9	335310
food and tobacco roasting, baking, and drying ...	0.91	53	96	3.6	10459
automotive and watercraft service attendants	0.83	38	95	3.8	95401
electrical, electronics, and electromechanical...	0.88	40	95	3.3	125354
molders, shapers, and casters, except metal an...	0.90	43	94	3.3	27658
sheet metal workers	0.82	31	94	3.0	117067
highway maintenance workers	0.87	42	94	3.9	104661
miscellaneous assemblers and fabricators	0.95	54	94	4.6	1033723
payroll and timekeeping clerks	0.97	52	94	3.7	157420
tellers	0.98	54	94	3.8	326735
surveying and mapping technicians	0.96	49	94	3.2	65904
cutting workers	0.75	27	93	3.3	76145
dredge, excavating, and loading machine operators	0.79	35	93	3.8	34532
forging machine setters, operators, and tender...	0.93	113	92	3.1	7109
couriers and messengers	0.94	53	92	4.8	223200
telemarketers	0.99	57	92	4.2	73578
counter and rental clerks	0.97	55	91	4.5	89766
miscellaneous transportation workers, includin...	0.94	47	91	3.2	31327
jewelers and precious stone and metal workers	0.95	53	90	4.0	35947
paving, surfacing, and tamping equipment opera...	0.83	42	90	4.3	13177
pumping station operators	0.88	43	89	3.5	24199
logging workers	0.84	36	88	3.6	61044
switchboard operators, including answering ser...	0.96	52	88	3.6	26750
correspondence clerks and order clerks	0.92	45	88	3.9	139638
hotel, motel, and resort desk clerks	0.94	46	87	3.6	156536
taxi drivers and chauffeurs	0.89	43	87	4.0	512412
miscellaneous plant and system operators	0.80	28	87	2.9	40204
agricultural and food science technicians	0.97	50	86	2.9	34544
furniture finishers	0.87	43	86	3.5	11957
library assistants, clerical	0.95	44	84	3.0	104454
dishwashers	0.77	30	84	3.9	339315
medical records and health information technic...	0.91	38	84	3.1	183551
textile bleaching and dyeing, and cutting mach...	0.96	63	84	3.2	8640
loan interviewers and clerks	0.92	40	82	3.1	130602
billing and posting clerks	0.96	48	82	4.0	503308
first-line supervisors of housekeeping and jan...	0.94	46	80	4.1	223307
tax preparers	0.99	52	79	4.1	108103
glaziers	0.73	23	79	3.2	43790
riggers	0.89	44	79	3.6	11930
earth drillers, except oil and gas	0.85	37	78	3.7	25024
miscellaneous production workers, including se...	0.87	41	76	4.7	1228570
chemical processing machine setters, operators...	0.82	28	75	3.0	54773
etchers and engravers	0.98	66	75	4.7	10908
food servers, nonrestaurant	0.86	36	74	4.0	189436
compensation and benefits managers	0.96	54	74	2.8	18167
data entry keyers	0.99	49	73	3.7	338777
door-to-door sales workers, news and street ve...	0.94	45	72	4.5	141344
painters and paperhangers	0.81	31	71	4.0	569733
bus and truck mechanics and diesel engine spec...	0.73	20	71	3.1	321240
transportation attendants, except flight atten...	0.75	23	70	3.2	37641
new accounts clerks	0.99	55	70	3.8	13546
welding, soldering, and brazing workers	0.78	25	70	3.5	581441
textile knitting and weaving machine setters, ...	0.73	24	70	3.0	9424
food preparation workers	0.87	40	70	5.2	1044322
engine and other machine assemblers	0.82	33	69	3.5	10943
medical transcriptionists	0.89	35	67	3.0	39673

security and fire alarm systems installers	0.82	26	66	3.0	64934
insurance sales agents	0.92	38	65	3.9	549157
credit analysts	0.98	51	64	3.5	28560
grounds maintenance workers	0.90	40	63	5.4	1375236
inspectors, testers, sorters, samplers, and we...	0.98	45	63	4.0	825242
file clerks	0.97	43	61	3.8	235733
conveyor operators and tenders, and hoist and ...	0.79	26	57	3.4	16135
miscellaneous vehicle and mobile equipment mec...	0.74	21	57	3.6	88241
fishing and hunting workers	0.83	27	56	3.3	38509
agricultural inspectors	0.94	47	56	3.2	13461
control and valve installers and repairers	0.77	21	56	3.0	19474
stationary engineers and boiler operators	0.89	31	56	3.0	87638
transportation security screeners	0.76	19	55	2.9	43369
procurement clerks	0.98	46	54	3.2	31177
helpers–installation, maintenance, and repair...	0.79	24	54	3.6	19979
heavy vehicle and mobile equipment service tec...	0.68	13	54	3.0	213383
buyers and purchasing agents, farm products	0.87	36	53	3.3	9577
interviewers, except eligibility and loan	0.94	37	53	3.8	140953
word processors and typists	0.81	23	53	3.4	313044
postal service mail carriers	0.68	13	52	3.1	331040
bookkeeping, accounting, and auditing clerks	0.98	43	52	5.4	1196491
cooks	0.88	36	52	6.6	2382677
paper goods machine setters, operators, and te...	0.67	14	51	3.2	26501
precision instrument and equipment repairers	0.78	20	51	3.0	65377
laundry and dry-cleaning workers	0.71	18	51	3.7	193833
real estate brokers and sales agents	0.92	33	50	3.7	861636
helpers, construction trades	0.79	22	50	3.6	46090
industrial and refractory machinery mechanics	0.74	18	50	3.4	385118
waiters and waitresses	0.94	39	50	6.5	2259571
photographic process workers and processing ma...	0.99	47	49	4.0	27647
food batchmakers	0.70	15	49	3.4	92236
laborers and freight, stock, and material move...	0.85	34	49	7.3	2283307
power plant operators, distributors, and dispa...	0.74	17	49	2.9	49947
tax examiners and collectors, and revenue agents	0.93	36	49	3.4	49429
nonfarm animal caretakers	0.82	24	49	3.6	257349
construction laborers	0.88	34	48	6.4	1782785
production, planning, and expediting clerks	0.88	28	48	3.4	344798
insulation workers	0.74	17	48	3.2	46519
bus drivers	0.78	21	48	3.7	599906
paralegals and legal assistants	0.94	35	47	3.5	403709
security guards and gaming surveillance officers	0.90	31	47	4.1	959921
machinists	0.65	12	47	3.2	335741
drywall installers, ceiling tile installers, a...	0.70	16	44	3.7	144448
home appliance repairers	0.72	16	44	3.4	37885
pest control workers	0.66	11	44	3.0	79375
motion picture projectionists	0.97	77	43	5.1	1975
geological and petroleum technicians, and nucl...	0.88	32	42	3.2	17229
locksmiths and safe repairers	0.77	22	42	3.5	27390
barbers	0.80	18	40	2.8	107200
cashiers	0.90	33	40	9.1	3451469
meter readers, utilities	0.85	26	39	3.0	27333
bartenders	0.77	18	38	3.8	461808
receptionists and information clerks	0.96	35	38	5.6	1178211
electric motor, power tool, and related repairers	0.76	16	38	3.0	25602
budget analysts	0.94	34	37	3.3	47354
driver/sales workers and truck drivers	0.82	27	37	7.7	3567888
medical, dental, and ophthalmic laboratory tec...	0.80	19	37	3.0	80787
brokerage clerks	0.98	66	34	4.4	7456
aircraft mechanics and service technicians	0.71	10	34	2.7	184209
aircraft structure, surfaces, rigging, and sys...	0.79	22	34	3.5	6609
heating, air conditioning, and refrigeration m...	0.65	10	33	3.4	396637
miscellaneous installation, maintenance, and r...	0.68	11	33	3.4	282890
derrick, rotary drill, and service unit operat...	0.74	14	32	3.3	26695
automotive service technicians and mechanics	0.59	10	31	4.0	864477
office clerks, general	0.96	31	31	6.0	1343439
human resources assistants, except payroll and...	0.90	27	31	3.4	54447
carpenters	0.72	16	30	5.3	1213622
forest and conservation workers	0.87	27	30	3.7	13748
boilermakers	0.68	10	30	3.2	16129
first-line supervisors of farming, fishing, an...	0.57	6	29	3.0	62631
maids and housekeeping cleaners	0.69	15	29	5.7	1604629
property, real estate, and community associati...	0.81	18	29	4.0	606977
veterinary assistants and laboratory animal ca...	0.86	23	28	3.0	49470
librarians	0.65	7	27	3.0	184980
human resources workers	0.97	32	27	3.8	816525
sales representatives, services, all other	0.85	21	27	4.2	652896
computer control programmers and operators	0.61	3	27	2.4	94653
maintenance and repair workers, general	0.64	9	26	4.0	528803
janitors and building cleaners	0.66	14	25	7.1	2569514
retail salespersons	0.92	25	25	9.4	3484967
technical writers	0.89	25	25	3.0	62551
packers and packagers, hand	0.38	7	23	4.3	479775
stock clerks and order fillers	0.64	12	22	6.5	1703928
water and wastewater treatment plant and syste...	0.61	5	22	2.9	86903

miscellaneous agricultural workers, including ...	0.13	8	22	4.3	816237
administrative services managers	0.73	11	20	3.8	154287
dispatchers	0.72	10	20	3.5	290101
electronic home entertainment equipment instal...	0.65	6	19	3.0	37652
accountants and auditors	0.94	24	18	5.4	1949643
helpers–production workers	0.66	6	17	3.7	40407
food service managers	0.08	6	16	4.6	980202
pipelayers, plumbers, pipefitters, and steamfi...	0.48	5	16	3.7	580644
lifeguards and other recreational, and all oth...	0.67	6	15	3.4	159981
first-line supervisors of construction trades ...	0.17	5	15	4.2	782879
first-line supervisors of retail sales workers	0.28	9	15	8.2	3169777
healthcare support workers, all other, includi...	0.78	12	15	3.4	156037
first-line supervisors of food preparation and...	0.63	5	14	4.1	592310
first-line supervisors of production and opera...	0.02	5	14	4.2	908023
computer operators	0.78	12	14	3.3	98174
purchasing agents, except wholesale, retail, a...	0.77	11	14	3.2	283980
eligibility interviewers, government programs	0.70	7	13	3.1	84918
models, demonstrators, and product promoters	0.74	9	12	4.1	55524
first-line supervisors of landscaping, lawn se...	0.57	4	12	4.0	165809
radio and telecommunications equipment install...	0.64	3	11	2.8	164583
secretaries and administrative assistants	0.90	16	11	8.0	3224120
transportation, storage, and distribution mana...	0.59	4	11	4.0	245232
first-line supervisors of non-retail sales wor...	0.08	4	10	5.4	1216522
miscellaneous legal support workers	0.74	8	10	3.2	166672
mining machine operators	0.56	2	9	3.4	47753
millwrights	0.59	2	9	3.1	40293
avionics technicians	0.70	8	8	2.4	22625
customer service representatives	0.55	5	8	7.7	2818247
cleaners of vehicles and equipment	0.37	2	8	3.8	384184
first-line supervisors of office and administr...	0.01	3	7	5.9	1378187
reservation and transportation ticket agents a...	0.61	2	7	3.5	137243
dental hygienists	0.68	4	7	2.8	180723
childcare workers	0.08	3	7	5.0	1312851
cost estimators	0.57	2	7	3.5	138624
miscellaneous material moving workers, includi...	0.55	2	7	3.9	47655
miscellaneous extraction workers, including ro...	0.61	2	6	3.7	53674
construction and building inspectors	0.63	2	6	3.2	91926
farmers, ranchers, and other agricultural mana...	0.05	1	5	4.0	564891
electricians	0.15	1	5	3.7	792129
personal care aides	0.74	6	4	5.5	1414793
drafters	0.67	3	3	2.7	164566
credit counselors and loan officers	0.51	1	3	3.2	323691
electrical and electronics repairers, transpor...	0.57	0	2	2.6	20476
construction managers	0.07	1	2	5.0	669466
financial managers	0.07	0	2	4.8	1169125
surveyors, cartographers, and photogrammetrists	0.63	1	2	3.1	36565
graders and sorters, agricultural products	0.41	0	2	3.5	54009
baggage porters, bellhops, and concierges	0.52	0	1	3.5	91661
market research analysts and marketing special...	0.61	0	0	3.4	306484
upholsterers	0.39	0	0	3.4	31729
structural metal fabricators and fitters	0.41	-1	0	3.0	25975
computer, automated teller, and office machine...	0.74	5	0	3.3	190368
clinical laboratory technologists and technicians	0.68	2	0	3.1	310615
nursing, psychiatric, and home health aides	0.43	-1	-1	6.3	2054283
registered nurses	0.06	-1	-1	6.0	3172434
chief executives and legislators	0.02	-2	-2	5.1	1224318
marketing and sales managers	0.01	-2	-2	4.5	966355
personal financial advisors	0.58	-1	-2	3.4	384466
opticians, dispensing	0.71	4	-2	3.3	66367
sales representatives, wholesale and manufactu...	0.55	-2	-3	5.5	1370870
general and operations managers	0.16	-2	-3	4.8	899832
automotive glass installers and repairers	0.55	-2	-5	3.3	20327
postsecondary teachers	0.01	-4	-5	4.3	1537967
miscellaneous entertainment attendants and rel...	0.59	-2	-6	3.8	214489
miscellaneous managers, including funeral serv...	0.50	-4	-6	10.1	4348902
broadcast and sound engineering technicians an...	0.60	-1	-6	2.9	109495
proofreaders and copy markers	0.84	17	-6	3.5	11554
teacher assistants	0.56	-3	-7	4.6	1043464
food cooking machine operators and tenders	0.61	-3	-7	4.2	11290
elementary and middle school teachers	0.14	-6	-8	7.2	3641301
other teachers and instructors	0.16	-4	-8	4.5	858714
chemical technicians	0.57	-2	-8	2.8	68131
licensed practical and licensed vocational nurses	0.06	-4	-8	4.5	858736
software developers, applications and systems ...	0.09	-5	-8	4.1	1276877
engineering technicians, except drafters	0.42	-3	-9	3.2	382362
advertising sales agents	0.54	-3	-9	3.7	182661
crossing guards	0.49	-3	-9	3.4	57351
designers	0.10	-4	-9	4.3	901105
preschool and kindergarten teachers	0.08	-5	-9	4.4	592015
secondary school teachers	0.01	-6	-10	5.6	782206
computer occupations, all other	0.01	-4	-10	3.5	661275
supervisors of transportation and material mov...	0.17	-4	-10	3.9	225935
nurse practitioners and nurse midwives	0.06	-5	-10	3.3	160752
social workers	0.01	-5	-10	3.9	863660

electronic equipment installers and repairers,...	0.61	-2	-10	3.3	8117
miscellaneous textile, apparel, and furnishing...	0.44	-3	-11	3.3	18869
first-line supervisors of gaming workers	0.41	-5	-11	4.3	20810
hazardous materials removal workers	0.53	-4	-12	3.8	32441
computer programmers	0.48	-4	-12	3.4	433851
first-line supervisors of mechanics, installer...	0.00	-5	-12	3.7	276727
counselors	0.01	-6	-12	4.0	805376
compensation, benefits, and job analysis speci...	0.47	-3	-12	3.0	53264
education administrators	0.01	-6	-12	4.2	910283
dental assistants	0.51	-3	-12	3.2	292682
miscellaneous personal appearance workers	0.51	-4	-13	3.2	354205
medical and health services managers	0.01	-6	-13	4.2	677197
miscellaneous mathematical science occupations...	0.42	-4	-13	2.8	64407
hairdressers, hairstylists, and cosmetologists	0.11	-5	-13	3.5	882002
management analysts	0.13	-6	-13	4.6	839173
telecommunications line installers and repairers	0.49	-4	-14	3.1	149341
special education teachers	0.01	-8	-14	4.6	269335
computer support specialists	0.01	-6	-14	3.5	676592
computer systems analysts	0.01	-6	-14	3.5	516815
miscellaneous office and administrative suppor...	0.16	-5	-14	4.0	595427
chefs and head cooks	0.10	-6	-15	3.9	455649
athletes, coaches, umpires, and related workers	0.42	-5	-15	3.5	312031
tour and travel guides	0.48	-4	-15	3.4	67004
computer hardware engineers	0.22	-5	-15	2.9	55243
financial specialists, all other	0.33	-6	-17	3.6	53025
lawyers, and judges, magistrates, and other ju...	0.28	-6	-17	3.4	1123104
miscellaneous engineers, including nuclear eng...	0.04	-6	-17	3.2	533884
first-line supervisors of personal service wor...	0.08	-5	-17	3.2	98091
police officers	0.33	-5	-17	3.0	744791
ship and boat captains and operators	0.44	-6	-18	3.5	37778
massage therapists	0.54	-4	-18	3.0	193115
physical scientists, all other	0.43	-6	-18	2.9	242345
bailiffs, correctional officers, and jailers	0.48	-5	-18	3.2	414811
archivists, curators, and museum technicians	0.45	-6	-19	3.2	52111
psychologists	0.01	-6	-19	2.7	209725
recreation and fitness workers	0.05	-7	-19	3.7	454783
wholesale and retail buyers, except farm products	0.29	-7	-19	4.0	211265
pharmacy aides	0.72	-2	-19	3.6	40190
court, municipal, and license clerks	0.46	-7	-20	3.9	69195
aircraft pilots and flight engineers	0.36	-4	-20	2.6	176718
physicians and surgeons	0.00	-8	-20	3.2	926544
miscellaneous life, physical, and social scien...	0.49	-6	-21	3.1	208520
medical assistants	0.30	-7	-21	3.7	527124
probation officers and correctional treatment ...	0.25	-5	-21	2.7	90143
electrical and electronics engineers	0.06	-6	-21	2.9	206423
other education, training, and library workers	0.13	-8	-21	3.8	122701
computer and information systems managers	0.04	-10	-21	4.2	618883
web developers	0.30	-7	-22	3.2	192776
health practitioner support technologists and ...	0.26	-7	-22	3.4	643061
detectives and criminal investigators	0.34	-5	-22	2.7	119543
statistical assistants	0.66	-3	-22	3.0	16800
other therapists, including exercise physiolog...	0.09	-7	-23	2.8	174502
industrial production managers	0.03	-9	-23	4.1	239245
social and community service managers	0.01	-9	-24	3.7	361012
miscellaneous law enforcement workers	0.46	-8	-24	3.7	11407
civil engineers	0.02	-8	-24	3.2	359024
miscellaneous social scientists, including sur...	0.15	-9	-25	3.4	38967
financial analysts	0.23	-8	-25	3.2	214130
medical scientists, and life scientists, all o...	0.10	-8	-25	2.9	138975
lodging managers	0.00	-9	-26	3.5	132944
mechanical engineers	0.01	-8	-26	2.9	279046
diagnostic related technologists and technicians	0.24	-8	-26	3.0	353310
artists and related workers	0.03	-9	-26	3.4	209673
economists	0.43	-8	-26	3.4	25922
private detectives and investigators	0.31	-7	-26	3.1	78918
physician assistants	0.14	-7	-26	2.8	105589
securities, commodities, and financial service...	0.02	-9	-27	3.4	227025
purchasing managers	0.03	-10	-27	3.5	199728
social and human service assistants	0.13	-8	-27	3.2	204091
miscellaneous media and communication workers	0.38	-9	-28	3.3	109464
human resources managers	0.01	-9	-28	3.3	427513
electrical power-line installers and repairers	0.10	-7	-28	2.8	115357
judicial law clerks	0.41	-8	-29	2.9	15999
atmospheric and space scientists	0.67	-3	-29	3.6	12097
air traffic controllers and airfield operation...	0.41	-8	-29	3.2	36448
public relations specialists	0.18	-9	-29	3.2	134459
biological scientists	0.09	-8	-30	2.8	80960
environmental scientists and geoscientists	0.23	-9	-30	3.0	74640
writers and authors	0.04	-9	-30	3.1	230356
industrial engineers, including health and safety	0.03	-9	-30	2.9	206604
compliance officers	0.08	-10	-30	3.4	248403
agents and business managers of artists, perfo...	0.24	-11	-30	3.8	49663
business operations specialists, all other	0.23	-11	-31	3.7	283078
other healthcare practitioners and technical o...	0.14	-10	-31	3.3	133400

shoe and leather workers	0.52	-11	-31	3.8	13388
network and computer systems administrators	0.03	-10	-31	3.0	217159
speech-language pathologists	0.01	-11	-32	3.1	150925
computer network architects	0.01	-9	-32	2.7	100876
actors	0.37	-10	-32	3.4	44015
training and development specialists	0.01	-11	-33	3.3	137674
miscellaneous health technologists and technic...	0.00	-11	-33	3.2	131295
operations research analysts	0.04	-11	-33	3.2	137109
flight attendants	0.35	-8	-33	2.7	108547
aerospace engineers	0.02	-9	-33	2.8	129188
miscellaneous community and social service spe...	0.04	-11	-33	3.4	94263
advertising and promotions managers	0.04	-13	-33	4.0	47081
announcers	0.41	-10	-33	3.2	51030
physical therapists	0.02	-9	-34	2.6	250563
database administrators	0.03	-10	-34	3.0	114301
animal trainers	0.10	-10	-34	3.2	43453
gaming cage workers	0.39	-18	-34	5.8	10207
veterinarians	0.04	-9	-34	2.8	84235
first-line supervisors of police and detectives	0.00	-8	-34	2.7	110517
architects, except naval	0.03	-12	-35	3.3	191993
dietitians and nutritionists	0.00	-10	-35	3.1	107942
occupational therapists	0.00	-10	-35	2.8	114741
gaming managers	0.09	-12	-35	3.6	18594
directors, religious activities and education	0.02	-10	-35	2.8	69960
public relations and fundraising managers	0.02	-12	-35	3.3	58808
musicians, singers, and related workers	0.04	-11	-35	3.3	203872
pharmacists	0.01	-11	-36	3.1	306813
sailors and marine oilers, and ship engineers	0.44	-10	-36	3.0	28666
computer and information research scientists	0.02	-10	-37	3.0	19185
television, video, and motion picture camera o...	0.46	-9	-37	2.7	62973
news analysts, reporters and correspondents	0.09	-10	-37	2.8	81904
clergy	0.01	-11	-37	2.9	449976
furnace, kiln, oven, drier, and kettle operato...	0.37	-12	-38	3.4	10942
emergency medical technicians and paramedics	0.05	-10	-38	3.0	214705
producers and directors	0.02	-13	-38	3.5	157009
editors	0.06	-10	-38	2.9	186208
embalmers and funeral attendants	0.46	-12	-38	3.4	15806
training and development managers	0.01	-13	-39	3.4	63996
nurse anesthetists	0.06	-13	-39	3.4	33607
travel agents	0.10	-15	-39	3.9	69566
architectural and engineering managers	0.02	-13	-39	3.2	153628
photographers	0.02	-14	-39	3.6	167100
information security analysts	0.01	-11	-39	2.9	85575
meeting, convention, and event planners	0.04	-13	-39	3.4	143292
chemists and materials scientists	0.06	-11	-39	3.0	85082
petroleum, mining and geological engineers, in...	0.15	-11	-40	2.9	37946
chemical engineers	0.02	-11	-40	2.8	68146
optometrists	0.14	-10	-41	2.6	38543
logisticians	0.01	-12	-41	3.1	142788
firefighters	0.17	-10	-41	2.8	286089
respiratory therapists	0.07	-11	-41	2.8	117397
biological technicians	0.30	-12	-42	3.1	21490
urban and regional planners	0.13	-13	-42	3.2	25019
phlebotomists	0.06	-11	-42	2.9	105106
physical therapist assistants and aides	0.31	-11	-43	2.7	102174
environmental engineers	0.02	-13	-43	3.1	31935
residential advisors	0.06	-13	-44	3.1	93500
ambulance drivers and attendants, except emerg...	0.25	-16	-44	3.7	13785
dentists	0.01	-11	-44	2.6	169442
first-line supervisors of correctional officers	0.02	-10	-44	2.6	57431
fundraisers	0.02	-14	-45	3.2	96945
conservation scientists and foresters	0.01	-13	-45	3.1	22327
financial examiners	0.17	-13	-46	3.0	15307
agricultural and food scientists	0.05	-16	-46	3.4	26313
explosives workers, ordnance handling experts,...	0.48	-14	-47	3.2	19851
natural sciences managers	0.02	-20	-47	4.2	20935
biomedical and agricultural engineers	0.26	-12	-47	2.9	18446
morticians, undertakers, and funeral directors	0.20	-18	-48	3.8	38463
materials engineers	0.02	-12	-48	2.7	35610
elevator installers and repairers	0.39	-13	-48	3.0	24617
sales engineers	0.00	-15	-49	3.1	38589
occupational therapy assistants and aides	0.15	-12	-49	2.7	21924
emergency management directors	0.00	-22	-49	4.7	10811
health diagnosing and treating practitioners, ...	0.02	-14	-49	2.9	32122
recreational therapists	0.00	-15	-50	3.1	12704
first-line supervisors of fire fighting and pr...	0.00	-11	-50	2.5	47474
actuaries	0.21	-12	-50	2.7	28578
podiatrists	0.00	-8	-50	2.2	7878
animal control workers	0.21	-18	-50	3.7	12553
astronomers and physicists	0.07	-15	-50	3.0	11678
marine engineers and naval architects	0.01	-13	-53	2.7	13677
dancers and choreographers	0.07	-21	-53	4.0	16360
chiropractors	0.03	-15	-54	2.7	59172
fire inspectors	0.26	-15	-56	2.8	19573

radiation therapists	0.34	-21	-57	3.8	13107
audiologists	0.00	-19	-61	3.1	14245

Table S3: Results for all occupations for the Frey and Osborne shock

Table S3: Results for all occupations for the Brynjolfsson et al. shock

Occupation	Probability of computerization	Percentage change in the average unemployment rate	Percentage change in the average long-term unemployment rate	Unemployment rate before shock	Target demand before shock
drafters	3.90	6	28	2.7	164566
baggage porters, bellhops, and concierges	3.80	6	19	3.5	91661
appraisers and assessors of real estate	3.70	4	16	3.0	93101
postal service clerks	3.66	3	16	2.8	114948
postal service mail carriers	3.65	3	14	3.1	331040
morticians, undertakers, and funeral directors	3.89	5	12	3.8	38463
travel agents	3.66	4	12	3.9	69566
office machine operators, except computer	3.74	3	12	3.2	47109
tax preparers	3.70	4	12	4.1	108103
tellers	3.71	3	11	3.8	326735
insurance underwriters	3.61	3	11	2.9	109663
medical transcriptionists	3.70	2	10	3.0	39673
insurance claims and policy processing clerks	3.67	3	10	3.4	388822
advertising and promotions managers	3.60	3	9	4.0	47081
couriers and messengers	3.71	4	9	4.8	223200
transportation inspectors	3.72	2	9	2.9	42943
market research analysts and marketing special...	3.62	3	9	3.4	306484
court, municipal, and license clerks	3.63	3	9	3.9	69195
insurance sales agents	3.62	3	9	3.9	549157
ushers, lobby attendants, and ticket takers	3.74	3	9	4.2	45805
phlebotomists	3.66	2	9	2.9	105106
file clerks	3.73	3	9	3.8	235733
clergy	3.62	2	9	2.9	449976
network and computer systems administrators	3.59	2	8	3.0	217159
directors, religious activities and education	3.62	2	8	2.8	69960
financial analysts	3.56	2	8	3.2	214130
reservation and transportation ticket agents a...	3.62	2	8	3.5	137243
database administrators	3.56	2	8	3.0	114301
compensation, benefits, and job analysis speci...	3.65	2	8	3.0	53264
news analysts, reporters and correspondents	3.62	2	8	2.8	81904
postal service mail sorters, processors, and p...	3.45	2	8	2.8	63159
word processors and typists	3.60	2	8	3.4	313044
door-to-door sales workers, news and street ve...	3.69	3	8	4.5	141344
data entry keyers	3.68	3	8	3.7	338777
tour and travel guides	3.64	2	8	3.4	67004
billing and posting clerks	3.64	3	7	4.0	503308
payroll and timekeeping clerks	3.58	2	7	3.7	157420
library assistants, clerical	3.65	2	7	3.0	104454
water and wastewater treatment plant and syste...	3.60	2	7	2.9	86903
miscellaneous community and social service spe...	3.62	2	7	3.4	94263
photographers	3.59	2	7	3.6	167100
counter and rental clerks	3.68	3	7	4.5	89766
parts salespersons	3.65	3	7	4.7	114849
industrial engineers, including health and safety	3.60	2	7	2.9	206604
editors	3.58	2	7	2.9	186208
miscellaneous office and administrative suppor...	3.72	3	7	4.0	595427
financial specialists, all other	3.56	2	7	3.6	53025
public relations and fundraising managers	3.52	2	7	3.3	58808
weighers, measurers, checkers, and samplers, r...	3.66	2	7	3.4	76815
computer network architects	3.53	1	6	2.7	100876
sales representatives, services, all other	3.63	2	6	4.2	652896
information security analysts	3.55	1	6	2.9	85575
operations research analysts	3.55	2	6	3.2	137109
technical writers	3.56	1	6	3.0	62551
web developers	3.55	2	6	3.2	192776
computer and information systems managers	3.55	2	6	4.2	618883
shipping, receiving, and traffic clerks	3.67	2	6	4.2	606014
training and development managers	3.54	2	6	3.4	63996
mail clerks and mail machine operators, except...	3.58	2	6	3.3	79211
dispatchers	3.62	2	6	3.5	290101
hotel, motel, and resort desk clerks	3.58	2	5	3.6	156536
advertising sales agents	3.53	2	5	3.7	182661
switchboard operators, including answering ser...	3.71	2	5	3.6	26750
social and community service managers	3.53	2	5	3.7	361012
hazardous materials removal workers	3.68	2	5	3.8	32441
residential advisors	3.57	1	5	3.1	93500
telephone operators	3.63	2	5	3.8	37960
prepress technicians and workers	3.62	1	5	2.9	25786
sewing machine operators	3.58	1	5	3.1	185332
transportation, storage, and distribution mana...	3.52	2	5	4.0	245232
industrial production managers	3.50	2	5	4.1	239245
marketing and sales managers	3.56	2	5	4.5	966355
computer hardware engineers	3.52	1	5	2.9	55243
artists and related workers	3.54	1	5	3.4	209673
accountants and auditors	3.49	2	5	5.4	1949643
aerospace engineers	3.49	1	5	2.8	129188

bookkeeping, accounting, and auditing clerks	3.72	2	5	5.4	1196491
credit counselors and loan officers	3.54	1	5	3.2	323691
loan interviewers and clerks	3.54	1	5	3.1	130602
production, planning, and expediting clerks	3.57	1	5	3.4	344798
compliance officers	3.55	2	5	3.4	248403
human resources workers	3.59	2	5	3.8	816525
credit authorizers, checkers, and clerks	3.57	1	5	3.3	32740
miscellaneous managers, including funeral serv...	3.39	3	4	10.1	4348902
first-line supervisors of housekeeping and jan...	3.52	1	4	4.1	223307
social and human service assistants	3.54	1	4	3.2	204091
jewelers and precious stone and metal workers	3.60	2	4	4.0	35947
education administrators	3.60	2	4	4.2	910283
first-line supervisors of retail sales workers	3.41	2	4	8.2	3169777
first-line supervisors of mechanics, installer...	3.55	1	4	3.7	276727
tool and die makers	3.61	1	4	2.6	59042
correspondence clerks and order clerks	3.54	1	4	3.9	139638
securities, commodities, and financial service...	3.53	1	4	3.4	227025
computer systems analysts	3.49	1	4	3.5	516815
sales representatives, wholesale and manufactu...	3.60	2	4	5.5	1370870
financial managers	3.55	2	4	4.8	1169125
real estate brokers and sales agents	3.56	1	4	3.7	861636
mechanical engineers	3.55	1	4	2.9	279046
electrical and electronics engineers	3.55	1	4	2.9	206423
customer service representatives	3.60	2	3	7.7	2818247
human resources assistants, except payroll and...	3.50	1	3	3.4	54447
pharmacists	3.50	1	3	3.1	306813
nurse practitioners and nurse midwives	3.49	1	3	3.3	160752
supervisors of transportation and material mov...	3.47	1	3	3.9	225935
special education teachers	3.49	1	3	4.6	269335
new accounts clerks	3.66	1	3	3.8	13546
bill and account collectors	3.52	1	3	3.6	149134
miscellaneous food preparation and serving rel...	3.54	1	3	4.2	349631
dishwashers	3.51	1	3	3.9	339315
first-line supervisors of landscaping, lawn se...	3.52	1	3	4.0	165809
nonfarm animal caretakers	3.52	1	3	3.6	257349
gaming services workers	3.55	1	3	3.2	98722
receptionists and information clerks	3.61	2	3	5.6	1178211
general and operations managers	3.47	1	3	4.8	899832
first-line supervisors of non-retail sales wor...	3.48	1	3	5.4	1216522
retail salespersons	3.58	2	3	9.4	3484967
models, demonstrators, and product promoters	3.55	1	3	4.1	55524
secretaries and administrative assistants	3.65	2	3	8.0	3224120
first-line supervisors of office and administr...	3.58	2	3	5.9	1378187
office clerks, general	3.62	2	3	6.0	1343439
chief executives and legislators	3.50	2	3	5.1	1224318
architectural and engineering managers	3.46	1	3	3.2	153628
secondary school teachers	3.50	2	3	5.6	782206
elementary and middle school teachers	3.49	2	3	7.2	3641301
environmental scientists and geoscientists	3.50	1	3	3.0	74640
human resources managers	3.43	1	3	3.3	427513
medical and health services managers	3.52	1	3	4.2	677197
tax examiners and collectors, and revenue agents	3.54	1	3	3.4	49429
social workers	3.50	1	3	3.9	863660
training and development specialists	3.51	1	3	3.3	137674
fundraisers	3.51	1	3	3.2	96945
purchasing agents, except wholesale, retail, a...	3.51	1	3	3.2	283980
miscellaneous mathematical science occupations...	3.51	1	3	2.8	64407
personal financial advisors	3.40	1	2	3.4	384466
computer occupations, all other	3.49	1	2	3.5	661275
computer programmers	3.47	1	2	3.4	433851
registered nurses	3.43	1	2	6.0	3172434
software developers, applications and systems ...	3.40	1	2	4.1	1276877
computer support specialists	3.47	1	2	3.5	676592
computer operators	3.49	1	2	3.3	98174
cashiers	3.62	2	2	9.1	3451469
claims adjusters, appraisers, examiners, and i...	3.40	0	2	3.3	293733
personal care aides	3.48	1	2	5.5	1414793
childcare workers	3.48	1	2	5.0	1312851
miscellaneous entertainment attendants and rel...	3.54	1	2	3.8	214489
nursing, psychiatric, and home health aides	3.41	1	2	6.3	2054283
counselors	3.47	1	2	4.0	805376
waiters and waitresses	3.45	1	2	6.5	2259571
bartenders	3.47	1	2	3.8	461808
cooks	3.37	1	2	6.6	2382677
management analysts	3.30	1	2	4.6	839173
logisticians	3.48	1	2	3.1	142788
preschool and kindergarten teachers	3.46	1	2	4.4	592015
bakers	3.50	1	2	3.8	235791
tailors, dressmakers, and sewers	3.48	1	2	3.4	76453
printing press operators	3.51	1	2	3.2	186104
stock clerks and order fillers	3.59	1	2	6.5	1703928
designers	3.43	1	2	4.3	901105
teacher assistants	3.45	1	2	4.6	1043464
purchasing managers	3.43	1	2	3.5	199728

writers and authors	3.45	1	2	3.1	230356
miscellaneous media and communication workers	3.52	1	2	3.3	109464
miscellaneous legal support workers	3.48	0	2	3.2	166672
laborers and freight, stock, and material move...	3.31	1	2	7.3	2283307
food service managers	3.48	1	2	4.6	980202
property, real estate, and community associati...	3.42	1	2	4.0	606977
wholesale and retail buyers, except farm products	3.48	1	2	4.0	211265
chemical technicians	3.52	0	1	2.8	68131
food preparation workers	3.40	1	1	5.2	1044322
janitors and building cleaners	3.38	1	1	7.1	2569514
refuse and recyclable material collectors	3.47	0	1	4.1	98068
medical, dental, and ophthalmic laboratory tec...	3.53	0	1	3.0	80787
maids and housekeeping cleaners	3.37	1	1	5.7	1604629
veterinary assistants and laboratory animal ca...	3.53	0	1	3.0	49470
inspectors, testers, sorters, samplers, and we...	3.55	0	1	4.0	825242
stationary engineers and boiler operators	3.48	0	1	3.0	87638
chemists and materials scientists	3.49	0	1	3.0	85082
miscellaneous engineers, including nuclear eng...	3.50	0	1	3.2	533884
architects, except naval	3.39	0	1	3.3	191993
food batchmakers	3.50	0	1	3.4	92236
eligibility interviewers, government programs	3.49	0	1	3.1	84918
heating, air conditioning, and refrigeration m...	3.50	0	1	3.4	396637
sheet metal workers	3.53	0	1	3.0	117067
first-line supervisors of food preparation and...	3.43	0	1	4.1	592310
other teachers and instructors	3.46	1	1	4.5	858714
licensed practical and licensed vocational nurses	3.43	1	1	4.5	858736
clinical laboratory technologists and technicians	3.48	0	1	3.1	310615
medical assistants	3.48	0	1	3.7	527124
health practitioner support technologists and ...	3.48	0	1	3.4	643061
postsecondary teachers	3.41	0	1	4.3	1537967
diagnostic related technologists and technicians	3.48	0	1	3.0	353310
physician assistants	3.50	0	1	2.8	105589
other education, training, and library workers	3.43	1	1	3.8	122701
public relations specialists	3.42	0	1	3.2	134459
procurement clerks	3.56	0	0	3.2	31177
construction managers	3.44	0	0	5.0	669466
miscellaneous social scientists, including sur...	3.39	0	0	3.4	38967
security and fire alarm systems installers	3.50	0	0	3.0	64934
miscellaneous production workers, including se...	3.50	0	0	4.7	1228570
miscellaneous health technologists and technic...	3.44	0	0	3.2	131295
surveyors, cartographers, and photogrammetrists	3.50	0	0	3.1	36565
miscellaneous agricultural workers, including ...	3.47	0	0	4.3	816237
psychologists	3.45	0	0	2.7	209725
photographic process workers and processing ma...	3.59	0	0	4.0	27647
miscellaneous assemblers and fabricators	3.45	0	0	4.6	1033723
first-line supervisors of personal service wor...	3.50	0	0	3.2	98091
recreation and fitness workers	3.44	0	0	3.7	454783
packaging and filling machine operators and te...	3.44	0	0	3.5	273293
physical scientists, all other	3.45	0	0	2.9	242345
first-line supervisors of farming, fishing, an...	3.48	0	0	3.0	62631
cutting workers	3.48	0	0	3.3	76145
farmers, ranchers, and other agricultural mana...	3.40	0	0	4.0	564891
chemical processing machine setters, operators...	3.51	0	0	3.0	54773
lodging managers	3.38	0	0	3.5	132944
biological scientists	3.47	0	0	2.8	80960
dietitians and nutritionists	3.41	0	0	3.1	107942
civil engineers	3.41	0	0	3.2	359024
telecommunications line installers and repairers	3.49	0	0	3.1	149341
welding, soldering, and brazing workers	3.50	0	0	3.5	581441
grounds maintenance workers	3.41	0	0	5.4	1375236
first-line supervisors of gaming workers	3.46	0	0	4.3	20810
agents and business managers of artists, perfo...	3.41	0	0	3.8	49663
broadcast and sound engineering technicians an...	3.42	0	0	2.9	109495
librarians	3.44	0	0	3.0	184980
meeting, convention, and event planners	3.42	0	0	3.4	143292
business operations specialists, all other	3.42	0	0	3.7	283078
budget analysts	3.39	0	0	3.3	47354
credit analysts	3.59	0	0	3.5	28560
respiratory therapists	3.50	0	0	2.8	117397
first-line supervisors of production and opera...	3.40	0	0	4.2	908023
maintenance and repair workers, general	3.47	0	0	4.0	528803
security guards and gaming surveillance officers	3.44	0	0	4.1	959921
computer control programmers and operators	3.50	0	0	2.4	94653
veterinarians	3.51	0	0	2.8	84235
highway maintenance workers	3.50	0	0	3.9	104661
chefs and head cooks	3.35	0	0	3.9	455649
machine tool cutting setters, operators, and t...	3.48	0	0	2.8	154172
lawyers, and judges, magistrates, and other ju...	3.38	0	0	3.4	1123104
healthcare support workers, all other, includi...	3.44	0	0	3.4	156037
combined food preparation and serving workers,...	3.45	0	0	4.5	412026
counter attendants, cafeteria, food concession...	3.48	0	0	4.9	200340
machinists	3.52	0	0	3.2	335741
food servers, nonrestaurant	3.41	0	0	4.0	189436
parking lot attendants	3.44	0	0	3.4	89396

taxi drivers and chauffeurs	3.40	0	0	4.0	512412
model makers, patternmakers, and molding machi...	3.56	0	0	3.0	43390
miscellaneous life, physical, and social scien...	3.50	0	0	3.1	208520
driver/sales workers and truck drivers	3.47	0	0	7.7	3567888
bus drivers	3.42	0	0	3.7	599906
miscellaneous metal workers and plastic worker...	3.51	0	0	3.4	407934
telemarketers	3.41	0	0	4.2	73578
paralegals and legal assistants	3.45	0	-1	3.5	403709
cabinetmakers and bench carpenters	3.42	-1	-1	3.6	57002
miscellaneous woodworkers, including model mak...	3.55	0	-1	3.5	32936
carpenters	3.40	-1	-1	5.3	1213622
first-line supervisors of police and detectives	3.46	0	-1	2.7	110517
insulation workers	3.51	0	-1	3.2	46519
cleaners of vehicles and equipment	3.39	-1	-1	3.8	384184
bailiffs, correctional officers, and jailers	3.44	0	-1	3.2	414811
detectives and criminal investigators	3.44	0	-1	2.7	119543
construction and building inspectors	3.40	0	-1	3.2	91926
police officers	3.43	0	-1	3.0	744791
administrative services managers	3.33	-1	-1	3.8	154287
private detectives and investigators	3.42	0	-1	3.1	78918
crossing guards	3.44	-1	-1	3.4	57351
electricians	3.47	0	-1	3.7	792129
construction laborers	3.47	-1	-1	6.4	1782785
miscellaneous extraction workers, including ro...	3.48	0	-1	3.7	53674
computer, automated teller, and office machine...	3.34	0	-1	3.3	190368
first-line supervisors of construction trades ...	3.37	-1	-1	4.2	782879
flight attendants	3.54	0	-1	2.7	108547
helpers–production workers	3.46	0	-1	3.7	40407
electrical, electronics, and electromechanical...	3.44	0	-1	3.3	125354
television, video, and motion picture camera o...	3.45	0	-1	2.7	62973
engineering technicians, except drafters	3.44	0	-1	3.2	382362
medical records and health information technic...	3.39	0	-1	3.1	183551
archivists, curators, and museum technicians	3.40	-1	-2	3.2	52111
automotive body and related repairers	3.42	-1	-2	3.2	136839
miscellaneous installation, maintenance, and r...	3.40	-1	-2	3.4	282890
automotive service technicians and mechanics	3.33	-1	-2	4.0	864477
graders and sorters, agricultural products	3.40	-1	-2	3.5	54009
electrical power-line installers and repairers	3.46	0	-2	2.8	115357
physicians and surgeons	3.40	-1	-2	3.2	926544
structural iron and steel workers	3.44	-1	-2	3.2	61207
cargo and freight agents	3.56	-1	-2	3.5	23548
sales engineers	3.49	-1	-2	3.1	38589
packers and packagers, hand	3.30	-1	-2	4.3	479775
industrial truck and tractor operators	3.31	-1	-2	4.0	608737
lifeguards and other recreational, and all oth...	3.38	-1	-2	3.4	159981
hosts and hostesses, restaurant, lounge, and c...	3.34	-1	-2	4.0	314557
other healthcare practitioners and technical o...	3.36	-1	-2	3.3	133400
molders, shapers, and casters, except metal an...	3.50	-1	-2	3.3	27658
crushing, grinding, polishing, mixing, and ble...	3.42	-1	-2	3.4	85752
power plant operators, distributors, and dispa...	3.50	0	-2	2.9	49947
painting workers	3.44	-1	-2	3.0	143925
interviewers, except eligibility and loan	3.34	-1	-2	3.8	140953
sawing machine setters, operators, and tenders...	3.50	-1	-3	3.3	32983
pest control workers	3.42	-1	-3	3.0	79375
helpers, construction trades	3.41	-1	-3	3.6	46090
painters and paperhangers	3.30	-1	-3	4.0	569733
speech-language pathologists	3.40	-1	-3	3.1	150925
gaming managers	3.54	-1	-3	3.6	18594
transportation security screeners	3.51	-1	-3	2.9	43369
pharmacy aides	3.42	-1	-3	3.6	40190
mining machine operators	3.43	-1	-3	3.4	47753
laundry and dry-cleaning workers	3.32	-1	-3	3.7	193833
miscellaneous textile, apparel, and furnishing...	3.58	-1	-3	3.3	18869
buyers and purchasing agents, farm products	3.71	-1	-3	3.3	9577
radio and telecommunications equipment install...	3.39	-1	-3	2.8	164583
aircraft pilots and flight engineers	3.44	-1	-3	2.6	176718
agricultural and food science technicians	3.50	-1	-3	2.9	34544
roofers	3.40	-1	-3	3.6	206655
hairdressers, hairstylists, and cosmetologists	3.33	-1	-3	3.5	882002
butchers and other meat, poultry, and fish pro...	3.32	-1	-3	3.6	271549
producers and directors	3.29	-1	-3	3.5	157009
materials engineers	3.45	-1	-3	2.7	35610
industrial and refractory machinery mechanics	3.33	-1	-3	3.4	385118
miscellaneous material moving workers, includi...	3.38	-1	-3	3.9	47655
automotive and watercraft service attendants	3.39	-1	-4	3.8	95401
heavy vehicle and mobile equipment service tec...	3.37	-1	-4	3.0	213383
miscellaneous vehicle and mobile equipment mec...	3.37	-1	-4	3.6	88241
fence erectors	3.46	-1	-4	3.6	31708
precision instrument and equipment repairers	3.41	-1	-4	3.0	65377
miscellaneous plant and system operators	3.46	-1	-4	2.9	40204
athletes, coaches, umpires, and related workers	3.27	-1	-4	3.5	312031
probation officers and correctional treatment ...	3.40	-1	-4	2.7	90143
gaming cage workers	3.77	-2	-4	5.8	10207
construction equipment operators except paving...	3.32	-2	-4	3.9	335310

surveying and mapping technicians	3.41	-1	-4	3.2	65904
medical scientists, and life scientists, all o...	3.28	-1	-4	2.9	138975
economists	3.46	-1	-4	3.4	25922
barbers	3.41	-1	-4	2.8	107200
urban and regional planners	3.48	-1	-4	3.2	25019
carpet, floor, and tile installers and finishers	3.34	-2	-4	3.6	166216
fishing and hunting workers	3.42	-1	-4	3.3	38509
cost estimators	3.33	-1	-4	3.5	138624
pipelayers, plumbers, pipefitters, and steamfi...	3.31	-1	-4	3.7	580644
miscellaneous transportation workers, includin...	3.44	-1	-5	3.2	31327
forest and conservation workers	3.47	-2	-5	3.7	13748
structural metal fabricators and fitters	3.50	-1	-5	3.0	25975
dental assistants	3.36	-1	-5	3.2	292682
environmental engineers	3.35	-1	-5	3.1	31935
drywall installers, ceiling tile installers, a...	3.35	-2	-5	3.7	144448
other therapists, including exercise physiolog...	3.39	-1	-5	2.8	174502
paper goods machine setters, operators, and te...	3.45	-1	-5	3.2	26501
miscellaneous personal appearance workers	3.35	-1	-5	3.2	354205
optometrists	3.62	-1	-6	2.6	38543
natural sciences managers	3.47	-2	-6	4.2	20935
first-line supervisors of correctional officers	3.42	-1	-6	2.6	57431
chemical engineers	3.30	-1	-6	2.8	68146
musicians, singers, and related workers	3.29	-2	-6	3.3	203872
statistical assistants	3.53	-2	-6	3.0	16800
small engine mechanics	3.36	-2	-6	3.0	44990
millwrights	3.42	-2	-6	3.1	40293
extruding, forming, pressing, and compacting m...	3.45	-2	-6	3.2	33072
bus and truck mechanics and diesel engine spec...	3.30	-2	-6	3.1	321240
logging workers	3.30	-2	-6	3.6	61044
electronic home entertainment equipment instal...	3.37	-2	-6	3.0	37652
emergency medical technicians and paramedics	3.36	-2	-6	3.0	214705
boilermakers	3.49	-2	-6	3.2	16129
brickmasons, blockmasons, stonemasons, and rei...	3.32	-2	-6	3.6	147447
earth drillers, except oil and gas	3.50	-2	-6	3.7	25024
transportation attendants, except flight atten...	3.38	-2	-6	3.2	37641
dredge, excavating, and loading machine operators	3.31	-2	-6	3.8	34532
machine feeders and offbearers	3.38	-2	-6	3.6	27175
helpers–installation, maintenance, and repair...	3.41	-2	-6	3.6	19979
coin, vending, and amusement machine servicers...	3.36	-2	-7	3.8	38224
embalmers and funeral attendants	3.67	-2	-7	3.4	15806
physical therapists	3.36	-1	-7	2.6	250563
dentists	3.38	-1	-7	2.6	169442
miscellaneous construction workers, including ...	3.35	-2	-7	3.2	82579
cement masons, concrete finishers, and terrazz...	3.31	-3	-7	3.8	59051
aircraft mechanics and service technicians	3.33	-2	-8	2.7	184209
derrick, rotary drill, and service unit operat...	3.37	-2	-8	3.3	26695
petroleum, mining and geological engineers, in...	3.43	-2	-8	2.9	37946
aircraft structure, surfaces, rigging, and sys...	3.54	-3	-8	3.5	6609
agricultural inspectors	3.65	-2	-8	3.2	13461
conservation scientists and foresters	3.46	-2	-8	3.1	22327
actors	3.32	-2	-8	3.4	44015
ambulance drivers and attendants, except emerg...	3.50	-3	-8	3.7	13785
library technicians	3.38	-2	-9	2.7	45887
paving, surfacing, and tamping equipment opera...	3.34	-4	-9	4.3	13177
opticians, dispensing	3.40	-3	-9	3.3	66367
crane and tower operators	3.37	-2	-9	3.1	60690
pressers, textile, garment, and related materials	3.29	-2	-9	3.1	40274
glaziers	3.38	-2	-9	3.2	43790
dental hygienists	3.32	-2	-9	2.8	180723
engine and other machine assemblers	3.52	-3	-9	3.5	10943
computer and information research scientists	3.42	-2	-9	3.0	19185
maintenance workers, machinery	3.30	-2	-9	3.0	27694
home appliance repairers	3.28	-3	-10	3.4	37885
upholsterers	3.39	-3	-10	3.4	31729
biological technicians	3.52	-3	-10	3.1	21490
firefighters	3.31	-2	-10	2.8	286089
geological and petroleum technicians, and nucl...	3.49	-3	-10	3.2	17229
health diagnosing and treating practitioners, ...	3.52	-2	-10	2.9	32122
electronic equipment installers and repairers,...	3.50	-3	-10	3.3	8117
woodworking machine setters, operators, and te...	3.43	-3	-10	3.5	18782
metal furnace operators, tenders, pourers, and...	3.55	-2	-10	2.8	24609
electric motor, power tool, and related repairers	3.32	-2	-10	3.0	25602
food cooking machine operators and tenders	3.44	-4	-10	4.2	11290
announcers	3.19	-3	-11	3.2	51030
print binding and finishing workers	3.45	-4	-11	3.8	19764
first-line supervisors of fire fighting and pr...	3.42	-2	-11	2.5	47474
proofreaders and copy markers	3.52	-3	-11	3.5	11554
pumping station operators	3.35	-3	-11	3.5	24199
agricultural and food scientists	3.26	-3	-11	3.4	26313
meter readers, utilities	3.53	-3	-11	3.0	27333
sailors and marine oilers, and ship engineers	3.42	-3	-11	3.0	28666
physical therapist assistants and aides	3.27	-2	-11	2.7	102174
animal trainers	3.20	-4	-12	3.2	43453
air traffic controllers and airfield operation...	3.44	-3	-12	3.2	36448

control and valve installers and repairers	3.41	-3	-12	3.0	19474
occupational therapists	3.30	-3	-12	2.8	114741
miscellaneous law enforcement workers	3.42	-4	-12	3.7	11407
railroad conductors and yardmasters	3.34	-3	-13	2.9	50138
judicial law clerks	3.45	-3	-13	2.9	15999
locomotive engineers and operators	3.44	-3	-14	2.7	48869
ship and boat captains and operators	3.35	-4	-14	3.5	37778
food and tobacco roasting, baking, and drying ...	3.47	-4	-14	3.6	10459
nurse anesthetists	3.48	-4	-14	3.4	33607
brokerage clerks	3.78	-4	-15	4.4	7456
electrical and electronics repairers, transpor...	3.47	-3	-15	2.6	20476
rolling machine setters, operators, and tender...	3.41	-4	-15	3.2	8607
emergency management directors	3.48	-7	-16	4.7	10811
furnace, kiln, oven, drier, and kettle operato...	3.45	-5	-16	3.4	10942
chiropractors	3.39	-3	-17	2.7	59172
compensation and benefits managers	3.39	-4	-17	2.8	18167
actuaries	3.54	-4	-18	2.7	28578
biomedical and agricultural engineers	3.49	-4	-18	2.9	18446
astronomers and physicists	3.39	-5	-18	3.0	11678
textile knitting and weaving machine setters, ...	3.54	-4	-18	3.0	9424
riggers	3.35	-6	-19	3.6	11930
motion picture projectionists	3.26	-9	-19	5.1	1975
plasterers and stucco masons	3.14	-6	-20	3.4	33364
adhesive bonding machine operators and tenders	3.47	-7	-20	3.7	8809
financial examiners	3.31	-5	-20	3.0	15307
furniture finishers	3.35	-6	-20	3.5	11957
marine engineers and naval architects	3.44	-4	-20	2.7	13677
dancers and choreographers	3.24	-8	-21	4.0	16360
subway, streetcar, and other rail transportati...	3.40	-4	-21	2.5	20806
rail-track laying and maintenance equipment op...	3.23	-6	-21	3.4	10864
etchers and engravers	3.43	-9	-22	4.7	10908
fire inspectors	3.38	-5	-23	2.8	19573
automotive glass installers and repairers	3.35	-6	-23	3.3	20327
locksmiths and safe repairers	3.42	-7	-24	3.5	27390
occupational therapy assistants and aides	3.32	-5	-24	2.7	21924
animal control workers	3.55	-8	-25	3.7	12553
conveyor operators and tenders, and hoist and ...	3.28	-8	-26	3.4	16135
elevator installers and repairers	3.40	-7	-26	3.0	24617
massage therapists	2.78	-7	-26	3.0	193115
textile bleaching and dyeing, and cutting mach...	3.50	-7	-26	3.2	8640
shoe and leather workers	3.48	-9	-27	3.8	13388
extruding and drawing machine setters, operato...	3.31	-6	-29	2.8	12126
textile winding, twisting, and drawing out mac...	3.57	-9	-30	3.3	10411
atmospheric and space scientists	3.42	-10	-30	3.6	12097
avionics technicians	3.52	-5	-30	2.4	22625
radiation therapists	3.50	-10	-30	3.8	13107
tire builders	3.28	-10	-31	3.6	14930
audiologists	3.44	-9	-33	3.1	14245
recreational therapists	3.26	-9	-34	3.1	12704
explosives workers, ordnance handling experts,...	3.39	-10	-35	3.2	19851
forging machine setters, operators, and tender...	3.50	-12	-45	3.1	7109
podiatrists	3.41	-7	-47	2.2	7878