The Unequal Effects of Trade and Automation across Local Labor Markets

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Abstract

We quantify the joint impact of the China shock and automation of labor, across US commuting zones (CZs) in the period 2000-2007. To this end, we employ a multi-sector gravity model of trade with Roy-Fréchet worker heterogeneity across sectors, where labor input can be automated. Automation and increased import competition from China are both sector-specific; they lead to contractions in a sector's labor demand and a decline in relative income for CZs more specialized in that sector, amplified by a voluntary reduction in hours worked and an increase in frictional unemployment. The estimated model fits well with the aggregate performance of manufacturing subsectors and with the variation across CZs in changes in average income, the hourly wage, hours worked, the employment rate and employment in manufacturing. By itself, the China shock has stronger distributional effects than automation, but its impact on aggregate gains is less than a third of automation's impact.

JEL: F11, F16, J23, J24, E24, E25

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1 Introduction

During the 2000-2007 period, employment in US manufacturing abruptly fell by 20.5%, or 3.5 million jobs (US Bureau of Labor Statistics, 2019), resulting in economic stagnation in many regions specialized in manufacturing. In the same period, the Chinese share in US imports roughly doubled, and the associated surge in Chinese import competition has contributed to the relative decline of US manufacturing regions (Autor, Dorn, and Hanson, 2013b). However, while manufacturing employment fell, value added in manufacturing continued to grow. This indicates that the "surprisingly swift" decline of US manufacturing employment is not only due to the"China shock" (Pierce and Schott, 2020), but also a consequence of the rise of labor-saving technology (Acemoglu and Restrepo, 2020).

This paper presents a unifying general equilibrium framework to quantify the impact of trade and automation on the decline of US manufacturing employment and the associated unequal effects across US local labor markets. Many studies examine the impact of either trade or technology on US manufacturing regions,[1] but there is little to no integrated general-equilibrium analysis of their joint impact. Importantly though, the interplay between the trade and automation shocks matters quantitatively. For instance, US productivity shocks due to automation affect world trade patterns, which are central to the calibration of the China shock. Hence, the joint calibration of the China and automation shocks may yield different quantitative results than when the shocks are calibrated separately. Moreover, the interplay of the shocks determines whether their distributional impact will be dampened or amplified – an aspect also missed when the shocks are analyzed in isolation.

Our unified framework starts from the combination of a multi-sector gravity model of trade (Arkolakis, Costinot, and Rodríguez-Clare, 2012), with a Roy-Fréchet setup for labor supply, where workers sort into sectors based on their comparative advantage (La-

[1] Fort, Pierce, and Schott (2018) provide an excellent review of the literature on this topic.

gakos and Waugh, 2013). Additionally, we introduce equipment as an imperfect substitute for labor, allowing labor to be automated. As explained in Galle, Rodríguez-Clare, and Yi (2023), the Roy-Fréchet model generalizes the specific factors intuition to a setting where labor is mobile across sectors. Specifically, the model allows for variation in the pattern of comparative advantage across commuting zones (CZs), and the resulting pattern of sectoral specialization determines how sensitive each CZ is to a particular sector-specific shock. In our model, both increased import competition and automation are sector-specific. Therefore, both can induce a contraction in a sector's labor demand and exert downward pressure on the wages it pays. As a result, CZs more specialized in sectors undergoing increased import competition or automation will tend to experience a relative decline in their average hourly wage. These relative differences are amplified by adjustments in the unemployment rate and in the number of hours worked.

To allow for these changes in unemployment and hours worked, we include a barebones search-and-matching framework and an intensive margin adjustment in our model, based on Kim and Vogel (2021). The resulting model has three central elasticities on the labor supply side: (i) the dispersion parameter of the Roy-Fréchet, which governs the cost of reducing sectoral specialization at the CZ-level; (ii) the intensive margin elasticity; and (iii) the elasticity of the employment rate to labor market tightness. We estimate these elasticities by employing a transparent shift-share estimation strategy and obtain parameter values that align with standard values in the literature. Our shift-share instrument captures any national sector-specific shocks, and the model explains how these shocks translate into relative changes in CZs' income.

Armed with our estimates, we jointly calibrate the China and automation shocks and quantify their impact on the US economy. We model the China shock as sector-specific Chinese technological growth and calibrate it by ensuring the model exactly matches the increase in US expenditure shares on Chinese manufacturing goods. In turn, we model automation as a shock to equipment-specific productivity, which lowers the cost share of labor in a sector. This is why we calibrate the automation shock such that the model exactly matches the changes in labor cost shares in US manufacturing sectors.

Our model finds that the combination of the automation and China shocks leads to an increase in aggregate US real income of 3.96%, while aggregate manufacturing employment declines by 0.81 percentage points. Given our parameter estimates, roughly 50% of the aggregate income gain arises from changes in the average hourly wage, while changes in hours worked and the employment rate account for the remaining 20% and 30% of the gain, respectively. Furthermore, we obtain a 0.97% standard deviation for the income gains across CZs, and – perhaps unsurprisingly – there is a strong concentration of low gains around the Rust Belt. More broadly, in line with the patterns described in Austin, Glaeser, and Summers (2018), large swaths of the Eastern Heartland tend to experience a decline in relative income due to these combined shocks.

When we simulate the individual shocks, we find that the distributional effects of the China shock are larger than the effects of automation. However, the aggregate gain from the rise of China is less than one third the size of automation's impact. Moreover, the impacts across CZs of the individual China and automation shocks are positively correlated. In turn, this positive covariance of the shocks' local effects implies that the variance in income effects of the joint shock is larger than the sum of the variance for the individual shocks. The importance of incorporating both shocks to understand the full distributional effects across CZs helps explain why in previous studies such as GRY, the variance of the model-predicted income effects of an individual shock appears too small compared to the observed variance.

The predictions from our estimated model fit well with the variation across CZs for the different margins of labor market adjustment. In terms of R^2, our joint China and automation shock explains e.g. 8% of the observed variation in changes in average CZ income and 29% of the variation in changes in the employment rate and the manufacturing employment share. In addition to explaining a substantial share of the variation, the model slightly underpredicts the magnitude of the variance in the observed changes. In part, this is driven by conservative choices for the intensive and extensive margin elasticities.

Turning from the model fit of the cross-CZ variation to the fit of the cross-sector variation, the joint shock continues to perform well. In contrast, for the individual shocks, there is a mismatch between the model and the data in the performance of value added across manufacturing subsectors. Indeed, the individual China shock predicts a decline in all subsectors' value added, while the automation shock predicts an increase for most. In reality, roughly half of the manufacturing subsectors undergo a decline in value added, while the other half experiences an increase – a pattern the combined shock does match well. This finding again underscores the importance of integrating both trade and automation in a single model to properly understand the impact of these correlated shocks both across local labor markets and on US manufacturing in general.

Literature Our paper is motivated by the large body of reduced-form work on the impact of trade and technology on local labor markets. Following the seminal work of Autor et al. (2013b) – henceforth ADH – many studies have examined the impact of trade on US localities, see for instance Hakobyan and McLaren (2016); Bloom, Handley, Kurman, and Luck (2019); Greenland, Lopresti, and McHenry (2019); Pierce and Schott (2020) and Besedeš, Lee, and Yang (2021).[2] In addition, Acemoglu and Restrepo (2020) and Dauth, Findeisen, Suedekum, and Woessner (2021) examine the impact of robotization across local labor markets.[3] Autor, Dorn, and Hanson (2015) is one of the few papers jointly examining trade and technology shocks. We complement this work by providing a unifying general equilibrium framework that can quantify such shocks' impact at the aggregate level.

[2]Notable contributions on the local impact of trade shocks outside the US are Topalova (2010); Kovak (2013); Dauth, Findeisen, and Suedekum (2014), and Dix-Carneiro and Kovak (2017).

[3]The reduced-form literature on the impact of trade and technology on local labor markets typically employs shift-share estimation, and the prominence of this estimation technique has motivated fundamental econometric work on identification and inference with shift-share instruments (Adão, Kolesár, and Morales, 2019; Borusyak, Hull, and Jaravel, 2020; Goldsmith-Pinkham, Sorkin, and Swift, 2020). The resulting deeper understanding of the potential limitations of shift-share estimation indicates the usefulness of a quantitative model to jointly analyze the implications of trade and technology shocks, both on aggregate and cross-sectional moments. Interestingly then, for the latter our model yields predictions both across sectors and across localities, which we will leverage in our model fit discussion.

Like us, Caliendo, Dvorkin, and Parro (2019), Adão, Arkolakis, and Esposito (2020), Rodríguez-Clare, Ulate, and Vasquez (2022) and Galle et al. (2023) – henceforth GRY – quantitatively examine the impact of the China shock on US local labor markets employing a gravity model of trade with a Roy-type labor supply side.[4] We build specifically on GRY since we introduce automation in this type of model in order to examine trade and automation shocks in a unified framework. Moreover, we follow Kim and Vogel (2021) and incorporate additional margins of labor market adjustment, which provide amplification mechanisms for the income effects of any shock. These amplification mechanisms, together with the combined impact of the correlated China and automation shocks, imply that our model matches the observed labor market changes substantially better than GRY.

Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018) and Burstein, Morales, and Vogel (2019) employ Roy models to examine the impact of computerization on inequality. In particular, the latter paper is close to ours since it also has a role for international trade. However, these papers examine the skill premium or the gender wage gap. The focus of our paper is different, as we examine inequality between US commuting zones. Moreover, their setup with a Cobb-Douglas production function for labor and equipment would not be able to account for the fall in the labor share within a manufacturing subsector.[5]

Outside the quantitative trade literature, there is extensive literature studying the impact of technical change on inequality or other labor market outcomes (Krusell, Ohanian, Ríos-Rull, and Violante, 2000; Acemoglu and Restrepo, 2018; Hémous and Olsen, 2022;

[4] Hsieh and Ossa (2016) also quantify the rise of China but do not focus on its distributional impact in the US. Other quantitative trade papers studying worker reallocation via a Roy model are Artuç, Chaudhuri, and McLaren (2010), Dix-Carneiro (2014), Adão (2016) and Curuk and Vannoorenberghe (2017) but they all employ a small open economy framework. More similar to us, Lee (2020) employs a gravity model but does not focus on the China shock. In addition, Lee and Yi (2018) examine the impact of trade with China but focus on the skill premium instead of regional inequality. Finally, gravity models are also employed to study the impact of trade on the skill premium (Burstein and Vogel, 2017), or on unequal price changes for different consumption baskets (Fajgelbaum and Khandelwal, 2016).

[5] In a recent contribution, Bernon and Magerman (2022) generalize the impact of productivity shocks on income inequality arising in general equilibrium in a Roy-Fréchet setup.

Moll, Rachel, and Restrepo, 2022). Most closely related to us, Acemoglu and Restrepo (2020) present a model for the local impact of technological shocks, but their model does not feature international trade or worker heterogeneity. A further contribution of our paper is that the generalized specific factors mechanism in the Roy-Fréchet framework can help to tractably analyze the impact of sector-specific automation on different worker groups.

This paper is organized as follows. Section 2 introduces the theory, Section 3 discusses the data, and Section 4 examines the model's shift-share approximation and estimates the key labor supply elasticities. Section 5 presents our quantitative results and discusses their fit with the data. Finally, Section 6 concludes.

2 Theory

2.1 Setup

The model consists of three blocks. First, for labor supply we have a discrete choice model of the labor market where workers sort across the S sectors. Specifically, we assume a standard Roy (1951) model, where workers' comparative advantage across sectors determines the sorting pattern. Second, demand for goods in each sector for each of the N countries is governed by a gravity model with an input-output loop as in Costinot and Rodríguez-Clare (2014) and Caliendo and Parro (2015). Finally, we introduce a CES production function where labor and equipment are imperfect substitutes. We model automation as an increase in the productivity of equipment, which leads to a decrease of the labor share in production. We keep track of all the Roman and Greek notation in the model in Appendix Tables A.1 and A.2.

Labor supply We start from a Roy-Fréchet model of labor supply as in Lagakos and Waugh (2013), and combine it with frictional unemployment and an intensive margin of labor supply as in Kim and Vogel (2021).[6] To start, wages w_{os} vary by country o and sector s; and workers differ in their productivity z_s across sectors. Given wages, workers apply to a specific sector to maximize their expected utility, which will be a function of $w_{os}z_s$. After applying, there is random matching between vacancies and workers. We asssume that unemployed workers have no income.[7] Conditional on being hired though, workers unilaterally decide how many hours of labor to supply. Specifically, they have a standard utility function with consumption of the final good (C) and hours worked (H) as elements:

$$U(C, H; og) = \delta_{og}C - \frac{H^{1+\mu}}{1+\mu},$$

where consumption is funded by the value of a worker's earnings, at price P_o. After output is realized, the worker and firm engage in Nash bargaining over the surplus of the match.

We are interested in between-group inequality. Each country o therefore has G_o groups of workers, analogous to the setups in Burstein et al. (2019), Hsieh, Hurst, Jones, and Klenow (2019) and GRY. In our application a group will be defined as a commuting zone (CZ), but the theory can be applied to worker groups defined by any predetermined characteristic. Groups differ in their productivity distributions, which will lead to differences in sectoral specialization across groups. Specifically, a worker from group g in country o has a number of effective units of labor z_s drawn from a Fréchet distribution with level parameter A_{ogs} and dispersion parameter κ.[8] Here, the A_{ogs} parameters govern differences in groups' absolute advantage for each sector, while κ determines

[6] As in Kim and Vogel (2021), we could also add voluntary non-employment by introducing home production as one of the sectors. We refrain from doing so since it would make the estimation less tractable (see Section 8.2 in GRY). As an aside, note that Kim and Vogel (2020) generalizes the setup from Kim and Vogel (2021) and derives sufficient statistics for welfare analysis of trade shocks.

[7] Since employment status is determined purely at random, it is relatively straightforward to introduce unemployment benefits in our framework, since they would not distort any decisions. However, we omit them for simplicity.

[8] Three parameters that we introduce in this section (κ, μ and χ) are allowed to be og-specific in the theory. However in the empirics we will only estimate one value for each parameter, as is common in the literature. We therefore leave out the og subscript from the start, to ease the notational burden.

the dispersion of productivity within a sector. Due to the properties of the Fréchet, κ will also determine the dispersion of workers' comparative advantage, and thereby the elasticity of their labor supply across sectors. L_{og} denotes the measure of workers for group og.

The Nash bargaining between the worker and the firm results in a share ν_{og} of revenue going to the worker.[9] We backwardly solve the other elements of the labor problem in Appendix Section G.1. There, given the properties of the Fréchet, we find that the share of workers in group og that apply to sector s is

$$\pi_{ogs} = \frac{A_{ogs} w_{os}^{\kappa}}{\Phi_{og}^{\kappa}},$$

where $\Phi_{og} \equiv (\sum_k A_{ogk} w_{ok}^{\kappa})^{1/\kappa}$ is a group-level index of sectoral wages, where the weights indicate the importance of each sector for group og. Next, average real income per worker in og is

$$\frac{\nu_{og} I_{ogs}}{\pi_{ogs} L_{og} P_o} = \eta e_{og} \delta_{og}^{\frac{1}{\mu}} \left(\frac{\nu_{og}}{P_o} \right)^{\frac{1+\mu}{\mu}} \Phi_{og}^{\frac{1+\mu}{\mu}},$$

with I_{ogs} nominal revenue in s for group og and $\eta \equiv \Gamma\left(1 - \frac{1+\mu}{\mu\kappa}\right)$. Consequently, the share of income obtained by workers of group og in sector s is also given by the sectoral employment share π_{ogs}. Total nominal revenue in group og is

$$I_{og} \equiv \sum_s I_{ogs} = \eta e_{og} \left(\frac{\delta_{og} \nu_{og}}{P_o} \right)^{\frac{1}{\mu}} \Phi_{og}^{\frac{1+\mu}{\mu}} L_{og}, \tag{1}$$

of which workers earn $\nu_{og} I_{og}$.

Relatedly, we can show that average expected utility in group og is

$$U_{og} = \frac{\mu}{1+\mu} \eta e_{og} \left(\delta_{og} \nu_{og} \right)^{\frac{1+\mu}{\mu}} \left(\frac{\Phi_{og}}{P_o} \right)^{\frac{1+\mu}{\mu}}, \tag{2}$$

[9] At the time of bargaining, the outside option of the match has zero value for both worker and firm, since hours worked and the cost of posting a vacancy are both sunk. Hence, at this point, the surplus of the match is exactly $w_{os} z_s$, multiplied by the number of hours worked.

and that both hours worked (h_{og}) and hourly income (i_{og}) are also functions of Φ_{og}:

$$h_{og} = \grave{\eta} \left(\delta_{og} \nu_{og}\right)^{\frac{1}{\mu}} \left(\frac{\Phi_{og}}{P_o}\right)^{\frac{1}{\mu}}, \tag{3}$$

$$i_{og} = \frac{\eta}{\grave{\eta}} \Phi_{og}. \tag{4}$$

Hence, Φ_{og} (a group's wage index) determines endogenous differences in average hourly labor income across groups and thereby also differences in average hours worked. Moreover, below we will see that it also determines differences in the employment rate, such that we can solve for I_{og} and U_{og} as a function of Φ_{og} and P_o.

Unemployment A Cobb-Douglas matching function with vacancies $\tilde{V}_{ogs}$ and applicants $\pi_{ogs} L_{og}$ as inputs entails that the employment rate is a function of labor market tightness $\psi_{ogs} \equiv \tilde{V}_{ogs} / (\pi_{ogs} L_{og})$:

$$e_{ogs} \equiv A_{og}^M \psi_{ogs}^{\chi},$$

where A_{og}^M measures matching efficiency and the employment rate elasticity is $0 < \chi < 1$. For the employer, the cost of posting a vacancy is $c_{og} P_o$, while the expected benefit is the share of revenue per vacancy accruing to the employer: $(1 - \nu_{og}) I_{ogs} / \tilde{V}_{ogs}$. The implied zero-profit condition together with the matching function determine the employment rate, which is indeed constant across sectors:

$$e_{og} = \left(A_{og}^M \left(\frac{\eta(1-\nu_{og})}{c_{og}}\right)^{\chi} \left(\delta_{og}\nu_{og}\right)^{\frac{\chi}{\mu}} \left(\frac{\Phi_{og}}{P_o}\right)^{\frac{\chi(1+\mu)}{\mu}} \right)^{\frac{1}{1-\chi}}, \tag{5}$$

where we can set parameters such that $0 < e_{og} < 1$. Intuitively, a shock that increases the real value of a typical worker (Φ_{og}/P_o), increases the return to posting a vacancy in group og across all sectors, and thereby pushes the employment rate up in all sectors. Importantly, the combinations of Equations (2) and (1) with (5) imply that

$$U_{og} \propto \frac{I_{og}}{P_o} \propto \left(\frac{\Phi_{og}}{P_o}\right)^{\frac{1+\mu}{(1-\chi)\mu}}.$$

Hence, the final good price (P_o) has a common effect on all groups' utility and real income, while sectoral wages lead to differences in utility and income across groups as measured by the group's index of sectoral wages (Φ_{og}). Also note that $I_{og} = e_{og}h_{og}i_{og}$, where the employment rate (e_{og}), hours worked (h_{og}), and the real hourly wage (i_{og}) are all functions of Φ_{og}/P_o. This is the reason for the amplification exponent in the welfare and income equation above, as an amplification of Φ_{og}/P_o through adjustments in employment (governed by $1/(1-\chi)$) and hours worked (governed by $(1+\mu)/\mu$).

Trade There are iceberg trade costs $\tau_{ods} \geq 1$ to export goods from origin country o to destination country d, with $\tau_{oos} = 1$. We work with the multi-sector version of the Eaton and Kortum (2002) gravity model. Hence, within each sector, there is a continuum of goods of measure one, which have constant returns to scale technologies and good-specific productivities drawn from a Fréchet distribution with shape parameter θ_s and level parameter T_{os} in country o and sector s. Preferences across goods within a sector are CES with elasticity of substitution $\sigma_s < \theta_s$.

This results in the following import shares for sector s in destination country d originating from country o:

$$\lambda_{ods} = \frac{T_{os}\left(\tau_{ods}c_{os}\right)^{-\theta_s}}{\sum_i T_{is}\left(\tau_{ids}c_{is}\right)^{-\theta_s}}, \tag{6}$$

where a good's marginal cost c_{os} is determined below. The price index in sector s in country d is then

$$P_{ds} = \tilde{\eta}_s^{-1}\left(\sum_o T_{os}\left(\tau_{ods}c_{os}\right)^{-\theta_s}\right)^{-1/\theta_s}, \tag{7}$$

where $\tilde{\eta}_s \equiv \Gamma(1-\frac{\sigma_s-1}{\theta_s})^{1/(1-\sigma_s)}$. The final good is the Cobb-Douglas composite of sectoral goods, with expenditure shares β_{ds}, and its price is $P_d = \prod_s P_{ds}^{\beta_{ds}}$.

Factor demand Each sector has a two-tiered production function, where the upper-tier is Cobb-Douglas:

$$Y_{os} = F_{os}^{\alpha_{os}} K_{os}^{1-\alpha_{os}-\gamma_{os}} \prod_k N_{oks}^{\gamma_{oks}}, \tag{8}$$

where N_{oks} are intermediate inputs sourced from sector k with $\gamma_{os} \equiv \sum_k \gamma_{oks}$, and K_{os} are structures. Next, F_{os} is a lower tier CES:

$$F_{os} = \xi_{os}^{\upsilon} \left[\xi_{os}^{\frac{1}{\rho}} M_{os}^{\frac{\rho-1}{\rho}} + Z_{os}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where $Z_{os} = \sum_{g \in G_o} Z_{ogs}$ are effective units of labor and M_{os} is equipment (or machines). Both K_{os} and M_{os} are units of the final good, purchased at cost P_o.[10] The parameter ξ_{os} appears twice; within the brackets it drives automation by shifting production toward equipment usage, while υ (outside the brackets) regulates the associated productivity gains. This is a tractable reduced-form approach of capturing the impact automation has in a task-based model.[11]

Cost minimization implies that ω_{os}, the labor share of expenditure on F_{os}, is

$$\omega_{os} = \frac{w_{os}^{1-\rho}}{\left[\xi_{os} P_o^{1-\rho} + w_{os}^{1-\rho} \right]}, \tag{9}$$

while c_{os}, the marginal cost for an extra unit of Y_{os}, has the standard form arising from

[10]Since we focus on hat algebra across static equilibria below, we abstract from investment and its dynamics for M_{os} and K_{os}, analogous to Burstein et al. (2019). This abstraction necessarily also entails that our model is not able to analyze the differential impact of automation on the income of asset holders versus workers – let alone the dynamics for these variables, as in Moll et al. (2022).

[11] We thank an anonymous referee for pointing us to this setup where υ regulates the productivity gains, and for pointing out how this is a reduced-form approach to modelling the production as in a task-based production setup, which can map into a CES production function (Acemoglu and Restrepo, 2018). Other papers modeling automation employing a CES production function are Krusell et al. (2000) or Hémous and Olsen (2022). These papers are interested in explaining changes in the skill premium, and this in part motivates their assumption that only low-skill labor can be automated. However, since our paper is primarily interested in inequality across CZs and less in inequality across skill groups, we do not introduce a distinction between skill groups in the baseline model. This is similar to Acemoglu and Restrepo (2020), who also focus on inequality across CZs and likewise do not distinguish between skill groups. In contrast to Acemoglu and Restrepo (2020), our model is tractable without introducing differences in tasks, and restrictions on the set of tasks that can be automated. This results from the combination of the CES production function and the imperfectly elastic labor supply to each sector in the Roy-Fréchet setup.

Cobb Douglas production functions. Given perfect competition, total revenue for a sector in country o is $R_{os} \equiv c_{os} Y_{os}$. Note that the above implies that the cost share of capital in production is $(1 - \alpha_{os} - \gamma_{os}) = P_o K_{os}/R_{os}$.

Equilibrium Cobb Douglas preferences and technologies imply that expenditure on a sector is $X_{ds} = \beta_{ds}(V_d + D_d) + \sum_{k=1}^{S} \gamma_{dsk} R_{dk}$. Here, value added is $V_d = \sum_{k=1}^{S}(1-\gamma_{dk})R_{dk}$, and trade deficits ($D_d$) are such that $\sum_d D_d = 0$. Goods market clearing implies that $R_{os} = \sum_d \lambda_{ods} X_{ds}$.

Total payments to labor in a sector are $\alpha_{os}\omega_{os}R_{os}$, while total labor income is $\sum_g \pi_{ogs} I_{og}$,[12] and in the labor market the two need to equalize in equilibrium. Hence, we can write excess labor demand in sector s of country o as

$$ELD_{os} = \alpha_{os}\omega_{os}R_{os} - \sum_g \pi_{ogs} I_{og}. \tag{10}$$

Note that ω_{os} (the labor share), R_{os} (revenue), π_{ogs} (employment shares), and I_{og} (labor income) are functions of the matrix of wages $\boldsymbol{w} \equiv \{w_{os}\}$. The system $ELD_{os} = 0$ for all o, s is therefore a system of equations in $\boldsymbol{w}$ whose solution gives the equilibrium wages and prices given a choice of numeraire.

2.2 Counterfactual equilibrium

When interested in the impact of changes in trade costs τ_{ods}, national technology T_{os}, equipment productivity ξ_{os}, or deficits D_d, we can use exact hat algebra, where $\hat{x} \equiv x'/x$, to solve for the proportional change in the endogenous variables (Dekle, Eaton, and Kortum, 2008). Formally, for shocks $\hat{\tau}_{ods}$ for $o \neq d$, $\hat{T}_{os}$, $\hat{\xi}_{os}$ or $\hat{D}_d$ we compute the counterfactual equilibrium with $ELD'_{os} = 0$ for all o, s.[13] To this end, we write $ELD'_{os} =$

[12] A group's supply of effective labor units to sector s is $Z_{ogs} = I_{ogs}/w_{os}$, and the Fréchet implies that $\pi_{ogs} I_{og} = w_{os} Z_{ogs}$.

[13] Throughout the analysis in this and the following sections, we assume for simplicity that $\hat{\nu}_{og} = 1$. It is straightforward to relax this.

0 as

$$\sum_g \hat{\pi}_{ogs}\pi_{ogs}\hat{I}_{og}I_{og} = \alpha_{os}\hat{\omega}_{os}\omega_{os}\sum_d \hat{\lambda}_{ods}\lambda_{ods} \left(\beta_{ds}\left(\hat{V}_d V_d + \hat{D}_d D_d\right) + \sum_{k=1}^{S}\gamma_{dsk}\hat{R}_{dk}R_{dk}\right). \tag{11}$$

This NxS system of equations can be solved for $\{\hat{w}_{os}\}$ given data on income levels I_{og}, trade shares λ_{ods}, expenditure shares β_{os}, revenue R_{os}, labor allocation shares π_{ogs}, cost shares α_{os}, ω_{os}, and γ_{oks}, and values for the exogenous shocks (see Appendix Section G.2).

Importantly, the change in a sector's labor share is

$$\hat{\omega}_{os} = \frac{\hat{w}_{os}^{1-\rho}}{\left[(1-\omega_{os})\hat{\xi}_{os}\hat{P}_o^{1-\rho} + \omega_{os}\hat{w}_{os}^{1-\rho}\right]}. \tag{12}$$

So conditional on wage and price changes, an increase in equipment productivity ($\hat{\xi}$), or "automation," lowers the labor share. On the trade side, trade or technology shocks will affect demand for each country's goods:

$$\hat{\lambda}_{ods} = \frac{\hat{T}_{os}\left(\hat{\tau}_{ods}\hat{c}_{os}\right)^{-\theta_s}}{\sum_i \lambda_{ids}\hat{T}_{is}\left(\hat{\tau}_{ids}\hat{c}_{is}\right)^{-\theta_s}}. \tag{13}$$

Shifts in labor demand lead to wage changes, which induce workers to move across sectors with elasticity κ:

$$\hat{\pi}_{ogs} = \frac{\hat{A}_{ogs}\hat{w}_{os}^{\kappa}}{\hat{\Phi}_{og}^{\kappa}}, \tag{14}$$

where $\hat{\Phi}_{og}$ is the change in the average hourly wage in group og (see Equation (4)), with

$$\hat{\Phi}_{og} = \left(\sum_k \pi_{ogk}\hat{A}_{ogk}\hat{w}_{ok}^{\kappa}\right)^{\frac{1}{\kappa}}. \tag{15}$$

Given that the change in the employment rate is

$$\hat{e}_{og} = \left(\hat{A}^M_{og}\right)^{\frac{1}{1-\chi}} \left(\frac{\hat{\Phi}_{og}}{\hat{P}_o}\right)^{\frac{\chi(1+\mu)}{(1-\chi)\mu}}, \tag{16}$$

and knowing the expressions for nominal income and utility from (1) and (2), the change in real income per worker is

$$\hat{U}_{og} = \frac{\hat{I}_{og}}{\hat{P}_o} = \left(\hat{A}^M_{og}\right)^{\frac{1}{(1-\chi)}} \left(\frac{\hat{\Phi}_{og}}{\hat{P}_o}\right)^{\frac{1}{(1-\chi)}\frac{1+\mu}{\mu}}. \tag{17}$$

Importantly, $\hat{\Phi}_{og}$ in Equation (15) has a generalized specific factors interpretation, with κ governing the degree to which workers are a specific factor. When $\kappa \to 1$, any sector's wage change translates directly to a change in nominal income, weighted by a group's specialization in that sector (π_{ogs}). At the other extreme, when $\kappa \to \infty$, labor supply is perfectly elastic across sectors and as a result, all sectors experience an identical wage change and all groups undergo the same income change. Hence, between-group distributional effects are stronger for κ close to 1, and disappear when $\kappa \to \infty$. In Equation (17), the exponent on $\hat{\Phi}_{og}/\hat{P}_o$ is increasing in the elasticity of the employment rate to labor market tightness (χ), and in the intensive margin elasticity ($1/\mu$). This term therefore represents an amplification effect driven by changes in the employment rate and hours worked.

3 Data

Estimation Data To estimate the labor supply-side parameters of the model, we use worker-level data from IPUMS (Ruggles, Flood, Goeken, Grover, Meyer, Pacas, and Sobek, 2019). There, we restrict the sample to individuals who are between 25 and 60 years old, and also exclude government or non-profit employees, family workers, and institutionalized individuals. IPUMS provides info on total earned income over the past year, total number of hours worked, and employment status. We measure the hourly wage as average income per hour, and the employment rate as the share of employed individuals in the labor force. The model predicts that sectoral employment shares ($\pi_{US,gs}$) in terms of income or hours worked should be perfectly correlated, while in practice the correlation is "only" 97% (see Appendix Figure A.1). Since the correlation appears a little less strong for the larger $\pi_{US,gs}$, we employ both the income- and hours-based measure for these shares in the estimation.

Our analysis focuses on changes over time with the year 2000 as the start period, which is the first year where IPUMS and our international trade dataset both have available data, and an end period before the onset of the Great Recession. For the year 2000, IPUMS provides the 5% sample of the Census, but for the end period only the American Community Survey (ACS) is available. Similar to the strategy in ADH, we therefore combine the ACS surveys for the years 2005-2006-2007 to ensure a more precise measurement of sector-level variables for all commuting zones. Throughout, we deflate income to 1999 dollars using the CPI.

Simulation data For the international trade data, we employ the 2016 release of the World Input-Output Database (WIOD) - see Timmer, Dietzenbacher, Los, Stehrer, and Vries (2015). In the simulations, we measure the labor compensation share ($\alpha_{os}\omega_{os}$) as the labor share of a sector's value added in the WIOD Socio Economic Accounts for all 43 countries in WIOD.

Given the observed values for $\alpha_{os}\omega_{os}$, we disentangle the values of α_{os} (the cost share of the lower-tier CES F_{os}) and ω_{os} as follows. First, we measure the share of structures in the total value of structures and equipment in each sector as $\zeta_{os} \equiv P_o K_{os}/(P_o K_{os} + P_o M_{os})$. Second, we note that $(P_o K_{os} + P_o M_{os})/Y_{os} = 1 - \gamma_{os} - \alpha_{os}\omega_{os}$ and therefore the output share of K_{os} is $(1 - \alpha_{os} - \gamma_{os}) = \zeta_{os}(1 - \gamma_{os} - \alpha_{os}\omega_{os})$, which allows us to solve for α_{os} and ω_{os}. We measure ζ_{os} based on sector-level data on structures and equipment from EU-KLEMS (The Conference Board, 2023; van Ark and Jäger, 2017) and the OECD (OECD, 2019). As in Krusell et al. (2000), we group structures and transportation equipment under K_{os} and the other asset types under M_{os}. Appendix Section F provides more background, as well as detailed summary stastistics for all the cost share parameters.

We employ sector definitions based on ISIC Rev.4, and to create consistent sectors across all estimation and simulation datasets, we aggregate sectors to 23 industries. Of these industries, two are in the primary sector and 11 are in manufacturing.[14] The full list is in Appendix Table A.3.

In the simulations, we need to ensure that groups' labor income is consistent with the WIOD revenue measures: $\sum_g I_{ogs} = \alpha_{os}\omega_{os}Y_{os}^{WIOD}$, where the superscript denotes the data source. To ensure this, we adjust IPUMS income to WIOD revenue as follows:

$$I_{US,gs} = \left(\frac{\nu_{US} I_{US,gs}}{\sum_h \nu_{US} I_{US,hs}}\right)^{IPUMS} \alpha_{US,s}\omega_{US,s}Y_{US,s}^{WIOD},$$

where we assume that $\nu_{US,g}$ is constant across US groups. We then measure group-level sectoral employment shares as $\pi_{US,gs} = I_{US,gs}/\sum_s I_{US,gs}$.

4 Estimation

4.1 A shift-share approximation

Our model features trade and technology shocks at the national level, which lead to changes in wages per effective unit of labor ($\hat{w}_{os}$), which in turn result in unequal changes in income and welfare across commuting zones (see Equations (15) and (17)). While the $\hat{w}_{os}$ are unobservable, we can derive an observable shift-share measure that closely approximates the model-predicted impact of changes in national wages across commuting zones. Specifically, assuming $\hat{A}_{og}^{M} = 1$ and defining sectoral labor income shares as

[14] The main data limitation here is arising from EU-KLEMS, which has data on just 11 manufacturing sectors. (WIOD has data on 19 manufacturing sectors.) Since we then only have these 11 manufacturing sectors, we are missing the additional variation in Chinese import penetration and changes in the labor share within these sectors. This may lead us to understate the aggregate and distributional effects of the China and automation shock.

$r_{os} \equiv \sum_g I_{ogs}/I_o$, we show in Appendix Section G.3 that:[15]

$$\frac{\hat{I}_{og}}{\hat{I}_o} \approx \left(\sum_s \pi_{ogs} \hat{A}_{ogs} \hat{r}_{os} \right)^{\frac{1+\mu}{\kappa(1-\chi)\mu}}. \tag{18}$$

We bring this approximation to US data with commuting zones as groups. In doing so, we simplify notation by dropping the country subscript and assume that groups face a uniform productivity shock across all sectors: $\hat{A}_{gs} = \hat{A}_g$. We can then estimate:

$$\ln \hat{I}_g = \alpha_{ss} + \beta_{ss} \ln \left(\sum_s \pi_{gs} \hat{r}_s \right) + \varepsilon_{ss,g}, \tag{19}$$

where $\alpha_{ss} \equiv \ln \hat{I}$, $\beta_{ss} \equiv \frac{(1+\mu)}{\kappa(1-\chi)\mu}$ and $\varepsilon_{ss,g} \equiv \ln \hat{A}_g^{\frac{(1+\mu)}{\kappa(1-\chi)\mu}}$. Here, $\sum_s \pi_{gs} \hat{r}_s$ measures a group's exposure to sectors' national expansion or contraction, weighted by initial employment shares. Our shift-share variable, therefore, incorporates the impact of any sector-specific supply or demand shock at the national level, including any trade or technology shocks. Below, we will use the estimate of β_{ss} as a consistency check for the individual estimates of κ, μ, and χ. Note that β_{ss} contains the same amplification term as in our welfare expression (17), arising from adjustments on the intensive and extensive margins. In addition, the term is now divided by κ, which is the parameter that measures workers' scope for reallocation across sectors.

We estimate the elasticity of our shift-share approximation in Table 1, both with and without controls and for our two measures of the employment shares π_{gs} (based on hours or income). While other shift-share estimations hinge on isolating the impact of one particular shock in their estimation (e.g. only the China shock or only robotization), this is not the case here since our shift-share variable incorporates all national-level shocks. We therefore estimate specification (19) using OLS.

The obtained estimates are strongly statistically significant, with coefficients between

[15] This approximation builds on a similar derivation in GRY, and here we extend its application to a setting with automation, unemployment and an intensive margin for labor supply. The approximation is exact when $\kappa(1-\chi)\mu/(1+\mu) = 1$. Moreover, using the simulated model, we show that the approximation also performs extremely well for other parameter values (see Appendix Figure B.1).

0.94 and 1.23. The 95% confidence intervals overlap across all four specifications. These estimates imply strong distributional effects since a coefficient above unity implies amplification effects on top of the specific factors case ($\kappa \to 1$).

Table 1: Estimating the model-implied shift-share approximation

	(1)	(2)	(3)	(4)
	$\ln \hat{I}_g$	$\ln \hat{I}_g$	$\ln \hat{I}_g$	$\ln \hat{I}_g$
$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$	1.23***	1.18***		
	(0.17)	(0.27)		
$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$			1.13***	0.94***
			(0.16)	(0.25)
Controls	No	Yes	No	Yes
Observations	722	722	722	722

The regressions in this table estimate Equation (19), where the π_{gs} are measured based on hours worked or income. $\hat{I}_g$ is the change in average income per person in the labor force in a CZ, with the unemployed earning zero income. The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentages are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Appendix B, we document the absence of pre-trends related to the shift-share estimation (Tables B.3, B.4), and that the variation in this variable is strongly affected by the ADH China and computerization shocks, as well as the robotization shock (Table B.5). Finally, we also calculate the Rotemberg weights for this estimation (Tables B.1, B.2).

4.2 Estimating μ, κ, and χ

We now estimate the parameters that govern the behavior of hours worked, the employment rate, and the degree of sectoral mobility.

4.2.1 Estimation equations

Estimating μ From Equation (3), we have that the change in average hours worked is $\hat{h}_{og} = \left(\hat{\Phi}_{og}\hat{\delta}_{og}/\hat{P}_o\right)^{1/\mu}$, while from Equation (4) the change in the hourly wage is $\hat{\imath}_{og} =$

$\hat{\Phi}_{og}$. By combining these results, we obtain the estimation equation for μ:

$$\ln \hat{h}_{og} = \alpha_\mu + \beta_\mu \ln \widehat{i}_{og} + \varepsilon_{\mu,og}, \tag{20}$$

where $\beta_\mu \equiv \frac{1}{\mu}$, $\alpha_\mu \equiv -\ln \hat{P}_o^{1/\mu}$ and $\varepsilon_{\mu,og} \equiv \ln \hat{\delta}_{og}^{1/\mu}$. The estimated elasticity $(1/\mu)$ governs how the supplied number of labor hours increases with the average hourly wage.

Estimating κ By combining $\hat{i}_{og} = \hat{\Phi}_{og}$ with Equation (14), we find that

$$\ln \hat{i}_{og} = \ln \hat{w}_{os} - \frac{1}{\kappa} \ln \hat{\pi}_{ogs} + \ln \hat{A}_{ogs}^{\frac{1}{\kappa}}. \tag{21}$$

Abstracting from local productivity shocks, this expression implies that $\hat{\pi}_{ogs}$ is a sufficient statistic for the change in the hourly wage relative to other groups. Moreover, this relation holds for any sector. To therefore exploit information from all sectors and thereby make this specification less sensitive to measurement in a single sector, we take an average of the previous specification across sectors:

$$\ln \hat{i}_{og} = \alpha_\kappa + \beta_\kappa \sum_s \omega_{\kappa,s} \ln \hat{\pi}_{ogs} + \varepsilon_{\kappa,og}, \tag{22}$$

where $\beta_\kappa \equiv -\frac{1}{\kappa}$, $\alpha_\kappa \equiv \sum_s \omega_{\kappa,s} \ln \hat{w}_{os}$, $\varepsilon_{\kappa,og} \equiv \sum_s \omega_{\kappa,s} \ln \hat{A}_{ogs}^{\frac{1}{\kappa}}$, and where the weights satisfy $0 \leq \omega_{\kappa,s} \leq 1$ and $\sum_s \omega_{\kappa,s} = 1$.[16] Here, the regressor measures the change in the degree of specialization. Since $\sum_s \pi_{ogs}\hat{\pi}_{ogs} = 1$, a higher average $\ln \hat{\pi}_{ogs}$ implies that smaller sectors are expanding while larger sectors are contracting – a decrease in sectoral specialization. Then, the lower is κ, the more negative the impact of decreasing sectoral specialization on the hourly wage.

Estimating χ From Equation (1), we find that the change in average income per worker is

[16] In our estimation, we weigh sectors by their employment shares (measured in terms of hours or income units), because percentage changes in employment for smaller sectors are more sensitive to measurement error, in particular at the CZ-level in the IPUMS data.

$$\hat{i}_{og}\hat{h}_{og} = \frac{\hat{I}_{og}}{\hat{e}_{og}} = \left(\frac{\hat{\delta}_{og}}{\hat{P}_o}\right)^{\frac{1}{\mu}} \hat{\Phi}_{og}^{\frac{1+\mu}{\mu}}.$$

Combining this expression with Equation (16) and assuming $\hat{c}_{og} = 1$, we obtain an estimation equation for the employment rate elasticity (χ)

$$\ln \hat{e}_{og} = \alpha_\chi + \beta_\chi \ln(\hat{i}_{og}\hat{h}_{og}) + \varepsilon_\chi, \tag{23}$$

where $\beta_\chi \equiv \frac{\chi}{1-\chi}$, $\alpha_\chi \equiv \ln \hat{P}_o^{\chi/(\chi-1)}$ and $\varepsilon_\chi \equiv \frac{1}{1-\chi} \ln \hat{A}_{og}^M$. In the model, the employment rate e_{og} increases with average income per worker, and a higher χ entails that e_{og} is more responsive to such changes, which is reflected in the estimation equation.

IV strategy In contrast to our shift-share estimation in Equation (19), the model now implies that for the κ estimation in specification (22) the error term is necessarily correlated with the regressor. Moreover, OLS estimation of the intensive margin elasticity in (20) suffers from division bias (Borjas, 1980).[17] We therefore cannot estimate these two specifications with OLS. However, employing an IV addresses the endogeneity concern for specification (22) and the division bias in (20). Finally, the IV strategy may also adress endogeneity concerns not captured by the model.

As an instrument, we utilize our shift-share variable $\sum_s \pi_{gs}\hat{r}_s$.[18] As explained by Goldsmith-Pinkham et al. (2020), a sufficient condition for this instrument to be valid is that the error terms are uncorrelated with the sector shares (π_{gs}). Importantly, the model also suggests this instrument to be highly relevant. It should therefore provide sufficiently strong first stages, in contrast to the ADH or Acemoglu and Restrepo (2020) shocks (see Appendix Table C.1).

[17] This division bias arises from calculating the hourly wage rate as the ratio of earnings over hours, such that the hours variable appears on both sides of the regression.

[18] We focus on the instrument in levels instead of logs, to be able to apply the standard identification framework for shift-share instruments – see e.g. Goldsmith-Pinkham et al. (2020). However, the instruments in levels and logarithms have a correlation of 99%, so all our findings are robust to employing the instrument in logarithms instead.

4.2.2 Results

Table 2 presents the results of our parameter estimation. For each specification, we employ two versions of our shift-share instrument: in columns 1 and 2, we measure the sectoral shares π_{gs} based on hours worked, while in columns 3 and 4, we measure them based on sectoral income shares. We perform the estimation without and with controls for each version of the instrument in the odd and even columns, respectively. We cluster standard errors at the state level. For all three parameters, our estimates are always strongly statistically significant. Moreover, the first stage is generally sufficiently strong since all the F-statistics are above 10, with one exception where it is 8.5.

For the elasticity of the intensive margin of labor supply $(1/\mu)$, Chetty (2012) provides bounds on the estimates in the literature between 0.28 and 0.54.[19] This interval covers our results for the specifications with controls (columns 2 and 4 in panel b). We set our preferred value to 0.4 – our estimate from column 4, with an implied inverse elasticity of $\mu = 2.5$. Our point estimates for κ fall within the interval of 2.1 - 2.88 (see Panel b). In somewhat different setups, Burstein et al. (2019), Hsieh et al. (2019) and GRY find estimates between 1.26 and 1.81. We therefore set our preferred value at $\kappa = 2.1$. Finally, for the employment elasticity χ, we obtain estimates between 0.17 and 0.3. These estimates are in line with the results from Shimer (2005), who estimates χ between 0.25 and 0.3, while Barnichon and Figura (2015) estimate $\chi = 0.33$.[20] We therefore set $\chi = 0.3$.

How do the distributional implications of our parameter values compare to the estimated shift-share elasticity from Table 1 (which informed us on how local exposure to national sectoral reallocation translates into local income changes)? Interestingly, with $\mu = 2.5, \kappa = 2.1$ and $\chi = 0.3$ we obtain a value for $\frac{1+\mu}{\kappa(1-\chi)\mu} = 0.95$. Since our estimates for this latter elasticity range from 0.94 to 1.23, our parameter values match the empirical

[19] As explained in Kim and Vogel (2021), our labor-leisure preferences have a zero income effect, such that the Marshallian labor supply elasticity equals the Hicksian one. Chetty (2012) focuses on the latter.

[20] Our setup is not identical to Shimer (2005) and Barnichon and Figura (2015), who employ a dynamic setting where only the currently unemployed are considered to be job applicants. In our static model, all workers are considered applicants.

Table 2: Parameter Estimation

(a) Estimation of $\frac{1}{\mu}$

	(1) $\ln \hat{h}_g$	(2) $\ln \hat{h}_g$	(3) $\ln \hat{h}_g$	(4) $\ln \hat{h}_g$
$\ln \hat{i}_g$	0.94***	0.32***	1.04***	0.40***
	(0.24)	(0.10)	(0.28)	(0.14)
Implied μ	1.07	3.12	0.96	2.48
F-First Stage	18.1	15.6	14.1	8.53
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

(b) Estimation of $-\frac{1}{\kappa}$

	(1) $\ln \hat{i}_g$	(2) $\ln \hat{i}_g$	(3) $\ln \hat{i}_g$	(4) $\ln \hat{i}_g$
$\sum_s \pi_s^{hours} \ln \hat{\pi}_{gs}^{hours}$	-0.44***	-0.48***		
	(0.11)	(0.096)		
$\sum_s r_s \ln \hat{\pi}_{gs}^{income}$			-0.36***	-0.35***
			(0.097)	(0.091)
Implied κ	2.27	2.10	2.81	2.88
F-First Stage	71.4	94.3	53.5	34.2
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

(c) Estimation of $\frac{\chi}{1-\chi}$

	(1) $\ln \hat{e}_g$	(2) $\ln \hat{e}_g$	(3) $\ln \hat{e}_g$	(4) $\ln \hat{e}_g$
$\ln \hat{i}_g \hat{h}_g$	0.39***	0.20***	0.42***	0.27***
	(0.052)	(0.053)	(0.059)	(0.079)
Implied χ	0.28	0.17	0.30	0.21
F-First Stage	39.4	16.9	33.2	11.0
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

Panel (a) presents estimation results for specification (20), where i_g is the average hourly wage and h_g is the average annual supply of hours. Panel (b) estimates specification (22) and Panel (c) specification (23), where e_g is the employment rate and $i_g h_g$ is the average annual income. The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentages are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

elasticity almost perfectly.

In Appendix C, we perform a series of robustness checks: (i) estimation with benchmark instruments, which are too weak for our setting (Table C.1), (ii) estimating κ separately for each sector (Table C.2), obtaining a median κ estimate of 2.17, and (iii) documentation on the Rotemberg weights for each parameter estimate (Tables C.3, C.4, C.5).

5 Counterfactuals

5.1 Calibration

Parameter values From the estimation we obtained values for the labor-side parameters, namely $\kappa = 2.1, \mu = 2.5$ and $\chi = 0.3$. We take values from the literature for ρ and θ. Specifically, for the elasticity of substitution between capital and labor we follow Karabarbounis and Neiman (2014) and set $\rho = 1.28$.[21] We also set a common trade elasticity for all sectors: $\theta = 5$, as in Head and Mayer (2014).

We also calibrate υ, the parameter that regulates the change in productivity arising from an automation shock. To do so, we target the elasticity from Moll et al. (2022) for productivity increases associated with a certain decline in the labor share. Specifically, Moll et al. (2022) parametrize their model such that an automation-induced decline in the labor share of 13% is associated with a productivity increase of 2.4%. In our calibration, targeting this elasticity for the manufacturing sector implies a value of $\upsilon = -1.86$.[22] [23]

[21]This value is in line with the recent estimate of $\rho = 1.35$ in Hubmer (2021).

[22]Equation (45) in the Appendix explains how υ governs the relationship between output increases and automation-induced changes in the labor share.

[23]In addition to calibrating υ in the above manner, in Appendix H we also estimate it by employing an indirect inference procedure that exploits the link between output increases and automation-induced declines in the labor share. We obtain a point estimate of $\upsilon = -2.2$, with a standard error of 0.256. Hence, the 95% confidence interval of our estimate includes the value employed here ($\upsilon = -1.86$). Because the standard error on the indirect inference estimate is substantial and the quantitative results are sensitive to the precise υ value, we prefer to determine υ based on the benchmark productivity effect of automation in Moll et al. (2022).

Shock calibration With these parameter values, we jointly calibrate the automation shock and the China shock for the manufacturing subsectors.[24] First, we model the China shock as changes in China's sectoral productivity ($\hat{T}_{China,s}$). Leveraging Equation (13), we calibrate these productivity shocks such that the model exactly matches the strong growth in Chinese manufacturing exports to the US ($\hat{\lambda}_{China,US,s}$).[25]

Second, for the automation shock, recall that the model predicts that automation leads to a decline in sectoral labor shares ($\hat{\omega}_{US,s}$) – see Equation (12). We therefore calibrate the changes in equipment productivity for US manufacturing sectors such that the model generates exactly the observed $\hat{\omega}_{US,s}$ in these sectors. Here, we categorize all labor-saving technological change under automation, including robotization, computer-driven automation of routine tasks, or other physical or intangible labor-saving technologies.[26]

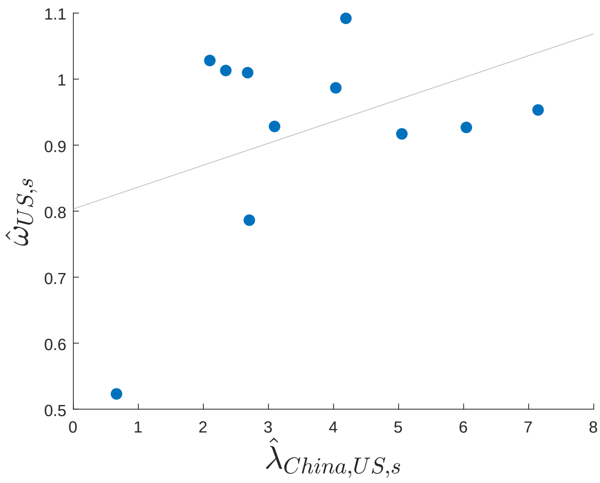
As indicated, the calibration targets for the shocks, namely the changes in the labor shares and the changes in the import shares from China, are also a function of equilibrium changes in factor prices (see Equations (12) and (13)). Since both the automation and the China shock affect these factor prices, both shocks can affect each of the calibration targets (labor shares and import shares from China). Hence, it is essential to calibrate these shocks jointly, which is what we do.

[24]Throughout our simulation analysis, we employ the Alvarez and Lucas (2007) algorithm to find the counterfactual equilibrium. To ensure this algorithm is well behaved, following Ossa (2014) and GRY, we first purge trade deficits from the data using the original Dekle et al. (2008) exercise and then perform the entire analysis on the resulting data with balanced trade.

[25]Equation (13) shows that an increase in $\hat{T}_{China,s}$ leads to an increase in import shares in all destination countries (including the US), taking into account changes in marginal costs. Our shock calibration matches observed import shares in a counterfactual general equilibrium. By design, it therefore incorporates changes in equilibrium prices and wages across all countries and sectors as well as in their marginal costs.

[26]It may not be a conservative modeling choice to map the full changes in the labor share into the automation shock, but we will see below that it provides a very good model fit for the cross-sector and the cross-CZ variation. Moreover, our calibrated value of υ, which governs the productivity increases associated with an automation-induced decline in the labor share, is corroborated by the observed relationship between reductions n the labor share and increases in output (see the υ estimation in Appendix Section H). Hence, our setup does not overstate the productivity gains associated with the observed declines in the labor share. Finally, in Section 5.7, we examine the robustness of our results to targeting the common trend in the labor shares across the US and 11 European countries instead of only the labor share changes in the US. Importantly, the common trends in the labor shares are arguably driven by common technological developments.

Figure 1: Changes in import shares from China and labor shares in US manufacturing



For manufacturing sectors over the period 2000-2007, the figure displays $\hat{\lambda}_{China,US,s}$ and $\hat{\omega}_{US,s}$, which are the targeted moments in our calibration. The correlation between the two variables is 40%.

Figure 1 details the two sets of targeted moments. With one exception, the US import shares for Chinese goods ($\hat{\lambda}_{China,US,s}$) more than double over the period 2000-2007. In fact, in our data, the average import share for manufacturing sectors increased from 1.02% in 2000 to 3.86% in 2007, which entails an increase of 278 percent over seven years. The textile sector, in particular, experienced a substantial increase in the import share, going from 3.8% in 2000 to 15.9% in 2007. Over the same period, the labor share declines by 8.3% on average in the manufacturing sectors. This pattern is not unique to the US since there is a correlation of 50% with the changes in the labor share in 11 European countries for which EU-KLEMS has detailed sector-level data. We return to this observation in Section 5.7. Such a high correlation is consistent with an automation shock common among these advanced economies. Note that there is also a correlation of 40% between the changes in the labor share and the changes in the import share from China.[27]

[27] Interestingly, due to the joint calibration of the China and automation shock, this pattern results in a correlation of 50% between the $\hat{T}_{China,s}$ and $\hat{\xi}_{US,s}$ vectors. Based on the positive correlation between $\hat{\omega}_{US,s}$ and $\hat{\lambda}_{China,US,s}$, and since there is a negative relation between $\hat{\xi}_{US,s}$ and $\hat{\omega}_{US,s}$, we might have expected a negative correlation between the calibrated shocks $\hat{T}_{China,s}$ and $\hat{\xi}_{US,s}$. However, the strong US automation shock in certain sectors, particularly in the petroleum refining sector, requires stronger Chinese productivity growth to match its $\hat{\lambda}_{China,US,s}$ target. This in turn leads to the positive correlation between $\hat{T}_{China,s}$ and $\hat{\xi}_{US,s}$ across manufacturing sectors.

Although these two moments are correlated, in our model, they have very different origins, as we will see in Section 5.4.1.

5.2 Impact of automation and the rise of China

Table 3: Impact of automation and the rise of China across commuting zones

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I}_g/\widehat{P}$	3.96	4.43	0.97	1.24	8.34
$\widehat{i}_g/\widehat{P}$	1.96	2.19	0.48	0.62	4.09
$\widehat{h}_g$	0.78	0.87	0.19	0.25	1.61
$\widehat{e}_g$	1.17	1.31	0.28	0.37	2.43
$\Delta\pi_{gM}$	-0.81	-0.82	0.39	-2.57	-0.02

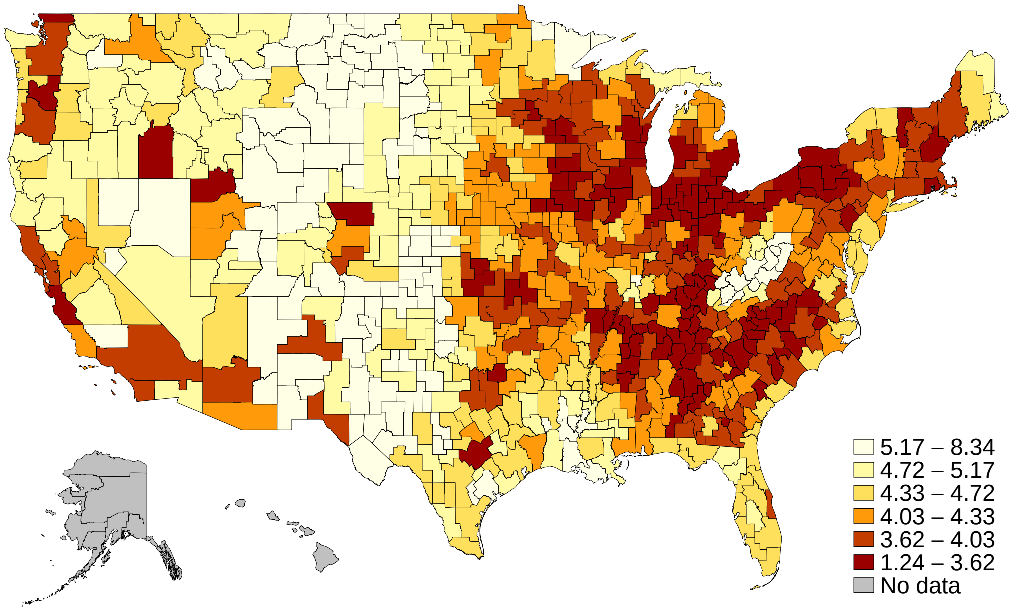
The table shows the impact of automation and the rise of China across US commuting zones. The first row displays the change in average real income, the second on the average hourly wage, the third row on hours worked per employee and the fourth on the employment rate. The final row shows the change in the share of employment in manufacturing. The first column shows the aggregate effect, and the second the average. The third column shows the standard deviation across commuting zones and the fourth and fifth column respectively show the minimum and maximum effect. All variables are measured in percentage changes, except $\Delta\pi_{gM}$ which is measured in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2).

The impact of automation and the rise of China is strongly positive for the US in the aggregate but widely unequal across US commuting zones (see Table 3). At the aggregate level, the US gains 3.96%, but the standard deviation across CZs is elevated at 0.97%. Some CZs gain up to 8.34% while for others this is limited to 1.24%.[28] The strongest concentration of low gains is concentrated around the Rust Belt (see Figure 2). More broadly, the non-coastal regions east of the Mississippi river - or the "Eastern Heartland" in the phrasing of Austin et al. (2018) - mostly experience low gains due to these combined shocks.

Recall that changes in the hourly wage drive changes in a CZ's earnings, hours

[28]When we employ alternative values for θ_s in the simulation, the aggregate gains increase to 4.45% and the standard deviation to 1.76% (please see Appendix Table E.1, Panel a). There, we follow Bartelme, Costinot, Donaldson, and Rodríguez-Clare (2019) and employ the median value for θ_s from the estimations in Caliendo and Parro (2015), Shapiro (2016), Bagwell, Staiger, and Yurukoglu (2018) and Giri, Yi, and Yilmazkuday (2018).

Figure 2: Geographical impact of the automation and China shock



The figure plots the geographic distribution of the percentage changes in groups' average real income for US commuting zones due to the combined effect of automation and the China shock.

worked, and the employment rate. Moreover, if there are only national-level shocks, then changes in a group's total real income ($\hat{I}_g/\hat{P}$) are perfectly correlated with changes in the real hourly wage, hours worked, and the employment rate. Specifically, we then have that

$$\frac{\hat{i}_g}{\hat{P}} = \left(\frac{\hat{I}_g}{\hat{P}}\right)^{\frac{(1-\chi)\mu}{1+\mu}}, \quad \hat{h}_g = \left(\frac{\hat{I}_g}{\hat{P}}\right)^{\frac{1-\chi}{1+\mu}}, \quad \hat{e}_g = \left(\frac{\hat{I}_g}{\hat{P}}\right)^{\chi}. \tag{24}$$

Given our parameter values, this implies that the hourly wage accounts for 50% of the log change in a group's real income, while hours worked and the employment rate respectively account for 20% and 30% of that change. For the US in the aggregate, this results in an increase of the real hourly wage by 1.96%, with a standard deviation of 0.48%, and increases in hours worked and the employment rate by 0.78% and 1.17% respectively (see Table 3). Since the trade and automation shocks occur in manufacturing – a sector that only accounts for 16% of employment in the year 2000, these numbers are substantial.

The change in commuting zones' manufacturing sector ($\Delta\pi_{gM}$) has a correlation of 74% with the income changes.[29] As a result of this high correlation, the manufacturing sector's decline also tends to be concentrated in the Eastern Heartland in general and in the Rust Belt in particular (see Appendix Figure D.3). We find that the aggregate decline in the manufacturing sector is 0.81 percentage points, with a standard deviation of 0.39 and a maximum decline of 2.57 percentage points.

5.3 Examining model fit

For all the different margins of adjustment discussed so far – income,[30] hourly wage, hours worked, employment rate and employment share in manufacturing – our model predictions fit well with the observed variation across commuting zones (see Appendix Figure A.3).[31] To examine the model fit more formally, we regress the observed changes in the data on the model's predicted changes after the combined China and automation shocks (see Table 4). We run this regression with and without control variables for each of the variables of interest. We find that there is a strongly significant positive relationship for all specifications between the model's predictions and the actual changes. To see how much of the variation in the observed changes the model can explain on its own, we focus first on the specifications without controls. There, we explain 28% or more of the variation for changes in hours worked, the employment rate, or the manufacturing share. For average income, the R^2 is 8%, and 4% for changes in the hourly wage. Part of the difference in these R^2 values arises from a stronger presence of outliers for the income variables, which may be due to larger measurement error (see Appendix Figure

[29] While we measure the other variables in Table 3 in percentage terms, we measure the change in the manufacturing employment share in percentage *points* ($\Delta\pi_{gM}$). This is because the variable in percentage terms ($\hat{\pi}_{gM}$) is extremely sensitive to the initial π_{gM}, while $\Delta\pi_{gM}$ is not (see Appendix Figure D.2). The wide variance in $\hat{\pi}_{gM}$ is probably due to measurement error in IPUMS, in particular for low initial values of π_{gM}.

[30] Since all CZs share the same price index, we focus on variation in nominal income in our model fit analysis.

[31] Throughout the model fit exercise, we use our WIOD-adjusted measure for changes in the manufacturing share, since this is the measure we need to employ in the simulations (see end of Section 3). This measure has a correlation of 82% with the raw measure from IPUMS.

A.3, panels a and b).

Table 4: Model fit of variation across commuting zones

	$\ln \widehat{I}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{I}_g$ - Both shocks	2.81	1.81								
	(0.60)	(0.79)								
$\ln \widehat{i}_g$ - Both shocks			1.98	2.81						
			(0.77)	(1.24)						
$\ln \widehat{h}_g$ - Both shocks					8.69	6.95				
					(0.90)	(1.08)				
$\ln \widehat{e}_g$ - Both shocks							4.78	2.95		
							(0.72)	(0.82)		
$\Delta\pi_{gM}$ - Both shocks									3.62	2.16
									(0.31)	(0.33)
R^2	0.08	0.29	0.04	0.20	0.37	0.44	0.29	0.37	0.28	0.43
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in the data for the period 2000 - 2007 on the model's predicted changes after the combined China and automation shock. The first two specifications examine average income, specifications 3 and 4 average hourly wage, specifications (5) and (6) hours worked per employee, specifications (7) and (8) the employment rate, and (9) and (10) the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). The even-numbered specifications include the following controls from ADH: dummies for the nine Census divisions, percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, and the average offshorability index of occupations, where these percentages are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses.

In addition to examining the share of the observed variation explained by the model, we ask if the magnitude of the model-implied changes is in line with the observed changes. This is the case if the estimated regression coefficient is around unity.[32] If the coefficient is larger, the model underpredicts the observed changes because a given change in the model translates into a larger change in the data. Once we add control variables,[33] we cannot reject a unity coefficient for CZ-level income variables ($\ln \hat{I}_g$). However, the degree of underprediction is stronger and significant for the other variablest. This might indicate that we have been too conservative in setting the intensive and extensive margin

[32]See also the model-fit discussion in Adão et al. (2020).

[33]These control variables capture shocks associated with regional fixed effects, the demographic composition of a CZ, the potential for offshorability of the local jobs, or the secular decline in manufacturing.

elasticities and that – if anything – we are underestimating the distributional impact of the shocks. Overall, our model with the combined China and automation shock fits the data quite well, regarding the share of the variation it explains and the magnitude of the predicted values.

In addition to the observed variation for labor market outcomes across CZs, the model also explains a large part of the aggregate decline in manufacturing employment. As is well known, during the period 2000-2007, the share of manufacturing employment in the US declined exceptionally fast, falling from 16.4% to 13% in our data.[34] In our model, the combined China and automation shock leads to a decline by 0.81 percentage points in $\pi_{US,M}$ (see Table 3), which means that our model explains 24% of the total decline in manufacturing employment. Other trends in demand and supply then account for the further erosion of manufacturing employment during this period.[35]

5.4 Comparing the automation and China shocks

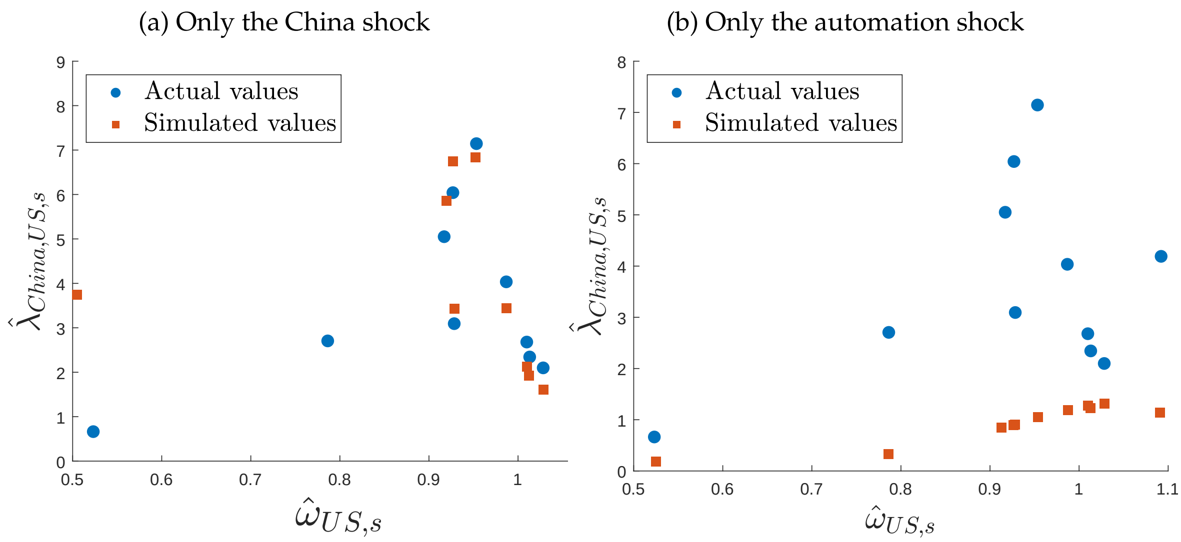
We now examine how the individual China and automation shocks contribute to the combined shock. From the calibration of the joint shock, we have obtained the values for productivity changes in China $(\hat{T}_{China,s})$ and on automation shocks in the US $(\hat{\xi}_{US,s})$. To simulate the counterfactual impact of the individual China shock and the individual automation shock, we therefore separately shock our model with these previously calibrated values for $(\hat{T}_{China,s})$ and $(\hat{\xi}_{US,s})$ respectively.

[34]The measured decline of 3.44 percentage points in the model-based measure is closely in line with the 3.78 percentage point decline in the raw IPUMS data. The difference in magnitude is due to adjusting the data to the WIOD value-added data, which is necessary to make the simulation data internally consistent (see Section 3).

[35]For instance, consistent with the literature on structural change (e.g. Ngai and Pissarides (2007) and Kehoe, Ruhl, and Steinberg (2018)), there has been a substantial downward trend in the consumption share of manufacturing since US final demand for manufacturing falls by two percentage points in our data. Moreover, the increase in global offshoring also negatively affects US manufacturing employment (see e.g. Ebenstein, Harrison, McMillan, and Phillips (2014), Feenstra (2017) and Fort (2017)). Finally, the increase in the US trade deficit also puts downward pressure on manufacturing employment. However, as explained in footnote 24, we remove the impact of trade deficits in our analysis by employing data purged from trade deficits.

5.4.1 Comparison of the sector-specific shocks

Figure 3: Changes in the labor share and imports from China for the individual shocks



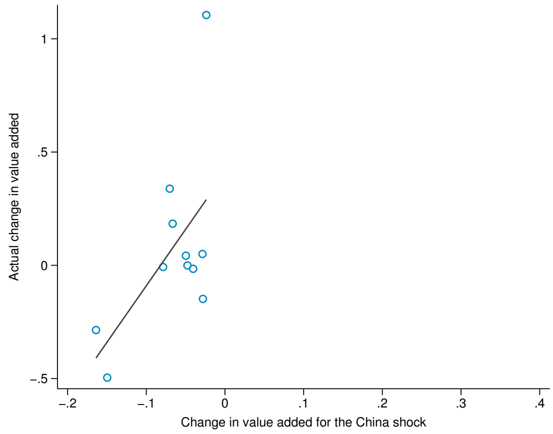
In both panels, the blue circles show the actual values for changes in US import shares from China ($\hat{\lambda}_{China,US,s}$) and the changes in the labor shares ($\hat{\omega}_{US,s}$) for US manufacturing subsectors, while the orange squares depict the simulated values after the China shock (Panel a) or the automation shock (Panel b).

Through the lens of our model, increased Chinese import penetration and changes in sectors' labor shares clearly have different origins (see Figure 3). For the individual China shock, the model completely fails to match the changes in the labor shares (Panel a). Analogously, in response to the individual automation shock, import shares from China tend to fall – sometimes substantially – instead of increase (Panel b).

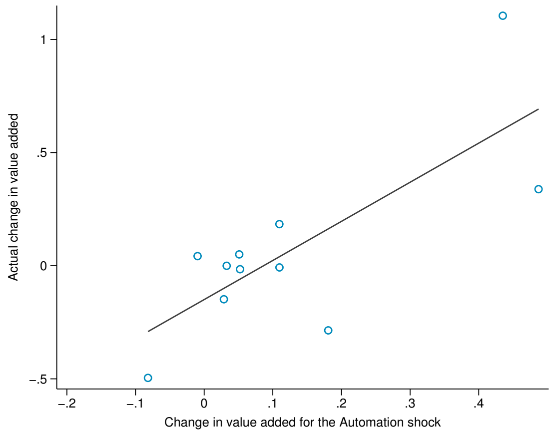
Of course, it may be highly intuitive that US automation does not lead to increased import shares from China and that Chinese technological progress does not induce drastic changes in US sectoral labor shares. In that case, this only emphasizes the need to account for the occurrence of *both* shocks during the period we study. Moreover, the finding that each shock tends to exert downward pressure on the primarily targeted moment for the other shock highlights the importance of *jointly* calibrating the shocks. Specifically, the China shock tends to increase the labor share, while the automation shock tends to

Figure 4: Predicted changes in manufacturing value added for the different shocks

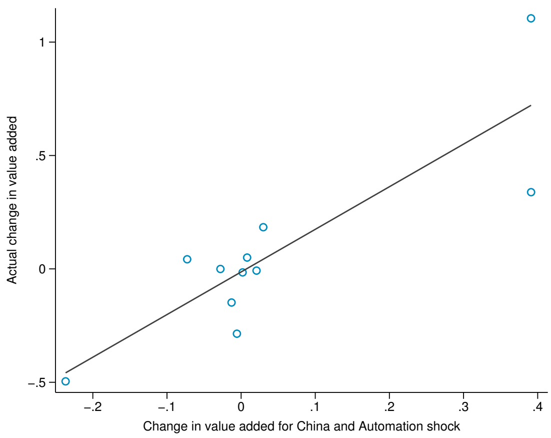
(a) Only the China shock, R^2 = 34%



(b) Only the automation shock, R^2 = 57%



(c) Combined China and automation shock, R^2 = 74%



The figure shows the percentage change in value added ($\hat{V}_{US,s} - 1$) for US manufacturing sectors for each of the shocks listed. The horizontal axis shows the model's predicted changes, while the vertical axis shows the actual changes.

lower imports from China. Hence, ignoring the impact of one shock in the calibration of the other shock leads to a type of omitted variable bias, which we overcome in the joint calibration.

Taking both shocks into account also matters for matching the changes in manufacturing subsectors' value added. Specifically, in a regression of the actual on the predicted changes in value-added, the combined shock yields an R^2 of 74%, which is substantially higher than the values of 34% or 57% for the individual China or automation shocks, respectively (see Figure 4). To understand why, first observe that in reality, roughly half of the manufacturing subsectors experience a decline in value-added, while the other half experience an increase. The individual shocks are unable to match this mixed pattern; the China shock predicts a general decline in manufacturing value-added, while the automation shock predicts an overall increase. Importantly though, when we combine the opposite impact of the individual shocks in the joint shock, the model matches the mixed pattern well (Figure 4, Panel c) and yields a substantially higher R^2.

5.4.2 Aggregate and distributional impact of the individual shocks

Turning to the effect of the shocks on aggregate US real income, we find that the impact of the individual automation shock is more than three times as large as that of the individual China shock, namely 2.90% versus 0.86% (see Table 5).[36] [37] Interestingly, we also find that the impact of the combined shock is 0.20 percentage points larger than the sum of the impact of the individual shocks.

Even though the China shock yields a lower aggregate gain than the automation shock, it leads to stronger distributional effects and a larger decline in manufacturing employment. Specifically, the China shock generates a standard deviation of 0.8 percent

[36] Appendix Table D.1 provides the full breakdown for the different margins of adjustment. As explained in Equation (24), the hourly wage accounts for 50% of the log change in a group's real income, hours worked for 20%, and employment for 30%.

[37] When we employ alternative values for θ_s in the simulation, the gains from automation increase to 3.64% and those from the China shock fall to 0.55% (see Appendix Table E.1). We employ the median value for θ_s from some prominent estimates in the literature, as in Bartelme et al. (2019).

Table 5: Impact of the individual shocks on real income across US commuting zones

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.86	1.47	0.80	-1.71	3.58	-0.60
Only Automation shock	2.90	2.81	0.51	1.44	5.22	-0.28
China and Automation Shock	3.96	4.43	0.97	1.24	8.34	-0.81

The table shows the impact of the individual China shock in the first row, the individual automation shock in the second row, and the combined China and automation shock in the third row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum, and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing in percentage points. Appendix Table D.1 provides the full breakdown of the different margins of adjustment.

in gains across CZs and a drop in manufacturing employment of 0.6 percentage points. This compares to a standard deviation for the gains of 0.51 percent and a manufacturing decline of 0.28 for the automation shock.[38]

We also find that the distributional impact of the combined shock (measured in variance) is slightly larger than the sum of the effect of the individual shocks. This is due to the income changes for the two shocks being positively correlated (at 8.7% - see Appendix Figure D.1), which implies the variance of the combined shock is larger than the sum of the variance of the individual shocks.[39]

Given the positive but imperfect correlation of the two shocks, the geographic incidence of the China shock and the automation shock is related but far from identical. For instance, the Midwest tends to receive low gains for both shocks. At the same time, the central and southern Appalachians have low gains for the China shock but relatively more positive effects for automation (see Appendix Figures D.5 and D.6). These latter regions have relatively high employment shares in the textile sector – the sector most negatively affected by the China shock – but very little employment in the sectors hit by

[38]Interestingly, the model-predicted income changes due to these two shocks are strongly correlated with closely related reduced-form measures. Specifically, the predicted income changes after the China shock have a correlation of -50% with the ADH China shock instrument, while the predicted income changes due to automation have a correlation of -24% with the Acemoglu and Restrepo (2020) robotization shock.

[39]The correlation in the income changes for the individual China and automation shocks is driven by the size of the manufacturing sector in a CZ. Specifically, when we regress the income change due to one shock on the income change due to the other shock, we obtain a significantly positive coefficient. However, this coefficient turns negative, and significantly so, when we control for the size of a CZ's manufacturing sector.

automation (coke and refined petroleum products).

5.4.3 Model fit across commuting zones for the different shocks

In Table 6, we run the model fit for the same variables as before in Table 4, but now for the individual shocks. Specifically, in the odd columns, we regress the observed values on the predicted changes for both the individual China and the individual automation shock. For comparison, we repeat the analysis from Table 4 for the combined shock in the even columns.

For the specifications with the predictions from both individual shocks, all coefficient values are positive and, with few exceptions, also statistically significant. Hence, just as for the combined shock, also for the individual shocks, there is a positive and usually significant correlation between the observed values in the data and the predictions from the model. This corroborates our model predictions for the individual shocks.

In turn, these significant correlations are reflected in substantial R^2 values for the specifications with the two shock predictions, implying that the model is empirically relevant for explaining the observed variation. More precisely, the R^2 for these specifications tends to be slightly higher than the R^2 for the combined shock. For instance, for CZ income ($\hat{I}_g$) or the employment rate ($\hat{e}_g$), the R^2 for the specification with both shocks is 12% and 31% respectively, while it is 8% and 29% for the specification with the combined shock.

Recall that the regression coefficient should be equal to unity for the model to match the magnitude of the variance in the data. There are several cases where we cannot reject this null hypothesis, e.g. for both shock's predictions on the hourly wage ($\hat{i}_g$), for the China shock's predictions on CZ income, or for automation's predictions on the change in manufacturing employment ($\Delta\pi_{gM}$).

In the other cases, there is some significant underprediction. In part, this could be because the model is understating certain aspects of the labor market impacts of the

Table 6: Model fit of the separate shocks

	$\ln \widehat{I}_g$ (1)	$\ln \widehat{I}_g$ (2)	$\ln \widehat{i}_g$ (3)	$\ln \widehat{i}_g$ (4)	$\ln \widehat{h}_g$ (5)	$\ln \widehat{h}_g$ (6)	$\ln \widehat{e}_g$ (7)	$\ln \widehat{e}_g$ (8)	$\Delta\pi_{gM}$ (9)	$\Delta\pi_{gM}$ (10)
$\ln \widehat{I}_g$ - China	1.14									
	(0.85)									
$\ln \widehat{I}_g$ - Automation	6.08									
	(1.39)									
$\ln \widehat{I}_g$ - Both shocks		2.81								
		(0.60)								
$\ln \widehat{i}_g$ - China			1.62							
			(0.75)							
$\ln \widehat{i}_g$ - Automation			2.58							
			(1.48)							
$\ln \widehat{i}_g$ - Both shocks				1.98						
				(0.77)						
$\ln \widehat{h}_g$ - China					10.01					
					(1.01)					
$\ln \widehat{h}_g$ - Automation					5.25					
					(1.26)					
$\ln \widehat{h}_g$ - Both shocks						8.69				
						(0.90)				
$\ln \widehat{e}_g$ - China							5.26			
							(0.79)			
$\ln \widehat{e}_g$ - Automation							3.41			
							(1.10)			
$\ln \widehat{e}_g$ - Both shocks								4.78		
								(0.72)		
$\Delta\pi_{gM}$ - China									4.55	
									(0.44)	
$\Delta\pi_{gM}$ - Automation									1.89	
									(0.51)	
$\Delta\pi_{gM}$ - Both shocks										3.62
										(0.31)
R^2	0.12	0.08	0.04	0.04	0.41	0.37	0.31	0.29	0.31	0.28
Controls	No	No	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in CZs' labor market outcomes in the data for the period 2000 - 2007 on the model's predicted changes for the different listed shocks. The odd columns regress the observed values on the predicted changes for both the individual China and the individual automation shock. The even columns repeat the analysis from Table 4 for the combined shock. The first two specifications examine average income, specifications 3 and 4 average hourly wage, specifications (5) and (6) hours worked per employee, specifications (7) and (8) the employment rate, and (9) and (10) the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). Standard errors, clustered at the state level, in parentheses.

shock.[40] [41] Alternatively, the model predictions for the different shocks may be correlated with other trends in the economy. When we address this latter issue by introducing controls in our model fit regressions (see Appendix Table D.2), as we also did in Table 4, we indeed notice again that the degree of underprediction falls. In several cases, the coefficient becomes insignificantly different from unity, but not generally so. At the same time, some of the coefficients become insignificant, for instance, the predicted effect of the China shock on CZ income. This is due to the strong correlation of these predictions with CZs' initial manufacturing share. This collinearity problem would raise estimation challenges in a reduced-form setup (see e.g. the estimation results on wage growth in Borusyak et al. (2020)), but does not imply that the China shock has no impact on CZs' income. Indeed, the benefit of our quantitative model is precisely that we can examine the China shock, its impact, and its relation to other shocks without relying only on reduced-form correlations and in isolation from any potential confounds.

Notice also that the predictions for the combined shock always remain statistically significant, in contrast to the predictions for the individual shocks. This is due to the smaller standard errors in case of the combined shock, which arise from the larger variance in the predictions for the joint shock. Therefore, analyzing the impact of the joint shock has the benefit of exploiting all the variation it generates and not being limited to the conditional variation for one shock, holding the impact of other shocks constant.

[40] For instance, Rodríguez-Clare et al. (2022) argue that downward nominal wage rigidity is important for understanding the labor market impact of the China shock, which is in line with our model underpredicting the impact of the China shock on the employment rate and the decline in manufacturing employment. We view incorporating nominal rigidities into the analysis of the joint equilibrium impact of trade and automation shocks as an excellent topic for further research.

[41] There is a strong association between the explanatory power (R^2) of the individual shock (observed in Appendix Table D.3), and its degree of underprediction. This is because a higher correlation, or more precisely the higher covariance, between the model predictions and the observed changes, increases the value of the coefficient estimate. Interestingly, still in Table D.3, the predictions from the combined shock yield a similar R^2 value as the most predictive individual shock but are associated with a lower degree of underprediction. This is because the predictions for the combined shock exhibit substantially larger variance than those of the individual shock, which lowers the estimated coefficient value.

5.4.4 Comparison to reduced-form analyses of trade and automation

As indicated above, our quantitative analysis is inspired by the seminal work on the China shock by ADH and Pierce and Schott (2020), and on robotization by Acemoglu and Restrepo (2020); i.e. the seminal papers that have put the distributional effects of trade and automation across local labor markets on the agenda. In this section, we first ask what the potential benefits are from analyzing these shocks with our general-equilibrium (GE) framework, and afterwards how our findings compare to those influential reduced-form findings.

The first benefit of our GE approach is that it allows for aggregation. Where the above shift-share analyses can only estimate relative effects across CZs, our approach analyzes both the aggregate and the distributional effects across local labor markets. Second, the estimates in our framework have a clear interpretation and are driven by transparent model-based shocks. This way, we also side-step complex identification issues, such as disentangling Chinese supply from US demand shocks as sources for the observed growth in Chinese import penetration or distinguishing exogenous changes in automation technology from endogenous technology adoption. While the above-referenced reduced-form studies carefully address these endogeneity concerns, it remains useful to have a quantitative framework available where these identification issues are side-stepped.

An additional advantage is that our framework estimates the full, unconditional effects of trade and technology shocks. In contrast, the reduced-form analyses necessarily focus on the effects of one shock, holding the other shock constant and conditioning on a further set of control variables. As is clear from above, our analysis can estimate the unconditional effects of both the joint and the individual trade and technology shocks, which makes it substantially more versatile than the reduced-form approaches. Relatedly, in some reduced-form analyses, collinearity issues can arise from including all required control variables for proper identification, e.g. when the shock is strongly correlated with the manufacturing employment share. This challenge does not arise in our setting.

Furthermore, our framework incorporates how shocks to one sector affect other sectors through sectoral labor reallocation and input-output linkages. While reduced-form analyses can attempt to approximate these effects, they may not succeed in capturing the full equilibrium cross-sectoral effects. To illustrate this, in our model, we construct an ADH-style exposure term to increased Chinese import penetration in the US after the joint China and automation shock. We then regress the model's predicted income effects for the individual China shock on this ADH-style exposure term and find that the exposure term explains 44% of the variation in the income effects due to the China shock. While this is substantial, it still means that 56% of the variation is not captured by this reduced-form measure. When we plot the model-based ADH exposure term on a map (see Appendix Figure D.7), we indeed notice a strong correlation with the impact of the individual China shock in our model (see Appendix Figure D.5). However, the latter often finds stronger negative effects in the Great Lakes Region (e.g. Ohio and upstate New York). An important part of the explanation for these differences, is that our model takes into account how the China shock to manufacturing differentially affects the various non-manufacturing sectors.

To sum up, conditional on the validity of our model, our quantitative GE analysis is more comprehensive, more precise, and more versatile than a reduced-form approach. Qualitatively though, our findings are closely in line with those in ADH and Acemoglu and Restrepo (2020), who both find that their respective shocks lead to relative declines in income and employment. Moreover, analogous to Acemoglu and Restrepo (2020), we also find that the distributional effects of the China shock are stronger than those of robotization (see their footnote 27).

Our automation shock is less comparable to the computerization shock in Autor et al. (2015). While this technology shock to routine-task intensive occupations is a type of automation, in manufacturing it primarily occurred in the 1980s and 1990s, i.e. before the

2000-2007 period that we are studying.[42] In addition, the main impact of the computerization shock is occupational polarization: employment mainly declines in routine-task intensive occupations while it stays stable or increases in other occupations. Our current framework is not set up to study the joint impact of trade and automation on occupational polarization, which is a great topic for further research.

5.5 Alternative elasticity of substitution between labor and equipment

There is debate in the macroeconomic literature on how elastic substitution between labor and equipment is; while Karabarbounis and Neiman (2014) and Hubmer (2021) estimate values for the elasticity of substitution (ρ) around 1.3, Oberfield and Raval (2021) argue that ρ is below unity, with a preferred value of $\rho = 0.72$. In our baseline analysis, we followed the former studies by setting $\rho = 1.28$, but here we examine the robustness of our results by setting $\rho = 0.72$. Due to this substantial fall in ρ, as explained in Appendix Section H.1,[43] the effect of automation shocks on productivity would substantially decline – other things equal. However, to ensure that the elasticity of productivity gains associated with automation-induced declines in the labor share remains at the same level as in Moll et al. (2022) – as in our baseline analysis, we now set $\upsilon = 2.4$.[44]

The effects of the combined shock under this scenario are quite close to our baseline results (see bottom row of Table 7). The aggregate gain in real income is now 4.35% and the standard deviation in the gains is 1.28%, compared to 3.96% and 0.97% in the

[42] Autor, Dorn, and Hanson (2013a) argue that their China and technology shocks are largely uncorrelated, which may create tension with our finding that the impact of the trade and automation shocks has a correlation of 8.7%. Our automation shock being distinct from the computerization shock resolves this tension. Moreover, Autor et al. (2013a) obtain a correlation close to zero after weighting CZs by their population. The unweighted correlation between their trade and technology exposure terms is 31%.

[43] Specifically, there we show that:

$$d\ln Y_{s|M_s,Z_s,K_s,N_{ks}} = \left[\upsilon + \frac{(1-\omega_s)}{\rho - 1}\right]\alpha_s d\ln \xi_s,$$

where the second term within the brackets switches sign at $\rho = 1$.

[44] Our value of $\upsilon = 2.4$, implied by the Moll et al. (2022) relation between productivity gains and automation, is close to the value that we obtain in our indirect inference estimation, namely $\upsilon = 2.34$, with a standard error of 0.26 (see Appendix Section H).

Table 7: Counterfactual results on real income across US CZs for $\rho = 0.72$.

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.86	1.35	0.78	-1.89	3.18	-0.59
Only Automation shock	3.51	3.76	1.04	-3.13	7.88	-0.77
China and Automation Shock	4.35	5.12	1.28	-1.74	8.07	-1.36

For the model with $\rho = 0.72$, the table shows the impact of the individual China shock in the first row, the individual automation shock in the second row, and the combined China and automation shock in the third row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum, and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing in percentage points.

baseline. In addition, the correlation in the welfare effects across the two versions of the model is substantial, at 41.5% (see Appendix Figure E.1). As a result, the model fit results are also fairly similar, as discussed in Appendix E.1.

5.6 Heterogeneity across education groups

In this section, we examine the heterogeneous effects of trade and automation on workers with different education levels. To this end, we split each CZ into two groups, consisting of workers with or without some college education.

Estimation Before turning to our counterfactual analysis, we re-estimate the labor-side parameters of the model for each education group. Specifically, we proceed as in the estimation in Table 2, but we estimate each specification separately for workers without or with some college education. Appendix Table E.3 has the results. There, we typically do not find strong patterns of heterogeneity across education groups, and the confidence intervals of the estimates usually overlap. As preferred values for μ and χ, we take the average estimate of the two specifications that include controls but have different instrument construction. This results in the following values for non-college workers: $\mu_{NC} = 2.845, \chi_{NC} = 0.185$; and these for college workers: $\mu_{CO} = 3.925; \chi_{CO} = 0.172$. Hence, these two worker types exhibit a highly similar employment elasticity (χ), while non-college workers have a more elastic intensive margin labor supply elasticity $(1/\mu)$

than college workers. Finally, we obtain that $\kappa_{NC} = 1.445$ and $\kappa_{CO} = 2.105$.

Welfare effects For the counterfactual exercise, aside from the estimated parameter values mentioned above, we return to our baseline calibration with $\rho = 1.28$, and $\upsilon = -1.86$. Table 8 then reports the results for the joint shock. Compared to our baseline results, we now obtain aggregate gains for the combined shock that are 0.86 percentage points lower, at 3.1%. This is mainly due to the lower values for the extensive and intensive margin elasticities (χ and $1/\mu$), which entails lower amplification effects of the shocks.

We do not find substantial heterogeneity in terms of the aggregate effects of the joint shock on non-college versus college workers (see Table 8). However, for college workers, the distributional effects are smaller than for non-college workers, with respective standard deviations in the welfare effects of 0.65% and 1.16%. A first reason is that college workers have a higher reallocation elasticity. Second, since a group's exposure to the joint shock depends mainly on the size of its overall manufacturing sector, this difference in the distributional effects is also due to non-college workers exhibiting a higher standard deviation in their initial share of manufacturing employment across CZs (10.3% versus 6.6%). Specifically, 22.6% of the non-college groups have at least 30% of their workforce employed in manufacturing, compared to 1.5% of college groups for which this is the case.

Turning to the individual shocks, we find that college workers gain slightly more from the automation shock (2.33% versus 2.14% for non-college workers; see Appendix Table E.4). That is because they tend to be less employed in manufacturing, where workers tend to be negatively exposed to automation, and more in services, where employees reap the benefits from automation in manufacturing due to consumer gains. In contrast, college workers gain somewhat less from the China shock (0.60% vs. 0.83% for non-college workers; see Appendix Table E.5). This is because college workers are less specialized in the primary sectors, which gain substantially from the China shock due to increased export demand in these sectors.

One reason our model does not generate strongly different effects for college versus non-college workers, is that here, automation is not biased toward a particular education group. To examine education-biased automation in our setup, one could introduce a CES production function with college and non-college labor as imperfect substitutes (as in Section 7.2 in GRY), where equipment is a stronger substitute for one of the education groups. We leave this exercise for further research.

Table 8: Heterogeneity across education groups for the combined shock

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
All groups	3.10	3.56	0.94	-0.43	7.53	-0.78
Non-college workers	3.12	3.58	1.16	-0.43	7.53	-0.77
College workers	3.10	3.53	0.65	1.09	6.58	-0.78

The table shows the impact of the combined China and automation shock for the model with groups defined by commuting zone and education level (some college education or not). The first row shows the effect of the shock on all groups in the top row, on the groups where workers have no college education in the middle row, and on groups with college education in the bottom row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum, and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing in percentage points.

5.7 Alternative shock calibration

So far, we have calibrated the China shock and the automation shock by respectively matching changes in US import shares from China and changes in US labor shares. Since neither increased imports from China nor automation are unique to the US, in this section, we can examine the robustness of our calibration by focusing on common trends across advanced economies. To this end, we return to our baseline model with a single group per CZ and $\rho = 1.28$, and we perform this analysis in Appendix Section E.3. There, we continue to find that the China shock has the lowest aggregate and the strongest distributional effects.

6 Conclusion

This paper presents a gravity model to examine the aggregate and distributional effects of sector-specific trade and automation shocks on US commuting zones. After transparently estimating the key labor-supply elasticities, the model predictions for the calibrated China and automation shocks match well with both the observed labor market outcomes across CZs and the pattern of value-added growth across manufacturing subsectors. This contrasts with the model fit for the individual China or automation shocks, which generate a mismatch for the pattern of value-added growth in manufacturing. Moreover, since the China and automation shocks are correlated, the individual shocks underpredict the magnitude of the observed variation in income changes across CZs. Taken together, our model provides a more comprehensive understanding of trends in inequality across local labor markets compared to existing quantitative papers that focus on a single shock.

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Appendix A Supplementary Tables and Figures

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Table A.1: List of Roman symbols in the model

Symbol	Description
A_{ogs}	Level parameter of the Roy-Fréchet distribution
A_{ogs}^{M}	Efficiency of the matching between workers and employers
c_{os}	Marginal cost of Y_{os}
e_{ogs}	Employment rate
D_d	Trade deficits
F_{os}	Lower-level CES production function with inputs Z_{os}, M_{os}
G_o	Number of groups
h_{og}	Average hours worked per worker
I_{ogs}	Nominal revenue
i_{og}	Average hourly wage rate
K_{os}	Structures, as input in production of Y_{os}
L_{og}	Measure of workers
M_{os}	Equipment, as input in production of F_{os}
N_{oks}	Intermediate inputs in production of Y_{os}
N	Number of sectors
P_o	Price of the final good
R_{os}	Total revenue
S	Number of sectors
T_{os}	Level parameter of the EK-Fréchet distribution
U_{og}	Utility
$\widetilde{V}_{ogs}$	Number of vacancies
V_d	Value added
w_{os}	Wage per effective labor unit
X_{ds}	Expenditure
Y_{os}	Physical output
Z_{ogs}	Supply of effective labor units
z_s	Number of effective units of labor for any worker

Table A.2: List of Greek symbols in the model

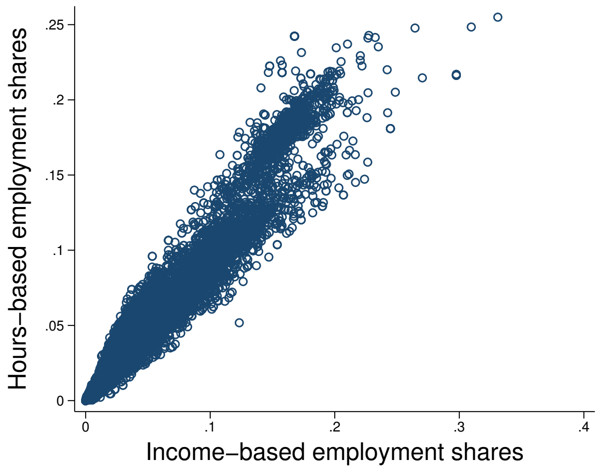
Symbol	Description
α_{os}	Cobb-Douglas share for F_{os} in production of Y_{os}
β_{ds}	Expenditure shares in consumption
Γ	Gamma function
γ_{oks}	Cobb-Douglas share for N_{oks} in production of Y_{os}
δ_{og}	Relative utility weight on consumption versus hours worked
ζ_{os}	Share of structures in the total value of structures and equipment
η	$\Gamma(1 - \frac{1+\mu}{\mu\kappa})$
$\grave{\eta}$	$\Gamma(1 - \frac{1}{\mu\kappa})$
$\tilde{\eta}_s$	$\Gamma(1 - \frac{\sigma_s - 1}{\theta_s})^{1/(1-\sigma_s)}$
θ_s	Dispersion parameter of the EK-Fréchet distribution
κ	Dispersion parameter of the Roy-Fréchet distribution
λ_{ods}	Trade shares
μ	Inverse of the intensive margin labor-supply elasticity
ν_{og}	Nash bargaining share of workers
ξ_{os}	Automation and productivity shifter
π_{og}	Sectoral employment shares
ρ	Elasticity of substitution between labor and equipment
σ_s	Elasticity of substitution across varieties
τ_{ods}	Iceberg trade costs
υ	Elasticity regulating productivity changes driven by automation
Φ_{og}	Index of sectoral wages
χ	Elasticity of the employment rate to labor market tightness
ψ_{ogs}	Labor market tightness
ω_{os}	Cost share of labor in production of F_{os}

Table A.3: Sector classification: overview and summary statistics

Sector	Sector Name	$\beta_{US,s}$	$\pi_{US,s}$	$\alpha_{US,s}$	$\omega_{US,s}$	$\gamma_{US,s}$
A	Agriculture, forestry, and fishing	0.004	0.011	0.287	0.755	0.593
B	Mining and quarrying	0.003	0.007	0.219	0.772	0.486
10-12	Food, beverages and tobacco	0.032	0.013	0.221	0.598	0.701
13-15	Textiles, apparel, and leatherware	0.014	0.007	0.289	0.838	0.668
16-18	Wood, paper, and printing	0.004	0.019	0.344	0.849	0.629
19	Coke and refined petroleum products	0.008	0.002	0.168	0.289	0.758
20-21	Chemical industry	0.013	0.013	0.355	0.464	0.578
22-23	Rubber, plastics, and other non-metallics	0.003	0.012	0.347	0.708	0.598
24-25	Basic metals and metal products	0.003	0.021	0.354	0.776	0.596
26-27	Electrical and optical equipment	0.032	0.030	0.381	0.735	0.576
28	Machinery and equipment	0.016	0.015	0.357	0.779	0.607
29-30	Transport equipment	0.041	0.023	0.293	0.698	0.668
31-33	Other manufacturing; repair and installation	0.016	0.012	0.445	0.762	0.495
D-E	Electricity, gas and water supply	0.019	0.013	0.238	0.664	0.498
F	Construction	0.074	0.061	0.471	0.897	0.490
G	Wholesale and retail trade, vehicle repair	0.124	0.131	0.503	0.820	0.298
H	Transportation and storage	0.018	0.037	0.394	0.935	0.481
I	Accommodation and food services	0.036	0.029	0.402	0.875	0.441
J	Information and communication	0.054	0.055	0.414	0.732	0.514
K-L	Financial and insurance activities	0.154	0.076	0.182	0.937	0.372
M-N	Professional and administrative services	0.039	0.121	0.525	0.847	0.373
R-S	Arts and entertainment, other services	0.028	0.033	0.517	0.913	0.338
O-P-Q-T-U	Social and personal services	0.262	0.260	0.562	0.959	0.344

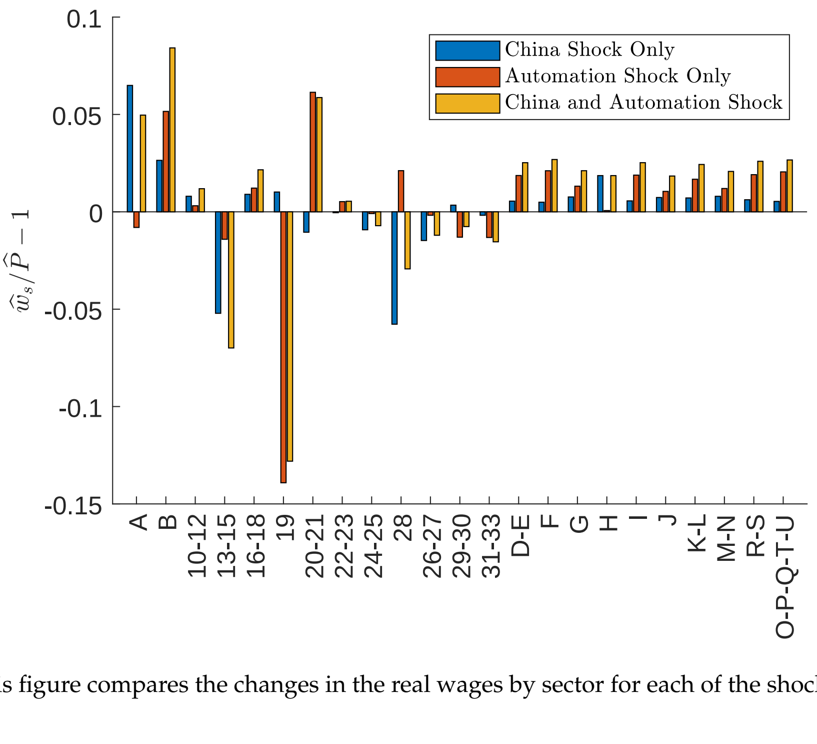
This table lists the sector classification used in our estimation and simulations. For each sector, the table provides the value in the US for the listed parameter in the year 2000.

Figure A.1: Comparison of π_{gs} measures



The figure compares different measures of sectoral employment shares (π_{gs}) for US commuting zones used in our estimation. On the horizontal axis, we have employment shares calculated based on labor income in each sector (π_{gs}^{income}), while on the vertical axis the shares are calculated based on the number of hours worked in a sector (π_{gs}^{hours}). The correlation between the two measures is 97%.

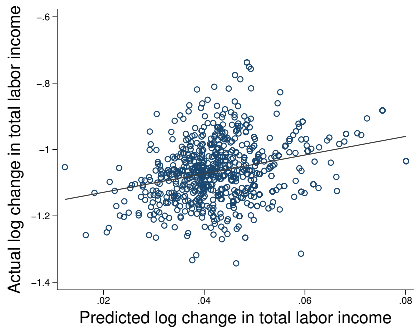
Figure A.2: Pattern of the wage changes for the different shocks



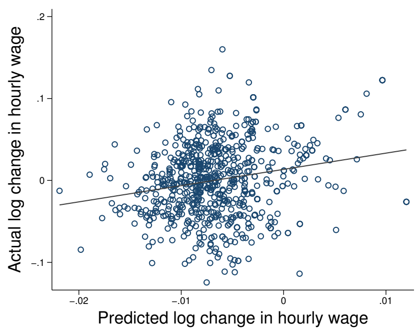
This figure compares the changes in the real wages by sector for each of the shocks.

Figure A.3: Fit of model's predicted changes to non-targeted moments

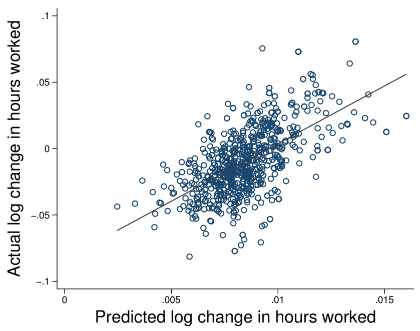
(a) $\ln \hat{I}_g$; correlation = 28%



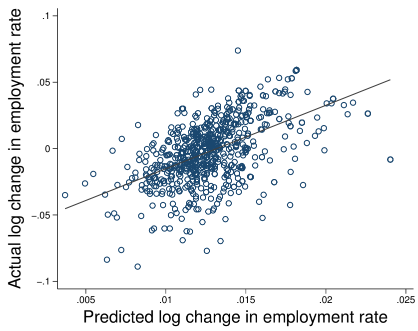
(b) $\ln \hat{i}_g$; correlation = 20%



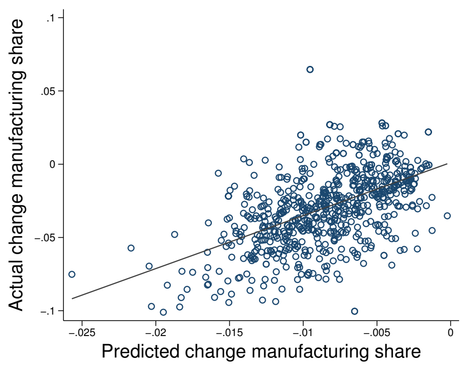
(c) $\ln \hat{h}_g$; correlation = 61%



(d) $\ln \hat{e}_g$; correlation = 54%



(e) $\Delta\pi_{gM}$; correlation = 54%



The table plots the observed values against the model's predicted values for log changes in CZs' income (I_g), average hourly wage (i_g), hours worked (h_g), employment rate (e_g), and manufacturing share (π_{gM}). In contrast to the other variables, the change in the manufacturing share is measured in percentage points.

Online Appendices for:

The unequal effects of trade and automation across local labor markets

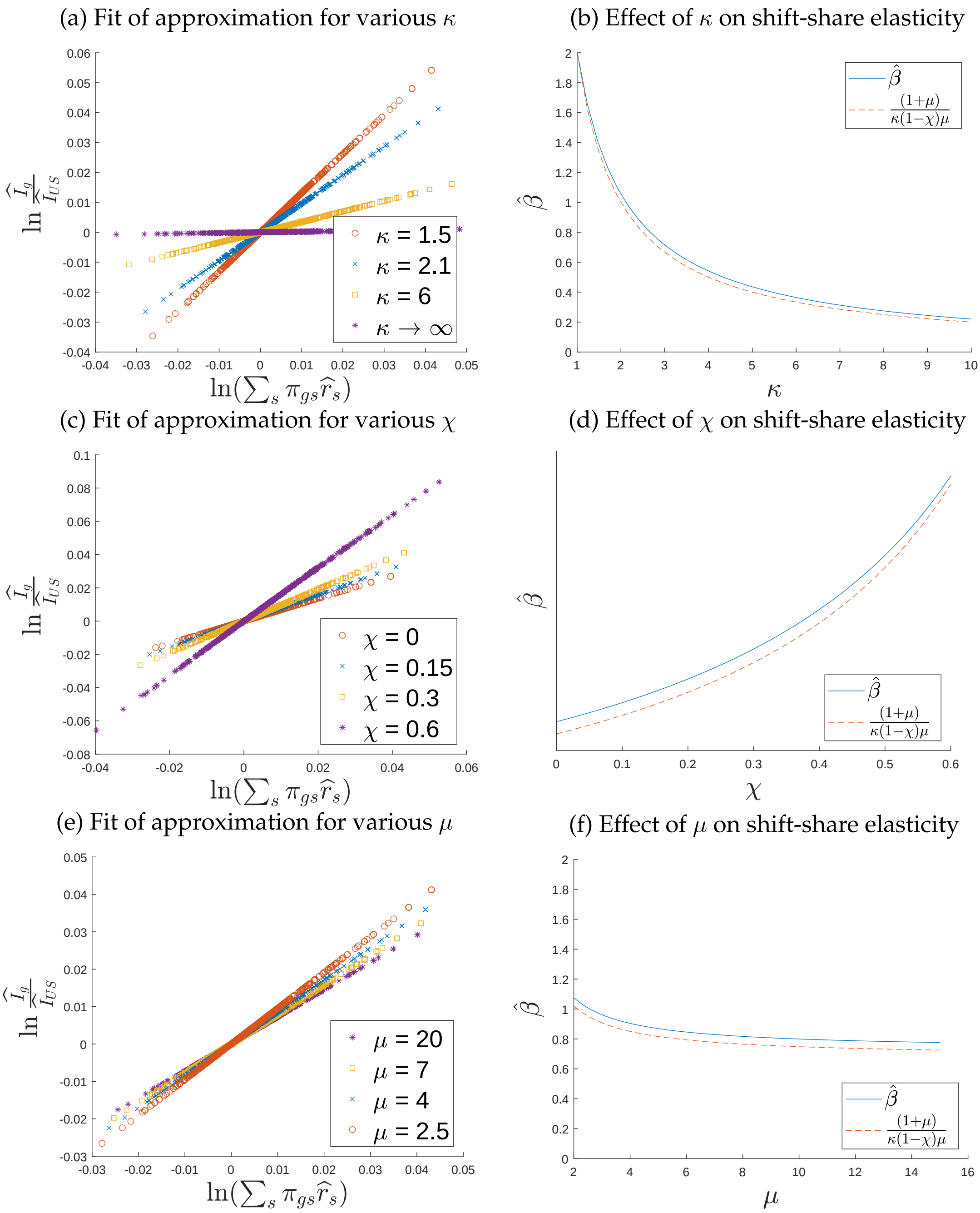
Appendix B Shift-share approximation: supplementary results

As explained in the main text, while other shift-share estimations typically hinge on isolating the impact of one particular shock in their estimation (e.g. only the China shock or only robotization), this is not the case for our shift-share variable since it incorporates all national-level shocks. We therefore estimate specification (19) using OLS.

What would bias our estimation, however, is if the error term (the *local* productivity shock, $\ln \hat{A}_g$) would be correlated with the regressor. To mitigate concerns about such bias, we control for potential trends in local productivity associated with a standard set of covariates from ADH, consisting of region-fixed effects and variables on demographic and industrial composition. In addition, we also analyze which sectors have the highest Rotemberg weights in our estimation, as in Goldsmith-Pinkham et al. (2020). We find that sectors B (mining and quarrying), M-N (professional, scientific, technical, and administrative services), and K-L (financial and real estate activities) tend to have the highest Rotemberg weights. Hence, productivity shocks correlated with the employment shares for these industries are the most important sources of potential bias (see Appendix Tables B.1 and B.2). If these productivity shocks are positively correlated with the industry shares, it will lead to an upward bias of our estimates and vice versa.

As a check for whether pre-trends are driving these findings, we run a placebo regression where the right-hand side remains identical to Equation (19), and where we have replaced the baseline left-hand side with the value for the previous census period (1990-2000). The results from our placebo regression indicate that pre-trends are absent; instead of the strongly positive relationship in the actual estimation, we find an insignif-

Figure B.1: Evaluating the performance of the model's shift-share approximation



The panels on the left show that, for different values of κ, χ and μ, in our simulations the shiftshare approximation in Equation 18 is almost perfectly linear for US commuting zones. The panels on the right first estimate $\ln \hat{I}_g = \alpha_{ss} + \beta_{ss} \ln\left(\sum_s \pi_{gs}\hat{r}_s\right) + \varepsilon_{ss,g}$ on the simulated data for the plotted values of the parameters and obtain a coefficient that is close to the model-implied value of $(1+\mu)/(\kappa(1-\chi)\mu)$. Note that the Fréchet distribution requires $\kappa > (1+\mu)/\mu$, but the counterfactual simulations still function when this condition is violated.

icant negative relationship between our shift-share variable and income growth in the pre-period (see Appendix Table B.3).

To further remove concerns about pre-trends driving our results, we run an additional robustness check where we add the changes in income from the pre-period as a control to the original specification in Equation (19). The resulting estimation results are highly similar to the baseline results, with point estimates between 0.86 and 1.20 and a maximal standard error of 0.23 (see Appendix Table B.4).

To shed light on which national shocks contribute to the variation in our shift-share variable, we regress it on some prominent trade or technology shocks from the literature in Appendix Table B.5. Specifically, we regress it on the ADH China shock, the computerization shock from Autor et al. (2015), and the robotization shock from Acemoglu and Restrepo (2020). All three shocks have a significant negative impact on our shift-share variable. The R^2 of the combined shocks for our shift-share variable is 40% (Panel a, columns 4 and 8), which indicates that our shift-share variable is indeed capturing these standard trade and technology shocks but that other shocks also contribute to the variation in our shift-share variable. When we add control variables to the specification, the relationship of the shocks with the shift-share variable becomes slightly weaker but typically continues to be at least borderline significant. In addition to our OLS estimation, we could, in principle, also perform an IV estimation with these trade and technology shocks as instruments. However, we have a weak first stage in all the specifications with controls (F-stat < 5), which is why we do not focus on these results. Interestingly, the point estimates are higher for the IV than for the OLS results.

Table B.1: Rotemberg weights for the $\sum_s \pi_{gs}^{hours} \hat{r}_s$

(a) Without controls

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	0.839	1.178	1.825	(1.10,2.50)	150.175	2.080
Agriculture, forestry, and fishing	0.463	0.980	5.013	N/A	11.680	6.644
Professional and administrative services	0.449	1.098	-0.146	(-1.50,0.60)	31.475	6.785
Accommodation and food services	0.413	1.045	0.833	(-0.10,1.30)	36.688	5.045
Financial and insurance activities	0.354	1.145	0.337	(-0.40,0.80)	37.193	6.100

(b) With controls

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	1.188	1.178	2.748	(1.40,3.90)	156.069	2.080
Professional and administrative services	0.526	1.098	-0.267	(-1.20,0.50)	90.200	6.785
Financial and insurance activities	0.501	1.145	-0.000	(-0.90,0.80)	89.585	6.100
Construction	0.244	1.107	-0.021	(-5.60,3.70)	14.777	9.705
Accommodation and food services	0.219	1.045	-0.990	(-5.80,1.30)	22.560	5.045

This table provides the Rotemberg weights for the estimation of our shift-share approximation with $\sum_s \pi_{gs}^{hours} \hat{r}_s$ as an instrument. Here, $\hat{\alpha}_s$ are the Rotemberg weights, $\hat{r}_s$ is the change in the national income share of a sector, $\hat{\beta}_s$ is the coefficient from the just-identified regression with the π_{gs} from this single industry as the instrument, the next column provides the associated weak-instrument robust 95% confidence interval using the method from Chernozhukov and Hansen (2008), $\hat{F}_s$ is the first-stage F-statistic for this estimation, and the final column shows $100\pi_{US,s}$ for this sector. Panels (a) and (b) show the results for the estimation without and with controls, respectively. In contrast to our baseline shift-share estimation, here we first instrument our regressor with its version in levels (i.e. $\sum_s \pi_{ogs} \hat{r}_{os}$). The correlation between $\ln \sum_s \pi_{ogs} \hat{r}_{os}$ and $\sum_s \pi_{ogs} \hat{r}_{os}$ is 99%, so instrumenting one with the other makes no meaningful difference for the estimates. However, the analysis of Rotermberg weights is only applicable to the shift-share variable in levels.

Table B.2: Rotemberg weights for $\sum_s \pi_{gs}^{income} \hat{r}_s$

(a) Without controls

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	1.038	1.178	1.681	(1.00,2.30)	168.718	2.546
Professional and administrative services	0.503	1.098	-0.169	(-1.50,0.60)	29.316	7.896
Financial and insurance activities	0.439	1.145	0.313	(-0.40,0.80)	41.271	7.296
Construction	0.349	1.107	1.080	(0.20,1.90)	31.874	10.136
Agriculture, forestry, and fishing	0.282	0.980	5.520	N/A	6.748	5.387

(b) With controls

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	1.408	1.178	2.415	(1.10,3.50)	186.246	2.546
Financial and insurance activities	0.595	1.145	-0.295	(-1.30,0.50)	84.405	7.296
Professional and administrative services	0.500	1.098	-0.553	(-1.70,0.40)	66.153	7.896
Construction	0.198	1.107	0.493	(-9.10,5.10)	7.402	10.136
Social and personal services	0.187	1.139	-3.086	N/A	2.577	10.684

This table provides the Rotemberg weights for the estimation of our shift-share approximation with $\sum_s \pi_{gs}^{income} \hat{r}_s$ as an instrument. Here, $\hat{\alpha}_s$ are the Rotemberg weights, $\hat{r}_s$ is the change in the national income share of a sector, $\hat{\beta}_s$ is the coefficient from the just-identified regression with the π_{gs} from this single industry as the instrument, the next column provides the associated weak-instrument robust 95% confidence interval using the method from Chernozhukov and Hansen (2008), $\hat{F}_s$ is the first-stage F-statistic for this estimation, and the final column shows $100\pi_{US,s}$ for this sector. Panels (a) and (b) show the results for the estimation without and with controls, respectively. In contrast to our baseline shift-share estimation, here we first instrument our regressor with its version in levels (i.e. $\sum_s \pi_{ogs} \hat{r}_{os}$). The correlation between $\ln \sum_s \pi_{ogs} \hat{r}_{os}$ and $\sum_s \pi_{ogs} \hat{r}_{os}$ is 99%, so instrumenting one with the other makes no meaningful difference for the estimates. However, the analysis of Rotermberg weights is only applicable to the shift-share variable in levels.

Table B.3: Placebo test on pre-trends for the shift-share approximation

	(1) $\ln \hat{I}_{g,t-1}$	(2) $\ln \hat{I}_{g,t-1}$	(3) $\ln \hat{I}_{g,t-1}$	(4) $\ln \hat{I}_{g,t-1}$
$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$	-0.19	-0.56*		
	(0.21)	(0.31)		
$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$			-0.15	-0.39
			(0.21)	(0.32)
Controls	No	Yes	No	Yes
Observations	722	722	722	722

The regressions in this table are a placebo test for the estimation of Equation (19) in Table 1, where the π_{gs} are measured based on hours worked or income. $\hat{I}_{g,t-1}$ is the change in average income per person in the labor force in a CZ in the previous census period (1990-2000), with the unemployed earning zero income. The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Estimating the model-implied shift-share approximation, controlling for pre-trends

	(1) $\ln \hat{I}_g$	(2) $\ln \hat{I}_g$	(3) $\ln \hat{I}_g$	(4) $\ln \hat{I}_g$
$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$	1.20***	1.06***		
	(0.15)	(0.23)		
$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$			1.10***	0.86***
			(0.15)	(0.21)
$\ln \hat{I}_{g,t-1}$	-0.21***	-0.22***	-0.21***	-0.22***
	(0.049)	(0.040)	(0.047)	(0.038)
Controls	No	Yes	No	Yes
Observations	722	722	722	722

The regressions in this table estimate Equation (19) as in Table 1, but now additionally controlling for $\hat{I}_{g,t-1}$, i.e. income growth in the previous census period (1990-2000). The π_{gs} are still measured based on hours worked or income. $\hat{I}_g$ is the change in average income per person in the labor force in a CZ, with the unemployed earning zero income. The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Impact of trade and technology shocks on our shift-share approximation

(a) Without controls

		$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$				$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to the China shock	-0.0056***			-0.0043***	-0.0058***			-0.0043***
	(0.0011)			(0.0010)	(0.0012)			(0.0010)
Exposure to computerization		-0.0042***		-0.0022***		-0.0044***		-0.0022***
		(0.0005)		(0.0006)		(0.0006)		(0.0006)
Exposure to robots			-0.0134***	-0.0060**			-0.0150***	-0.0076***
			(0.0043)	(0.0027)			(0.0045)	(0.0028)
R^2	0.29	0.21	0.16	0.40	0.27	0.21	0.18	0.40
F-stat	25.40	62.66	9.56	35.99	24.77	58.72	11.05	36.31
Controls	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722

(b) With controls

		$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$				$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to the China shock	-0.0007*			-0.0006*	-0.0008*			-0.0008*
	(0.0003)			(0.0003)	(0.0004)			(0.0004)
Exposure to computerization		-0.0011**		-0.0011*		-0.0012*		-0.0010
		(0.0006)		(0.0006)		(0.0006)		(0.0006)
Exposure to robots			-0.0014	-0.0009			-0.0024*	-0.0019
			(0.0011)	(0.0011)			(0.0012)	(0.0012)
R^2	0.77	0.77	0.76	0.77	0.74	0.74	0.74	0.75
F-stat	3.93	4.14	1.66	2.60	3.43	3.46	4.04	3.39
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722

The specifications in this table regress two measures for our shift-share approximation on a prominent set of trade or technology shocks in the literature. Specifically, "exposure to the China shock" is measured as exposure to increased Chinese import penetration to other countries, as defined by ADH; "exposure to computerization" is based on the routine share of occupations as measured in Autor et al. (2015); and "exposure to robots" is measured as in Acemoglu and Restrepo (2020). Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C Parameter estimation: supplementary results

Alternative instruments How do our parameter estimates change if we employ the China shock from ADH or the robotization shock from Acemoglu and Restrepo (2020) as instruments instead of our shift-share variable? Appendix Table C.1 looks into this question. We obtain values for the employment elasticity χ between 0.2 and 0.23, which aligns with our results above. For the intensive margin elasticity, the robotization shock and particularly the China shock yield estimates that are substantially larger than our baseline estimate. For instance, while our preferred value is $1/\mu = 0.4$, the specification with controls with the ADH shock as instrument estimates $1/\mu = 1.11$. Hence, this suggests that our model will understate the intensive margin response to the China shock. Finally, the alternative instruments are too weak for the reallocation elasticity κ, with a first stage F-statistic below 4 in all four specifications. Since the standard rule-of-thumb requires an F-statistic above 10 to ensure sufficiently strong instruments, we refrain from drawing any conclusions from these alternative κ estimates.

Estimation of κ by sector As a robustness check to our main κ estimation, we estimate κ separately by sector. To this end, we invert Equation (21) to obtain:

$$\ln \hat{\pi}_{ogs} = \ln \hat{w}_{os}^{\kappa} - \kappa \ln \hat{i}_{og} + \ln \hat{A}_{ogs}.$$

We use this inverted relationship to sidestep the challenge of a weak first stage when instead having $\ln \hat{\pi}_{ogs}$, which is sensitive to measurement error, as the regressor. In Table C.2, we obtain a median κ estimate of 2.17. Moreover, 17 of our 22 estimates are not significantly different from our baseline value of 2.1, while the five significantly different point estimates have values of 0.23, 0.54, 0.83, 4.06 and -4.14. Overall, our results are therefore well in line with our our baseline κ value. However, the one negative κ value is inconsistent with our Roy-Fréchet framework. To render the model fully con-

Table C.1: Parameter Estimation with the ADH and AR instruments

(a) Estimation of $\frac{1}{\mu}$

	(1)	(2)	(3)	(4)
	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$
$\ln \hat{i}_g$	0.89***	1.11***	0.67***	0.72***
	(0.17)	(0.27)	(0.083)	(0.095)
Implied μ	1.12	0.90	1.48	1.38
F-First Stage	19.3	9.52	28.4	30.9
Instrument	ADH (2013)	ADH (2013)	AR (2020)	AR (2020)
Controls	No	Yes	No	Yes
Observations	1444	1444	1444	1444

(b) Estimation of $-\frac{1}{\kappa}$

	(1)	(2)	(3)	(4)
	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$
$\sum_s r_s \ln \hat{\pi}_{gs}^{income}$	-3.60	-2.58	-110.6	-13.7
	(2.84)	(1.70)	(1827.6)	(26.7)
Implied κ	0.28	0.39	0.0090	0.073
F-First Stage	1.44	2.00	0.0036	0.28
Instrument	ADH (2013)	ADH (2013)	AR (2020)	AR (2020)
Controls	No	Yes	No	Yes
Observations	1444	1444	1444	1444

(c) Estimation of $\frac{\chi}{1-\chi}$

	(1)	(2)	(3)	(4)
	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$
$\ln \hat{i}_g \hat{h}_g$	0.29***	0.29***	0.24***	0.25***
	(0.022)	(0.024)	(0.018)	(0.022)
Implied χ	0.23	0.22	0.20	0.20
F-First Stage	43.4	21.3	42.1	52.7
Instrument	ADH (2013)	ADH (2013)	AR (2020)	AR (2020)
Controls	No	Yes	No	Yes
Observations	1444	1444	1444	1444

This table performs our parameter estimation but now employing either the ADH or Acemoglu and Restrepo (2020) shocks as instruments. Instead of only focusing on the 2000-2007, we now also include the 1990-2000 period in a stacked estimation. Panel (a) presents estimation results for specification (20), where i_g is the average hourly wage and h_g is the average annual supply of hours. Panel (b) estimates specification (22) and Panel (c) specification (23), where e_g is the employment rate and $i_g h_g$ is the average annual income. The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sistent with the data, one would have to introduce more flexible skill distributions into the Roy reallocation setup, see e.g. Adão (2016) and Lorentzen (2022). These alternative modeling strategies sacrifice some tractability to obtain further realism in the within-CZ distributional effects. Since our paper focuses on the between-CZ distributional effects, we prefer the simplicity and transparency of Roy-Fréchet.

Rotemberg weights As suggested by Goldsmith-Pinkham et al. (2020), we calculate the Rotemberg weights for our parameter estimation in Appendix Tables C.3, C.4 and C.5. The industries with the highest weights are Mining and quarrying, Construction, Professional and administrative services, and Agriculture, Forestry, and Fishing. For each industry with a high Rotemberg weight, we run the just-identified IV with only this industry's π_{gs} as an instrument. For the intensive margin elasticity, the first stages of this estimation are typically too weak to infer anything. For the other two parameters, roughly half of the just-identified specifications have a sufficiently strong first stage. For the employment elasticity, we find very similar results, while for the reallocation elasticity, the implied κ is higher.

Table C.2: Estimation of κ by sector

Dependent variable: $\ln \hat{\pi}_{gs}^{hours}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$-\ln \hat{i}_g$	3.12*	7.66	3.53*	8.95	5.87	-0.29	-0.0038	5.35**	-2.45	11.5**	-4.14**	0.65
	(1.74)	(5.58)	(1.90)	(6.56)	(3.66)	(2.44)	(1.75)	(2.41)	(3.53)	(5.32)	(1.96)	(1.08)
F-First Stage	15.6	15.6	15.6	10.6	15.8	15.6	15.6	15.6	15.6	15.6	15.6	15.6
$H_0 : \hat{\kappa} = -2.1$	0.56	0.32	0.45	0.30	0.30	0.33	0.23	0.18	0.20	0.077	0.0014	0.18
Sector Code	10-12	13-15	16-18	19	20-21	22-23	24-25	26-27	28	29-30	31-33	A
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	636	721	722	722	722	722	722	722	722

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
$-\ln \hat{i}_g$	1.65	3.21	0.83	0.54	1.49**	2.17*	1.08	2.98***	4.06***	2.49***	0.23
	(3.19)	(2.08)	(0.61)	(0.45)	(0.75)	(1.14)	(1.49)	(0.77)	(0.97)	(0.95)	(0.72)
F-First Stage	15.7	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6
$H_0 : \hat{\kappa} = -2.1$	0.89	0.59	0.037	0.00055	0.42	0.95	0.49	0.25	0.042	0.68	0.0098
Sector Code	B	D-E	F	G	H	I	J	K-L	M-N	O-P-Q-T-U	R-S
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	721	722	722	722	722	722	722	722	722	722	722

The regressions in this table estimate the following equation separately by sector: $\ln \hat{\pi}_{gs} = \ln \hat{w}_s^{\kappa} - \kappa \ln \hat{i}_g + \ln \hat{A}_{gs}$, and the table reports the κ estimate for each sector. The row labelled $H_0 : \hat{\kappa} = -1.36$ reports the p-value for this hypothesis test. Throughout, π_{gs} is measured based on hours worked and our instrument is $\sum_s \pi_{gs} \hat{r}_s$. Note that $\hat{i}_g$ is the change in average hourly wage rate in a CZ. We always include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Rotemberg weights for the μ estimation

(a) Instrument: $\sum_s \pi_{gs}^{hours} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	2.015	1.178	0.751	N/A	4.311	2.080
Construction	0.612	1.107	-0.893	N/A	1.446	9.705
Professional and administrative services	0.576	1.098	-1.031	(-4.30,-0.50)	7.580	6.785
Agriculture, forestry, and fishing	0.319	0.980	7.362	N/A	0.344	6.644
Financial and insurance activities	0.220	1.145	-0.658	N/A	1.013	6.100

(b) Instrument: $\sum_s \pi_{gs}^{income} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	2.947	1.178	0.748	N/A	4.257	2.546
Construction	0.740	1.107	-0.696	N/A	1.280	10.136
Professional and administrative services	0.647	1.098	-1.341	N/A	3.503	7.896
Arts and entertainment, other services	0.218	0.968	-0.797	N/A	0.907	4.029
Rubber, plastics, and other non-metallics	0.186	0.815	-0.745	N/A	0.812	1.830

This table provides the Rotemberg weights for the estimation of μ in Table 2. Here, $\hat{\alpha}_s$ are the Rotemberg weights, $\hat{r}_s$ is the change in the national income share of a sector, $\hat{\beta}_s$ is the coefficient from the just-identified regression with the π_{gs} from this single industry as the instrument, the next column provides the associated weak-instrument robust 95% confidence interval using the method from Chernozhukov and Hansen (2008), $\hat{F}_s$ is the first-stage F-statistic for this estimation, and the final column shows $100\pi_{US,s}$ for this sector. Panels (a) and (b) show the results for the listed instrument, with controls.

Table C.4: Rotemberg weights for the κ estimation

(a) Instrument: $\sum_s \pi_{gs}^{hours} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Construction	128.393	1.107	-0.120	(-0.30,0.00)	78.699	9.705
Professional and administrative services	59.310	1.098	-0.244	(-0.50,-0.10)	27.424	6.785
Accommodation and food services	57.247	1.045	0.063	(-0.20,0.30)	37.792	5.045
Transport equipment	41.366	0.860	0.287	(-0.10,0.90)	7.430	2.503
Social and personal services	30.752	1.139	-0.023	N/A	3.144	10.177

(b) Instrument: $\sum_s \pi_{gs}^{income} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Construction	29.528	1.107	-0.126	(-0.40,0.00)	46.504	10.136
Professional and administrative services	24.256	1.098	-0.134	(-0.30,0.00)	37.676	7.896
Financial and insurance activities	12.013	1.145	-0.000	(-0.40,0.30)	6.340	7.296
Transport equipment	11.460	0.860	0.313	(-0.20,1.50)	5.246	2.795
Electrical and optical equipment	10.949	0.766	0.046	(-0.10,0.20)	34.639	2.028

This table provides the Rotemberg weights for the estimation of κ in Table 2. Here, $\hat{\alpha}_s$ are the Rotemberg weights, $\hat{r}_s$ is the change in the national income share of a sector, $\hat{\beta}_s$ is the coefficient from the just-identified regression with the π_{gs} from this single industry as the instrument, the next column provides the associated weak-instrument robust 95% confidence interval using the method from Chernozhukov and Hansen (2008), $\hat{F}_s$ is the first-stage F-statistic for this estimation, and the final column shows $100\pi_{US,s}$ for this sector. Panels (a) and (b) show the results for the listed instrument, with controls.

Table C.5: Rotemberg weights for the χ estimation

(a) Instrument: $\sum_s \pi_{gs}^{hours} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	2.672	1.178	0.233	(0.20,0.50)	10.008	2.080
Agriculture, forestry, and fishing	2.022	0.980	0.265	(0.10,0.50)	13.640	6.644
Electricity, gas and water supply	0.170	0.901	0.473	N/A	1.327	1.257
Financial and insurance activities	0.057	1.145	-1.004	N/A	0.084	6.100
Construction	0.050	1.107	-1.102	N/A	0.013	9.705

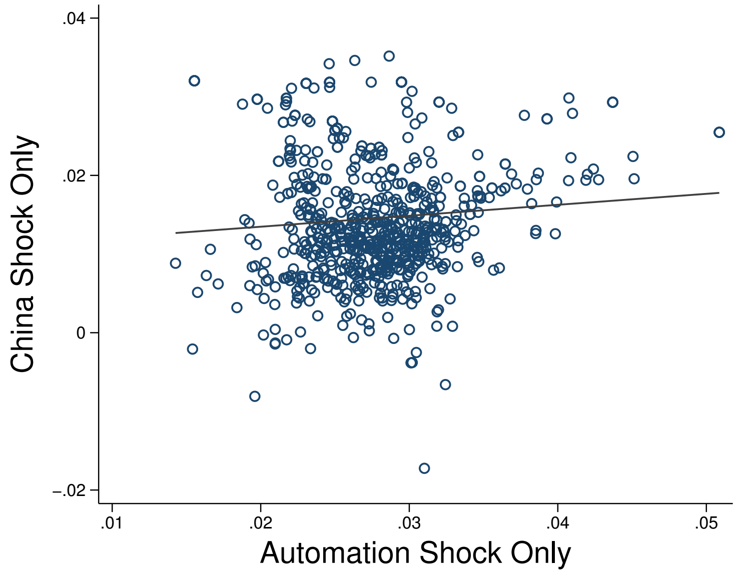
(b) Instrument: $\sum_s \pi_{gs}^{income} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	3.669	1.178	0.234	(0.10,0.50)	9.048	2.546
Agriculture, forestry, and fishing	1.652	0.980	0.287	(0.10,0.70)	9.669	5.387
Electricity, gas and water supply	0.350	0.901	0.456	N/A	1.907	1.810
Construction	0.160	1.107	-0.187	N/A	0.096	10.136
Rubber, plastics, and other non-metallics	0.034	0.815	-2.458	N/A	0.021	1.830

This table provides the Rotemberg weights for the estimation of χ in Table 2. Here, $\hat{\alpha}_s$ are the Rotemberg weights, $\hat{r}_s$ is the change in the national income share of a sector, $\hat{\beta}_s$ is the coefficient from the just-identified regression with the π_{gs} from this single industry as the instrument, the next column provides the associated weak-instrument robust 95% confidence interval using the method from Chernozhukov and Hansen (2008), $\hat{F}_s$ is the first-stage F-statistic for this estimation, and the final column shows $100\pi_{US,s}$ for this sector. Panels (a) and (b) show the results for the listed instrument, with controls.

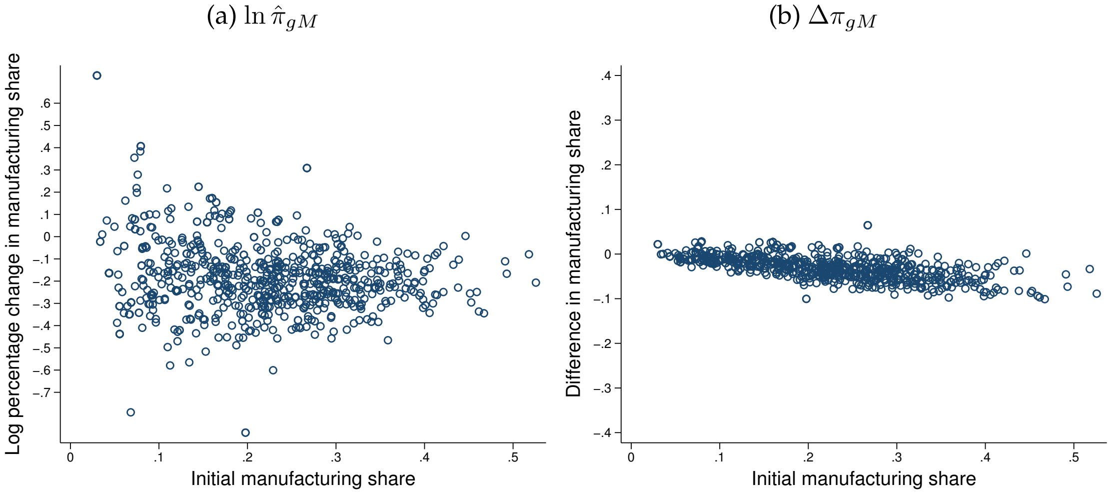
Appendix D Counterfactual analysis: further results

Figure D.1: Predicted $\ln \hat{I}_g$ for the individual automation and China shocks.



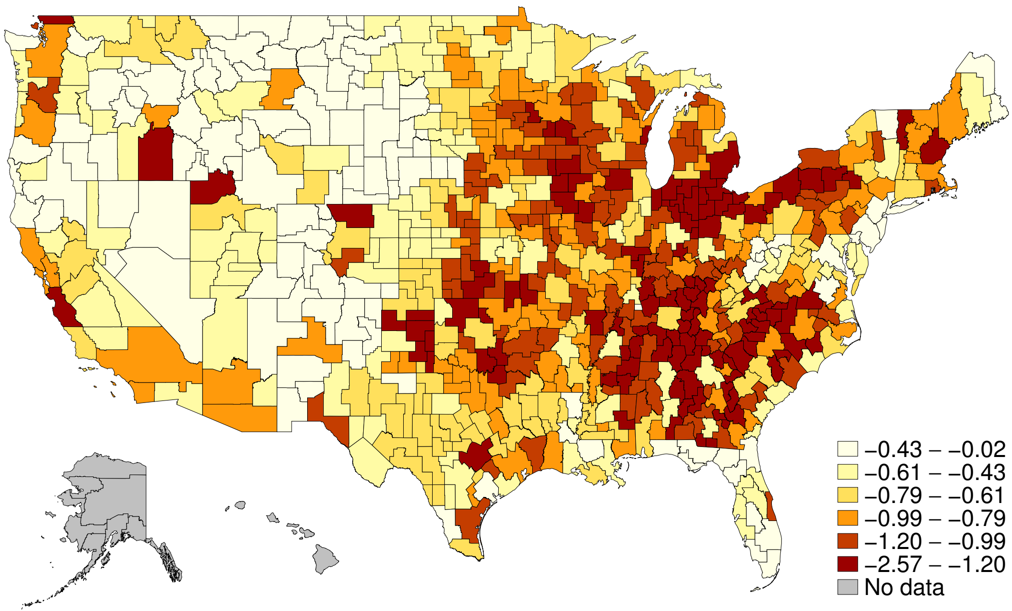
This figure shows the predicted $\ln \hat{I}_g$ for the individual automation shock (horizontal axis), and the individual China shock (vertical axis). The correlation in $\hat{I}_g$ across the two shocks is 8.7%.

Figure D.2: Measurement of change in manufacturing share



The figure demonstrates that there is large variance in the actual $\ln \hat{\pi}_{gM}$, in particular for low initial π_{gM}. In part, this is due to measurement error in IPUMS. In contrast the variance in $\Delta \pi_{gM}$ is far more mitigated in the data, and – in stark contrast to $\ln \hat{\pi}_{gM}$ – is close to zero for low initial π_{gM}.

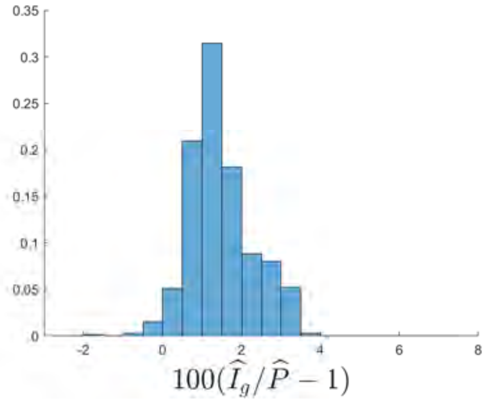
Figure D.3: Decline in the manufacturing share due to automation and the China shock



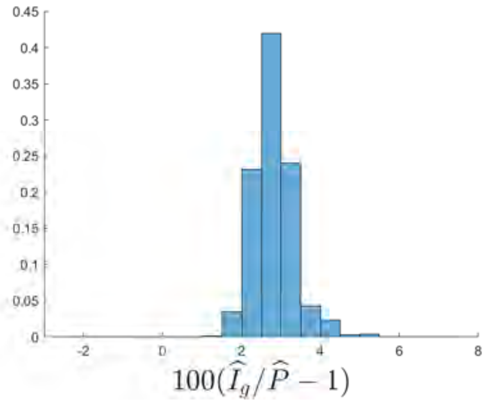
The map plots the predicted $\Delta \pi_{gM}$ after the combined China and automation shock.

Figure D.4: Distribution of the income changes for the different shocks

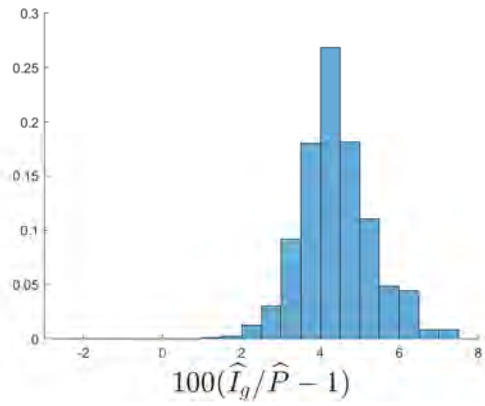
(a) Only the China shock



(b) Only the automation shock

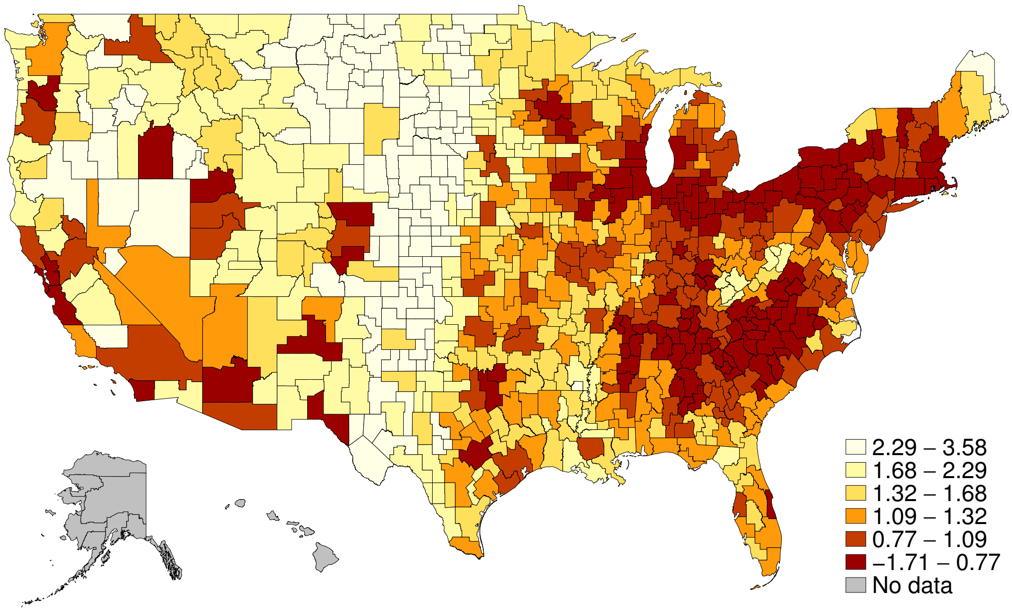


(c) Combined China and automation shock



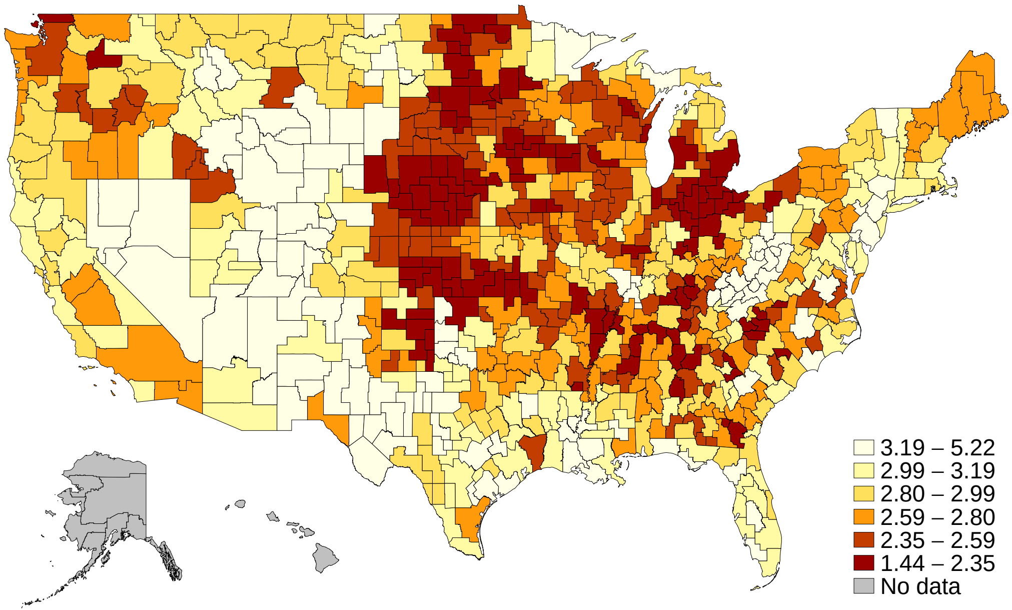
The histograms plot the distribution of the changes in CZs' real income, for the shocks listed in each panel.

Figure D.5: Change in real income due to the China shock



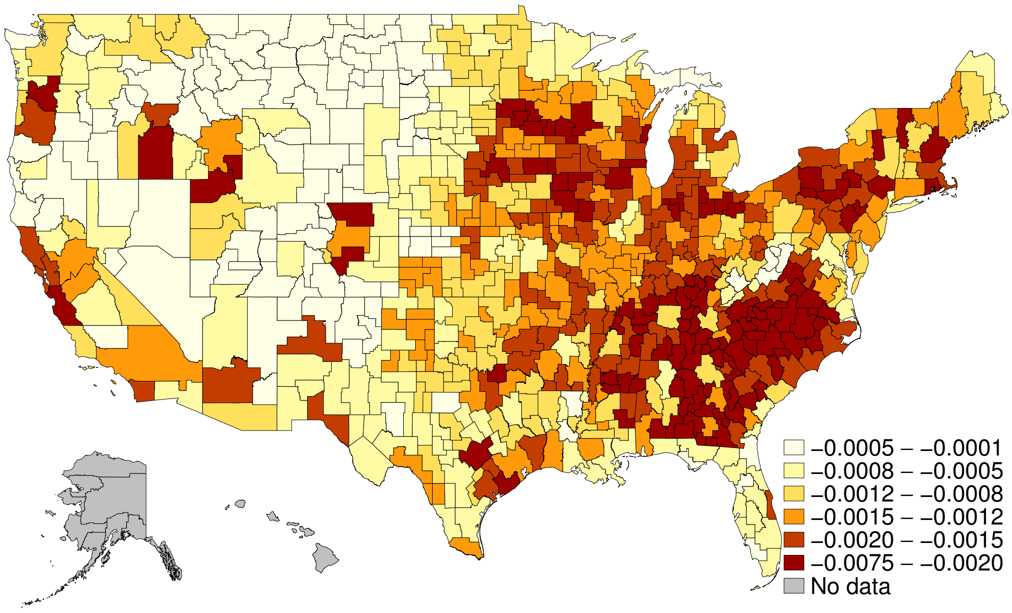
The map plots the predicted $\hat{I}_g/\hat{P} - 1$ due to the China shock.

Figure D.6: Change in real income due to the automation shock



The map plots the predicted $\hat{I}_g/\hat{P} - 1$ due to the automation shock.

Figure D.7: Exposure to an ADH-style shift-share measure in the model data



The map plots $-\sum_{s\in M} \pi_{gs}\Delta X_{China,Other,s}$, where $\Delta X_{China,Other,s}$, the change in exports from China to ADH's "Other" countries, is calculated after the counterfactual joint China and automation shock in our model. The set of Other countries consists of Australia, Denmark, Finland, Germany, Japan, and Spain. Note that in our counterfactual data, $\sum_{s\in M} \pi_{gs}\Delta X_{China,Other,s}$ has a correlation of 98% with $\sum_{s\in M} \pi_{gs}\Delta X_{China,US,s}$.

Table D.1: Impact of the individual shocks across commuting zones

(a) Impact of only the China shock

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I_g}/\widehat{P}$	0.86	1.47	0.80	-1.71	3.58
$\widehat{i_g}/\widehat{P}$	0.41	0.73	0.40	-0.86	1.77
$\widehat{h}_g$	0.18	0.29	0.16	-0.34	0.71
$\widehat{e}_g$	0.27	0.44	0.24	-0.52	1.06
$\Delta\pi_{gM}$	-0.60	-0.54	0.29	-2.42	-0.05

(b) Impact of only the automation shock

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I_g}/\widehat{P}$	2.90	2.81	0.51	1.44	5.22
$\widehat{i_g}/\widehat{P}$	1.45	1.40	0.25	0.72	2.58
$\widehat{h}_g$	0.57	0.56	0.10	0.29	1.02
$\widehat{e}_g$	0.86	0.84	0.15	0.43	1.54
$\Delta\pi_{gM}$	-0.28	-0.36	0.23	-1.30	0.29

Panel (a) shows the impact of the rise of China across US commuting zones, while Panel (b) documents the impact of the automation shock. In each panel, the first row displays the change in average real income, the second on the average hourly wage, the third row on hours worked per employee and the fourth on the employment rate. The final row shows the change in the share of employment in manufacturing. The first column shows the aggregate effect, and the second the average. The third column shows the standard deviation across commuting zones and the fourth and fifth column respectively show the minimum and maximum effect. All variables are measured in percentage changes, except $\Delta\pi_{gM}$ which is measured in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2).

Table D.2: Model fit of the separate shocks, with controls

	$\ln \widehat{I}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{I}_g$ - China	0.05									
	(1.05)									
$\ln \widehat{I}_g$ - Automation	4.17									
	(1.57)									
$\ln \widehat{I}_g$ - Both shocks		1.81								
		(0.79)								
$\ln \widehat{i}_g$ - China			1.73							
			(1.00)							
$\ln \widehat{i}_g$ - Automation			4.19							
			(1.84)							
$\ln \widehat{i}_g$ - Both shocks				2.81						
				(1.24)						
$\ln \widehat{h}_g$ - China					8.96					
					(1.33)					
$\ln \widehat{h}_g$ - Automation					4.06					
					(1.57)					
$\ln \widehat{h}_g$ - Both shocks						6.95				
						(1.08)				
$\ln \widehat{e}_g$ - China							3.64			
							(1.00)			
$\ln \widehat{e}_g$ - Automation							2.00			
							(1.39)			
$\ln \widehat{e}_g$ - Both shocks								2.95		
								(0.82)		
$\Delta\pi_{gM}$ - China									3.29	
									(0.41)	
$\Delta\pi_{gM}$ - Automation									0.86	
									(0.57)	
$\Delta\pi_{gM}$ - Both shocks										2.16
										(0.33)
R^2	0.31	0.29	0.20	0.20	0.46	0.44	0.38	0.37	0.46	0.43
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in CZs' labor market outcomes in the data for the period 2000 - 2007 on the model's predicted changes for the different listed shocks. The odd columns regress the observed values on the predicted changes for both the individual China and the individual automation shock, and the even columns repeat the analysis from Table 4 for the combined shock. The first two specifications examine average income, specifications 3 and 4 average hourly wage, specifications (5) and (6) hours worked per employee, specifications (7) and (8) the employment rate and (9) and (10) the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). All specifications include the controls from ADH listed in the note to Table 4. Standard errors, clustered at the state level, in parentheses.

Table D.3: Model fit to non-targeted moments - no controls

		$\ln \widehat{I}_g$			$\ln \widehat{i}_g$			$\ln \widehat{h}_g$			$\ln \widehat{e}_g$			$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$\ln \widehat{I}_g$ - China	1.47														
	(1.01)														
$\ln \widehat{I}_g$ - Automation		6.24													
		(1.35)													
$\ln \widehat{I}_g$ - Both shocks			2.81												
			(0.60)												
$\ln \widehat{i}_g$ - China				1.76											
				(0.82)											
$\ln \widehat{i}_g$ - Automation					2.81										
					(1.51)										
$\ln \widehat{i}_g$ - Both shocks						1.98									
						(0.77)									
$\ln \widehat{h}_g$ - China							10.29								
							(1.07)								
$\ln \widehat{h}_g$ - Automation								6.64							
								(1.56)							
$\ln \widehat{h}_g$ - Both shocks									8.69						
									(0.90)						
$\ln \widehat{e}_g$ - China										5.45					
										(0.82)					
$\ln \widehat{e}_g$ - Automation											4.14				
											(1.25)				
$\ln \widehat{e}_g$ - Both shocks												4.78			
												(0.72)			
$\Delta\pi_{gM}$ - China													4.93		
													(0.48)		
$\Delta\pi_{gM}$ - Automation														3.39	
														(0.84)	
$\Delta\pi_{gM}$ - Both shocks															3.62
															(0.31)
R^2	0.02	0.11	0.08	0.02	0.02	0.04	0.37	0.06	0.37	0.27	0.06	0.29	0.29	0.08	0.28
Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in the data for the period 2000 - 2007 on the model's predicted changes after the China shock, the automation shock, or the combined shock. The first three specifications examine average income, specifications 4-6 average hourly wage, specifications 7-9 hours worked per employee, specifications 10-12 the employment rate and 13-15 the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). None of the specifications include control variables. Standard errors, clustered at the state level, in parentheses.

Appendix E Counterfactuals: sensitivity and heterogeneity

Table E.1: Sensitivity check: simulation results for alternative θ_s

(a) Impact of the China and automation shock

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I_g}/\widehat{P}$	4.45	5.21	1.76	0.99	14.51
$\widehat{i_g}/\widehat{P}$	2.19	2.57	0.85	0.49	7.01
$\widehat{h}_g$	0.88	1.02	0.33	0.20	2.75
$\widehat{e}_g$	1.32	1.53	0.50	0.30	4.15
$\Delta\pi_{gM}$	-0.90	-0.92	0.41	-3.10	-0.10

(b) Impact of only the China shock

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I_g}/\widehat{P}$	0.55	1.11	0.72	-1.95	2.98
$\widehat{i_g}/\widehat{P}$	0.26	0.55	0.36	-0.98	1.48
$\widehat{h}_g$	0.11	0.22	0.14	-0.39	0.59
$\widehat{e}_g$	0.17	0.33	0.22	-0.59	0.89
$\Delta\pi_{gM}$	-0.56	-0.49	0.27	-2.35	-0.04

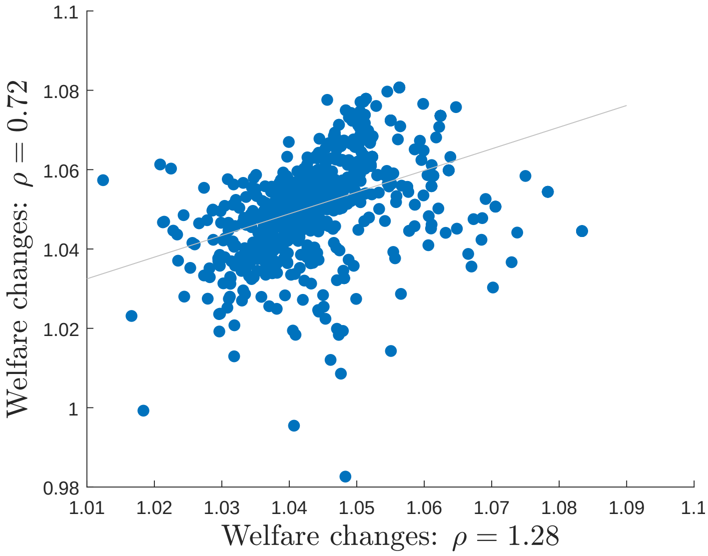
(c) Impact of only the automation shock

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I_g}/\widehat{P}$	3.64	3.88	1.31	1.67	11.55
$\widehat{i_g}/\widehat{P}$	1.81	1.92	0.64	0.83	5.62
$\widehat{h}_g$	0.71	0.76	0.25	0.33	2.21
$\widehat{e}_g$	1.08	1.15	0.38	0.50	3.33
$\Delta\pi_{gM}$	-0.42	-0.50	0.26	-1.64	0.28

This table presents results for the different shocks under alternative values of the trade elasticities θ_s. Specifically, the θ_s are set to the median value of prominent estimates in the literature, reported in Table B.3, column 5 of Bartelme et al. (2019). In each panel, the first row displays the change in average real income, the second on the average hourly wage, the third row on hours worked per employee and the fourth on the employment rate. The final row shows the change in the share of employment in manufacturing. The first column shows the aggregate effect, and the second the average. The third column shows the standard deviation across commuting zones and the fourth and fifth column respectively show the minimum and maximum effect. All variables are measured in percentage changes, except $\Delta\pi_{gM}$ which is measured in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2).

E.1 Counterfactual results for the model with $\rho = 0.72$

Figure E.1: Correlation of the welfare effects for different values of ρ



This figure plots against each other the CZ-level welfare changes due to the combined China and automation shock under two different values for ρ. The correlation in the welfare changes is 41.5%.

This section focuses on the results for the model with $\rho = 0.72$. In terms of model fit across CZs, we find that the positive correlation between predicted and observed changes falls for all variables compared to the baseline but that it often remains significant (see Appendix Table E.2). Combined with higher variance in the predicted variables, the estimated regression coefficients are lower now. This implies that this model typically matches the magnitude in the data well for the variables where the baseline underpredicted the effects (hours worked, employment rate, and manufacturing employment share). However, for the income and wage variables, which are the variables with the largest measurement error, the coefficients for the regressions with controls become insignificant.

Focusing on the individual shocks instead of the combined shock, we notice that the impact of the China shock is highly similar both for the aggregate and the distributional effects (see top rows of Tables 5 and 7). For the automation shock though, the aggregate and distributional effects are now larger. at 3.5% versus 2.9% and 1.04% versus 0.51% respectively. The increase in the distributional effects of the automation shock arises from the larger dispersion in the wage changes (compare Appendix Figures A.2 and E.2). In turn, this larger wage change dispersion arises partly from the productivity decline among the sectors that experience the largest automation shock.[45]

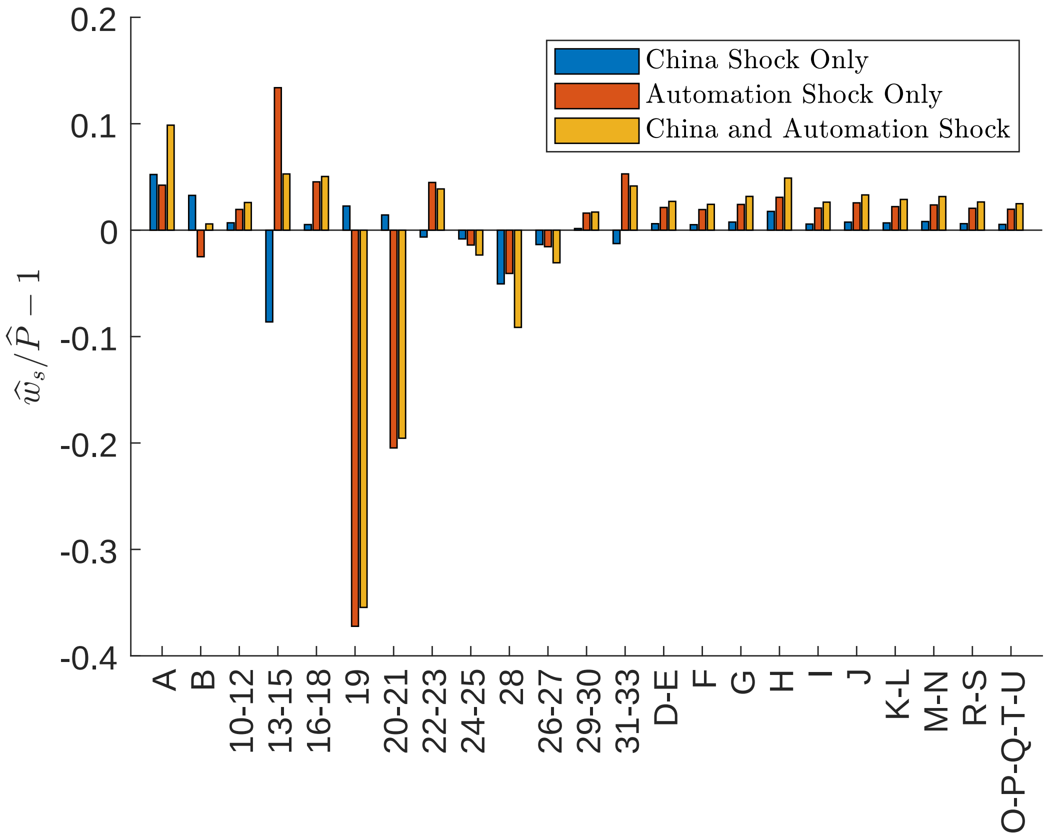
Table E.2: Model fit of variation across commuting zones for $\rho = 0.72$

	$\ln \widehat{I}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predicted $\ln \widehat{I}_g$	0.82	0.05								
	(0.52)	(0.38)								
Predicted $\ln \widehat{i}_g$			0.75	0.13						
			(0.42)	(0.31)						
Predicted $\ln \widehat{h}_g$					3.92	1.71				
					(0.96)	(0.78)				
Predicted $\ln \widehat{e}_g$							2.10	0.79		
							(0.59)	(0.38)		
Predicted $\Delta\pi_{gM}$									0.99	0.70
									(0.29)	(0.17)
R^2	0.01	0.28	0.01	0.17	0.13	0.37	0.10	0.34	0.08	0.42
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in the data for the period 2000 - 2007 on the predicted changes from the model with $\rho = 0.72$ after the combined China and automation shock. The first two specifications examine average income, specifications 3 and 4 average hourly wage, specifications (5) and (6) hours worked per employee, specifications (7) and (8) the employment rate and (9) and (10) the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). The even-numbered specifications include the following controls from ADH: dummies for the nine Census divisions, percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women and the average offshorability index of occupations, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses.

[45] In Appendix Section H.1, we show that to a first-order approximation, the output increase arising from an automation shock is given by $d \ln Y_{s|M_s,Z_s,K_s,N_{ks}} = [\upsilon + (1-\omega_s)/(\rho-1)]\, \alpha_s d \ln \xi_s$. Since the sectors with the largest automation shock also have the largest initial equipment share $(1-\omega_s)$, a higher υ would be required to render the productivity impact of automation positive in their case.

Figure E.2: Pattern of the wage changes for the different shocks, $\rho = 0.72$



This figure compares the changes in the real wages by sector for each of the shocks, for the model with $\rho = 0.72$. Note that the range of the vertical axis is [-0.5, 0.2], instead of [-0.25, 0.15] in Figure A.2.

E.2 Heterogeneity across education groups

Table E.3: Heterogeneous parameters across education groups

(a) Estimation of $\frac{1}{\mu}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$	$\ln \hat{h}_g$
$\ln \hat{i}_g$	0.81***	0.72***	0.35***	0.18	0.82***	0.90**	0.35***	0.45
	(0.16)	(0.25)	(0.094)	(0.20)	(0.16)	(0.37)	(0.093)	(0.67)
Implied μ	1.24	1.39	2.87	5.65	1.22	1.11	2.82	2.20
F-First Stage	28.2	10.3	29.2	6.31	26.8	6.38	30.5	0.67
Instrument	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}
Controls	No	No	Yes	Yes	No	No	Yes	Yes
College	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722

(b) Estimation of $-\frac{1}{\kappa}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$	$\ln \hat{i}_g$
$\sum_s \pi_s^{hours} \ln \hat{\pi}_{gs}^{hours}$	-0.59***	-0.79***	-0.68***	-0.75**				
	(0.13)	(0.29)	(0.13)	(0.31)				
$\sum_s \pi_s^{hours} \ln \hat{\pi}_{gs}^{income}$					-0.52***	-0.57**	-0.71***	-0.35
					(0.15)	(0.23)	(0.20)	(0.41)
Implied κ	1.70	1.26	1.48	1.33	1.92	1.77	1.41	2.88
F-First Stage	49.5	15.8	55.5	18.3	21.5	13.6	9.43	6.94
IV Share	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}
Controls	No	No	Yes	Yes	No	No	Yes	Yes
College	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722

(c) Estimation of $\frac{\chi}{1-\chi}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$
$\ln \hat{i}_g \hat{h}_g$	0.39***	0.24***	0.22***	0.10	0.40***	0.28***	0.23***	0.33
	(0.047)	(0.052)	(0.046)	(0.072)	(0.048)	(0.064)	(0.048)	(0.31)
Implied χ	0.28	0.19	0.18	0.093	0.28	0.22	0.19	0.25
F-First Stage	46.7	22.8	31.9	6.38	45.6	16.2	31.8	1.02
Instrument	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{hours}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}	π_{gs}^{income}
Controls	No	No	Yes	Yes	No	No	Yes	Yes
College	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722

This table performs estimations analogous to Table 2, but now separately for worker types defined by education level (having some college education or not). Panel (a) presents estimation results for specification (20), where i_g is the average hourly wage and h_g is the average annual supply of hours. Panel (b) estimates specification (22) and Panel (c) specification (23), where e_g is the employment rate and $i_g h_g$ is the average annual income. Each column indicates whether or not we use the following set of controls: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.4: Heterogeneity across education groups for the automation shock

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
All groups	2.26	2.18	0.52	0.75	4.52	-0.29
Non-college workers	2.14	2.05	0.61	0.75	4.52	-0.34
College workers	2.33	2.31	0.37	0.89	4.24	-0.23

The table shows the impact of the individual automation shock for the model with groups defined by commuting zone and education level (some college education or not). The first row shows the effect of the shock on all groups in the top row, on the groups where workers have no college education in the middle row, and on groups with college education in the bottom row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points.

Table E.5: Heterogeneity across education groups for the China shock.

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
All groups	0.68	1.27	0.78	-1.74	3.45	-0.56
Non-college workers	0.83	1.43	0.87	-1.47	3.45	-0.49
College workers	0.60	1.11	0.64	-1.74	3.18	-0.64

The table shows the impact of the individual China shock for the model with groups defined by commuting zone and education level (some college education or not). The first row shows the effect of the shock on all groups in the top row, on the groups where workers have no college education in the middle row, and on groups with college education in the bottom row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points.

E.3 Alternative shock calibration

So far, we have calibrated the China shock and the automation shock by respectively matching changes in US import shares from China and changes in US labor shares. Since neither increased imports from China nor automation are unique to the US, in this section, we can examine the robustness of our calibration by focusing on common trends across advanced economies. To this end, we return to our baseline model with a single group per CZ and $\rho = 1.28$.

For the China shock, we start by running a specification related to ADH's first-stage regression, similar to the calibrations in Caliendo et al. (2019) and GRY:

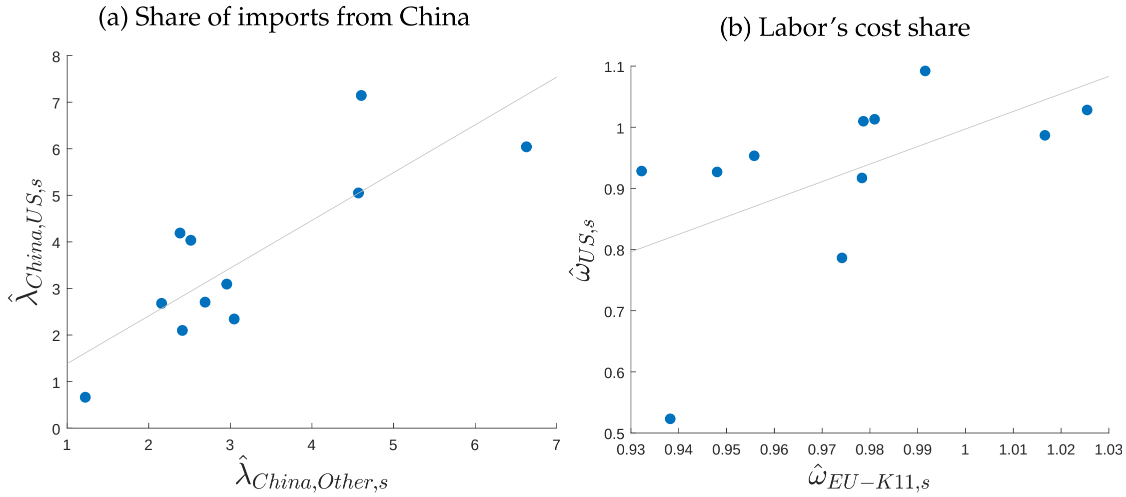
$$\hat{\lambda}_{China,US,s} = \alpha + \beta\hat{\lambda}_{China,Other,s} + \varepsilon_s, \tag{25}$$

where $\hat{\lambda}_{China,Other,s} \equiv \frac{\sum_{j\in Other}\lambda^{2007}_{China,j,s}}{\sum_{j\in Other}\lambda^{2000}_{China,j,s}}$, and the set of "other" countries consists of Australia, Denmark, Finland, Germany, Japan and Spain.[46] From this regression, we obtain the predicted changes in US expenditure shares on Chinese goods as $\widehat{\hat{\lambda}_{China,US,s}} = \hat{\alpha} + \hat{\beta}\hat{\lambda}_{China,Other,s}$. Importantly, the correlation between $\hat{\lambda}_{China,Other,s}$ and $\hat{\lambda}_{China,US,s}$ is high, at 82% (see Figure E.3, Panel a). Indeed, China's export growth to the US is similar to its export growth to other advanced countries.

For the automation shock, recall that over the period 2000-2007, $\omega_{US,s}$ typically declined for US manufacturing sectors (see Figure E.3, panel b). This is also the case in the 11 EU countries where EU-KLEMS has detailed sector-level capital data (see Section 3), henceforth denoted as EU-11. In fact, the correlation in labor share declines for the US and the EU-11 is relatively high, at 55%, which is consistent with a common automation shock in all these countries. To focus on trends in sectoral labor shares that are common across the US and the EU-11, we run the following regression

[46] This list of other countries is similar to the one in ADH. However, ADH also include New Zealand and Switzerland, which are not covered in the WIOD data.

Figure E.3: Sector-level moments for the calibration



Panel (a) shows the relation between $\hat{\lambda}_{China,Other,s} \equiv \frac{\sum_{j \in Other} \lambda^{2007}_{China,j,s}}{\sum_{j \in Other} \lambda^{2000}_{China,j,s}}$ and $\hat{\lambda}_{China,US,s}$, where the correlation is 82%. Panel (b) shows the relation between $\hat{\omega}_{EU-K11,s} \equiv \frac{1}{J} \sum_{j \in EU-K11} \hat{\omega}_j$ and $\hat{\omega}_{US,s}$, where the correlation is 55%.

$$\hat{\omega}_{US,s} = \alpha + \beta \hat{\omega}_{EU-11,s} + \varepsilon_s. \tag{26}$$

From this regression, we obtain predicted changes in the US labor share $\widehat{\hat{\omega}_{US,s}} = \hat{\alpha} + \hat{\beta} \hat{\omega}_{EU-11,s}$. We then jointly calibrate $\hat{T}_{China,s}$ and $\hat{\xi}_{US,s}$ such that the simulated $\hat{\lambda}_{China,US,s}$ and $\hat{\omega}_{US,s}$ perfectly fit the predicted $\widehat{\hat{\lambda}_{China,US,s}}$ and $\widehat{\hat{\omega}_{US,s}}$. When we only calibrate the China shock, we calibrate $\hat{T}_{China,s}$ by targeting $\widehat{\hat{\lambda}_{China,US,s}}$; and when we only calibrate the automation shock, we calibrate $\hat{\xi}_{US,s}$ by targeting $\widehat{\hat{\omega}_{US,s}}$.

To ensure that the elasticity in the manufacturing sector of the productivity increase to the automation-induced decline in the labor share continues to be in line with the value in Moll et al. (2022), we now set $\upsilon = -1.46$. This slight update to the υ value is because the composition of the automation shocks across sectors changes, and each sector's initial labor share affects the impact of the automation shock on productivity.

As we see in Table E.6, the results for the different shocks are relatively close to those from the baseline calibration in Table 5. For the combined shock, the aggregate effects are

Table E.6: Impact of the individual shocks for the alternative calibration

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.77	1.31	0.77	-1.35	3.45	-0.61
Only Automation shock	2.15	1.95	0.34	0.63	2.65	-0.04
China and Automation Shock	3.25	3.53	0.43	1.03	4.34	-0.53

The table shows the impact of the individual China shock in the first row, the individual automation shock in the second row, and the combined China and automation shock in the third row for the calibration of the specified shocks in this section. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum, and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing in percentage points.

somewhat lower than in the baseline (3.25% versus 3.96%), while the difference is more considerable for the distributional effects (a standard deviation of 0.43% versus 0.97%). The decline in the manufacturing sector is now 0.53 percentage points compared to 0.81 before. For the model fit of the variation across commuting zones, the performance of the China shock and the combined shock remains decent. However, for the automation shock, the coefficient sometimes takes on the wrong sign (see Appendix Tables E.7 and E.8).

Table E.7: Model fit to non-targeted moments for the alternative calibration (no controls)

	$\ln \widehat{I}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{I}_g$ - China	4.89									
	(1.27)									
$\ln \widehat{I}_g$ - Automation	8.88									
	(3.08)									
$\ln \widehat{I}_g$ - Both shocks		4.54								
		(1.51)								
$\ln \widehat{i}_g$ - China			2.21							
			(1.13)							
$\ln \widehat{i}_g$ - Automation			1.48							
			(2.46)							
$\ln \widehat{i}_g$ - Both shocks				3.09						
				(1.45)						
$\ln \widehat{h}_g$ - China					8.96					
					(1.31)					
$\ln \widehat{h}_g$ - Automation					-5.17					
					(2.41)					
$\ln \widehat{h}_g$ - Both shocks						16.53				
						(2.17)				
$\ln \widehat{e}_g$ - China							7.14			
							(1.22)			
$\ln \widehat{e}_g$ - Automation							4.54			
							(2.62)			
$\ln \widehat{e}_g$ - Both shocks								10.06		
								(1.50)		
$\Delta\pi_{gM}$ - China									4.39	
									(0.40)	
$\Delta\pi_{gM}$ - Automation									8.19	
									(1.82)	
$\Delta\pi_{gM}$ - Both shocks										5.79
										(0.55)
R^2	0.06	0.04	0.02	0.02	0.39	0.27	0.27	0.26	0.33	0.31
Controls	No	No	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in the data for the period 2000 - 2007 on the model's predicted changes for the shocks calibrated in Section E.3. The first three specifications examine average income, specifications 4-6 average hourly wage, specifications 7-9 hours worked per employee, specifications 10-12 the employment rate and 13-15 the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). None of the specifications include control variables. Standard errors, clustered at the state level, in parentheses.

Table E.8: Model fit to non-targeted moments for the alternative calibration (with controls)

	$\ln \widehat{I}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{I}_g$ - China	0.79									
	(1.29)									
$\ln \widehat{I}_g$ - Automation	4.47									
	(2.91)									
$\ln \widehat{I}_g$ - Both shocks		1.11								
		(1.59)								
$\ln \widehat{i}_g$ - China			0.63							
			(1.24)							
$\ln \widehat{i}_g$ - Automation			-1.31							
			(2.48)							
$\ln \widehat{i}_g$ - Both shocks				1.52						
				(1.52)						
$\ln \widehat{h}_g$ - China					5.59					
					(1.30)					
$\ln \widehat{h}_g$ - Automation					-7.05					
					(3.37)					
$\ln \widehat{h}_g$ - Both shocks						8.63				
						(1.84)				
$\ln \widehat{e}_g$ - China							4.17			
							(1.05)			
$\ln \widehat{e}_g$ - Automation							2.96			
							(2.41)			
$\ln \widehat{e}_g$ - Both shocks								5.55		
								(1.27)		
$\Delta\pi_{gM}$ - China									2.96	
									(0.44)	
$\Delta\pi_{gM}$ - Automation									5.07	
									(1.22)	
$\Delta\pi_{gM}$ - Both shocks										3.79
										(0.45)
R^2	0.29	0.28	0.17	0.17	0.45	0.39	0.36	0.36	0.46	0.46
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722	722	722

The specifications in this table regress observed changes in the data for the period 2000 - 2007 on the model's predicted changes for the shocks calibrated in Section E.3. The first three specifications examine average income, specifications 4-6 average hourly wage, specifications 7-9 hours worked per employee, specifications 10-12 the employment rate and 13-15 the manufacturing employment share. We measure $\Delta\pi_{gM}$ in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM} (see Appendix Figure D.2). All specifications include the following ADH control variables: dummies for the nine Census divisions, percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women and the average offshorability index of occupations, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses.

Appendix F Measurement of $\alpha_{os}\omega_{os}, \alpha_{os}, \omega_{os}$

In the WIOD Socio Economic Accounts, we observe the labor share of sectors' gross revenue $\alpha_{os}\omega_{os}$. We remove outliers in $\alpha_{os}\omega_{os}$ by winsorizing it at the 1st and 99th percentile. Since the model requires that $\alpha_{os}\omega_{os} < 1 - \gamma_{os}$, in 2.5% of the observations we need to lower $\alpha_{os}\omega_{os}$ to just below this upperbound. We impute $\alpha_{os}\omega_{os}$ for the Rest of the World as the average across the 43 countries in WIOD.

As mentioned in the main text, we need to measure $\zeta_{os} \equiv P_o K_{os}/(P_o K_{os} + P_o M_{os})$ to disentangle the values of α_{os} (the cost share of the lower-tier CES F_{os}) and ω_{os} as follows. As in Krusell et al. (2000), we group structures and transportation equipment under K_{os} and the other asset types, namely "Other machinery equipment," ICT and "Intellectual property products," under M_{os}. We measure ζ_{os} based on sector-level data on capital and equipment from EU-KLEMS and the OECD. For seventeen countries in those datasets, we can obtain a measure ζ_{os} for the share of capital in the total value of structures and equipment in each sector, since there we observe the asset value by asset type and by sector. In EU-KLEMS we measure $P_o K_{os}$ and $P_o M_{os}$ as the nominal capital stock for Austria, the Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden, the UK and the US. In the OECD, we measure $P_o K_{os}$ and $P_o M_{os}$ as net fixed assets for Belgium, Canada, Greece, Japan and Norway. For the remaining countries, we imput ζ_{os} as the average value across the countries with detailed sector-level data on structures and equipment.

Table F.1: Values for cost shares in our simulations

(a) Summary Statistics, 2000

	(1)						
	Mean	SD	min	p5	Median	p95	max
$\gamma_{o,s}$	0.545	0.149	0.094	0.282	0.562	0.773	0.971
$\alpha_{o,s}\omega_{o,s}^{Unadj.}$	0.252	0.135	0.022	0.076	0.230	0.535	0.709
$\alpha_{o,s}\omega_{o,s}$	0.249	0.129	0.022	0.076	0.230	0.511	0.709
$\alpha_{o,s}$	0.332	0.116	0.027	0.152	0.327	0.550	0.722
$\omega_{o,s}$	0.725	0.192	0.100	0.346	0.751	0.974	1.000
$\zeta_{o,s}$	0.553	0.214	0.058	0.238	0.524	0.935	0.995
$\alpha_{o,s}\omega_{o,s}/(1-\gamma_{o,s})$	0.546	0.202	0.049	0.208	0.556	0.884	1.000
Observations	1012						

(b) Summary Statistics, 2007

	(1)						
	Mean	SD	min	p5	Median	p95	max
$\gamma_{o,s}$	0.559	0.152	0.094	0.275	0.576	0.780	0.977
$\alpha_{o,s}\omega_{o,s}^{Unadj.}$	0.240	0.138	0.018	0.066	0.210	0.538	0.714
$\alpha_{o,s}\omega_{o,s}$	0.236	0.131	0.018	0.066	0.209	0.514	0.714
$\alpha_{o,s}$	0.317	0.118	0.022	0.142	0.306	0.541	0.723
$\omega_{o,s}$	0.715	0.200	0.066	0.333	0.734	0.974	1.000
$\zeta_{o,s}$	0.561	0.215	0.070	0.246	0.524	0.936	0.996
$\alpha_{o,s}\omega_{o,s}/(1-\gamma_{o,s})$	0.530	0.205	0.040	0.188	0.537	0.889	1.000
Observations	1012						

The table presents summary statistics for production-function parameters in our simulations. The model requires that $\alpha_{os}\omega_{os} < 1 - \gamma_{os}$, in 2.5% of the observations we need to lower $\alpha_{os}\omega_{os}$ to just below this upperbound. The table reports both the unadjusted and adjusted values.

Figure F.1: Histogram for $\gamma_{o,s}$

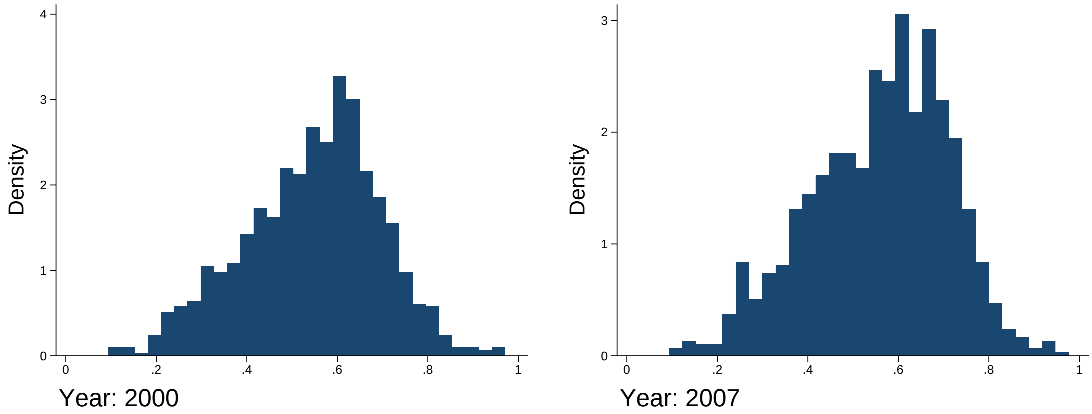


Figure F.2: histogram for $\alpha_{o,s}\omega_{o,s}$

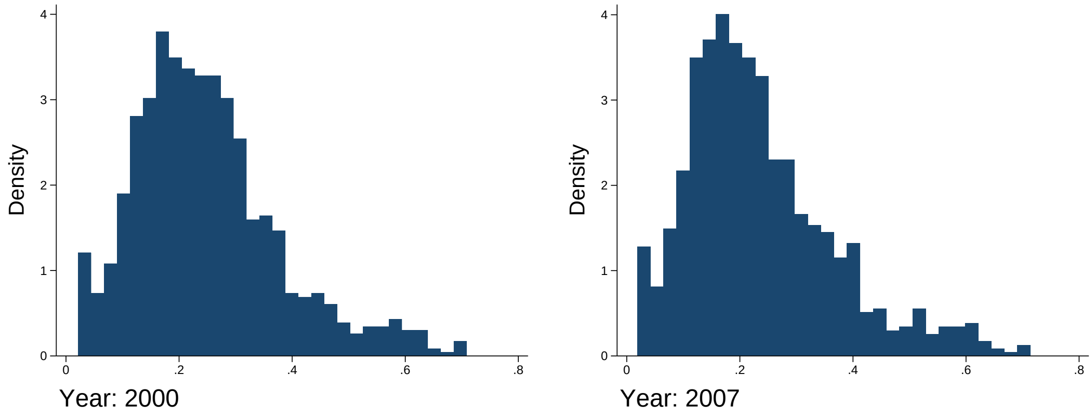


Figure F.3: histogram for $\alpha_{o,s}\omega_{o,s}^{Unadj.}$

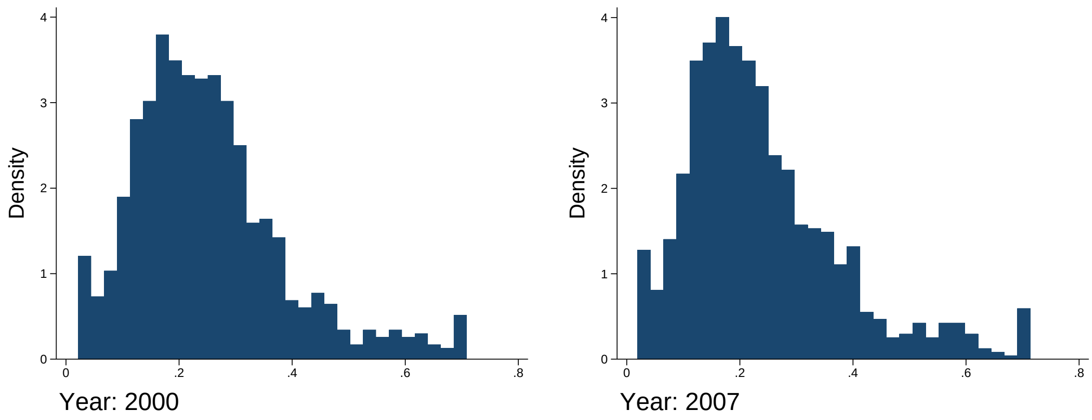


Figure F.4: histogram for $\alpha_{o,s}$

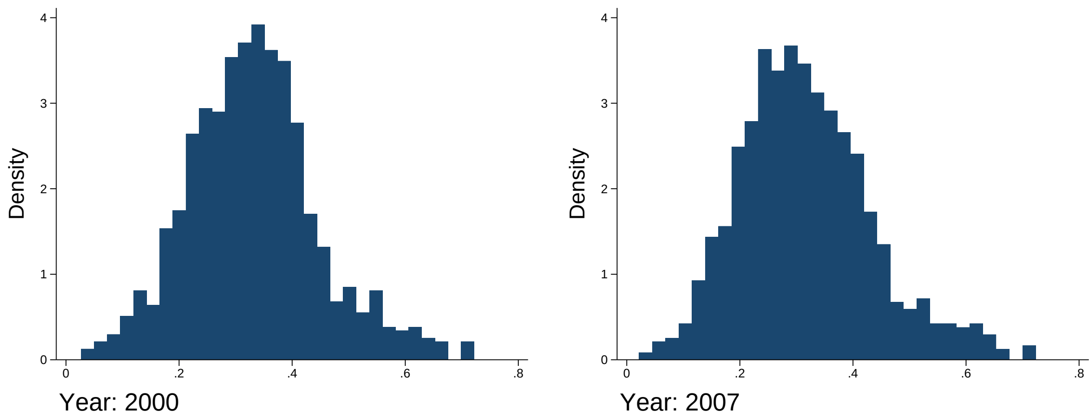


Figure F.5: histogram for $\omega_{o,s}$

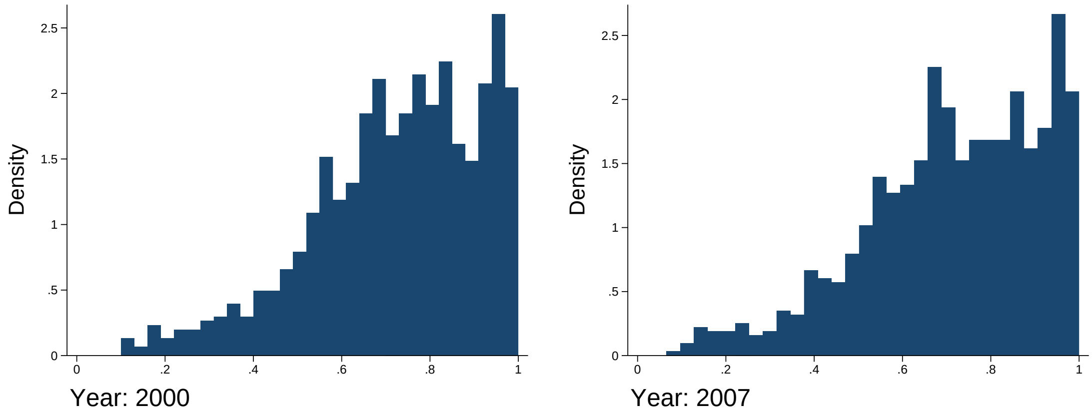


Figure F.6: histogram for $\zeta_{o,s}$

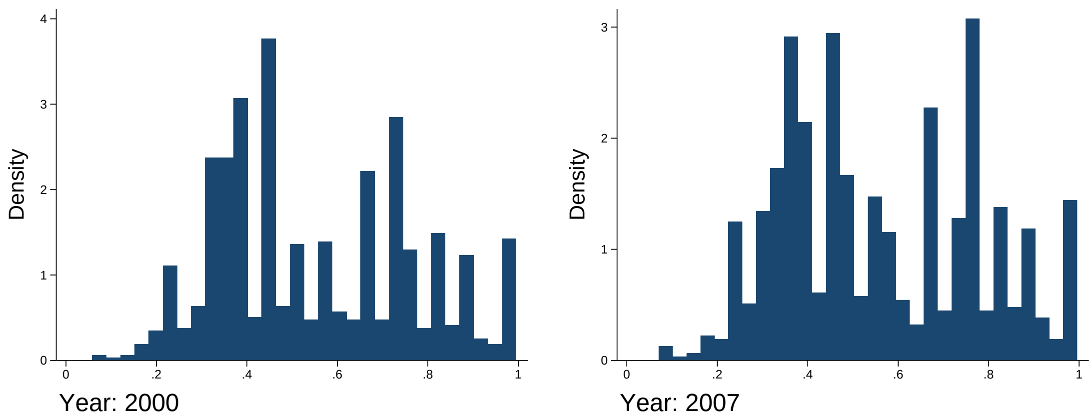
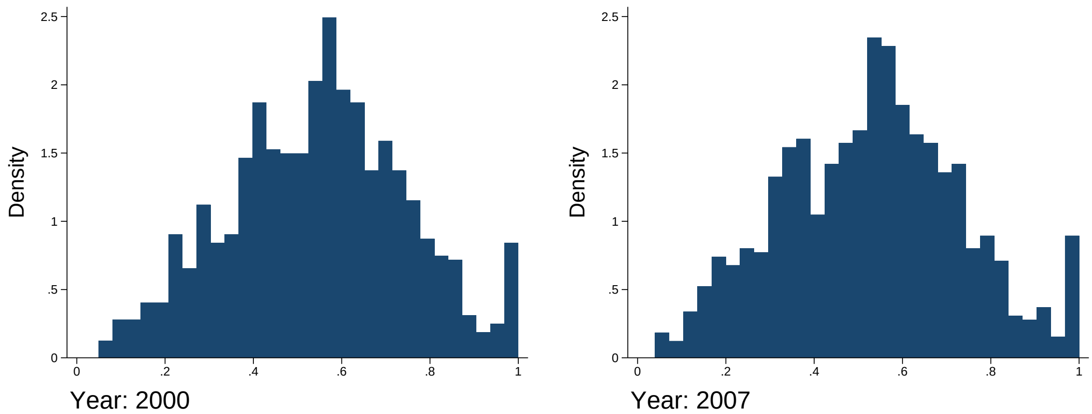


Figure F.7: histogram for $\alpha_{o,s}\omega_{o,s}/(1-\gamma_{o,s})$



Appendix G Theory

G.1 Labor supply

How many hours of labor does a worker then supply, conditional on being hired in sector s? Given their preferences for consumption and work hours, a worker with productivity z_s supplies the following hours of labor:

$$H = \left(\delta_{og}\nu_{og}\frac{w_{os}}{P_o}z_s\right)^{1/\mu},$$

which implies that $1/\mu$ is the Marshallian elasticity of labor supply. The worker's real income is therefore

$$\frac{C}{P_o} = \delta_{og}^{1/\mu}(\nu_{og}w_{os}z_s/P_o)^{(1+\mu)/\mu}.$$

Since there are no unemployment benefits, utility when unemployed is zero. To solve for expected utility prior to workers applying to vacancies, we now guess, and verify below, that the employment probability is constant across sectors: $e_{ogs} = e_{og}$. Given this employment probability, and workers' real income and hours worked when employed, expected utility in sector s is

$$\frac{\mu}{1+\mu}e_{og}\left(\delta_{og}\nu_{og}\frac{w_{os}}{P_o}z_s\right)^{\frac{1+\mu}{\mu}}. \tag{27}$$

As a result, the only variation in expected utility across sectors is driven by $w_{os}z_s$. Hence, formalizing the sorting pattern across sectors, let $\boldsymbol{w}_o \equiv (w_{o1}, ..., w_{oS})$, let $\boldsymbol{z} \equiv (z_1, z_2, ..., z_S)$ and let

$$\Omega_s(\boldsymbol{w}_o) \equiv \{\boldsymbol{z} \text{ s.t. } w_{os}z_s \geq w_{ok}z_k \text{ for all } k\}.$$

A worker with productivity vector $\boldsymbol{z}$ in country o will apply to sector s iff $\boldsymbol{z} \in \Omega_s(\boldsymbol{w}_o)$. Given the properties of the Fréchet, the share of workers in group og that apply to sector

s is therefore

$$\pi_{ogs} = \frac{A_{ogs} w_{os}^{\kappa}}{\Phi_{og}^{\kappa}},$$

where $\Phi_{og} \equiv (\sum_k A_{ogk} w_{ok}^{\kappa})^{1/\kappa}$ is a group-level index of sectoral wages, where the weights indicate the importance of each sector for group og. We will see below that this wage index determines the average hourly wage in group og.

Given the sorting pattern and each workers real income, we now solve for average utility and income of the workers in a group. First, note that for any $b \geq 1$, with $\kappa > b$:[47]

$$E[z_s^b | s] = \tilde{\eta}_b \left(\frac{\Phi_{og}}{w_{os}} \right)^b, \tag{28}$$

with $\tilde{\eta}_b \equiv \Gamma\left(1 - \left(\frac{b}{\kappa}\right)\right)$. Therefore, given Equation (27), average utility in group og is equalized across sectors:

$$U_{og} = \frac{\mu}{1+\mu} \eta e_{og} \left(\delta_{og} \nu_{og}\right)^{\frac{1+\mu}{\mu}} \left(\frac{\Phi_{og}}{P_o} \right)^{\frac{1+\mu}{\mu}}.$$

Moreover, given (28) and the expression for each worker's real income, average real income per worker in og is

$$\frac{\nu_{og} I_{ogs}}{\pi_{ogs} L_{og} P_o} = \eta e_{og} \delta_{og}^{\frac{1}{\mu}} \left(\frac{\nu_{og}}{P_o} \right)^{\frac{1+\mu}{\mu}} \Phi_{og}^{\frac{1+\mu}{\mu}},$$

with I_{ogs} nominal revenue in s for group og and $\eta \equiv \Gamma\left(1 - \frac{1+\mu}{\mu\kappa}\right)$. Consequently, the share of income obtained by workers of group og in sector s is also given by the sectoral employment share π_{ogs}. Total nominal revenue in group og is

$$I_{og} \equiv \sum_s I_{ogs} = \eta e_{og} \left(\frac{\delta_{og} \nu_{og}}{P_o} \right)^{\frac{1}{\mu}} \Phi_{og}^{\frac{1+\mu}{\mu}} L_{og},$$

of which workers earn $\nu_{og} I_{og}$.

Finally, we can show that both hours worked (h_{og}) and hourly income (i_{og}) are also

[47] We learn this from Johnson, Kotz, and Balakrishnan (1995) or footnote 18 in Eaton and Kortum (2002).

functions of Φ_{og}:[48]

$$h_{og} = \grave{\eta} \left(\frac{\delta_{og}\nu_{og}}{P_o} \right)^{\frac{1}{\mu}} \Phi_{og}^{\frac{1}{\mu}}, \tag{29}$$

$$i_{og} = \frac{\eta}{\grave{\eta}} \Phi_{og}. \tag{30}$$

Hence, Φ_{og} (a group's wage index) determines endogenous differences in average hourly labor income across groups and thereby also differences in average hours worked. Moreover, below we will see that it also determines differences in the employment rate, such that we can solve for I_{og} as a function of Φ_{og} and P_o.

G.2 System of hat equations

From Equation (11), we know that we can write the counterfactual equilibrium as:

$$\begin{aligned} \sum_g \hat{\pi}_{ogs}\pi_{ogs}\hat{I}_{og}I_{og} =& \hat{\omega}_{os}\alpha_{os}\omega_{os} \sum_d \hat{\lambda}_{ods}\lambda_{ods} \\ & \left(\beta_{ds} \left(\hat{V}_d V_d + \hat{D}_d D_d \right) + \sum_{k=1}^{S} \gamma_{dsk} \hat{R}_{dk} R_{dk} \right). \end{aligned}$$

where

$$\hat{R}_{os}R_{os} = \sum_d \lambda_{ods}\hat{\lambda}_{ods} \left(\beta_{ds} \left(\hat{V}_d V_d + \hat{D}_d D_d \right) + \sum_{k=1}^{S} \gamma_{dsk} \hat{R}_{dk} R_{dk} \right), \tag{31}$$

with changes in the labor share as

$$\hat{\omega}_{os} = \frac{\hat{w}_{os}^{1-\rho}}{\left[(1-\omega_{os})\hat{\xi}_{os}\hat{P}_o^{1-\rho} + \omega_{os}\hat{w}_{os}^{1-\rho} \right]}, \tag{32}$$

which is a function of the changes in costs and price of the final good

[48]First, to derive hours worked h_{og}, we use Equation (28) and the implied value for $E[z_s^{1/\mu}|s]$. Second, average labor revenue per employed worker $(I_{og}/(e_{og}L_{og}))$ together with the expression for average hours per worker (3), imply that average hourly labor revenue $i_{og} \equiv I_{og}/(h_{og}e_{og}L_{og})$ is given by (4).

$$\hat{c}_{os} = \hat{c}_{F,os}^{\alpha_{os}} \hat{P}_o^{1-\alpha_{os}-\gamma_{os}} \prod_k \hat{P}_{ok}^{\gamma_{oks}}, \tag{33}$$

$$\hat{c}_{F,os} = \hat{\xi}_{os}^{-\upsilon} \left[(1-\omega_{os}) \hat{\xi}_{os} \hat{P}_o^{1-\rho} + \omega_{os} \hat{w}_{os}^{1-\rho} \right]^{\frac{1}{1-\rho}}, \tag{34}$$

$$\hat{P}_o = \prod_s \left(\sum_i \lambda_{ios} \hat{T}_{is} \left(\hat{\tau}_{ios} \hat{c}_{is} \right)^{-\theta_s} \right)^{-\beta_{os}/\theta_s}; \tag{35}$$

with changes in trade shares and sectoral labor shares as a function of cost and wage changes as in Equation (13):

$$\hat{\lambda}_{ods} = \frac{\hat{T}_{os} \left(\hat{\tau}_{ods} \hat{c}_{os} \right)^{-\theta_s}}{\sum_i \lambda_{ids} \hat{T}_{is} \left(\hat{\tau}_{ids} \hat{c}_{is} \right)^{-\theta_s}}, \tag{36}$$

$$\hat{\pi}_{ogs} = \frac{\hat{A}_{ogs} \hat{w}_{os}^{\kappa_{og}}}{\sum_k \pi_{ogk} \hat{A}_{ogk} \hat{w}_{ok}^{\kappa_{og}}}; \tag{37}$$

and changes in value-added, income and employment all as a function of wage changes

$$\hat{V}_d V_d = \sum_s (1-\gamma_{ds}) \frac{\sum_g \hat{\pi}_{dgs} \pi_{dgs} \hat{I}_{dg} I_{dg}}{\alpha_{ds} \hat{\omega}_{ds} \omega_{ds}}, \tag{38}$$

$$\hat{e}_{og} = \left(\hat{A}_{og}^M \right)^{\frac{1}{(1-\chi)}} \left(\frac{\hat{\Phi}_{og}}{\hat{P}_o} \right)^{\frac{\chi(1+\mu)}{(1-\chi)\mu}}, \tag{39}$$

$$\frac{\hat{I}_{og}}{\hat{P}_o} = \left(\hat{A}_{og}^M \right)^{\frac{1}{(1-\chi)}} \left(\frac{\hat{\Phi}_{og}}{\hat{P}_o} \right)^{\frac{1+\mu}{(1-\chi)\mu}} \tag{40}$$

and

$$\hat{\Phi}_{og} = \left(\sum_k \pi_{ogk} \hat{A}_{ogk} \hat{w}_{ok}^{\kappa_{og}} \right)^{\frac{1}{\kappa_{og}}}. \tag{41}$$

These equations can be solved for $\{\hat{w}_{os}\}$ given data on income levels I_{og}, trade shares λ_{ods}, expenditure shares β_{os}, revenue R_{os}, labor allocation shares π_{ogs}, labor cost shares $\alpha_{os}\omega_{os}$, and intermediate cost shares γ_{oks}, and given values for the automation shocks $\hat{\xi}_{os}$, the trade-cost shocks, $\hat{\tau}_{ods}$, the national technology shocks $\hat{T}_{os}$, the local technology shocks $\hat{A}_{ogs}$, and the deficit shocks $\hat{D}_d$. From $\{\hat{w}_{os}\}$, we can then solve for all other relevant changes.

G.3 Derivation of the shift-share approximation

Here, we derive our shift-share approximation (18). To start, assume $\hat{A}^M_{og} = 1$ and combine Equations (15) and (17) to find

$$\frac{\hat{I}_{og}}{\hat{I}_o} = \frac{\hat{P}_o}{\hat{I}_o}\left(\sum_s \pi_{ogs}\hat{A}_{ogs}\left(\frac{\hat{w}_{os}}{\hat{P}_o}\right)^{\kappa}\right)^{\frac{1+\mu}{\kappa(1-\chi)\mu}}.$$

Defining sectoral labor income shares as $r_{os} \equiv \sum_g I_{ogs}/I_o$, and noting that $I_{ogs} = \pi_{ogs}I_{og}$, changes in these sectoral income shares are $\hat{r}_{os} = \sum_g \pi_{ogs}\hat{\pi}_{ogs}I_{og}\hat{I}_{og}/(I_o\hat{I}_o r_{os})$. Combining this with Equation (14) and Equation (17), we can obtain

$$\hat{r}_{os} = \left(\frac{\hat{w}_{os}}{\hat{P}_o}\right)^{\kappa}\left(\frac{\hat{P}}{\hat{I}_o}\right)^{\frac{\kappa(1-\chi)\mu}{(1+\mu)}}\sum_g \frac{\pi_{ogs}I_{og}}{I_o r_{os}}\hat{A}_{ogs}\left(\frac{\hat{I}_{og}}{\hat{I}_o}\right)^{1-\frac{\kappa(1-\chi)\mu}{1+\mu}}.$$

Combining this result with the expression above, we obtain Equation (18):

$$\frac{\hat{I}_{og}}{\hat{I}_o} \approx \left(\sum_s \pi_{ogs}\hat{A}_{ogs}\hat{r}_{os}\right)^{\frac{1+\mu}{\kappa(1-\chi)\mu}}. \tag{42}$$

Appendix H Indirect Inference for the estimation of υ

H.1 Estimation equation

First we derive an approximation for the change in the labor share due to automation. Here, Equation (9) implies that

$$\frac{\partial \ln \omega_s}{\partial \xi_s} = -\frac{P^{1-\rho}}{\left[\xi_s P^{1-\rho} + w_s^{1-\rho}\right]} = -\frac{(1-\omega_s)}{\xi_s}.$$

Using that $d\xi_s \approx \xi_s d\ln\xi_s$, we can obtain the following approximation (holding factor prices constant):[49]

$$d \ln \omega_s \approx -(1-\omega_s) d \ln \xi_s. \tag{43}$$

We will see below that, even though this expression is derived holding factor prices constant, this approximation tends to be highly accurate in our setup.

Next, we derive an approximation for the change in output due to automation. Here, our production function in Equation (8) implies that

$$\frac{\partial \ln Y_s}{\partial \xi_s} = \alpha_s \left[\frac{\upsilon}{\xi_s} + \frac{1}{\rho - 1} \left[\frac{\xi_s^{\upsilon} M_s}{F_s} \right]^{\frac{\rho-1}{\rho}} \xi_s^{\frac{1-\rho}{\rho}} \right].$$

We also have from optimal factor demand that

$$\frac{M_s}{F_s} = \frac{\xi_s P^{-\rho}}{\xi_s^{\upsilon} \left[\xi_s P^{1-\rho} + w_s^{1-\rho} \right]^{\frac{\rho}{\rho-1}}}.$$

Combining the previous two equations, we then obtain

$$\frac{\partial \ln Y_s}{\partial \xi_s} = \alpha_s \left[\frac{\upsilon}{\xi_s} + \frac{1}{\rho - 1} \frac{(1-\omega_s)}{\xi_s} \right]. \tag{44}$$

Here we can see that the impact of automation shocks on output changes with the elasticity of substitution between labor and capital. For instance, when $\upsilon = 0$, the impact of automation on output is positive when $\rho > 1$, but negative when $\rho < 1$.

Again using that $d\xi_s \approx \xi_s d \ln \xi_s$, as well as the above Equation (43), we arrive at the approximation:

$$d \ln Y_s \approx -\alpha_s \left[\frac{\upsilon}{(1-\omega_s)} + \frac{1}{\rho - 1} \right] d \ln \omega_s, \tag{45}$$

which immediately yields our estimation equation:

[49] More formally, we take the derivative of $\ln \omega(\xi_s, P(\xi_s), w_s(\xi_s))$ w.r.t. ξ_s, but omitting $\partial P(\xi_s)/\partial \xi_s$ and $\partial w_s(\xi_s)/\partial \xi_s$.

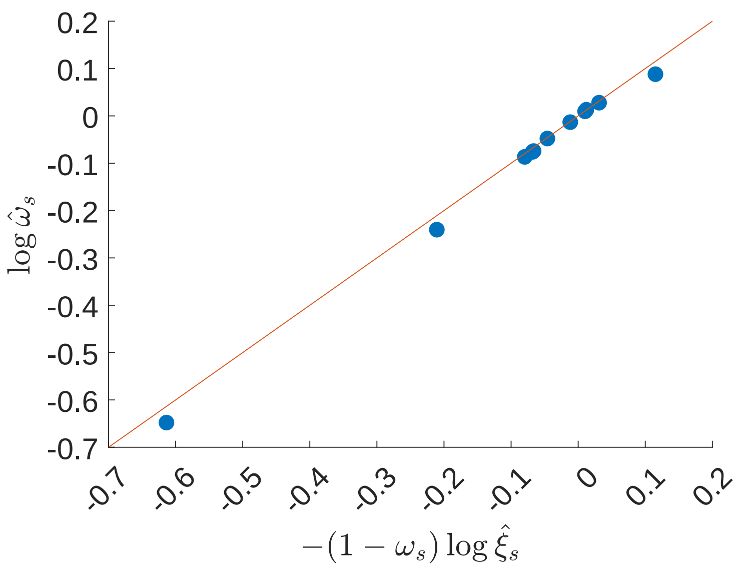
$$d \ln Y_s + \frac{\alpha_s}{\rho - 1} d \ln \omega_s \approx -\upsilon \left[\frac{\alpha_s}{(1 - \omega_s)} \right] d \ln \omega_s. \tag{46}$$

Employing this specification, we will estimate υ for both $\rho = 1.28$ as in Karabarbounis and Neiman (2014), and for $\rho = 0.72$ as in Oberfield and Raval (2021).

H.2 Groundwork for the indirect inference

We now employ our model to examine the nature of these approximations. First, we examine the accuracy of our approximation of automation shocks with changes in the labor share. Specifically, from the counterfactual data under the joint China and automation shock, we plot both sides of Equation (43) and find that the approximation is highly accurate since all observations fall almost exactly on the 45 degree line (see Figure H.1).

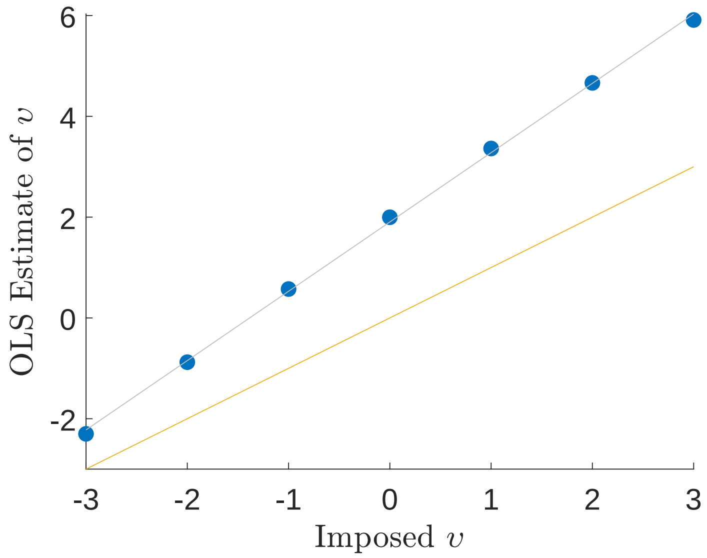
Figure H.1: Approximation of the automation shock



The Figure plots both sides of Equation (43) from the counterfactual data under the joint China and automation shock, as well as the 45 degree line (in red).

We also examine our estimation equation by estimating (46) with OLS. We do this again on the counterfactual data under the joint China and automation shock, but now we recalibrate the shocks for a large range of imposed υ values. We find that the estimated υ has a clear upward bias compared to the imposed υ, which arises from changes in factor prices and the level of inputs. Precisely to remove this bias we perform our indirect inference procedure, where we calibrate υ such that the OLS estimate in the actual data matches the estimate in the counterfactual data. The fact that the OLS estimate is monotonically increasing with the imposed υ – and strongly so – allows us to perform this indirect inference.

Figure H.2: Simulation evidence on the bias in the OLS regression



The Figure plots the point estimates of υ from estimating (46) with OLS on the counterfactual data under the joint China and automation shock, with the shocks recalibrated for each imposed υ value. The solid red line is the 45 degree line. Throughout, we set $\rho = 1.28$ as in Karabarbounis and Neiman (2014).

H.3 Data and results

To measure $d \ln Y_s = \ln \hat{Y}_s$ in the data, we use that in our model, $\hat{R}_s = \hat{c}_s \hat{Y}_s$. We measure $\hat{R}_s$ from WIOD and $\hat{c}_s$ based on the producer price index from the Producer Price Index Revision-Current Series (pc) provided by the US Bureau of Labor Statistics (BLS) for the years 2003, 2010, 2011, 2012 and 2013.[50] For the current version of this data series, 2003

[50]We transfer the data from NAICS US sector definitions to ISIC sector definitions in the following way (NAICS US - ISIC): 311 - 10, 312 - 11 and 12, 313 - 13, 315 - 14, 316 - 15, 321 - 16, 322 - 17, 323 - 18, 324 - 19, 325 - 20 and 21, 326 - 22, 327 - 23, 331 - 24, 332 - 25, 334 - 26, 335 - 27, 336 - 28, 336 - 29, 226 - 30. We drop the

is the first year where this producer price index is available. To mitigate the impact of measurement error and other noise in our estimation, the minimum length of a period in our long difference specification (Equation 46) is seven years.

We aggregate the sectoral price indices up to our set of sectors following the BLS procedure, i.e. by using a modified Laspeyres index:

$$P_s = \frac{\sum_k Q_k P_k \hat{P}_k}{\sum_k Q_k P_k} \tag{47}$$

where we measure $Q_k P_k$ as gross output in 2003, obtained from the OECD.

Table H.1: Estimating υ using OLS

(a) OLS estimation of υ with $\rho = 1.28$

	$d\ln Y_s - \frac{\alpha_s}{\rho-1} d\ln\omega_s$			
	2010	2011	2012	2013
$-\frac{\alpha_s}{(1-\omega_s)} d\ln\omega_s$	-1.639	-1.205	-1.01	-1.074
	(0.396)	(0.46)	(0.445)	(0.368)

(b) OLS estimation of υ with $\rho = 0.72$

	$d\ln Y_s - \frac{\alpha_s}{\rho-1} d\ln\omega_s$			
	2010	2011	2012	2013
$-\frac{\alpha_s}{(1-\omega_s)} d\ln\omega_s$	1.171	1.891	1.975	1.764
	(0.524)	(0.437)	(0.453)	(0.421)

Here we estimate specification (46) using weighted OLS, with sectors' revenue in 2003 as weights. The data consists of 10 manufacturing subsectors. The start year of the period is always 2003, which is the first year where we have all the required data. The end year of the period is listed at the top of the column. In panel (a), we set $\rho = 1.28$ as in Karabarbounis and Neiman (2014), while in panel (b), we set $\rho = 0.72$ as in Oberfield and Raval (2021).

ISIC sectors 31-33 due to limited overlap with NAICS US sector definitions.

We estimate specification (46) using weighted OLS in Table H.1, with sectors' revenue in 2003 as weights for our two ρ values. We focus first on the results for $\rho = 1.28$, which is the value used in our baseline quantification. Here, we obtain coefficient estimates between -1.64 and -1.01 (see Panel a). Our preferred value is -1.074, which is the estimate with the most precise standard error, obtained for end year 2013. This coefficient value is also closely in line with the values for 2011 and 2012 as end years (-1.205 and -1.01 respectively). The coefficient value for end year 2010 is more negative (at -1.639), but this may in part be due to the immediate aftermath of the Great Recession. Most importantly, the confidence intervals for all four estimates are overlapping.

We run the indirect inference procedure for our preferred value of -1.074 and obtain an estimated upsilon of -2.204. Note that this adjustment is in line with the upward bias in the OLS displayed in Figure H.2. Based on the Delta method, the standard error for the calibrated υ can be computed based on its standard error in the OLS, multiplied with the numerical derivative measuring how the calibrated value for υ changes with its OLS estimate. Employing this procedure, we obtain a standard error of 0.26. Importantly, this standard error implies that our estimation cannot reject the value employed in our baseline analysis of $\upsilon = -1.86$.

In Section 5.5, we examine the robustness of our quantification results to setting $\rho = 0.72$, as in Oberfield and Raval (2021). We therefore also perform an indirect inference estimation of υ under the assumption that $\rho = 0.72$. Panel (b) of Table H.1 has the results from the weighted OLS. First, we notice that the values for υ change sign, which is because the impact of automation on output has also switched sign (see Equation (44)). Specifically, we now obtain point estimates between 1.17 and 1.97, whose 95% confidence intervals are all overlapping. Our preferred OLS value is 1.764, which has the tightest standard error (0.421). According to our indirect inference procedure, this corresponds to an $\upsilon = 2.34$, which is very close to 2.4 – the value we employ in Section 5.5, based on the productivity effect of automation in Moll et al. (2022). These values are especially close in light of the standard error of 0.26 for our indirect inference estimate.