Additional Material (Not for publication)

Table of Contents

B Data Construction

B.1 Data on industrial robots

The IFR collects data on shipments and operational stocks of *industrial robots* by country and industry since 1993 "based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2021, p.25). Industrial robots are defined as "automatically controlled, reprogrammable, multipurpose manipulator[s] programmable in three or more axes, which can be either fixed in place or mobile for use in 13 industrial automation applications" (IFR, 2021, p.29). Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing (common in manufacturing industries), and harvesting and inspecting of equipment (prevalent in agriculture and the utilities industry) (IFR, 2021, p.31–38).

The IFR data has a few limitations. While it reports aggregate robot stocks from 1993 onwards, it only contains a breakdown by industry for the US starting in 2004. For the years before 2004, we therefore attribute the aggregate number of robots to industries proportionally to industries' shares of the overall stock in 2004 (following Acemoglu and Restrepo, 2020). Moreover, the IFR classification contains three industries that do not directly correspond to an industry covered in the US census data. These are "Other manufacturing" and "Other non-manufacturing" as well as "Unspecified". We attribute these robots according to each industry's share of robots within each of these categories.[49] Finally, robot shipments to the US also include robot shipments to Canada and Mexico before 2011. Even though this introduces measurement error, it is worth noting that the US accounts for the vast majority of robot shipments to North America (over 90%). Our IV strategy, discussed in detail in Section 2.2, should correct for this kind of measurement error.

B.2 Skill content of occupation groups

In Section 5, we investigate the effects of robots and Chinese imports on employment by industry-skill group. While industries are well defined, the concept of *skills* is slightly more vague. Two potential proxies for skills are education levels and occupations. We

[49] For example, robots reported as "Other manufacturing" are assigned to more specific manufacturing industries in a way that is proportional to each industry's share of precisely assigned robots in manufacturing.

decide to use the latter, and in particular, the predominant task requirement of occupation groups. The main advantage of using occupational task requirements is that it seems more tightly connected to the capabilities of some technologies. For the same reason, the existing literature also focuses on tasks rather than education levels. In light of some of the literature's findings, using education levels may even yield misleading results. For example, automation of routine tasks may displace low-education workers performing routine occupations (machine operators), but have positive spillovers on non-routine, low-education occupations (personal services). Examining only the subgroup "low-educated" workers would miss this crucial nuance. Therefore we prefer occupational task requirements over education levels as a proxy for skills.

We follow Autor et al. (2003) in differentiating skills along four dimensions: abstract/routine and cognitive/manual. We use data from the Dictionary of Occupational Titles (DOT) from 1980 to get a proxy for the average task intensity in each of these dimensions for eight occupation groups. In particular we use the following variables from the DOT, each of which is rated from zero (low) to ten (high):

- **Abstract:** Average of *Variety & change* and *Dealing with people*
- **Routine:** *Working under specific instructions*
- **Cognitive:** *Numerical aptitude*
- **Manual:** Average of *Eye-hand-foot coordination* and *Manual dexterity*

We then compute the four products of abstract/routine and cognitive/manual, respectively, and choose the skill dimension with the largest value as an occupation's predominant skill requirement. The results of this are shown in Table B1. Using this methodology, managerial & professional as well as sales support occupations require mainly abstract, cognitive skills. Administrative support & clerical occupations are the only group requiring mainly routine, cognitive skills, and machine operators, fabricators & laborers the only one requiring mainly routine, manual skills. All remaining groups (technical support, services – such as nurses, janitors, cooks – agricultural, crafts & repair) use mostly abstract, manual abilities.

Table B1: Occupation Groups and Skill Content

	Skill dimension			
	Cognitive		Manual	
Occupation group	Abstract	Routine	Abstract	Routine
Managerial, professional	+	–	–	–
Technical support	–	–	+	–
Sales support	+	–	–	–
Administrative support	+	+	–	+
Services	–	+	+	+
Agricultural	–	–	+	+
Production, crafts, repair	+	+	+	–
Operators, laborers	–	+	–	+

Note: Skill content of occupation groups along four dimensions. Areas shaded in gray indicate the highest value for each occupation group. Plus and minus signs indicate that the score of this occupation group is above and below the median of all groups, respectively.

C Robustness Checks

C.1 Pre-trends

One potential threat to our identification strategy is that areas more exposed to robots and Chinese imports may have experienced differential migration trends prior to the treatment period. For example, if areas more exposed to robots had significantly lower population growth before the invention of robots, our results may reflect secular trends in migration patterns and not the effect of robots. Our analysis controls for potential pre-existing trends by including them as a covariate. However, to provide greater clarity on pre-existing patterns, we explore these more directly in this section.

We estimate the same regressions as before, now focusing on years 1970–1990, a time when robot technology was, if anything, still in its infancy and China had not started its surge in exports. We regress changes in the log counts of the working-age population in this pre-period on the *future* exposure to robots and Chinese imports, defined as the average exposure in the three subsequent time periods 1993/91–2000, 2000–7 and 2007–15. Results are reported in columns 1 and 2 of Table C1. In column 1, we include all the covariates from our preferred specification (Table 2, column 5), except for the contemporaneous changes, which may have played a smaller role between 1970 and 1990. In column 2, we include also the control variables for contemporaneous changes interacted with time periods, so as to replicate exactly our preferred specification. Reassuringly, coefficients are not statistically significant in either column.

In columns 1 and 2, we cannot detect any statistically significant pre-trends in overall population growth in areas exposed to robots or Chinese imports, given the standard errors of the estimates. However, the point estimates are relatively similar (e.g., –0.59 in column 2 compared to –0.56 in our preferred specification). It is thus possible that not accounting for pre-trends may bias our results. In particular, if population growth patterns are persistent, the coefficients on the exposures to robots and to Chinese imports may be biased. For this reason, we control for pre-trends in all of our results.

In columns 3–6, we again turn to the period 1990–2015 and explore how sensitive our main results are to the inclusion of pre-trends in different ways. In column 3, we repeat our main specification from column 5, Panel B of Table 2, which includes the change in the log working-age population between 1970 and 1990. Note that the effect of the pre-trends themselves is positive and statistically significant at the 1%

level, suggesting that there is some persistence in population growth patterns over time. Column 4 replicates column 3 without including pre-trends. Not accounting for pre-trends changes the estimated coefficient on the exposure to robots and Chinese imports in the expected direction. Compared to our preferred specification, the effect of robots becomes slightly larger in absolute value (–0.68 vs. –0.56) and remains statistically significant at conventional levels. The effect of Chinese imports becomes more positive and appears to be marginally statistically significant (at the 10% level) when not accounting for pre-trends.

In columns 5 and 6, we probe the robustness of our findings to different strategies for accounting for pre-trends. In column 5, we interact changes in log working-age population from 1970–90 with time period dummies, thus allowing pre-existing trends to potentially dissipate over time. The effects of robots and Chinese imports remain unchanged, and there is some evidence for pre-existing patterns becoming less important over time. In column 6, we include the change in working-age population during the preceding period (rather than from 1970 to 1990). We are worried that by doing so, we might add a variable that has itself been affected by robots and Chinese imports (i.e., a "bad control" using the terminology in Angrist and Pischke, 2008). Nonetheless, it is reassuring that our main results remain unchanged also in this specification.

In sum, these results indicate that our estimates are unlikely to be influenced by pre-existing differential trends in population growth across CZs. As an additional robustness exercise, we also replicated our analysis replacing region-time dummies ($9 \times 3 = 27$) with more granular state-time dummies ($48 \times 3 = 144$), in order to account for any state-specific, time-varying unobservable characteristics. Reassuringly, results remain almost identical (i.e., -0.59** vs. -0.56*** for robots, and statistically insignificant, positive coefficients for China).

Table C1: Effects on migration, pre-trends (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	1970–1990		1990–2015			
US exposure to robots	-0.56	-0.59	-0.56***	-0.68***	-0.57***	-0.39**
	(0.35)	(0.36)	(0.12)	(0.23)	(0.12)	(0.16)
US exposure to Chinese imports	0.82	1.02	0.45	1.39*	0.28	0.91
	(0.83)	(0.69)	(0.78)	(0.71)	(0.78)	(0.59)
Δ_{70-90} log working-age population			0.38***			
			(0.09)			
Δ_{70-90} log working-age population × 1990–2000					0.49***	
					(0.16)	
Δ_{70-90} log working-age population × 2000–2007					0.49***	
					(0.07)	
Δ_{70-90} log working-age population × 2007–2015					0.14***	
					(0.04)	
Δ_{t-1} log working-age population						0.35***
						(0.12)
Kleibergen-Paap F	70.7	73.0	25.3	24.9	25.7	25.3
Region × time	✓	✓	✓	✓	✓	✓
Demog. × time & ind. sh. × time	✓	✓	✓	✓	✓	✓
Contemp. changes × time		✓	✓	✓	✓	✓

Note: The dependent variable is the decadal change in the log working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). In columns 1–2 and 3–6, there are two and three time periods and 722 CZs each period, resulting in N=1,444 and N=2,166, respectively. In columns 1–2, US exposure to robots/Chinese imports refers to the average of the changes from 1993/91–2000, 2000–7 and 2007–15. Both US exposure variables are standardized to have a mean of zero and a standard deviation of 1. All columns includes census division dummies, initial demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and initial shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Columns 2–6 also include the initial share of routine jobs and the average offshorability index, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's initial share of the national working-age population. In columns 1–2, the initial values refer to the year 1970, in columns 3–6 to the year 1990. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.2 Alternative definition of Chinese imports

In contrast with our results, Greenland et al. (2019) find that Chinese imports triggered a migration response. However, their analysis differs from ours in that they rely mostly on the Pierce and Schott (2016) definition of the shock, and estimate stacked difference regressions for the time periods 1990–2000 and 2000–2010. Since we are worried about the Great Recession as a potential confounder, in our baseline specification, we chose to end our second period in 2007. In Table C2, we explicitly test whether using the Pierce and Schott (2016) treatment of the Chinese imports shock changes our results. The effect of Chinese imports on population growth is negative and statistically significant only when using a relatively parsimonious specification. However, these results are not robust to controlling for demographics, industry shares or contemporaneous changes, or to focusing on the time period before 2007. We thus interpret the discrepancy between our findings and those in Greenland et al. (2019) as due to the different (more stringent) set of controls included in our analysis.

C.3 Alternative mechanisms

We now explore the possibility that the two shocks may differ systematically along key dimensions, and for this reason led to differential migration responses. Broadly, we view these alternative explanations as falling in two (non-mutually exclusive) categories: first, the two shocks may differ in the time period during which they affected the economy; second, the set of regions exposed to either shock may differ according to some pre-existing characteristics.

Affected time periods. First, the two shocks may differ from each other in terms of the time period, and thus the macroeconomic conditions, during which they hit the economy. This may in turn affect the transmission of a shock throughout the economy and, in particular, whether or not it induces a migration response. For instance, it is conceivable that prospective in-migrants are more cautious in their location choice when labor markets are slacker at the national level. In the case of the two shocks we consider, the surge in Chinese imports had largely flattened out before the Great Recession, whereas the introduction of robots steadily continued at a similar speed during and after the crisis. However, in what follows, we document that differences in the macro-economic environment pre-post the Great Recession cannot explain the differential effects estimated above.

Table C2: Effects on migration, Pierce and Schott (2016) Chinese import shock (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	1990–2015			1990–2007		
	A. Interacting baseline controls with time dummies					
Exposure to robots	-0.46***	-0.50***	-0.46***	-0.36***	-0.36***	-0.34***
	(0.13)	(0.11)	(0.10)	(0.12)	(0.11)	(0.10)
NTR Gap × post-2000	-1.14***	0.18	-0.15	-0.65	0.19	-0.22
	(0.32)	(0.61)	(0.49)	(0.50)	(0.72)	(0.60)
	B. Not interacting baseline controls with time dummies					
Exposure to robots	-0.34***	-0.41***	-0.36***	-0.31**	-0.33**	-0.28**
	(0.12)	(0.11)	(0.10)	(0.12)	(0.13)	(0.12)
NTR Gap × post-2000	-0.98***	-0.20	-0.43	-0.38	0.00	-0.20
	(0.36)	(0.61)	(0.56)	(0.54)	(0.52)	(0.50)
Region dummies & pre-trends	✓	✓	✓	✓	✓	✓
Demographics & industry shares		✓	✓		✓	✓
Contemp. changes			✓			✓

Note: The dependent variable is the change in the log working-age population. In columns 1–3 there are three time periods (1990–2000, 2000–7 and 2007–15) and 722 CZs each period, resulting in N=2,166. In columns 4–6, the time period 2007–15 is dropped, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. Columns 1 and 4 include census division dummies, time period dummies, and the outcome variable between 1970 and 1990 as covariates. Columns 2 and 5 also control for demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing). In Panel A, census division dummies, demographic characteristics, broad industry shares and contemporaneous changes are interacted with time period dummies. Columns 3 and 6 also include the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

First, we estimate the migration response to both shocks now omitting the post-2007 period. Results are reported in Panel A of Table C4, which follows the same structure of Table 2. The pattern is almost identical to our initial results that included the post-2007 period: throughout all specifications, robots have a significant, negative impact on population growth, whereas Chinese imports have no effect. As before, the effect of robots roughly halves in size after including a more stringent set of covariates. According to our preferred specification (column 5), the magnitude of the effect is almost identical to that estimated including the post-2007 period (–0.56 vs. –0.62). Given their standard errors, these are not statistically different from each other. Moreover, even in this pre-2007 period we do not detect any migration response to Chinese imports in any of the specifications.

Second, in Panel B of Table C4, we return to the full sample (incl. post-2007), but now add interactions between shocks and a post-2007 dummy. We are particularly interested in the coefficient on the interaction between exposure to robots and the post-2007 period dummy. If recessionary conditions mediate the migration response to robots, the coefficient on the interaction should be significant (negative or positive, depending on the direction of the effect of the Great Recession). Results from our most preferred specification (column 5) show that this is not the case. The coefficient on the interaction term is negative but not statistically significant, suggesting that the size of the migration response to robots does not significantly differ between the pre- and post-crisis period.

Affected regions. Even if regions affected by robots and by Chinese imports are relatively similar, one may be worried that some differences exist between them along a few variables (Table 1). To address this concern, we include all such variables as controls in our preferred specification to account for potential confounding effects along these characteristics. However, one may still be worried that the mediation of the employment effect (and in particular, whether it causes a migration response) depends on some of these characteristics. For example, it is possible that the same shock only causes a migration response in areas with a large share of college-educated individuals. If areas affected by robots housed significantly more college-educated workers, the reason for the differential migration response between the two shocks might partly lie in the initial characteristics of the affected regions, rather than in the shocks themselves. To rule out this possibility, we run a battery of tests (unreported) in which we interact each of the shocks with the initial covariates that significantly differ between the regions affected by the two shocks (as in Table 1, column 8). Reassuringly, none of these results support the view that differences in initial, observable characteristics of affected regions explain the differential migration response associated with the two shocks.

Table C3: Effects on migration, long differences (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2015		
US exposure to robots	-1.28***	-0.70***	-0.73***	-0.85***	-0.77***
	(0.44)	(0.24)	(0.20)	(0.16)	(0.16)
US exposure to Chinese imports	0.25	-0.36	-0.22	-0.40	-0.48
	(0.64)	(0.47)	(0.51)	(0.58)	(0.58)
Kleibergen-Paap *F*	160.5	153.3	110.8	59.1	54.4
			B. 1990–2007		
US exposure to robots	-1.37**	-0.66**	-0.64***	-0.74***	-0.66***
	(0.54)	(0.26)	(0.25)	(0.19)	(0.20)
US exposure to Chinese imports	-0.11	-0.56	-0.30	-0.59	-0.54
	(0.98)	(0.80)	(0.80)	(0.85)	(0.86)
Kleibergen-Paap *F*	54.5	53.7	42.3	22.3	19.8
Region dummies	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics			✓	✓	✓
Industry shares				✓	✓
Contemp. changes					✓

Note: The dependent variable in Panel A and B is the 1990–2015 and 1990–2007 change in the log count of the working-age population, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are N=722 CZs. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. Column 1 includes census division dummies as covariates. Column 2 also includes the change in the log count of the working-age population between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing). Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table C4: Effects on migration, different time periods (2SLS and reduced form)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2007		
US exposure to robots	-1.11***	-0.49***	-0.53***	-0.48***	-0.42***
	(0.41)	(0.19)	(0.19)	(0.12)	(0.12)
US exposure to Chinese imports	-0.53	-0.83	-0.33	-0.17	0.01
	(1.18)	(1.03)	(0.93)	(1.07)	(1.01)
Kleibergen-Paap F	41.0	41.6	38.4	17.3	16.3
			B. 1990–2015 (with post-2007 interactions)		
Exposure to robots	-0.87***	-0.47***	-0.49***	-0.42***	-0.36***
	(0.25)	(0.15)	(0.15)	(0.10)	(0.10)
Exposure to Chinese imports	-0.46	-0.52	-0.20	0.04	0.12
	(0.67)	(0.57)	(0.54)	(0.43)	(0.40)
Exposure to robots	-0.25	-0.15	-0.19	-0.22	-0.23
× post-2007	(0.19)	(0.20)	(0.13)	(0.15)	(0.16)
Exposure to Chinese imports	1.11**	0.77*	0.30	0.20	0.16
× post-2007	(0.47)	(0.45)	(0.29)	(0.25)	(0.23)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log count of the working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. Panel A only includes two time periods (1990–2000, 2000–7) and Panel B includes all three (also 2007–15), resulting in N=1,444 and N=2,166, respectively. Column 1 includes only time period and census division dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing). Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of employment (Panel A) and the working-age population (Panel B). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.4 Standard errors correction

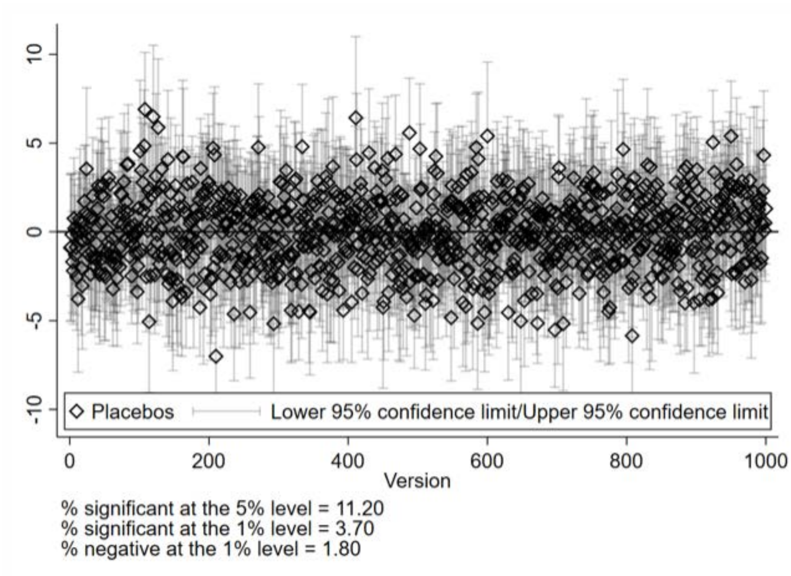
In our main results, standard errors allow for arbitrary clustering at the state level (48 states). It is, however, possible that errors are clustered not only within state borders, but across space more generally. For this reason, we perform a robustness exercise in Table C5, where we repeat the estimation of our preferred specification (column 5 in Table 2), estimating standard errors using the method proposed by Conley (1999). In particular, we allow for arbitrary spatial correlation with CZs that lie within varying distances, from less than 100 miles away (column 1) to less than 500 miles away (column 5). Reassuringly, although standard errors become slightly larger as we increase the radius, results remain unchanged.

In addition to spatial correlation, one concern with Bartik-style instruments is that standard inference procedures may deliver excessively small standard errors, if errors are correlated across observations that are geographically far apart but have similar employment shares (Adao et al., 2019). We address this issue by performing a set of placebo checks suggested by Adao et al. (2019). Similar to Derenoncourt (2022), we interact the employment shares used to construct the instruments for robots and Chinese imports with industry-specific shocks drawn from a random normal distribution.

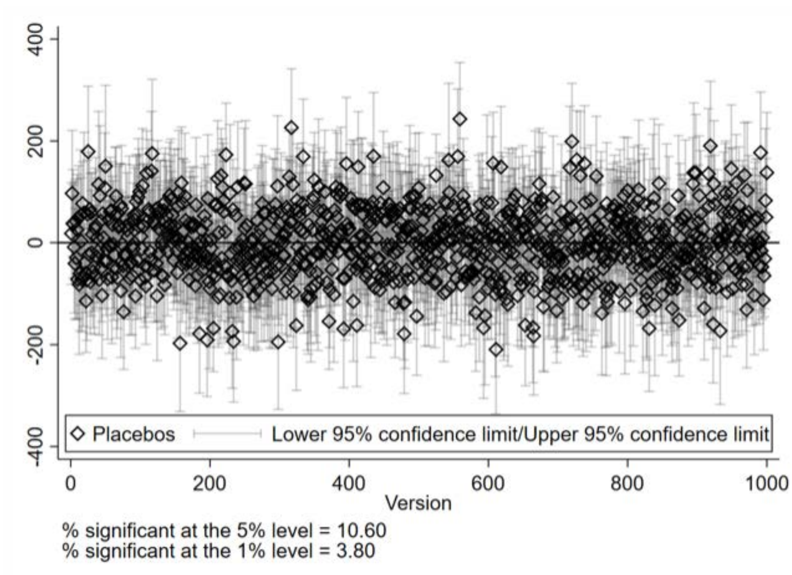
We iterate this procedure 1,000 times, and report the share of iterations for which results (for exposure to robots and to Chinese imports, respectively) are statistically significant at the 5% and 1% level. Panels A and B of Figure C1 document that the coefficients on the placebo instruments for exposure to robots and to Chinese imports are statistically significant at the 5% level 11.2% and 10.6% of the times, respectively. This is more than 5 times lower compared to the application shown in Adao et al. (2019), where the placebo shocks are statistically significant at the 5% level 55% of the times. Moreover, our placebo shocks are statistically significant at the 1% level only about 3.8% of the times.

Taken together, results in Figure C1 suggest that, even though standard errors may be too small due to the presence of correlated shocks, the estimated effects of robot exposure and Chinese import competition are unlikely to be driven by noise.

Figure C1: Placebo industry-level shocks



A. Exposure to robots



B. Exposure to Chinese imports

Note: This figure plots the coefficients on exposure to robots (Panel A) and exposure to Chinese imports (Panel B) in 1,000 separate reduced form regressions with randomly generated industry-level shocks. The specification is identical to column 5 in Table 2.

Table C5: Adjusting standard errors for spatial correlation following Conley (1999)

	(1)	(2)	(3)	(4)	(5)
	100 mi.	200 mi.	300 mi.	400 mi.	500 mi.
			A. Migration		
US exposure to robots	-0.56***	-0.56***	-0.56***	-0.56***	-0.56**
	(0.13)	(0.18)	(0.19)	(0.20)	(0.23)
US exposure to Chinese imports	0.45	0.45	0.45	0.45	0.45
	(0.76)	(0.73)	(0.74)	(0.76)	(0.77)
			B. House prices		
US exposure to robots	-2.55***	-2.55**	-2.55*	-2.55*	-2.55*
	(0.94)	(1.14)	(1.32)	(1.32)	(1.31)
US exposure to Chinese imports	0.49	0.49	0.49	0.49	0.49
	(2.94)	(2.78)	(2.69)	(2.43)	(2.67)
			C. In-migration		
US exposure to robots	-1.76***	-1.76***	-1.76***	-1.76***	-1.76***
	(0.54)	(0.57)	(0.61)	(0.67)	(0.65)
US exposure to Chinese imports	1.65	1.65	1.65	1.65	1.65
	(1.10)	(1.26)	(1.27)	(1.34)	(1.22)
			D. Out-migration		
US exposure to robots	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.58)	(0.52)	(0.51)	(0.60)	(0.53)
US exposure to Chinese imports	0.43	0.43	0.43	0.43	0.43
	(1.46)	(1.54)	(1.51)	(1.63)	(1.61)

Note: The dependent variable in Panel A is the change in the log count of working-age individuals (15-64), in Panel B the change in the log house price index (see Section 4.1 for details), and in Panels C and D the log count of in-migrants and out-migrants, respectively. There are three time periods in Panel A, and two time periods in Panels B, C and D, and 722 CZs each period, resulting in N=2,166 and N=1,444, respectively. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable in the pre-period (1970-1990 in Panel A, 1990/92-2000 in Panels B, C and D). Standard errors allow for arbitrary spatial correlation with CZs within 100 mi., 200 mi., 300 mi., 400 mi., and 500 mi. in columns 1, 2, 3, 4, and 5, respectively. Regressions are weighted by a CZ's 1990 national share of the outcome group in each Panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.5 In- and out-migration robustness checks

In Table 3, we define "close" and "far" moves using a threshold of 300 miles. This admittedly arbitrary cutoff is a convenient proxy for within-state and across-state moves. To verify that results are insensitive to the specific value chosen, we replicate the analysis using cutoffs of 200 miles and 400 miles, respectively. Results, reported in Tables C6 and C7, remain the same.

Table C6: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration			Out-migration		
	Overall	<200 mi.	>200 mi.	Overall	<200 mi.	>200 mi.
	A. Log count of migrants					
US exposure to robots	-1.76***	-2.10***	-1.84***	-0.01	-1.94***	0.41
	(0.53)	(0.51)	(0.69)	(0.55)	(0.49)	(0.81)
US exposure to Chinese imports	1.65	2.94**	0.06	0.43	1.45	0.56
	(1.12)	(1.20)	(1.52)	(1.43)	(1.35)	(1.74)
	B. Migration rate					
US exposure to robots	-2.03*	-0.11	-2.11**	-0.16	-1.11*	0.83
	(1.20)	(0.90)	(1.06)	(1.12)	(0.57)	(1.05)
US exposure to Chinese imports	4.40	2.23	1.02	-1.35	-1.12	-0.04
	(4.52)	(3.52)	(4.85)	(4.44)	(1.64)	(3.97)

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table C7: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration			Out-migration		
	Overall	<400 mi.	>400 mi.	Overall	<400 mi.	>400 mi.
	A. Log count of migrants					
US exposure to robots	-1.76***	-2.17***	-1.62**	-0.01	-1.42***	0.51
	(0.53)	(0.47)	(0.70)	(0.55)	(0.48)	(0.79)
US exposure to Chinese imports	1.65	2.96**	0.13	0.43	0.97	0.28
	(1.12)	(1.25)	(1.58)	(1.43)	(1.43)	(1.77)
	B. Migration rate					
US exposure to robots	-2.03*	-0.45	-1.47*	-0.16	-1.11**	0.76
	(1.20)	(0.94)	(0.88)	(1.12)	(0.56)	(0.91)
US exposure to Chinese imports	4.40	3.07	0.09	-1.35	-0.47	-1.21
	(4.52)	(3.80)	(4.48)	(4.44)	(1.90)	(3.45)

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table C8: Effects on in- and out-migration, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log count of migrants			Migration rates		
			A. In-migration			
US exposure to robots	-2.21***	-1.85***	-1.76***	-5.86***	-1.82	-2.03*
	(0.68)	(0.52)	(0.53)	(1.43)	(1.14)	(1.20)
US exposure to Chinese imports	0.53	1.22	1.65	-0.72	2.04	4.40
	(1.05)	(1.04)	(1.12)	(4.34)	(4.01)	(4.52)
			B. Out-migration			
US exposure to robots	-0.72	-0.31	-0.01	-1.95	-0.60	-0.16
	(0.76)	(0.55)	(0.55)	(1.64)	(1.19)	(1.12)
US exposure to Chinese imports	0.44	1.00	0.43	-1.93	-0.32	-1.35
	(1.08)	(1.37)	(1.43)	(3.61)	(4.54)	(4.44)
Region × time & pre-trends	✓	✓	✓	✓	✓	✓
Demographics × time & industry shares × time		✓	✓		✓	✓
Contemp. changes × time			✓			✓

Note: The dependent variables in columns 1–3 and 4–6 are the log count of migrants and migration rate, respectively. Panel A focuses on in-migration and Panel B on out-migration. For example, the log count of in-migrants in columns 1–3 of Panel A is defined as the log of the sum of in-migrants in all the years of the subperiod (e.g., 2000–2007). The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. Columns 1 and 4 include interactions between census division and time period dummies, and the change in the outcome variable between 1992 and 2000. Columns 2 and 5 also control for demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Columns 3 and 6 also include the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

D Theoretical results

D.1 Detailed exposition of the theoretical model

Environment. We consider an economy with $n = 1, ..., N$ CZs. Each CZ produces a unique differentiated variety of a good, and CZs are connected via a bilateral transport network under symmetric iceberg trade costs: $d_{ni} = d_{in} > 1, n \neq i$ with $d_{nn} = 1$. There is a mass $\overline{L}$ of representative consumers who are mobile across CZs and endowed with one unit of labor that they supply inelastically with no disutility.[50]

Preferences over varieties take the constant elasticity of substitution (CES) form:

$$U_n = C_n = \left[\sum_{i=1}^{N} {c_{ni}}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where c_{ni} denotes consumption in CZ n of the variety produced in i, and σ denotes the elasticity of substitution across varieties. The budget constraint is given by:

$$\sum_{i=1}^{N} p_{ni} c_{ni} = w_n,$$

where w_n is the wage prevailing in CZ n and p_{ni} is the price of variety i in that CZ. The dual price index in turn is given by:

$$P_n = \left[\sum_{i=1}^{N} {p_{ni}}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}.$$

There are only two sectors per CZ: a manufacturing sector, subject to *location-specific* shocks, and a non-manufacturing sector that is only indirectly affected.[51] Firms

[50] An elastic labor supply is not necessary to generate endogenous labor supplies across CZs, because representative agents are geographically mobile.

[51] This differs slightly from Autor et al. (2013) and Acemoglu and Restrepo (2020), who model the economy as having many industries, all of which are affected by the shocks to the same degree regardless of the location. There is one conceptual and one technical reason for choosing this alternative approach. Conceptually, this allows us to derive results in a parsimonious way with a minimal set of ingredients. This comes at the cost of weakening somewhat the link with our empirical strategy, which is characterized by many *industry-specific* shocks that, together, amount to an average location-specific shock. However, our goal is to clarify the mechanisms at play, rather than motivating the empirical strategy. The technical reason for our modeling choice is that, in the existence and uniqueness results derived below, we follow Allen and Arkolakis (2014), who rely on mathematical results for linear operators like the celebrated Perron-Frobenius theorem. To the best of our knowledge, no equivalent

in the manufacturing sector produce each variety with a constant returns to scale technology and under perfect competition. In the quantitative exercises described below, we assume that firms can either automate or offshore some tasks in their production process, but not both.[52] In particular, the firm located in CZ i operates under:

$$Q_i^h = A_i \left[\left(\min_{\nu \in [0,1]} \left\{ \tau_i^h (\nu) \right\} \right)^{\frac{\varepsilon_i^h - 1}{\varepsilon_i^h}} + I_i^{h \frac{\varepsilon_i^h - 1}{\varepsilon_i^h}} \right]^{\frac{\varepsilon_i^h}{\varepsilon_i^h - 1}} , h = R, O$$

where I_i^h is an intermediate non-tradeable input (e.g. professional services), A_i represents the productivity of location i, and $\tau_i^h (\nu)$ represents the amount of task ν used in production out of a continuum of tasks indexed by $\nu \in [0, 1]$. The parameter ε_i^h is the industry elasticity of substitution (i.e.s.), which governs the degree of substitution between manufacturing tasks and non-manufacturing inputs. This is one of the key parameters we focus on in our quantitative exercises below. The superscripts index with $h = R$ firms with tasks subject to automation, and $h = O$ firms subject to offshoring.

The functional form for $\tau_i^R (\nu)$ is similar to that in Acemoglu and Restrepo (2020):

(D.1)
$$\tau_i^R (\nu) = \begin{cases} \gamma_R R_i (\nu) + \gamma_L^R L_i^R (\nu) & \text{if} \quad \nu \leq \theta_i^R \\ \gamma_L^R L_i^R (\nu) & \text{if} \quad \nu > \theta_i^R \end{cases} ,$$

where $R_i (\nu)$ and $L_i^R (\nu)$ are the amounts of industrial robots and human labor used in producing task ν, respectively. The parameters γ_R and γ_L^R capture their respective productivities. The intuition is that tasks below the threshold θ_i^R are subject to automation, with industrial robots being perfect substitutes of human labor, whereas tasks above θ_i^R can only be performed by human labor.

We assume that firms have access to an international market for industrial robots. In each location i, firms can purchase one robot at price p_i^{R*}, which they take as given. This is consistent with the fact that US firms largely rely on imports to purchase industrial robots.[53] Denoting the domestic wage with w_i, it is easy to show that, if

result exists for economies with many industries per region and geographically mobile agents.

[52] This is consistent with the low correlation (0.06) between CZs' exposures to robots and Chinese imports.

[53] Out of the 28 robot supplier members in the International Federation of Robotics (IFR), only one is based in the United States (Leigh and Kraft, 2018).

$1-\frac{\gamma_L^R}{\gamma_R}\frac{p_i^{R*}}{w_i}>0$, firms adopt robots for all tasks $\nu \leq \theta_i^R$. In our equilibrium, and from now on, we focus on this case.

To model $\tau_i^O(\nu)$, we follow Grossman and Rossi-Hansberg (2008):

$$\tau_i^O(\nu) = [\beta t(\nu)]^{-1}\gamma_L^O L_i^F(\nu) + \gamma_L^O L_i^O(\nu), \tag{D.2}$$

where $L_i^F(\nu)$ and $L_i^O(\nu)$ are the number of foreign and domestic workers used to perform task ν, respectively. The parameter γ_L^O captures total productivity of each form of labor, whereas $\beta t(\nu) \geq 1$ captures the higher relative productivity of domestic labor. Tasks are ordered so that $t(\nu)$ is non-decreasing. This implies that task ν can be performed with foreign labor, but only at the cost of higher input requirements.

To increase the comparability of the two shocks, we further customize equation (D.2). Let w_i^* be the foreign wage faced by firms engaging in offshoring. Then, firms' optimization under the specification in equation (D.2), with $t(\nu)$ non-decreasing and $\beta t(0)w_i^* < w_i$, implies that there is a threshold below which firms offshore all tasks. However, this threshold is endogenous and changes with the model's parameters, thereby complicating the comparison to a shift in θ_i^R in equation (D.1). For this reason, we adopt a more specific form for the schedule $t(\cdot)$, and assume:

$$t(\cdot) = \begin{cases} \underline{t} & \nu \leq \theta_i^O \\ \bar{t} & \nu > \theta_i^O \end{cases},$$

with $1 \leq \beta\underline{t} < \beta\bar{t}$. As in the case of robots, we focus on the case in which $\beta\underline{t}w_i^* < w_i < \beta\bar{t}w_i^*$. In this scenario, firms find it optimal to offshore all tasks $\nu \leq \theta_i^O$, and hire domestic labor for tasks $\nu > \theta_i^O$.

In the existence and uniqueness results, we work with a slightly more general version of the model by assuming that firms in all CZs operate:

$$x_i = \vec{A}_i \left[Q_i^R\right]^{\phi_i}\left[Q_i^O\right]^{1-\phi_i}, \tag{D.3}$$

where $\vec{A}_i = A_i(\phi_i)^{-\phi_i}(1-\phi_i)^{-(1-\phi_i)}$ and $\phi_i \in (0,1)$. The product $(\phi_i)^{-\phi_i}(1-\phi_i)^{-(1-\phi_i)}$ in $\vec{A}_i$ is just a convenient normalization. One can thus think about the quantitative exercises performed below as imposing $\vec{A}_i = A_i$ along with $\phi_i = 1$ for firms that automate some of their tasks and $\phi_i = 0$ for those that offshore them.

For simplicity, we assume that the non-tradeable service is produced under perfect competition with a constant returns technology given by:

$$x_i^S = A_i^S E_i^S,$$

where E_i^S is non-manufacturing labor, and A_i^S captures its productivity.

Equilibrium. The assumption of CES preferences implies that consumers' indirect utility function from living in CZ n is given by $V_n = \frac{w_n}{P_n}$. Labor mobility implies that welfare is equalized across CZs:

$$V_n = \overline{V}. \tag{D.4}$$

For the aggregate labor market to clear it must hold that:

$$\sum_{n=1}^{N} L_n = \overline{L}, \tag{D.5}$$

where L_n is CZ n population, and we normalize $\sum_{i=1}^{N} w_i = 1$. We define a *spatial equilibrium* as a distribution of economic activity such that (a) consumers and firms make optimal choices, (b) markets clear and, in particular, equation (D.5) holds, and (c) welfare is equalized, that is, equation (D.4) holds.

In this model, the purchases of robots and the offshoring of tasks imply that the economy as a whole is open, i.e., there are trade and financial transactions with the rest of the world. With no export demand, domestic income must be accompanied by a current account deficit (borrow from the rest of the world), for markets to clear. Otherwise, domestic income alone would not suffice to finance the purchase of the entire home production. In a fully dynamic model, this would be determined as part of the equilibrium. Given the static nature of our model, we need to add either exports or current account deficit in a somewhat *ad-hoc* fashion. We prefer to add a foreign demand. This is because, with exports, transactions take place within the same time period and our model is static. Thus, we assume that each variety i faces an additional export demand given by:

$$x_{r_n i}^d = \frac{d_{in}^{1-\sigma}}{d_{ir_n}^{1-\sigma}} \left(\frac{p_{r_n i}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \left(\frac{1-\kappa_n}{\kappa_n}\right), \tag{D.6}$$

where r_n is the foreign location associated with n, and $\kappa_n \in (0,1)$ is an exogenous parameter related to domestic labor demand that we specify in Appendix D.2. The intuition is that the resources paid by CZ n in exchange for its robots purchases and offshored tasks are spent by recipients of those resources, according to equation (D.6), in all varieties i that are produced in the home country. There is one such foreign location r_n for each CZ n. The exact form of these demands is useful for proving our existence and uniqueness result, and serves no other purpose.[54]

To show the existence and uniqueness of a spatial equilibrium, we apply Theorem 1 in Allen and Arkolakis (2014), which builds on the Perron-Frobenius theorem. We assume that both the price of robots and the wages of foreign labor faced by CZ i are the product of the local wage in i and an international price and wage, respectively. That is, $p_i^{R*} = p^{R*} w_i$ and $w_i^* = w^* w_i$. Requiring that both p_i^{R*} and w_i^* depend on local economic conditions and on economic conditions in international markets seems reasonable. Since distance to those markets is also likely to influence prices, another specification might have been the following: $p_i^{R*} = p^{R*} d_{iR}^{\phi_i^d} w_i^{\phi_i^R}$ and $w_i^* = w^* d_{ic}^{\phi_i^d} w_i^{\phi_i^w}$, where d_{iR} measures the distance from CZ i to the international robots market (e.g., some of the robot producing countries in Europe), and d_{ic} measures the distance from i to China. Each margin could in turn have different weights, depending on the coefficients ϕ_i^d, ϕ_i^R and ϕ_i^w. To prove existence and uniqueness in our model, it is important that $\phi_i^R = \phi_i^w = 1$, but the condition $\phi_i^d > 0$ can be accommodated. However, given that this is not a relevant margin for our quantitative results, we set $\phi_i^d = 0$ in order to have a more parsimonious specification.

With this, we have:

Proposition 1. *Suppose that that each variety i faces an additional export demand given by* (D.6). *Then:*

1. *There is a unique spatial equilibrium.*

2. *The equilibrium can be computed as the uniform limit of a simple iterative procedure.*

As with all results in this section, the proof is provided in Appendix D.2.

[54] Equivalent formulations, such as all export demand coming from the same foreign location, would achieve the same result with appropriate functional form adjustments.

Equilibrium impact of the shocks. Having established the existence and uniqueness of the spatial equilibrium, we investigate the equilibrium impact of both shocks on CZ population. Our goal is to examine *i*) how CZ population responds to robot exposure and Chinese imports, and *ii*) what labor market forces, within and outside manufacturing, mediate such responses.

We begin by examining more closely the forces shaping labor demand. Given equilibrium prices and the technology in equation (D.3), firms face a constant unit cost of production given by:

$$\Psi_i = w_i \varphi_i$$

where:

$$\varphi_i = \frac{1}{A_i} \left(\mathbb{P}_{Q^R}\right)^{\phi_i} \left(\mathbb{P}_{Q^O}\right)^{(1-\phi_i)}$$

$$\mathbb{P}_{Q^R} = \left[\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}\right]^{\frac{1}{1-\varepsilon_i^R}}$$

$$\mathbb{P}_{Q^O} = \left[\left(\frac{1-\theta_i^O\left(1-w^*\beta \underline{t}\right)}{\gamma_L^O}\right)^{1-\varepsilon_i^O} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^O}\right]^{\frac{1}{1-\varepsilon_i^O}}.$$

These objects play a crucial role in the proposition introduced next, which shows that changes in CZ population are a weighted average of changes in manufacturing and non-manufacturing employment – forces that can in turn be decomposed into three different effects. For our next result and henceforth, we specialize the environment and take $\phi_i = 1$ and $\phi_i = 0$ for a CZ subject to automation and to offshoring, respectively.[55] We denote by E_i^M manufacturing employment in CZ i (recall that E_i^S denotes non-manufacturing employment).

Proposition 2. *Suppose that all regions are homogeneous, then:*

$$d\ln L_i = \Omega_i d\ln E_i^M + (1-\Omega_i)\, d\ln E_i^S \tag{D.7}$$

[55] When the type of region is not explicitly stated, the statement applies to both.

where, for $h = R, O$*:*

$$\text{(D.8)}\quad d\ln E_i^M = -\frac{d\theta_i^h}{1-\theta_i^h} - \sigma d\ln\varphi_i - \varepsilon_i^h d\ln\left[\left\{\left(\mathbb{P}_{Q^h}\right)^{1-\varepsilon_i^h} - \left(A_i^S\right)^{-\left(1-\varepsilon_i^h\right)}\right\}^{\frac{1}{1-\varepsilon_i^h}} / \mathbb{P}_{Q^h}\right] + \zeta$$

$$\text{(D.9)}\quad d\ln E_i^S = -\sigma d\ln\varphi_i - \varepsilon_i^h d\ln\left[\left(A_i^S\right)^{-1} / \mathbb{P}_{Q^h}\right] + \zeta$$

$$\text{(D.10)}\qquad \Omega_i = \frac{E_i^M}{L_i}.$$

Remark. *Given the assumption that* $d_{nn} = 1$*, imposing homogeneity implies that there are no trade costs.*[56] *The reason for taking this approach is that it allows us to tie our empirical estimates to the model in the quantitative exercises performed below. At the same time, the assumption is innocuous, because the forces highlighted in Proposition 2 would still be present without it, and our focus here is not on studying differences in trade costs.*

For a detailed discussion of the implications of Proposition 2, see Section 6.

D.2 Proofs

In this subsection we provide the proofs for Propositions 1 and 2.

Proof of Proposition 1: From firm's i cost minimization problem we get:

$$\text{(D.11)}\qquad \gamma_L^R L_i^R = Q_i^R \left\{ \frac{\frac{w_i\left\{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right\}}{\gamma_L^R}}{\mathcal{P}_{Q^R}} \right\}^{-\varepsilon_i^R}$$

$$\text{(D.12)}\qquad I_i^R = Q_i^R \left\{ \frac{p_i^S}{\mathcal{P}_{Q^R}} \right\}^{-\varepsilon_i^R}$$

[56] However, only the condition $d_{in} = \overline{d}$ is needed. Whether $\overline{d} = 1$ or $\overline{d} > 1$ is immaterial for our purposes.

where:

$$Q_i^R = x_i \frac{\phi_i}{A_i} \frac{\left(\mathcal{P}_{Q^R}\right)^{\phi_i} \left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)}}{\mathcal{P}_{Q^R}} \tag{D.13}$$

$$\mathcal{P}_{Q^R} = \left[\left\{ \frac{w_i \left\{ 1 - \theta_i^R \left(1 - p^{R*} \frac{\gamma_L^R}{\gamma_R} \right) \right\}}{\gamma_L^R} \right\}^{1-\varepsilon_i^R} + \left(p_i^S\right)^{1-\varepsilon_i^R} \right]^{\frac{1}{1-\varepsilon_i^R}} \tag{D.14}$$

$$\mathcal{P}_{Q^O} = \left[\left\{ \frac{w_i \left\{ 1 - \theta_i^O \left(1 - w^* \beta \underline{t} \right) \right\}}{\gamma_L^O} \right\}^{1-\varepsilon_i^O} + \left(p_i^S\right)^{1-\varepsilon_i^O} \right]^{\frac{1}{1-\varepsilon_i^O}} . \tag{D.15}$$

Similarly, we also get:

$$\gamma_L^O L_i^O = Q_i^O \left\{ \frac{\frac{w_i \left\{ 1 - \theta_i^O (1 - w^* \beta \underline{t}) \right\}}{\gamma_L^O}}{\mathcal{P}_{Q^O}} \right\}^{-\varepsilon_i^O} \tag{D.16}$$

$$I_i^O = Q_i^O \left\{ \frac{p_i^S}{\mathcal{P}_{Q^O}} \right\}^{-\varepsilon_i^O} \tag{D.17}$$

with:

$$Q_i^O = x_i \frac{(1-\phi_i)}{A_i} \frac{\left(\mathcal{P}_{Q^R}\right)^{\phi_i} \left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)}}{\mathcal{P}_{Q^O}}. \tag{D.18}$$

These in turn imply a constant unit cost given by:

$$\Psi_i = \frac{1}{A_i} \left(\mathcal{P}_{Q^R}\right)^{\phi_i} \left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)} . \tag{D.19}$$

Now, total labor demand in commuting zone i is given by:

$$\begin{aligned} L_i^D &= \left[1 - \theta_i^R\right] L_i^R + \left[1 - \theta_i^O\right] L_i^O + \frac{1}{A_i^S} \left(I_i^R + I_i^O\right) \\ &= x_i \kappa_i \underbrace{\frac{\left(\mathbb{P}_{Q^R}\right)^{\phi_i} \left(\mathbb{P}_{Q^O}\right)^{(1-\phi_i)}}{A_i}}_{=\varphi_i}, \end{aligned} \tag{D.20}$$

where:

$$\kappa_i \coloneqq \phi_i \left(\frac{\left[\frac{1-\theta_i^R}{\gamma_L^R}\right] \left(\frac{1-\theta_i^R \left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R} \right)^{-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}}{\mathbb{P}_{Q^R}^{1-\varepsilon_i^R}} \right)$$

$$+ (1-\phi_i) \left(\frac{\left[\frac{1-\theta_i^O}{\gamma_L^O}\right] \left(\frac{1-\theta_i^O (1-w^* \beta \underline{t})}{\gamma_L^O} \right)^{-\varepsilon_i^O} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^O}}{\mathbb{P}_{Q^O}^{1-\varepsilon_i^O}} \right).$$

Moreover, given the CES form of preferences we also have:

$$c_{ni} = \left(\frac{p_{ni}}{P_n}\right)^{-\sigma} C_n$$
$$C_n = \frac{w_n}{P_n}.$$

Hence, market clearing in commuting zone i labor market requires:
(D.21)
$$L_i (\kappa_i)^{-1} = \varphi_i \left\{ \sum_{n=1}^{N} d_{in} \left[\left(\frac{p_{ni}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \right] + \sum_{n=1}^{N} d_{ir_n} \left[\frac{d_{in}^{1-\sigma}}{d_{ir_n}^{1-\sigma}} \left(\frac{p_{r_n i}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \left(\frac{1-\kappa_n}{\kappa_n}\right) \right] \right\}$$

Given the assumption of perfect competition, the final price of a good produced in i and sold in any location n equals the marginal cost of production and shipping:

$$p_{ni} = w_i \varphi_i d_{in}.$$

So we can rewrite (D.21) as:

(D.22)
$$L_i (\kappa_i)^{-1} = \varphi_i \sum_{n=1}^{N} d_{in} \left[\left(\frac{w_i \varphi_i d_{in}}{P_n}\right)^{-\sigma} \frac{w_n L_n (\kappa_n)^{-1}}{P_n} \right].$$

If we substitute P_n using $V_n = \frac{w_n}{P_n}$ and manipulate somewhat the expression we get:

(D.23)
$$w_i^\sigma L_i (\kappa_i)^{-1} = \sum_{n=1}^{N} \left[(\varphi_i d_{in})^{1-\sigma} V_n^{1-\sigma} w_n^\sigma L_n (\kappa_n)^{-1} \right].$$

Moreover, using the expression for the price index P_n together with $V_n = \frac{w_n}{P_n}$ and equilibrium prices yields:

$$P_n = \left[\sum_{i=1}^{N} {p_{ni}}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

$$\frac{w_n}{V_n} = \left[\sum_{i=1}^{N} (w_i \varphi_i d_{in})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{D.24}$$

If we impose welfare equalization in (D.23) and (D.24) we get:

$$w_i^{\sigma} L_i (\kappa_i)^{-1} = V^{1-\sigma} \sum_{n=1}^{N} \left[(\varphi_i d_{in})^{1-\sigma} w_n^{\sigma} L_n (\kappa_n)^{-1}\right] \tag{D.25}$$

$$w_n^{1-\sigma} = V^{1-\sigma} \left[\sum_{i=1}^{N} (\varphi_i d_{in})^{1-\sigma} w_i^{1-\sigma}\right]. \tag{D.26}$$

Both (D.25) and (D.26) are linear operators with the same eigenvalue, $V^{\sigma-1}$, and with eigenvectors $w_n^{\sigma} L_n (\kappa_n)^{-1}$ and $w_i^{1-\sigma}$, respectively. Following Theorem 1 in Allen and Arkolakis (2014), we can apply the celebrated Perron-Frobenius theorem to conclude there is a unique (up to scale) positive eigenvector, for each of (D.25) and (D.26), associated with a positive real eigenvalue. Moreover, given that the matrices that describe these operators are the transpose of each other, we know the eigenvalues coincide. Following the arguments in Allen and Arkolakis (2014) we can show there is a simple iterative procedure that converges to the solution. Finally, using the normalization $\sum_{i=1}^{N} w_i = 1$ and aggregate market clearing in the labor market, $\sum_{i=1}^{N} L_i = \overline{L}$, we pin down the scales. ■

Proof of Proposition 2: Imposing homogeneity and differentiating (D.25) and (D.26) yields:

$$d\ln L_i = d\ln\kappa_i + (\sigma-1)\, d\ln\varphi_i^{-1} + \zeta. \tag{D.27}$$

To ease notation, we work with a commuting zone subject to automation for the rest of this proof. The exact same arguments apply to a region subject to offshoring. Using (D.11)-(D.19) we can write:

$$E_i^M = \left[1-\theta_i^R\right] L_i^R = \frac{x_i}{A_i}\left(\frac{1-\theta_i^R}{\gamma_L^R}\right)\left(\frac{\left(\gamma_L^R\right)^{-1}\left[1-\theta_i^R\left(1-p^{R*\frac{\gamma_L^R}{\gamma_R}}\right)\right]}{\mathbb{P}_{Q^R}}\right)^{-\varepsilon_i^R}$$

$$E_i^S = \left(A_i^S\right)^{-1} I_i^R = \frac{x_i}{A_i}\left(A_i^S\right)^{-1}\left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}}\right)^{-\varepsilon_i^R}.$$

If we differentiate these expressions we get:

$$d\ln E_i^M = d\ln x_i + d\ln\left(\frac{1-\theta_i^R}{\gamma_L^R}\right) - \varepsilon_i^R d\ln\left(\frac{\left(\gamma_L^R\right)^{-1}\left[1-\theta_i^R\left(1-p^{R*\frac{\gamma_L^R}{\gamma_R}}\right)\right]}{\mathbb{P}_{Q^R}}\right) \tag{D.28}$$

$$d\ln E_i^S = d\ln x_i - \varepsilon_i^R d\ln\left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}}\right). \tag{D.29}$$

If we impose equilibrium in (D.20) and differentiate we can express:

$$d\ln L_i = d\ln x_i + d\ln\varphi_i + d\ln\kappa_i, \tag{D.30}$$

so if we combine (D.27) and (D.30) we get:

$$d\ln x_i = -\sigma d\ln\varphi_i + \zeta.$$

Hence, if we substitute in (D.28) and (D.29) we get:

$$d\ln E_i^M = d\ln\left(\frac{1-\theta_i^R}{\gamma_L^R}\right) - \sigma d\ln\varphi_i - \varepsilon_i^R d\ln\left(\frac{\left(\gamma_L^R\right)^{-1}\left[1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right]}{\mathbb{P}_{Q^R}}\right) + \zeta \tag{D.31}$$

$$d\ln E_i^S = -\sigma d\ln\varphi_i - \varepsilon_i^R d\ln\left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}}\right) + \zeta. \tag{D.32}$$

Equation (D.32) is the one given in the text. Using the fact that:

$$d\ln\left(\frac{1-\theta_i^R}{\gamma_L^R}\right) = -\frac{d\theta_i^R}{1-\theta_i^R}$$

in (D.31) gives (D.8).

Finally, using (D.20) again we know:

$$d\ln L_i = \Omega_i d\ln E_i^M + (1-\Omega_i)\, d\ln E_i^S$$
$$\Omega_i = \frac{E_i^M}{L_i},$$

which gives (D.7) and (D.10) in the text. ■

D.3 Additional details on the quantitative exercises

In this section, we provide a more detailed exposition of the quantitative results of Section 6.2. We combine evidence from other studies with our own empirical estimates $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Section 4.1 to perform two different sets of quantitative exercises:

- First, we assume that Proposition 2 holds, and use the functional forms above to link the estimated reduced form coefficients (β^r, β^c) to the i.e.s. and the cost savings. Using external information, we pin down all parameters in the model except for the i.e.s. and cost savings. Then, we solve for the values of these parameters that are consistent with our 2SLS estimates of (β^r, β^c) in Table 2. This allows us to compare the model consistent i.e.s. and cost savings with the external evidence on them. In line with the existing evidence, the model implies that cost savings (resp. i.e.s.) are larger for import competition (resp. robots).

- Second, we show that, by partially reducing the cost savings associated with Chinese imports, we can equate the estimated effect of robots on migration, to the effect of the Chinese imports in the model. In other words, in this model, the difference in cost savings is enough to explain the different migration responses triggered by local labor market shocks, and mediated by employment. Instead, while increasing the i.e.s. of import competition brings $\hat{\beta}^c$ closer to $\hat{\beta}^r$, the former always remains larger than the latter.

Empirical evidence on cost savings and the i.e.s. As discussed above, the i.e.s. and cost savings are key in shaping the strength of each of the three effects in Proposition 2. These effects, in turn, determine the total effect on local population growth. Even though they are difficult to observe, there exists evidence, albeit imperfect, on both of them and for both shocks. BCG (2015) estimates that, between 2000 and 2015, the cost savings of US firms generated by (cheaper) Chinese imports were between 50% and 70%. Since this number does not include shipping costs, which are estimated to reduce cost savings by around 10 percentage points (AlixPartners, 2009), the total cost savings associated with Chinese imports are in the range of 40 to 60%. Acemoglu and Restrepo (2020) instead estimate that the cost savings from using robots rather than US labor are only around 30%. That is, trade with China generated substantially higher cost savings than robots, according to these estimates.

Reliable estimates for the i.e.s. are even more difficult to obtain than for cost savings, given the daunting task of measuring elasticities of substitution more generally.

The fact that, in our model, the i.e.s. regulates the complementarity between manufacturing and non-manufacturing makes the measurement of the i.e.s. even harder. The most reliable estimates in the literature measure elasticities with respect to all inputs, or across all industries. For example, Atalay (2017) estimates values of around 1, on average. However, this masks heterogeneity across industries: while elasticities tend to be above one for industries most exposed to automation (e.g., automotive and chemicals), they are below one for industries most exposed to Chinese imports (e.g., textiles and electronics). Focusing exclusively on non-manufacturing, rather than all, inputs would likely yield higher values, due to the weaker linkages across sectors. This suggests that complementarity with the service sector should be higher for Chinese-imports-exposed than for robot-exposed industries.

Parameter choices. Table D1 summarizes our parameter choices. Following the trade literature (Simonovska and Waugh, 2014), we set the elasticity of substitution between tradeable varieties to $\sigma = 5$. We choose A_i^S in order to match a ratio of manufacturing to total (domestic) employment of 10%, which is consistent with the levels of this ratio for the period in our sample.[57] These values apply to both shocks.

Turning to parameter choices specific to Chinese import competition, when we fix the cost savings we set them at 40% ($w^* \beta \underline{t} = 0.6$) – the lower bound of the range suggested by the external evidence described above. This value allows us to match not only $\hat{\beta}^c$ but also the signs of the effects on manufacturing and on non-manufacturing employment. When fixing the i.e.s., we set $\varepsilon^O = 0.8$, which, consistent with Atalay (2017), is slightly below 1. Since the ratio of foreign to domestic labor payroll in the model equals $\theta_i^O \left[1 - \theta_i^O\right]^{-1} w^* \beta \underline{t}$, we can pin down θ_i^O. Since data on foreign labor payroll is hard to find, we rely on the (employment-weighted) ratio of net imports from China to the US (from the UN Comtrade database) to labor compensation in the US (from the BEA) in the electronics and textiles industries in the year 2005. We focus on these two industries to mimic a hypothetical CZ that is fully "treated" with the trade shock. We choose 2005 because, in this year, both shocks are roughly half way between their 1990 and 2015 values, and it thus provides a sensible point at which to evaluate our first order approximations. Picking this value for the ratio implies $\theta_i^O = 0.619$. Finally, we set $\beta \underline{t} = 12.5$, which, together with $w^* \beta \underline{t} = 0.6$, implies $w^* = 0.048$. This, in turn, means that $w_i / w_i^* = 20.83$, which is also consistent with BCG (2015).

For automation, when we fix the cost savings, we use 22.78% $\left(p^{R*} \frac{\gamma_L^R}{\gamma_R} = 0.77\right)$. We

[57] See https://fred.stlouisfed.org/graph/?g=Cssj.

choose this value because it allows us to match not only $\hat{\beta}^r$, but also the signs of the effects on manufacturing and non-manufacturing employment. We return to this point when discussing the numerical results below. When fixing the i.e.s., we use $\varepsilon^R = 1.1$, consistent with Atalay (2017). To fix θ_i^R, we use the fact that, in the model, the ratio of industrial robots to manufacturing employment is given by $\theta_i^R \left[1-\theta_i^R\right]^{-1} \left(\gamma_L^R/\gamma_R\right)$. Combining data from the IFR and the BEA to calculate the number of robots per worker in the automotive and chemicals industry (again, to mimic a "treated" CZ) in 2005, we get around 30 robots per 1,000 workers. This implies $\theta_i^R = 0.154$. Finally, we set $\gamma_R/\gamma_L^R = 6$, consistent with the evidence discussed in Acemoglu and Restrepo (2020).

Connecting the model with the empirical estimates. The quantitative exercises below use Proposition 2 to tie the effects in the model to the empirical estimates in Section 4.1. However, given that the quantities $d\ln\theta_i^h$ are unobservable, the connection between the two requires an additional step.

For automation, the empirical results measure exposure as:

$$Exposure\ to\ robots_i = \frac{d\left(machines_i\right)}{labor_i} - \frac{dY_i}{Y_i}\frac{machines_i}{labor_i}.$$

Thus, in order to connect the elasticities within the model with our empirical estimates, we need to map changes in $\ln\theta_i^h$ to this measure of exposure. After some algebra, one can show that:

$$\text{(D.33)}\qquad \frac{d\left(machines_i\right)}{labor_i} - \frac{dY_i}{Y_i}\frac{machines_i}{labor_i} = \left(\frac{\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}\left[\frac{1+\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\left(\varepsilon_i^R-1\right)}{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}\right]}{\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}}\right) * \frac{machines_i}{labor_i} d\ln\theta_i^R.$$

For Chinese imports, we rely on the same relationship (replacing the appropriate robot parameters in (D.33) for their offshoring counterparts). Even though the trade shock lacks the output growth normalization of this exposure measure, we nonetheless believe that the latter is the best way to perform the match. This is for two reasons. First, the estimates we obtain are coming from a 2SLS strategy, which has as central goal that of capturing the pure technological changes from the shock, as opposed to any scale changes that might be happening simultaneously. Exploiting variation coming from other developed countries should achieve this goal. Second, treating the data symmetrically allows us to rule out any differences coming from small changes in how we match the shocks in the model with the estimates.

1st set of exercises: backing out model consistent i.e.s. and cost savings. With the parameter choices described above, we turn to the quantitative exercises. For the first part of this set of exercises, we fix the cost savings at 40% and 22.78% for the trade and the robot shock, respectively. We then solve for the i.e.s. that matches $\left(\hat{\beta}^r, \hat{\beta}^c\right) = (-0.56, 0.45)$, the estimates from our preferred specification in Table 2 (column 5). We obtain $\left(\hat{\varepsilon}^R_{model}, \hat{\varepsilon}^O_{model}\right) = (5.001, 4.33)$. This indicates that the i.e.s. consistent with the model are in line with those in Atalay (2017), i.e. $\hat{\varepsilon}^R_{model} > \hat{\varepsilon}^O_{model}$. As noted before, it is difficult to compare the levels of the i.e.s. in our model and in Atalay (2017), because the latter measures the substitutability within a narrower set of inputs. While it is reasonable to expect the i.e.s. in our model to be larger, we lack any specific estimates to make this comparison. Nonetheless, since our goal is to compare the two shocks, the model suggests that robot affected industries have a larger i.e.s. than those affected by Chinese import competition.

In this exercise, we not only match our estimates on migration $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Table 2, but also the signs of the effects on manufacturing and non-manufacturing employment in Table 5. A wide range of values for the cost savings are consistent with the model matching both the point estimate for the effects of Chinese imports on migration, $\hat{\beta}^c = 0.45$, and the signs of the effects on manufacturing (negative) and non-manufacturing employment (positive). For robots, instead, matching these objects is only possible for a small range. This is why we chose 22.78% as the parameter for robots' cost savings before.

In the second part of this set of exercises, we fix $\left(\varepsilon^R, \varepsilon^O\right) = (1.1, 0.8)$, and solve for the model consistent cost savings. Before diving into it, note that in the previous exercise we got $\hat{\varepsilon}^R_{model} = 5.001$. This is only slightly above 5, which is the value for σ. As it turns out, in this model, to get a negative effect on non-manufacturing employment it must hold that $\varepsilon^h > \sigma$. Hence, in this second exercise – where we fix the i.e.s. at lower values following the broad estimates in Atalay (2017) – it is impossible to match the negative employment effects of automation on non-manufacturing. However, we view this exercise as valuable, because it allows the model to match our empirical estimates by altering the cost savings instead of the i.e.s. The result we obtain is $(\widehat{cs}_{R_{model}}, \widehat{cs}_{O_{model}}) * 100 = (20.79\%, 25.1\%)$. This difference is lower than what the external evidence suggests. At the same time, as for the i.e.s. results obtained before, it is consistent with the external evidence in the sense that the trade shock displays higher cost savings than the robot shock.

2nd set of exercises: relative importance of i.e.s. vs. cost savings. As the previous results show, the model implies a higher i.e.s. for robot affected industries, but higher cost savings for Chinese import competition. We now investigate whether these margins play an equal role within the model. First, we ask how much lower the cost savings would have to be for the trade shock to match an effect of $\hat{\beta}^r = -0.56$, instead of $\hat{\beta}^c = 0.45$. We conduct this exercise using the parametrization of our first result, so that $\left(\varepsilon^R, \varepsilon^O\right) = (5.001, 4.33)$ and $(cs_R, cs_O) * 100 = (22.78\%, 40\%)$.[58] We obtain a reduction from $cs_O * 100 = 40\%$ to $\overline{cs}_O * 100 = 31.16\%$. That is, reducing the cost savings for the trade shock from 40% to 31.16% is enough to move from $\hat{\beta}^c_{model} = 0.45$ to $\hat{\beta}^c_{model} = -0.56 = \hat{\beta}^r$.

We repeat the same procedure by increasing the i.e.s. (rather than lowering the cost savings) of the trade shock so as to match the results obtained for robots. In this case, we are unable to get all the way through to $\hat{\beta}^r = -0.56$. Increasing ε^O from 4.33 to 5.001 reduces $\hat{\beta}^c_{model}$ from 0.45 to 0.04. Thus, as for the cost savings, increasing the i.e.s. helps explain the difference between automation and the trade shock. Yet, in contrast to the cost savings, this is not enough. In other words, even though both a higher i.e.s. for robots and a higher cost savings for Chinese imports help explain the different effects of the shocks, only cost savings are able to fully explain them.

[58] The same conclusions hold when using the alternative parametrization of $\left(\varepsilon^R, \varepsilon^O\right) = (1.1, 0.8)$ and $(cs_R, cs_O) * 100 = (20.79\%, 25.1\%)$.

Table D1: Calibration summary

Parameter	Description	Value
	Common Parameters	
σ	elasticity of substitution between tradeable varieties	5
A_i^S	TFP of non-manufacturing sector	target $E_i^M/L_i = 0.1$
	Trade Competition	
$1 - w^* \beta \underline{t}$	cost savings (%)	40
ε^O	industry elasticity of substitution (i.e.s.)	0.8
θ_i^O	threshold of tasks subject to offshoring	0.619
w_i/w_i^*	ratio of domestic to foreign wage	20.83
	Robots	
$1 - p^{R*} \frac{\gamma_L^R}{\gamma_R}$	cost savings (%)	22.78
ε^R	industry elasticity of substitution (i.e.s.)	1.1
θ_i^R	threshold of tasks subject to automation	0.154
γ_R/γ_L^R	relative productivity of robots vs labor	6

Note: The table presents a summary of the calibration.