How well does EITC help low-income households in the age of automation?

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November 27, 2019

Abstract

Recent studies suggest that technological progress such as robots and Artificial Intelligence (AI) is replacing human labor, and not just routine-intensive jobs. At the same time, welfare programs for low-income families in the U.S. have increasingly emphasized in-work aid over out-of-work aid since the 1990s. Consequently, the U.S. safety net provides only modest benefits to non-workers. In this paper, I empirically examine to whether low-income families are still supported by Earned Income Tax Credit (EITC) under automation by exploiting variation in exposure to industrial robot adoption across commuting zones. The results show that there is no significant difference in the EITC recipiency rates across commuting zones and a negative effect on the average benefit for the married filers with children. Also, the estimates present some suggestive effects. For the married with children, the EITC recipiency rates appear to decrease in commuting zones with low routine share due to an increase in the share of families with higher earnings. For the single filers with children, auotmation could increase their recipiency rate in commuting zones with high routine share. Overall, there is no evidence that current EITC is ineffective in local labor markets experiencing growth in automation.

1 Introduction

Google DeepMind developed AlphaGo, a computer program based on Machine Learning (ML), and it defeated Sedol Lee, one of the top professional Go players, 4-1 in March 2016. Since the board game Go has long been considered challenging work in the field of Artificial Intelligence (AI), the result was quite shocking and has made people fear how far AI and robot technology can develop and what they can do in the future.

As active research about the effect of recent technological development on labor markets is ongoing, frequently cited Frey and Osborne (2017) estimate that about 47% of total US employment is at high risk due to computerization in the next few decades due to recent advances in technology such as ML, AI, and Mobile Robotics (MR). This figure may be an overestimate for several reasons. First, they consider only technological capabilities which may exceed actual adoption of new technologies. Second, Arntz *et al.* (2016) point out that workers in the same occupation can actually do different tasks and that automation usually takes place at specific tasks rather than the whole occupation level, which show that only 9% of jobs in the US are automatable based on the task-based approach. Third, the introduction of new technology can have indirect or equilibrium effects on labor market mitigating its negative direct impact; for example, increases in employment through improved productivity and the creation of new jobs. Regardless of the exact number, in light of our historical experiences such as the first industrial revolution, one certainty is that some individuals will suffer from unemployment and wage adjustments due to technological developments, even if such developments are beneficial to society as a whole. More importantly, both previous studies suggest that probabilities of automation are likely to be higher in jobs occupied by low-skilled and low-income workers.

While technology has progressed, making a much broader range of tasks or jobs automatable, the U.S. safety net for low-income individuals has evolved since the 1990s to require work to be eligible for many benefits. Earned Income Tax Credit (EITC), providing cash assistance to working families with low-income, was introduced in 1975 and has substantially expanded, especially during the 1990s, whereas the 1996 federal welfare reform changed the traditional cash programs by imposing work requirements. This leads to the growing importance of EITC, and now has become the primary safety net program for families with low- and moderate-income in the U.S. As shown in Figure 1, EITC has the largest expenditure as a single program, although the expenditure of Supplemental Nutrition Assistance Program (SNAP) has sharply increased due to work requirement waivers after the economic crisis in 2008.

Note that there are other cash transfer programs with work requirements that are less important than EITC, particularly in terms of expenditure size. For example, Aid to Families with Dependent Children (AFDC), one of the main safety net programs in the U.S. before 1996, did not require to work for being eligible for cash benefits, and in fact, its benefits fall with labor income. The Personal Responsibility and

Work Opportunity Reconciliation Act of 1996 (PRWORA) replaced AFDC with Temporary Assistance for Needy Families (TANF) that has strong work requirements. The other main safety net program is SNAP, previously known as Food Stamps. The 1996 PRWORA imposed work requirements on Able-Bodied Adults Without Dependents (ABAWD) to receive the SNAP benefits. However, the specific work requirements vary with programs. To be eligible for EITC, you must have earnings, but AFDC/TANF as well as SNAP accept work-related activities such as participation in job training. So, their work requirements are not as binding as EITC, and they still provide benefits to non-workers. Hence, in this paper, I focus on EITC as in-work aid programs since it is the most important safety net program and has a more explicit and stronger work requirement–positive earnings for a year, clearly reflecting employment and easily recognized in public data, unlike TANF or SNAP.

The purpose of safety net programs with work requirements is generally to achieve income redistribution by providing income assistance through encouraging work, and in particular, there is a huge amount of literature about the positive effects of EITC on employment and poverty (Nichols and Rothstein, 2015). However, EITC provide no benefit to non-workers. If recent technological advance displaces workers by automating much broader ranges of tasks rather than routine-intensive ones, then EITC would not provide any assistance to displaced workers if they could not find other jobs. In this respect, there is a lively discussion recently about Universal Basic Income (UBI) that provides a certain amount of money for all citizens regardless of their income or employment status.[1] But, UBI without any eligibility criteria would require much more spending beyond the whole current safety net programs, as pointed out in Hoynes and Rothstein (2019), and we do not have strong evidence that recent technology will cause massive (long-term) unemployment yet.

Hence, my research starts with questioning whether automation actually pushes low- and moderate-income families outside the existing in-work benefits. When workers get laid off due to automation, they can stay unemployed with other out-of-work aids. Or, the existence of in-work aid provides incentives for them to make an effort to find another job. And then, even if their new job has a lower wage than their previous one, they can make their income to approach the former level by receiving in-work aid. So, they can stay within the in-work aid system as long as they work. To analyze it directly, we should be able to discern workers who are dismissed by automation and track their employment status (and welfare benefits) over time, which is not possible with the current public data. Thus, in this paper, I investigate it at the local aggregate level indirectly by examining whether there is any difference in the EITC usage across locations by

[1] See Hoynes and Rothstein (2019) for further detail. The paper defines a UBI and discuss the potential role of UBI, by comparing it with the existing safety nets - welfare programs including TANF and SNAP, disability programs, Social Security Retirement, and in-work tax credit - and by providing possible effects of UBI on labor supply and human capital accumulation based on public policy related literature. The paper argues that generous UBI without eligibility would be much more expensive than the whole expenditure of current safety nets, which means that the government should substantially increase tax revenue.

the extent of automation, based on changes in family earnings and their interaction with the EITC system.

Since a taxpayer should have positive earnings below a certain level to be eligible for the EITC, job loss or changing jobs due to automation will affect the EITC usage through changes in family earnings. However, it is not clear a priori how the EITC usage will change under automation because technological development like automation differently affects labor market outcomes such as employment and earnings. First, automation may displace some tasks and workers, which makes them unemployed or reduces their (aggregate) working hours and earnings due to short-term unemployment, change into lower-paid jobs, or the decrease in wages. So, the EITC recipiency rate at the local aggregate level may decrease due to increased unemployment, or it increases when automation moves more families into the eligible range of earnings. Second, automation may improve the productivity of some workers if it is complementary to human labor or increase demand for workers in non-automated tasks due to the reduction of production cost if it substitutes for human labor. Overall, it can increase the earnings of some workers due to the increase in wages or by providing opportunities to get higher-paid jobs, and thus it may decrease the EITC recipiency rate by moving some families beyond the eligible region of earnings. Third, automation may create new tasks and jobs so that it can increase employment, aggregate working hours, or earnings, but the change in the EITC recipiency rate depends on for whom newly created tasks/jobs are more favorable (ex. low-skilled or high-skilled people). Lastly, all of these effects of automation may differ across locations depending on the share of routine (or automatable) tasks/jobs.

To sum up, the effects of automation on employment move family earnings in different directions so that it changes the EITC recipiency rates in opposite ways. Therefore, overall changes in the EITC usage depend on the strength of different effects. On the one hand, the EITC usage could increase in locations with higher automation if displaced workers by automation keep working by finding another (less-paid) job (maybe with the increased jobs favorable for low-skilled workers), which may be consistent with the literature about job polarization, from routine (more-skilled) jobs to non-routine manual (less-skilled) jobs. In this case, we can say that EITC still support low- and moderate-income families. On the other hand, the EITC recipiency rate could be lower in regions with higher automation if displaced workers cannot find a job or if improvements in productivity and creations of new tasks/jobs paying relatively high wages are stronger than the other effects so that there are more families with earnings outside of eligible criteria. While the former case may suggest the decreased ability of EITC supporting low-income families, the latter case does not.

To empirically examine the question of whether EITC still can support low-income families under technology-induced shocks to labor markets, automation is approximated by the adoption of industrial robots following Acemoglu and Restrepo (2017). To be specific, my empirical strategy exploits variation in exposure to industrial robot adoption across local labor markets, defined as commuting zones, to estimate the relationship between the extent of automation and EITC beneficiary. For the analysis, I use industrial robot data from the International Federation of Robotics (IFR) and Census micro-data from the IPUMS.

The results suggest that automation overall does not affect EITC usage across commuting zones and that automation could have heterogeneous effects across commuting zones depending on the initial employment share in routine jobs. For the married filers with children, the average benefit for the married filers with children significantly decreases in commuting zones more exposed to robots, which seems to come from the decline in the share of EITC filers in the flat region. Also, the EITC recipiency rates for the married with children appear to fall in commuting zones with low routine share, and the estimates suggest that it could come from an increase in the share of families with higher earnings, they are insignificant though. For the single filers with children, the result is suggestive of a positive effect on the recipiency rate in commuting zones with high routine share. In commuting zones with low routine share, their recipiency rates seem to be unchanged, but the results suggest the increases in the shares of families in the near phase-out and above the phase-out regions. When considering that the earnings in the near phase-out region are still lower than the median household income, the expansion of EITC eligibility could reach more families with automation. Lastly, EITC still can help single parents get out of poverty under automation, which especially concentrates on single filers with children whose income is under 50 percent or 200 percent of official poverty thresholds.

What policy should be set up for the age of automation is a quite broad question, but when we especially focus on low- and middle-income families affected by labor-replacing technology and job (or wage) polarization, the expansion of EITC or the increase in minimum wage level are often suggested as possible policy tools.[2] To the best of my knowledge, this paper is the first empirical study investigating how automation is moving families around the earnings distribution and how that affects EITC usage to understand how EITC supports low-income families under automation.[3] When considering that automation can negatively affect labor demand, my work contributes to the literature on EITC under economic downturns (Bitler *et al.,* 2017; Jones, 2015). Also, my work contributes to the literature on the discussion about impacts of automation and its policy implications (Goos, 2018; Hoynes and Rothstein ,2019; Lordan and Neumark, 2018).

The rest of the paper proceeds as follows. Section 2 outlines the EITC, the impacts of recent labor-replacing technology, and the relevant policy discussion. Section 3 describes the empirical specification and data. The results are presented in Section 4, and I conclude in Section 5.

[2] There are a couple of studies about the effect of automation on low-skilled employment by using minimum wage changes. They show mixed results about the ability of minimum wage policy to mitigate the negative impact of automation, as discussed below.

[3] Although I particularly focus on automation in this paper, it can be generally interpreted as one source of systemic negative shocks to employment.

2 Background and related literature

2.1 Brief background about Earned Income Tax Credit (EITC)

The transformation from out-of-work aid to in-work aid is one of the most important things that the U.S. safety net programs have undergone since the 1990s. The Earned Income Tax Credit (EITC), a kind of negative income tax, was first introduced in 1975 and its benefit levels and criteria have changed several times, though the most dramatic modification was made by Omnibus Budget Reconciliation Act of 1993: the expansion of credit amount and the credit differences by the number of children. Now, it becomes the most important cash transfer program of federal welfare programs and the total amount of the refundable portion of the credits reached at about $58.8 billion in 2015. Figure 1 shows the expenditure of major federal safety net programs: Nagtive Income Tax (the EITC and Child Tax Credit), Supplemental Nutritional Assistance Program, Temporary Assistance for Needy Families, Supplemental Security Income, and Others.[4] The expenditure on the EITC has been increasing and accounts for about 16.6 percent of the total spending on major federal safety net programs in 2015.

The EITC was the federal tax credit in the first place, but these days many states have their EITCs that add to the federal EITC. As of 2018, twenty-nine states and the District of Columbia have enacted their EITCs. Of them, 23 states and DC have refundable EITCs, while 6 states have non-refundable EITCs.[5] More importantly, nearly all of them follow federal EITC eligibility rules, and also they determine the credits as a specific percentage of the federal credit (although it is quite different across states). Given state EITCs built on federal EITC, the number of people covered by EITC hardly change when adding state EITCs. Thus, I focus on only federal EITC in this paper.

To be eligible for the EITC, taxpayers must work (as employees or self-employed), and their earnings should lie in a certain range. The earnings range for EITC is divided into three regions: i) phase-in, ii) plateau, and iii) phase-out. In the phase-in region, the credit constantly increases at the phase-in rates, ranging from 7.65% to 45% depending on the number of children. For example, you receive 40 cents for an additional dollar if you have two children. In the plateau region, the credit remains constant at the maximum amount. In the phase-out region, the credit keeps decreasing at the phase-out rates of between 7.65% and 21.06%. So, if you have two children, your credit reduces by 20 cents for an extra dollar until the phase-out

[4] Others include the following federal welfare programs: Housing Assistance from the department of Housing and Urban Development, Child Nuturition such as school lunch, Head Start, Job Training, WIC (Women, Infant and Children), Child Care, LIHEAP (Low Income Home Energy Assistance Program).

[5] Puerto Rico is not eligible for federal EITC and has a separate schedule with a maximum credit of between $300 and $2,000 based on familiy size. States with refundable EITCs are WA, OR, CA, MT, CO, NM, NE, KS, MN, IA, LA, WI, IL, MI, IN, ME, VT, NY, MA, RI, CT, NJ, MD, and DC. States with non-refundable EITCs are OK, OH, DE, VA, SC, and HI. For more details about the state EITC, see https://www.cbpp.org/research/state-budget-and-tax/states-can-adopt-or-expand-earned-income-tax-credits-to-build-a

ends, where the credit equals to zero.

The thresholds for each region of earnings varies with marital status and the number of children. Since the eligible earnings ranges widen by the filing status and the number of children, EITC can support not only low-income working families but also a part of middle-income families, especially families with children. Figure 2 shows that, when you have two children, the maximum earnings eligible for the EITC goes to \$44,454 for a single tax filer or \$49,974 for a married tax filer in 2015, but the eligible income ranges for tax filers without children are quite limited. The credit difference by the number of children is more apparent in Figure 3, which plots the maximum credit by the number of children over time and all values are in 2015 US\$. Even though it shows a large expansion before and after 1996 due to OBRA93, the credit for childless filers is still substantially small.

The large literature studying EITC shows its positive employment effect, especially on single mothers, and that is a successful way to help low-income families out of poverty (Nichols and Rothstein, 2015; Hoynes and Rothstein 2016).[6] My work may be more related to a few studies about EITC under economic downturns when considering the negative impact of automation on employment. While high unemployment rates can arise from negative aggregate supply or demand shocks, automation is one of the sources causing negative shocks on labor demand directly, though it can also derive other positive impacts on employment as discussed below. Bitler *et al.* (2017) and Jones (2015) explore whether the EITC can respond to economic downturns by using the state unemployment rate as the measure of the economic downturn. Their results suggest that the stabilizing effect of the EITC against high unemployment rates is concentrated on married couples with children who are capable of cushioning negative effects from the recession, whereas there is no significant effect on single parents who are the majority of EITC recipients.

2.2 Related literature

Let me briefly discuss the impacts of automation on employment and wages, which are indirectly reflected in the EITC participation and benefit because EITC requires earnings for its eligibility. There are several theoretical hypotheses about the effects of technological progress affecting labor demand, but the routine-biased technological change model of Acemoglu and Autor (2011), based on the task assignment framework, is recently referred the most frequently.[7] In their task framework, factors producing each task are perfect

[6] Note that the most recent paper, Kleven (2019), provides that the employment effects of EITC in the 1990s are closely related with exposure to welfare reform (ex. state waivers and the replacement of AFDC) aided by favorable economic conditions.

[7] In the model, a task is defined as "*a unit of work activity producing (intermediate) output*" and a skill is "*a worker's endowment of capabilities for performing various tasks.*" The explicit distinction between tasks and skills allows us to model the recent technology that can perform tasks previously done by workers with certain skills. While skills are applied to tasks in the task-based model, skills directly produce the final output in the Skill-Biased Technological Chage (SBTC) hypothesis. The SBTC, where technology is described in a factor-augmenting form, shows that the technological change in favor of the skilled labor leads to an increase in the relative demand for skilled labor and the skill premium. However, it cannot explain the prevailing empirical phenomenon: employment polarization in the earnings distribution and wage stagnation for less-skilled

substitutes for each other, although tasks are imperfect substitutes in the production of final goods. But, each factor has a comparative advantage in different tasks with single crossing assumption,[8] which leads to the equilibrium that each factor is assigned to a different task, for examples low-skilled workers to the least complex tasks and high-skilled workers to the most complex tasks. When the digital technology has a comparative advantage in doing middling (routine) tasks than middle-skilled workers, it replaces middle-skilled workers by performing routine tasks and leads to the expansion of low and high skill tasks, which implies that some of the middle-skilled workers are allocated to tasks previously done by low- and high-skilled workers.[9] Autor and Dorn (2013) provide empirical evidence that commuting zones historically more specialized in routine-intensive occupations experienced more rapid growth in low-skill service occupations. Besides, the technology displacing middle-skilled workers decrease their wages relative to both low and high skill workers, which is related to wage polarization empirically observed.[10]

Previous studies examining the effect of digital technology like the expansion of computer usage combined with ICT (Information and Communication Technology) usually pay attention to its substitutability for routine tasks because they are easily programmable and codifiable (Auto *et al.*, 2003), and routine-task-intensive jobs are known to be generally laid in the middle of the wage distribution. But, the recent stream of technological advance like ML and AI enables us to automate tasks without fully specified instructions, so that its replaceability will not be limited on routine tasks.[11] For examples, Google has been developing a driverless car, but driving a car is considered as manual-task-intensive jobs that have a relatively lower wage than routine jobs. Besides, paralegals and medical diagnosis, which have a relatively high wage and used to be regarded as having strong complementarity with computers, is facing automation with developments of big data and ML.

The task-based framework modeling automation has been more generally elaborated by Acemoglu and Restrepo (2018a, 2018b, 2018c, 2019). In their model, automation has the displacement effect and the productivity effect: the former decreases labor demand in tasks previously performed by human labor, the

labor.

[8]It means that high-skilled workers are better than middle-skilled workers and middle-skilled workers are better than low-skilled workers as tasks are getting more complex.

[9]In Acemoglu and Autor (2011), tasks are defined in only one dimension, complexity, which I think that it is defined from the human perspective. Unlike this, Feng and Graetz (2015) define tasks in two dimensions, training requirements and complexity from an engineering perspective. So, there are two types of tasks, training intensive and innate ability tasks, and each task is differentiated by complexity. In their task-based model, the firm will automate the task with more training requirements when two tasks have equal engineering complexity. By using comparative advantage properties, they show that low and high skill workers are relatively protected from techonologies that facilitate automation, which tend to cause job polarization. Middle skill workers replaced by machines experience downward pressure on their wages. In addition, they show that wage inequality goes up at the top, but falls at the bottom of the distribution.

[10]However, the impact on the relative wage of high-skilled workers compared to the low-skilled is uncertain: it increases if middle-skilled workers replaced by machines have a stronger comparative advantage in low skill tasks than high skill ones, it decreases otherwise.

[11]According to Taddy (2018), classical AI depends on "hand-specified logic rules" to solve problems, which requires that we must have full lists of all possible cases and know how to translate problems into structured data scheme. However, new AI driven by ML can input related information and learn how human acts to solve the problems.

latter raises labor demand in non-automated tasks through productivity increase. However, new technology, in general, creates new types of tasks (or jobs) as you can see it from our historical experience, which Acemoglu and Restrepo (2018a, 2018c, 2019) emphasize as a more powerful force to directly countervail the displacement effect by assuming that newly created tasks are more complex so that human has a comparative advantage in these tasks.[12] Their recent empirical analysis decomposing the wage bill shows that acceleration of displacement and deceleration of creating new tasks contribute to the stagnation of labor demand for the last three decades, especially since 2000.

Meanwhile, the empirical studies about the effects of automation, measured by industrial robots, on employment and wages so far have shown mixed results (Barbieri *et al.* 2019). Graetz and Michaels (2018) show the positive impacts of industrial robots on value-added and labor productivity–measured by value-added per hour worked–at the country-industry level analysis, but the negative effect on aggregated hours worked for low-skilled and middle-skilled workers. While the results in Acemoglu and Restrepo (2017), focusing on the U.S. local labor market, present the negative effects of industrial robots on both employment and wages, Chiacchio *et al.* (2018) for six European countries show the significant displacement effect on employment rate, particularly of middle-educated workers and young cohort, but no impact on wage growth. Besides, Dauth et al. (2017) present that, in German, robots change the composition of aggregate employment; job losses in the manufacturing sector are fully offset by increased jobs in the service sector.

What seems obvious from the theoretical and empirical analyses is that the ongoing technological progress hurts some workers, relatively in low/middle-skilled or manufacturing jobs, even though its impact on aggregate employment is not very clear. Hence, we need to contemplate in what directions our policy should respond to automation. When especially paying attention to people harmed by the technology,[13] McAfee and Brynjolfsson (2016) claim that the policy in the age of automation still should encourage work by emphasizing the value of work beyond just making money, so they advocate the expansion of EITC or similar wage subsidy rather than giving cash assistance regardless of need. Korinek and Stiglitz (2017) also suggest wage subsidies and EITC for wage declines due to decreases in demand for specific types of labor who are replaced by machines. In respect of compensating for the wage declines, increasing the minimum wage can be helpful. Besides, Downey (2016) focuses on the feature that automation occurs partially through deskilling–new technology simplifies tasks so that they can be performed by the technology and less-skilled

[12] On the other hand, Bessen (2018) emphasizes the role of demand to explain how new labor-saving technology affects employment. There is the inverted U pattern of employment in the manufacturing industry during the 20th century, which can be explained by change in price (or income) elasticity of demand. The author attributes the employment increase following the adoption of new technology to sufficient elasticity of demand. If the price elasticity of demand is greater than one or if the new technology applies to largely unmet needs, the price drop due to productivity improvement increases the demand enough to offset the negative impact on employment. Note that his argument is based on a premise that technology does not completely replace human.

[13] On the other hand, when considering that the current tax system is in favor of capital rather than labor, research about taxing robots is also ongoing. See Abbott and Bogenschneider (2018), Guerreiro *et al.* (2017), and Thuemmel (2018).

workers, and presents that the minimum wage increase slows down the adoption of routine-replacing technologies. However, other empirical studies exploiting the minimum wage variation show that it negatively affects the employment of low-skilled (or low-wage) workers in routine-intensive jobs (Aaronson and Phelan, 2017; Lordan and Neumark, 2018).

3 Empirics

My empirical analysis is conducted at the local labor market level, defined as Commuting Zones (CZs) which are groups of counties with strong commuting ties. It has been developed by Tolbert and Killian (1987) and Tolbert and Sizer (1996) to provide geographical units representing local labor markets, based on residence-to-work commuting data from the 1980 and 1990 Census. A problem when applying the concept of CZs to public microdata is that the microdata report only areas that have at least 100,000 residents due to data confidentiality laws. Dorn (2009) suggests a way to identify CZs using Public Use Microdata Areas (PUMAs) which is the most disaggregated geographic unit provided in the Integrated Public Use Microdata Series (IPUMS) Census.[14] Here, I use Dorn's crosswalk files to map each PUMA to 1990 CZs.[15] Though the 1990 Census data identifies 741 CZs, I focus on 722 CZs that cover the entire region of the U.S. except for Alaska and Hawaii.

In this section, I start with explaining the empirical specification and then describe how to construct main outcome variables–the (simulated) EITC recipiency rates and the average amount of credits, explanatory variable–the exposure to industrial robots suggested by Acemoglu and Restrepo (2017), and datasets used in the empirical analysis.

3.1 Empirical model

My research aims at examining whether the EITC can still support low- and moderate-income families under automation. For this, I estimate the effect of automation on EITC usage by using local variation in exposure to industrial robot adoption which stems from spatial variation in the location of industries across commuting zones. The baseline specification is as follows:

$$\triangle y_{gcs,t_1-t_0} = \alpha + \beta_1 \cdot EIR^{US}_{c,t_1-t_0} + \beta_2 \left(EIR^{US}_{c,t_1-t_0} \cdot \textit{share in routine jobs}_{c,t_0} \right) + \mathbf{X}_{c,t_0}\mathbf{\Gamma} + \delta_g + \theta_s + \varepsilon_{gcs} \quad (1)$$

[14] Since a PUMA code can represent multiple counties due to data confidentiality laws, it also can correspond to multiple CZs. Brifely, Dorn (2009) calculates a probability that a household who lives in PUMA code i also resides in CZ j, which is used for adjusting the original personal weight of IPUMS census data. See the appendix of Dorn (2009) for more details.

[15] The files are provided at http://www.ddorn.net/data.htm.

where subscripts represent tax filing group g (filing status [single, married] $\times$ number of children [0, 1, 2+])[16], commuting zone c, and state s. The outcome variable is defined as the change between years t_0 and t_1, and two types of variables primarily used are as follows: i) EITC recipiency rate $(y_{gcs,t}) = \left(\frac{\text{EITC filers}}{\text{Total filers}}\right)_t$, and ii) the average amount of credits $(y_{gcs,t}) = \left(\frac{\text{Total amount of EITC}}{\text{Total filers}}\right)_t$. EIR^{US}_{c,t_1-t_0} is the exposure to robots in commuting zone c in the U.S. between years t_0 and t_1, which is instrumented with EIR^{EU}_{c,t_1-t_0} based on the use of industrial robots in European countries. $\mathbf{X}_{c,t_0}$ includes demographic and economic characteristics in commuting zone c in the year t_0: the ratio of the working-age population, the ratio of female population, the ratio of the population with college and more education, the ratio of non-white population, the ratio of manufacturing employment, and the exposure to Chinese imports.

The employment share of routine jobs, frequently used as the measure for the Routine-Biased Technological Change (RBTC), is constructed based on the Routine Task Intensity in occupations. In the RBTC hypothesis, digital technologies have comparative advantages over medium-skilled workers in producing these tasks, which ends up displacing medium skilled labor. So, that measure can reflect the possibility of a broad range of automation, especially including other machines and computer software which do not fit into the definition of industrial robots, whereas the industrial robots can be considered as directly representing one specific type of automation.[17] So, I include it and its interaction term with the exposure to robots to take into account the possibility that the effects of exposure to robots on the EITC usage may be heterogeneous across the levels of employment share in routine jobs in commuting zones.

We can think about the way that makes this heterogeneous effect. On the one hand, in commuting zones with initially high employment share in routine jobs, more workers are at risk of being replaced by industrial robots so that, among other impacts by automation, the displacement effect could be more expanded in those regions. On the other hand, initially high employment share in routine jobs can imply that other forms of automation technology may reduce the displacement impact of robots as tasks are already replaced by them. Autor and Dorn (2013) show that commuting zones with an initially higher share of employment in routine-intensive jobs experienced larger growth of computer adoption over the subsequent decades. However, Table A4 presents that a commuting zone with the initially higher level of employment share in routine jobs seems to be less exposed to industrial robots, which is not statistically significant though. Thus, for example, a commuting zone with a relatively high share of employment in routine jobs in 1990 may have more adopted other types of automation technologies. Hence, it may affect the possibility of introducing industrial robots as well as the overall impact of industrial robots on labor markets through affecting the extent of each

[16] The classification of tax filing group follows Bitler *et al.* (2017), which shows the possibility of heterogeneous effects of automation on EITC usage by tax filing status.

[17] The results from simple OLS regressions in Table A5 indicate that two different measures affect the EITC usage in a different way.

possible effects of robots (ex. displacement effect, productivity effect, and so on).

The above empirical models are estimated, separately, for three groups: childless tax filers, single tax filers with children, and married tax filers with children. Here δ_g is group specific intercepts to capture variations of credits by marital status and the number of children. So, for childless tax filers, δ_g equals to one if he/she is married, whereas the other tax filers with children, δ_g is one if he/she has two or more children. The constant term α is added to absorb federal EITC policy changes during the period 1990-2015 that are commonly applied to all commuting zones,[18] and θ_s is the state fixed effects.[19] Lastly, both outcome variables have the total number of potential tax filers as the denominator, so I run the regressions by using the relevant number of potential tax filers in the baseline year as the weight, and the standard errors are clustered at the state level to allow for arbitrary correlation at the state level.

As shown in Figure 2, the EITC amounts change with earnings in the opposite direction: your total credit will increase with an extra dollar of earnings as long as your earnings fall within the phase-in region, but if your earnings lie in the phase-out region, total credit that you receive will decrease with an extra dollar of earnings. Of course, your credit will be constant at the maximum level with an extra dollar earned if your earnings are still in the flat region. This feature implies that, for example, the decrease in the EITC expenditure could happen when the EITC recipients are more distributed in the phase-in and the phase-out regions than in the plateau region. Hence, I examine the change in share of EITC recipients in each eligible earnings region, rather than just focusing on the overall change in the recipiency rate.

More importantly, you can move out of the EITC eligibility because of either unemployment or earnings growth, which means that looking just at the overall recipiency rate and average benefit could miss the important point. To understand how automation is moving families around in the earnings distribution, I thus categorize the range of earnings into six groups: i) phase-in, ii) flat, iii) phase-out, iv) near phase-out, v) above the near phase-out, and vi) zero earnings. By calculating the ratio of each group of filers relative to the total filers, its changes over time are used as outcome variables. The earnings criteria for the first three groups follow the eligibility rule of EITC,[20] and I define the near phase-out region from the end of the phase-out to 25 percent or 50 percent above the end earnings of the phase-out region. The above the near phase-out region includes all observations with positive family earnings above the end of the near phase-out.[21] In the zero earnings region, there are two types of families: non-filers whose earnings as well as the total income are zero, and filers who have positive total income with zero earnings. Note that earnings criteria for the

[18] Technically the intercept term is redundant since the state fixed effects will also capture anything common to all states.

[19] A commuting zone can correspond to more than one state. If so, this commuting zone is assigned to a state which has the largest share of population within the commuting zone. Visit http://www.ddorn.net/data.htm.

[20] To be eligible for the EITC, both your earnings and adjusted gross income (AGI) should belong to a specific range of income. Since the AGI is not available in the Census/ACS, I depend on only earnings.

[21] The detailed criteria are given in Table A6 in the Appendix.

childless filers are not available in 1990 because they were not eligible for EITC at that time. Thus, for the childless filers in 1990, the ratio of filers in each group is assumed to zero.

In the analysis, the main coefficients of interest are β_1 and β_2. Since I have the interaction term, β_1 only represents the effect of the exposure to industrial robots on the change in EITC usage if the share of employment in routine jobs is zero. So, the marginal effect of the exposure to robots should be regarded as $\left(\beta_1 + \beta_2 \cdot \textit{share in routine jobs}_{c,t_0}\right)$, which depends on the level of employment share in routine jobs. If the sum of coefficients is positive at the mean value of the share in routine jobs, it implies that the higher exposure to industrial robots tends to increase the ratio of EITC recipients in the commuting zone which has the average level of employment share in routine-intensive jobs.

3.2 Measuring key variables

A. Outcome variables: EITC recipients and benefits

The main outcome variables are the changes in the EITC recipiency rate and average EITC benefit at the commuting zone level. To construct these variables, I first need to measure EITC eligibility and benefits for each tax filer unit and then to aggregate the data by the commuting zone. Here, I use the 1990 Census and the 2015 American Community Survey (ACS) datasets from IPUMS.[22] Since the Census and the ACS data do not contain information on the EITC usage, I should obtain it through TAXSIM which is a publically available microsimulation program provided by NBER.[23] But, the problem is that the IPUMS Census and ACS collect information in the household and the individual level which are not exactly matched with tax filing units. Thus, I need to convert the sample unit of those data into the family unit before I utilize TAXSIM. Hence, I briefly explain how I define the tax unit, and further details are given in the Appendix.

I start with determining whether an individual is a qualifying child based on the tax instruction of Internal Revenue Service (IRS): a child who is under age 19, or a child who is a full-time student under age 24, or an individual who is permanently and totally disabled.[24] I also assign qualifying relatives to individuals based on the IRS instruction, and then define a "family" based on group identifier variables and assign the head of

[22] Note that the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (ACS) from IPUMS has not only more detailed information on income but also the values of the EITC, though tax-related variables come from the Census Bureau's tax model, not from the direct questioning. However, the ASEC (or CPS) does not contain the PUMAs, and the smallest geographical unit is county so that I am not able to identify CZs of more than half of surveyed households. Thus, I use the Census and the ACS data to construct outcome variables at the CZ level. Besides, their sample sizes are much larger than the ASEC. The decennial Census samples for 1990 include 5 percent of the U.S. population, and the ACS samples include 1 percent of the U.S. population.

[23] TAXSIM is the NBER's FORTRAN program for calculating liabilities under US Federal and State income tax laws from individual data. For more information, see Feenberg and Coutts (1993) and visit http://users.nber.org/~taxsim/taxsim27/

[24] According to the IRS instruction, a person is permanently and totally disabled if he/she cannot engage in any gainful activity because of a physical and mental condition, and a doctor has determined that the condition has lasted or can be expected to continue for at least a year. Because any variables cannot directly specify the disabled, I use three variables to indirectly measure disability. So, individuals are assigned as the disabled if they have both independent living difficulty (DIFFMOB) and self-care difficulty (DIFFCARE) as well as they are not in the labor force.

each family by using relationship indicator variables. After assigning a spouse of the head according to the relationship with the head of the family, I finally define the "tax filing unit" by assuming that every head is a tax filer who claims his/her qualifying children and relatives as dependents. There are four types of filing status depending on the head's marital status, the presence of a spouse, and qualifying dependents: single, head of household, married filing jointly, and married filing separately.

Tax filers whose age is 15 or less are excluded in the analysis, but tax filers whose total family income is less than or equal to zero with zero earnings are included as non-filers. If the total (family) income of tax unit is positive even though the sum of earnings of all family members is zero, this unit is considered as (potential) tax filers. The estimated number of tax filers through the Census and the ACS are about 98 percent of official statistics of IRS in terms of total filers, but the number of married filing jointly is overestimated (See Table A2). Now, I use this tax filing unit data as inputs for TAXSIM, but some income inputs for TAXSIM are assumed to be zero because income variables of the Census and the ACS datasets are not exactly corresponding to them (See Table A1). Also, TAXSIM does not allow negative values for wage variables, so the negative self-employment income in the Census and the ACS is set to zero by assuming it as zero net earnings. The results through TAXSIM are reported in Table A3, which shows that the simulated total amount of EITC benefits is about 75∼79% of the official statistics. It is similar to Meyer (2010) that compares the distributions of EITC from two datasets, IRS and CPS ASEC, and that suggests possible reasons for the discrepancy: i) IRS payments to ineligible recipients, ii) too low sample weight for EITC recipients in the CPS, and iii) underreporting of earnings in the CPS.

After combining the Census/ACS with the simulated federal EITC data at the tax filer level, I define the EITC recipiency rate as the number of EITC filer (tax filers with positive federal EITC) per tax filer at the CZ level, and the average amount of EITC as the amount of federal EITC per tax filer (or per EITC filer) at the CZ level,[25] where I use the personal weight of the individual specified as the head of a family when I aggregate these variables by the commuting zone.

Technically, the EITC recipiency rate defined above is more like *the EITC eligibility rate* because TAXSIM calculates the credits only based on eligibility rules, which does not imply actual take-up of the EITC. Recent studies estimating the EITC take-up rate suggest that about 80 percent among eligible taxpayers participated in the program (Jones, 2014; Plueger, 2009). However, this is not an issue because my research question focuses on the ability of EITC to support workers who could be hurt by automation. Even if some eligible workers could not utilize EITC, it does not change the conclusion regarding the overall ability of EITC to support workers.

[25] As metioned before, I do not consider the state EITCs since they have been built on federal EITC; nearly all of them provide just additional credits by following the same eligibility rules as federal EITC.

B. Explanatory variable: Exposure to industrial robot adoption

Acemoglu and Restrepo (2017) build a theoretical model in which robots can technologically perform a range of tasks $[0, M_i]$ in industry i. They show that the total equilibrium impact of robots is the sum of displacement and productivity effect, where each effect can be expressed as a function of technological changes in robot adoption. More specifically, they derive the following expression by assuming that the amount of automatable tasks, M_i, is close to zero, $M_i \approx 0$:

$$\sum_{i \in I} l_{ci} \frac{dM_i}{(1 - M_i)} \approx \sum_{i \in I} l_{ci} \frac{dR_i}{L_i} \equiv \textit{exposure to robots}_c \tag{2}$$

where l_{ci} is baseline employment shares in industry i in commuting zone c, L_i is baseline employment in industry i, and dR_i is changes in robot usage in industry i.

Regarding this primary explanatory variable, I utilize the industrial robots data from the International Federation of Robotics (IFR). It provides consolidated worldwide robot statistics by collecting data from robot suppliers as well as several national robot associations, and categorizes robots into two types: industrial and service robots.[26] The IFR defines the industrial robot as "*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more zexs, which can be either fixed in place or mobile for use in industrial automation applications.*" While the definition of the industrial robot excludes other types of technologies having the potential to complement or substitute for human labor, for examples, self-checkout machines and especially software like AI, it provides an internationally comparable measurement of one of the latest technology (Acemoglu and Restrepo, 2017).

The IFR provides two kinds of information on industrial robots: the annual sales and the operational stock of industrial robots. The IFR estimates the latter by assuming that each robot serves for 12 years on average and it is immediately removed after 12 years. I use the latter dataset for the period 1993-2015 at the country-industry level because it seems a more suitable way to measure how much we are exposed to robots, considering their life span. According to IFR (2017), industrial robot sales have been growing by about 12 percent per year since 2011 and reached 294,312 units in 2016. About 74 percent of the sales were delivered to five major countries, China, South Korea, Japan, the United States, and Germany, and about 61 percent of the sales were shipped in two industries, automotive and electrical/electronics industry. The operational stock of industrial robots was 1,828,000 units in 2016.

Following Acemoglu and Restrepo (2017), I construct the exposure to industrial robots (EIR_c) in the U.S. for each commuting zone c as follows:

[26] A service robot is defined by the IFR as "*a robot that performs useful tasks for humans or equipment excluding industrial automation application,*" and the classification of robots is based on their *intended application*.

$$EIR_c^{US} = \sum_{i \in I} l_{ci,1990} \left(\frac{IR_{i,2015}^{US}}{L_{i,1990}^{US}} - \frac{IR_{i,2004}^{US}}{L_{i,1990}^{US}} \right) \tag{3}$$

where $l_{ci,1990}$ is the 1990 employment share of industry i in commuting zone c, which is calculated from the 1990 Census, $IR_{i,t}$ is the operational stock of industrial robots in industry i and year t from the IFR data, and $L_{i,1990}^{US}$ is the number of workers in industry i in 1990 from the EU KLEMS data. Here, $\frac{IR_{i,t}}{L_{i,1990}}$ is the measure of industrial robot density, the operational stock of industrial robots per thousand workers, in industry i and year t. Note that I use 1990 as the baseline year because it is closer to the theoretical assumption. The industries include nineteen sectors–6 non-manufacturing and 13 manufacturing sectors,[27] which is the classification of the IFR data. They contain only private sectors, so the following industries are excluded when calculating the employment shares at the commuting zone level: public administration and defense, private households, and extra-territorial organizations and bodies. Figure 4 shows changes in robot density in the U.S. between 2004 and 2015, which is normalized by the change of the automotive industry because it has the largest increase over the period. Although the changes in robot density of other industries except the automotive are relatively small, comparatively large increases among them are found in the electrical/electronics, the basic metal, and the other manufacturing industry.

Since the EITC usage depends on employment, any shocks influencing the labor demand in commuting zone c may affect the decision of firms in that area to use robots in their production process. To deal with the possiblity of endogeneity problems, I use robot usage in other nine European countries to construct an instrument, which is suggested in Acemoglu and Restrepo (2017) and defined as follows:

$$EIR_c^{EU} = \sum_{i \in I} l_{ci,1980} \left(p_{30} \left(\frac{IR_{i,2015}^{EU}}{L_{i,1990}^{EU}} \right) - p_{30} \left(\frac{IR_{i,1993}^{EU}}{L_{i,1990}^{EU}} \right) \right) \tag{4}$$

where $l_{ci,1980}$ is the 1980 employment share of industry i in commuting zone c in the U.S., which comes from the 1980 Census, the industrial robot density in industry i, $\left(\frac{IR_{i,t}}{L_{i,1990}}\right)$, is calculated for each European country based on the IFR and EU KLEMS data, and $p_{30}\left(\frac{IR_{i,t}}{L_{i,1990}}\right)$ denotes the 30th percentile of industrial robot density among nine European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. When constructing this instrument variable, I use the 1980 employment distribution of commuting zones (CZs), which help us mitigate bias due to contemporaneous changes in employment by expected robot adoption and focus more on the historical difference in specialized industries

[27] Six non-manufacturing industries are as follows: agriculture, hunting, forestry, and fishing; mining and quarrying; electricity, gas and water supply; construction; education, research and development; and other non-manufacturing industries. The manufacturing industry is categorized into 13 sectors: food products, beverages, and tobacco products; textiles, leather, and wearing apparel; wood and wood products; paper, paper products, and printing; plastic and chemical products; glass, ceramics, stone, and mineral products; basic metals; metal products; industrial machinery; electrical/electronics; automotive; other transport equipment; all other manufacturing sectors.

across CZs.[28] Since the industry-level robot data of the U.S. starts from 2004, I convert EIR_c^{US} to a 22-year equivalent change when it is instrumented with EIR_c^{EU}. For more detailed information on the construction of exposure to industrial robots, refer to the Appendix and Acemoglu and Restrepo (2017).

Figure 5 plots the robot adoption per thousand workers in the US and nine EU countries, which is measured in terms of the total amount of robots and employment.[29] Figure 6 gives the geographical distribution of exposure to robots in the U.S. from 2004 to 2015, which shows that traditional manufacturing (northeast) and high-technology (coastal) areas are relatively more exposed by industrial robots.

C. Other variables

The Routine Task Intensity (RTI) measure has been frequently exploited in literature, especially explaining job polarization, to represent the routine-based technology. So, as mentioned before, I use the share of employment in routine-intensive jobs as not only one of the control variables but also its interaction with the exposure to industrial robots, and the data comes from Autor and Dorn (2013), where defines it as follows:

$$\textit{employment share in routine jobs}_{c,1990} \equiv \sum_{j \in J} \frac{L_{cj,1990} \cdot 1\left[RTI_j > RTI^{P66}\right]}{L_{c,1990}} \tag{5}$$

where L_{cj} denotes the employment in occupation j in commuting zone c, and RTI_j measures relative routine task inputs of occupation j based on the U.S. Dictionary of Occupational Titles 1977.[30]

On the other hand, China's export surge has been regarded as one of the important factors affecting local labor markets in the U.S. since the 1990s. To control effects induced by changes in trade pattern, I construct an additional variable, the exposure to Chinese imports, by following previous studies (Autor *et al.*, 2013; Acemoglu *et al.*, 2016). Specifically, the exposure to Chinese imports in commuting zone c from 1991 to 2015 is defined as follows:

$$\textit{exposure to China imports}_c \equiv \sum_{i \in I} l_{ci,1990} \left\{ \frac{\triangle M_i^{UC}}{Y_{i,1991} + (M_{i,1991} - X_{i,1991})} \right\} \tag{6}$$

where l_{ci} is employment shares in industry i in commuting zone c and $\triangle M_i^{UC} \equiv M_{i,2015}^{UC} - M_{i,1991}^{UC}$ is the change in imports from China into the U.S. in industry i which is normalized by domestic absorption, approximated by the sum of domestic shipments (Y_i) and net imports ($M_i - X_i$). Trade data is available in SIC 4-digit level from World Integrated Trade Solution (WITS), and the domestic shipments data in SIC

[28] Acemoglu and Restrepo (2017) primarily use the 1970 employment share, $l_{ci,1970}$, but they show that the results are similar when they use the distribution of employment across industries in 1980.

[29] The total amount of industrial robots are from the IFR, which equals the sum of industrial robots in each industry. In case of employment from EU KLEMS, the total is the sum of workers in all industries except three industries: Public admin and defense, compulsory social security; Private household with employed persons; Extra-territorial organizations and bodies.

[30] $RTI_j = \ln(T_{j,1980}^R) - \ln(T_{j,1980}^M) - \ln(T_{j,1980}^A)$, where T_j^R, T_j^M, and T_j^A denote the routine, manual, and abstract task inputs in occupation j. See Autor and Dron (2013) for detailed information.

4-digit level come from the NBER-CES Manufacturing Industry Database. Since I use the 1990 Census data to calculate the employment shares, l_{ci}, the trade data with SIC 4-digit codes are converted to the data with the Census industry codes of 1990 (Lake and Millimet, 2018).[31] While the domestic shipments data is available only for the manufacturing industry, the trade data includes some of the agriculture, forestry, fisheries, and mining industries. For these industries, I use the mean value of domestic shipments across all 4-digit SIC manufacturing industries. All dollar amounts are adjusted to 2015 US dollars using the Personal Consumption Expenditures (PCE) price index.

Similar to the exposure to robots, there is the potential endogeneity of US exposure to China imports in the sense that any shocks affecting employment in commuting zone c also influence industry import demand. Following Acemoglu *et al.* (2016) and Lake and Millimet (2018), I construct an instrumental variable using Chinese exports to eight high income countries except for the U.S.,[32] which is based on the fact that the growth of China imports since the 1990s has been mostly driven by supply-side shocks such as the increased competitiveness of Chinese manufacturing industry, the lowered trade barriers of China, and China's WTO entry (Autor *at el.*, 2013).

$$\text{IV for } \textit{exposure to China imports}_c \equiv \sum_{i \in I} l_{ci,1980} \left\{ \frac{\triangle M_i^{OC}}{Y_{i,1989} + (M_{i,1989} - X_{i,1989})} \right\} \tag{7}$$

where l_{ci} is employment shares in industry i in commuting zone c, and $\triangle M_i^{OC} \equiv M_{i,2015}^{OC} - M_{i,1991}^{OC}$ is the change in Chinese exports to eight non-US countries in industry i which is normalized by the U.S. domestic absorption in 1989.[33]

4 Results

4.1 Baseline results

Table 1 shows descriptive statistics of variables used in the regression analyses at the commuting zone level. The main outcome variables are defined as the change between 1990 and 2015 so that they can be positive or negative. Briefly looking at outcome variables, they all have positive values on average, which implies that more taxpayers become eligible for the EITC and receive more credits in 2015 compared to 1990. However, based on the minimum values, some commuting zones have negative numbers, which means that taxpayers in these CZs are less eligible and paid fewer credits in 2015 even though the EITC has been more generous

[31]SIC code 3341 is matched two Census industry codes, 272 and 280. Hence, values of variables with SIC code 3341 are assigned to each Census code with the probability 0.5.

[32]The eight countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[33]In COMTRADE data, US exports and imports are available after 1991. So, the US exports and imports in 1989 come from https://dataweb.usitc.gov.

over time. I should note that, unlike other types of tax-filers, childless taxpayers can not have negative values in their outcome variables because they are not eligible for the EITC in 1990.

The baseline results are presented in Table 2 and Table 3. Table 2 shows results from OLS regressions using the exogenous exposure to robots, measured by the 30th percentile of exposure to robots in nine European countries, which is used as the instrumental variable.[34] And then, Table 3 presents IV estimates by Two-Stage Least Squares (2SLS), where the exposures to robots and Chinese imports in the U.S. are instrumented with the relevant variables previously defined in Section 3.[35] For the interaction term, the product of the 30th percentile of exposure to robots in European countries and the employment share in routine jobs in 1990 is used as an instrumental variable. In both tables, the upper table (a) shows results without the interaction term between the exposure to robots and the employment share in routine jobs in 1990, and the lower table (b) presents estimates with the interaction term. The first column shows estimates for the pooled sample so that it has 722 observations. The remaining columns display estimates for three different groups, where each column has 1,444 observations: 722 CZs$\times$2 types of marital status [single or married] for childless filers and 722 CZs$\times$2 children groups [1 or 2+] for single/married filers with children. Panel A shows estimates for changes in ratio of EITC filers to total (potential) tax-filer and Panel B presents results for changes in the amount of EITC per (potential) tax-filer in 2015 U.S. dollar.

Without the interaction term, both OLS and IV estimates show that the exposure to robots does not have statistically significant effects on EITC usage, whereas more taxpayers, especially tax-filers with children, are eligible for EITC in commuting zones with initially high employment share in routine-intensive jobs. When considering that, for taxpayers with children, earnings criteria for the EITC are more generous so that they include moderate-income families, the positive relation between share in routine jobs and EITC usage seems to reflect previous studies about routine-biased technology: a decrease in middle-wage jobs and an increase in low-wage service jobs.

The bottom table (b) in Table 2 and Table 3 presents results from the estimation equation (1). The most estimates on the interaction term have an opposite sign to coefficients on the exposure to robots so that it seems to weaken the marginal effect of exposure to robots as commuting zones have a higher share in routine jobs. However, it hardly changes the sign of the marginal effect of robots given that the share of employment in routine-intensive jobs in 1990 has values in the range of 0.2 to 0.377. In Panel A of Table 3-(b), the IV estimates for the different types of tax-filers show a negative relationship between the exposure to industrial robots and the change in the EITC recipiency rate in a commuting zone, they are statistically

[34] Since the exposure to China imports may have the potential endogeneity problems, the instrument variable, measured by Chinese exports to non-US high-income countries, is used in OLS regressions.

[35] I also construct another instrument variable for the exposure to robots in the U.S. by using the mean of industrial robot usage among nine European countries, which results are reported in Table A7.

insignificant though. Also, Panel B of Table 3-(b) presents that the EITC benefits per taxpayer decrease in commuting zones more exposed to industrial robots, and the size of coefficients is quite different by tax filing groups, which seems obvious as credits are more generous with children and marriage. But, note that the estimates are significant for only the married tax-filers with children. Given that commuting zones have the average value in the share of routine jobs, the EITC benefits for the married filers with children in a commuting zone where the exposure to robots equals to 1 are $115 less than ones in a commuting zone not exposed to robots.

Figure 7 displays the marginal effect of exposure to robots on EITC usage, which varies with the employment share of routine jobs in the baseline year. The left column shows its effect on the EITC recipiency rate by the tax filing group, whereas the right side presents its effect on EITC benefits per taxpayer by the tax filing group. For the married filers with children, the results are imprecise, but suggestive of a negative effect on the recipiency rate in commuting zones with low routine share and no effect in commuting zones with high routine share. It is consistent with the hypothesis of net increases in earnings due to stronger productivity effects in commuting zones with less reliance on routine jobs. It is also consistent with the expectation that the improvement in the productivity and earnings of some workers could be completely offset by reductions in employment and/or hours for other workers performing routine tasks in commuting zones with greater reliance on routine jobs. In the case of single filers with children, the marginal effects are still insignificant, but suggestive of a positive effect on recipiency rate as the share of routine jobs in commuting zones becomes higher. It might reflect the possibility that the single filers with children could work in areas relatively more exposed to the displacement effect.

For the married filers with children, the effects of automation on the average EITC benefits show a pattern similar to its impacts on recipiency rate: the automation decreases the average benefits in commuting zones with low routine share, which seems to be offset as the routine share in commuting zones increases. The average credits for single filers with children do not seem to change by the share of routine jobs in commuting zones, but overall, the results suggest the negative effect on the average EITC benefits. The lower EITC expenditure per potential tax-filer may happen since taxpayers eligible for EITC in commuting zones with more exposed to robots are distributed more in phase-in or phase-out regions. More importantly, note that negative effects on both the recipiency rate and the average benefit reflect results that mix reductions in EITC claims and benefits due to unemployment with reductions due to earnings growth that push families above the eligibility cut-off. Thus, it has a shortcoming just looking at the overall recipiency rate.

4.2 Additional results

To supplement the weakness of baseline results, I turn to the extended model in this section to exmaine how automation is moving families around in the earnings distribution. For this, I divide the range of earnings into six regions: i) phase-in, ii) flat, iii) phase-out, iv) near phase-out, v) above the near phase-out, and vi) zero earnings. So, outcome variables are defined as changes in the share of filers in each region between 1990 and 2015. The first three regions follow the earnings criteria of EITC, and the near phase-out region begins from the end of the phase-out region to 25 percent above the end earnings of the phase-out region.[36] The above the near phase-out region includes all families with positive earnings above the end of the near phase-out. Note that the childless filers are not eligible for EITC in 1990, so there are no relevant earnings criteria for them. Hence, I assume that their shares in each region of earnings in 1990 are zero.

Table 4 presents IV estimates. The coefficients in the first three panels are about the effect of automation on the change in the share of tax-filers potentially eligible for EITC by different regions of earnings.[37] It shows that in commuting zones with the average share of routine jobs, the ratio of potential EITC filers within the phase-in earnings seems to be higher as the exposure to robots increases, except for the childless filers with children (although the coefficients are statistically insignificant). In the plateau region, the result for the married filers with children indicates a negative relationship between the exposure to robots and the change in the ratio of potential EITC filers.

The remaining three panels in Table 4 shows the effect on the ratio of tax-filers by earnings regions out of eligibility for the EITC. Surprisingly, for the pooled sample and the separate filing groups, the estimates for the main effect of robots present a positive relationship between the exposure to robots and the change in the ratio of filers with earnings above the near phase-out. But, the coefficients on the interaction term have the opposite sign, so the main effect reduces as the employment share in routine jobs in the baseline year changes. Note that the overall effect on filers in the region of earnings above the near phase-out is still positive at the average level of share of routine jobs, while it turns into a negative value as the employment share of routine jobs approaches the maximum. Since the earnings of filers assigned to this region begin from a relatively lower level of median family income (up to any positive earnings above),[38] the negative sign on the interaction term may imply some extent of the effect of routine-biased technology on job polarization in the U.S., hollowing out of the middle-wage jobs. The last panel shows that a commuting zone with exposure to robots is likely to have fewer filers with zero earnings compared to a commuting zone not exposed to

[36] I also use a different criterion to define the near phase-out region that begins from the end of the phase-out region to 50 percent above the earnings at the end of the phase-out region. The results are shown in Table 9A.

[37] The reason I refer to tax-filers as "potentially eligible for EITC" is that they are classified by only earnings regardless of simulation results from TAXSIM.

[38] According to the 2015 ACS, the median income of the family and the nonfamily households is \$68,260 and \$33,617, respectively. In the 1990 Census, the median family income (in 1989) is reported as \$35,225.

robots, most of the estimates are insignificant though.

Figure 8a and Figure 8b display the marginal effect of exposure to robots on the share of tax-filers by each region of earnings, which changes with the employment share of routine jobs in commuting zones, for the different groups of taxpayers. The figures show that automation has the heterogeneous effect across commuting zones, although most estimates are statistically insginificant as shown in Table 4. In the case of sigle filers with children, the baseline result for commuting zones with high routine share–suggestion a positive effect on the EITC recipiency rate–seems to be affected by an increase in the share of tax-filers in the phase-in region and a decrease in the share of taxpayers above the near phase-out region. For commuting zones with low routine share, the baseline model–no change in the recipiency rate–seems to reflect the mixed results of an increase in flat region and a decrease in phase-out region. But, we can see an increase in the share of tax-filers in the near phase-out region, and it might suggest that EITC's future expansions in eligibility could support more single parents with automation, given that the earnings of the near phase-out region are still lower than median household income.

On the other hand, the results for the married filers with children are imprecise as shown in Figure 8b, but it could suggest some movement of families through the earnings distribution, which impacts their EITC eligiblity. For commuting zones with low routine share–where EITC recipiency rates and benefits appear to fall in the baseline model, we see a decline in the share of families with zero earnings and earnings in the flat and phase-out region. It is accompanied by a small increase in the share of families in the phase-in region, but mostly an increase in the share of families who are not eligible for EITC due to higher earnings. For commuting zones with high routine share, there is little change in the share of tax-filers across different regions of their earnings.

To check whether the increase in the share of tax-filers above the near phase-out region in Table 4 is affected by migrations across commuting zones, I also construct outcome variables in a different way: the numerator is a change in the number of tax-filers in each region of earnings between 1990 and 2015, and the denominator is fixed at the total number of tax-filers in 1990. The estimates are presented in Table A10 in the Appendix, and the marginal effects of automation by different groups of tax-filers and the routine share of commuting zones are displayed in Figure A2a and Figure A2b. The marginal effect of automation on the change in tax-filers above the near phase-out region has a similar pattern, but the size of coefficients becomes larger. Although using the fixed denominator is not a perfect way to control migrations, it suggests that the previous result is not solely because families with higher earnings move into commuting zones more exposed to robots.

Lastly, to examine the ability of EITC supporting low-income families in the age of automation more directly, I explore whether the effect of EITC on poverty depends on the extent of exposure to industrial robots in commuting zones. So, following Bitler *et al.* (2017), I calculate how many taxpayers have income below 50 percent, 100 percent, 150 percent, and 200 percent of official poverty thresholds in 1990 and 2015 at the commuting zone level[39], and then define outcome variables as changes in the ratio of tax-filers under certain levels of income relative to total filers. Here, I use two types of income: total pre-tax income, which is the sum of family members' income of tax-filer, and total income added by the EITC. By comparing the size of estimates between two different measure, it can tell us whether the added EITC helps people out of poverty. The estimates are provided in Table 5, where we can see that they are statistically significant only for single filers with children, especially when focusing on the change in the ratio of filers under 50 percent and 200 percent of official poverty thresholds. For single filers with children, the ratio fo tax-filers under 50 (and 200) percent of official poverty thresholds seems to decrease in commuting zones more exposed to robots, and its extents vary depending on the share of routine jobs in commuting zones. Its negative impact on the ratio of families under certain poverty thresholds is large in commuting zones with low routine share, and this effect seems to be diminished in commuting zones with high routine share by the displacement effect. Since the third column in Table 5 presents that automation reduces families under certain level of poverty, we can say that EITC helps families get out of poverty when the absolute values of coefficients in seventh column are larger. Figure 9 shows this relationship for single filers with children.

5 Conclusion

With expectations that the recent technology such as robots and AI could have large systemic negative effects on employment through automating tasks (or jobs) previously performed by human labor, there is ongoing research about its impact on labor markets and what policy needs to mitigate negative shocks. While welfare programs in the U.S. have been transformed toward in-work aid since the 1990s, emphasizing to give work incentives to be eligible for benefits, the recent technological development leads to a discussion about Universal Basic Income (UBI) that does not impose any work requirements for cash assistance. In this paper, by focusing on EITC that is now the most important and the largest cash assistnace in the U.S., I try to examine whether the current in-work aid still can help low-income families in the sense that they still can access benefits if they can find another job after being laid off due to automation. Unfortunately, It is not possible to discern unemployed workers due to automation at the individual level with current microdata, so my empirical specification is set up to investigate the above statement indirectly by questioning whether there is a difference in EITC usage across local labor markets by the extent of automation. For this, automation

[39] Since income variables in the 1990 Census are measured based on the previous survey year, I use the 1989 thresholds. For the official poverty thresholds, visit https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

is measured by the exposure to industrial robots at the commuting zone level, suggested by Acemoglu and Restrepo (2017).

When using the difference in EITC usage from 1990 and 2015 as the outcome variables, the results show that there is overall no statistically significant difference in EITC recipiency rates and average benefits across commuting zones depending on the exposure to robots. However, despite their imprecision, the estimates are suggestive of heterogeneous effects of automation on EITC usage at the commuting zone level by the 1990 employment share in routine-intensive jobs. For the single filers with children, the EITC recipiency rates appear to increase in commuting zones with high routine share, which seems to come from an increase in the share of families with earnings in the phase-in region. In contrast, their recipiency rates seem to be unchanged in commuting zones with low routine share, but the results suggest the possibility of increases in the shares of families in the near phase-out and above the phase-out regions. Given that earnings in the near phase-out region are still mostly below the median household income, the expansion of EITC eligibility could support more single parents under automation. Also, the analysis presents that EITC helps the single filers with children out of poverty under automation, especially their pre-tax income is under 50 percent or 200 percent of official poverty thresholds.

Although my work suggests that EITC has supported low- and moderate-income families under automation at the local aggregate level to date, it could not say explicitly that EITC still has the employment effect under automation, which needs to be explored in further research. Also, the results in this paper may be affected by the still low adoption of industrial robots, although it is growing rapidly, which implies that continued research will be necessary for the future.

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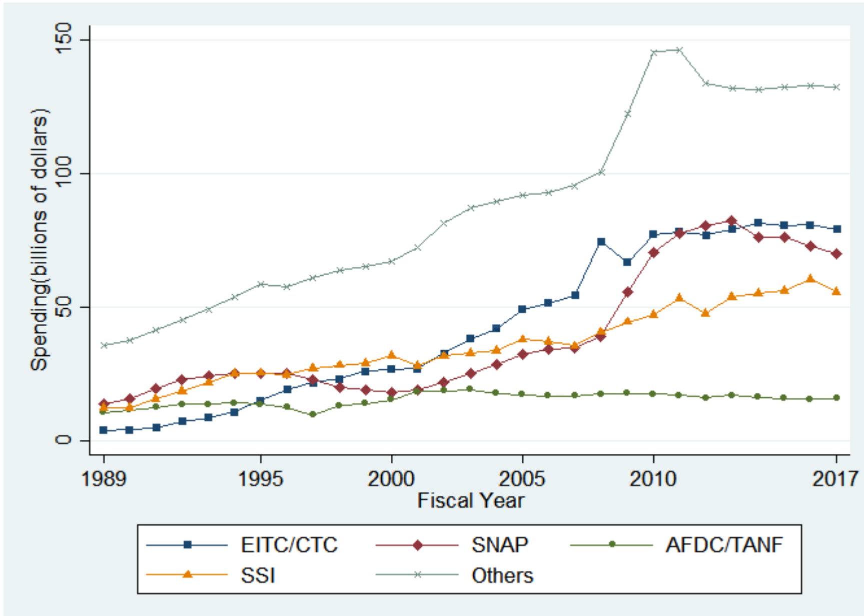
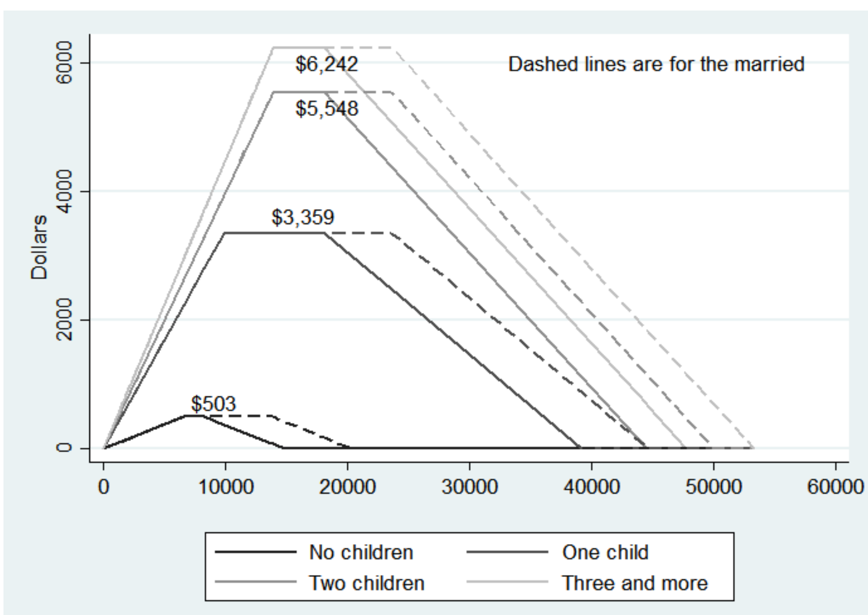
Figure 1: The spending of safety net programs



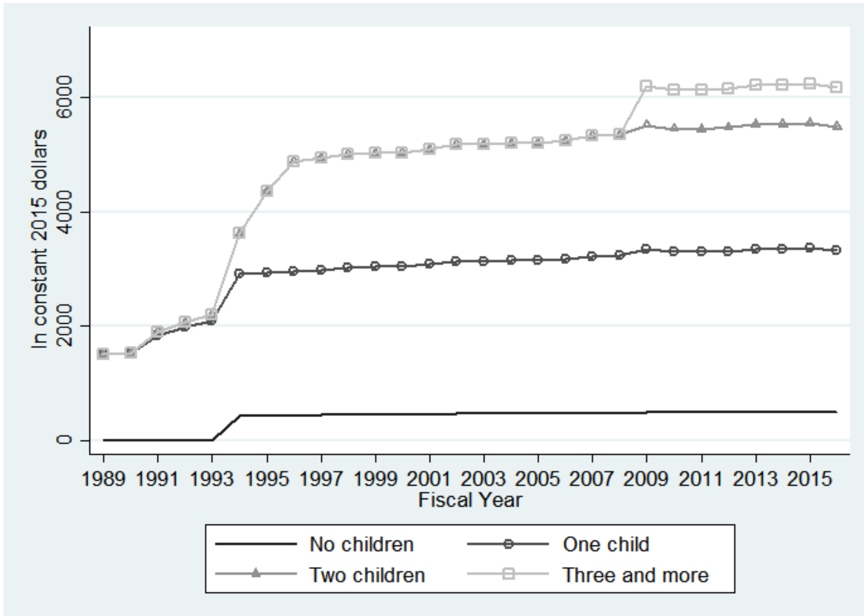
Notes: Data, except for Aid to Families with Dependent Children (AFDC), come from https://www.usgovernmentspending.com. The specific spending categories for each program are based on the information at http://federalsafetynet.com. The EITC and the Child Tax Credit (CTC) includes only the refundable portion of the credit. Others include the following federal welfare programs: Housing Assistance from the Department of Housing and Urban Development, Child Nutrition such as school lunch, Head Start, Job Training, WIC (Women, Infant, and Children), Child Care, LIHEAP (Low Income Home Energy Assistance Program). The federal spending of AFDC is available at https://aspe.hhs.gov/system/files/pdf/167036/4spending.pdf.

Figure 2: The EITC by the number of children and the marital status in 2015



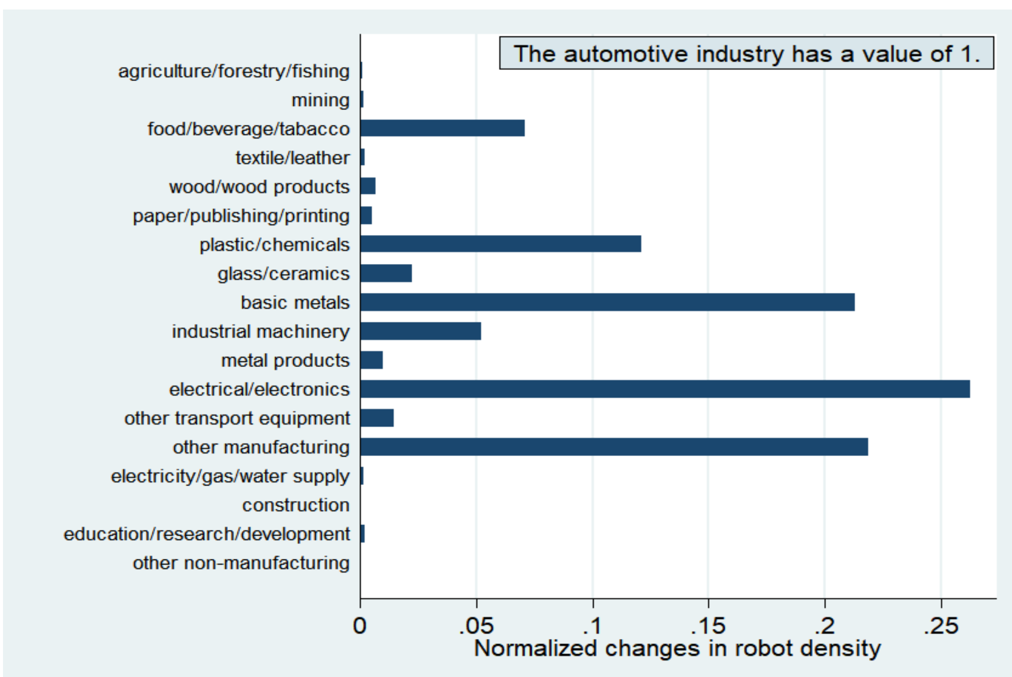
Notes: The figure is illustrated by author based on EITC parameters which are available at www.taxpolicycenter.org

Figure 3: The maximum credit by the number of children



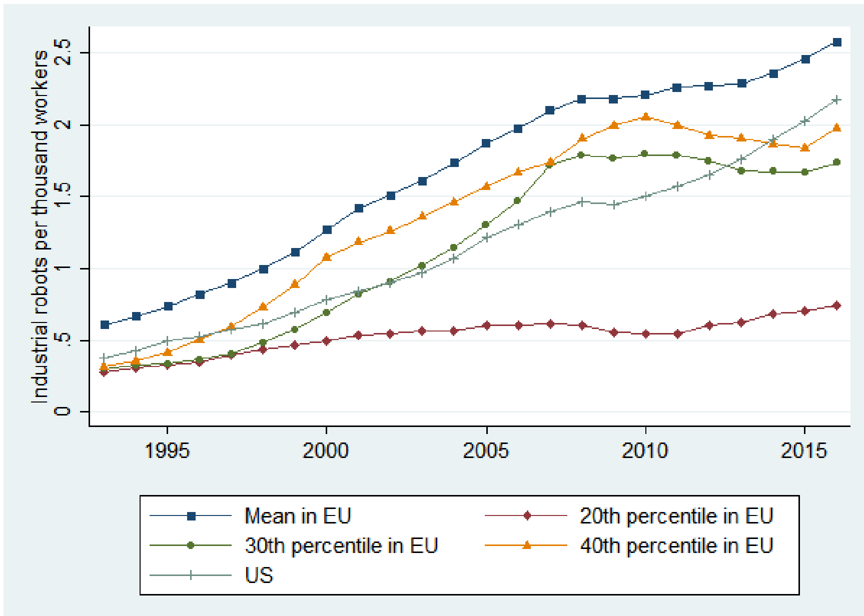
Notes: All values are in 2015 US dollars using the Personal Consumption Expenditures (PCE) price index.

Figure 4: The change in robot density by industry in the U.S., 2004-2015



Notes: The industrial robot data comes from the IFR and the information on the number of workers in 1990 is from the EU KLEMS data. The robot density is defined as the operational stock of industrial robots per thousand workers. Changes in robot density by industry are normalized by the change of automotive industry which has the largest change over time. Thus, the normalized value of automotive industry is 1.

Figure 5: The robot density by time and country



Notes: The industrial robot data comes from the IFR and the information on the number of workers in 1990 is from the EU KLEMS data. The robot density is defined as the operational stock of industrial robots per thousand workers.

Figure 6: Exposure to industrial robots in the U.S. by commuting zone, 2004-2015

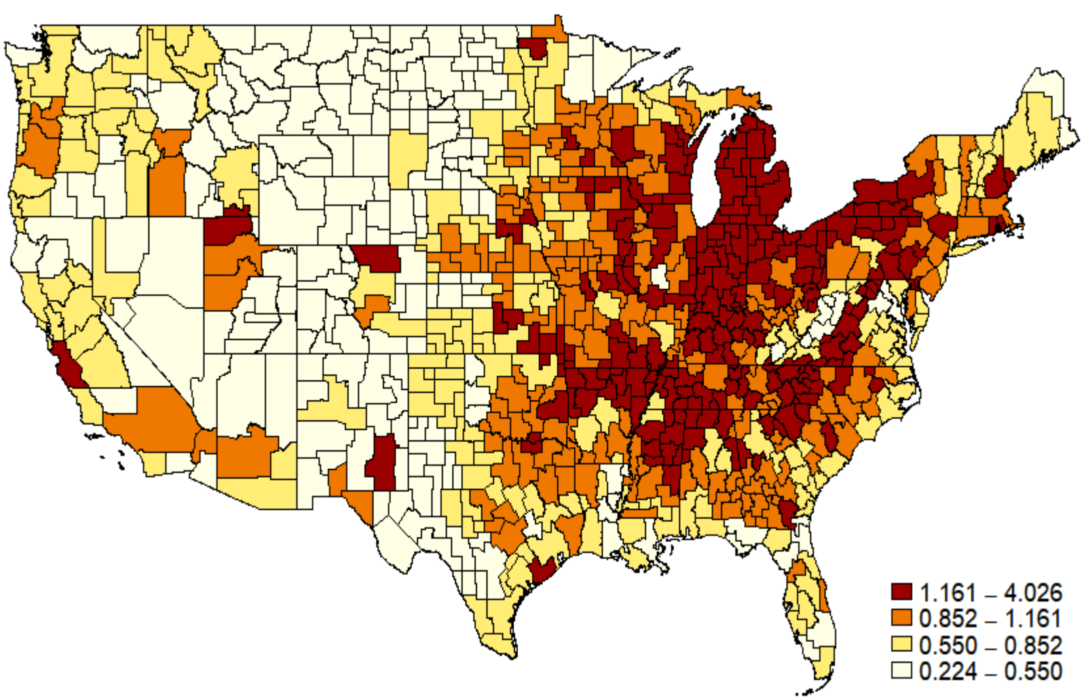
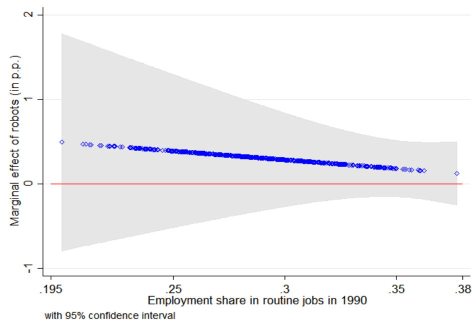
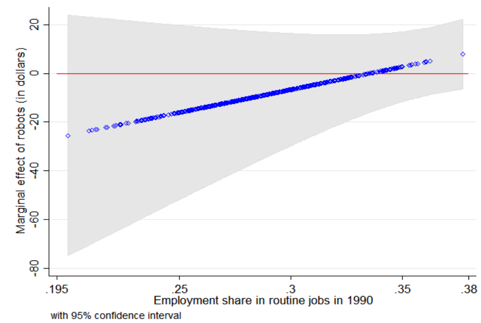


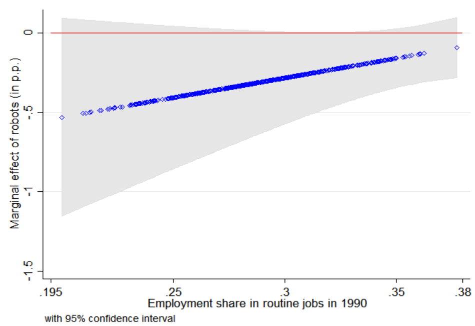
Figure 7: Marginal effects of industrial robots on EITC usage, 1990-2015



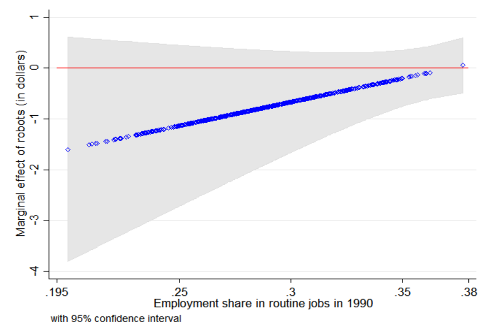
(a) All, recipiency rate



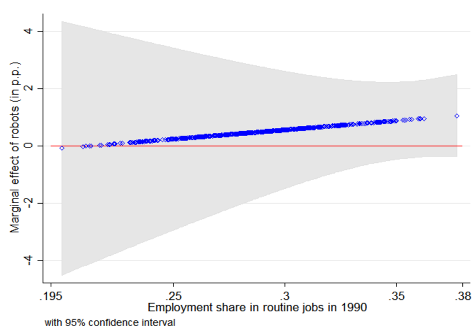
(b) All, credits per tax-filer



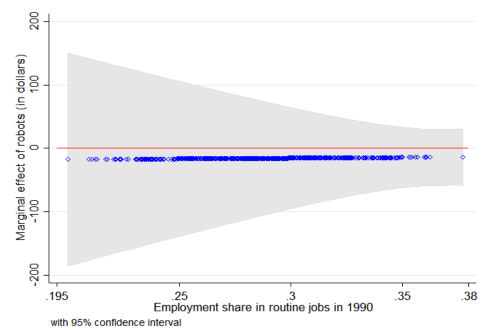
(c) Childless, recipiency rate



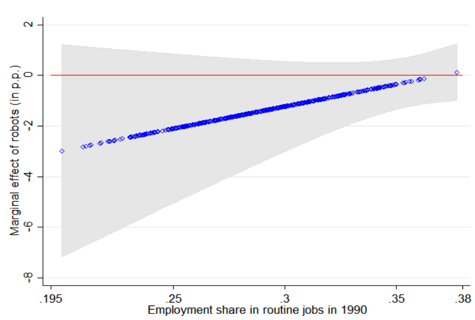
(d) Childless, credits per tax-filer



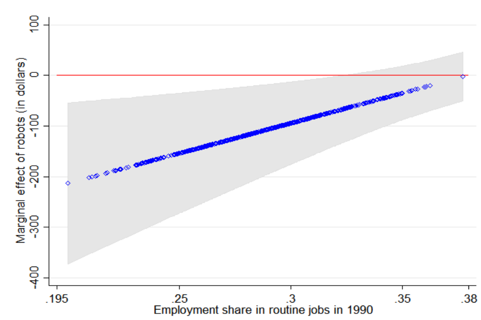
(e) Single w/ children, recipiency rate



(f) Single w/ children, credits per tax-filer



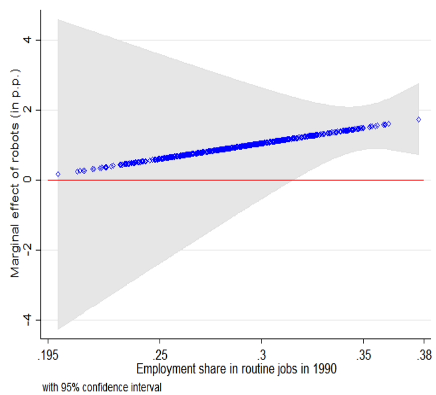
(g) Married w/ childrenl, recipiency rate



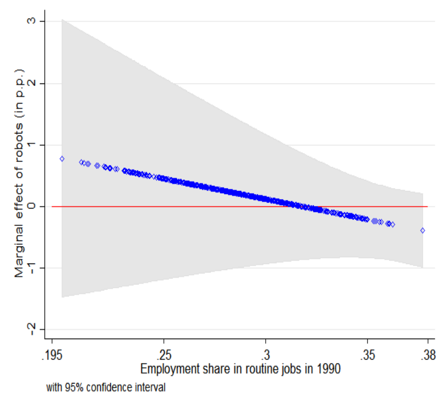
(e) Married w/ children, credits per tax-filer

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 3-(b).

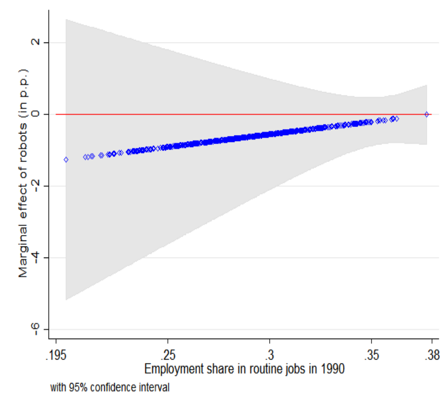
Figure 8a: Marginal effects of industrial robots on the ratio of tax-filers by earnings region, 1990-2015, Single filers with children



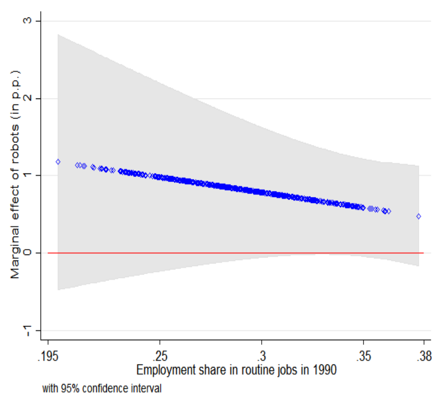
(a) Phase-in region



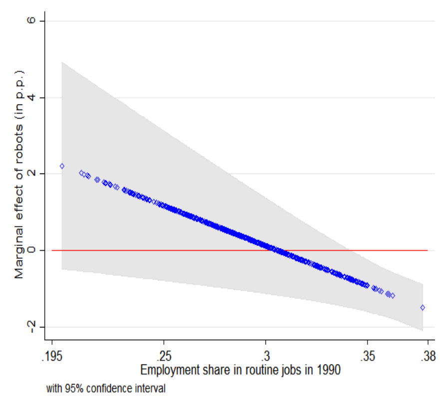
(b) Flat region



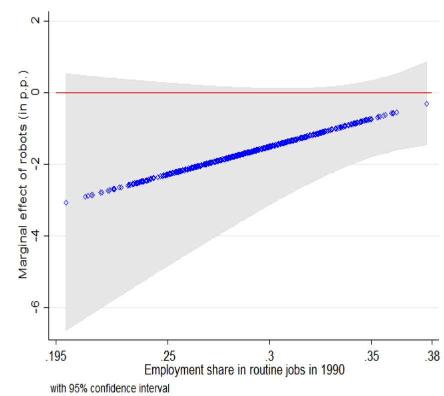
(c) Phase-out region



(d) Near phase-out region



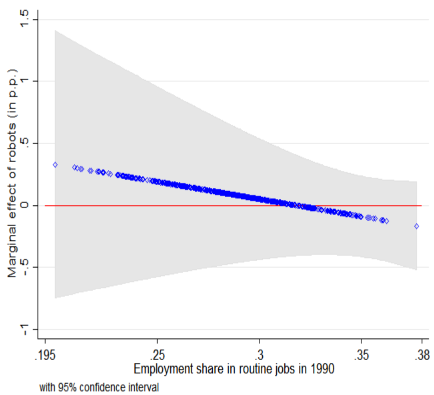
(e) Above the near phase-out region



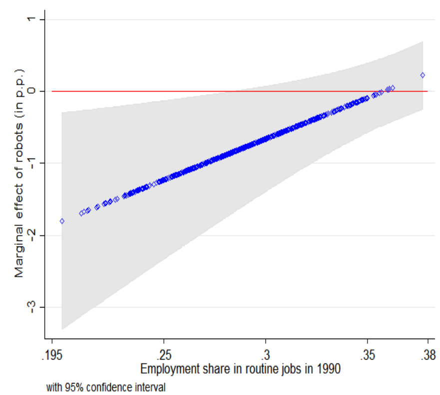
(f) Zero earnings

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 4. The near phase-out region is from the end of the phase-out to 25% above the end of the phase-out that is the beginning of the region above the near phase-out.

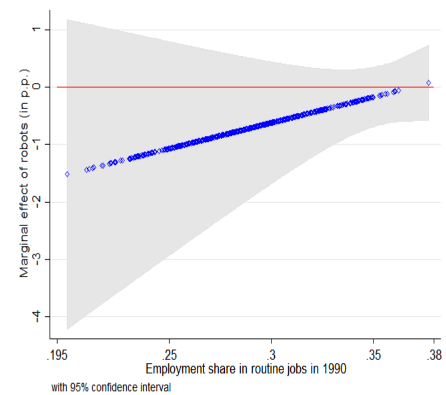
Figure 8b: Marginal effects of industrial robots on the ratio of tax-filers by earnings region, 1990-2015, Married filers with children



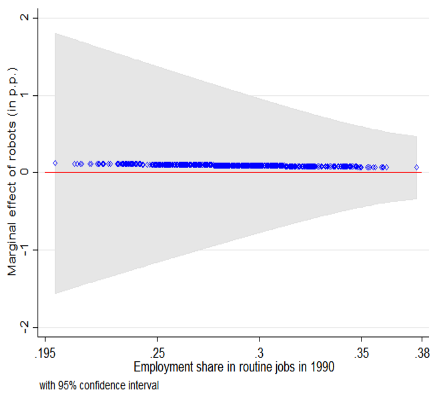
(a) Phase-in region



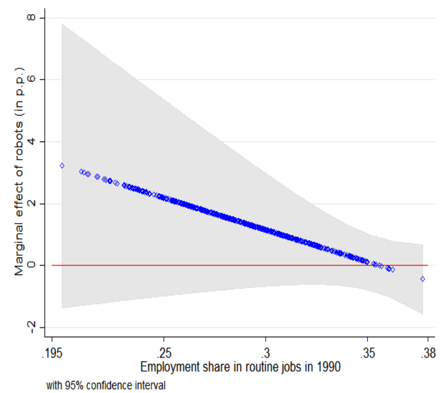
(b) Flat region



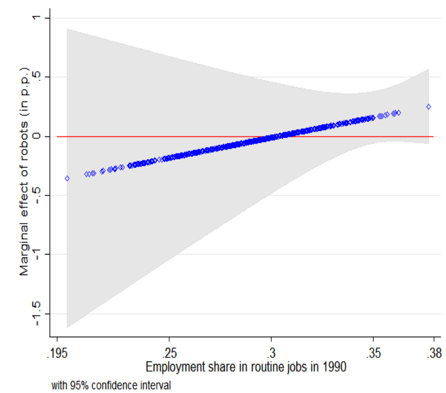
(c) Phase-out region



(d) Near phase-out region



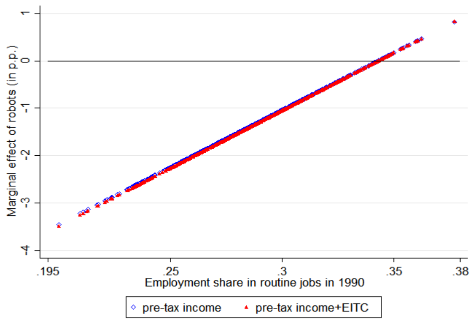
(e) Above the near phase-out region



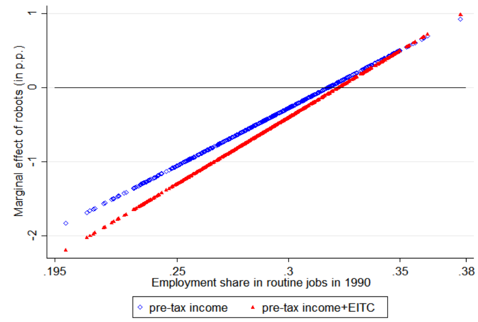
(f) Zero earnings

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 4. The near phase-out region is from the end of the phase-out to 25% above the end of the phase-out that is the beginning of the region above the near phase-out.

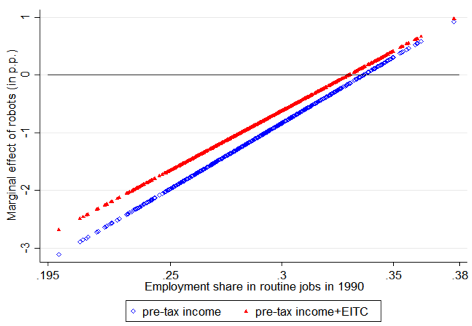
Figure 9: Marginal effects of industrial robots on the ratio of single filers with children below official poverty thresholds, 1990-2015



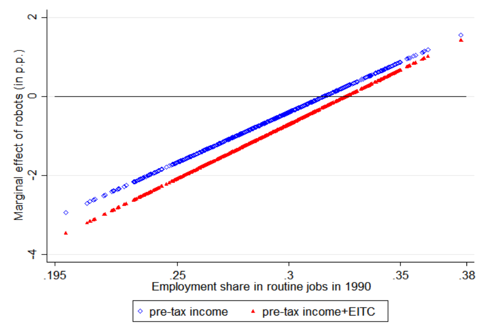
(a) Under 50% of official poverty threshold



(b) Under 100% of official poverty threshold



(c) Under 150% of official poverty threshold



(d) Under 200% of official poverty threshold

Notes: The marginal effects are calculated based on the IV estimates in Table 6.

Table 1: Summary statistics

	Mean	S.D.	Min	Max
Change in ratio of EITC filers to total filers from 1990 to 2015 (in p.p.)				
Childless filers	6.676	3.098	0.441	16.161
Single filers w/ children	1.370	10.895	-36.009	39.791
Married filers w/ children	5.028	8.953	-20.746	31.977
Change in EITC amount per tax filer from 1990 to 2015 (2015 US$)				
Childless filers	19.900	9.144	1.175	49.794
Single filers w/ children	1204.341	617.930	-100.879	3243.089
Married filers w/ children	576.723	393.469	-141.459	2004.210
Change in EITC amount per EITC filer from 1990 to 2015 (2015 US$)				
Childless filers	301.908	47.551	60.765	458.493
Single filers w/ children	1957.065	785.979	-14.932	4206.648
Married filers w/ children	1925.490	751.609	119.364	4232.837
Exposure to industrial robots				
US from 2004 to 2015	0.946	0.557	0.224	4.026
30th percentile of EU from 1993 to 2015	1.030	0.616	0.235	5.107
Mean of EU from 1993 to 2015	1.687	0.972	0.447	8.277
Other controls				
Ratio of working-age population in 1990	0.616	0.032	0.526	0.704
Ratio of female population in 1990	0.511	0.010	0.474	0.537
Ratio of population with college or more in 1990	0.286	0.062	0.137	0.468
Ratio of non-white population in 1990	0.130	0.119	0.007	0.628
Ratio of manufacturing employment in 1990	0.177	0.087	0.032	0.470
Exposure to China imports from 1991 to 2015	0.024	0.018	0.004	0.141
Share of employment in routine-intensive jobs in 1990	0.283	0.034	0.200	0.377

Notes: All values are defined at the commuting zone level, so the number of observations is 722. The EITC-related variables are calculated simulation results from TAXISM by using the 1990 Census and the 2015 ACS. See text for the detailed information on variable definitions and data sources.

Table 2: The impact of exposure to industrial robots on EITC usage, 1990-2015 (OLS estimates)

(a) Without interaction term

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in EU	0.198	-0.190*	1.099	-0.503
1993-2015 (p30)	(0.215)	(0.112)	(0.795)	(0.671)
share in routine jobs, 1990	39.110***	-2.521	42.420*	80.819***
	(4.706)	(4.903)	(25.045)	(12.600)
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in EU	-0.223	-0.314	-19.810	-51.039
1993-2015 (p30)	(7.643)	(0.324)	(27.367)	(34.921)
share in routine jobs, 1990	830.134***	-14.322	1102.804*	1820.824***
	(203.745)	(13.913)	(573.729)	(530.690)
Observations	722	1444	1444	1444

(b) With interaction term

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in EU	0.567	-0.847	-2.692	-6.706
1993-2015 (p30)	(1.603)	(0.668)	(5.482)	(5.380)
Exposure to robots in EU	-1.080	1.922	11.097	18.218
× share in routine jobs, 1990	(4.715)	(1.973)	(15.984)	(15.597)
share in routine jobs, 1990	40.244***	-4.539	30.792	61.632***
	(5.864)	(4.717)	(35.711)	(16.566)
Joint significance (p-value)	0.623	0.122	0.338	0.381
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in EU	-93.079*	-3.867	-12.423	-471.453***
1993-2015 (p30)	(54.511)	(2.431)	(177.908)	(144.293)
Exposure to robots in EU	272.057*	10.403	-21.628	1234.723***
× share in routine jobs, 1990	(159.554)	(6.984)	(504.949)	(414.307)
share in routine jobs, 1990	544.402***	-25.245*	1125.468	520.421
	(193.372)	(14.814)	(685.844)	(554.841)
Joint significance (p-value)	0.242	0.238	0.762	0.005
Observations	722	1444	1444	1444

Notes: The tables show estimates of the impact of exposure to industrial robots on EITC usage. The dependent variable is the change in EITC filers to total filers ratio between 1990 and 2015 in Panel A, measured in percentage points, and the change in EITC amount per tax filer between 1990 and 2015 in Panel B. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. In both tables, automation is measured by the 30th percentile of exposure to robots in European countries. Table (a) does not include the interaction term between automation and share in routine jobs, but table (b) include it. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as total filers of CZs in 1990. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 3: The impact of exposure to industrial robots on EITC usage, 1990-2015 (IV estimates)

(a) *Without interaction term*

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in US	0.186	-0.166*	0.861	-0.413
2004-2015	(0.176)	(0.097)	(0.678)	(0.570)
share in routine jobs, 1990	39.517***	-2.670	40.801*	81.173***
	(5.191)	(4.652)	(23.543)	(11.263)
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in US	2.184	-0.226	-14.571	-39.121
2004-2015	(7.114)	(0.287)	(24.854)	(31.730)
share in routine jobs, 1990	881.902***	-13.491	1151.540*	1916.332***
	(232.916)	(14.255)	(590.063)	(527.656)
Weak IV F-stat	36.471	36.806	40.472	39.414
Observations	722	1444	1444	1444

(b) *With interaction term*

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in US	0.905	-1.025	-1.355	-6.481
2004-2015	(1.456)	(0.687)	(4.909)	(4.760)
Exposure to robots in US	-2.070	2.472	6.381	17.507
× share in routine jobs, 1990	(4.065)	(1.883)	(13.569)	(13.252)
share in routine jobs, 1990	43.680***	-7.664	28.164	46.057*
	(9.051)	(5.532)	(41.544)	(25.292)
Joint significance (p-value)	0.534	0.153	0.348	0.377
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in US	-63.047	-3.470	-22.250	-451.113***
2004-2015	(54.327)	(2.437)	(180.948)	(166.382)
Exposure to robots in US	187.872	9.338	22.117	1188.740***
× share in routine jobs, 1990	(148.085)	(6.627)	(485.148)	(436.501)
share in routine jobs, 1990	504.016	-32.354	1107.735	-467.988
	(319.232)	(19.746)	(1041.825)	(831.998)
Joint significance (p-value)	0.338	0.362	0.820	0.024
Weak IV F-stat	20.129	20.553	21.576	21.531
Observations	722	1444	1444	1444

Notes: The tables show IV estimates of the impact of exposure to industrial robots on EITC usage, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variable is the change in EITC filers to total filers ratio between 1990 and 2015 in Panel A, measured in percentage points, and the change in EITC amount per tax filer between 1990 and 2015 in Panel B. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. In both tables, automation is measured by the 30th percentile of exposure to robots in European countries. Table (a) does not include the interaction term between automation and share in routine jobs, but table (b) include it. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as total filers of CZs in 1990. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 4: The impact of exposure to industrial robots on the change in the ratio of tax-filers by the region of earnings, 1990-2015 (IV estimates)

	All	Childless	Single, children	Married, children
Panel A. Change in Phase-in region				
Exposure to robots in US	-0.305	-1.444*	-1.608	0.890
2004-2015	(0.766)	(0.777)	(5.222)	(1.207)
Exposure to robots in US	0.882	3.530	8.843	-2.798
× share in routine jobs, 1990	(2.174)	(2.175)	(14.892)	(3.365)
share in routine jobs, 1990	1.277	-20.182***	31.773	19.228**
	(4.965)	(4.677)	(32.787)	(9.074)
Joint significance (p-value)	0.920	0.015	0.000	0.579
Panel B. Change in Flat region				
Exposure to robots in US	-0.092	-0.701	2.098	-4.079**
2004-2015	(0.599)	(0.457)	(2.463)	(1.628)
Exposure to robots in US	0.225	1.962	-6.602	11.393***
× share in routine jobs, 1990	(1.586)	(1.253)	(6.658)	(4.403)
share in routine jobs, 1990	5.698	-10.664***	22.635	7.903
	(4.182)	(3.398)	(15.602)	(9.704)
Joint significance (p-value)	0.984	0.282	0.333	0.033
Panel C. Change in Phase-out region				
Exposure to robots in US	0.890	0.266	-2.676	-3.307
2004-2015	(1.159)	(0.933)	(4.479)	(3.113)
Exposure to robots in US	-1.955	-0.451	7.045	8.949
× share in routine jobs, 1990	(3.336)	(2.747)	(12.504)	(8.761)
share in routine jobs, 1990	19.279***	-2.267	-32.094	19.494
	(6.737)	(6.788)	(28.087)	(18.145)
Joint significance (p-value)	0.156	0.566	0.760	0.516
Panel D. Change in Near Phase-out region: from the end of phase-out to 25% above it				
Exposure to robots in US	0.473	-0.695	1.962	0.183
2004-2015	(0.554)	(0.660)	(1.787)	(1.721)
Exposure to robots in US	-1.030	1.806	-3.926	-0.311
× share in routine jobs, 1990	(1.519)	(1.821)	(4.903)	(4.378)
share in routine jobs, 1990	7.275*	-4.910	-2.879	10.130
	(4.312)	(4.789)	(12.999)	(10.820)
Joint significance (p-value)	0.400	0.461	0.159	0.949
Panel E. Change in Above Near Phase-out region				
Exposure to robots in US	7.929**	9.733**	6.396**	7.350
2004-2015	(3.563)	(3.906)	(2.920)	(5.270)
Exposure to robots in US	-24.126**	-28.300***	-20.885***	-20.649
× share in routine jobs, 1990	(10.556)	(10.869)	(7.811)	(14.796)
share in routine jobs, 1990	76.374***	127.066***	17.400	-53.960**
	(26.093)	(26.807)	(17.854)	(27.113)
Joint significance (p-value)	0.065	0.011	0.000	0.377

Continued

Table 4: (continued)

	All	Childless	Single, children	Married, children
Panel F. Change in Zero earnings				
Exposure to robots in US	-5.402**	-7.159**	-6.172	-1.037
2004-2015	(2.630)	(3.461)	(4.011)	(1.478)
Exposure to robots in US	15.441**	21.453**	15.524	3.416
× share in routine jobs, 1990	(7.156)	(9.606)	(11.148)	(4.204)
share in routine jobs, 1990	-65.348***	-89.043***	-36.834	-2.794
	(17.966)	(24.551)	(31.195)	(8.066)
Joint significance (p-value)	0.067	0.023	0.188	0.253
Weak IV F-stat	20.129	20.553	21.576	21.531
Observations	722	1444	1444	1444

Notes: Notes: The tables show 2SLS estimates of the impact of exposure to industrial robots on the share of tax-filers in each region of earnings, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variablea are the change in the ratio of tax-filers in each region relative to total taxpayers from 1990 to 2015. The first three regions follow the earnings criteria for EITC. The near phase-out region begins from the end of the phase-out region to 25The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as taotal tax-filers of CZs in 1990. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 5: The effect of exposure to industrial robots on the ratio of tax filers under official poverty thresholds (IV estimates)

	Pre-tax income				Pre-tax income+EITC			
	All	Childless	Single, children	Married, children	All	Childless	Single, children	Married, children
Panel A. Change in ratio of tax filers under 50% of official poverty threshold, 1990-2015								
Exposure to robots in US	-1.608	-1.509*	-8.272**	-0.168	-1.632	-1.458	-8.350***	0.003
2004-2015	(1.108)	(0.906)	(3.253)	(1.472)	(1.014)	(0.912)	(3.220)	(1.120)
Exposure to robots in US	4.709	4.225*	24.104***	0.470	4.779*	4.139*	24.304***	0.016
× share in routine jobs, 1990	(3.021)	(2.417)	(8.968)	(4.031)	(2.797)	(2.440)	(9.024)	(3.061)
share in routine jobs, 1990	3.931	2.957	-21.945	10.482	3.517	2.709	-15.544	10.965
	(6.908)	(7.303)	(22.356)	(9.758)	(6.527)	(7.369)	(21.969)	(6.729)
Joint significance (p-value)	0.128	0.142	0.012	0.993	0.108	0.129	0.021	0.998
Panel B. Change in ratio of tax filers under 100% of official poverty threshold, 1990-2015								
Exposure to robots in US	-1.268	-1.181	-4.941	-2.239	-1.025	-1.313	-5.778	0.640
2004-2015	(1.601)	(1.671)	(4.029)	(3.194)	(1.589)	(1.665)	(4.330)	(2.699)
Exposure to robots in US	4.578	4.458	15.542	6.411	3.761	4.851	17.908	-1.890
× share in routine jobs, 1990	(4.500)	(4.725)	(11.031)	(9.131)	(4.445)	(4.702)	(12.232)	(7.760)
share in routine jobs, 1990	38.026***	43.429***	22.695	39.769**	34.525***	42.758***	6.234	44.697***
	(10.702)	(13.254)	(24.231)	(18.174)	(10.408)	(13.202)	(25.801)	(15.650)
Joint significance (p-value)	0.024	0.093	0.124	0.781	0.042	0.069	0.149	0.970
Panel C. Change in ratio of tax filers under 150% of official poverty threshold, 1990-2015								
Exposure to robots in US	-2.197	-2.439	-7.664*	-1.563	-1.711	-2.462	-6.812	0.667
2004-2015	(1.993)	(1.939)	(4.523)	(4.631)	(1.995)	(1.936)	(4.659)	(4.365)
Exposure to robots in US	7.829	8.822	22.758*	4.773	6.493	8.900	20.630	-1.185
× share in routine jobs, 1990	(5.652)	(5.541)	(12.466)	(12.973)	(5.663)	(5.533)	(13.043)	(12.277)
share in routine jobs, 1990	46.085***	49.914***	8.355	68.927***	47.224***	49.696***	12.282	78.202***
	(14.394)	(15.979)	(31.460)	(22.954)	(13.972)	(15.931)	(29.114)	(21.759)
Joint significance (p-value)	0.013	0.022	0.122	0.905	0.009	0.020	0.179	0.886

Continued

Table 5: (continued)

	Pre-tax income				Pre-tax income+EITC			
	All	Childless	Single, children	Married, children	All	Childless	Single, children	Married, children
Panel D. Change in ratio of tax filers under 200% of official poverty threshold, 1990-2015								
Exposure to robots in US	-2.292	-2.027	-8.013**	-5.299	-2.269	-2.037	-8.965**	-4.355
2004-2015	(2.215)	(2.231)	(3.638)	(5.103)	(2.217)	(2.234)	(3.806)	(5.097)
Exposure to robots in US	8.633	7.732	25.366***	15.809	8.522	7.755	27.505***	13.459
× share in routine jobs, 1990	(6.209)	(6.263)	(9.437)	(14.443)	(6.211)	(6.274)	(9.854)	(14.425)
share in routine jobs, 1990	53.291***	57.293***	0.322	66.906**	52.673***	57.340***	-7.245	71.485***
	(15.703)	(18.237)	(26.150)	(26.123)	(15.843)	(18.233)	(27.162)	(25.749)
Joint significance (p-value)	0.005	0.018	0.000	0.480	0.005	0.019	0.000	0.479
Weak IV F-stat	20.129	20.553	21.576	21.531	20.129	20.553	21.576	21.531
Observations	722	1444	1444	1444	722	1444	1444	1444

Notes: Notes: The tables show 2SLS estimates of the impact of exposure to industrial robots on the share of tax-filers under official poverty thresholds, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variablea are the change in the ratio of tax-filers whose income are below official poverty thresholds to total taxpayers from 1990 to 2015. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as taotal tax-filers of CZs in 1990. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

A Data Appendix

A.1 Simulating the amount of EITC using Census and ACS (American Community Survey) data

In this paper, I use the decennial Censuses data for 1990 and 2000 and the ACS data for the periods after 2000 to calculate the Earned Income Tax Credit (EITC) through TAXSIM provided by NBER.[40] The Census and ACS data have less income-related variables than the CPS data, but they contain the Public Use Microdata Area (PUMA) which is a geographic variable at the most disaggregated level so that I can assign commuting zones to each household by using crosswalk files of David Dorn.[41] The thing is that the Census and ACS data are collected in the household and the individual level, which both are not directly matched with tax filing units. So firstly, I tried to convert the household and individual level data into the family level data by using several variables such as the relationship with the head of household, marital status, age, etc. Then, I estimated the amount of EITC through TAXSIM.

Now I explain in detail how I define the tax units. First, I determine qualifying children and relatives based on the tax instruction of IRS, which is one of the main factors used to calculate the EITC. Actually, according to the instruction, for a primary tax filer to claim someone as qualifying children or relatives, they should be related to the primary tax filer like sons, daughters, siblings, etc.[42] However, when I use the Census and ACS survey data, I cannot make sure who is actually claimed for tax filing even though the data has a variable showing the relationship with the head of household or the reference person. For example, a person whose age is 16 and relationship with the head of household is non-relatives cannot be considered as a qualifying child if I use the relationship condition, but there is still a chance for him or her to be claimed as a qualifying child of someone who is not observed in the survey data. Since the number of qualifying children is very important for the amount of EITC, I do not use the relationship restriction to include every possible qualifying child. Note that I used the IRS instruction of the year before each survey year until 2000 because the Census data for 1990 and 2000 collected income information during the previous calendar year. The ACS data for the periods after 2000 surveys income information during 12 months prior to the survey date, so I use the IRS instruction of the ACS survey year. More specifically, the following individuals are assumed as qualifying children and relatives:

[40] TAXSIM is the NBER's FORTRAN program for calculating liabilities under US Federal and State income tax laws from individual data. For more information, see http://users.nber.org/~taxsim/taxsim27/

[41] Visit the following website: http://www.ddorn.net/data.htm

[42] In addition, according to the IRS instruction for taxpayers, for qualifying dependents to be claimed, they also should be U.S. citizen, U.S. national, U.S. resident alien, or a resident of Canada or Mexico. However, there are not proper variables in the Census and ACS data to apply the citizen test. There is a variable indicating the citizenship status, but it says that about 95% of respondents have citizenship. So, I assume that all observations meet the requirement of the citizenship test.

- A qualifying child is an individual who is not the head of household (subfamily) or the spouse of the head, and
  - he or she is under age 19, or
  - he or she is under age 24 and in school, or
  - he or she has both independent living difficulty (DIFFMOB) and self-care difficulty (DIFFCARE), and he or she is not in labor force.[43]
- A qualifying relative is an individual who is not assigned as a qualifying child and is not the head of household (subfamliy) or the spouse of the head, and
  - his or her gross income is less than a certain amount ($2,000 in 1990, $2,750 in 2000, $3,650 in 2010, and $4,000 in 2015).[44]

Second, I define a "family" based on several group identifier variables in the dataset, and then assign the head of a family by using relationship variables. Hence, the group identifiers in the Census and ACS data do not work perfectly so that there are families who do not have the head after I assign it. Also, there are qualifying children who are not linked to (the head of) a family. In one part, it happens because I define qualifying children without considering the relationship with head of household, but, in other part, it occurs due to the inaccuracy of group variables. Therefore, I make a few assumptions to reflect and adjust these issues.

- A same-sex married couple is not treated as a married couple. Each individual of the couple is considered the head of each family unit.
- If a qualifying child defined in the first step does not have a mother or a father within a household, this child is linked to the head of the household.[45]
- If a qualifying child defined in the first step has a parent but does not have the head because of the inaccuracy of group identifiers, this child is assigned to his or her parent and that parent is considered the head of the family.

[43] The third condition is for including “permanently and total disabled” individuals as a candidate for qualifying children. DIFFMOB indicates that the respondent is difficult or impossible to perform basic activities outside the home alone for at least 6 months. DIFFCARE indicates that respondents have difficulty for at least 6 months to take care of their own personal needs, such as bathing, dressing, or getting around inside the home.

[44] Hence, the gross income is calculated by subtracting the sum of two income variables, INCWELFR (public assistance income) and INCSUPP (supplementary security income), from total personal income (INCTOT).

[45] When I check whether a qualifying child without a head has a mother or a father, I use variables that indicate a personal number of the child’s mother or father. Notice that these "mom (pop) location" variables are constructed after the survey finished so that they even embrace a link between children and their possible parents.

- I exclude observations who are defined as qualifying children but do not have any other persons in the same household.

Third, I assign a spouse of the head by using the relationship with the reference person, and I finally define tax filing units by assuming that each head is a tax filer who represents his or her family and claims his or her qualifying children and relatives as dependents. The determination of filing status depends on the head's marital status, whether the head has a spouse or not, and whether the head has qualifying dependents or not. Note that "No spouse" or "No dependents" mean that the head does not have a spouse or dependents within the *surveyed* same unit.

- Single Filing Status: The head does not have the spouse or dependents, and the head's marital status is not "married, spouse present" or "married, spouse absent."
- Head of Household: The head whose marital status is not "married, spouse present" does not have the spouse but dependents.[46]
- Married Filing Jointly: The head whose marital status is "married, spoue present" has the spouse.
- Married Filing Separately: The head whose marital status is "married, spouse absent" does not have the spouse or dependents.

Before moving on to the next step, there are remaining observations whose filing status is not yet assigned. They are neither qualifying children nor qualifying relatives as defined above so that they cannot be linked to a primary taxpayer (family head).[47] For example, they can be a child who lives with his or her parents but is not qualifying children or qualifying relatives, parents who live with their children but are not qualifying relatives, an unmarried partner or one of the same-sex married couple who does not have any qualifying children, and so on. I basically assume that they are single filers, but include only observations who do not have their own children or qualifying children within the surveyed household because I want to at least rule out the possibility that they can file tax returns with dependents. For example, if a household consists of the head, two qualifying children, and the unmarried partner, each adult, the head and unmarried partner, could claim one child as a dependent separately.

Given the tax filing units defined above, now I need income information for each tax filer to simulate the EITC amounts through TAXSIM. Table A1 shows which variables of the Census/ACS datasets are used for TAXSIM inputs. Some TAXSIM inputs are set to zero because there are no corresponding variables

[46] Since a same-sex married couple is not considered a married couple in this analysis, one of the couple is treated as "Head of household" if he or she has dependents.

[47] Since I use only the income criterion when defining qualifying relatives, some of the remaining observations are categorized as qualifying relatives. However, they are non-relatives of the head according to the relationship variable.

in the Census/ACS data. In TAXSIM, *pwages* and *swages* include wage and salary income as well as self-employment income that can be a negative value in the Census/ACS. Since TAXISM does not allow negative numbers for wage variables, I assume that negative business and farm income means "no net earnings from self-employment," and change negative values to zero.

Note that TAXSIM requires the number of dependents to reflect personal exemptions and the number of children under the certain age to estimate some relevant credits. According to the introductory page of TAXSIM, the number of children under age 18 seems to be used for the calculation of EITC, but I use the number of qualifying children as defined in this paper because it follows the requirements for the EITC even though it is not measured exactly due to the data availability.

Table A2 shows the number of potential tax filers, which is population estimates weighted by the person weight of the family head. The numbers in square brackets are the official number of tax filers by filing status from IRS. The estimated numbers are about 90 percent of official statistics in terms of total filers, but the married jointly filers are relatively overestimated. Table A3 reports results through TAXSIM, the number of tax filers with positive federal earned income credits and the sum of federal earned income credits by the number of qualifying children, which shows that the total number of EITC filers and the total amount of credits are estimated less than the official statistics. Meyer (2010) compares the distributions of EITC by the filing status and the number of qualifying children in two different datasets: IRS and CPS ASEC. It shows that both the total number of EITC recipients and the total benefits calculated from the CPS are less than two-thirds of those from the IRS. The author suggests possible reasons for this discrepancy: i) IRS payments to ineligible recipients, ii) too low sample weight for EITC recipients in the CPS, and iii) underreporting of earnings in the CPS. In addition, the numbers of EITC filers with one qualifying child are relatively underestimated when compared to official statistics, whereas the numbers of EITC filers with three or more qualifying children are overestimated which are not reported separately in Table A3. The figures from the CPS ASEC of Meyer (2010) have a similar pattern: the CPS captures less amount of EITC of filers with one qualifying child, compared to filers with two or more qualifying children. This result may occur due to the three reasons mentioned above, or it might imply the strategic behavior of EITC filers with more than two children by claiming and splitting eligible children.

A.2 Constructing the 'exposure to robots' variable

The industrial robot data comes from the International Federation of Robotics (IFR) who collects data provided by almost all industrial robot suppliers all over the world. The IFR calculates the operational stock of robots based on the annual sales of robots by assuming that their service life is 12 years on average. The industrial robot data are available for the period 1993-2016, but during the same period, the industry-level data are only available for 9 European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.[48] In the US, the industry-level data starts from 2004.[49] For those ten countries, I use information on the operational stock of robots in 19 industries, as in Acemoglu and Restrepo (2017): 6 non-manufacturing sectors and 13 manufacturing sectors.[50] However, as mentioned in Acemoglu and Restrepo (2017), some robots still remain unspecified, and the number of unspecified robots are not small in some countries and some time periods even though its total share of the total robots has declined over time, 19.2% in 2011 to 12.8% in 2016. I allocate these unspecified robots to 19 industries, using the proportion of each industry to the total by country. In addition, Denmark's robot data are not classified by industry from 1993 to 1995, so I impute missing values by deflating the 1996 robot stocks by industry using the growth rate of the total stock of robots of Denmark between each missing year and 1996.

The measure of robot density, the number of industrial robots per thousand workers ($\frac{R_i}{L_i}$), for ten countries utilizes employment information of EU KLEMS data[51] released in March 2008.[52] According to the IFR's report, the industrial classification has followed the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 since 2010,[53] whereas the 2008 KLEMS data is classified by the ISIC Rev. 3. So, I reassign the industry codes on the basis of the release note of EU KELMS 2012 to make the 2008 data roughly follow the ISIC Rev. 4. Also, I use the number of US equivalent workers when calculating the number of industrial robots per thousand workers for European countries as mentioned in Acemoglu and Restrepo (2017). It is because the same number of workers may not imply the same labor intensity between countries unless they have the same total hours worked.[54]

Lastly, I calculate employment shares in industry i in commuting zone c, $l_{ci} = \frac{L_{ci}}{L_c}$, using the U.S. decennial censuses from 1980 and 1990. A small problem is that the U.S. Census Bureau has its own industrial classification. So, I assign the industry codes of ISIC Rev. 3 to each Census industrial categories

[48] According to the IFR's report, the industrial classification has followed the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 since 2010.

[49] Until 2010, the IFR reports only the overall stock of robots for North America (the United States, Canada, and Mexico). However, based on reports after 2010, the operational stock of robots in the US accounts for more than 90 percent on average.

[50] Six non-manufacturing industries are as follows: agriculture, hunting, forestry, and fishing; mining and quarrying; electricity, gas and water supply; construction; education, research and development; and other non-manufacturing industries. The manufacturing industry is categorized into 13 sectors: food products, beverages, and tobacco products; textiles, leather, and wearing apparel; wood and wood products; paper, paper products, and printing; plastic and chemical products; glass, ceramics, stone, and mineral products; basic metals; metal products; industrial machinery; electrical/electronics; automotive; other transport equipment; all other manufacturing sectors.

[51] Since the EU KLEMS data do not include information on Norway, I use the mean value of employment in three Scandinavian countries (Denmark, Finland, and Sweden).

[52] The EU KELMS data released after 2012 follows ISIC Rev. 4 industry classification. But it is available from 1995, so for the periods before 1995 it includes only the estimates. Besides, the EU KLEMS data classified by ISIC Rev.4 have 34 inudstry categories, whereas the data under ISIC Rev.3 have 72 categories. More importantly, the 1990's data on two countries, Sweden and the US, are not available under the ISIC Rev 4.

[53] However, the industry categories of the IFR do not correspond completely with the ISIC Rev. 4.

[54] I first calculate the hours worked per worker by industry in the US, then divide the total hours worked in each EU country by the working hours of one US worker.

and then make it follow the ISIC Rev. 4 in the same way as the EU KLEMS data. The detailed procedures are given in the Appendix A3. Note that, when I calculate the total employment by CZs from the Census or by countries from the KLEMS, the following industries are excluded in this analysis: public administration and defense, private households, and extra-territorial organizations and bodies.

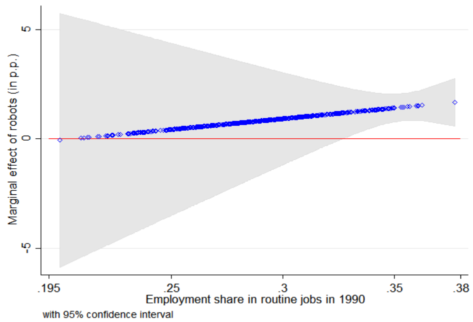
A.3 The adjustment of industry classficiation from Census to ISIC Rev. 4

The detailed procedures to make the Census industry codes roughly correspond to the ISIC Rev. 4 are as follows: (i) Assign 1987 SIC 4-digit codes to Census 1990 industry codes (*ind1990*) using the 1990 Census Sample Codebook.[55] Because one Census code often corresponds to multiple SIC codes, I calculate the employment share of each SIC code within a Census code using 1990 County Business Pattern (CBP) data and use it as the weight mapping from the Census industry to SIC 4-digit industry. Assuming that the employment shares by SIC 4-digit are not different across commuting zones, I use the information only at the national level. Note that some industries in the 1990 CBP data are actually reported at 3-digit level, not 4-digit level. Hence, if an industry is reported only at the 3-digit level and the 3-digit code has only one 4-digit code, the 3-digit code is considered equivalent to the 4-digit code. If the CBP data reports an industry only at the 3-digit level and the 3-digit code is disaggregated into multiple 4-digit codes, I assign equal probabilities to each 4-digit code in the 3-digit code. (ii) Based on the industry concordance from 1987 SIC 4-digit to ISIC Rev 3. 4-digit,[56] I can assign 2-digit codes of ISIC Rev. 3 to each Census industry with the final weight indicating the share of each Census industry that maps to a given 2-digit ISIC Rev. 3 code. But, according to the industry concordance, one SIC 4-digit code is often mapped to multiple ISIC Rev. 3 4-digit codes. Since I could not figure out the share of each ISIC 4-digit code corresponding to a given SIC 4-digit code, I assign equal probabilities to each ISIC 4-digit code. iii) The ISIC Rev. 3 codes assigned to every Census industry code are eventually mapped to the ISIC Rev. 4 codes by following the release note of EU KELMS 2012.

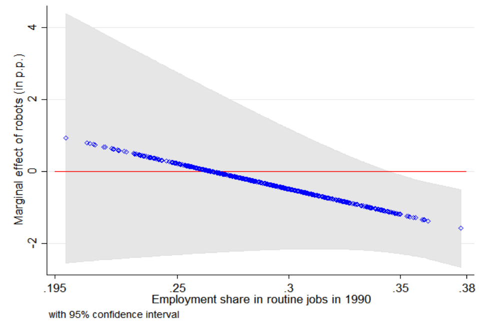
[55] See https://usa.ipums.org/usa/volii/codebooks.shtml

[56] For the industry concordance, visit https://www.macalester.edu/research/economics/page/haveman/Trade.Resources/tradeconcordances.html

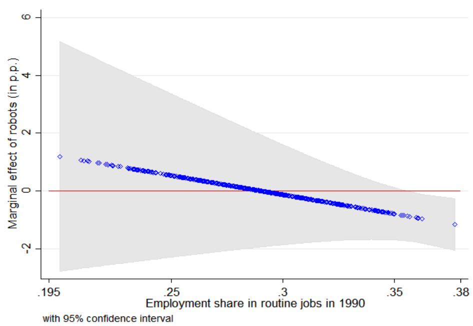
Figure A1: Marginal effects of industrial robots on the share of EITC filers within the eligible region, 1990-2015



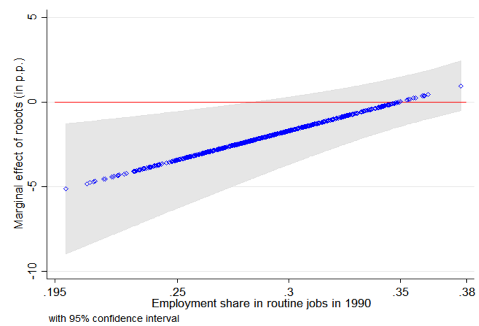
(a) Phase-in, single w/ children



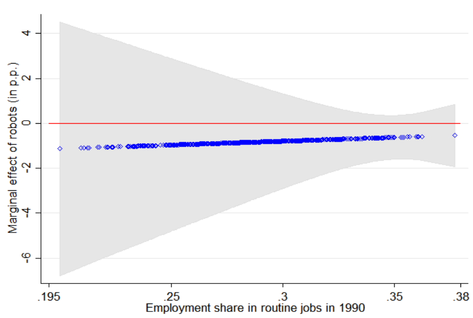
(b) Phase-in, married w/ children



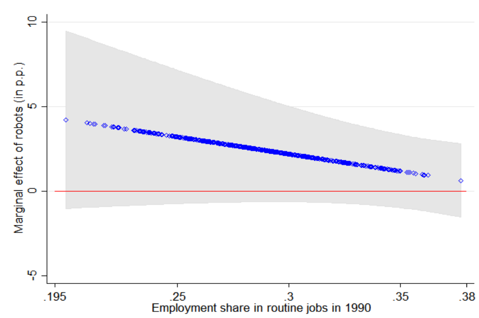
(c) Flat, single w/ children



(d) Flat, married w/ children



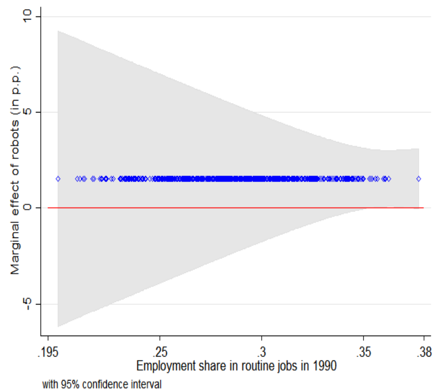
(e) Phase-out, single w/ children



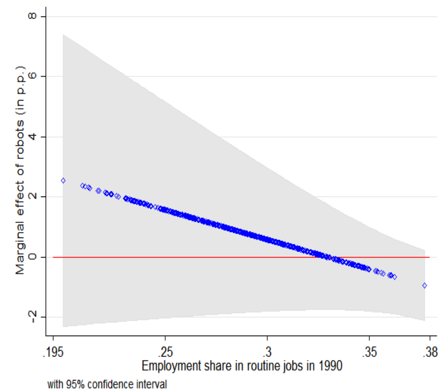
(f) Phase-out, married w/ children

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 4.

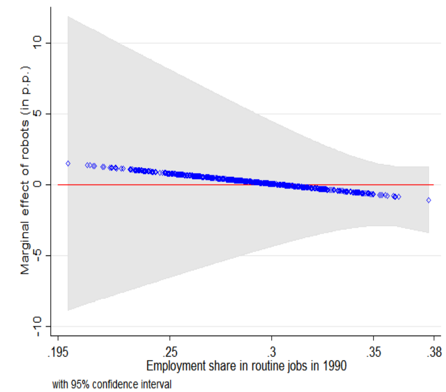
Figure A2a: Marginal effects of industrial robots on the ratio of tax-filers by earnings region, 1990-2015, Single filers with children (fixed denomintor)



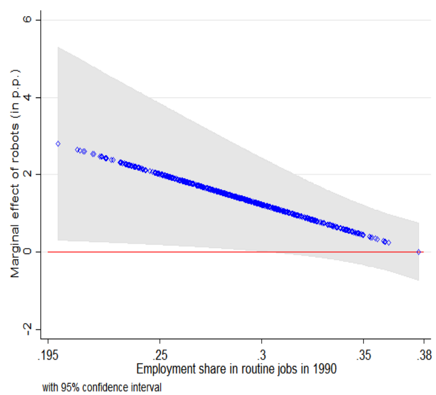
(a) Phase-in region



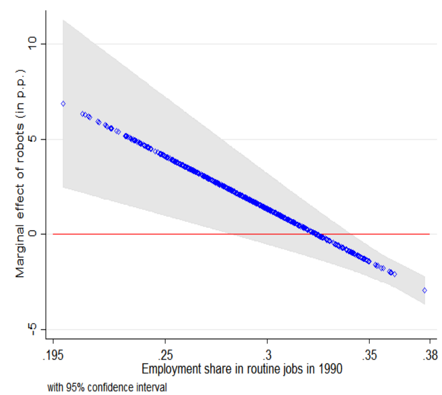
(b) Flat region



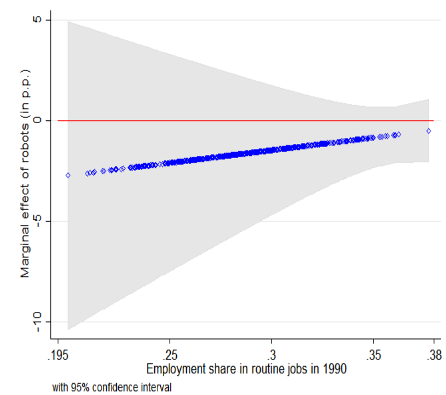
(c) Phase-out region



(d) Near phase-out region



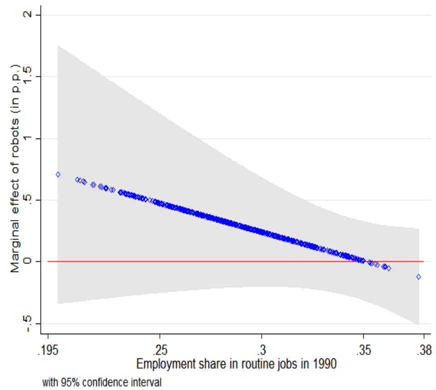
(e) Above the near phase-out region



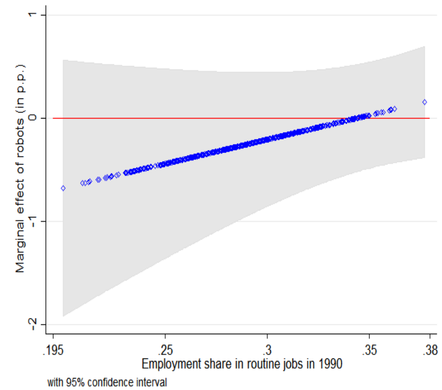
(f) Zero earnings

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 5. The near phase-out region is from the end of the phase-out to 25% above the end of the phase-out that is the beginning of the region above the near phase-out.

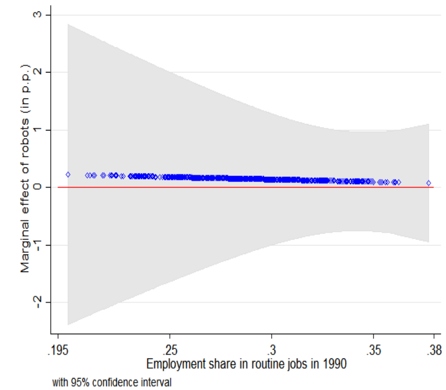
Figure A2b: Marginal effects of industrial robots on the ratio of tax-filers by earnings region, 1990-2015, Married filers with children (fixed denominator)



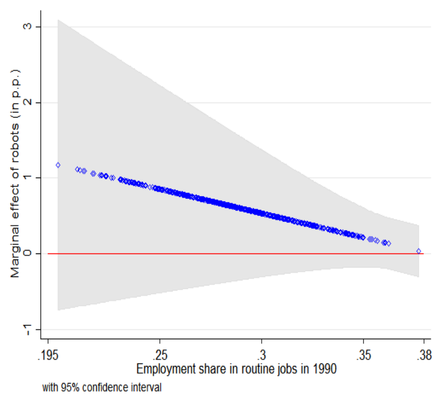
(a) Phase-in region



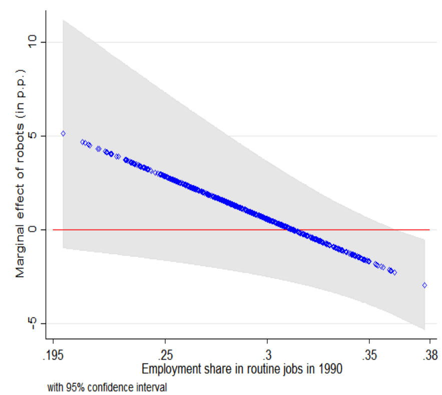
(b) Flat region



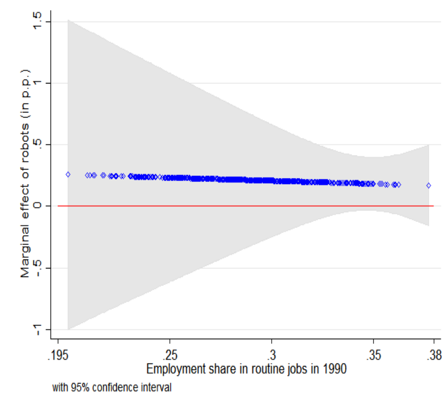
(c) Phase-out region



(d) Near phase-out region



(e) Above the near phase-out region



(f) Zero earnings

Notes: The marginal effects and confidence intervals for each sample are calculated based on the IV estimates in Table 5. The near phase-out region is from the end of the phase-out to 25% above the end of the phase-out that is the beginning of the region above the near phase-out.

Table A1: TAXSIM inputs corresponding income-related variables from the Census/ACS

TAXSIM		**Census/ACS**	
Inputs	Definition	Variables	Definition
pwages	wage and salary income of primary taxpayer (include self-employment)	incwage, incbus	wage and salary income, business and farm income
swages	wage and salary income of spouse (include self-employment)	incwage, incbus	wage and salary income, business and farm income
dividends	dividend income	-	set to zero
intrec	interest received	-	set to zero
stcg	short term capital gains and losses	-	set to zero
ltcg	long term capital gains and losses	-	set to zero
otherprop	other property income, including unearned partnership and S-corp income, rent, non-quali.ed dividends, capital gains distributions on form 1040, other income or loss not otherwise enumerated here	incinvst	interest, dividend, and rental income
nonprop	other non-property income such as alimony, fellowships, state income tax refunds (itemizers only) adjustments and items such as alimony paid, Keogh and IRA contributions, foreign income exclusion, NOLs	-	set to zero
pensions	taxable pensions and IRA distributions	incretir	retirement income
gssi	gross social security benefits	incss	social security income
ui	unemployment compensation received	-	set to zero
transfers	other non-taxable transfer income such as welfare, workers comp, veterans benefits	incwelfr, incsupp	welfare (public assistance) income, supplementary security income
rentpaid	rent paid	-	set to zero
proptax	real estate taxes paid	-	set to zero
otheritem	Other Itemized deductions that are a preference for the Alternative Minimum Tax	-	set to zero
childcare	child care expenses	-	set to zero
mortgage	Deductions not included in "otheritem" and not a preference for the AMT	-	set to zero

Notes: Definitions of all TAXSIM inputs are available at https://users.nber.org/ taxsim/taxsim27.

Table A2: The number of potential tax filers by filing status

Filing Status	1990	2000	2010	2015
Single	40,945,293	48,308,239	58,105,871	64,158,258
	NA	[56,927,117]	[64,846,356]	[71,086,947]
Head of household	11,916,518	15,426,213	19,264,278	19,590,580
	NA	[17,781,482]	[21,916,717]	[22,134,303]
Married, jointly	52,270,664	56,262,140	57,265,226	58,471,498
	NA	[49,980,900]	[53,526,090]	[54,294,820]
Married, separately	1,151,280	1,803,227	2,007,645	2,483,756
	NA	[2,385,646]	[2,532,292]	[2,977,192]
Non-filer	2,037,417	3,101,752	3,853,861	4,249,706
Total of Potential filers	108,321,172	124,901,571	140,496,881	148,953,798
	NA	[127,075,145]	[142,892,051]	[150,493,263]

Notes: Data come from the decennial Censuses and the ACS, and they are converted from the household level to the family level data to calculate the number of tax filers. To get population estimation, I used the personal weight of the reference person in a family. The "Non-filer" is the smaples who have both zero (or negative) earnings and zero (or negative) total familiy income. Samples that primary taxpayers are under age 16 are excluded. The numbers in square brackets are official statistics from IRS website.

Table A3: Simulated number of EITC filers and amounts of EITC

	TAXSIM Results				**Official Statistics**	
	Number		Amount		Number	Amount
All filers						
1990	9,707,848	(83%)	5,092,376,519	(77%)	11,696,000	6,595,000,000
2000	17,006,068	(88%)	24,078,072,092	(75%)	19,258,715	31,901,107,000
2010	24,367,166	(89%)	47,013,929,006	(79%)	27,367,756	59,562,029,000
2015	24,183,844	(89%)	52,217,223,339	(77%)	27,305,404	67,783,979,000
Filers with no qualifying children						
1990	-	-	-	-	-	-
2000	3,857,894	(120%)	696,130,128	(108%)	3,222,299	644,529,000
2010	7,129,271	(107%)	1,877,094,444	(107%)	6,647,462	1,752,786,000
2015	7,325,571	(108%)	2,166,107,788	(112%)	6,756,859	1,932,666,000
Filers with one qualifying child						
1990	4,675,931	-	2,475,062,136	-	NA	NA
2000	5,635,819	(72%)	7,848,965,491	(65%)	7,802,846	12,005,739,000
2010	7,422,605	(74%)	14,212,121,960	(68%)	10,000,746	21,014,164,000
2015	7,390,815	(73%)	16,034,960,383	(66%)	10,090,090	24,426,268,000
Filers with two or more qualifying children						
1990	2,986,546	-	1,549,126,910	-	NA	
2000	7,512,355	(91%)	15,532,976,472	(81%)	8,233,571	19,250,839,000
2010	9,815,290	(92%)	30,924,712,602	(84%)	10,719,546	36,795,083,000
2015	9,467,458	(91%)	34,016,155,169	(82%)	10,458,452	41,425,045,000

Notes: TAXSIM results are simulated values obtained through TAXSIM with the Census/ACS data. The official statistics are from www.taxpolicycenter.org, which does not provide statistics of EITC distribution by the number of qualifying children in 1990 (Fiscal Year 1989).

Table A4: The relationship between exposure to robots and share of employment in routine jobs

(a) *Time period: from 1990 to 2015*

	EIR93-15, EU, 30th	**EIR93-15, EU, mean**	**EIR04-15, US**
share of routine jobs in 1990	-0.732	-0.393	-0.783
	(1.850)	(2.959)	(2.226)
ratio of working-age population, 1990	0.209	0.529	-1.507
	(2.856)	(4.564)	(3.436)
ratio of female population, 1990	6.398	9.702	2.219
	(8.068)	(12.690)	(9.708)
ratio of population with college or more, 1990	1.471	1.891	3.102**
	(0.981)	(1.611)	(1.180)
ratio of non-white population, 1990	0.233	0.189	-0.081
	(0.551)	(0.901)	(0.663)
ratio of manufacturing employment, 1990	8.086***	12.411***	11.374***
	(1.714)	(2.735)	(2.062)
Exposure to China imports from 1991 to 2015	-16.116***	-23.258***	4.977
	(5.205)	(8.198)	(6.263)
constant	-3.887	-6.076	-1.492
	(5.794)	(9.192)	(6.973)
Observations	722	722	722

(b) *Time period: from 2005 to 2015*

	EIR05-15, US
share of routine jobs in 2000	-0.322
	(1.426)
ratio of working-age population, 2005	-0.459
	(0.944)
ratio of female population, 2005	0.355
	(3.755)
ratio of population with college or more, 2005	1.079**
	(0.472)
ratio of non-white population, 2005	-0.032
	(0.313)
ratio of manufacturing employment, 2005	6.188***
	(0.728)
Exposure to China imports from 2005 to 2015	14.030***
	(3.492)
constant	-0.216
	(2.498)
Observations	722

Notes: Both tables show the results of OLS regression examining whether commuting zones initially highly specialized routine jobs are more exposed to industrial robots in the subsequent periods. In table (a), the dependent variables are the 30th percentile and the mean of exposure to robots of EU countries from 1993 to 2015 in the first two columns, respectively. In the third column, the dependent variable is the exposure to robots of US from 2004 to 2015, which is the predicted values by the regression with the 30th percentile of the exposure to robots of the EU countries from 1993 to 2015. In table (b), the dependent variable is the exposure to robots of US from 2005 to 2015. All regressions include state fixed effects and are weighted by commuting zone share of national population in 1990. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A5: The impact of each measure of technology on EITC usage, 1990-2015

(a) The impact of routine-biased technology

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015				
share of empolyment in routine jobs, 1990	38.412***	-2.740	41.361*	79.796***
	(4.381)	(4.523)	(24.032)	(11.045)
Panel B. Change in EITC amount per tax filer from 1990 to 2015 (2015 US$)				
share of empolyment in routine jobs, 1990	842.258***	-14.677	1106.443*	1883.188***
	(195.814)	(12.966)	(579.458)	(514.996)
Observations	722	1,444	1,444	1,444

(b) The impact of exposure to industrial robots

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015				
Exposure to robots in EU 1993-2015 (p30)	0.017	-0.241*	1.177	-0.879
	(0.227)	(0.120)	(0.834)	(0.675)
Panel B. Change in EITC amount per tax filer from 1990 to 2015 (2015 US$)				
Exposure to robots in EU 1993-2015 (p30)	-4.874	-0.495	-29.071	-59.624*
	(7.797)	(0.349)	(26.293)	(33.816)
Observations	722	1,444	1,444	1,444

Notes: The table shows the OLS estimates of the impact of each measure of technology, the share of employment in routine jobs in 1990 and the exposure to industrial robots, on EITC usage. In the table (a), regressions do not include the latter measure of technology, whereas the first measure is excluded in the regressions of table (b). The dependent variable is the change in EITC filers to total filers ratio between 1990 and 2015 in Panel A, measured in percentage points, and the change in EITC amount per tax filer between 1990 and 2015 in Panel B. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, and the exposure to China imports. Also, all regression, except those for the pooled sample, include group-specific intercepts and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as total filers of CZs in 1990. Note that the number of EITC filers of Childless sample is zero in 1990 so I use the number of total filers in 1990 as the weight. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A6: The beginning earnings of each regions by filing groups

	Num. of qualifying children	1990 (FY1989) Single/Married	2015 Single	2015 Married
Flat	0	NA	6,580	
	1	6,500	9,880	
	2	6,500	13,870	
	3+	6,500	13,870	
Phase-out	0	NA	8,240	13,760
	1	10,240	18,110	23,630
	2	10,240	18,110	23,630
	3+	10,240	18,110	23,630
Near Phase-out	0	NA	14,820	20,340
	1	19,340	39,131	44,651
	2	19,340	44,454	49,974
	3+	19,340	47,747	53,267
Above the Near Phase-out (25% above the end of phase-out)	0	NA	18,525	25,425
	1	24,175	48,914	55,814
	2	24,175	55,568	62,468
	3+	24,175	59,684	66,584
Above the Near Phase-out (50% above the end of phase-out)	0	NA	22,230	30,510
	1	29,010	58,697	66,977
	2	29,010	66,681	74,961
	3+	29,010	71,621	79,901

Notes: The table shows the criteria for each region of earnings. Note that each number is also the ending earnings of the previous level of earnings region. The near phase-out region begins from the end of phase-out earnings, and the region above near phase-out starts from 25% or 50% above the end of phase-out earnings.

Table A7: The impact of exposure to industrial robots on EITC usage, 1990-2015 (IV estimates using the mean of exposure to robots in other countries)

(a) *Without interaction term*

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in US	0.175	-0.147	0.844	-0.308
2004-2015	(0.168)	(0.091)	(0.646)	(0.514)
share in routine jobs, 1990	39.502***	-2.640	40.793*	81.284***
	(5.169)	(4.677)	(23.555)	(11.407)
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in US	3.009	-0.204	-11.900	-32.732
2004-2015	(6.755)	(0.272)	(24.538)	(27.724)
share in routine jobs, 1990	883.002***	-13.457	1152.851*	1923.068***
	(233.542)	(14.269)	(591.487)	(536.605)
Weak IV F-stat	42.699	42.846	49.483	46.015
Observations	722	1444	1444	1444

(b) *With interaction term*

	All	Childless	Single, children	Married, children
Panel A. Change in ratio of EITC filers to total filers, 1990-2015 (in p.p.)				
Exposure to robots in US	0.439	-0.924	-1.989	-6.472
2004-2015	(1.534)	(0.686)	(5.006)	(4.801)
Exposure to robots in US	-0.756	2.222	8.107	17.680
× share in routine jobs, 1990	(4.312)	(1.889)	(13.863)	(13.433)
share in routine jobs, 1990	41.024***	-7.135	24.727	45.783*
	(8.914)	(5.312)	(42.189)	(24.564)
Joint significance (p-value)	0.575	0.191	0.318	0.389
Panel B. Change in EITC amount per tax filer, 1990-2015 (2015 US$)				
Exposure to robots in US	-77.181	-3.749	-19.452	-448.125***
2004-2015	(51.399)	(2.462)	(164.897)	(158.450)
Exposure to robots in US	229.633	10.145	21.618	1191.318***
× share in routine jobs, 1990	(142.961)	(6.729)	(442.919)	(422.687)
share in routine jobs, 1990	420.507	-33.981*	1110.012	-469.066
	(276.262)	(18.988)	(950.340)	(776.570)
Joint significance (p-value)	0.225	0.313	0.883	0.018
Weak IV F-stat	24.631	24.886	28.029	26.349
Observations	722	1444	1444	1444

Notes: The tables show IV estimates of the impact of exposure to industrial robots on EITC usage, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the mean of EU's exposure to robots, the interaction term is also instrumented with the product of the mean of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variable is the change in EITC filers to total filers ratio between 1990 and 2015 in Panel A, measured in percentage points, and the change in EITC amount per tax filer between 1990 and 2015 in Panel B. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. In both tables, automation is measured by the 30th percentile of exposure to robots in European countries. Table (a) does not include the interaction term between automation and share in routine jobs, but table (b) include it. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as total filers of CZs in 1990. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A8: The impact of automation on the change in the share of EITC filers within eligible region, 1990-2015 (IV estimates)

	All	Childless	Single, children	Married, children
Panel A. Change in Phase-in region				
Exposure to robots in US	0.322	-1.602	-2.030	3.750
2004-2015	(4.465)	(6.623)	(6.774)	(3.759)
Exposure to robots in US	-2.290	1.934	9.831	-14.103
× share in routine jobs, 1990	(12.945)	(19.006)	(19.122)	(10.188)
share in routine jobs, 1990	47.248*	-35.282	46.870	53.514*
	(26.410)	(40.071)	(40.338)	(28.823)
Joint significance (p-value)	0.501	0.315	0.000	0.012
Panel B. Change in Flat region				
Exposure to robots in US	-1.721	-4.034	3.841	-12.020***
2004-2015	(2.388)	(4.112)	(4.402)	(4.110)
Exposure to robots in US	4.505	13.020	-13.212	34.369***
× share in routine jobs, 1990	(6.487)	(11.282)	(12.030)	(11.125)
share in routine jobs, 1990	-1.153	-34.728	25.524	-12.664
	(16.778)	(27.925)	(23.675)	(25.781)
Joint significance (p-value)	0.761	0.270	0.043	0.007
Panel C. Change in Phase-out region				
Exposure to robots in US	1.398	5.636	-1.811	8.270
2004-2015	(5.107)	(5.439)	(6.618)	(5.552)
Exposure to robots in US	-2.215	-14.954	3.381	-20.266
× share in routine jobs, 1990	(14.786)	(15.452)	(18.809)	(14.996)
share in routine jobs, 1990	-46.095	70.010**	-72.394*	-40.850
	(31.158)	(33.387)	(40.431)	(32.742)
Joint significance (p-value)	0.565	0.479	0.447	0.282
Weak IV F-stat	24.176	20.553	23.478	26.894
Observations	722	1444	1444	1444

Notes: The tables show 2SLS estimates of the impact of exposure to industrial robots on the share of EITC filers in each eligible region, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variable is the change in the share of EITC filers in phase-in region between 1990 and 2015 in Panel A, the change in flat region in Panel B, and the change in phase-out region in Panel C. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as EITC filers of CZs in 1990. Note that the number of EITC filers of Childless sample is zero in 1990 so I use the number of total filers in 1990 as the weight. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A9: The impact of automation on the change in the ratio of tax-filers in earnings region above EITC eligiblity, 1990-2015 (IV estimates)

	All	Childless	Single, children	Married, children
Panel A. Near phase-out region: from the end of phase-out to 50% above it				
Exposure to robots in US 2004-2015	1.448*	-0.530	4.592*	1.551
	(0.828)	(1.547)	(2.572)	(1.733)
Exposure to robots in US × share in routine jobs, 1990	-3.600	0.985	-12.023*	-2.285
	(2.290)	(4.307)	(6.591)	(4.785)
share in routine jobs, 1990	18.907**	-0.944	11.451	15.625
	(7.937)	(10.503)	(19.695)	(12.468)
Joint significance (p-value)	0.087	0.110	0.189	0.048
Panel B. Above near phase-out region				
Exposure to robots in US 2004-2015	6.953*	9.568**	3.766*	5.982
	(3.628)	(4.035)	(2.234)	(5.098)
Exposure to robots in US × share in routine jobs, 1990	-21.557**	-27.480**	-12.788**	-18.675
	(10.753)	(11.183)	(5.990)	(14.184)
share in routine jobs, 1990	64.742**	123.100***	3.070	-59.455**
	(26.301)	(27.328)	(11.076)	(24.245)
Joint significance (p-value)	0.094	0.021	0.000	0.101
Weak IV F-stat	20.129	20.553	21.576	21.531
Observations	722	1444	1444	1444

Notes: The tables show 2SLS estimates of the impact of exposure to industrial robots on the share of EITC filers in each eligible region, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variables are the changes in the ratio of tax-filers above the eligible region for EITC, where the near phase-out region starts from the end of the phase-out to 50% above it. The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as EITC filers of CZs in 1990. Note that the number of EITC filers of Childless sample is zero in 1990 so I use the number of total filers in 1990 as the weight. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A10: The impact of exposure to industrial robots on the change in the ratio of tax-filers with the fixed denominator, 1990-2015 (IV estimates)

	All	Childless	Single, children	Married, children
Panel A. Change in Phase-in region				
Exposure to robots in US	-0.975	-2.874	1.539	1.638
2004-2015	(1.274)	(1.802)	(8.580)	(1.221)
Exposure to robots in US	2.211	6.536	0.013	-4.658
× share in routine jobs, 1990	(3.528)	(5.051)	(23.462)	(3.513)
share in routine jobs, 1990	3.500	-29.889***	91.303**	31.599***
	(7.334)	(10.535)	(43.504)	(9.936)
Joint significance (p-value)	0.338	0.001	0.112	0.406
Panel B. Change in Flat region				
Exposure to robots in US	-0.642	-1.226	6.484	-1.616
2004-2015	(1.133)	(1.082)	(5.121)	(1.343)
Exposure to robots in US	1.542	3.090	-19.666	4.694
× share in routine jobs, 1990	(3.048)	(3.023)	(13.418)	(3.714)
share in routine jobs, 1990	11.599*	-14.406**	107.882***	37.573***
	(6.761)	(7.062)	(28.990)	(9.477)
Joint significance (p-value)	0.753	0.184	0.090	0.442
Panel C. Change in Phase-out region				
Exposure to robots in US	0.446	0.183	4.435	0.391
2004-2015	(2.462)	(2.279)	(11.603)	(3.021)
Exposure to robots in US	-1.363	-0.688	-14.568	-0.830
× share in routine jobs, 1990	(7.018)	(6.650)	(31.883)	(8.678)
share in routine jobs, 1990	44.598***	0.778	190.690***	93.229***
	(15.814)	(14.909)	(60.675)	(24.355)
Joint significance (p-value)	0.973	0.959	0.660	0.967
Panel D. Change in Near Phase-out region				
Exposure to robots in US	0.681	-1.460	5.948**	2.451
2004-2015	(1.034)	(1.645)	(2.692)	(2.104)
Exposure to robots in US	-2.098	3.480	-15.731**	-6.388
× share in routine jobs, 1990	(2.839)	(4.611)	(7.254)	(5.674)
share in routine jobs, 1990	21.198**	-6.239	66.640***	49.670***
	(8.545)	(10.890)	(20.959)	(14.438)
Joint significance (p-value)	0.614	0.134	0.086	0.459
Panel E. Change in Above Near Phase-out region				
Exposure to robots in US	17.342***	15.877**	17.935***	14.163**
2004-2015	(5.555)	(7.224)	(4.900)	(6.623)
Exposure to robots in US	-55.725***	-51.802***	-55.295***	-45.338**
× share in routine jobs, 1990	(15.576)	(19.460)	(13.351)	(18.230)
share in routine jobs, 1990	247.128***	270.255***	172.332***	119.272*
	(60.433)	(70.967)	(32.729)	(62.058)
Joint significance (p-value)	0.000	0.000	0.000	0.009

Continued

Table A10: (continued)

	All	Childless	Single, children	Married, children
Panel F. Change in Zero earnings				
Exposure to robots in US	-8.440*	-16.802**	-5.257	0.359
2004-2015	(4.991)	(8.531)	(8.579)	(1.486)
Exposure to robots in US	21.904	44.903*	12.583	-0.503
× share in routine jobs, 1990	(13.804)	(23.870)	(23.558)	(4.254)
share in routine jobs, 1990	-37.941	-130.540**	49.959	14.307
	(28.612)	(53.501)	(55.024)	(9.534)
Joint significance (p-value)	0.175	0.087	0.539	0.243
Weak IV F-stat	20.129	20.553	21.576	21.531
Observations	722	1444	1444	1444

Notes: Notes: The tables show 2SLS estimates of the impact of exposure to industrial robots on the share of tax-filers in each region of earnings, where the exposure to robots in the U.S. between 2004 and 2015 is instrumented with the 30th percentile of EU's exposure to robots, the interaction term is also instrumented with the product of the 30th percentile of EU and the share in routine jobs, and the exposure to China imports is instrumented with other eight countries' exposure to China imports. The dependent variablea are the change in the ratio of tax-filers in each region relative to total taxpayers from 1990 to 2015, but the denominator is fixed as the total tax-filers in 1990. The first three regions follow the earnings criteria for EITC. The near phase-out region begins from the end of the phase-out region to 25The models for the pooled sample have one observation per commuting zone (CZ), whereas the remaining models have two observations per CZ. Specifically, Childless sample is estimated at the marital status-CZ level, and the others are estimated at the number of children-CZ level. All regressions include a constant, demographic characteristics of CZs in 1990 (tha ratio of working-age population, the ratio of female population, the ratio of population with college or more education, the ratio of non-white population), the share of employment in manufacturing, the exposure to China imports, and the share of employment in routine jobs in 1990 (from Autor and Dorn, 2013). Also, all regression include group-specific intercepts (except for the pooled sample) and state fixed effects. In addition, all regressions are weighted by relevant denominators of each outcome variable such as taotal tax-filers of CZs in 1990. The weak IV test reports F-statistics of Kleibergen-Paap. Standard errors are clustered by state and shown in parentheses. *p<0.10, **p<0.05, ***p<0.01.