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**HOW HAVE AUTOMATION AND TRADE AFFECTED
THE TAXABLE SHARE OF COVERED EARNINGS?**

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Abstract

Over the past few decades, U.S. income inequality has grown, with high earners experiencing disproportionate growth. This pattern has increased the top earners' share of national income and reduced the share of earnings taxable by Social Security from 87.1 percent to 82.7 percent since 1994, weakening the program's fiscal situation. Yet the drivers of earnings inequality, and thus the taxable share, are poorly understood. This paper combines data from several sources with administrative earnings records from the Social Security Administration to estimate the contribution of two factors to the declining taxable share between 1994 and 2015: industrial automation and trade with China. The effect of each factor on different sections of the earnings distribution is estimated through a series of instrumental variables quantile regressions. The resulting coefficients are used to construct a counterfactual 2015 earnings distribution, assuming the factors had remained constant at their 1994 levels.

The paper found that:

- The two factors had negative effects on earnings throughout the distribution, but the impact was less severe at the very top, accounting for 15 percent of the increase in the top 1-percent share of earnings between 1994 and 2015.
- The two factors alone explain 0.4 percentage points of the 3.4-percentage-point decline in taxable earnings, or 11 percent of the decline.
- Chinese trade was by far the more important factor and accounted for 10 percent of the decline in the taxable share between 1994 and 2015.
- While other factors, like non-automation skill-biased technological change, trade with other nations, the growth of non-wage compensation, and the erosion of norms surrounding executive pay also likely played a role, these factors were harder to quantify.

The policy implications of the findings are:

- As industrial automation and Chinese trade seem poised to increase in the near term, the taxable share will likely decline by another 0.2 percentage points by 2026.
- The large share of the decline left unaccounted for suggests the taxable share will most likely fall even below this linear projection.

Introduction

Over the past two decades, income inequality in the U.S. has increased, causing the share of income taxable by Social Security to decrease and harming the program's finances. At the same time, dramatic changes in the U.S. labor market have occurred, with a sharp increase in the automation of tasks that were once performed by workers and an increase in competition from abroad through trade. These changes have not impacted all workers in the same way. Some labor markets sustained a much more direct hit from automation and trade than others, and some jobs within these markets are more sensitive to such shocks than others. How much has the unequal distribution of these impacts contributed to the well-documented increase in earnings inequality and to the subsequent decline in the taxable share? To answer this question, this paper brings Social Security administrative data on earnings together with an analysis based on the recent literature on automation and trade.

The taxable share of earnings plays an important role in Social Security's finances. The Social Security Trust Fund is sustained by a 12.4 percent tax on payroll; however, this tax is levied only on annual earnings below a ceiling known as the "taxable maximum." Earnings above this cap are not subject to the payroll tax, nor do they enter a beneficiary's benefit calculation. While this arrangement, on the surface, should have no effect on the program's finances, since both revenue and benefits are reduced, in fact a reduction in the share of taxable earnings harms program finances in two ways. First, the progressivity of the benefit formula means that the reduction in benefits due to the exclusion of earnings above the cap may not be commensurate with the foregone revenue. Second, even though earnings above the cap do not factor into benefit calculations for their earners, these earnings do enter into the calculation of the Average Wage Index (AWI), which is used to inflate the earnings of all beneficiaries.

Given the harm to the program from a declining taxable share, it is troubling that this measure is expected to continue to fall over the next few decades (Technical Panel on Assumptions and Methods 2015). The taxable share has already fallen from 90 percent in 1983, to 87.1 percent in 1994, and 82.7 percent in 2016 (U.S. Social Security Administration 2018). The main cause of this decline has been a rapid increase in earnings at the very top of the earnings distribution, which have gone primarily to a fraction of the top 1-percent (Technical Panel on Assumptions and Methods 2011).¹

¹ See also Piketty and Saez (2003 and 2016); Kopczuk, Saez, and Song (2007); and Bakija, Cole, and Heim (2010).

Despite its importance to both Social Security and to the equity of the economy generally, the reasons for the increase in earnings at the top of the distribution are not well understood. Hypothesized mechanisms include skill-biased technological change (Autor, Katz, and Kearney 2006); technologies fostering “superstars” (Rosen 1981) and a corresponding increase in executive pay (Kostiuk 1990; Bebchuk and Fried 2003; Bebchuk and Grinstein 2005; Gabaix and Landier 2008; Frydman and Jenter 2010; and Frydman and Saks 2010); increasing labor-market concentration (Azar, Marinescu, and Steinbaum 2017; Benmelech, Bergman, and Kim 2018, and Naidu, Posner, and Weyl forthcoming); the decline of countervailing labor-market institutions such as unions (DiNardo, Fortin, and Lemieux 1996; Levy and Temin 2007; and Farber et al. 2018); and the erosion of norms regarding pay inequality in English-speaking countries (Atkinson, Piketty, and Saez 2011).

This paper focuses on two well-identified factors that have been hypothesized to contribute to the recent increase in the top share of earnings and for which the literature has developed straightforward measures: 1) automation, measured by industrial robots per 1,000 workers (following Acemoglu and Restrepo 2017, henceforth “AR”); and 2) trade, as measured by imports from China (following Autor, Dorn, and Hanson 2013, henceforth “ADH”).² The analysis relies on data from the Social Security Administration’s *Continuous Work History Sample* (CWSH) for wage and salary earners to calculate the earnings distributions in 1994 and in 2015. These data provide administrative earnings records for a large sample that should be more accurate than self-reported earnings; furthermore, these records are not top-coded as most surveys are, allowing analysis of the very top of the earnings distribution.

The analysis combines the CWSH data with industry-level automation and trade measures calculated by AR and ADH, respectively. These measures are instrumented by the industry-level penetration of industrial robots and Chinese imports in other developed countries’ industries, as in AR and ADH, in order to prevent bias in the estimates due to local shocks in the United States. With these data, instrumental variables quantile regressions are estimated for every earnings decile up to the 80th percentile and for every percentile above that to the 99th to

² The focus on Chinese imports is due to the large and exogenous change in trade driven by China’s entry into world markets around the turn of the century, which may have adversely affected competing U.S. producers.

account for how the association between the two factors and earnings changes at different points in the distribution.³

The analysis shows that increases in automation and trade have generally had negative effects on earnings throughout the distribution. Trade has a monotonically decreasing (in absolute value) effect across the earnings distribution. Automation, in contrast, displays a U-shaped pattern consistent with the labor-market polarization associated with skill-biased technological change found in previous literature.⁴ However, the effects of automation are still distinctly negative even approaching the top 1-percent of earners, consistent with AR's findings that automation negatively impacts even high earners.

Despite the divergent patterns for the two factors, both together impacted the lower and middle parts of the earnings distribution more negatively than the extreme upper part, contributing to the increasing share of earnings accruing to the highest earners. Using the estimates from the regressions, the analysis calculates a counterfactual 2015 earnings distribution had these factors remained at their 1994 levels. This counterfactual reveals that the two factors alone accounted for about 15 percent of the increase in the top 1-percent share of total earnings, and about 11 percent of the decline in the taxable share of total earnings (0.4 percentage points of the 3.4 percentage point decline) between 1994 and 2015.

The vast majority of the effect on top-earner shares is due to trade. Automation had negative impacts across a broad swath of even high earners, and thus had a very small effect on the shares of earnings accruing to the top few percentiles. The remainder of the differences between the top 1-percent shares and taxable shares in 1994 and 2015 is likely attributable to factors which are harder to quantify or estimate. Such factors include increasing market concentration, the erosion of norms surrounding managerial compensation, and an increasing share of compensation paid as untaxable benefits.

Other aspects of skill-biased technological change outside of industrial automation and growing trade with other nations besides China likely also contribute to increased earnings inequality. Industrial robots and imports from China make up a relatively small share of total

³ The higher resolution of the estimates in the top quintile of the distribution is in recognition of the fact that the share of earnings going to top earners is the main driver of changes in the taxable share of earnings. The methodology is based on methods described in Chernozhukov and Hansen (2005) and Chernozhukov, Fernandez-Val, and Melly (2013).

⁴ See, for example, Autor, Katz, and Kearney (2006 and 2008); Acemoglu and Autor (2011); and Autor and Dorn (2013). This literature stresses that technological change may allow substitution of routine tasks, mostly affecting middle-earning jobs, and having less effect on non-routine jobs in both low- and high-earnings service industries.

automation and trade, respectively. For example, the measure of automation, relying on industrial robots, does not speak to the increased computerization of jobs in the service sector or to rapidly developing technologies such as artificial intelligence. Likewise, though China is the United States' largest source of imports, imports from that country make up only 21 percent of total U.S. imports as of 2016 (Office of the United States Trade Representative 2018). Thus the results in this paper should be interpreted as illustrating general patterns of the effects of these two factors on the earnings distribution, rather than capturing the full magnitude of their impacts.

The rest of the paper proceeds as follows. The second section describes the determination of the taxable share, how it is affected by changes in the earnings distribution, and its implications for Social Security's finances. The third section describes the four main data sources used in the analysis. The fourth section describes the methodological approach. The fifth section presents the results of the analysis and discusses the implications for the taxable share. The final section concludes that increases in automation and, particularly, trade modestly contributed to the decline in the taxable share, and that further increases in these and related factors are likely to worsen Social Security's long-run fiscal situation.

Background

This section first provides background on a key determinant of the taxable ratio: the cap on taxable earnings. More detail is then provided on how the taxable share affects Social Security's finances.

The Cap on Taxable Earnings

The cap on taxable earnings limits the contributions and benefits of Old Age, Survivors, and Disability Insurance (OASDI) of high earners, presumably because they are likely to have private savings and unlikely to rely on such benefits (Mulvey 2010). Earnings accruing to individuals at or above the cap are not subject to the 12.4 percent Social Security payroll tax and are also not included in the calculation of lifetime earnings that forms the basis for OASDI benefits. When the Social Security program was first instituted in 1937, the cap was set at \$3,000 and remained at this level, unadjusted for inflation, until 1950. Following reforms in that year, the cap was periodically raised, at first through legislation and, after 1975, through a

formula indexed by average wages. The 1977 reforms of the program further accelerated the rise in the cap to shore up the rapidly diminishing Trust Fund.

Until 1994, employees and employers each also paid a 1.45 percent payroll tax toward Medicare, up to a maximum level of earnings. In 1994, this Medicare tax became uncapped. This makes 1994 a convenient starting point for the analysis, as individual earnings above the OASDI cap become easily observable in the data.⁵ Furthermore, the formula for calculating the taxable maximum, also known as Social Security's wage base, also conveniently uses 1994 as its base year. For every year after 1994, the formula multiplies the 1994 cap of \$60,600 by the AWI lagged by two years divided by the AWI in 1992, which was \$22,935. The result is then rounded to the nearest multiple of \$300.⁶ Thus the cap increases proportionally with AWI, with a roughly constant ratio of 2.64 ($\$60,600/\$22,935$). In calculating the taxable share under counterfactual conditions the analysis will therefore carefully account for changes in the AWI in these scenarios.⁷

Despite the mechanical adjustment of the wage base with the AWI, the taxable share has been roughly countercyclical in the past few decades (see Figure 1). This pattern arises because recent periods of expansion have benefited those earning above the cap more than those earning below it, and recent recessions have had the opposite impacts (Piketty and Saez, 2013). Furthermore, in recent decades the taxable share has declined to a lower nadir with every subsequent expansion, tracking the progressively increasing peaks in top-earner shares of earnings. In line with these historical patterns, as the current economic recovery entered its

⁵ Calculating the share of earnings above the cap before that year requires aggregating earnings across multiple employers of the same individual.

⁶ The formula has a few quirks. One is that if the AWI *decreases*, the cap is *not* reduced. Another is that the formula only applies at all in a year in which OASDI benefits are subjected to a Cost of Living Adjustment. Indeed, in 2016 there was no Cost of Living Adjustment due to negligible inflation as measured by the Consumer Price Index (CPI). This was despite an increase in the AWI in that year. Consequently in 2017, once a COLA was applied to benefits again, the increase in the cap was extraordinarily large, at 7.3 percent, as it accounted for two years' worth of growth in average wages.

⁷ The adjustment of the taxable maximum with AWI means that increases in the earnings of workers earning above the cap have an ambiguous effect on the share of taxable earnings. On the one hand, such earnings are not taxed, by definition. On the other hand, such earnings do contribute to a rising AWI, which in turn raises the cap and brings more earnings below it. Intuitively, then, the taxable share declines most when growth in earnings above the cap is offset by a decline in earnings below the cap, such that the AWI is unchanged. In other words, the taxable share would be most impacted by a mean-preserving spread of the earnings distribution that increases inequality not only by raising earnings for those at the top, but also reducing them for those at the bottom.

seventh year in 2016, the taxable share declined to its third-lowest level since 1983, at 84.6 percent.⁸

The Implications of the Taxable Share for Social Security's Finances

Because earnings above the cap do not count toward OASDI benefits even as they are exempted from the Social Security payroll tax, it might seem that the taxable share should have no impact on program finances. However, earnings above the cap are detrimental to Social Security's long-term fiscal position for two reasons: the method of calculating the AWI and the progressivity of benefits. High earnings also have short-term impacts on the program's finances.

The first way that earnings above the cap affect Social Security's long-term finances is that those earnings still enter into the calculation of the AWI. The AWI is used in calculating benefits for all workers, including those with earnings below the taxable cap. Thus an increase in the AWI due to the earnings of high earners raises the benefits for all beneficiaries without directly contributing any revenue to cover those added costs.

The second way in which earnings above the cap hurt Social Security's long-term fiscal situation is through the progressivity of the OASDI benefit formula. If the AWI is held constant, a decline in the taxable share by necessity implies a decline in lower earners' earnings. The progressivity of the benefit formula means that benefits for low earners may not decline proportionally to the revenue lost from their lower earnings.

As a consequence of these two channels, increased earnings above the cap are a burden on the OASDI program's long-term finances. In addition, there is a temporary hit to program finances from a reduction in the taxable share, since it reduces revenues immediately, while its effect on reducing benefits is only slowly realized.

The Social Security Office of the Chief Actuary estimates that a decline of 1 percentage point in the taxable share reduces the 75-year actuarial balance of the Trust Fund by 0.11 percent of taxable payroll (U.S. Social Security Administration 2018). In other words, a decline of 1 percentage point in the taxable share would increase the payroll tax rate necessary for a 75-year

⁸ This taxable share level, and all subsequent ones, refer to the taxable shares for wage and salary earners. The share is generally lower for the self-employed. Under the current formula for the wage base, the taxable share has only been lower in 2000 (84.5 percent) and in 2007 (84.3 percent), each the final year of its respective expansion. The taxable share was as low as its 2016 level in 2012. It is worth noting that, with a broader historical perspective, the taxable share has been much lower, averaging about 83 percent (Whitman and Shoffner 2011), and dipping to 74.1 percent in 1965. In that period, however, the cap was only adjusted through explicit legislation.

balance in the Trust Fund by 0.11 percent. The decrease of 3.4 percentage points observed since 1994 would need to be offset by an increase in the payroll tax of 0.374 percentage points. That increase represents about one-seventh of the 2.84-percentage-point increase currently needed to restore a 75-year balance in the system (U.S. Social Security Administration 2018). Given the role of the taxable share in Social Security’s finances, estimating which factors led to its decline is an important task. The next section introduces the data needed to perform that task.

Data

The empirical analysis in this paper relies on four main datasets, which are combined to estimate the effects of automation and trade on the earnings distribution.

Automation

As a measure of automation, the analysis uses the operationalization developed by AR, which is based on the number of robots per 1,000 workers, calculated for 19 different industries. Although the current analysis is focused on the U.S. earnings distribution, the paper uses an instrumental variables approach, where U.S. automation is instrumented by automation in European countries (as in AR).⁹ Specifically, the instrument for a given U.S. state is the level of automation based on that state’s industrial mix in 1990 but assuming the robot-use by industry in European countries.¹⁰ The U.S. and European country data to construct this instrument were collected by AR from the International Federation of Robots (for number of industrial robots), the EUKLEMS dataset (for number of workers by industry in Europe), and from the U.S. Census and the American Community Survey (for equivalent U.S. worker counts). This paper takes the robots/1,000 workers numbers by industry directly from Table A1 in AR.

The robots/1,000 workers ratio is observed for the years 1993, 2004, 2007, and 2014 for European robot penetration; and for 2004, 2007, and 2014 for U.S. robot penetration. The analysis here uses these industry-level measures to calculate state-year level robot penetration through the following procedure: first, three-digit industry codes from the CPS are classified into

⁹ The European countries are: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.

¹⁰ For example, if Massachusetts in 1990 had 50 percent of its workforce in agriculture and 50 percent in automobiles, and in 2014 agriculture in Europe had 0.029 robots per 1,000 workers and automobiles 47.1, then the value of the instrument for Massachusetts in 2014 would be 23.6 ($0.029 \cdot .5 + 47.1 \cdot .5$).

the 19 industry categories enumerated in AR.¹¹ Second, the shares of employment of these 19 categories in each state are calculated from the 1990 CPS (prior to the analysis period). Third, state-year robot penetration is calculated twice in the observed years of 1994-2015: once based on the European industry-level robots/1,000 workers number weighted by the 1990 state industry shares, and once based on the U.S. robots/1,000 workers number with the same weights.¹² Finally, the measure is interpolated linearly between the observed years to arrive at relevant values for 1994 and 2015.¹³

Trade

The measure of trade is based on data on Chinese imports to the United States and to other developed countries from ADH.¹⁴ These data are at the Commuting Zone (CZ) level, and available in 1990, 2000, and 2007. They are aggregated to the state level, weighted by the share of the national population of CZs in 1990. The data are then interpolated linearly between 1990 and 2000, and held constant after 2007 (to ensure that the variation in trade is driven by the plausibly exogenous rapid entrance of China into world trade, and not by its more moderate and possibly demand-driven growth since) to arrive at 1994 and 2015 values.

As with the automation measure, the trade data are calculated twice: once using Chinese import penetration in each U.S. industry, and once using import penetration in each industry in other developed countries, in both cases weighted by U.S. industry shares in 1990 (before the analysis period).¹⁵ This procedure results in two measures, one based on other countries' import penetration, weighted by U.S. industry shares; and one based on U.S. industry-level penetration weighted by U.S. industry shares. As with automation, and following the approach in ADH, the U.S.-based measure is instrumented by the "other country" measure to avoid potential endogeneity of imports to local demand shocks (see next section for further details). These U.S.

¹¹ A crosswalk is available from the authors upon request.

¹² In calculating the European shares, the paper follows AR and uses the 30th percentile of robot penetration by industry in Europe, which is empirically more predictive of U.S. industry robot penetration than the European mean.

¹³ To "interpolate" the 1994 U.S. value, robot penetration is assumed to have been 0 in the U.S. in 1980. Furthermore, since the last observed year is 2014, the 2015 values are assumed to have remained at their 2014 levels.

¹⁴ The original data were acquired by ADH from the U.N. Comtrade database. The ADH data are available online at <http://www.ddorn.net/data.htm>

¹⁵ These countries are: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

data and the analysis exclude Alaska and Hawaii. However, Washington, DC is counted as a state.

Other Control Variables

Other controls used in the regressions are taken from the CPS *Annual Social and Economic Supplement* conducted each March. These include the share of workers in firms with over 1,000 employees, unionization rates, and the rate of offers of employer health insurance.¹⁶ Furthermore, the 1990 shares of employment in each 3-digit industry used to construct the automation measure described above are also from the CPS. These shares are calculated using the March Supplement household weights to account for the sampling structure of the survey.

Data on Labor Earnings

Data on earnings come from the CWS, a 1-percent sample of earnings of U.S. workers. In the paper, the data are restricted to wage and salary earners in the years 1994 and 2015, ages 16 to 70, with at least \$1 of annual earnings. Due to computational limitations in the regressions described below, these data are further restricted to a random 50 percent of the full sample, totaling 1.4 million person-year observations.

The data contain the variables year of birth, year of death, gender, state of residence, and earnings. The earnings measure from the CWS covers all earnings and deferred compensation (e.g., 401(k) contributions) subject to the payroll tax.¹⁷ All dollar amounts are in constant 2015 dollars, adjusted by the CPI. Within each year, individuals are divided into 100 equal-sized bins,

¹⁶ While these variables provide proxies for other factors that may affect the taxable share – namely, increasing market concentration, decreasing worker bargaining power, and relative increases in non-wage compensation at the expense of cash wage growth – the measures are too flawed to rely upon to quantify these factors' effects due to measurement error and lack of clear identification of their impacts.

¹⁷ The earnings measure is not adjusted for two factors that could affect taxable earnings but are quantitatively small and irrelevant for estimation of top earner shares. The first is that workers who earned above the cap because they worked for multiple employers in the same year do not pay payroll taxes on their earnings above the cap, but the employer share of the tax is paid on all earnings. The second factor is that before 2001 military deemed wage credits are included in taxable earnings. To simplify the analysis it is assumed that both earnings above the cap and military deemed wage credits are entirely untaxed.

numbered from 1 to 100.¹⁸ The mean of each of these bins is interpreted as the earnings percentile corresponding with the bin number.¹⁹

The first two rows of Table 1 display the characteristics of the earnings distributions in the CWS data for wage and salary earners in 1994 and in 2015. Mean earnings of \$36,978 in 1994 have grown to \$45,412 in 2015, a change of \$8,434. However, median earnings have grown more moderately, from \$25,522 to \$28,946, an increase of only \$3,423 (largely driven by increasing earnings among women). This small increase in the median relative to the mean reflects the particularly rapid growth in earnings at the top of the distribution, and particularly slow growth in its middle region.

Figure 2 plots the percentage change in earnings between 1994 and 2015 at each percentile, displaying a stark U-shape (similar to findings in, for example, Acemoglu and Autor 2011). While earnings in the 5th percentile, for example, grew by 36 percent, and earnings at the 95th percentile grew by 29 percent, earnings at the 50th percentile grew by only 13 percent. This unequal distribution of gains is a major contributor to the decline of the taxable share of earnings over the period. The next section seeks to quantify what role automation and trade play in driving this large gain in the top earners' share.

Empirical Approach

This section describes the two main steps of the analysis. The first is estimation of instrumental variables quantile regressions to find the impact of automation and trade at different points in the earnings distribution.²⁰ The second step takes those estimates and adjusts the 2015 factual earnings distribution to construct counterfactual distributions under alternative scenarios in which each one of the factors and both together had remained at their 1994 levels. These counterfactual earnings distributions are used to calculate counterfactual taxable shares of earnings.

¹⁸ To ensure equally sized bins, the analysis breaks ties between individual earners by adding a random number between -0.01 and 0.01 to every log(earnings) record. This noise will have a negligible effect on the outcomes, as it represents less than one hundredth of one percent of annual earnings.

¹⁹ To be precise, the maximum of each bin is the percentile. However, for the analysis it is convenient to rely on the means of the bins. The calculation of total earnings below or above a percentile, to arrive at earnings shares, relies on summing total earnings by multiplying mean earnings within a bin by the bin-size, 1 percent.

²⁰ This approach is in the spirit of Chernozhukov, Fernandez-Val, and Melly (2013).

Instrumental Variables Quantile Regressions

The analysis calls for separate estimates of the impact of each factor of interest on different points in the earnings distribution. To estimate these regressions the analysis first follows the approach in AR and ADH, respectively, to isolate the plausibly exogenous variation in automation and trade. The concern with both these measures is that they may be driven by local shocks to supply and demand in the U.S., rather than being the drivers of such shocks. For example, the number of robots in a state could increase because of a decline in labor supply, rather than because technological change has made the use of robots more attractive to firms. Similarly, Chinese imports may increase because demand for those goods has grown, rather than because of greater export capacity of Chinese firms.²¹

As discussed in the data section, to circumvent some of these concerns, each of the two factors is measured in two ways: based on penetration by industry in other developed countries, and based on the actual penetration by industry in the United States. In both cases, the state-level measure is calculated using the actual U.S. industry shares from 1990. With these two measures in hand, ordinary least-squares regressions of state-level differences between 1994 and 2015 of the following form are estimated.²² They yield a measure of automation (trade) that would have resulted from the industrial robot (Chinese import) penetration predicted from the corresponding penetration in other countries:

$$Factor_{f,s,t}^{US} = \theta + \beta_1 Robots_{s,t}^{Other} + \beta_2 Imports_{s,t}^{Other} + \beta_3 Q_{s,t} + \sigma_s + \tau_t + \varepsilon_{f,s,t}$$

where $Factor_f$ is either *Robots* or *Imports*, and the *US* superscript indicates that the variable is based on U.S. industry-level penetration while the *Other* superscript indicates the

²¹ As in AR and ADH, these instruments will not correct for bias stemming from global shocks to labor supply and product demand.

²² The analysis estimates these differences regressions following AR and ADH. Unlike in those papers, however, this is implemented through use of state fixed effects rather than first differences, since the second stage described below is estimated on a repeated cross-section of individuals, rather than a panel of geographical units. This produces identical coefficients to the state-level differences regressions, but imposes stronger assumptions on the structure of error terms. The standard errors of the coefficients estimated in these regressions should account both for the fact that two of the explanatory variables are themselves estimated, and for the fact that the variation driving these factors is at the state-year level rather than the individual level. Neither of these corrections is easily implementable in SAS, the statistical package used in the analysis. Therefore, the standard errors yielded by these regressions should be approached with caution, and the results below focus on point estimates. Future work will account for the instrumental variables approach and the potential correlations within state-year cells by block-bootstrapping.

variable is based on other-country industry-level penetration.²³ s indexes state and t indicates whether the observation is in 1994 or 2015. These first-stage regressions also include other controls, $Q_{s,t}$: the share of workers in the CPS in state s in year t who work in a firm that has more than 1,000 employees; the share of workers who have an offer of employer-sponsored health insurance; and the share of workers represented by a union. These controls capture factors hypothesized to also affect the earnings distribution; however, they are endogenous in the analysis and so are only used as controls but not included in the counterfactual experiments described below. The regressions also contain state fixed effects, σ_s , and an indicator τ for year 2015. The first stage F-statistics on the excluded instruments are high: 179 for the automation regression, and 79 for the import regression. For results of these first stage regressions see Table A1 in the Appendix.

From these first-stage OLS regressions, $\widehat{Robots}_{s,t}^{US}$ and $\widehat{Imports}_{s,t}^{US}$ are estimated. These two predicted variables are then used in a series of quantile regressions of the form:

$$\begin{aligned} Earnings_{q,i,s,t} &= \theta_q + \beta_{q,1}\widehat{Robots}_{s,t}^{US} + \beta_{q,2}\widehat{Imports}_{s,t}^{US} + \beta_{q,3}Q_{s,t} + \alpha_{q,i} + \gamma_{q,i} + \sigma_{q,s} + \tau_{q,t} \\ &+ \varepsilon_{q,i,s,t} \end{aligned}$$

where variables and indexes are as above, except that q indexes the quantile being estimated, and i indexes individuals. Furthermore, in addition to the previous controls, these regressions also contain age and gender fixed effects, $\alpha_{q,i}$ and $\gamma_{q,i}$. These earnings quantile regressions are estimated for every decile up to the 8th, and for every percentile above that up to the 99th, i.e., $q=0.1, \dots, 0.8, 0.81, \dots, 0.99$.²⁴ The dependent variable, *Earnings*, is in logs, to normalize residuals. However, values are transformed back to dollar terms for the following analysis.

²³ Estimation of an instrument with OLS for use in a second-stage quantile regression follows the approach outlined in Chernozhukov and Hansen (2005, 2006). In this context the preferred approach is a two-sample IV regression, since the first stages can be estimated on public data at the state level, and then matched to restricted individual-level data for the second stage.

²⁴ This choice of the set of q is chosen to provide good resolution of the effect of each factor near the top of the earnings distribution, where there is greater variance with respect to the effects of each factor, and where small changes have disproportionate impacts on the taxable share.

The main results do not depend on including the potentially endogenous controls of unionization rates, rates of employer-sponsored health insurance offer, and share of workers in large firms. To assess whether the endogeneity of these variables is biasing the estimates of the effects of the other factors, the regressions are also estimated excluding these controls. The qualitative patterns of coefficient estimates for automation and trade are robust to this exclusion. See figures A1 and A2 in the Appendix for figures illustrating this robustness.

Counterfactual Earnings Distributions and Taxable Shares

Once the coefficients on the two factors of interest are estimated for each quantile, they are scaled. This scaling is helpful because the two variables are measured on different dimensions, making it difficult to compare coefficients on their own. A natural scale to use in this regard is the factual change in each factor between 1994 and 2015. Thus the coefficients for all quantiles for each factor X are multiplied by the factor's change at the median of earnings between 1994 and 2015, Δ_X .

Following the scaling, construction of counterfactual 2015 earnings distributions is straightforward. For any factor or combination of factors to be held at 1994 levels, the scaled coefficient of that factor for each quantile is subtracted from the corresponding 2015 quantile.²⁵ Thus, the counterfactual 2015 earnings at quantile q holding a subset vector X of the two factors of interest at its 1994 levels is:

$$\text{Exp}(\text{Earnings}_q^{CF,X}) = \text{Exp}(\text{Earnings}_q^F - \beta_{qX}\Delta_X)$$

where $\text{Earnings}_q^{CF,X}$ is the log of earnings at quantile q of the 2015 counterfactual distribution holding X constant; Earnings_q^F is the log of earnings at the q th quantile of the factual 2015 earnings distributions; and β_{qX} is the coefficient on X for the q th quantile.

Of course, the counterfactual earnings distribution may have different average earnings than the factual 2015 distribution, so the AWI would likely be different in the counterfactual scenario. The counterfactual would also have a different taxable maximum, because of the

²⁵ To arrive at a finer resolution of earnings below the 80th percentile, it is assumed that the coefficient of each factor for percentiles between the deciles is equal to the coefficient at the next decile. For example, the coefficients for the 4th percentile are assumed to be the same as for the 10th percentile.

difference in the AWI. Calculating average earnings is accomplished by taking a weighted sum of the factual and counterfactual earnings at each percentile, where the weights are 0.01 for each percentile. Because the earnings at each “percentile” bin are the mean within that bin, this calculation yields the mean earnings under the factual and counterfactual distribution.

The formula for the 2015 counterfactual taxable maximum is: $TaxMax_{2015}^{CF} = \frac{TaxMax_{1994}}{AWI_{1992}} * AWI_{2013}^{CF} = \frac{60600}{23753.53} * AWI_{2013}^{CF}$, rounded to the nearest multiple of 300. To calculate the counterfactual 2015 taxable maximum some approximation of the counterfactual 2013 AWI is therefore required. This counterfactual is approximated by assuming that the difference in average earnings between the 2015 counterfactual and factual distributions would have held for the 2013 counterfactual versus factual distribution, as well. In sum, the counterfactual 2015 taxable maximum is given by: $TaxMax_{2015}^{CF} = \frac{60600}{23753.53} * [AWI_{2013}^F + (\overline{Earnings}_{2015}^{CF} - \overline{Earnings}_{2015}^F)]$, rounded to the nearest multiple of 300.

With the counterfactual taxable maximum in hand, the taxable share is calculated simply as the sum of taxable earnings divided by the sum of total earnings. Similarly, the top 1-percent’s earnings share can be calculated by taking the ratio of the top 1-percent’s earnings in either the factual or counterfactual distribution, divided by the appropriate sum of total earnings.

Results

This section presents the results on the effect of automation and trade on different points in the earnings distribution. It then applies those estimates to construct counterfactual earnings distributions in 2015 had one or both of these factors remained at their 1994 levels. Relying on these counterfactuals, the analysis decomposes the decline in the taxable share of earnings to the portion contributed by these factors in total, and by each in isolation, to assess how much of the increase in the top share of earnings, and the corresponding decline in the taxable share, is attributable to each factor.

Instrumental Variables Quantile Regression Estimates

Figures 3 and 4, respectively, show $\beta_{qx}\Delta_X$ – that is, the estimated coefficient multiplied by the factor’s change from 1994 to 2015 – for automation and for trade on different parts of the

earnings distribution.²⁶ Both factors have negative effects on the vast majority of wage and salary earners. However, the patterns vary between the two factors in how they hit different parts of the distribution.

Automation had essentially no effect at the 10th percentile. However, the effect rapidly turns negative further up the distribution, at -1.4 percent for the 20th percentile, and then declines further, until reaching a nadir of -3.7 percent at the 90th percentile. The effect then diminishes in absolute value, but remains negative until the 98th percentile, where it is -3.2 percent. The estimates for the 99th percentile are extremely volatile across different specifications; thus for the remainder of the analysis it is assumed that the effect of automation on the 99th percentile is equal to the effect on the 98th percentile.

The pattern of automation having its most severe negative impacts between the 80th and 95th percentile of earnings is consistent with the kinds of industries most impacted by industrial robots, particularly durable and automobile manufacturing, and where workers in those industries fall along the earnings distribution. Figure 5 displays the change in the share of workers in each earnings decile working in durable manufacturing and in automobile manufacturing between 1994 and 2015.²⁷ It is striking that many of the jobs lost over the period in these industries have been in the top two deciles of the earnings distribution. It is therefore unsurprising that industrial automation hit this section of the earnings distribution particularly hard.²⁸

The pattern of impacts of trade as measured by Chinese imports is somewhat different (Figure 4). Trade had a strong deleterious effect at the bottom of the distribution of -11 percent at the 10th percentile. This negative impact declines in absolute value, essentially disappearing

²⁶ The results are displayed graphically for ease of interpretation and brevity. Full regression outputs in tabular form before scaling of the coefficients are available for the 20th, 50th, 80th, and 95th percentiles in Table A2 in the Appendix. Full results for other quantiles are available from the authors.

²⁷ This figure is based on CPS data, which are top-coded for earnings. Thus, the displayed earnings deciles do not correspond precisely to the earnings distributions from the regression estimates; the top decile in the CPS data is roughly equivalent to the 9th decile in the regression analysis.

²⁸ The outcome measure of earnings considered in AR is somewhat different. The authors examine self-reported hourly wages rather than administrative annual earnings. Nevertheless, their findings are broadly similar regarding the negative impacts of automation across most of the wage distribution, though they find the most negative effects at the bottom of the distribution, with generally decreasing magnitude until the median, and then roughly constant towards the top. Their earnings data are top-coded and thus do not allow them to observe effects around the top 5-percent of earners, and they cannot speak to effects at the very top of the earnings distribution. The U-shaped pattern of automation's impact is consistent with the wage polarization effects of skill-biased technical change highlighted, for example, by Autor, Katz, and Kearney (2006, 2008); Acemoglu and Autor (2011); and Autor and Dorn (2013).

around the 70th percentile. In contrast with automation, the strongly negative effects of Chinese trade at the bottom of the distribution are sensible given that the types of goods imported from China tend to be produced by low-skill workers.²⁹ Further up the distribution the effect of trade grows less negative. Unlike automation, however, this trend leads trade to have a slightly *positive* impact on the top 1-percent of earners.

In total, automation and trade have lowered earnings throughout the distribution, but their joint impact declines with earnings percentile. The total effect is -11 percent at the 10th percentile, -5.7 percent at the median, -5.1 percent at the 90th percentile, and only -2.1 percent at the 99th percentile. The disproportionately negative impacts at the bottom of the distribution have contributed to the growing share of earnings going to those above the taxable maximum, and to the top 1-percent of earners.³⁰

The Counterfactual 2015 Earnings Distribution

Subtracting the estimated change in earnings due to any factor between 1994 and 2015 from every percentile in the 2015 earnings distribution yields a counterfactual earnings distribution under the assumption that the factor remained at its 1994 levels. Rows 3-5 of Table 1 present statistics for the counterfactual 2015 earnings distributions, holding each of the factors constant, and holding both constant simultaneously. Across these rows, it is apparent that mean earnings are somewhat sensitive to holding each of these factors, particularly automation, at their 1994 levels. Mean earnings would have been \$45,881 if just trade had been held constant but \$46,993 when only automation is held constant, and \$47,423 had both remained constant (4.4 percent higher than the factual 2015 mean earnings). The implication of this comparison is that trade has relatively little effect on average growth in earnings, while automation is actually a drag on average earnings (relative to the factual 2015 mean of earnings), consistent with automation generally reducing the labor share of income (Karabarbounis and Neiman 2014; and Autor and Salomons 2018).

²⁹ In 2015 the top 10 categories of goods imported from China were, in descending order: cell-phones and other household goods; computers; computer accessories; telecommunications equipment; toys, games, and sporting goods; apparel, textiles, non-wool or cotton; furniture, household goods; other parts and accessories of vehicles; apparel, household goods - cotton; and household appliances (U.S. Census Bureau 2018).

³⁰ This U-shaped impact of automation and the monotonically declining absolute impact of trade are quite robust across specifications and datasets. Similar patterns hold in the absence of controls, and in CPS data. See the Appendix for full results.

Note that these means do not imply that automation or trade have a negative effect on prosperity in general. The earnings measure employed does not account for capital income, which is likely to be directly increased by an increase in industrial robots. Likewise, the measure does not account for a general equilibrium effect either of these factors may have on the relative prices of consumer goods, besides holding the overall price level fixed through use of CPI adjusted dollars.³¹

This ranking of the factors in terms of their effect on mean earnings is different when considering impacts at different points in the distribution. For example, the bigger drag on earnings at the 25th percentile is trade, while growth in automation had only a small effect on earnings at that percentile. The reverse is true at the 75th percentile.

Implications for the Top 1-Percent Share of Earnings

Trade is the factor most responsible for the rise in the top 1-percent share of earnings, whereas automation had a negligible effect on this share. The estimates indicate that the top 1-percent share of earnings would have been 11.1 percent in 2015 if automation and trade had stayed constant at 1994 levels. This level is 0.2 percentage points lower than the factual top 1-percent share of earnings in 2015, 11.3 percent. In other words, of the 1.7 percentage-point increase from 1994 to 2015, these two factors account for $0.2/1.7 = 15$ percent.

Furthermore, almost the entirety of the portion of the increase in the top 1-percent share that these factors can explain is due to trade with China, rather than industrial automation. Automation alone accounts for only 1.6 percent of the increase in the top 1-percent share, while trade accounts for 14 percent. Important context for this finding is that the analysis considers only the labor earnings of wage and salary workers, not a broader measure of income from a more complete cross-section of the population that includes the self-employed. Furthermore, automation has impacted the extensive margin of labor more near the bottom of the earnings distribution than near the top (as shown, for example, in Acemoglu and Autor 2011). The data in this paper only include workers with positive earnings, thus missing the fact that automation induces some people to leave the workforce altogether; if these individuals were included, income inequality would likely have grown by even more. It is probable that industrial robots'

³¹ See also Baily and Bosworth (2014) for a summary of the literature on the effect of trade with China on manufacturing employment.

impact on a broader measure of income would show evidence of greater effects on top income shares and income inequality more generally.

In sum, the estimates imply that a substantial share of the growth in the top 1-percent share of earnings is attributable solely to trade with China. Considering that imports from China account for only one-fifth of U.S. imports, this estimate suggests that the effects of trade more broadly could account for a large part of the increase in the top 1-percent share over the last twenty years.³² However, the share is probably not five times larger than just the Chinese import effect, as some increase in imports is likely due to increased demand in the U.S., which does not necessarily crowd-out local production. Furthermore, a large share of imports is from developed countries which may substitute for more skilled labor.

Implications for the Taxable Share

How have these changes to the earnings distribution affected the taxable share? The estimates suggest that the proliferation of industrial robots had a very small effect on the taxable share, contributing just 0.1 percentage points of the 3.4 percentage points' decline in the taxable share in the 1994-2015 period. In contrast, trade with China alone is responsible for 0.3 percentage points of the decline in the taxable share, or 10 percent of the total decline. When both factors are combined, the estimates above imply that automation and trade contributed 0.4 percentage points of the 3.4 percentage point decline in the taxable share over the last twenty years – or 11 percent of the decline.

This estimate is a lower bound of the total effects of automation and trade, since it captures only the effects of proxies for these broader phenomena. In particular, the automation measure includes only industrial robots, and not the myriad effects of other forms of automation, such as advances in information technology. In terms of trade, the measure of imports from China fails to capture the effects of the remaining 80 percent of imports. Thus these estimates should be considered indications of the general pattern of effects of automation and trade, rather than a comprehensive account of their effects.

Bearing this qualification in mind, the estimates can inform projections of the taxable share going forward. A simple approach is to linearly project the changes in the factors forward

³² Similarly, in terms of import *growth*, imports from China account for 25 percent of increased imports over the 1994-2015 period (U.S. Census Bureau 2018).

11 years from 2015 to 2026, based on their average rate of growth since 1994. This exercise implies that by 2026 the two factors will increase by an additional 52 percent relative to their increase between 1994 and 2015. Combining this projected change in the factors with their estimated coefficients, the 2015 distribution of earnings can be further adjusted to test how much its taxable share would have declined in the presence of 152 percent of the growth in the two factors since 1994, all else equal. The resulting calculation implies that the taxable share would decline by a further 0.2 percentage points if the factors grow at their historical rates until 2026.

The estimates in this analysis are based on wage and salary earners. Assuming the same effects hold for the self-employed, and starting from the 2018 Trustees Report estimate of the taxable share for 2016 of 82.7 percent (U.S. Social Security Administration 2018), the 2026 taxable share will be 82.5 based on past trends in the two factors alone. This is remarkably close to the Trustees' long-run intermediate estimate of 82.5 percent and the 2015 Technical Panel's recommendation of a long-range estimate of 82.2 percent (Technical Panel on Assumptions and Methods 2015). These results should increase the confidence in those projections.

Nevertheless, a more comprehensive projection of future trends in the taxable share based on the estimates above may be useful, particularly one that employs a more sophisticated extrapolation of the two factors. If the change in the factors is accelerating over time – for example, because automation may move beyond human-programmed industrial robots and into artificial intelligence – the taxable share is likely to fall below this linear projection. Furthermore, it should be borne in mind that the two factors capture a small part of the decline over the last 20 years, and further declines beyond those predicted by these factors are therefore very much in line with historical precedent. This idea further justifies the Technical Panel's recommendation that the forecasted taxable share in the low- and high-cost scenarios be asymmetric around the intermediate cost scenario, with more potential downside risk (Technical Panel on Assumptions and Methods 2015).

What explains the large remaining share of the increase in the top 1-percent share, and the decline in the taxable share since 1994? As mentioned above, some of these changes are likely due to trade and automation through aspects not captured by the measures used in this analysis. Alternative hypotheses for drivers of top-earner shares, such as erosion of norms against extremely high compensation for executives, likely contribute to the unexplained portion

of the 1-percent share, though they are probably less relevant to the top 5-percent share on which the taxable share relies.³³

A more promising avenue for exploration of the top 5-percent share is the increase in non-wage compensation. The expected result of this increase is that as the cost of non-wage compensation, particularly health insurance benefits, climbed, earnings growth would slow. The difficulty in estimating this effect is that simple models (including results from this project reported in the Appendix) find a positive correlation between earnings and health insurance coverage, driven by unobservable job and worker characteristics – for example, “good jobs” usually both pay well and offer health benefits. Causal estimates of the compensating differential of non-wage compensation are necessary to determine how the large increase in health insurance premiums has affected the taxable earnings distribution; these estimates are left for further research.

Conclusion

This paper estimates the impact of two major structural changes in the economy between 1994 and 2015 on the distribution of earnings and on the share taxable by the Social Security payroll tax. The two factors considered are automation and trade. Coupling administrative data on earnings from the CWSHS with instrumental variables quantile regression methods, it was estimated that these two factors alone explained at least 11 percent of the decline in the taxable share over the last 20 years. Trade contributed the bulk of the explained decline (0.3 percentage points), while automation explained a much smaller share (0.1 percentage points). These two factors also go some way toward explaining the increasing concentration of earnings among the top 1-percent of earners, accounting for at least 15 percent of the change in this share over the past two decades.

All told, the two factors can explain a fairly modest portion of the top 1-percent share’s increase and of the decline in the taxable share. Nevertheless, the measures used for these factors represent a small share of the total effects of automation and trade. The estimates therefore represent a lower bound of the effect of automation and trade more broadly, outside the narrow focus on industrial robots and Chinese imports. Beyond these two factors, much remains

³³ Recall that approximately 6 percent of earners have had annual earnings over the taxable cap in each year since 1983.

to be studied regarding what else contributed to these changes over the past few decades, including increasing market concentration, the growth of non-wage compensation, and the erosion of norms regarding executive compensation. Questions also remain regarding how trade and automation, as well as other factors, have impacted broader measures of income, including capital income.

The literature has offered many complementary explanations for the growth in inequality. This paper accounts for two of those explanations and finds that trade, in particular, has played a material role in the increasing concentration of earnings, at least among wage and salary workers. Much remains to be studied on this topic, which is of first-order importance to the Social Security program, to the economy, and to society at large.

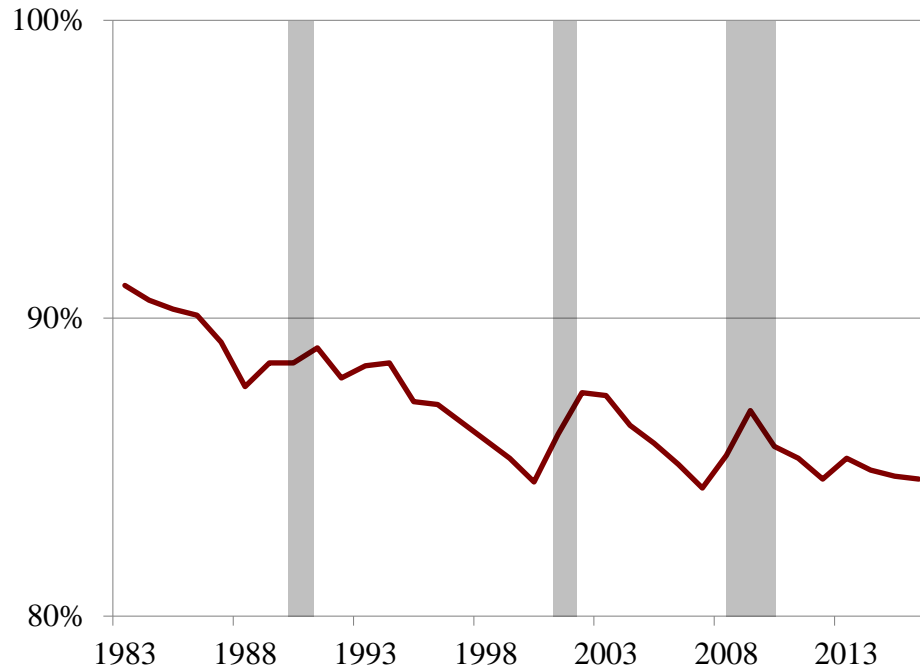
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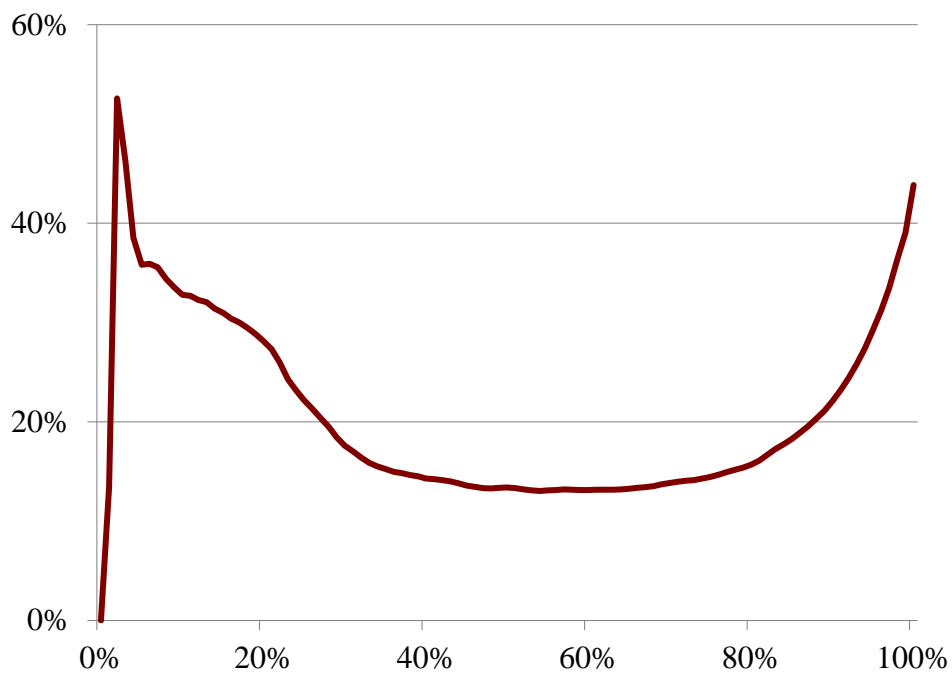
Figure 1. *The Share of Taxable Earnings for Wage and Salary Workers, by Year*



Note: Shaded areas reflect recessions as defined by the National Bureau of Economic Research.

Source: U.S. Social Security Administration (2017).

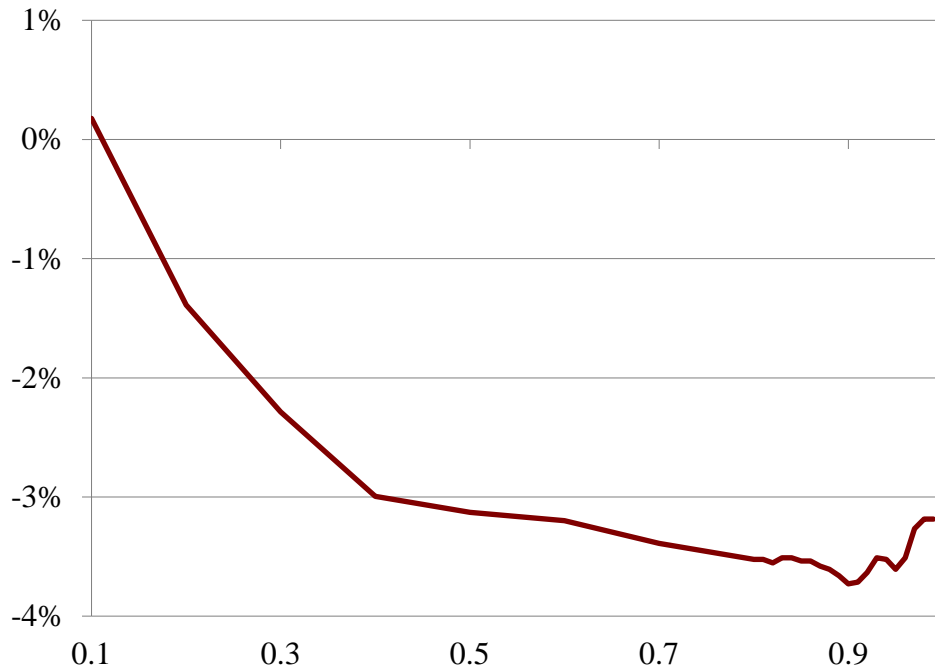
Figure 2. *Percent Change in Annual Earnings between 1994 and 2015, by Percentile*



Note: Reflects changes in constant 2015 dollars among wage and salary workers.

Source: Continuous Work History Sample, 1994 and 2015.

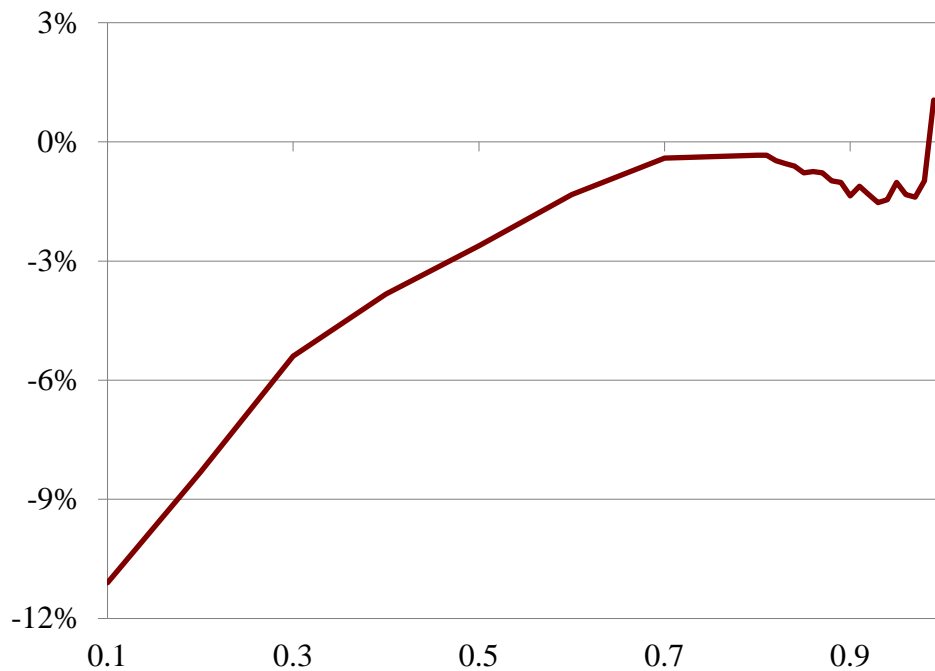
Figure 3. *Percent Change in Earnings by Quantile Due to Automation, 1994-2015*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on the *Continuous Work History Sample*, 1994 and 2015.

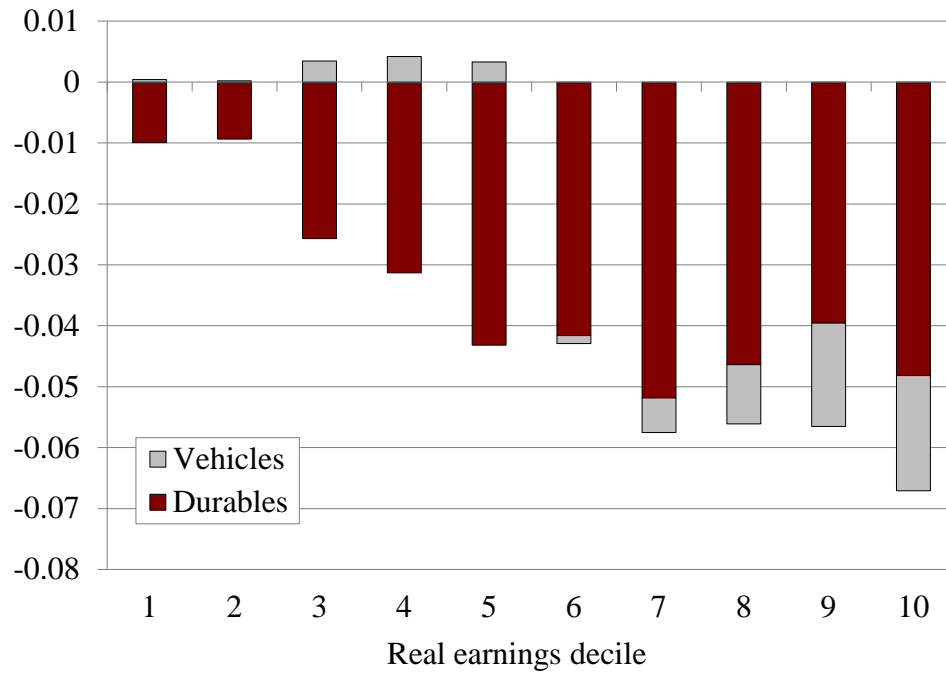
Figure 4. *Percent Change in Earnings by Quantile Due to Imports, 1994-2015*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on the *Continuous Work History Sample*, 1994 and 2015.

Figure 5. 1994-2015 Change in the Share Employed in Durable and Vehicle Manufacturing, by Earnings Decile



Source: Authors' calculations based on the *Current Population Survey*, 1994 and 2015.

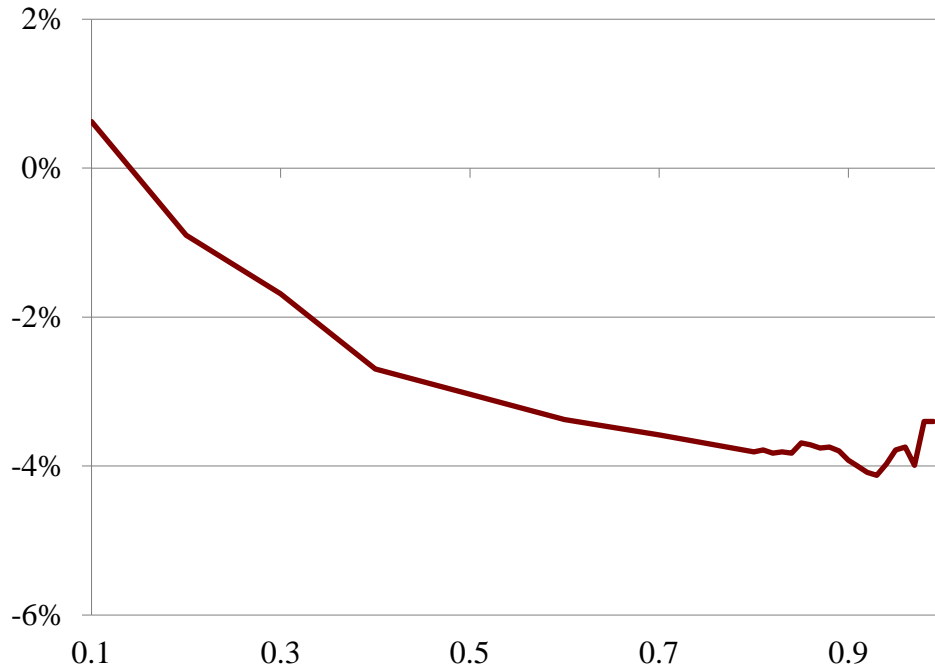
Table 1. *Characteristics of Factual and Counterfactual Earnings Distributions*

	Mean	25 th percentile	50th percentile	75th percentile	99th percentile	Top 1-percent share	Taxable share
Factual 1994	\$36,978	\$9,396	\$25,522	\$48,430	\$358,026	9.7%	88.9%
Factual 2015	45,412	11,482	28,946	55,439	515,065	11.3	85.6
Only automation at 1994 level	46,993	11,748	29,866	57,428	531,733	11.3	85.6
Only trade at 1994 level	45,881	12,119	29,712	55,628	509,674	11.1	85.9
Both factors at 1994 level	47,423	12,399	30,657	57,624	526,167	11.1	85.9

Notes: All numbers are in 2015 dollars. The 1994 taxable share is calculated using a tax-max equal to the actual cap in 1994 adjusted by CPI to 2015 dollars.
Source: Authors' calculations based on the *Continuous Work History Sample*, 1994 and 2015.

Appendix

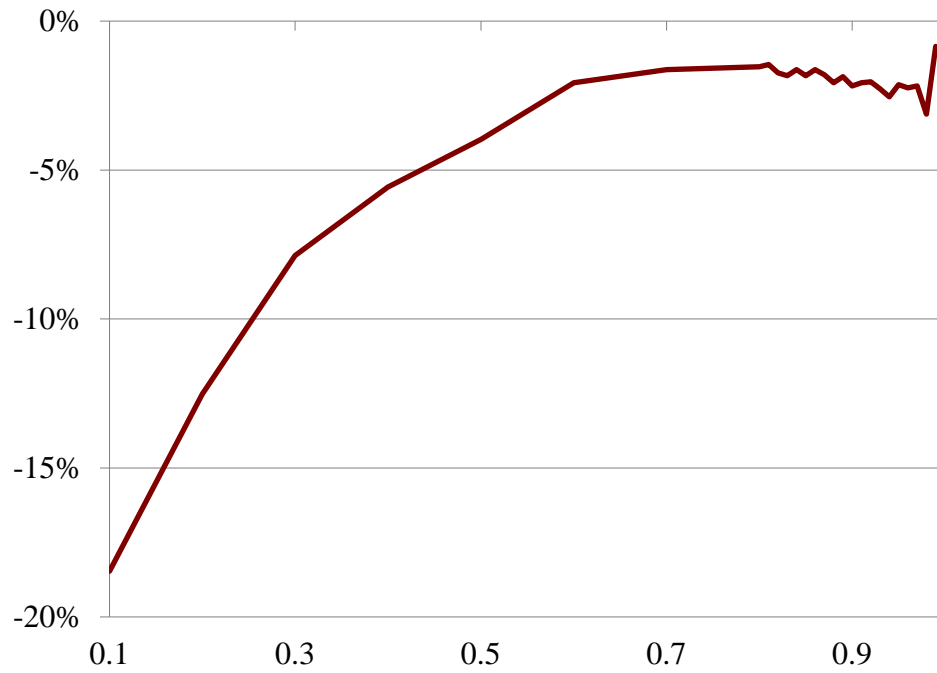
Figure A1. *Percent Change in Earnings by Quantile Due to Automation, 1994-2015, without Endogenous Controls*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on a 33 percent subsample of the *Continuous Work History Sample*, 1994 and 2015.

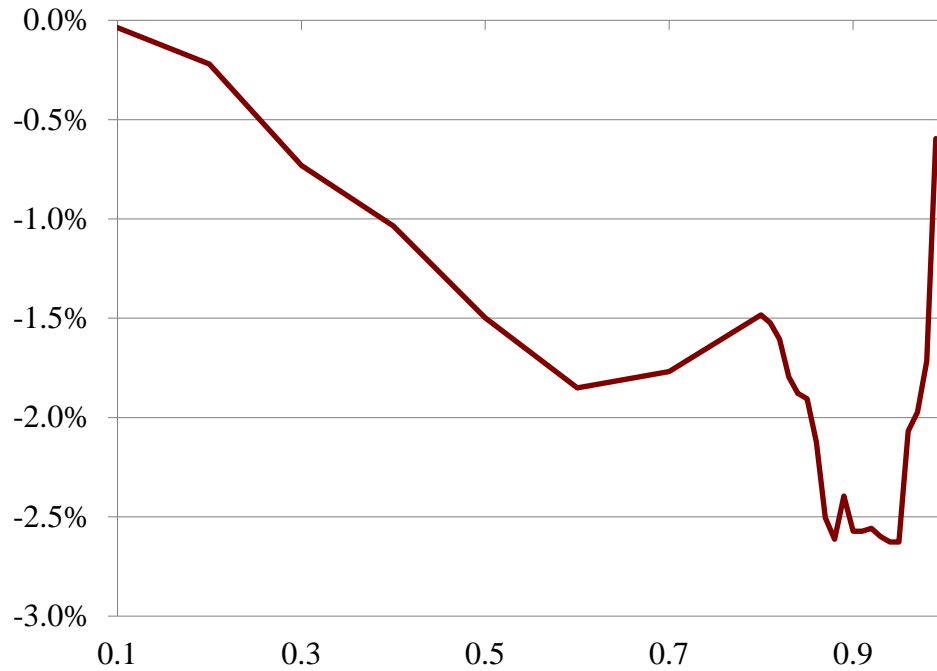
Figure A2. *Percent Change in Earnings by Quantile Due to Imports, 1994-2015, without Endogenous Controls*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on a 33 percent subsample of the *Continuous Work History Sample*, 1994 and 2015.

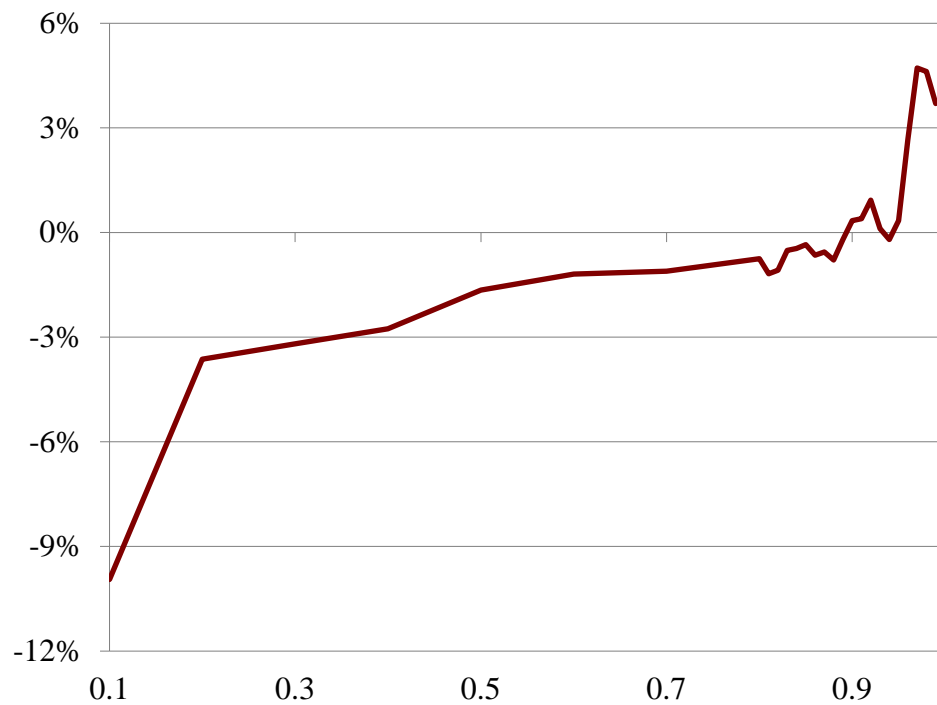
Figure A3. *Percent Change in Earnings by Quantile Due to Automation in CPS, 1994-2015*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on the *Current Population Survey*, 1994 and 2015.

Figure A4. *Percent Change in Earnings by Quantile Due to Imports in CPS, 1994-2015*



Note: Coefficients from quantile-regression estimates.

Source: Authors' calculations based on the *Current Population Survey*, 1994 and 2015.

Table A1. *First-Stage OLS Regressions of US Automation and Import Measures*

	U.S. robots/ 1,000 workers	U.S. imports from China
Other country robots/1,000 workers	1.827*** (0.149)	0.143 (0.101)
Other country imports from China	0.0126 (0.0523)	1.024*** (0.0823)
Share unionized	0.334 (1.109)	-1.306 (2.327)
Share with employer-sponsored health insurance offer	1.083 (1.616)	2.933 (3.302)
Share working in a firm with over 1,000 workers	-0.478 (1.422)	5.083 (3.274)
State fixed effect	Yes	Yes
Year fixed effects	Yes	Yes
N	98	98
First stage F-statistic	179.52	79.01

Notes: Standard errors clustered by state are in parentheses below their coefficient. *** indicates results significant at the 1 percent level.

Source: Authors' calculations based on the *Continuous Work History Sample*, 1994 and 2015.

Table A2. *IV Quantile Regression Outputs for Select Quantiles*

	20th percentile	50th percentile	80th percentile	95th percentile
Robots/1,000 workers	-0.0102 (0.0025)	-0.023 (0.0013)	-0.0259 (0.0012)	-0.0265 (0.0019)
Imports from China	-0.0245 (0.0034)	-0.0077 (0.0018)	-0.001 (0.0016)	-0.003 (0.0025)
Share unionized	-0.0254 (0.0911)	-0.0578 (0.0474)	0.0318 (0.0425)	0.1637 (0.0671)
Share with employer-sponsored health insurance offer	0.9988 (0.1574)	0.8864 (0.0818)	0.8858 (0.0734)	1.0179 (0.1160)
Share working in a firm with over 1,000 workers	-0.1524 (0.1094)	0.0492 (0.0569)	0.0756 (0.0510)	0.0224 (0.0806)
Age fixed effects	Yes	Yes	Yes	Yes
Gender fixed effects	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	1,399,068	1,399,068	1,399,068	1,399,068

Notes: Standard errors are in parentheses below their coefficient. The standard errors do not adjust for clustering, heteroscedasticity, or the first-stage estimation. Work to calculate standard errors accounting for these factors through block-bootstrapping is ongoing.

Source: Authors' calculations based on the *Continuous Work History Sample*, 1994 and 2015.

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