Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States*

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Abstract

After a decade in which wages and employment fell precipitously in low-skill occupations and expanded in high-skill occupations, the shape of U.S. earnings and job growth sharply polarized in the 1990s. Employment shares and relative earnings rose in both low and high-skill jobs, leading to a distinct U-shaped relationship between skill levels and employment and wage growth. This paper analyzes the sources of the changing shape of the lower-tail of the U.S. and wage and employment distributions. A first contribution is to document a hitherto unknown fact: the twisting of the lower tail is substantially accounted for by a single proximate cause—rising employment and wages in low-education, in-person service occupations. We study the determinants of this rise at the level of local labor markets over the period of 1950 through 2005. Our approach is rooted in a model of changing task specialization in which 'routine' clerical and production tasks are displaced by automation. We find that in labor markets that were initially specialized in routine-intensive occupations, employment and wages polarized after 1980, with growing employment and earnings in both high-skill occupations and low-skill service jobs.

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1 Introduction

A vast body of research documents a steep rise in wage inequality in the United States starting in the 1980s. This spreading of the wage distribution is evident in the upper panel of Figure 1, which plots changes in real hourly wages by percentiles of the hours-weighted earnings using data from the Census Integrated Public Use Microsamples for 1980, 1990 and 2000 (Ruggles et al. 2004). During the 1980s, wage growth was strongly monotone in wage percentiles, with either zero or negative growth in the bottom quartile of the distribution, modest wage growth in the second and third quartiles, and relatively sizable wage growth in the top quartile. This monotone pattern continued in part into the decade of the 1990s, but only in the upper half of the distribution. Wage growth below the median, by contrast, reversed course: wage gains were smallest at the median and monotonically increasing at lower percentiles, giving rise to a U-shaped pattern of wage growth that has been termed 'polarization.'[1]

These diverging patterns of wage growth in the 1980s and 1990s have clear counterparts in contemporaneous changes in the structure of skilled and unskilled employment. The upper panel of Figure 2 plots changes in the share of U.S. employment by occupational skill level, where the skill level of an occupation is proxied by the mean log wages of its workers in 1980.[2] Akin to the pattern for wages, employment growth in the 1980s was strongly monotone in occupational skill levels: occupations with the lowest skill levels lost employment shares, those in the middle held constant or grew, and occupations in the top quintile expanded substantially. This monotone relationship gave way to 'polarized' employment growth during the 1990s, with occupations in both the bottom and top quintiles of the skill distribution gaining strongly in employment shares at the expense of the middle.

A comparison of changes in wages and changes in employment over these two decades warrants two conclusions. First, the clear correspondence between price and quantity movements—i.e., changes in wages and employment by percentile—in both the 1980s and 1990s suggests that demand shifts play a central part in any economic explanation of the changing structure of wages over these decades. Second, understanding these demand shifts requires explaining a central difference between the two decades, namely, the twisting of the lower-tail of the wage and employment distributions in the 1990s and forward.[3]

This paper studies both theoretically and empirically the forces behind the changing shape of low-wage and low-skill employment in the U.S. labor market. A first contribution of the paper is to document a hitherto unknown fact: the twisting of the lower tail is substantially accounted

[1] Goos and Manning coin the term 'polarization' in a 2003 working paper (Goos and Manning, 2003). Acemoglu (1999), Goos and Manning (2003, 2007), Autor, Katz and Kearney (2006, 2008), Spitz-Oener (2006), Dustmann, Ludsteck and Schönberg (2007), and Smith (2008) present evidence that employment polarization has occurred during the last two decades in the UK, West Germany and US.

[2] We use a consistent ranking based on 1980 wages to fix a baseline occupational skill level.

[3] Another key difference between the two periods is that the entire locus of wage growth is shifted upward in the 1990s. This movement corresponds to the rapid productivity increases commencing in the mid 1990s (Oliner and Sichel, 2000).

for by a single, proximate cause, which is rising employment and wages in a category of work that the Census Bureau classifies as *service occupations*. Service occupations are jobs that involve assisting or caring for others, including: food service workers; security guards; janitors, cleaners and gardeners; home health aides; child care workers; and personal appearance and recreation occupations.[4] Though among the least educated and lowest paid categories of employment, the share of U.S. labor hours in service occupations grew by 35 percent between 1980 and 2005, after having been flat or declining in the three prior decades (Table 1).[5] The rise in service employment was even steeper for non-college workers—those with no more than a high school education. The share of non-college hours in service occupations rose by 53 percent between 1980 and 2005, from 13.9 to 21.2 percent, while declining in all other major occupational categories (Appendix Table 1). Simultaneously, real wage growth in service occupations averaged seven percent per decade between 1980 and 2005, substantially exceeding wage growth in other blue collar occupations (Table 1b).[6]

To see the magnitude of the contribution that service jobs make to employment and wage polarization, we consider a simple counterfactual case where employment and relative wage levels in service occupations are held at their 1980 levels. This counterfactual, shown in the lower panels of Figures 1 and 2, alters the picture of employment polarization considerably. Figure 2b shows that, holding service employment at its 1980 level, the upward twisting of the lower-tail of the employment distribution during the 1990s is largely eliminated. Moreover, this counterfactual exercise noticeably steepens the relationship between skill level and employment growth during the 1980s, reflecting the rapid growth of service occupations in this decade.[7] Figure 1b shows that, holding service occupation relative wages (rather than employment) constant at their 1980 level, has an analogous though less dramatic dampening effect on wage polarization during the 1990s—essentially eliminating the upward twist of the lower tail in the 1990s.[8] Similar to the case for

[4] It is critical to distinguish service occupations, a group of low-education occupations providing personal services and comprising 14.9 percent of labor input in 2005 (Table 1), from the service *sector*, a broad category of industries ranging from health care to communications to real estate and comprising 81 percent of non-farm employment in 2000 (source: www.bls.gov).

[5] Part-time jobs are relatively prevalent in service occupations, and hence the share of service *jobs* in US employment is even larger than their share in total labor input. For example, Hecker (2005) reports that service occupations accounted for nearly one in five jobs in 2004 whereas our calculations based on the 2005 American Community Survey find that service occupations contribute approximately one in seven hours of labor input.

[6] Though farm occupations are estimated to have experienced comparable wage growth in this time interval, one should place little weight on these numbers. Census data are unlikely to capture farm earnings accurately in recent decades since a substantial share of U.S. farm labor after 1980 is supplied by illegal immigrants.

[7] The figure is generated using a simple variant of the DiNardo, Fortin and Lemieux (1996) density reweighting method. We pool Census data from either 1990 or 2000 with Census data from 1980 and estimate a weighted logit model for the odds than an observation is drawn from 1980 Census sample (relative to the actual sampling year) using as predictors a service occupation dummy and an intercept. Weights used are the product of Census sampling weights and annual hours of labor supply. We reweight observations in 1990 and 2000 using the inverse of the estimated odds multiplied by the hours-weighted Census sampling weight. This procedure weights down the frequency of service occupations in 1990 and 2000 to match their 1980 frequency. Given the absence of other covariates in the model, the extra probability mass is implicitly allocated uniformly over the remainder of the distribution.

[8] We fit a weighted OLS regression in each decade of real log hourly wages on a constant and a service occupation dummy using only observations from service occupations, production, craft and repair occupations, and operator, fabricator and laborer occupations. These regressions are weighted by the product of Census sampling weights and annual hours of labor supply (annual weeks worked times average weekly hours). To produce the figure, we adjust

employment, the positive relationship between wage levels and wage growth in the 1980s becomes steeper when relative wages of service occupation are held constant. These facts motivate our inquiry into the growth of service occupation employment. Because rising employment in service occupations appears central to the twisting of the lower-tail of the wage and employment distributions in the 1990s and forward, we believe that understanding their rise will provide conceptual leverage on the phenomenon of employment polarization more generally.

This paper explores the rise of service employment at the level of local labor markets. Our identification strategy exploits the fact that the output of service occupations is non-storable and non-transportable, and hence largely immune to trade and outsourcing.[9] Since consumers and producers of service occupation outputs must collate, it is fruitful to study the determinants of service employment at the detailed geographic labor market level, ideally within the local market in which service workers and service consumers both reside. We measure levels and changes in economic variables over 1980 through 2005 within 722 consistently defined, fully inclusive Commuting Zones using data from the Census IPUMS 5 percent samples for 1980, 1990 and 2000 and from the American Community Survey for 2005.[10]

The primary hypothesis that we pursue is that the rapid, secular rise in service employment since 1980 is attributable in part to non-neutral changes in productivity among job tasks spurred by advances in information technology. Concretely, this hypothesis stems from the observation that the physical and interpersonal activities performed in service occupations—such as personal care, table-waiting, order-taking, housekeeping, janitorial services—have proven cumbersome and expensive to computerize. The reason, explained succinctly by Pinker (2007, p. 174), is that, "Assessing the layout of the world and guiding a body through it are staggeringly complex engineering tasks, as we see by the absence of dishwashers that can empty themselves or vacuum cleaners that can climb stairs."[11]

This observation motivates our theoretical model. A central thrust of recent technological change has been the automation of a large set of 'middle education' routine cognitive and manual tasks, such as bookkeeping, clerical work and repetitive production tasks (Autor, Levy and Murnane, 2003; ALM, hereafter). These tasks are readily computerized because they follow precise, well-understood procedures. Computerization of routine tasks complements the 'abstract' creative, problem-solving, and coordination tasks performed by highly-educated workers (e.g., professionals and managers), for whom data analysis is an input into production. Paradoxically, computerization

service occupation wages in 1990 and 2000 by subtracting off the estimated service occupation premium from the current decade and replacing it with the estimated 1980 service occupation premium.

[9] Indeed, many service activities—such as hair cutting, child care, and home health assistance—require physical contact between worker and customer.

[10] An important input into our empirical analysis is a time-consistent definition of local labor markets based on 'commuting zones' (Tolbert and Sizer 1996). Commuting zones are built from clusters of counties with strong commuting ties and are intended to approximate local US labor markets.

[11] The quotation continues, "...But our sensorimotor systems accomplish these feats with ease, together with riding bicycles, threading needles, sinking basketballs, and playing hopskotch. 'In form, in moving, how express and admirable' said Hamlet about man."

of routine tasks neither directly substitutes for nor complements the core jobs tasks of numerous low-education occupations, in particular those that rely heavily on physical dexterity and flexible interpersonal communications. We refer to these activities as 'manual tasks.' Service occupations are disproportionately comprised by such manual tasks, as we document below. We hypothesize that the rapid growth of service occupations commencing in the 1980s reflects an interaction between non-neutral technological progress—which raises productivity in routine tasks but does little to augment manual tasks—and consumer preferences. In particular, if consumer preferences do not admit close substitutes for the tangible outputs of service occupations—such as restaurant meals, house-cleaning, security services, and home health assistance—increasing output of goods (i.e., non-service activities) will raise aggregate demand for service outputs, and ultimately employment and wages in service occupations.

To explore these observations formally, we analyze a simple general equilibrium model of 'routine-task' replacing technological change, building upon ALM and Weiss (2008).[12] Technological progress in this model takes the form of an ongoing fall in the cost of computerizing Routine tasks, which are performed by both machinery and low-skilled labor in the production of Goods. Automation of these tasks—a form of capital deepening—raises the productivity of high-skilled ('college') workers who perform Abstract tasks but substitutes for the labor input of low-skilled ('non-college') workers who perform Routine tasks. Responding to falling wages in routine tasks, non-college workers may reallocate labor supply to Service occupations, which exclusively use Manual tasks and do not experience technological progress. This labor influx causes service output to rise but has ambiguous impacts on service wages.

We study the allocation of labor between goods and services, and the inequality of wages between high and low-skill workers, as automation drives the price of routine tasks towards zero. A key result of the model is that the limiting behavior of employment and wage inequality hinges critically on the elasticity of substitution between goods and services in consumption. If goods and services are gross substitutes, ongoing technical progress ultimately drives service consumption and service employment to zero. Wage inequality between college and non-college workers rises without bounds as the wages paid to routine tasks are eroded and the productivity of abstract labor is augmented.

If, instead, goods and services are weakly complementary, non-college labor may be drawn into service occupations as goods output rises. If so, wages paid to manual tasks—and hence non-college earnings—ultimately converge to a steady growth rate, which, depending upon the complementarity between goods and services, equals or exceeds the growth rate of college wages. Thus, inequality ultimately converges to a steady-state level or collapses.[13] Numerical simulations

[12] We modify and extend the model of Weiss (2008) to encompass two types of low-skilled labor activities—routine and manual—and to permit self-selection of low-skilled workers among these tasks. These extensions highlight the dynamics of wages and employment of low-skilled workers as they self-select between goods and services sectors in response to ongoing technical change. The limiting cases of our model are qualitatively comparable to Weiss (2008). We thank Matthias Weiss for his input on the model.

[13] In the latter case, the low-skilled wage rises relative to the high-skilled wage and eventually surpasses it.

of the model show that if goods and services are complements, the time path of wage inequality may be non-monotone. Service output grows and service wages fall as low-skilled workers initially reallocate labor from goods to services—thus, from routine to manual tasks. When labor flows to services stabilize, low-skilled wages rise. Consequently, wage inequality between high and low-skilled workers may initially increase then plateau or fall. It bears emphasis that this mechanism does *not* operate through income effects. Indeed, consumers in the model have homothetic preferences. Rather, it derives from the interaction between productivity growth and imperfect substitutability in consumption.

A primary implication of the conceptual model is that both service occupations and wage inequality between 'Abstract' and 'Routine' occupations should rise in commuting zones undergoing displacement of routine tasks. Consistent with this notion, a careful, contemporaneous study by Mazzolari and Ragusa (2008) finds robust evidence that variation across Metropolitan Statistical Area (MSA) in the growth of wage inequality over 1980 through 2005 is strongly correlated with contemporaneous growth in service employment. This pattern suggests a potential link between labor demand shifts and the growth of service employment, as posited by our model. Because cross-MSA growth variation in wage inequality is primarily treated as exogenous by the Mazzolari-Ragusa study, it is not entirely clear—at least within our conceptual framework—how this correlation should be interpreted.[14]

To address the potential simultaneity between wage inequality and service employment, our identification strategy draws on the theoretical model of changing task specialization. If the secularly falling price of computing leads to displacement of routine labor input, the extent of routine task displacement in local labor markets should depend on the initial concentration of routine job activities in these markets. Using task measures from the Dictionary of Occupational Titles paired to Census data on occupational structure, we generate a simple index of the share of non-college labor employed in routine task-intensive occupations in each commuting zone at the start of the relevant time period. This routine-share measure proves strikingly predictive of the changes in employment and wage structure predicted by the model. In commuting zones with an initial concentration in routine-intensive occupations, we find substantially larger growth of employment in service occupations, coupled with differential reallocation of labor input away from routine-intensive occupations. These changes in task allocation occur both in aggregate and within major education groups, with the greatest reductions in routine labor input among non-college workers. The differential growth of service employment in routine-intensive commuting zones is accompanied by a distinct pattern of wage inequality: relative wages rise in both low-skilled service occupations and highly-skilled managerial, professional, technical, sales and administrative occupations; relative wages fall across the remaining set of low-skilled occupations, consistent with a reduction in

[14]Mazzolari and Ragusa also pursue instrumental variables estimates by projecting national earnings trends in high-skill occupations onto cross-MSA differences in initial employment shares in these occupations. This approach is appropriate where wage growth in high-wage occupations is an externally determined phenomenon, as is posited by their conceptual framework. This approach would not be logical in our model.

demand for routine-intensive activities. In summary, these results reveal a process of employment and wage polarization within regional labor markets that parallels the polarization of employment observed in aggregate data.

This paper contributes to a long-standing literature debating the determinants of service employment in industrialized countries. Our model of rising service employment, driven by rapid productivity growth in goods production, may be viewed as a contemporary manifestation of Baumol's (1967) classic thesis that unbalanced technical progress leads to the expansion of sectors that have relatively slow productivity growth. The model is not, however, a simple restatement of Baumol's hypothesis. We demonstrate that unbalanced productivity growth is not itself sufficient to generate rising employment in technically lagging sectors. In fact, this result depends critically on the ratio of elasticities of substitution and consumption.[15] Perhaps of greater interest, the model underscores, consistent with Weiss (2008), that ongoing, skilled-labor augmenting technical change does *not* necessarily imply ongoing rises in wage inequality. Consumer preferences can attenuate or even reverse the effect of factor augmenting technical change on wage inequality in the longer run—thus leading to employment and wage polarization.

Alongside unbalanced productivity growth, the recent rise of service employment and accompanying polarization may have other contributing causes, which we consider and test below. Influential work by Clark (1957) finds that the income elasticity of demand for services is greater than unitary, implying that preferences are non-homothetic. If so, rising prosperity will increase the share of income devoted to services, even with balanced productivity growth. We refer to this as the income-effect hypothesis. A related but distinct hypothesis, explored in papers by Manning (2004), Ngai and Pissarides (2007), and Mazzolari and Ragusa (2008), focuses on substitution rather than income effects. These studies posit that rising returns to skill in advanced countries spur high skilled workers to substitute market for home-based production of household services. This permits high skilled workers to increase their labor supply and earnings, while simultaneously raising demand for service jobs.

While these alternative explanations appear both plausible and complementary to the hypothesis we purse, we stress two key points of differentiation. A first is that our theoretical framework does not rely on either income effects in consumption or substitution effects in labor supply to generate concurrent rises in high and low-skill employment and earnings in general equilibrium. Indeed, consumers in our model have homothetic preferences and do not engage in household production.[16] Second, to the degree that we can empirically test these hypotheses, we find at best modest empirical support. Growth of service employment within commuting zones is *negatively* correlated with changes in the hours worked of male and female college graduates, which appears

[15]In the setting we study, a necessary condition for the Baumol result to hold is that the degree of complementarity between labor and capital in goods production, weighted by the labor share in goods, is smaller than the complementarity between goods and labor-intensive services in consumption.

[16]Since technical change in our model raises the relatively earnings of high-skilled workers, allowing either non-homothetic preferences or the possibility of household 'marketization' would of course augment the model's prediction for growing service employment.

inconsistent with the household substitution hypothesis. Similarly, rising high wages in commuting zones, as measured by growth in the 90th wage percentile, is only weakly correlated with increases in service employment, which appears inconsistent with the income effect hypotheses. Notably, both of these alternative explanatory variables—college labor supply and rising top wages—are positively correlated with our key explanatory measure, the routine employment share, which is in turn highly robust to their inclusion.

Alongside these demand side determinants of service occupation employment, we also carefully control for a host of other likely contributors, including: a rising supply of low-skilled immigrants who may reduce the market price of services (Cortes, 2008); dwindling manufacturing employment and rising unemployment, which may reduce job opportunities for less educated workers (Harrison and Bluestone, 1988); and increases in the educational attainment, elderly population share, and female labor force participation of commuting zone residents. Each of these factors might be expected to contribute to rising employment in service occupations—and indeed, all are significantly correlated with increased penetration of service jobs in local labor markets. Nevertheless, controlling for these factors does not substantially affect the main inference: regions that were initially specialized in routine-intensive occupations experienced a disproportionate degree of employment and wage polarization commencing in the 1980s.

Our study is also related to papers by Doms and Lewis (2006) and Beaudry, Doms and Lewis (2006), who explore the determinants of computer adoption and changes in education returns across MSA during the period of 1980 through 2000.[17] These papers are motivated by a model of endogenous technology adoption proposed by Beaudry and Green (2003) in which geographic variation in computer adoption is driven by the relative abundance or scarcity of skilled workers, who are complemented by computer technology. Though computer adoption is not a primary focus of our paper, we do present results on this outcome and discuss their relationship to the Beaudry, Doms and Lewis (2006) results.

In the next section, we outline a model of unbalanced productivity growth and derive implications for trends in labor allocation and wage inequality. Section 3 describes the data sources and details how we measure local labor markets, job tasks and, in particular, routine task-intensity. Sections 4 and 5 present empirical tests of our hypotheses for service employment, task specialization, and wage polarization. Section 6 concludes.

2 Theoretical framework

Building on work in ALM (2003) and Weiss (2008), this section offers a simple theoretical model to explore the effects of ongoing, routine task-replacing technological change on three general equilibrium outcomes: the allocation of labor among competing low-skilled activities (in particular,

[17] The city-level computer adoption measure employed below was developed by Doms and Lewis (2006) and generously provided to us by the authors. This measure is also used in Beaudry, Doms and Lewis (2006).

routine versus manual tasks); the scale of service employment; and the inequality of wages between high and low-skill workers.

2.0.1 Environment

We consider an economy with two consumption items, goods and services, $j = g, s$ and four factors of production. Three of these factors are labor (task) inputs: Manual, Routine and Abstract ($L = m, r, a$). These labor inputs are supplied by two types of workers, $i = H, U$. The fourth factor of production is computer capital. In each sector, a continuum of mass one of firms produce consumption goods.

Production of Goods combines Routine labor, Abstract labor, and computer capital (K), measured in efficiency units, using the following technology:

$$Y_g = L_a^{1-\beta} \left[(1-\lambda) (\alpha_r L_r)^{\mu} + \lambda (\alpha_k K)^{\mu} \right]^{\beta/\mu}, \tag{2.1}$$

with $\beta, \mu \in (0, 1)$. In this production function, the elasticity of substitution between Abstract labor and the Routine task input is 1 while the elasticity of substitution between Routine labor and computer capital is $\sigma_r = 1/(1-\mu)$ and, by assumption, is greater than 1. By implication, K is a *relative complement* to Abstract labor and a *relative substitute* for Routine labor.[18]

The second sector, which produces Services, uses only Manual labor, measured in efficiency units as L_m:

$$Y_s = \alpha_s L_m, \tag{2.2}$$

where $\alpha_s > 0$ is an efficiency parameter. We will normalize α_s to 1 in the rest of the paper, and so α_r may be thought of as a relative efficiency term.

There is a continuum of mass one of high-skilled workers, H, who are fully specialized in Abstract labor. Each H worker supplies Abstract labor inelastically to the good sector.

There is a continuum of mass one of low-skilled workers, U, each of whom supplies either Manual or Routine labor. Low-skill workers have homogeneous skill at performing manual tasks. If all U workers were to perform manual tasks, they would supply a unit mass of Manual labor.

Low-skilled workers have heterogeneous skills in performing Routine tasks. Let η equal a worker's skill in routine tasks, measured in efficiency units, with density and distribution functions $f(\eta)$ and $F(\eta)$. There is a mass of one of potential Routine labor input: $\int \eta f(\eta)\, d\eta = 1$. Each worker of type U supplies labor inelastically to the task offering the highest income level given her endowment, η.

It is convenient to choose a functional form for $f(\eta)$ to permit analytic solutions of the model. The choice of functional form is innocuous, however, since the long run equilibrium of the model (i.e., as $t \to \infty$) depends on technology and preferences, not on labor supply per se. Let η be distributed exponentially on the interval $[0, \infty]$ with $f(\eta) = e^{-\eta}$.

[18]In the Theory Appendix, we also consider the case where $\mu < 0$ and so L_r and K are gross complements.

Computer capital, K, is produced and competitively supplied using the following technology:

$$K = Y_k(t)\, e^{\delta t}/\theta. \tag{2.3}$$

where $Y_k(t)$ is the amount of the final consumption good allocated to production of K, $\delta > 0$ is a positive constant, and $\theta = e^{\delta}$ is an efficiency parameter. Productivity is rising at δ, reflecting technological progress. At time 1, one unit of the consumption good Y can be used to produce one efficiency unit of computer capital:

$$1 = e^{\delta}/\theta. \tag{2.4}$$

Competition will guarantee that the real price of computer capital (measured in efficiency units) is equal to marginal (and average) cost. So, at time $t = 1$, $p_k = 1$. As time advances, this price falls, with

$$p_k = \frac{Y_k}{K} = \theta e^{-\delta t}. \tag{2.5}$$

All workers/consumers have identical CES utility functions defined over consumption of Goods and Services:

$$u_i = \left(c_{si}^{\rho} + c_{gi}^{\rho}\right)^{1/\rho}, \tag{2.6}$$

$$\text{where } \rho < 1. \tag{2.7}$$

The elasticity of substitution in consumption between goods and services is $\sigma_c = 1/(1-\rho)$. Consumers hold equal shares of all firms.

Consumers take prices and wages as given and maximize utility subject to the budget constraint that wages equal consumption. Firms maximize profits taking the price of consumption goods and wages as given. The CRS technology insures that equilibrium profits will be zero.

Of interest in this model is the long-run (as $t \to \infty$) allocation of low-skilled labor to goods and services, and the evolution of inequality, measured by the Manual to Abstract and Manual to Routine wage ratios.

2.1 Equilibrium

We normalize the price of good g to 1, i.e. $p_g(t) = 1$ for all t, without loss of generality. We can define the equilibrium as follows.

Definition 1 *An equilibrium in this economy is a tuple of aggregate allocations and prices* $(Y_s(t), Y_g(t), C_s(t), C_g(t), K(t), L_a(t), L_m(t), L_r(t), p_s(t), w_a(t), w_m(t), w_k(t))$ *and a cutoff skill for unskilled workers* $\eta^*(t)$ *such that*

1. *The representative consumer maximizes* (2.6) *subject to the budget constraint*

$$C_g(t) + C_s(t)\,p_s(t) \leq L_a(t)\,w_a(t) + L_m(t)\,w_m(t) + L_r(t)\,w_r(t)\,.$$

2. *The firms that produce services and goods maximize profits, that is*

$$\begin{aligned}
w_m(t) &= \alpha_s p_s(t) && (2.8)\\
w_a(t) &= \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dL_a(t)} && (2.9)\\
w_r(t) &= \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dL_r(t)} && (2.10)\\
w_k(t) &= \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dK(t)} && (2.11)
\end{aligned}$$

The firms that can convert output goods to capital goods (within the period) maximize profits, that is

$$w_k(t) \leq \theta e^{-\delta t} \text{ (with equality if } K(t) > 0) \qquad (2.12)$$

The unskilled workers allocate their labor between routine and manual tasks optimally, that is

$$w_m(t) \begin{cases} \geq \eta^*(t)\,w_r(t) \text{ if } L_m(t) = 1 \\ = \eta^*(t)\,w_r(t) \text{ if } L_m(t) \in (0,1) \\ \leq \eta^*(t)\,w_r(t) \text{ if } L_m(t) = 0. \end{cases} \qquad (2.13)$$

3. *Labor and goods markets clear, that is*

$$\begin{aligned}
L_a(t) &= 1, \\
L_m(t) &= \int_0^{\eta^*} e^{-\eta} d\eta = 1 - e^{-\eta^*} && (2.14)\\
L_r(t) &= \int_{\eta^*}^{1} \eta e^{-\eta} d\eta = (\eta^* + 1)\,e^{-\eta^*} && (2.15)\\
C_s(t) &= Y_s(t) = \alpha_s L_m(t) \\
C_g(t) + K(t)\,\theta e^{-\delta t} &= Y_g(t)\,. && (2.16)
\end{aligned}$$

2.2 Capital demand

First note that there are no dynamic linkages, hence the equilibrium at each t can be separately characterized given the level of productivity $\theta e^{-\delta t}$.

We claim that the choice of capital in this economy solves

$$\max_{K(t)\in\mathbb{R}_+} L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu}+\lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}-\theta e^{-\delta t}K(t). \tag{2.17}$$

This can be seen by combining Eqs. (2.11) and (2.12) and noting that the choice of capital satisfies the first order condition for the above concave maximization problem. Note that, by the market clearing condition (2.16), the objective function for Problem (2.17) is equal to C_g. Therefore, the choice of capital in equilibrium maximizes net output in the economy (which is consumed by the representative agent). We denote the optimal value of Problem (2.17) $F(L_a(t), L_r(t), t)$. We have that $F(L_a(t), L_r(t), t)$ is strictly increasing and differentiable in $L_a(t)$ and $L_r(t)$ with derivatives

$$w_r = \frac{dF(L_a(t), L_r(t), t)}{dL_r(t)} \tag{2.18}$$

$$w_a = \frac{dF(L_a(t), L_r(t), t)}{dL_a(t)} \tag{2.19}$$

where the equivalence with wages w_r and w_a comes from the equilibrium conditions (2.10) and (2.9) along with the envelope theorem for Problem (2.17). We will not explicitly solve for F since the exact algebraic expression is messy. Instead we will derive its asymptotic properties (sufficient for our analysis) for each of the cases we analyze below.

2.3 Demand for manual labor

We next derive a demand and a supply curve for $L_m(t)$ given price p_s, which will characterize the static equilibrium. The consumer optimization implies

$$p_s = \left(\frac{L_m(t)}{F(1, L_r(t), t)}\right)^{-1/\sigma_c}. \tag{2.20}$$

Note that, given the cutoff $\eta^*(t)$, we have that $L_m(t)$ and $L_r(t)$ are given by Eqs. (2.14) and (2.15), hence they are related with

$$\begin{aligned} L_r(t) &= (1-\log(1-L_m(t)))(1-L_m(t)) \\ &\equiv g(L_m(t)), \end{aligned} \tag{2.21}$$

where $g:[0,1]\to[0,1]$ is a strictly decreasing function with $g(0)=1$ and $g(1)=0$. Plugging this in Eq.(2.20) gives

$$p_s = \left(\frac{F(1, g(L_m(t)), t)}{L_m(t)}\right)^{1/\sigma_c}, \tag{2.22}$$

which gives a demand equation for $L_m(t)$. Note that F is strictly increasing in the second variable and g is strictly decreasing, so the demand curve is strictly decreasing. Note that the demand curve starts from $p_s(L_m=0)=\infty$ and goes down to $p_s(L_m=1)=(F(1,0,t))^{1/\sigma_c}$ (which is 0 when

$\mu < 0$, but may be positive when $\mu > 0$).

2.4 Supply of manual labor

To derive a supply equation for $L_m(t)$, we use Eqs. (2.8) and (2.18) in the equation

$$w_m(t) = \eta^*(t)\, w_r(t)\,.$$

to get

$$p_s(t) = \eta^*(t)\,\frac{dF(1, L_r(t), t)}{dL_r(t)}.$$

Plugging in $L_r(t) = g(L_m(t))$ and also

$$\eta^*(t) = \eta(L_m) \equiv -\log(1 - L_m(t))\,,$$

we have

$$p_s(t) = -\log(1 - L_m(t))\,\frac{dF(1, g(L_m(t)), t)}{dL_r(t)}. \tag{2.23}$$

The supply equation will typically be increasing, but it may not be increasing everywhere. It starts from $p_s(L_m = 0) = 0$ and limits to $p_s(L_m = 1) = \infty$ hence the supply and demand curves always intersect.

Putting the demand and supply equations together, we have

$$F(1, g(L_m(t)), t)^{1/\sigma_c} = -L_m(t)^{1/\sigma_c}\log(1 - L_m(t))\,\frac{dF(1, g(L_m(t)), t)}{dL_r(t)}. \tag{2.24}$$

which characterizes the equilibrium value of $L_m(t)$. The following proposition shows that an equilibrium always exists.

Proposition 1 *An equilibrium exists. The equilibrium level of $L_m(t)$ is characterized as the solution to Eq.* (2.24)*. Once $L_m(t)$ is determined, the remaining variables are determined from the equilibrium conditions in Definition 1.*

Typically, there will be a unique intersection for supply and demand curves and we will be able to analyze the dynamics (as technology progresses) by looking at how the intersection point moves. We will study the dynamics in a simulation. Next, we will analyze the limiting behavior of this economy as $t \to \infty$.

2.5 Asymptotic Equilibrium

Assume (it is easy to verify this assumption) that $L_m(t)$ asymptotes to a constant in the limit, $\lim_{t\to\infty} L_m(t) = L_m^*$. Note that the Theorem of the Maximum applied to Problem (2.17) implies that the optimum level of $K(t)$ is increasing in t. Moreover, at $t=\infty$, cost of capital would be zero and $K=\infty$ would be optimal, hence optimal $K(t)$ will be arbitrarily large for sufficiently large t, i.e., we have $\lim_{t\to\infty} K(t)=\infty$. To make progress for solving Eq. (2.24) in the limit, we need to evaluate the limit values for $F(1, g(L_m(t)), t)$ and $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$.

2.5.1 Capital input

Rewrite Problem (2.17) as

$$\max_{K(t)\in\mathbb{R}_+} \lambda^{\beta/\mu}(\alpha_k K(t))^{\beta} \frac{[(1-\lambda)(\alpha_r L_r(t))^{\mu}+\lambda(\alpha_k K(t))^{\mu}]^{\beta/\mu}}{\lambda^{\beta/\mu}(\alpha_k K(t))^{\beta}} - \theta e^{-\delta t} K(t). \tag{2.25}$$

Note that the term $\frac{[(1-\lambda)(\alpha_r L_r(t))^{\mu}+\lambda(\alpha_k K(t))^{\mu}]^{\beta/\mu}}{\lambda^{\mu/\beta}(\alpha_k K(t))^{\beta}} \downarrow 1$ as $K(t)\to\infty$. This suggests that we introduce another maximization problem

$$G(1,t) = \max_{K(t)} \lambda^{\beta/\mu}(\alpha_k K(t))^{\beta} - \theta e^{-\delta t} K(t), \tag{2.26}$$

and denote its solution by $\tilde{K}(t)$. We claim that, in the limit, the value and the optimal solution to this maximization problem behaves like those of the optimization problem in (2.25). More specifically, we claim

$$\lim_{t\to\infty} \frac{F(1, g(L_m(t)), t)}{G(1,t)} = 1 \text{ and } \lim_{t\to\infty} \frac{K(t)}{\tilde{K}(t)} = 1. \tag{2.27}$$

To prove this statement formally, consider the first order condition for Problem (2.25)

$$\beta\lambda\alpha_k^{\mu} K(t)^{\mu-1}[(1-\lambda)(\alpha_r L_r(t))^{\mu}+\lambda(\alpha_k K(t))^{\mu}]^{(\beta-\mu)/\mu} = \theta e^{-\delta t}.$$

Similarly, consider the first order condition for Problem (2.26)

$$\beta\lambda^{\beta/\mu}\alpha_k^{\beta}\tilde{K}(t)^{\beta-1} = \theta e^{-\delta t}.$$

Dividing the last two displayed equations, taking the limit and noting that $K(t)\to\infty$ proves our claim in Eq. (2.27). Note that by straightforward algebra, $G(1,t)$ and $\tilde{K}(t)$ can be calculated as

$$\tilde{K}(t) = \left(\lambda^{\mu/\beta}(\alpha_k)^{\beta}\frac{e^{\delta t}}{\theta}\right)^{1/(1-\beta)} \text{ and } G(1,t) = (1-\beta)\lambda^{\mu/\beta}\alpha_k^{\beta}\tilde{K}(t)^{\beta}.$$

Combining the last equation and Eq. (2.27), we have

$$\lim_{t\to\infty} \frac{F(1, g(L_m(t)), t)}{c_1 K(t)^{\beta}} = 1, \tag{2.28}$$

where $c_1 \equiv (1-\beta)\lambda^{\mu/\beta}\alpha_k^{\beta}$ is some constant. Eq. (2.28) characterizes the behavior of F in the limit. In words, in the limit, routine labor become less and less important in production (since $\mu > 0$) and F behaves as a production function that does not use routine labor at all.

Next, we consider $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$. Since $K(t) \to \infty$, we have

$$
\begin{aligned}
& \lim_{t\to\infty} \frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{\beta(1-\lambda)\alpha_r^{\mu}\lambda^{(\beta-\mu)/\mu}L_r(t)^{\mu-1}(\alpha_k K(t))^{(\beta-\mu)}} \\
= & \lim_{t\to\infty} \frac{\beta(1-\lambda)\alpha_r^{\mu}L_r(t)^{\mu-1}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu}+\lambda(\alpha_k K(t))^{\mu}\right]^{(\beta-\mu)/\mu}}{\beta(1-\lambda)\alpha_r^{\mu}\lambda^{(\beta-\mu)/\mu}L_r(t)^{\mu-1}(\alpha_k K(t))^{(\beta-\mu)}} \\
= & \ 1,
\end{aligned}
$$

where the first line uses the expression in (6.5) and the last line uses the fact that $\lim_{t\to\infty} K(t) = \infty$. Hence we have

$$
\lim_{t\to\infty} \frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1} K(t)^{\beta-\mu}} = 1, \tag{2.29}
$$

where $c_2 \equiv \beta(1-\lambda)\alpha_r^{\mu}\lambda^{(\beta-\mu)/\mu}\alpha_k^{\beta-\mu}$ is some constant and we have used $L_r(t) = g(L_m(t))$. This characterizes the limiting behavior for $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$.

2.5.2 Labor supply asymptotics

We now use Eqs. (2.28) and (2.29) in Eq. (2.24) to solve for the asymptotic equilibrium level of $L_m(t)$. We can rewrite Eq. (2.24) as

$$
\begin{aligned}
& \left[\frac{F(1,g(L_m(t)),t)}{c_1 K(t)^{\beta/(1-\beta)}}\right]^{1/\sigma_c} c_1^{1/\sigma_c} K(t)^{\beta/\sigma_c} \\
= & \ -L_m(t)^{1/\sigma_c}\log(1-L_m(t))\, c_2 K(t)^{\beta-\mu} g(L_m(t))^{\mu-1}\left[\frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1}K(t)^{\beta-\mu}}\right]
\end{aligned}
$$

which, with some algebra and using Eq. (2.21), can be simplified to

$$
\begin{aligned}
& \frac{c_1^{1/\sigma_c}}{c_2}\frac{\left[\frac{F(1,g(L_m(t)),t)}{c_1 K(t)^{\beta/(1-\beta)}}\right]^{1/\sigma_c}}{\left[\frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1}K(t)^{\beta-\mu}}\right]} K(t)^{\beta/\sigma_c-(\beta-\mu)} \\
= & \ -\log(1-L_m(t))\, L_m(t)^{1/\sigma_c}(1-\log(1-L_m(t)))^{\mu-1}(1-L_m(t))^{\mu-1}.
\end{aligned}
$$

When we take the limit as $t \to \infty$, the terms in brackets go to 1, hence

$$\begin{aligned} & \frac{c_1^{1/\sigma_c}}{c_2} \lim_{t\to\infty} K(t)^{\beta/\sigma_c - (\beta-\mu)} \qquad (2.30) \\ = & \lim_{t\to\infty} -\log(1 - L_m(t)) L_m(t)^{1/\sigma_c} (1 - \log(1 - L_m(t)))^{\mu-1} (1 - L_m(t))^{\mu-1}. \end{aligned}$$

Since $K(t) \to \infty$, the left hand side either goes to 0 or ∞ depending on the sign of $\beta/\sigma_c - (\beta - \mu)$. The right hand side goes to 0 if $L_m(t) \to 0$, and to ∞ if $L_m(t) \to 1$.[19] Hence, the fact that the equality above holds in the limit implies

$$\lim_{t\to\infty} L_m(t) = \begin{cases} 0 \text{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta} \\ 1 \text{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}. \end{cases} \qquad (2.31)$$

In words, if share of machines in goods production is sufficiently small ($\beta < \mu$) or if goods and services are sufficiently complementary $\left(\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}\right)$, then then in the limit all unskilled labor is drawn to manual tasks. Else if $\beta > \mu$ and $\frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}$, that is, the share of machine in goods production is large and goods and services are sufficiently substitutable, then routine tasks continue to be important in the limit and all labor is drawn to routine tasks.

2.5.3 Wage inequality asymptotics

We calculate the limiting behavior for abstract, manual and routine wages. For manual wages, we have

$$w_m(t) = p_s(t) = \left(\frac{F(1, g(L_m(t)), t)}{L_m(t)}\right)^{1/\sigma_c},$$

where we have used the demand equation. Hence, using Eq. (2.28), we have

$$\lim_{t\to\infty} \frac{w_m(t)}{c_1^{1/\sigma_c}\left(K(t)^\beta / L_m(t)\right)^{1/\sigma_c}} = 1, \qquad (2.32)$$

For abstract wages, we have

$$w_a(t) = \frac{dF(1, g(L_m(t)), t)}{dL_a(t)} = (1-\beta) F(1, g(L_m(t)), t),$$

[19] Proving that the RHS limits to ∞ as $L_m(t) \to 1$ requires some careful algebra. First, note that, as $L_m(t) \to 1$ $\lim_{t\to\infty} \frac{(1-\log(1-L_m(t)))^{\mu-1}}{-\log(1-L_m(t))^{\mu-1}} = 1$. Then, in this case the RHS limit can be rewritten as

$$(-\log(1 - L_m(t)))^\mu L_m(t)^{1/\sigma_c} (1 - L_m(t))^{\mu-1}.$$

Recall that we are analyzing the case $\mu > 0$. Hence the first term in this expression goes to ∞ at exponential rate. If $\mu < 1$, then the last term goes to ∞ as well and the limit is ∞ as claimed. Else if $\mu > 1$, the last term goes to 0, but it goes to zero at a polynomial rate. Since the first term goes to ∞ at an exponential rate and the last term goes to zero at polynomial rate, the product goes to ∞ as claimed. This step can more rigorously be proven using the L'Hospital Rule.

hence using Eq. (2.28), we have

$$\lim_{t\to\infty} \frac{w_a(t)}{(1-\beta)\, c_1 K(t)^{\beta}} = 1. \tag{2.33}$$

Now using the fact that

$$w_m(t) = w_r(t)\, \eta(L_m)$$

in equilibrium, we also derive the limiting behavior for routine wages as

$$\lim_{t\to\infty} \frac{w_r(t)}{c_1^{1/\sigma_c} K(t)^{\beta/\sigma_c} / \left[L_m(t)^{1/\sigma_c} \times -\log(1-L_m)\right]} = 1. \tag{2.34}$$

We are also interested in relative wages. From $w_m(t) = w_r(t)\, \eta(L_m)$, we clearly have

$$\frac{w_m(t)}{w_r(t)} = \eta(L_m) = \begin{cases} 0 \text{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta} \\ \infty \text{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}. \end{cases}$$

Also, from Eqs.(2.32) and (2.33), we have

$$\lim_{t\to\infty} \frac{w_a(t)}{w_m(t)} = \lim_{t\to\infty} \frac{(1-\beta)\, c_1 K(t)^{\beta}}{c_1^{1/\sigma_c} \left(K(t)^{\beta} / L_m(t)\right)^{1/\sigma_c}} = \begin{cases} \infty \text{ if } \sigma_c > 1 \\ (1-\beta) \text{ if } \sigma_c = 1 \\ 0 \text{ if } \sigma_c < 1. \end{cases}$$

Hence, we summarize our findings for wages and relative wages in this case ($\mu > 0$) as follows. We have that wages for manual and abstract labor always go to infinity. The relative wage of manual labor to routine labor $w_m(t)/w_r(t)$ go to infinity if $\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}$ and to zero otherwise (which is, not surprisingly, the same condition which determines the limiting value of $L_m(t)$). Finally, relative wages for abstract to manual labor depend on σ_c: If $\sigma_c < 1$, then $w_a(t)/w_m(t)$ is 0; if $\sigma_c = 1$, then $w_a(t)/w_m(t)$ is $(1-\beta)$, and if $\sigma_c < 1$, then $w_a(t)/w_m(t)$ is 0. We summarize our findings in the following proposition.

Proposition 2 *When $\mu > 0$, we have $L_m(t) \to 1$ if $\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}$ and $L_m(t) \to 0$ if $\frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}$. For the limit wages, we have*

$$\begin{aligned} \lim_{t\to\infty} \frac{w_m(t)}{w_r(t)} &= \begin{cases} \infty \text{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta} \\ 0 \text{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}. \end{cases} \\ \lim_{t\to\infty} \frac{w_a(t)}{w_r(t)} &= \infty \\ \lim_{t\to\infty} \frac{w_a(t)}{w_m(t)} &= \begin{cases} 0 \text{ if } \sigma_c < 1, \\ \infty \text{ otherwise.} \end{cases} \end{aligned}$$

2.6 Summary and empirical implications

In summary, the ongoing substitution of computer capital for routine labor input in our model (driven by the falling price of computer power) spurs low-skilled workers to reallocate labor input from routine tasks in goods production to manual tasks in the production of services. Employment and wages in middle-skill clerical and routine production jobs declines. Employment in low-skill service occupations rises. Wage inequality rises between high and middle-skill workers due to the combination of rising productivity of abstract tasks and and a falling price of routine tasks. Inequality between high and low-skill workers may ultimately converge to a state or may expand indefinitely. Specifically:

1. When the share of routine tasks in goods production is sufficiently small ($\beta < \mu$) or the elasticity of substitution between goods and services is sufficiently small ($1/\sigma_c > [(\beta - \mu)/\beta]$), then all unskilled labor gets allocated to manual tasks, and the wages of routine labor relative to manual labor go to 0.

2. When the share of routine tasks in goods production is sufficiently large ($\beta > \mu$) and the elasticity of substitution between goods and services is sufficiently large ($1/\sigma_c < [(\beta - \mu)/\beta]$), then all unskilled labor is allocated to routine tasks in the limit. The manual wage to routine wage ratio limits to 0. The abstract wage to routine wage ratio in this case always limits to infinity (since we necessarily have $\sigma_c > 1$). Hence, in the limit, the abstract wage is greater than the routine wage which is in turn greater than the manual wage.

3. The relative wage of abstract to manual labor limits to infinity if $\sigma_c > 1$, to zero if $\sigma_c < 1$, and to $1 - \beta$ if $\sigma_c = 1$.

One element intentionally left absent from the model is the opportunity for workers to invest in human capital.[20] While in reality, rising earnings inequality spur further skills investment, we omit this possibility from the model to emphasize that even with human capital stocks held constant, ongoing skilled–labor augmenting technical change need not imply ongoing growth of inequality.

Can this aggregate model be applied to the analysis of employment and wages in detailed geographic areas, such as cities or commuting zones? The answer depends on whether these areas can plausibly be treated as approximating separate markets. If yes, the model predicts that markets with higher initial concentration in routine tasks—corresponding to higher values of β in local goods production—will see greater growth of service employment and greater polarization of wages as computerization progresses.[21] If no, we must consider to what extent the model applies in local labor markets that interact in a full spatial equilibrium.

[20] Indeed, in our data, the non-college share of worked hours falls from 58 to 38 percent between 1980 and 2005.

[21] Formally, we could rewrite equation (2.1) at the city (or commuting zone) level with a city-specific routine task intensity: $y_{jg} = \alpha_g R^{b_j} A^{1-b_j}$ where j denotes cities and a higher value of b_j indicates greater initial routine task intensity. If all other preference and labor supply parameters are comparable across cities (that is, uncorrelated with b_j), a uniform decline in the routine task price that is common across cities will induce greater growth in wage inequality and service employment in high b cities.

There is one key factor that aids the identification of the model in the more general, spatial equilibrium case: the output of service occupations is non-traded, and hence inter-region trade is not expected to enforce a uniform service wage across geographic areas. In the short run, local demand shocks should affect local service occupation wage levels. And the rate at which these regional wage differences are arbitraged depends upon the responsiveness of labor movements to cross-region wage variation. Much evidence suggests that mobility responses to labor demand shocks across US cities and states are typically slow and incomplete (Topel, 1986; Blanchard and Katz, 1992; Glaeser and Gyourko, 2005). Mobility is particularly low for the less-educated, who comprise the majority of service occupation workers (Bound and Holzer, 2000). It is therefore plausible that local demand shocks may affect service wages even over the medium term.

The non-tradeability of service outputs has a second useful implication: because demanders and suppliers of service occupations must collocate, the geographic analysis can potentially identify the local determinants of the demand for service jobs, even in the case when service wage levels are not set locally. Consequently, we expect the 'quantity' implications of the theoretical framework to hold at the local labor market level, even in full spatial equilibrium. The wage side of the analysis must be treated as more speculative.

3 Data sources and measurement

3.1 Data sources

Our empirical analysis draws on the Census Integrated Public Use Micro Samples (Ruggles et al. 2004) for the years 1950, 1970, 1980, 1990, and 2000 and the American Community Survey (ACS) for 2005.[22] The Census samples for 1980, 1990 and 2000 include 5 percent of the US population, the 1970 Census and ACS sample include 1 percent of the population, and the 1950 Census sample includes approximately 0.2 percent of the population.[23] Large sample sizes are needed for an analysis of changes in labor market composition at the detailed geographic level.

A time-consistent definition of local labor markets is a requirement for analyzing geographic variation over time. Previous research has often used Metropolitan Statistical Areas (MSAs) as a proxy for local labor markets (e.g., Beaudry, Doms, and Lewis 2006). MSAs are defined by the US Office for Management and Budget for statistical purposes; they consist of a large population nucleus and adjacent communities that have a high degree of social and economic integration with the core city. The geographic definition of MSAs is periodically adjusted to reflect the growth of cities. Despite efforts to improve the time-consistency of MSA definitions (e.g., Jaeger et al. 1998), the information provided by the Census Public Use Micro Samples does not allow for a consistent measurement of MSAs. This lack of geographic consistency is problematic for an analysis of changes

[22] We do not use Census data for the year 1960 because detailed geographic information is not available.

[23] The 1950 sample-line subsample on which we rely is only one-fifth as large as the full 1 percent public use sample. We use the sample-line file because it contains education and occupation variables, which are key to our analysis.

in employment composition. Of particular concern is that the employment characteristics of the suburban areas that are gradually added to MSAs are likely to systematically differ from the characteristics of the core cities. In addition, MSAs do not cover the rural parts of the US.

This study pursues an alternative approach for the definition of local labor markets based on the concept of Commuting Zones (CZs). Tolbert and Sizer (1996) used privileged access to 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. The analysis focuses on the 722 CZs that cover the entire mainland of the US, including both metropolitan and rural areas. Relative to other geographic units used for analysis of local labor markets, commuting zones have two advantages: they are based primarily on economic geography rather than incidental factors such as minimum population or state boundaries; and they cover the entire US. In addition, it is possible to use Census Public Use Micro Areas (PUMAs) to consistently match Census geography to CZs for the full period of our analysis.[24] We are not aware of prior economic research that makes use of this geographic construct.

We matched the geographic information that is available in the Census Public Use samples to the CZ geography. The most disaggregated geographic unit reported in the Census samples is the PUMA or, prior to 1980, the similarly defined county groups or state economic areas. A PUMA is a subarea of a state that comprises a population of 100,000 to 200,000 persons but has otherwise no clearly inherent economic interpretation. The 2000 Census splits the US into more than 2,000 PUMAs. The Census Bureau reports how the population of a PUMA is distributed over counties. If a PUMA overlaps with several counties, our procedure to match PUMAs to CZs assumes that all residents of that PUMA have the same probability of living in a given county. The aggregation of counties to CZs then allows computing probabilities that a resident of a given PUMA falls into a specific CZ. In every Census year, a clear majority of PUMAs can be matched to a single CZ, while the residents of the remaining PUMAs are attributed to several CZs using probability weights based on the relative share of a PUMA's population that falls into a given CZ. This technique allows us to calculate the population characteristics of residents of each CZ consistently in each year of our data.

Our sample of workers consists of individuals who were between age 16 and 64 and who were working in the year preceding the survey. Residents of institutional group quarters such as prisons and mental institutions are dropped along with unpaid family workers. Labor supply is measured by the product of weeks worked times usual number of hours per week. For individuals with missing hours or weeks, labor supply weights are imputed using the mean of workers in the same education-occupation cell, or, if the education-occupation cell is empty, the mean of workers in the same education group. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight and the weight derived from the geographic matching process.

[24] We use the Tolbert and Sizer (1996) definition of commuting zones based on commuting patterns in the 1990 Census. Tolbert and Killian (1987) earlier developed commuting zones using the 1980 Census. These commuting zones are largely but not fully identical with the 1990 definitions.

The computation of wages excludes self-employed workers and individuals with missing wages, weeks or hours. Hourly wages are computed as yearly wage and salary income divided by the product of weeks worked and usual weekly hours. Topcoded yearly wages are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. Hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile. The computation of full-time full-year weekly wages is based on workers who worked for at least 40 weeks and at least 35 hours per week. Wages are deflated using the Personal Consumption Expenditure Index.

The Census classification of occupations changed over time, particularly between 1970 and 1980 and between 1990 and 2000. We use a slightly modified version of the crosswalk developed by Meyer and Osborne (2005) to create time-consistent occupation categories. Our changes to the crosswalk are mainly aimed at improving the consistency of service occupations at the most detailed level, such as creating consistent subgroups of restaurant workers. The designation of occupations as "service occupations" is based on the occupational classification of the 2000 Census. We subdivide service occupations into nine groups: food preparation and service workers; building and grounds cleaning workers and gardeners; health service support workers (such as health and nursing aides, but excluding practical or registered nurses); protective service workers; housekeeping, cleaning and laundry workers; personal appearance workers (such as hairdressers and beauticians); child care workers; recreation and hospitality workers (such as guides, baggage porters, or ushers); and other personal service workers. Protective service occupations are further subdivided into policemen and fire fighters, and guards. Because police officers and firefighters have much higher educational attainment and wage levels than all other service workers, we exclude them from our primary definition of service occupations (though our results are not sensitive to their inclusion). The detailed code for forming the occupational classification is available from the authors.

3.2 Measuring the 'routine employment share'

Our empirical work below analyzes the degree to which commuting zones that are initially specialized in routine task activity experience polarization of employment and wages as the price of computing secularly declines. This analysis requires a summary index of employment in routine activities within commuting zones. We infer this information from the occupational composition of employment. To measure routine task-intensity in each occupation, we draw on data from ALM, who merge job task requirements—manual, routine and abstract—from the fourth edition of the US Department of Labor's *Dictionary of Occupational Titles* (US Department of Labor, 1977; 'DOT' hereafter) to their corresponding Census occupation classifications.[25] For each occupation k, we

[25] Following Autor, Katz and Kearney (2006), we collapse ALM's original five task measures to three task aggregates: the manual task index corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination"; the routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; the abstract task measure is the average of two DOT variables: "direction control and plan-

form an index of routine task-intensity, RTI:

$$RTI_k = \ln\left(\hat{R}_{k,1980}/\hat{M}_{k,1980}\right), \tag{3.1}$$

where $\hat{R}$ and $\hat{M}$ are, respectively, the intensity of routine and manual task input in each occupation in 1980, measured on a 0 to 10 scale.[26] This measure is rising in the relative importance of routine tasks within an occupation and falling in the relative importance of manual tasks. Since RTI does not have a cardinal scale, we standardize it with a mean of zero and an employment weighted, cross-occupation standard deviation of unity in 1980.

This simple measure appears to capture well the job categories that motivate our conceptual framework. Table 2 shows that among the 10 most routine task-intensive occupations, 5 are clerical and accounting occupations and several others represent repetitive physical motion activities. Among the 10 least routine task intensive occupations, 4 are service occupations, and the remainder involve driving motor vehicles.[27] Appendix Table 2 lists the full set of Census service occupations and their rankings. Of these 30, 17 fall in the bottom quintile of RTI scores and 23 of fall below the median. Thus, in the cross-section, this index appears to perform well.

To apply this index to commuting zones, we must aggregate the occupation level data to the geographic level. For ease of interpretation, we use a simple binary approach in which occupations are classified as routine task-intensive ($ROCC_k = 1$) if they fall in the top-third of the employment-weighted distribution of the RTI in 1980:

$$ROCC_k = \begin{cases} 1 & \text{if} \sum_{i=1}^{k} L_{i,1980} \leq \frac{1}{3}\sum_{i=1}^{K} L_{i,1980} \\ 0 & \text{otherwise} \end{cases}. \tag{3.2}$$

In this expression, L is equal to hours of labor supply in an occupation in 1980 and K is the count of occupations. We then assign each commuting zone, j, an aggregate routine-share measure (RS) equal to the fraction of employment that falls in routine task-intensive occupations in a given year:

$$RS_{jt} = \frac{\sum_{i=1}^{k} L_{jkt} \times ROCC_k}{\sum_{i=1}^{K} L_{jkt}}. \tag{3.3}$$

By construction, the mean of this measure is 0.33 in 1980.[28]

ning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements. Further details on these variables are found in Appendix Table 1 of ALM. The ALM measures are also employed by Goos and Manning (2007) and Peri and Sparber (2007) among others.

[26]For the 5 percent of microdata observations with the lowest manual task score (which is zero for most of these observations), we use the manual score of the 5th percentile.

[27]Motor vehicle operation closely fits our definition of manual tasks, requiring little formal education but considerable ability to respond flexibly to a changing environment. Such occupations are classified as transportation and material moving rather than service in the Census. These occupations do not, however, possess the strong supplier-demander collocation attribute of service occupations. Thus, they are not well suited to our geographic analysis.

[28]We have experimented with alternative commuting zone routine intensity measures, including counting the share of employment in the top 20 or top 50 percent of routine occupations (rather than the top third) or simply taking

We perform two summary analyses to assess whether the aggregate trends in task input match the basic assumptions of the model. Table 3 provides means and standard deviations of the three DOT task variables—routine, manual, abstract—for the years 1980 through 2005. Here, each variable is standardized with mean zero and cross-occupation standard-deviation of one in 1980. Consistent with expectations, abstract tasks show a secular rise over 1980 through 2005 and routine tasks show a secular decline. The magnitudes of these changes is large. The mean abstract task score in 2005 lies 1.4 standard deviations above its 1980 mean, while the mean routine task score falls 2.6 standard deviations below its 1980 mean. Manual tasks also display a distinctive time pattern. The mean manual task score falls by 0.3 standard deviations between 1980 and 1990, then rises over the subsequent 15 years. By 2005, manual task input slightly exceeds its 1980 level. It bears emphasis that the over-time variation in these measures is driven exclusively by shifts in occupational composition (since DOT characteristics for each occupation, based on the 1977 DOT file, are static). If, plausibly, within-occupation changes in task content trend in the same direction as between-occupation changes, our measures will understate the extent of task change.[29]

As a geographic level analogue to these occupational-level measures, Appendix Table 3 summarizes commuting zone level trends in the RS measure. The overall RS measure falls in each period between 1980 and 2005, with the most rapid decline between 2000 and 2005. Disaggregating the RS measure by education group reveals that employment in routine task-intensive occupations is always highest among workers with a high school degree or some college education ('middle educated' workers in our model), and lower for college graduates and, particularly, high school dropouts. Notably, he aggregate decline in RS over 1980 through 2005 occurs for all four education groups, with the largest declines for the education groups initially most specialized in routine occupations. Taken together, these patterns suggest that the RS measure may serve as a reasonable proxy for the task constructs posited by the model.

4 Predicting the growth of service employment

A primary implication of our conceptual model is that commuting zones that are initially specialized in routine task activity will experience differential growth of service employment as routine tasks are supplanted by computerization. The scatter plot in the upper panel of Figure 3, which depicts the bivariate relationship between commuting zone Routine Share (RS) in 1980 and the change in the share of non-college labor input in service occupations over the subsequent 25 years, provides strong initial support for this prediction. Each plotted point in this figure represents one of 722 commuting zones, while the regression line corresponds to the following weighted OLS regression of the change in the service employment share on the initial RS, where weights are equal

the mean routine-intensity score in each commuting zone. All of these measures perform similarly in our analysis.

[29]Similar results are reported by ALM, though their occupation-level data only extend to 1998.

to commuting zone shares of national population in 1980:

$$\Delta SVC_{j,1980-2005} = -0.033 + \underset{(t=17.8)}{0.323 \times RS_{j,1980}} + e_{jt} \qquad R^2 = 0.30 \tag{4.1}$$

The explanatory power of this bivariate relationship is substantial. The coefficient of 0.323 on the RS measure implies that a commuting zone with the mean Routine Share in 1980 is predicted to increase its share of non-college labor in service employment by 7.4 percentage points between 1980 and 2005.[30] Given an 80th/20th percentile range of the RS variable of approximately 0.10, the model predicts that the 80th percentile commuting zone increased its non-college service share by 3.2 percentage points more than the 20th percentile commuting zone.

To provide a more concrete sense of the geography underlying this pattern, the lower panel of Figure 3 plots the relationship between initial routine share and the growth of service employment over 1980 through 2005 for the 40 commuting zones in the sample with populations over 1 million. The bivariate relationship found in the full sample of 722 commuting zones remains robust and of comparable magnitude in this vastly reduced sample. The city names appearing next to each plotted point also highlight an important attribute of cities that are initially intensive in routine employment: these are not for the most part fading industrial cities; rather, they tend to be relatively intensive in finance, technology, government, and education.[31] The reason that these high-skill industries are associated with high levels of routine-intensive employment is that they employ large fractions of workers in supporting occupations, such as clerical work and accounting, which are themselves highly routine-intensive.

Table 4 explores the simple bivariate relationship between the routine employment share and growth of service employment over five and one-half decades (1950 to 2005) using specifications of the following form:

$$\Delta SVC_{js\tau} = \alpha_t + \beta_\tau \cdot RS_{jst} + \gamma_s + e_{js\tau}. \tag{4.2}$$

In this equation, τ represents a decadal change, t denotes the start year of the corresponding decade τ, and s denotes the state in which the commuting zone is located.[32] The inclusion of a vector of state dummies, γ, means that the coefficient of interest, β, is identified by within-state cross-CZ variation.[33] A striking pattern that emerges from this table is that the strong, positive predictive relationship between the routine employment share and growth of service employment is not detected prior to the decade of the 1980s, and actually has the opposite sign in the 1950 to 1970

[30] $\Delta SVC = -0.033 + 0.323 \times 0.333 = 0.074$

[31] The five cities with the highest concentration of routine employment in 1980 are New York, Washington, DC, San Francisco, Detroit, and Chicago. The five cities at the bottom of the ranking are Pittsburgh, San Antonio, New Orleans, Tampa, and Syracuse.

[32] The dependent variable for 1950 to 1970 is divided by two and the one for 2000 to 2005 is multiplied by two to place them on the same decadal time scale.

[33] If a commuting zone contains adjacent counties that cross state boundaries, we implicitly redefine state boundaries so that the commuting zone is located in the state contributing a larger share of its population.

period.[34] Beginning in 1980, this relationship becomes positive and significant, and its magnitude rises in each subsequent time interval.

4.1 Controlling for skill supply, labor market conditions, and demographics

We next explore a host of explanatory factors that may potentially determine geographic variation in the growth of service employment using an augmented version of equation (4.2). In particular, we estimate stacked first-difference models of the form

$$\Delta SVC_{js\tau} = \alpha + \beta_1 \times RS_{jst} + \beta_2 \times RS_{jst} \times I\left[t \geq 1980\right] + \beta_3 \Delta X_{js\tau} + \delta_\tau + \gamma_s + e_{js\tau}, \qquad (4.3)$$

where the sample includes each decadal change from Table 4 over the period 1950 to 2005, and we include a full set of time period effects, state effects, and measures of contemporaneous changes in a number of relevant human capital, labor market, and demographic variables.

The first column of the Table 5a pools all five and one-half decades of data to estimate the RS-service employment slope over the full period. Consistent with the results in Table 4, the strong, positive relationship between routine employment share and growth of service employment is non-existent prior to the 1980s. Column 2 shows that this finding is not sensitive to the inclusion of the state dummy variables, which function as state-specific trends in the first-differenced specification.

Subsequent columns of Table 5a sequentially control for a number of key factors that may contribute to growth of service employment within CZ's. Column 3 adds two variables intended to capture shifts in the demand and supply of services: the change in the college-educated share of the population and the change in the share of the population that is non-college immigrants. These controls enter with the expected sign: a rise in the highly-educated population or an increase in immigrant penetration predicts growth in service employment among non-college workers (Cortes, 2006).

Column 4 adds two variable that measure local labor market conditions: the change in the local unemployment rate and the change in the share of non-college employment in manufacturing. The service employment share rises significantly with the unemployment rate and also increases when manufacturing employment falls. This evidence suggests that service employment is less cyclical than non-service employment and that workers may choose service occupations when higher paying work is unavailable.

Column 5 considers two additional variables that may shift demand for service work: the employment to population rate of females and the population share of seniors (age 65+). If services substitute for household production, a rise in female labor supply may increase service demand

[34] One speculative explanation for the negative relationship between RS and the growth of service employment is based on the observation that US farm employment contracted rapidly in these two decades, falling from 11 to 3 percent of employment. Logically, farm-intensive commuting zones had low levels of the RS in 1950. The movement of labor from farming into services in these CZs may potentially explain the negative relationship between the RS and growth of service employment in this period.

(as well as potentially increase labor supply to service occupations). Contrary to expectations, increased female employment is associated with a lower growth of service employment.[35] A growing share of senior citizens in the population—who may have relatively high demand for services—is predictive of growth in service employment.

Notably, inclusion of these explanatory variables leaves the significant, positive relationship between the routine employment share and growth of service employment largely unaffected. When all explanatory variables are simultaneously included (column 6), the point estimate on the RS falls by about 45 percent, but the precision of the point estimate rises.

It also bears note that the Table 5a specifications likely 'over-control' for alternative causal factors, since many of these explanatory variables—immigration, unemployment, and falling manufacturing employment—may stem (in part) from a common cause: labor demand shifts against routine-intensive occupations. Indeed, when the Table 5a models are re-estimated in Table 5b using as controls start-of-period *levels* of the six additional explanatory variables rather than contemporaneous changes, the size and significance of the routine share measure in predicting growth of service employment is only slightly affected by their inclusion.[36] In net, initial employment concentration in routine-intensive occupations is a far stronger predictor of growth in service employment than any other human capital, labor market, or demographic variable that we have explored.[37]

4.2 Which service occupations and which workers?

We now explore whether the robust, geographic link between routine task-intensity and growth of service employment is pervasive among service employment categories and among demographic sub-groups of non-college workers. Estimates of equation (4.3) fit separately for each major service occupation group (Table 6) reveal that the aggregate relationship between the routine employment share and subsequent growth of service employment is driven by a broad set of service occupations, including food service, personal appearance, child care, recreation, and building cleaning and gardening.[38] In fact, point estimates are positive for all nine service occupation categories for 1980-2005 period, and are statistically significant in five of them. Notably, while healthcare support occupations are the third largest contributor to service employment growth over 1980 to

[35] But this relationship flips sign when we condition on other explanatory variables, particularly the unemployment rate (see column 6).

[36] We nevertheless report the contemporaneous change specification in Table 5 and elsewhere to demonstrate robustness.

[37] This result is particularly noteworthy given the strong correlations between the RS and many of the explanatory variables. In a multivariate cross-sectional regression for 1980 shown in Appendix Table 4, the RTI is rising in the college share of the population, the immigrant share of non-college employment, the female employment to population ratio, and (weakly) the manufacturing employment share and CZ unemployment rate. It is falling in the elderly share of population.

[38] The 1950 to 1980 comparisons of detailed service occupation employment are somewhat unreliable because the 1950 Census classifies many service workers in broad "not elsewhere classified" categories. This gives rise to large spurious increases in many subcategories of service employment over 1950 to 1980, balanced by an offsetting drop in "miscellaneous service occupations." This consistency issue affects comparisons at this very disaggregated level only, and does not contaminate the overall measure of service occupation employment.

2005 (after food service and janitorial services), their growth is not strongly predicted by routine task-intensity. Plausibly, rising demand for healthcare support services derives from other sources, particularly the aging of the US population.

Complementing these results for occupations, Table 7 estimates equation (4.3) for four demographic sub-groups of non-college workers. Consistent with expectations, the relationship between the *RS* and rising service employment is largest for females and foreign-born workers. It is also positive and significant for males and US-born workers.

4.3 Changes in service employment in matched commuting zones

While our main findings are highly robust to inclusion of various controls and to numerous cuts of the data, it remains the case that the results derive from a comparison of commuting zones that differ initially on numerous observable dimensions. As a further means to maximize the validity of comparisons across commuting zones, we matched commuting zones on their *expected* routine employment share and then use only unexpected (residual) variation in the routine share to predict growth in service employment. To implement this test, we first regress the routine share measure in 1980 on all of covariates used above:

$$RS_{j,1980} = \alpha + \beta \cdot X_{j,1980} + \gamma_s + e_{j,1980}. \tag{4.4}$$

The explanatory power of this model is quite high, as shown in Appendix Table 4, yielding an R-squared of 0.83. One might legitimately suspect that the unexplained variation remaining in RS would not therefore be predictive of subsequent changes in service occupation employment.

We test this proposition by grouping the 722 commuting zones into evenly sized terciles based on their *predicted* routine share in 1980, $\widehat{RS}_{j,1980}$, from the model above. We then regress commuting zone level changes in service employment over 1980 through 2005 within each tercile of predicted routine-share on the unexplained component of routine-employment, $\widetilde{RS}_{j,1980} = RS_{j,1980} - \widehat{RS}_{j,1980}$:

$$\Delta SVC_{j\tau} = \alpha_\tau + \lambda \cdot \widetilde{RS}_{j,1980} + \omega_{j\tau}. \tag{4.5}$$

Estimates in Table 8 demonstrate a remarkably consistent pattern: the *unexplained* component of routine employment specialization in 1980 is strongly predictive of subsequent growth in service employment within commuting zones. Point estimates for λ are comparable in magnitude across all three terciles, and are significant in two of three cases. These results again underscore that initial occupational specialization predicts subsequent changes in labor market outcomes that are not otherwise predicted by measures of skill supply, industrial structure, or demographic composition.

4.4 Testing alternative demand-side explanations

Growing employment in low-skilled service jobs could also arise from two other demand-side forces noted in the Introduction: rising high incomes, which may generate additional demand for outputs of service occupations if they produce luxury goods; and rising market returns to skill, which may spur high skill workers to increase their labor supply and purchase additional household services to compensate for foregone household production.

We explore the evidence for these income and substitution effects by augmenting the baseline regression model for 1980 through 2005 with two additional measures. To proxy for wage structure shifts that may generate income effects, we control for changes in the 90th percentile of the log weekly wage distribution among full-time, full-year workers in each commuting zone.[39] To measure the evolving market participation of high-skilled workers, we control for changes in mean annual hours worked by college-graduates in each commuting zone. These outcomes are, as expected, strongly predicted by the initial routine-share variable, $RS_{j,1980}$. High wages and high-skilled hours rose by significantly more over 1980 through 2005 in commuting zones that were initially specialized in routine-intensive employment.[40]

Somewhat surprisingly, estimates in Table 9 find that these proxies for income and substitution effects are not strong correlates of changes in service employment. Growth in the 90th percentile weekly wage is only weakly correlated with rising service employment, and this relationship turns negative when the RS variable is added. Annual hours worked by college graduates are *negatively* related to service employment growth, and this pattern is true whether we measure college labor labor overall or separately by gender. Moreover, the routine share measure remains in all cases highly predictive of rising service employment, and is essentially unaffected by inclusion of these controls.

In summary, the results in Tables 4 through 9 provide robust support for a key prediction of the conceptual model: geographic areas that were specialized in routine-intensive occupations prior to the era of rapid computerization experienced significantly greater growth of service employment in the ensuing decades. This predictive relationship is pervasive across categories of service work, and affects employment trends among different groups non-college workers, i.e., male and female, foreign and US-born. The link between the routine employment share and rising service employment does not take hold until the 1980s, and it accelerates in the two subsequent decades. Most notably, this simple measure of occupational structure appears to capture a significant dimension of local economic activity that is not well measured by a host of other labor supply, labor demand, and demographic proxies, including education, immigration, unemployment, female labor force participation, and population aging, as well as proxies for other demand-side forces.[41] Subsequent sections

[39] This is arguably the best proxy of the market price of 'high' skills available from the Census data since it captures the wage commanded by workers with strong labor force attachment. Other wage measures yield similar results but have lower explanatory power.

[40] A table of results is available from the authors.

[41] With sufficient degrees of freedom, it would clearly be feasible to construct a multivariate index of occupational

explore further predictions of the model, using the RS measure as a key predictive variable.

5 Task specialization, computer adoption, and wage inequality

Our conceptual model makes four further predictions about the relationship between initial specialization in routine occupations and subsequent commuting zone level outcomes. First, displacement of routine labor input should lead to shifts in job specialization, as workers—particularly the less-educated—move out of routine-intensive occupations. Second, computer adoption should be more extensive in these regions, since higher routine task-intensity implies greater demand for computer capital. Third, changing task prices should spur rises in earnings inequality—particularly in the upper-half of the distribution—as the abstract task price rises relative to the routine task price. Finally, wages in service occupations may rise relative to other activities performed by less skilled workers in the same commuting zones if goods and services are complements in consumption. As noted in section (2), the 'price' implications of our model are less robust than the 'quantity' implications since they hinge on imperfect arbitrage on wage rates across commuting zones. Thus, the third and fourth implications appear less clear cut.

5.1 Task specialization

Our conceptual framework implies that the differential rise in service employment evident in routine task-intensive regions is one manifestation of a general phenomenon of shifts in task specialization away from routine-intensive labor. We test this implication by estimating a variant of equation (4.3) in which the dependent variable is the *change* in the routine employment share within a commuting zone, both overall and within broad education categories. Table 10 shows that during the 1980 to 2005 period, commuting zones with high routine employment shares occupations saw larger declines in routine-intensive employment—a relationship that is robust to the full set of contemporaneous labor market and demographic controls used in prior models (column 2). In particular, the coefficient of 0.082 in column 1 indicates that the 80th percentile commuting zone experienced about 0.8 percentage points larger a fall in routine employment per decade than the 20th percentile commuting zone (a 2.0 percentage point differential over 25 years). Given an aggregate decline of 1.6 percentage points in employment shares in routine-intensive occupations in this period, this magnitude is sizable. Notably, there is a negative significant relationship between start of period RS and movements out of routine-intensive occupations even prior to the 1980s. But the magnitude of this relationship increases by more than 50 percent during the post-1980 period.

Subsequent panels of Table 10 examine this relationship separately for college and non-college workers. The decline in routine task-intensive employment for college workers in high RS com-

structure that is more predictive of subsequent changes in commuting zone characteristics—and in particular the growth of service employment—over 1980 through 2005. A complete set of occupation dummies would, for example, absorb all variation in RS.

muting zones commences prior to the 1980s, and does not accelerate thereafter. By contrast, the differential rate of decline in routine-intensive employment among non-college workers more than doubles after 1980. Consonant with the conceptual model, the recent movement out of routine-intensive occupations is concentrated among less educated workers.[42]

5.2 Computer adoption

The conceptual model unambiguously predicts that the decline in routine *labor* input within commuting zones should be accompanied by the adoption of information technology (which substitutes for routine labor)—and that this process should be more pronounced in areas initially specialized in routine occupations. We test this implication using a measure of geographic computer penetration developed by Doms and Lewis (2006). Based on private sector survey data on computer inventories, these data measure the number of personal computers per employee at the firm level. Doms and Lewis aggregate this variable to the level of Metropolitan Statistical Areas (MSAs) and purge it of industry by establishment-size effects using a linear regression model.[43] We use the Doms and Lewis 'adjusted computers-per-worker' measure for the years 1990 and 2002, which we match to commuting zones.[44] Following the approach of Doms, Dunne and Troske (1997), we treat the 1990 level of this variable as the 'change' from 1980 to 1990 (thus assuming that the level was close to zero in all areas in 1980). We measure the change in this variable over the subsequent decade using 5/6 of the 1990 to 2002 first-difference.[45]

We estimate models predicting computer adoption (PCs per worker) across commuting zones of the following form:

$$\Delta C_{js\tau} = \alpha + \beta_{1\tau} \times RS_{jst} + \beta_{2\tau} \Delta X_{js\tau} + \gamma_s + e_{js\tau}, \tag{5.1}$$

where the dependent variable is the Doms-Lewis measure of computer adoption over time interval τ in commuting zone j in state s, RS_{jst} is the start of period routine task index, and $X_{sj\tau}$ is a vector of contemporaneous controls. The first two columns of Table 11 present separate, by-decade OLS regressions of commuting zone computer adoption during the 1980s and 1990s on the RS measure, state dummies and a constant. The RS has substantial predictive power for computer adoption in both decades (with t-ratios well over 9). The implied difference in computer adoption between the 80th and 20th percentile commuting zone is larger than one full standard deviation of the computer adoption measure in each decade.

[42] Michaels (2007) finds that clerical occupations demanded highly educated labor at the start of the twentieth century. But by the 1950s, these were no longer elite occupations. The results in Table 8 likely reflect the fact that the movement of highly-educated labor out of routine occupations was well underway before the computer era.

[43] The variable is not adjusted for the educational or occupational composition of MSAs.

[44] Approximately 50 of the 722 commuting zones do not have corresponding computer adoption data and so are dropped from the analysis.

[45] The level of the PC-per-worker measure is not readily interpretable because it is 'residualized,' as above. The cross commuting zone standard deviation of this variable is 0.048 for the 1980 to 1990 change and 0.053 for the 1990 to 2000 change.

Subsequent columns of Table 11 probe the robustness of this relationship by regressing the stacked decadal changes in computer adoption on initial RS and the full set of contemporaneous labor force and demographic change variables used earlier. Surprisingly, all of these covariates are significant predictors of computer adoption in this time period. The RS measure is nevertheless highly robust to their inclusion; with these variables added, its magnitude drops by less than a third and the t-ratio remains above nine. Thus, even accounting for contemporaneous changes in key labor market and demographic variables, it is apparent that commuting zones that were initially specialized in routine occupations adopted computer technology at a differentially rapid rate over the subsequent two decades—presumably to substitute physical capital for human capital in performing routine tasks.

5.3 Wage inequality

We finally explore the relationship between task specialization and wage inequality. The analysis first examines the relationship between a commuting zones's routine share and the evolution of aggregate wage inequality—in particular, earnings polarization—as measured by the 90/50 and 50/10 log wage ratios. We next turn to microdata to provide a tightly controlled analysis of changes in wage structure between occupations within commuting zones, holding constant all observable determinants of earnings.

5.3.1 Aggregate wage structure

We estimate stacked first-difference regressions for changes in wage inequality within commuting zones, as measured by the 90/10, 90/50 or 50/10 log weekly wage ratio for full-time, full-year workers. Following the format of earlier equations, all models include the start-of-period RS, and a full set of state and time dummies, with alternate specifications containing the full set of labor market and demographic controls used above.

These estimates in Table 12 reveal a striking pattern: commuting zones with a greater routine employment share in 1980 saw a large, differential *polarization* of earnings in the subsequent 25 years. In particular, upper-tail (90/50) inequality rose and lower-tail (50/10) inequality fell in high-RS regions during the 1980-2005 period relative to earlier trends. These relationships are economically large.[46] They are either substantially smaller or of opposite sign in the prior three decades. Thus, the wage polarization seen in economy-wide data for this period is replicated in commuting zones experiencing rapid displacement of routine work.

[46] To benchmark magnitudes, note that the predicted differential rise (fall) in the 90/50 (50/10) wage differential in the 75th relative to the 25th percentile commuting zone (ranked by 1980 RTI) is 3.0 (-4.3) log points over 1980 through 2005. The contemporaneous weighted mean within-CZ rise in 90/50 (50/10) inequality in this period is 12.0 (5.6) log points (Table 10).

5.3.2 Evidence from microdata

Do these patterns of aggregate wage structure change affecting commuting zones specialized in routine employment primarily reflect *compositional* shifts in worker characteristics and occupational characteristics—or, instead, changes in the wage paid to given worker characteristics within a geographic area? To develop a more precise answer to this question, we next turn to microdata on earnings.

Pooling microdata on real log hourly wages from the 1980 Census and the 2005 American Community Survey, we run a set of standard log wage equations augmented with time dummies, commuting-zone dummies, a full set of person-level covariates interacted with time dummies, and an interaction between the start-of-period routine employment share and the 2005 dummy. These models are estimated separately for each of the six major occupation categories discussed in the Introduction (ranging from Professional to Service, see Table 1). In particular, we estimate by OLS:

$$\begin{aligned} \ln w_{ijkt} &= \alpha_k + \beta_{1k} RS_{j,t-1} + \beta_{2k} \{RS_{j,t-1} \times I[t \geq 1980]\} \\ &\quad + X'_{ijkt}\beta_{kt} + \delta_{tk} + \gamma_{jk} + e_{ijkt}, \end{aligned} \tag{5.2}$$

where i denotes workers, j denotes commuting zones, t denotes times (1980, 2005) and k denotes occupation. To account for the fact that the main predictive variable, RS, varies only on the commuting zone level and, moreover, that wage levels are not independent among workers in nearby locations, the standard errors of these estimates are clustered at the state by year level. Results are displayed in Table 13.

The first two columns of Table 13 show that commuting zones with a higher routine employment share in 1980 saw large, real wage increases among workers in highly educated ('abstract') occupations between 1980 and 2005. A 10 percentage point larger routine share in 1980 predicts 6.5 log points greater wage growth in managerial and professional occupations and 9.2 log points greater wage growth in technical, sales and administrative occupations (both for males) over these two decades. Effects for females are somewhat larger in professional occupations and smaller in administrative occupations.

Columns 3 and 4 estimate analogous wage models for workers in production and operative occupations—roughly corresponding to middle-skill ('routine') occupations in our conceptual framework. Opposite to the pattern for highly-skilled occupations, a higher routine share of employment in 1980 predicts significant real wage declines in these occupations: a 10 percentage point routine share in 1980 predicts 2.5 to 8.1 log point declines in wages.[47]

Column 5 presents wage estimates for workers in service occupations.[48] Distinct from other

[47]While the precision of the point estimate for wages of females in production occupations is low, the table also makes evident that there are only 10 percent as many females as males in production occupations, whereas there are 40 percent as many females as males in operative occupations.

[48]We do not include wage estimates for farm occupations since a large share of farm labor is undocumented and

low-education occupations (i.e., production workers and operatives), the relationship between initial routine task share and service wages is small in magnitude and generally weakly positive. When wages in service occupations are directly compared to those in productive and operative positions in column 6, relative wage growth in service occupations is found to be greater in routine-occupation intensive commuting zones.

The second row of each panel of Table 13 re-estimates these models, augmented with a full set of person-level demographic controls including nine dummies for years of education, a quartic in potential experience, and dummies for married, non-white and foreign-born. These covariates are further interacted with time dummies to allow their slopes to differ by period. The pattern of results is only modestly affected by the inclusion of these additional variables. Estimates for high-skilled occupations are essentially unaffected. Estimates for middle-skilled occupations become less negative, indicating that part of the negative wage relationship is due to adverse changes in skill composition in these occupations in initially routine-intensive commuting zones. Finally, the estimates for service occupation wages become substantially more positive (and significantly so for females) when these controls are added, suggesting that compositional shifts may mask *rising* real wages in these occupations.[49]

Reinforcing the earlier results for 90/50 and 50/10 wage inequality, these microdata estimates confirm that commuting zones that were previously specialized in routine jobs saw a distinct pattern of polarizing wage growth among occupations over the subsequent 25 years, with strongly rising wages in high-skill occupations, declining wages in moderately-skilled occupations, and stable wages in low-skill service occupations. Thus, the data clearly support the prediction that displacement of routine tasks within commuting zones is accompanied by growth in both service employment and service wages. What makes this finding particularly compelling is that service occupations are the only low-skill job category that appear to benefit from this process.

6 Conclusions

While the past 25 years have seen declining or stagnating real (and relative) earnings and employment of less educated workers, employment in low-skill service occupations presents a striking exception. Between 1980 and 2005, the share of hours worked in service occupations among those with high school or lower education rose by more than 50 percent. Simultaneously, real hourly wages in service occupations increased by 20 log points, considerably exceeding wage growth in other low-skill occupations. In fact, the upward twist of the lower-tail of the U.S. earnings and job distributions that took form during the 1990s is substantially accounted for by rising employment and wages in service occupations.

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hence we expect that earnings self-reports in the Census are unreliable.

[49]At a minimum, these results make it appear unlikely that the rising relative wages of service occupations relative to other low-education occupations seen in Table 11 is driven by selection of relatively skilled workers into service jobs.

We offer a hypothesis for the rising demand for service work based on changes in task specialization induced in part by technical change. Our conceptual framework builds from the observation that the primary job tasks of service occupations are difficult to either automate or outsource since these tasks require interpersonal and environmental adaptability as well as direct physical proximity. Our conceptual model shows that if the demand for the outputs of service occupations does not admit close substitutes, the substitution of information technology for routine tasks used in goods production may, in the long run, lead to rising wages and employment in service occupations.

Motivated by the observation that workers in service occupations must collocate with demanders of their services, we study the determinants of employment and wages in services during 1950 through 2005 in 722 consistently defined commuting zones covering all of US mainland employment. The analysis contrasts the period 1980 to 2005 during which a rapid adoption of information technology took place with a previous period from 1950 to 1980. We use an empirical approach built on the theoretical model, which predicts that, if commuting zones differ initially in the share of employment in routine-intensive occupations, markets with higher routine shares will see larger increases in service occupation employment and greater polarization of earnings between high and middle-skill workers as time advances. If goods and services are sufficiently complementary, the model further implies that wages in service occupations will rise along with service employment.

We explore these predictions using a simple measure of initial specialization in routine-task-intensive employment based on the occupational structure of commuting zones at the start of the sample period. This measure proves strikingly predictive of the changes in task and wage structure implied by the model: reallocation of labor activity from routine tasks; employment growth in low-skilled service occupations; differential adoption of information technology; and polarization of earnings growth. Thus, the changes in task structure that we document accompany growth in wages at the tails of the distribution but not elsewhere.

These findings reveal a process of employment and wage polarization within regional labor markets that parallels the polarization of employment seen at the aggregate level in the US, UK and West Germany. In net, our results suggest an important role for changes in labor specialization—potentially spurred by displacement of routine task activities—as a driver of rising employment and wages in service occupations, and of polarization of employment and wage growth more generally.

References

Acemoglu, Daron. 1999. "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence." *American Economic Review*, 89 (December), 1259-1278.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review*, 96:2 (May), 189-194.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*. 90(2), May, 300-323.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Investigation." *Quarterly Journal of Economics*, 118(3), November, 1279-1333.

Baumol, William J. 1967. "Macroeconomics of Unbalanced Growth: Anatomy of an Urban Crisis." *American Economic Review*, 57(3), June, 415-426.

Beaudry, Paul and David A. Green. 2003. "Wages and Employment in the United States and Germany: What Explains the Differences?" *American Economic Review*, 93(3), 573-602.

Beaudry, Paul, Mark Doms, and Ethan Lewis. 2006. "Endogenous Skill Bias in Technology Adoption. City-Level Evidence from the IT Revolution." NBER Working Paper 12521, September.

Blanchard, Olivier Jean and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1), 1-75.

Clark, Colin. 1957. *The Conditions of Economic Progress*. London: Macmillan.

Cortes, Patricia. 2008. "The Effect of Low-Skilled Immigration on US Prices: Evidence from CPI Data," *Journal of Political Economy*, 116(3), 381-422.

DiNardo, John E., Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64(5), 1001-1044.

Doms, Mark E., Timothy Dunne, and Kenneth R. Troske. 1997. "Workers, Wages, and Technology." *Quarterly Journal of Economics*, 112(1), 253-290.

Doms, Mark E. and Ethan G. Lewis. 2006. "Labor Supply and Personal Computer Adoption." Federal Reserve Bank of Philadelphia Working Paper No. 06-10, June.

Dustmann, Christian, Johannes Ludsteck and Uta Schönberg. 2007. "Revisiting the German Wage Structure." Mimeograph, University of Rochester, February.

Glaeser, Edward L. and Josephy Gyourko. 2005. "Urban Decline and Durable Housing." *Journal of Political Economy*, 113(2), 345-375.

Goos, Maarten and Alan Manning. 2003. "Lousy and Lovely Jobs: The Rising Polarisation of Work in Britain." CEPR Working Paper No. 0604, December.

Goos, Maarten and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *Review of Economics and Statistics* 89 (February), 118-33.

Harrison, Bennett and Barry Bluestone. 1988. *The Great U-turn : Corporate Restructuring and the Polarizing of America*. New York: Basic Books.

Hecker, Daniel E. 2005. "Occupational Employment Projections to 2014." *Monthly Labor Review*, 128(11): 70-101.

Jaeger. David A., Susanna Loeb, Sarah E. Turner and John Bound. 1998. "Coding Geographic Areas across Census Years: Creating Consistent Definitions of Metropolitan Areas." NBER Working Paper W6772, October.

Manning, Alan. 2004. "We Can Work it Out: the Impact of Technological Change on the Demand for Low-Skill Workers." *Scottish Journal of Political Economy*, 51(5), November, 581-608.

Mazzolari, Francesca and Giuseppe Ragusa. 2008. "Spillovers from High-Skill Consumption to Low-Skill Labor Markets." Mimeograph, University of California at Irvine, May.

Meyer, Peter B. and Anastasiya M. Osborne. 2005. "Proposed Category System for 1960-2000 Census Occupations. *Bureau of Labor Statistics Working Paper* 383, September.

Michaels, Guy. 2007. "The Division of Labor, Coordination, and the Demand for Information Processing." CEPR Working Paper DP 6358, June.

Ngai, L. Rachel and Christopher Pissarides. 2007. "Structural Change in a Multisector Model of Growth." *American Economic Review*, 97(1), March, 429-443.

Oliner, Stephen D. and Daniel E. Sichel. 2000. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives,* 14(4), Fall, 3-22.

Peri, Giovanni and Chad Sparber. 2007. "Task Specialization, Comparative Advantages and the Effects of Immigration on Wages." Mimeograph, University of California at Davis, July.

Pinker, Steven. 2007. *The Stuff of Thought: Language as a Window into Human Nature.* New York: Viking Adult (Penguin).

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2004. *Integrated Public Use Microdata Series: Version 3.0* [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

Smith, Christopher L. 2008. "Implications of Adult Labor Market Polarization for Youth Employment Opportunities." MIT working paper, July 2008.

Spitz-Oener, Alexandra. 2006. "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure." *Journal of Labor Economics* 24 (April), 235-70.

Tolbert, Charles M. and Molly Sizer Killian. 1987. "Labor Market Areas for the United States." Staff Report No. AGES870721. Washington, DC: Economic Research Service, US Department of Agriculture.

Tolbert, Charles M. and Molly Sizer. 1996. "U.S. Commuting Zones and Labor Market Areas. A 1990 Update." Economic Research Service Staff Paper No. 9614.

Topel, Robert H. 1986. "Local Labor Markets." *Journal of Political Economy*, 94(3), 111-143.

U. S. Department of Labor, Employment and Training Administration. 1977. *Dictionary of Occupational Titles: Fourth Edition* (Washington, DC: US Government Printing Office).

Weiss, Matthias. 2008. "Skill-biased Technical Change: Is There Hope for the Unskilled?" *Economics Letters*, 100(3), September, 439-441.

Theory appendix

Here we derive the solution to the model for a case where L_r and K are complements ($\mu < 1$). Note that we have $K(t) \to \infty$, so

$$\lim_{t\to\infty} \left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu} = (1-\lambda)^{\beta/\mu}(\alpha_r L_r^*)^{\beta}. \tag{6.1}$$

Consequently,

$$\begin{aligned}
\lim_{t\to\infty} F\left(1, g\left(L_m(t)\right), t\right) &= \lim_{t\to\infty}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k K(t)\right)^{\mu}\right]^{\beta/\mu} - \theta e^{-\delta t} K(t) \\
&\leq \lim_{t\to\infty}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k K(t)\right)^{\mu}\right]^{\beta/\mu} \\
&= (1-\lambda)^{\beta/\mu}\left(\alpha_r g\left(L_m^*\right)\right)^{\beta}
\end{aligned} \tag{6.2}$$

Moreover, since $K(t)$ solves Eq. (2.17), it does better than an arbitrary choice for the capital function. In particular, it does better than $\tilde{K}(t) = t$. Then, we have

$$\begin{aligned}
\lim_{t\to\infty} F\left(1, g\left(L_m(t)\right), t\right) &\geq \lim_{t\to\infty}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k \tilde{K}(t)\right)^{\mu}\right]^{\beta/\mu} - \theta e^{-\delta t} \tilde{K}(t) \\
&= \lim_{t\to\infty}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k \tilde{K}(t)\right)^{\mu}\right]^{\beta/\mu} \\
&= (1-\lambda)^{\beta/\mu}\left(\alpha_r g\left(L_m^*\right)\right)^{\beta}.
\end{aligned} \tag{6.3}$$

Combining Eqs. (6.2) and (6.3), we have

$$\lim_{t\to\infty} F\left(1, g\left(L_m(t)\right), t\right) = (1-\lambda)^{\beta/\mu}\left(\alpha_r g\left(L_m^*\right)\right)^{\beta}. \tag{6.4}$$

In words, since L_r and K are gross complements and K grows, in the limit $L_r(t) = g\left(L_m(t)\right)$ becomes the bottleneck and determines the production.

Next consider

$$\frac{dF\left(1, g\left(L_m(t)\right), t\right)}{dL_r(t)} = \beta(1-\lambda)\alpha_r^{\mu} L_r(t)^{\mu-1}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k K(t)\right)^{\mu}\right]^{(\beta-\mu)/\mu} \tag{6.5}$$

Since $K(t) \to \infty$, taking the limit of this expression yields

$$\lim_{t\to\infty} \frac{dF\left(1, g\left(L_m(t)\right), t\right)}{dL_r(t)} = \beta(1-\lambda)^{\beta/\mu}\alpha_r^{\beta} g\left(L_m^*\right)^{\beta-1}. \tag{6.6}$$

Taking the limit of Eq. (2.24) and plugging in Eqs. (6.4) and (6.6), we have

$$\left[(1-\lambda)^{\beta/\mu}\left(\alpha_r g\left(L_m^*\right)\right)^{\beta}\right]^{1/\sigma_c} = -{L_m^*}^{1/\sigma_c}\log\left(1-L_m^*\right)\beta(1-\lambda)^{\beta/\mu}\alpha_r^{\beta} g\left(L_m^*\right)^{\beta-1}. \tag{6.7}$$

The equilibrium level of L_m^* in the limit is the solution to the previous equation, which will be in the interval $(0,1)$.

Moreover, in this case we have

$$p_s \to p_s^*,\ w_m \to w_m^*,\ w_r \to w_r^*,\ w_a \to w_a^*,\ \eta \to \eta^*,$$

i.e. all variables converge to a finite constant. Intuitively, in this case machines and routine labor are gross complements so technological progress is not sufficient to increase output beyond a finite limit (since routine labor becomes the bottleneck). Consequently, the price of services and hence the wage for the manual labor also remain constant. The wage for routine labor remains constant since the routine labor is the bottleneck so there is still value to routine tasks. The abstract wage is also constant since the abstract workers receive a constant share of output, which is constant.

In this case, $w_a(t)/w_m(t)$ ratio also goes to a constant w_a^*/w_m^* regardless of σ_c, in contrast with the conjecture. We summarize our results in the following proposition.

Proposition 3 *When $\mu < 0$, $\lim_{t\to\infty} L_m(t) = L_m^*$ where $L_m^* \in (0,1)$ is a solution to Eq. (6.7). In the limit, unskilled labor works in both manual and routine tasks and the wages limit to finite levels*

$$w_m \to w_m^*,\ w_r \to w_r^*,\ w_a \to w_a^*.$$

Figure 1a

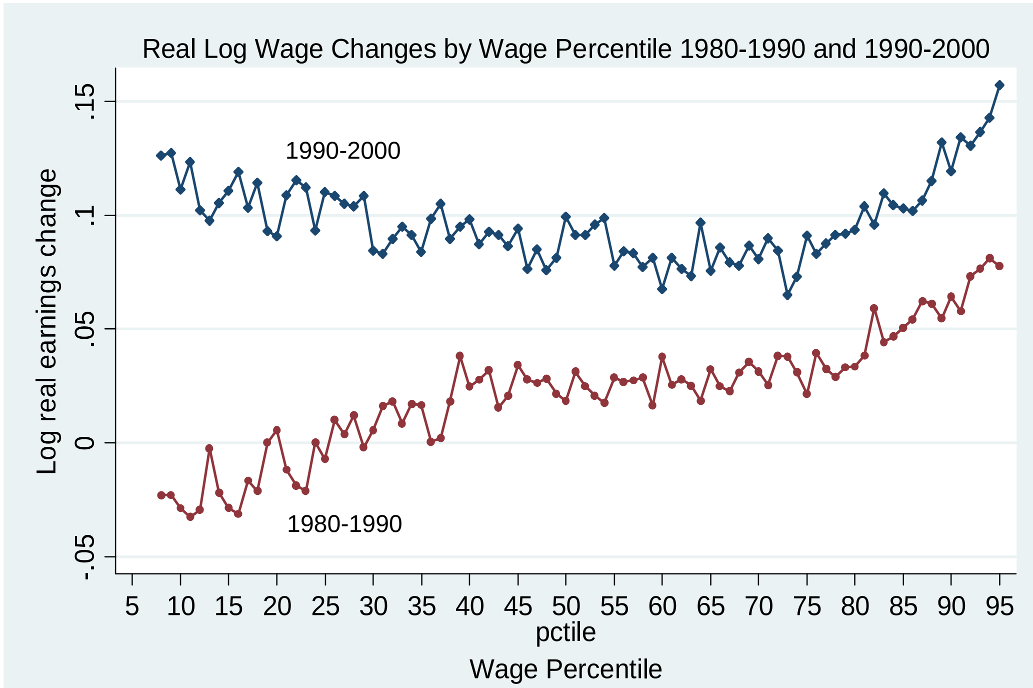

Figure 1b

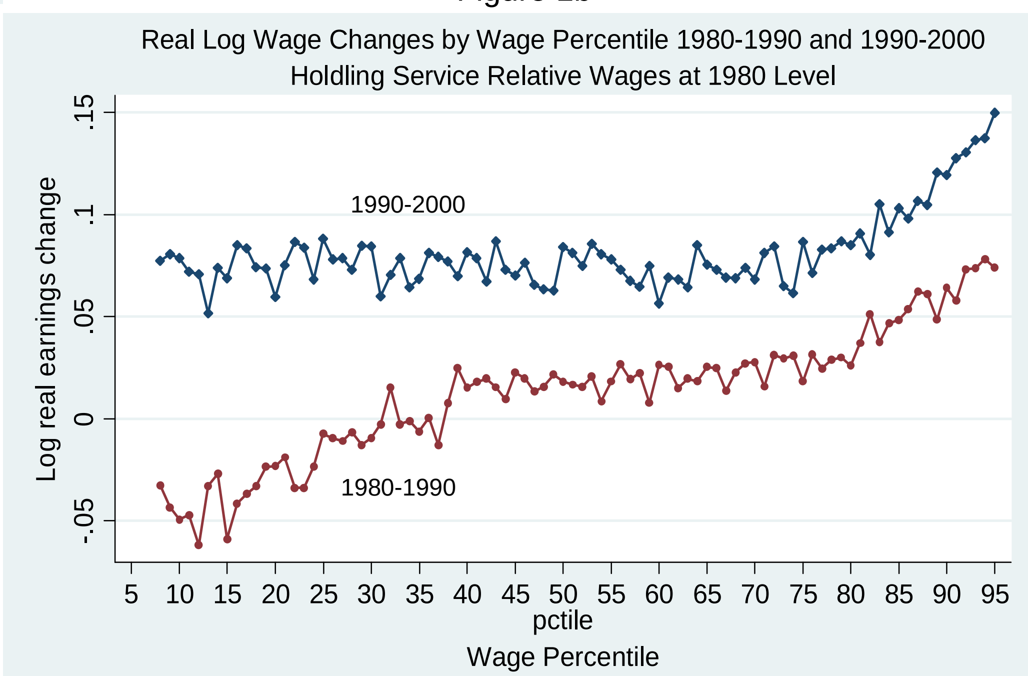

Figure 2a

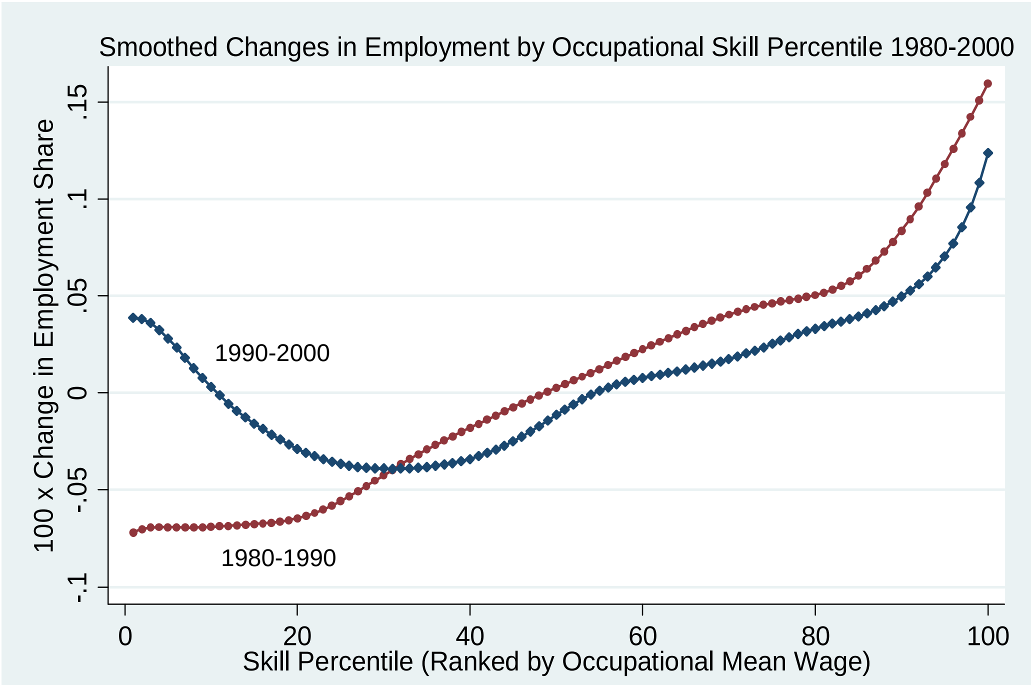

Figure 2b

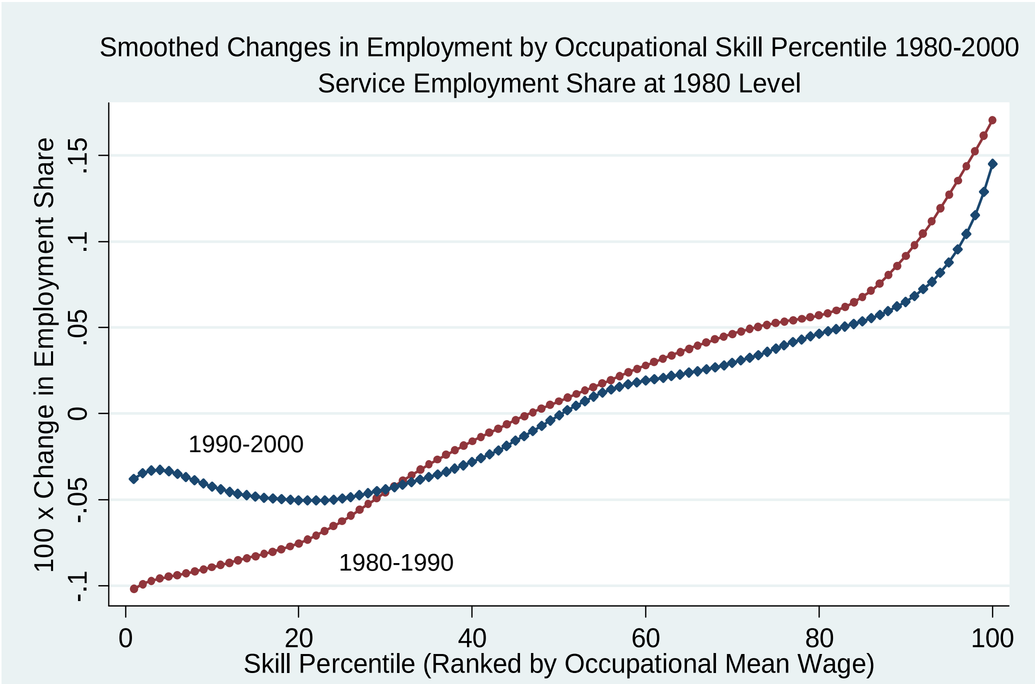

Figure 3a

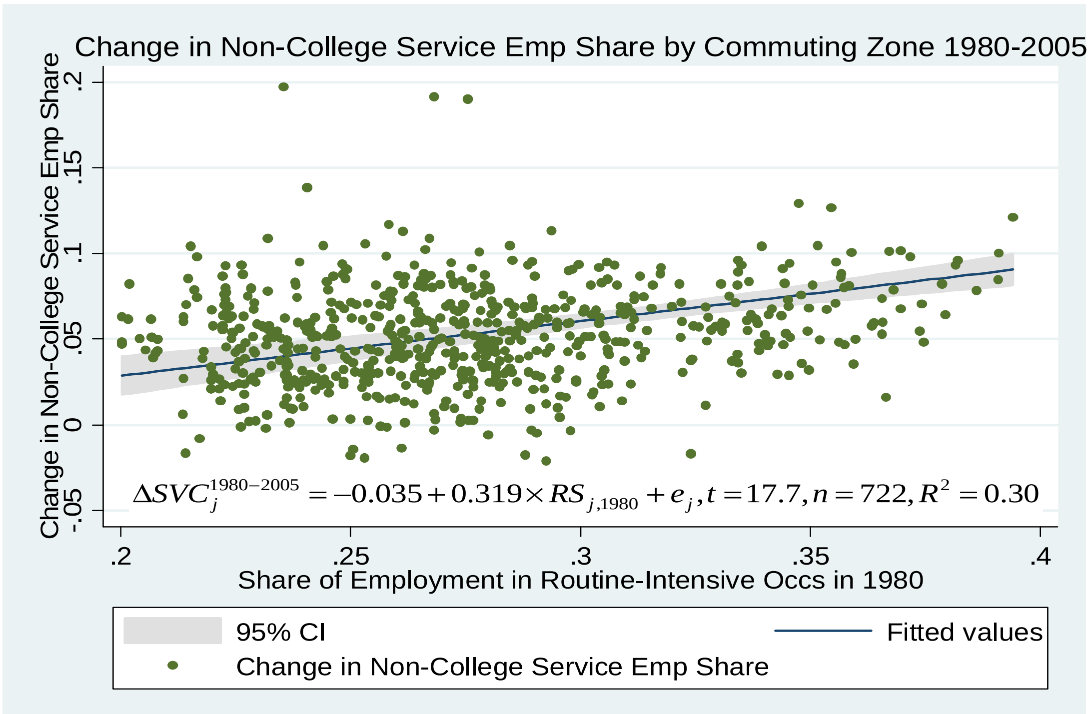

Figure 3b

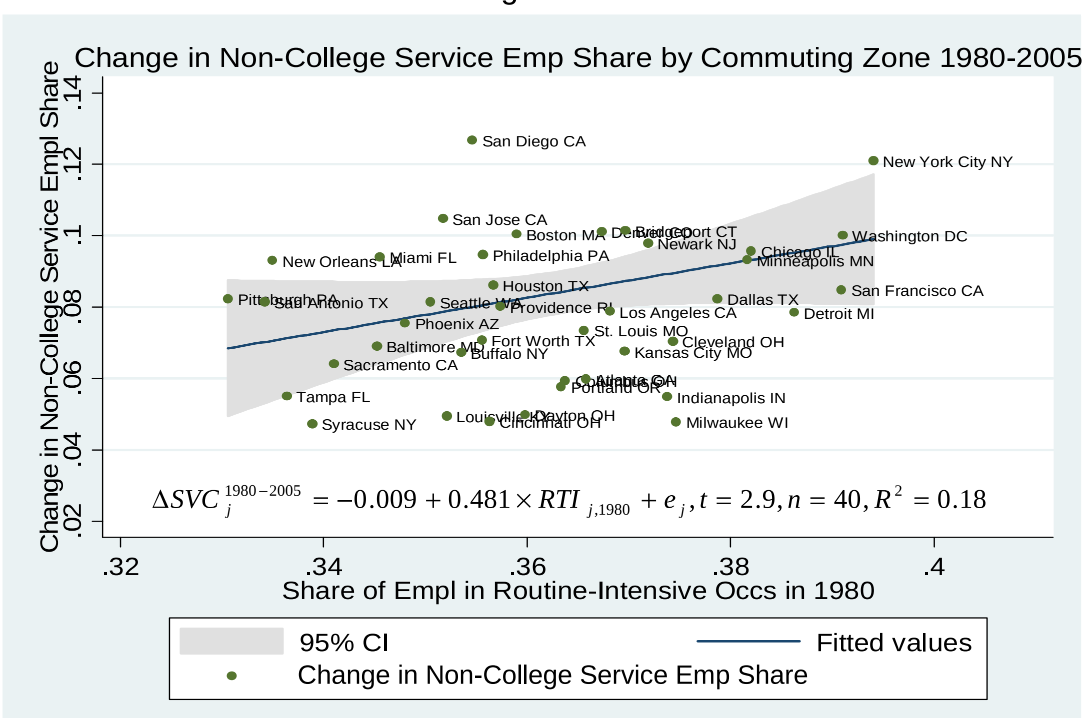

Table 1. Levels and Changes in Employment Share and Mean Real Hourly Wages by Occupation, 1950-2005

	Level						Decadal Growth Rate (%)	
	1950	1970	1980	1990	2000	2005	1950-80	1980-05
			A. Share of Employment (%)					
Managers/Professionals	20.8	21.5	23.8	27.8	30.0	30.9	4.6	10.4
Technicians/Sales/Admin	21.7	26.6	28.9	30.8	29.6	29.0	10.0	0.6
Production/Craft/Repair	13.3	13.9	14.3	12.4	12.1	11.6	2.5	-7.3
Operators/Fabricat/Laborers	22.8	22.6	19.2	15.4	13.9	13.0	-5.5	-13.3
Farming/Fishery/Forestry	10.7	3.8	2.8	1.8	1.3	1.3	-36.3	-24.8
Service Occupations	11.4	11.7	11.0	11.8	13.0	14.3	-1.1	8.9
			B. Mean Real Log Hourly Wage (2005$)					
Managers/Professionals	2.24	2.89	2.87	2.94	3.05	3.16	23.4	9.9
Technicians/Sales/Admin	2.00	2.49	2.48	2.53	2.64	2.72	17.3	8.6
Production/Craft/Repair	2.21	2.71	2.73	2.69	2.73	2.75	19.1	0.1
Operators/Fabricat/Laborers	2.00	2.46	2.49	2.45	2.52	2.53	17.9	1.4
Farming/Fishery/Forestry	1.10	1.77	2.00	2.05	2.15	2.17	34.7	6.7
Service Occupations	1.50	2.09	2.17	2.22	2.33	2.34	24.8	7.0

Source: Census 1% samples for 1950 and 1970; Census 5% samples for 1980, 1990, 2000; American Community Survey 2005. Sample includes persons who were aged 18-64 and working in the prior year. Occupation categories are defined according to the Census 2000 classification. Hourly wages are defined as yearly wage and salary income divided by the product of weeks worked times usual weekly hours. Employment share is defined as share in total hours worked. Labor supply is measured as weeks worked times usual weekly hours in prior year. All calculations use labor supply weights.

Table 2. Occupations with Highest and Lowest RTI Scores

A. Occupations with Highest RTI Scores	
1	Secretaries
2	Bank Tellers
3	Pharmacists
4	Payroll and Timekeeping Clerks
5	Stenographers
6	Motion Picture Projectionists *
7	Boilermakers
8	Butchers and Meat Cutters
9	Solderers
10	Accountants and Auditors
B. Occupations with Lowest RTI Scores	
1	Parking Lot Attendants
2	Fire Fighting, Prevention and Inspection *
3	Bus Drivers
4	Taxi Cab Drivers and Chauffeurs
5	Public Transportation Attendants and Inspectors *
6	Police, Detectives, and Private Investigators *
7	Materials Movers: Stevedores and Longshore Wks.
8	Truck, Delivery, and Tractor Drivers
9	Garbage and Recyclable Material Collectors
10	Crossing Guards *

Notes: * denotes service occupations according to Census 2000 classification. The Routine Task Index (RTI) measures the average log routine/manual task ratio for each detailled occupation. The ranking consists of 354 occupations, including 30 service occupations. For occupations with equal RTI score, the tie is split by giving a higher ranking to the occupation with largest share in total US employment in 1980. Residual occupations groups ("not elsewhere classified") are excluded.

Table 3. Levels and Changes in Standardized Task Measures, 1980-2005

	Standardized Task Score				Ten Times Average Annual Change			
	1980	1990	2000	2005	1980-1990	1990-2000	2000-2005	1980-2005
Abstract Tasks	0.00	0.60	1.10	1.35	0.60	0.51	0.49	0.54
	(1.00)	(1.17)	(1.31)	(1.36)				
Routine Tasks	0.00	-0.76	-1.67	-2.59	-0.76	-0.92	-1.83	-1.03
	(1.00)	(0.84)	(0.82)	(0.98)				
Manual Tasks	0.00	-0.33	-0.24	0.05	-0.33	0.08	0.59	0.02
	(1.00)	(0.91)	(0.83)	(0.91)				

n = 741 Commuting Zones in each decade, weighted by start of period commuting zone share of national population. Abstract, Routine and Manual task measures are based on the Dictionnary of Occupational Titles (DOT) and defined according to Autor-Levy-Murnane (2003). Task scores by commuting zones are standardized to a mean of zero and a standard deviation of one in 1980.

Table 4. Routine Employment Share and Growth of Service Employment within Commuting Zones, 1950 - 2005.
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	1950 - 1970		1970 - 1980		1980 - 1990		1990 - 2000		2000 - 2005	
Share of Routine Occs.$_{-1}$	-0.106	**	0.035		0.081	**	0.085	**	0.316	**
	(0.022)		(0.034)		(0.024)		0.037		(0.084)	
Constant	0.028	**	-0.031	**	-0.013	~	-0.003		-0.040	
	(0.003)		(0.009)		(0.007)		0.011		(0.026)	
State dummies	Yes		Yes		Yes		Yes		Yes	
R^2	0.483		0.435		0.535		0.5962		0.331	

N= 722 commuting zones. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 5a. Routine Employment Share and Growth of Service Employment within Commuting Zones, 1950 - 2005: Stacked First Differences.
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Share of Routine Occs.$_{-1}$ × 1980-05	0.169 **	0.158 **	0.087 **	0.138 **	0.153 **	0.080 **
	(0.027)	(0.026)	(0.022)	(0.024)	(0.027)	(0.018)
Share of Routine Occs.$_{-1}$	-0.018	-0.040 *	-0.048 **	-0.044 *	-0.043 *	-0.041 **
	(0.011)	(0.016)	(0.015)	(0.017)	(0.017)	(0.014)
Δ College/Non-college pop			0.017 **			0.022 **
			(0.005)			(0.005)
Δ Immigr/Non-college pop			0.102 **			0.097 **
			(0.032)			(0.032)
Δ Manufact/empl				-0.047 ~		-0.066 **
				(0.025)		(0.022)
Δ Unempl rate				0.323 **		0.400 **
				(0.044)		(0.049)
Δ Female empl/pop					-0.057 **	0.097 **
					(0.021)	(0.022)
Δ Age 65+/pop					0.090	0.202 **
					(0.054)	(0.049)
1970-1980 dummy	-0.014 **	-0.013 **	-0.018 **	-0.021 **	-0.011 *	-0.034 **
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
1980-1990 dummy	-0.039 **	-0.033 **	-0.019 **	-0.028 **	-0.030 **	-0.025 **
	(0.008)	(0.008)	(0.007)	(0.006)	(0.008)	(0.006)
1990-2000 dummy	-0.043 **	-0.037 **	-0.024 **	-0.030 **	-0.038 **	-0.016 **
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
2000-2005 dummy	-0.030 **	-0.024 **	-0.007	-0.028 **	-0.025 **	-0.009
	(0.008)	(0.008)	(0.008)	(0.006)	(0.008)	(0.006)
Constant	0.017 **	0.019 **	0.022 **	0.020 **	0.022 **	0.012 **
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
State dummies	No	Yes	Yes	Yes	Yes	Yes
R^2	0.345	0.373	0.392	0.425	0.378	0.452

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 5b. Routine Employment Share and Growth of Service Employment, 1950 - 2005: Stacked First Differences using Start-of-Period Controls.
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Share of Routine Occs.$_{-1}$ × 1980-05	0.169 **	0.158 **	0.122 **	0.115 **	0.165 **	0.093 **
	(0.027)	(0.026)	(0.021)	(0.023)	(0.020)	(0.014)
Share of Routine Occs.$_{-1}$	-0.018	-0.040 *	-0.051 *	-0.024 ~	0.014	0.045 *
	(0.011)	(0.016)	(0.021)	(0.014)	(0.020)	(0.022)
College/Non-college pop 1980			0.006			0.007
			(0.004)			(0.004)
Immigr/Non-college pop 1980			0.025 ~			0.008
			(0.014)			(0.014)
Manufact/empl 1980				-0.043 **		-0.024 **
				(0.010)		(0.007)
Unemployment rate 1980				-0.099 *		-0.280 **
				(0.042)		(0.066)
Female empl/pop 1980					-0.099 **	-0.153 **
					(0.028)	(0.028)
Age 65+/pop 1980					-0.054 ~	-0.042 ~
					(0.032)	(0.024)
1970-1980 dummy	-0.014 **	-0.013 **	-0.012 *	-0.012 **	-0.002	0.004
	(0.003)	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)
1980-1990 dummy	-0.039 **	-0.033 **	-0.022 **	-0.017 *	-0.016 ~	0.022 *
	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.009)
1990-2000 dummy	-0.043 **	-0.037 **	-0.029 **	-0.023 **	-0.011	0.028 *
	(0.007)	(0.007)	(0.005)	(0.007)	(0.009)	(0.011)
2000-2005 dummy	-0.030 **	-0.024 **	-0.020 **	-0.012	0.003	0.038 **
	(0.008)	(0.008)	(0.007)	(0.008)	(0.011)	(0.012)
Constant	0.017 **	0.019 **	0.020 **	0.030 **	0.040 **	0.063 **
	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.008)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.345	0.373	0.380	0.386	0.394	0.421

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 6. Routine Task Intensity and Growth of Employment in Detailled Service Occupations among Non-College Workers within Commuting Zones, 1950 - 2005: Stacked First Differences.
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Specific Service Occupation

	Food Service		Building Clean/ Garden		Health Support		House Clean/ Laundry		Child Care		Personal Appear-ance		Security Guards		Recreat-ion		Misc Personal Svcs	
	A. OLS Estimates																	
Share of Routine Occs.$_{-1}$ × 1980-05	0.054	**	0.033	**	0.005		0.010		0.015	*	0.021	**	0.005		0.012	**	0.003	
	(0.012)		(0.007)		(0.011)		(0.010)		(0.006)		(0.003)		(0.003)		(0.004)		(0.007)	
Share of Routine Occs.$_{-1}$	-0.005		0.005		-0.007	~	-0.004		-0.006	*	-0.005	**	0.005	*	-0.007	**	-0.015	*
	(0.006)		(0.004)		(0.004)		(0.006)		(0.003)		(0.002)		(0.002)		(0.002)		(0.006)	
Constant	0.009	**	0.005	**	0.007	**	0.004	**	0.003	**	0.001	**	-0.001		-0.001	*	-0.007	**
	(0.001)		(0.001)		(0.001)		(0.001)		0.000		0.000		0.000		0.000		(0.002)	
State dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.098		0.258		0.112		0.483		0.132		0.159		0.092		0.247		0.588	
	B. Share in Total Non-College Employment																	
Empl. share 1980	4.18%		3.11%		1.88%		1.41%		0.51%		0.75%		0.63%		0.15%		0.31%	
Empl. share 2005	6.55%		4.69%		3.04%		1.86%		1.00%		0.94%		0.88%		0.43%		0.44%	
Change 1980-2005	2.37%		1.58%		1.16%		0.45%		0.49%		0.19%		0.25%		0.28%		0.13%	

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 7. Routine Task Intensity and Growth of Service Employment among Non-College Workers by Gender and Nativity, 1950 - 2005: Stacked First Differences.

Dependent Variable: 10 × Annual Change in Share of Non-College

	Males		Females		US Borns		Foreign Borns	
Share of Routine Occs.$_{-1}$ × 1980-05	0.076	**	0.126	**	0.035	*	0.256	**
	(0.024)		(0.041)		(0.017)		(0.074)	
Share of Routine Occs.$_{-1}$	0.032		0.102	*	0.058	**	-0.019	
	(0.020)		(0.043)		(0.020)		(0.077)	
Constant	0.024	**	0.098	**	0.056	**	0.094	**
	(0.005)		(0.018)		(0.006)		(0.026)	
Control variables	Yes		Yes		Yes		Yes	
State dummies	Yes		Yes		Yes		Yes	
R^2	0.254		0.515		0.306		0.059	

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models include controls for start-of-period levels of college/non-college population, share of immigrants among non-college population, manufacturing share, unemployment rate, female labor force participation, and population share above age 65. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 8. Growth of Service Employment by Tercile of Predicted Routine Task Intensity, 1980 - 2005.
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	C'zones by Predicted 1980 Routine Share			
	All	Top 1/3	Middle 1/3	Bottom 1/3
Residual Share of Routine Occs.$_{-1}$	0.119 *	0.093	0.135 *	0.104 ~
	(0.053)	(0.066)	(0.061)	(0.062)
N	2,166	723	720	723
R^2	0.055	0.079	0.030	0.016

Predicted routine share is based on the predicted values from a regression of routine share on college/non-college population, share of immigrants among non-college population, manufacturing share, unemployment rate, female labor force participation, population share above age 65, and state dummies. Residual routine share equals the residuals of that regression. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population and contain a constant and time dummies. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 9. Predicting Changes in Service Occupation Employment using Proxies for Income and Substitution Effects, 1980 - 2005.

	Dep Var: Δ Non-Coll Emp in Service Occs					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Routine Occs$_{-1}$		0.137 **		0.134 **	0.139 **	0.121 **
		(0.024)		(0.025)	(0.025)	(0.023)
Δ ln(P90) Weekly Wage	0.014	-0.010				
	(0.015)	(0.015)				
Δ Avg Annual Hours per Coll Grad ÷ 2080			-0.091 **	-0.099 **		
			(0.034)	(0.034)		
Δ Avg Annual Hours per Male Coll Grad ÷ 2080					-0.049 *	
					(0.019)	
Δ Avg Annual Hours per Female Coll Grad ÷ 2080						-0.071 **
						(0.024)

N=2166 (3 time periods x 722 commuting zones). Robust SE's in parentheses are clustered on state. Models are weighted by commuting zones' share in total labor supply in a given year. All models include an intercept, state dummies, and time dummies . ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 10. Changes in Share of Routine Occupations within Commuting Zones, Overall and by Education Level, 1950 - 2005: Stacked First Differences.
Dependent Variable: 10 × Annual Change in Share of Employment in Routine Occupations

	All		College		Non-College	
	(1)		(2)		(3)	
Share of Routine Occs.$_{-1}$ × 1980-05	-0.082	**	-0.005		-0.179	**
	(0.017)		(0.026)		(0.025)	
Share of Routine Occs.$_{-1}$	-0.172	**	-0.190	**	-0.125	**
	(0.016)		(0.023)		(0.016)	
State dummies	Yes		Yes		Yes	
R^2	0.726		0.354		0.647	

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 11. Routine Employment Share and Computer Adoption 1980-2000. Dependent Variable: 'Adjusted PCs per Employee' (Doms and Lewis 2006)

	1980 - 1990		1990 - 2000		1980 - 2000			
	(1)		(2)		(3)		(4)	
Share of Routine Occs.$_{-1}$	0.722	**	0.529	**	0.667	**	0.661	**
	(0.051)		(0.056)		(0.034)		(0.061)	
College/Non-college pop 1980							0.003	
							(0.013)	
Immigr/Non-college pop 1980							-0.063	*
							(0.024)	
Manufact/empl 1980							-0.134	**
							(0.029)	
Unemployment rate 1980							-0.212	~
							(0.119)	
Female empl/pop 1980							-0.003	
							(0.050)	
Age 65+/pop 1980							0.05	
							(0.093)	
1990-2000 dummy					0.022	**	0.016	~
					(0.007)		(0.010)	
Constant	-0.296	**	-0.192	**	-0.268	**	-0.219	**
	(0.015)		(0.017)		(0.010)		-0.036	
State dummies	Yes		Yes		Yes		Yes	
R^2	0.656		0.378		0.457		0.495	
N	675		660		1335		1335	

The Doms-Lewis measure of computer adoption reflects the number of personal computers per employee, controlling for 950 industry/establishment interactions. Data for computer adoption in commuting zones is available to us for the years 1990 and 2002; we assume zero computers per worker in 1980 and use 5/6 of the change in computer adoption between 1990 and 2002 as our measure for computer adoption during the 1990s. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 12. Routine Employment Share and Changes in Wage Inequality, 1950 - 2005.
Dependent Variable: 10 × Annual Change in Wage Inequality

	P90/50				P50/10				P90/10			
	(1)		(2)		(3)		(4)		(5)		(6)	
	A. Mean Changes (10 × Annual Change)											
Years 1980-2005	0.049		(0.031)		0.022		(0.034)		0.071		(0.050)	
Years 1950-1980	0.031		(0.030)		-0.005		(0.075)		0.026		(0.088)	
	B. Regression Analysis											
Share of Routine	0.303	**	0.335	**	-0.431	**	-0.460	**	-0.128		-0.125	
Occs.$_{-1}$ × 1980-05	(0.063)		(0.062)		(0.116)		(0.097)		(0.121)		(0.101)	
Share of Routine	0.074	*	0.046		0.621	**	0.578	**	0.695	**	0.624	**
Occs.$_{-1}$	(0.029)		(0.040)		(0.069)		(0.091)		(0.080)		(0.102)	
Control variables	No		Yes		No		Yes		No		Yes	
State dummies	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.183		0.209		0.277		0.299		0.309		0.349	

N=3610 (5 time periods x 722 commuting zones). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Models with control variables include start-of-period levels of college/non-college population, share of immigrants among non-college population, manufacturing share, unemployment rate, female labor force participation, and population share above age 65. Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 13. Routine Employment Share and Wage Changes by Major Occupation, 1980 - 2005.
Dependent Variable: Log Real Hourly Wage.
Microdata Estimates using Pooled 1980/2005 Census and ACS Samples

	Manager / Prof'nl (1)	Tech / Sales / Admin (2)	Produc-tion (3)	Opera-tives (4)	Service Occs (5)	Service / Prod., Operat. (6)
				A. Males		
				C'zone dummies, w/o Person-Level Controls		
Share of Routine Occs.$_{-1}$ x 2005	0.630 **	0.985 **	-0.326 **	-0.643 **	-0.254 ~	0.308
	(0.091)	(0.141)	(0.115)	(0.137)	(0.145)	(0.192)
				C'zone dummies, with Person-Level Controls		
Share of Routine Occs.$_{-1}$ x 2005	0.656 **	0.557 **	0.148	-0.342 *	0.052	0.327 *
	(0.104)	(0.136)	(0.135)	(0.144)	(0.155)	(0.155)
n	986,192	855,051	1,030,723	1,306,582	526,063	2,863,368
				B. Females		
				C'zone dummies, w/o Person-Level Controls		
Share of Routine Occs.$_{-1}$ x 2005	1.118 **	0.816 **	0.257	-0.656 **	-0.136	0.773 **
	(0.106)	(0.102)	(0.182)	(0.131)	(0.128)	(0.223)
				C'zone dummies, with Person-Level Controls		
Share of Routine Occs.$_{-1}$ x 2005	1.005 **	0.781 **	0.281	-0.156	0.108	0.368 *
	(0.106)	(0.106)	(0.173)	(0.161)	(0.124)	(0.166)
n	939,947	1,811,561	92,706	528,202	840,657	1,461,565

Note: Column (6) pools production workers, operatives, and service workers; it reports the coefficient of an interaction term between share of routine occupations in 1980 and a dummy for service workers. Robust standard errors in parentheses are clustered on state-year cells. Models are weighted by a worker's share in total labor supply in a given year. Each cell corresonds to a separate OLS regression. All models include an intercept, and a time dummy for the second period, and commuting zone dummies. Models with person-level controls also include nine dummies for years of education, a quartic in potential experience, dummies for married, non-white and foreign-born, and interactions of all individual level controls with the time dummy. Hourly wages are defined as yearly wage and salary income diveded by the product of weeks worked times usual weekly hours. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Appendix Table 1. Occupational Composition by Education Group: Level and Change of Share of Education Category Employed in Each Major Occupation Group, 1980-2005

	Managers Professi-onals	Technic. Sales Admin.	Product. Craft Repair	Operators Fabrictrs. Laborers	Farming Fishery Forestry	Service Occs.
			A. Δ 1980 - 2005 (% pts)			
Non-College	-0.2	-1.2	-0.5	-4.1	-1.4	7.4
Less than High School	-1.3	0.0	0.2	-7.6	-0.7	9.4
High School	-0.5	-4.3	-0.4	-1.1	-1.3	7.6
Some College	-0.3	-2.7	-0.2	-1.4	-1.0	5.5
College Graduate	-1.5	1.2	-1.3	-0.4	-0.6	2.6
			B. 1980 (% pts)			
Non-College	9.1	26.7	18.5	28.1	3.7	13.9
Less than High School	5.8	13.9	19.9	37.3	5.1	17.9
High School	10.8	33.4	17.8	23.3	2.9	11.7
Some College	23.7	39.9	12.4	11.5	1.9	10.7
College Graduate	67.4	21.8	4.1	2.4	1.1	3.2
			C. 1990 (% pts)			
Non-College	9.1	27.1	17.7	26.4	2.9	16.7
Less than High School	4.9	15.2	18.7	34.3	4.6	22.3
High School	10.9	32.1	17.3	23.1	2.2	14.4
Some College	23.9	40.7	12.2	10.6	1.2	11.5
College Graduate	66.2	24.4	2.9	2.2	0.7	3.6
			D. 2000 (% pts)			
Non-College	8.5	25.6	18.5	25.5	2.4	19.5
Less than High School	4.5	15.3	19.3	31.5	4.2	25.2
High School	10.0	29.5	18.2	23.3	1.7	17.4
Some College	23.7	38.1	12.6	10.3	0.9	14.3
College Graduate	66.9	22.7	2.7	2.1	0.5	5.1
			E. 2005 (% pts)			
Non-College	8.9	25.5	18.1	24.0	2.3	21.2
Less than High School	4.5	13.9	20.2	29.7	4.4	27.3
High School	10.3	29.1	17.4	22.2	1.6	19.3
Some College	23.4	37.3	12.2	10.1	0.9	16.2
College Graduate	66.0	23.0	2.8	2.1	0.5	5.8

Source: Census 5% samples for 1980, 1990, 2000; American Community Survey 2005. Sample includes persons who were aged 18-64 and working in the prior year. Labor supply is measured as weeks worked times usual weekly hours in prior year. All calculations use labor supply weights.

Appendix Table 2. Ranking of Occupations by RTI Score (Lowest to Highest): Service

	Top Quintile of Ranking (Least Routine Intensive)
2	Fire Fighting, Prevention and Inspection
5	Public Transportation Attendants and Inspectors
6	Police and Detectives, Public Service
10	Crossing Guards
14	Waiter, Waitress
18	Cleaners, Maids, Housekeepers, Butlers
19	Sherrifs, Bailiffs, Correctional Institution Officers
26	Baggage Porters, Bellhops and Concierges
31	Recreation and Fitness Workers
36	Misc. Food Preparation and Service Workers
39	Gardeners and Groundskeepers
44	Recreation Facility Attendants
46	Health and Nursing Aides
55	Guides
56	Supervisors of Building and Cleaning Service
60	Janitors
61	Food Preparation Workers
	Second to Fourth Quintile of Ranking
79	Superv. of Landscaping, Gardening, and Groundskeep.
92	Ushers
126	Animal Caretakers, except Farm
154	Child Care Workers
163	Guards and Police, except Public Service
166	Supervisors of Guards
182	Laundry and Dry Cleaning Workers
237	Bartenders
272	Hairdressers and Cosmetologists
282	Cooks
	Bottom Quintile of Ranking (Most Routine Intensive)
330	Dental Assistants
335	Barbers
348	Motion Picture Projectionists

Notes: The Routine Task Index (RTI) measures the average log routine/manual task ratio for each detailled occupation. The ranking consists of 354 occupations, including 30 service occupations. Residual occupations groups ("not elsewhere classified") are excluded.

Appendix Table 3. Levels and Changes of Share of Employment in Routine Occupations, Overall and by Education Group, 1980-2005

	Standardized Task or RTI Score				Ten Times Average Annual Change			
	1980	1990	2000	2005	1980-1990	1990-2000	2000-2005	1980-2005
	Share of Employment in Routine Occupations, by Education							
Overall	0.333	0.335	0.333	0.318	0.002	-0.002	-0.030	-0.006
	(0.47)	(0.47)	(0.47)	(0.46)				
College Graduates	0.335	0.339	0.334	0.322	0.004	-0.005	-0.023	-0.005
	(0.47)	(0.47)	(0.47)	(0.47)				
Some College	0.380	0.370	0.366	0.351	-0.009	-0.005	-0.029	-0.012
	(0.48)	(0.48)	(0.48)	(0.48)				
High School Graduates	0.364	0.339	0.328	0.310	-0.025	-0.011	-0.035	-0.022
	(0.48)	(0.47)	(0.47)	(0.46)				
High School Dropouts	0.215	0.225	0.236	0.215	0.010	0.011	-0.042	0.000
	(0.41)	(0.41)	(0.42)	(0.41)				

n = 722 Commuting Zones in each decade, weighted by start of period commuting zone share of national population. Abstract, Routine and Manual task measures are based on the Dictionnary of Occupational Titles (DOT) and defined according to Autor-Levy-Murnane (2003). Routine occupations are defined the occupations with largest routine task / manual task ratios that account for one third of overall employment in 1980.

Appendix Table 4. Cross-Sectional Correlates of the Routine Employment Share in 1980

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College/Non-college pop 1980		0.166 **						0.054 *
		(0.020)						(0.020)
Immigr/Non-college pop 1980			0.262 **					0.163 **
			(0.063)					(0.039)
Manufact/empl 1980				-0.012				0.043
				(0.068)				(0.046)
Unemployment rate 1980					-1.456 **			0.098
					(0.179)			(0.149)
Female empl/pop 1980						0.642 **		0.437 **
						(0.044)		(0.075)
Age 65+/pop 1980							-0.906 **	-0.376 **
							(0.309)	(0.120)
Constant	0.203 **	0.212 **	0.289 **	0.294 **	0.398 **	-0.027	0.393 **	0.020
	(0.024)	(0.009)	(0.001)	(0.019)	(0.013)	(0.022)	(0.035)	(0.037)
R^2	0.434	0.676	0.485	0.395	0.560	0.721	0.533	0.832
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

n=722 Commuting Zones. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population and include an intercept. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.