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

David H. Autor
MIT and NBER

David Dorn
CEMFI

April 2010

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. 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.

JEL: E24, J24, J31, J62, O33
Keywords: Skill Demand, Job Tasks, Inequality, Polarization, Technological Change, Occupational Choice

*We thank Daron Acemoglu, Joshua Angrist, Kerwin Charles, Luis Garicano, Maarten Goos, Caroline Hoxby, Lawrence Katz, Alan Manning, and numerous seminar participants for excellent suggestions. We thank Amanda Pallais and Jessica Pan for superb research assistance, and Mark Doms and Ethan Lewis for generous assistance with data. We are deeply indebted to Rachel Nagi and Alp Simsek for assistance with the theoretical model. Autor acknowledges support from the National Science Foundation (CAREER award SES-0239538). Dorn acknowledges funding from the Swiss National Science Foundation.

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 distribution 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.'

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 lower panel of Figure 1 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.[1] 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.[2]

A comparison of changes in wages and changes in employment over these two decades warrants two inferences. 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 must play a key role in any economic explanation of the changing structure of wages and employment in both decades. Second, while a rich literature surveyed by Katz and Autor (1999) studies the monotone-in-skill rise of U.S. wage and employment inequality during the 1980s, the causal hypotheses explored by that literature neither predict nor explain the twisting of the lower-tail of the wage and employment

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

[2] Papers by Juhn (1994 and 1999) are the first studies that we are aware of that report evidence of declining demand for 'middle-skill' occupations. Goos and Manning coin the term 'polarization' in a 2003 working paper (Goos and Manning, 2003 and 2007), referring to the polarization of employment in the U.K. Autor Katz, and Kearney (2006, 2008) and Lemieux (2008), find polarization of both employment and, notably, wage growth in the U.S. commencing in the late 1980s. Acemoglu (1999), Spitz-Oener (2006), Smith (2008), and Dustmann, Ludsteck and Schönberg (2009) present further evidence of employment polarization in the UK, West Germany and US, and Goos, Manning and Salomons (2009a) find employment polarization in 14 of 16 European OECD countries using data from 1996 to 2007.

distribution in the subsequent two decades.[3] Analyzing the proximate and underlying causes of this phenomenon is, we believe, central to understanding the evolving structure of employment and wages in the U.S. and other industrialized economies.[4]

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 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 and gardeners, cleaners; home health aides; child care workers; hairdressers and beauticians, and recreation occupations.[5] 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).[6] This growth of service occupations stands in striking contrast to declining employment in all similarly low-educated occupation groups (production, craft and repair occupations, operative, fabricator and laborer occupations, and agriculture, forestry and fishing occupations) and instead parallels the growth rate of managerial and professional specialty occupations, the most highly educated occupation group. The rise in service employment was even steeper for non-college workers—those with no more than a high school education. The share of service occupation employment among non-college workers rose by 50 percent between 1980 and 2005, from 13.8 to 20.7 percent, while employment in all other major occupational categories declined. 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.[7]

To benchmark the magnitude of the contribution that growth in service occupations makes 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

[3] Card and DiNardo (2002) and Lemieux (2006) offer critiques of this literature.

[4] 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).

[5] It is critical to distinguish service *occupations*, a group of low-education occupations providing personal services and comprising 14.3 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).

[6] Part-time jobs are relatively prevalent in service occupations, and hence the share of service *jobs* in U.S. 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.

[7] Though farm occupations are estimated to have experienced comparable wage growth in this time interval, the accuracy of these numbers is doubtful because Census data likely undercounts illegal immigrants who provide a substantial share of U.S. farm labor.

Figure 2, alters the above picture of employment polarization considerably. Holding service employment at its 1980 level, the upward twisting of the lower-tail of the employment distribution during the 1990s is largely eliminated. [8] Moreover, the counterfactual exercise noticeably steepens the relationship between skill level and employment growth in the 1980s. The difference between the two decadal graphs reflects two countervailing trends in low-skill employment: rising employment in low-skill service occupations and falling employment in other lower-tail occupations. While the growth of service occupations only partly mitigated the declining employment in other low-skill occupations in the 1980s, it led to an aggregate growth of lower-tail occupations and to a pattern of employment polarization in the 1990s. Similarly, holding service occupation relative wages (rather than employment) constant at their 1980 level has an analogous though less dramatic dampening effect on lower-tail wages in both decades. In particular, it essentially eliminates the upward twist of the lower tail in the 1990s.[9]

These facts motivate our inquiry. 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 this rise will provide analytic leverage on the phenomenon of wage and employment polarization more generally. 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."

This reasoning underlies our theoretical model. A central thrust of recent technological change

[8] 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 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.

[9] 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, all of which have comparably low education levels. 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 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.

has been the automation of a large set of 'middle skill' 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 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 intensive in 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—rising output of goods (i.e., non-service activities) spurred by productivity gains will raise aggregate demand for service outputs, and ultimately employment and wages in service occupations.

We explore these implications formally in a simple general equilibrium model of 'routine-task' replacing technological change, building upon ALM (2003), Weiss (2008), and in a broader sense, Baumol's (1967) model of unbalanced growth.[10] Technological progress in this model takes the form of an ongoing decline in the cost of computerizing routine tasks—which are repetitive tasks performed both by machinery and low-skilled ('non-college') workers in the production of goods. This process complements the high-skilled ('college') workers who perform abstract tasks in goods production but substitutes for low-skilled ('non-college') workers in goods production, who in turn reallocate their labor supply to service occupations, which use exclusively manual tasks and do not experience technological progress.

We use the model to analyze the allocation of labor between goods and services, and the inequality of wages holding constant the supply of high and low-skill workers, as automation drives the price of routine tasks towards zero. A key result is that the limiting behavior of employment and wage in-

[10] In other related work, Ngai and Pissarides (2007) derive a multisector model where unbalanced productivity growth leads to declining employment in the manufacturing sector that experiences largest productivity gains. Our model modifies and extends 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.

equality 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 will be drawn into service occupations as goods output rises. Wages paid to manual tasks—and hence non-college earnings—then 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. It bears emphasis that this mechanism does *not* operate through income effects—in fact, consumers in the model have homothetic preferences. The long run positive effect of technical change on service employment and wages results from the interaction between productivity growth that favors goods and preferences that weakly favor services.

Our primary empirical analysis explores the rise of service employment at the level of local labor markets. The identification strategy exploits the fact that the output of low-skill service occupations is typically non-storable and non-transportable, and hence largely immune to trade and outsourcing.[11] 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 Public Use Micro Samples for 1950, 1970, 1980, 1990 and 2000 and from the American Community Survey for 2005.

To isolate potentially exogenous variation in the susceptibility of local labor markets to substitution of information technology for routine labor input, the identification strategy draws on the theoretical model of changing task specialization. We posit that the extent of routine task displacement will depend on the initial concentration of routine job activities within local labor markets, since these jobs are most likely to be automated as the price of computing falls. Using task measures from the Dictionary of Occupational Titles paired with Census data on occupational structure, we generate a simple index measuring the share of labor employed in routine task-intensive occupations in each commuting zone at the start of the relevant time period.[12]

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

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

[12] Simon (2004) pursues a parallel strategy of relating changes in industrial structure over the course of multiple decades to initial occupational and skill structure.

routine labor input among non-college workers. Consistent with the model, the rapid reduction of routine employment in initially routine-intensive commuting zones is accompanied by a contemporaneous, differential increase in workplace computer use in these same local labor markets.[13] 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 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.

The recent rise of service employment and accompanying polarization may also have other contributing causes, many of which we explore 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 increases 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 (2008) and Mazzolari and Ragusa (2008) focuses on substitution rather than income effects. These studies posit that rising returns to skill spur high-skilled workers to substitute market for home-based production of household services, thus increasing their labor supply and earnings while simultaneously raising demand for service jobs.[14]

While these alternative explanations appear both plausible and complementary to our main hypothesis, 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. Second, to the degree that we can empirically test these alternative hypotheses, we find limited support. Growth of service employment within commuting zones is *negatively* correlated with changes in the hours worked of male and female college graduates, 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, a pattern that is inconsistent with

[13] We use Doms and Lewis' (2006) measure of personal computer penetration at the geographic level. This measure, generously shared by Mark Doms and Ethan Lewis, is also used by Beaudry, Doms and Lewis (2006) to explore the determinants of computer adoption and changes in education returns across metropolitan areas during the period of 1980 through 2000. Their analysis is motivated by a model of endogenous technology adoption, building on Beaudry and Green (2003), in which geographic variation in computer adoption is driven by the relative abundance or scarcity of skilled workers.

[14] Leonardi (2008) explores the hypothesis that skilled workers demand both more high- and low-skill intensive goods than do unskilled workers. Hence, rising education may cause demand polarization.

the income effect hypotheses. Notably, our key explanatory measure, the routine employment share, proves highly robust to controlling for these alternative explanatory variables.

Alongside these demand side determinants of service occupation employment, we also carefully control for a host of other likely contributors, including: rising supply of low-skilled immigrants, which 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 have the expected correlation with rising 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.

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

2.1 Environment

We consider an economy with two sectors ($j = g, s$) that produce goods and services for consumption using 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 ($i = H, U$) corresponding to college and non-college workers. The fourth factor of production is computer capital, which is an intermediate (non-consumption) good. In each sector, a continuum of mass one of firms produces output.

Production of goods combines routine labor, abstract labor, and computer capital (K), measured

in efficiency units, using the following technology:

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

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.[15]

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

$$Y_s = \alpha_s L_m, \tag{2}$$

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 goods 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 $f(\eta) = e^{-\eta}$.

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

$$K = Y_k(t)\, e^{\delta t}/\theta. \tag{3}$$

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

[15] An alternative way of capturing capital-skill complementarity would be to consider a production function of the form $Y + G[L_r F(L_a, K)]$. We use the production function in equation (1) because it reflects what we view as a key mechanism by which information technology influences labor demand: direct substition of computer capital for labor input of routine tasks.

efficiency unit of computer capital:

$$1 = e^{\delta}/\theta. \tag{4}$$

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

$$p_k(t) = \frac{Y_k}{K} = \theta e^{-\delta t}. \tag{5}$$

To close the model, we model all consumers/workers as having identical CES utility functions defined over consumption of goods and services:

$$u = \left(c_s^{\rho} + c_g^{\rho}\right)^{1/\rho}, \tag{6}$$

$$\text{where } \rho < 1. \tag{7}$$

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. We next derive the static solution of the model and its asymptotic equilibrium. Section (2.3) summarizes the model's solution and empirical implications.

2.2 The planner's problem

Since there are no distortions, the equilibrium allocations can be characterized by solving for the social planner's problem. The equilibrium prices of factors can then be characterized by calculating the marginal products of factors.

Note also that capital fully depreciates between periods. In particular, the capital in each time is produced using the final good of that time. Hence, the equilibrium at each time can be analyzed in isolation. Note also that the only changing parameter over time is $p_k(t)$.

Given $p_k(t)$ at time t, the social planner's problem at time t is to solve:

$$\begin{aligned}
&\max_{K,\eta} \left(C_s^{\frac{\sigma-1}{\sigma}} + C_g^{\frac{\sigma-1}{\sigma}} \right)^{\sigma/(\sigma-1)} \\
&\text{s.t. } C_g = Y_g - p_k(t) K \\
&\qquad C_s = Y_s = L_m = 1 - \exp(-\eta^*) \\
&\text{where } Y_g = L_a^{1-\beta} X^{\beta} \\
&\qquad X = \left[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu} \right]^{1/\mu} \\
&\qquad L_r = (\eta^* + 1) \exp(-\eta^*) \\
&\qquad L_a = 1,
\end{aligned}$$

where we write σ_c as σ to simplify notation. The above problem can further be simplified to:

$$\max_{K,L_m} \left(L_m^{\frac{\sigma-1}{\sigma}} + (Y_g - p_k(t) K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{8}$$

$$\text{where} \quad Y_g = X^{\beta} \text{ and } X = \left[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu} \right]^{1/\mu} \tag{9}$$

$$L_r = g(L_m) \equiv (1 - \log(1 - L_m))(1 - L_m),$$

where $g(\cdot)$ is a function with the property that $g(0) = 1$ and $g(1) = 0$. Note that the social planner essentially chooses the level of capital, $K(t)$, and the allocation of labor $L_m(t)$ to service tasks (and thus, also the allocation $L_r(t) = g(L_m(t))$ to routine tasks).

We next characterize the solution to problem (8). The first order conditions with respect to capital K and labor L_m respectively give:

$$\frac{\partial Y_g}{\partial K} = p_k(t). \tag{10}$$

$$L_m^{-1/\sigma} = (Y_g - p_k K)^{-1/\sigma} \frac{\partial Y_g}{\partial X} \frac{\partial X}{\partial L_r} (-\log(1 - L_m)), \tag{11}$$

where we have used

$$g'(L_m) = \log(1 - L_m) = -\eta^*.$$

The system in $(10) - (11)$ constitutes a system of two equations in two unknowns (L_m, X), which uniquely solves for the equilibrium at any time t.

We next characterize the behavior of the solution. We first consider the asymptotic equilibrium as $t \to \infty$ (equivalently, as $p_k(t) \to 0$). We then characterize the dynamics of this equilibrium.

Asymptotic equilibrium

Note that the intermediate good X is produced with a CES production function with elasticity $\frac{1}{1-\mu} > 1$ over the inputs L_r and K. Note also that L_r is bounded from above. Then, it can be seen that Eq. (10) holds as $p_k \to 0$ only if $K \to \infty$. In other words, we have

$$\lim_{t\to\infty} K(t) = \infty. \tag{12}$$

Since L_r is bounded from above, and since L_r and K are gross substitutes in the production of X, the production of X in the limit will be essentially determined by the capital level. Formally, we have

$$\lim_{t\to\infty} X/\alpha_k K = 1.$$

Let $x \sim y$ be a shorthand for the notation that $\lim_{t\to\infty} x/y = 1$. Then, the previous limit expression can be expressed as

$$X \sim \alpha_k K. \tag{13}$$

Using Eq. (9) and Eq. (10) respectively, we further have

$$Y_g \sim (\alpha_k K)^{\beta} \text{ and } p_k K \sim \beta (\alpha_k K)^{\beta}. \tag{14}$$

From these expressions, net output (consumption) satisfies

$$C_g = Y_g - p_k K \sim \kappa_1 K^{\beta}, \tag{15}$$

where we define $\kappa_1 = (1-\beta)\alpha_k^{\beta}$. Using these expressions in Eq. (11), it can be seen that the asymptotic manual labor choice $L_m^* \equiv \lim_{p_k\to 0} L_m(p_k)$ is the solution to:

$$(L_m^*)^{-1/\sigma} = \kappa_1^{-1/\sigma}\kappa_2 K^{\beta-\mu-\beta/\sigma} L_r^{\mu-1}\left(-\log(1-L_m^*)\right) \tag{16}$$

where recall that $L_r = g(L_m^*)$, and we define $\kappa_2 = \beta\alpha_k^{\beta-\mu}\alpha_r^{\mu}$. Using this equation and Eq. (12), the asymptotic level of L_m^* is uniquely solved as follows:[16]

$$L_m^* = \begin{cases} 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \\ \bar{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \end{cases}. \tag{17}$$

[16] Here, $\bar{L}_m$ is the solution to the equation:

$$\left(\bar{L}_m\right)^{-1/\sigma} = \kappa_1^{-1/\sigma}\kappa_2 g\left(\bar{L}_m\right)^{\mu-1}\left(-\log\left(1-\bar{L}_m\right)\right).$$

To see the relevance of the key inequality in eq. (17), note that $\frac{1}{\sigma} \gtreqless \frac{\beta-\mu}{\beta}$ can be rewritten as:

$$\frac{\mu}{\rho} \gtreqless \beta,$$

where $\frac{\mu}{\rho} > \beta \Longleftrightarrow \frac{1}{\sigma} > \frac{\beta-\mu}{\beta}$. Recalling that $\sigma_c = 1/(1-\rho)$ and $\sigma_r = 1/(1-\mu)$, this expression says that the asymptotic allocation of non-college labor to services versus goods production depends on the relative magnitude of the elasticity of substitution *in production* between computer capital and routine labor and the elasticity of substitution *in consumption* between goods and services (both of which demand non-college labor). If this ratio exceeds unity, technological progress (i.e., falling p_k) ultimately leads to a relative increase in non-college labor demand in service employment. Moreover, the lower is the routine share in goods production (i.e., lower β), the smaller is the critical value of μ/ρ required for non-college labor to flow into services. The reason is that lower β implies that a smaller share of the gains to technical progress accrue to routine labor through q-complementarity and a correspondingly larger share accrues to abstract labor.

Dynamics of equilibrium

Recall that L_r is bounded from above and K limits to ∞ (cf. Eq. (12)). Hence, $\frac{L_r(t)}{K(t)}$ will be decreasing for sufficiently large t. Suppose that $p_k(0)$ is sufficiently small that $\frac{L_r(t)}{K(t)}$ is decreasing for all t (intuitively, use of machines relative to routine labor monotonically increases). Under this initial parameterization, the dynamics of the model are straightforward. Note that:

$$\frac{X}{K} = \left[\alpha_r^{\mu}\left(\frac{L_r}{K}\right)^{\mu} + \alpha_k^{\mu}\right]^{1/\mu}$$

will be strictly decreasing and it will limit to α_κ. Let $x \downarrow y$ (resp. $x \uparrow y$) correspond to a shorthand for the notation that $\frac{x(t)}{y(t)}$ will be strictly decreasing and will limit to 1 (resp. will be strictly increasing and will limit to 1). Then, we have $X \downarrow \alpha_k K$. In summary, we have the following dynamics:

$$X \downarrow \alpha_k K, \qquad Y_g \downarrow \alpha_k^{\beta} K^{\beta}, \qquad p_k K \uparrow \beta \alpha_k^{\beta} K^{\beta}, \text{ and } C_g \downarrow \kappa_1 K^{\beta}. \tag{18}$$

The dynamics of $L_m(t)$ can be obtained by using these expressions in Eq. (11).[17]

Equilibrium wages

Having characterized the asymptotic allocations, we turn to the characterization of equilibrium wages. We normalize the price of the good g to 1 at each time t. Factors will be paid their marginal

[17] The dynamic analogues of Eqs. (14) and (15) can also be obtained.

products. Hence,

$$w_a = \frac{dY_g}{dL_a} = (1-\beta)\, Y_g \downarrow \kappa_1 K^{\beta}, \tag{19}$$

where the last line uses the dynamics in Eq. (18). Similarly, note that

$$w_r = \frac{\partial Y_g}{\partial X}\frac{\partial X}{\partial L_r} = \beta X^{\beta-\mu}\alpha_r^{\mu} g\left(L_m\right)^{\mu-1} \sim \kappa_2 K^{\beta-\mu} g\left(L_m\right)^{\mu-1} \tag{20}$$

where we used $L_r = g\left(L_m\right)$.[18]

Finally,

$$w_m = p_s = \left(\frac{C_s}{C_g}\right)^{-1/\sigma} = \left(L_m\right)^{-1/\sigma} C_g^{1/\sigma} \sim \left(L_m\right)^{-1/\sigma} \kappa_1^{1/\sigma} K^{\beta/\sigma}. \tag{21}$$

From these expressions, relative wages and their dynamics can be determined. We are most interested in $\frac{w_m}{w_r}$, the relative wages of non-college workers in goods versus services production. To obtain the asymptotics of this ratio, note that the first order condition (11) can also be written as:

$$w_m = w_r \eta^* = w_r \left(-\log\left(1 - L_m^*\right)\right).$$

Then, using the characterization in (17), we have

$$\frac{w_m}{w_r} = \begin{cases} \infty \text{ if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ = \left(-\log\left(1-L_m^*\right)\right) \text{ if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 \text{ if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases}. \tag{22}$$

Thus, the equilibrium behavior of the manual to routine wage ratio drives the flow of labor between goods and services derived in Eq. (17). When $\frac{1}{\sigma} > \frac{\beta-\mu}{\beta}$, the manual to routine wage ratio eventually exceeds unity and rises without bound, leading all non-college labor to flow to services.

We are also interested in the behavior of the ratio $\frac{w_a}{w_m}$. Using Eqs. (19) and (21), we have:

$$\frac{w_a}{w_m} \sim \frac{\kappa_1 K^{\beta}}{\left(L_m\right)^{-1/\sigma} \kappa_1^{1/\sigma} K^{\beta/\sigma}}. \tag{23}$$

First consider the case

$$\sigma > \frac{\beta}{\beta-\mu} \text{ (which is greater than 1).}$$

In this case, Eq. (17) shows that $L_m^* = 0$. But then, Eq. (23) shows that the ratio $\frac{w_a}{w_m}$ is indetermi-

[18] Note that, unlike w_a, the dynamic nehavior of w_r is not necessarily monotonic. In particular, note that Eq. (20) can also be written as

$$w_r = \frac{\partial Y_g}{\partial K}\frac{\partial X/\partial L_r}{\partial X/\partial K} = p_k \frac{\alpha_r^u}{\alpha_k^u}\left(\frac{L_r}{K}\right)^{\mu-1}.$$

The fact that p_k is decreasing drives down w_r, because routine labor and machines are gross substitutes. On the other hand $\frac{L_r}{K}$ is falling because of the increases in capital use. When $\mu < 1$ (so that the inputs are not perfect substitutes), the increase in the use of the complementary factors (capital) also tends to push up the wages of routine labor. Hence, the dynamic path of routine wages might be non-monotonic.

nate.[19] Consider, next the empirically more relevant case

$$\frac{1}{\sigma} > \frac{\beta - \mu}{\beta}.$$

This case is empirically more relevant because it ensures $L_m^* > 0$ (which is the general pattern we observe). In this case, Eq. (23) shows that the asymptotic behavior of $\frac{w_a}{w_m}$ depends on σ. In particular,

$$\frac{w_a}{w_m} = \begin{cases} \infty \text{ if } \sigma < 1 \\ 1 \text{ if } \sigma = 1 \\ 0 \text{ if } \sigma > 1 \end{cases}, \text{ when } \frac{1}{\sigma} > \frac{\beta - \mu}{\beta}. \tag{24}$$

Finally, we are also interested in the behavior of $\frac{w_a}{w_r}$. Eqs. (19) and (20) show that

$$\lim_{t \to \infty} \frac{w_a}{w_r} = \frac{\kappa_1 K^{\beta}}{\kappa_2 K^{\beta-\mu} g\left(L_m\right)^{\mu-1}} = \frac{\kappa_1 K^{\mu}}{\kappa_2 g\left(L_m\right)^{\mu-1}} = \infty \text{ when } \frac{1}{\sigma} \leq \frac{\beta - \mu}{\beta},$$

where the last equality follows since $K \to \infty$, and since $L_r = g\left(L_m\right) > 0$ when $\frac{1}{\sigma} < \frac{\beta-\mu}{\beta}$ (so that $g\left(L_m\right)^{\mu-1}$ is bounded from above). But the empirically relevant case corresponds to the parametric condition $\frac{1}{\sigma} > \frac{\beta-\mu}{\beta}$. In this case, the ratio $\frac{w_a}{w_r}$ does not necessarily limit to ∞, because $L_r = g\left(L_m\right)$ decreases to zero, and $g\left(L_m\right)^{\mu-1}$ might also limit to ∞ (it does so when $\mu < 1$). Note, however, that in this empirically relevant case, the wages of routine labor are kept high for a rather superficial reason. In this case, routine tasks are not very important in production, and thus the economy allocates labor away from routine tasks. As there are so few workers remaining in routine tasks, each of them might be receiving a significant wage. This intuition suggests that the routine sector overall should be receiving a lower wage payment, even though each routine laborer might be receiving a high wage. In other words, the intuition suggests that we should instead attempt to prove the following:

$$\lim_{t \to \infty} \frac{L_a w_a}{L_r w_r} = \infty \text{ when } \frac{1}{\sigma} > \frac{\beta - \mu}{\beta}. \tag{25}$$

That is, the share of abstract labor relative to the share of routine labor limits to infinity. To prove this, consider Eqs. (19) and (20) (and use $L_r = g\left(L_m\right)$) to get:

$$\lim_{t \to \infty} \frac{L_a w_a}{L_r w_r} = \lim_{t \to \infty} \frac{\kappa_1 K^{\beta}}{\kappa_2 K^{\beta-\mu} g\left(L_m\right)^{\mu}} = \frac{\kappa_1}{\kappa_2} \left(\frac{K}{g\left(L_m\right)} \right)^{\mu} = \infty,$$

where the last equality follows since K increases but $g\left(L_m\right)$ is bounded from above. This proves the

[19] However, this indeterminacy is for a rather superficial reason. As the manual sector is not very important, the economy allocates most of the labor away from this sector. Thus, the wages of the few remaining labor may in this sector may be high. This intuition also suggests that the right object to look at may be the *total share* of manual labor. When we consider this for this case, we indeed have:

$$\lim_{t \to \infty} \frac{L_a w_a}{L_m w_m} \sim \frac{\kappa_1 K^{\beta}}{\left(L_m\right)^{1-1/\sigma} \kappa_1^{1/\sigma} K^{\beta/\sigma}} = 0,$$

where the last equality follows because $\sigma > 1$ (so that $1 - 1/\sigma > 0$, and $\left(L_m\right)^{1-1/\sigma} = 0$).

limit in (25), and completes our analysis for relative wages. Our main results regarding relative wages are summarized in (22) , (24) and (25).

2.3 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 rises due to the combination of rising productivity of abstract tasks and a falling price of routine tasks. Inequality between high and low-skill workers may ultimately converge to a steady state, or may expand indefinitely.[20] In particular:

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 wage of routine labor relative to manual labor goes to zero.

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 ratio of manual wage to routine wage limits to zero. The ratio of abstract wage to routine wage 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 of realism intentionally omitted from the model is the potential endogeneity of the supply of skilled labor. In reality, changes in earnings inequality will alter the path of skills accumulation, thus preventing wage inequality from either rising without bound or collapsing.[21] We omit this

[20] Numerical simulations 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. A set of figures from this simulation is available from the authors.

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

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.[22] If no, we must consider to what extent the model applies in local labor markets that interact in a full spatial equilibrium.

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 therefore affect local service occupation wage levels. The rate at which these regional wage differences are arbitraged over the longer run 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.

In addition, the non-tradability 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

We provide key details on data construction and measurement in this section, with many further details of our sample construction, geographic matching and occupational classification scheme provided in the Data Appendix.

[22] Formally, we could rewrite equation (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.

3.1 Data sources

Large sample sizes are essential for an analysis of changes in labor market composition at the detailed geographic level. Our 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.[23] The Census samples for 1980, 1990 and 2000 include 5 percent of the U.S. 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.[24]

Our analysis also requires a time-consistent definition of local labor markets. 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 U.S. 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 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.

We pursue an alternative approach to defining local labor markets based on the concept of Commuting Zones (CZs), developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs.[25] Our 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. We are not aware of prior economic research that makes use of this geographic construct.

[23] Comparable detailed geographic information is not available in the 1960 Census.

[24] 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.

[25] 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.

3.2 Measuring the 'routine employment share'

A crucial input into our analysis is a summary index of routine task activities within commuting zones. We compute this information from the occupational composition of employment. We measure routine task-intensity in each occupation using data from ALM (2003), 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.[26] For each occupation k, we form an index of routine task-intensity, RTI:

$$RTI_k = \ln\left(\hat{R}_{k,1980}/\hat{M}_{k,1980}\right), \tag{26}$$

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.[27] 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-CZ standard deviation of unity in 1980. This simple measure appears to capture well the job categories that motivate our conceptual framework. Appendix Table 1 shows that among the 10 most routine task-intensive occupations, 6 are clerical and accounting occupations and several others represent repetitive physical motion activities. Among the 10 least routine task intensive occupations (not tabulated), 4 are service occupations, and the remainder involve driving motor vehicles.[28]

To measure cross-market variation in employment in routine task-intensive occupations, we apply a simple binary approach to distinguish 'routine' and 'non-routine' occupations. We classify as routine occupations those that fall in the top-third of the employment-weighted distribution of the RTI measure in 1980, and we assign to each commuting zone j a routine employment share measure (RSH_{jt}) equal to the fraction of CZ employment at the start of a decade that falls in routine task-intensive occupations. The mean of this measure in 1980 is equal to 0.33 by construction, and the

[26] 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; and the abstract task measure is the average of two DOT variables: "direction control and planning," 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.

[27] 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.

[28] 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 and so are not well suited to our geographic analysis. Of the full set of 31 Census-classified service occupations, 17 fall in the bottom quintile of RTI scores and 23 of fall below the median.

population weighted 80/20 percentile difference in routine employment share is 10 percentage points (specifically, $RSH^{P20} = 0.275$ and $RSH^{P80} = 0.373$).[29]

To provide a point of comparison, we further subdivide the remaining two-thirds of employment into two even halves, using average 1980 occupational wages to allocate occupations to high- and low-wage non-routine clusters. These occupational clusters, described in Appendix Table 1, appear to accord well with the non-routine task categories defined above, i.e., abstract and manual. The high wage non-routine cluster is largely composed of professional specialty and technical occupations, with 54 percent of workers college-educated (relative to 45 percent of workers in routine-intensive occupations) and mean log hourly wages that are 30 log points above the routine occupation mean. The low-wage non-routine group is largely composed of low-education service, labor, and operative occupations, with 27 percent of workers college-educated and mean log hourly wages 24 log points below the routine occupation mean. Notably, average routine task-intensity is closely comparable between high and low-wage non-routine groups, in both cases approximately 1.8 standard deviations below the routine-intensive occupation mean. This reinforces the point that non-routine occupations lie at the poles of the wage distribution whereas routine-intensive occupations are concentrated towards the middle. Routine task-intensity is thus strongly non-monotone in education and wages.[30]

The identification in the subsequent empirical analysis exploits geographical differences in the use of routine labor across local labor markets. We predict that local labor markets that make intensive use of routine labor will adopt more computer technology that substitutes for routine labor, and that these locations will therefore experience stronger displacement of routine labor, larger increases of low-skill service employment, and perhaps a stronger polarization of wages.

Geographic variation in the use of routine labor inputs is to an important degree determined by historical differences in industry structures of local labor markets. The empirical analysis formally establishes this link by instrumenting local routine employment shares in 1950-2000 with a prediction of the routine share that builds on the industry structure of a local labor market in 1950. Specifically,

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

[30] Trends in aggregate DOT task variables reveal substantial movements in the predicted directions. Standardizing each variable with mean zero and cross-commuting zone standard deviation of one in 1980, the abstract task score of the mean commuting zone rises by 1.5 standard deviations over the subsequent 25 years while the routine task score of the mean commuting zone falls by 2.3 standard deviations. The mean manual task score falls by 0.3 standard deviations between 1980 and 1990, plateaus in the subsequent decade, and rises between 2000 and 2005.

we compute the predicted share of routine employment among non-college workers in 1950 as

$$PRSH_{j,1950} = \sum_{i=1}^{N} s_{i,j,1950} RSH_{i,-j,1950} \tag{27}$$

where $s_{i,j,1950}$ is the share of industry $i \in 1, ..., N$ in total non-college employment of commuting zone j in 1950, and $RSH_{i,-j,1950}$ is the share of routine occupations among non-college employees of industry i in all U.S. states except the one of commuting zone j in 1950. This industry mix instrument is highly predictive for the geographic variation in routine occupation employment in any Census year from 1950 to 2000 which suggests that there are important historical determinants for the use of routine labor.

4 First evidence on computer adoption, displacement of routine labor, and employment polarization

A crucial prediction of our analytic framework is that commuting zones which are specialized in routine task-intensive activities will experience larger shifts in occupational composition when information technology substitutes for workers engaged in routine tasks. Figure 3 provides a first evaluation of this prediction. Following the methodological approach of Figure 1b as described in the Introduction, it plots the change in occupations' share in overall employment at each percentile of the occupational skill distribution for the two decades 1980-1990 and 1990-2000. The difference relative to Figure 1b is that the sample is split into routine-intensive commuting zones with an above-median routine employment share in 1980 (Figure 3a), and not routine-intensive commuting zones with a below-median routine share (Figure 3b). The comparison between the two panels of Figure 3 reveals a striking pattern: Routine-intensive commuting zones experienced a mild polarization of occupational employment growth already in the 1980s, and in the 1990s, polarization became very pronounced with the rate of employment growth at the bottom of the occupational skill distribution nearly matching the growth at the top. By contrast, low-routine areas experienced less employment growth at the extremes of the skill distribution in both decades while the contraction of employment shares in the middle of the distribution was more muted so that no evident polarization trend is visible in this subsample.

The evidence from Figure 3 confirms the prediction that routine-intensive local labor markets should experience a more pronounced trend of employment polarization. The remainder of this section assesses the relationship between local routine intensity, technology adoption, and displacement of routine labor while the following section will study the main outcome of our empirical analysis, the growth of low-skill service employment among non-college workers.

We first test the assumption that commuting zones with large initial routine employment will

experience larger subsequent adoption of computers. To this end, we use a measure of geographic computer penetration developed by Doms and Lewis (2006). Based on private sector surveys on computer inventories, these data measure the number of personal computers per employee at the firm level—which is a relevant, though incomplete, measure of computer adoption. Doms and Lewis purge this measure of industry by establishment-size fixed effects using a linear regression model and aggregate the adjusted variable to the level of local labor markets. We use the Doms and Lewis 'adjusted computers-per-worker' measure for the years 1990 and 2002, which is matched to commuting zones.[31] 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 PC use was close to zero in all areas in 1980. We approximate the change in this variable over the subsequent decade using 5/6 of the 1990 to 2002 first-difference.[32]

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

$$\Delta C_{js\tau} = \alpha + \beta_{1\tau} \times RSH_{jst} + \beta_{2\tau} \Delta X_{js\tau} + \gamma_s + e_{js\tau}, \tag{28}$$

where the dependent variable is the change in the Doms-Lewis measure of computer adoption over decade τ in commuting zone j in state s, and RSH_{jst} is that commuting zone's share of routine employment in year t at the start of the decade. The first two columns of Panel A in Table 2 present separate, by-decade OLS regressions of commuting zone computer adoption during the 1980s and 1990s on the RSH measure, state dummies and a constant. The RSH variable 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 zones is larger than one full standard deviation of the computer adoption measure in each decade. The third column in Panel A stacks the two decadal first differences and regresses the change in computer penetration on the start-of-period levels of routine intensity. The estimated effect closely resembles the results of the decade-specific regressions. These results suggest that commuting zones which were initially specialized in routine task-intensive occupations adopted computer technology at a differentially rapid rate over the subsequent two decades.

Our analytical framework assumes that computer technology is a substitute for routine labor. Therefore, the relatively rapid adoption of computers in routine-intensive local labor markets should lead to a differential decline in routine employment. Panel B of Table 2 evaluates this prediction

[31] We thank Mark Doms and Ethan Lewis for providing us with this commuting zone-level data for 1990 and 2002. Approximately 50 of the 722 commuting zones do not have corresponding computer adoption data and so are dropped from the analysis. These commuting zones account for less than 1% of US population.

[32] The *level* of the PC-per-worker measure is not readily interpretable because it is a regression residual, as explained above. The cross commuting zone standard deviation of the change in this variable is 0.048 for 1980-1990 and 0.053 for 1990-2000.

by regressing the change in the commuting zone share of routine employment among all workers or workers of a specific education level on the initial routine intensity of the commuting zone. These regressions use the same stacked-first differences setup as the model in the first column of Panel A.

Panel B shows that during 1980 through 2005, commuting zones with higher initial share of routine occupations saw larger subsequent declines in routine-intensive employment. The estimate in column (1) suggests that the commuting zone at the 80th percentile of 1980 RSH experienced a 2.4 percentage points larger contraction of the routine occupation share per decade than did the 20th percentile commuting zone. Columns (2) and (3) of the table estimate this relationship separately for college and non-college workers. Both estimates are highly significant, but interestingly the decline in routine employment is greater for non-college workers (high school or lower education) than for college workers (at least one year of college). Thus, consonant with the model, the recent movement out of routine-intensive occupations is concentrated among less educated workers.[33]

If the movement out of routine-intensive work reflects a change in specialization, in what activities do workers specialize instead? Using our prior division of non-routine occupations into high- and low-wage groups (Appendix Table 1), panels C and D of Table 2 show that relative declines in routine occupations within CZs are primarily offset by relative employment *gains* in low-skill non-routine occupations—jobs that are on average significantly less skill-intensive and lower-paying than the routine occupations that are displaced. The degree of downward movement differs substantially, however, between college and non-college workers. Among the college-educated, movement out of routine-intensive occupations is approximately equally absorbed by movements into high- and low-wage non-routine occupations. Among non-college workers, by contrast, occupational reallocation is entirely accounted for by employment gains in low-wage, non-routine jobs.[34]

Overall, the estimates of Table 2 provide support for our hypothesis that routine-intensive commuting zones experience both a more rapid adoption of computer technology and a larger decrease in routine employment. The decline in routine-intensive work contributes to employment polarization, with labor reallocation away from 'middle-skilled' jobs and towards occupations at either end of the skill and wage distribution. Downward movements are much more evident among non-college workers, however, likely because they have a comparative advantage in manual relative to abstract tasks, while the reverse is true for college-educated workers.

[33] Concretely, it appears likely that less educated workers in routine-intensive occupations perform a disproportionate share of routine tasks and thus are differentially subject to displacement. 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.

[34] Autor and Dorn (2009) further consider how occupational movements between routine and non-routine occupations differ by age as well as education.

5 Predicting the growth of service employment

A primary insight of the descriptive analysis of occupational employment in the Introduction of this paper is that employment growth at the bottom of the occupational skill distribution is primarily driven by low-skill service occupations. This main section of the empirical analysis assesses whether 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 4 provides strong initial support for this prediction by plotting the bivariate relationship between initial commuting zone routine share (RSH_{1980}) and the change in the share of non-college labor employed in service occupations over the subsequent 25 years. Each plotted point represents one of 722 commuting zones, and the regression line corresponds to the following weighted OLS regression of the change in the service employment share on the initial RSH, where weights are equal to commuting zone shares of national population in 1980:

$$\Delta SVC_{j,1980-2005} = -0.039 + \underset{(t=18.1)}{0.323 \times RSH_{j,1980}} + e_{jt} \qquad R^2 = 0.31 \tag{29}$$

The explanatory power of this bivariate relationship is substantial. The coefficient of 0.323 on RSH 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 6.9 percentage points between 1980 and 2005, while the expected increase in non-college service employment in the commuting zone at the 80th percentile of RSH is 3.2 percentage greater than in the 20th percentile commuting zone.

To provide insight into the geography of this relationship, the lower panel of Figure 4 plots the bivariate relationship between initial routine share and the growth of service employment for the 40 commuting zones in the sample with populations over 1 million. Each CZ is identified by the name of its largest city in the figure. The relationship between initial routine share and subsequent growth of service jobs found in this greatly reduced sample is comparable in magnitude to the full sample and is highly significant. This figure also underscores an important characteristic of initially routine occupation-intensive cities: they are not for the most part industrial cities such as Syracuse or Pittsburgh, but rather knowledge-intensive cities like New York, Chicago, and Dallas. Routine-intensive occupations, such as clerical work and accounting, were commonplace in these high-skill cities in the 1980s because they serve as supporting occupations to the professions.

The top panel of Table 3 explores the bivariate relationship between the routine employment share and growth of service employment by decade between 1950 and 2005 using specifications of the following form:

$$\Delta SVC_{js\tau} = \alpha_t + \beta_\tau \times RSH_{jst} + \gamma_s + e_{js\tau}. \tag{30}$$

In this equation, τ represents a decadal change, t denotes the start year of the corresponding decade, and s denotes the state in which the commuting zone is located.[35] The inclusion of a vector of state dummies, γ, means that the coefficient of interest, β, is identified by within-state cross-CZ variation.[36] A central 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 period.[37] Beginning in 1980, this relationship becomes positive and significant, and its magnitude rises in each subsequent time interval.

The second and third panel of Table 3 show the two stages of an IV estimation for the impact of local labor markets' routine intensity on subsequent growth of low-skill service employment. In these specifications, the share of routine occupations is instrumented by a prediction of routine employment in 1950 which is based on commuting zones' industry mix in 1950 and out-of-state routine employment shares by industry in that year. The first stage results in the bottom panel of the table show that regional differences in the 1950 industry mix are a powerful predictor for geographic variation in routine employment shares even half a century later at the start of the 2000-2005 time period. The second stage results in the second panel of the table are qualitatively similar to the OLS results and show a increasingly positive relationship between routine employment share and subsequent growth of low-skill service employment.

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

Alongside routine task-intensity, a host of factors may explain geographic variation in the growth of service employment. We explore these factors in Table 4 using an augmented version of equation (30):

$$\Delta SVC_{js\tau} = \alpha + \beta_1 \times RSH_{jst} \times I\left[t \geq 1980\right] + \beta_2 \times RSH_{jst} + \beta_3 X_{js\tau} + \delta_\tau + \gamma_s + e_{js\tau}. \qquad (31)$$

This model stacks all decadal changes used in Table 2 over the interval 1950 to 2005, and includes a full set of time period effects, state effects, and measures of start-of-period levels in a number of relevant human capital, labor market, and demographic variables. The routine share variables are

[35] 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.

[36] 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.

[37] One speculative explanation for the negative relationship between *RSH* and the growth of service employment is based on the observation that US farm employment contracted rapidly between 1950 and 1970, falling from 11 to 3 percent of employment. Farm-intensive commuting zones had low levels of the *RSH* in 1950. Thus, the movement of labor from farm occupations into services in these CZs may potentially explain the negative relationship between the *RSH* and growth of service employment in this period.

instrumented with interactions between the 1950 industry mix instrument and time dummies. These interactions allow that the relationship between the instrument and the start-of-period routine share varies by period, as documented in panel three of Table 3.

The first column of the table reiterates the finding from estimates of (30) that the strong, positive relationship between routine employment share and growth of service employment found for 1980 through 2005 is not present in prior decades. Column 2 shows that this finding relationship is insensitive to the inclusion of the state dummy variables, which function as state-specific trends in the first-differenced specification. Subsequent columns control for a variety of 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 log relative supply of college educated individuals in the population and the change in the share of the non-college population that is foreign born. 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, 2008).

Column 4 adds two variables whose first-differences measure changes in local labor demand conditions: the unemployment rate and the share of employment in manufacturing. Service employment rises significantly when unemployment increases and when manufacturing employment declines.

Column 5 considers two demand shifters: the elderly population share and the female labor force participation rate. Because the elderly have high demand for specific services such as home health assistance, a rising share of senior citizens in the population may contribute to rising service employment, and this pattern is affirmed in column (5). Likewise, many services, such as restaurant meals or housekeeping, serve as substitutes for household production, and so a rise in female labor supply might be expected to raise demand for services (Mazzolari and Ragusa, 2008). Surprisingly, increased female employment is associated with a decline in service employment, though the sign of this relationship is sensitive to inclusion of other controls (see column 6).

Inclusion of the full set of explanatory variables (column 6) substantially raises the explanatory power of the model. Moreover, all control variables are highly significant and have the expected sign. Nevertheless, the robust positive relationship between initial routine employment share and growth of service employment in the post-1980 period remains largely intact. Comparing columns (1) and (6), the point estimate on RSH is about half as large as in the most inclusive model, but the precision of the estimate is greater.

Arguably, the empirical approach used by equation (31) is unduly conservative in that it likely 'over-controls' for contemporaneous factors—including unemployment and contraction of manufacturing—that may stem (in part) from a common underling cause: labor demand shifts against routine-intensive

occupations. When specification (31) is re-estimated using as controls start-of-period *levels* of the six additional explanatory variables rather than contemporaneous changes (panel B), the coefficient on the post-1980 routine share variable is similar in magnitude and more precisely estimated than in panel A.

In summary, commuting zones' initial employment concentration in routine-intensive occupations is a robust predictor of their subsequent increases in service employment. Indeed, the routine share measure has greater predictive power for growth of service employment than any other human capital, labor market, or demographic variable that we have identified.

5.2 Which service occupations and which workers?

Is the relationship between routine task-intensity and growth of service employment specific to a subset of service occupations or one demographic subgroup? Estimates of equation (31) fit separately for each major service occupation group in Appendix Table 2 find that the aggregate relationship between the routine employment share and subsequent growth of service employment is common across 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 six. Notably, while health care support occupations are the third largest contributor to service employment growth over 1980 to 2005 (after food service and janitorial services), their growth is not strongly predicted by routine task-intensity. Plausibly, rising demand for health care support services derives from other sources, particularly the aging of the US population.

Complementing the results for occupations, Table 5 estimates equation (31) for four demographic sub-groups of non-college workers. The relationship between the RSH and rising service employment is of similar magnitude for both males and females though the coefficients for females are estimated with much less precision. Furthermore, routine intensive labor markets experienced a particularly large growth of low-skill service employment among foreign borns after 1980 but also positive effect for US-born workers.

[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 but does not contaminate the overall measure of service occupation employment.

5.3 Testing alternative explanations

This section devotes particular attention to two alternative hypotheses for the recent growth in low-skilled service employment: First, the displacement of workers from other low-skill occupations might be driven by offshoring rather than automation, and second, growing demand for low-skill services could result from any income and labor supply shocks to highly skilled individuals instead of a general equilibrium wealth effect for the overall population.

A rapidly growing theoretical and empirical literature studies offshoring, the arrangement where firms carry out specific tasks of the production process abroad. (e.g., Grossman and Rossi-Hansberg 2008, Bergin, Feenstra and Hanson 2009, Blinder 2009). A potential for offshoring generally exists for all occupational tasks that do not require physical proximity to domestic people or places. While this condition may be fulfilled in many production or clerical tasks, it does usually not hold for service occupations: Many service occupations are characterized by face-to-face interactions with customers (e.g., hairdressers or waiters), or they require proximity to a specific work site (e.g., cleaners or security guards). Therefore, it seems plausible that low-skill employment will become more concentrated in service occupations as other jobs are being offshored.

Our empirical test of the offshoring hypothesis assesses whether the growth of low-skilled service occupations in commuting zones is predicted by the offshoring potential of their occupations rather than the share of routine occupations.[39] To measure the non-offshorability of an occupation, we take a simple average of the two variables *Face-to-Face Contact* and *On-Site Job* that Firpo, Fortin and Lemieux (2009) derived from O*Net task data.[40] The resulting non-offshorability measure thus captures the degree to which an occupation requires either direct interpersonal interaction, or proximity to a specific work location.[41] Commuting zones' potential susceptibility to offshoring is measured by the average non-offshorability score of its occupations in a given year, and the resulting non-offshorability index is rescaled to a mean of zero and standard deviation of one in 1980.

The first two columns of Table 6 assess the relationship between commuting zones' potential for

[39] Blinder (2009) notes that the clearly defined procedures of routine tasks may make them particularly prone to offshoring but he argues that the overlap between routine content and offshoring potential is incomplete. In our analysis, there is a correlation coefficient of -0.48 between commuting zones' routine employment share and their non-offshorability score.

[40] Firpo, Fortin and Lemieux (2009) define *Face-to-Face Contact* as the average value of the O*Net variables *Face-to-Face Discussions*, *Establishing and Maintaining Interpersonal Relationships*, *Assisting and Caring for Others*, *Performing for or Working Directly with the Public*, and *Coaching and Developing Others*. *On-Site Job* is the average of the O*Net variables *Inspecting Equipment, Structures, or Material*, *Handling and Moving Objects*, *Operating Vehicles, Mechanized Devices, or Equipment*, and the mean of *Repairing and Maintaining Mechanical Equipment* and *Repairing and Maintaining Electronic Equipment*.

[41] According to this metric, the five least offshorable occupations in our data are respiratory therapists, dentists, fire fighters, elevator installers, and podiatrists while the most offshorable occupations are clothing pressing machine operators, weighers, statisticians, operations researchers, and financial records processing clerks.

offshoring and the growth of service occupation employment among non-college workers. The regression in column (1) finds the expected negative relationship between non-offshorability and subsequent growth of low-skill service employment but the coefficient estimate is small and not statistically significant. Column (2) simultaneously controls for the routine share and the non-offshorability of commuting zones' employment and finds that only the former measure predicts the growth of service occupations. [42]

Two further alternative explanations for the rise in low-skill service employment are rising high incomes, which may generate additional demand for outputs of service occupations if they are consumed as 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, as per Manning (2004) and Mazzolari and Ragusa (2008).

It is useful to notice that one could plausibly embed demand effects that originate from rising top incomes and from substitution for household production in our theoretical model of technological change. In fact, the model already predicts that routine-intensive commuting zones should experience both an increase in the wages of highly skilled workers and in low-skill service employment. The alternative hypotheses considered here however assess the possibility that there is a more mechanical relationship between the top and the bottom of the labor market where any shock to top incomes and labor supply translates to a change in low-skilled service employment irrespective of the shock's causes.

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 use changes in the 90th percentile of the log weekly wage distribution among full-time, full-year workers in each commuting zone.[43] As a measure of the labor supply of high-skilled workers, we use changes in mean annual hours worked among college graduates in each commuting zone. Both 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.[44]

Despite their substantial correlations with RSH, estimates in Table 6 indicate that these proxies

[42] In a similar vein, Goos, Manning and Salomons (2009b) argue that offshoring contributed less to occupational polarization in Europe than technological change.

[43] This distributional statistic 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 considered yield similar results but have lower explanatory power.

[44] Regression estimates imply that the commuting zone at the 80th percentile of RSH in 1980 experienced a 8 log points greater decadal growth in the 90th percentile of wages and an 11 hours greater decadal increase in annual labor supply of college graduates than the 20th percentile commuting zone over the 1980 - 2005 period. A full table of results is available from the authors.

for income and substitution effects do not have a strong direct relationship with growth 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 RSH variable is added. Annual hours worked by college graduates is *negatively* related to service employment growth, and this is true whether we measure college labor overall or separately by gender. Notably, the RSH variable 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 3 through 6 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 of non-college workers, i.e., male and female, foreign and US-born. The strong positive 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.

6 Mobility and Wages

We finally explore the relationship between task specialization, labor mobility, and occupational wage growth. For simplicity, our analytic framework models a single closed economy. Labor supply is fixed and changes in labor demand therefore translate to local wage effects. The model predicts that computer adoption will lead to an increase in the wage of skilled workers while among less skilled jobs, the ratio of manual to routine wage should increase. Since the rate of computer adoption varies across commuting zones, one might expect that there is also geographic variation in the wage effects that the model predicts.

Empirical evidence however suggests that local labor demand shocks will trigger a reallocation of workers across markets, with the labor mobility response of highly educated workers typically exceeding the mobility of less educated labor (e.g., Notowidigdo 2010). It is therefore plausible that labor mobility will at least partially offset geographic wage differentials. This section assesses both the impact of RSH on local skill supply and on occupational wage growth.

Table 7 assesses the relation between commuting zones' initial routine intensity and subsequent changes in the education structure of the workforce. Panel A reveals a striking pattern: A higher

level of RSH predicts a greater polarization of educational attainment, with both the proportions of college graduates and high school dropouts increasing relative to the fractions of workers with some college or with high school education. These results are consistent with a response of labor supply to an increasing demand for highly skilled workers that specialize in abstract tasks, and a growing demand for low-skill services which tend to employ workers with very low educational qualifications.

Panel B specifically addresses geographic mobility of workers as a source of changes in commuting zones' education structure in the two full decades 1980-1990 and 1990-2000. The dependent variable in this Panel refers to the education structure in the last year of the respective decade; it measures the difference between the share of individuals with education level e among recently 'immigrated' workers and the share of individuals with education level e among 'non-immigrant' workers. Migrant workers are defined as persons who lived out-of-state five years ago while non-migrant workers are those that were already present in the same state five years earlier.[45] The estimates show that in routine intensive local labor markets, recently arrived migrants are more likely to be college graduates and, to a lesser degree, more likely to be high school dropouts than non-migrant workers. These results suggest that geographic mobility of workers contributes to an increasing relative supply of workers at both ends of the educational spectrum in high routine areas.

The final part of the empirical analysis studies whether the wage effects that are predicted by the theoretical model are observable at the level of local labor markets despite the mitigating force of labor mobility. We pool microdata on real log hourly wages from the 1980 Census and the 2005 American Community Survey to estimate a set of OLS log wage equations of the following form:

$$\begin{aligned} \ln w_{ijkt} &= \alpha_k + \beta_{1k} \left\{ RSH_{j,1980} \times I\left[t = 2005\right] \right\} \\ &\quad + X'_{ijkt}\beta_{2kt} + \delta_{jk} + \gamma_{jk} + e_{ijkt}, \end{aligned} \tag{32}$$

where i denotes workers, j denotes commuting zones, k denotes occupation, and t denotes times (1980, 2005). These models include 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. We perform estimates separately for each of the major occupation categories in Table 1 (except for farm occupations). Standard errors are clustered at the commuting zone level since to account for the fact that the main predictive variable, RSH, does not vary within commuting zones. [46]

[45] The definition of migrants based on states of residence is an imperfect proxy for migration across commuting zones. The PUMS files for the decennial Censuses report place of residence five years ago only at a relatively high level of geographic aggregation while residence five years ago is missing altogether in the 2005 ACS.

[46] We also experimented with clustering estimates by state and year. Because this produced smaller standard errors, we conservatively report the commuting zone-clustered standard errors in the table.

Estimates in the first two columns of Table 8 show that commuting zones specialized in routine employment in 1980 saw large real wage increases among workers in the two occupation groups with highest education levels between 1980 and 2005. A 10 percentage point higher routine share in 1980 predicts 8.3 log points greater wage growth in managerial and professional occupations and 13.1 log points greater wage growth in technical, sales and administrative occupations (both for males) over these two decades. Estimates for females are of the same order of magnitude.

The next two columns estimate analogous wage models for workers in production and operative occupations—many of them corresponding to relatively low skilled 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.[47]

The fifth column presents wage estimates for workers in service occupations. Distinct from other low-education occupations (i.e., production workers and operatives), the relationship between initial routine task share and service wages is positive though not statistically significant. When wages in service occupations are directly compared to those in productive and operative positions in the final column, relative wage growth in service occupations is found to be greater in routine intensive commuting zones.

The second row of each panel of Table 10 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. While estimates for high-skilled occupations are not systematically affected, all coefficient estimates for the less skilled occupations in columns (3) to (5) become less negative or more positive, indicating an adverse changes in skill composition in these occupations in initially routine-intensive commuting zones. After controlling for individual-level covariates, a higher initial routine share not only predicts a significant relative wage gain of service occupations compared to other low-skilled occupations but also a significantly higher absolute wage growth.[48]

These microdata estimates confirm that commuting zones that were initially 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, stable or declining wages in less skilled production

[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] These results underscore that rising relative wages in service relative to other low-education occupations in Table 10 are unlikely to be driven by unobserved selection of relatively high-skilled workers into service jobs.

and operative occupations, and moderately growing wages in low-skill service occupations. This pattern of occupational wage growth has a close qualitative resemblance to the pattern of occupational wage changes at the national level as reported in Table 1. The data clearly support the view that displacement of routine tasks within commuting zones is accompanied by relative 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 appears to benefit from this process.

7 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 17 log points, considerably exceeding wage growth in other low-skill occupations. In fact, the upward twisting of the lower-tail of the U.S. earnings and job distributions commencing in the 1990s is substantially accounted for by rising employment and wages in service occupations.

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 U.S. 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 away 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 U.S., the U.K. and West Germany. 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. and David Dorn. 2009. "This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure." *American Economic Review Papers and Proceedings*, 99(2), 45-51.

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(4), 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.

Bergin, Paul R., Robert C. Feenstra and Gordon H. Hanson. 2009. "Offshoring and Volatility: Evidence from Mexico's Maquiladora Industry." *American Economic Review*, 99(4), 1664-1671.

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

Blinder, Alan S. 2009. "How Many US Jobs Might Be Offshorable?," *World Economics*, 10(2), 41-78.

Card, David and John E. DiNardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics*, 20, October, 733-83.

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

Cortes, Patricia. 2008. "The Effect of Low-Skilled Immigration on U.S. 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.

Dorn, David. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." Dissertation University of St. Gallen no. 3613, September 2009.

Dustmann, Christian, Johannes Ludsteck and Uta Schönberg. 2009. "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124(2), May, 843-881.

Firpo, Sergio, Nicole Fortin and Thomas Lemieux. 2009. "Occupational Tasks and Changes in the Wage Structure." Mimeo, September.

Glaeser, Edward L. and Joseph 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), 118-133.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009a. "Job Recent Changes in the European Employment Structure: The Roles of Technology and Globalization." *American Economic Review Papers and Proceedings*, 99(2), May, 58-63.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009b. "Job Polarization in Europe." Mimeo, September.

Grossman, Gene M. and Esteban Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review*, 98(5): 1978-1997.

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.

Juhn, Chinhui. 1994. "Wage Inequality and Industrial Change: Evidence from Five Decades." NBER Working Paper No. 4684, March.

Juhn, Chinhui. 1999. "Wage Inequality and Demand for Skill: Evidence from Five Decades." *Industrial and Labor Relations Review*, 52(3), April, 424-443.

Katz, Lawrence F. and David H. Autor. 1999. "Changes in the Wage Structure and Earnings Inequality." In O. Ashenfelter and D. Card, eds. *Handbook of Labor Economics*, volume 3, North Holland.

Lemieux, Thomas. 2006. "Increased Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill." *American Economic Review*, 96, June, 461–498.

Lemieux, Thomas. 2008. "The Changing Nature of Wage Inequality." *Journal of Population Economics*, 21(1), January, 21-48.

Leonardi, Marco. 2008. "Product Demand Shifts and Wage Inequality." University of Milan Working Paper, 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.

Ngai, L. Rachel and Christopher Pissarides. 2008. "Trends in Hours and Economic Growth." *Review of Economic Dynamics*, 11, April, 239-256.

Notowidigdo, Matthew J. 2010. "The Incidence of Local Labor Demand Shocks." Mimeo, January.

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].

Simon, Curtis J. 2004. "Industrial Reallocation across U.S. Cities, 1977-1997." *Journal of Urban Economics*, 56, 199-143.

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

Spitz-Oener, Alexandra. 2006. "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure." *Journal of Labor Economics* 24 (April), 235-270.

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

Data appendix

Measuring labor supply and earnings

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 psychiatric 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.

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 inflated to the year 2004 using the Personal Consumption Expenditure Index in order to be comparable to those of the 2005 ACS.

Matching Census geography to commuting zones (CZs)

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 Public Use Micro Area (PUMA or, prior to 1990, 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 U.S. 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 is to match PUMAs to counties assuming that all residents of a 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. Many PUMAs (e.g., 81% of those in the 2000 Census) match fully into a single CZ, while observations from the remaining PUMAs are proportionally assigned to several CZs. This geographic matching technique allows us to calculate the population characteristics of residents of each CZ consistently in each year of our data.

Building consistent occupations

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 create a balanced panel of 330 occupations for the years 1980 to 2005 that allows to follow a consistently defined set of occupations over time. The occupation categories of the 1950 to 1970 Census are also matched to this

occupation system but not all 330 occupations are observed in every year.

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). Details of the construction of the occupational classification are given in Dorn (2009).

Figure 1a

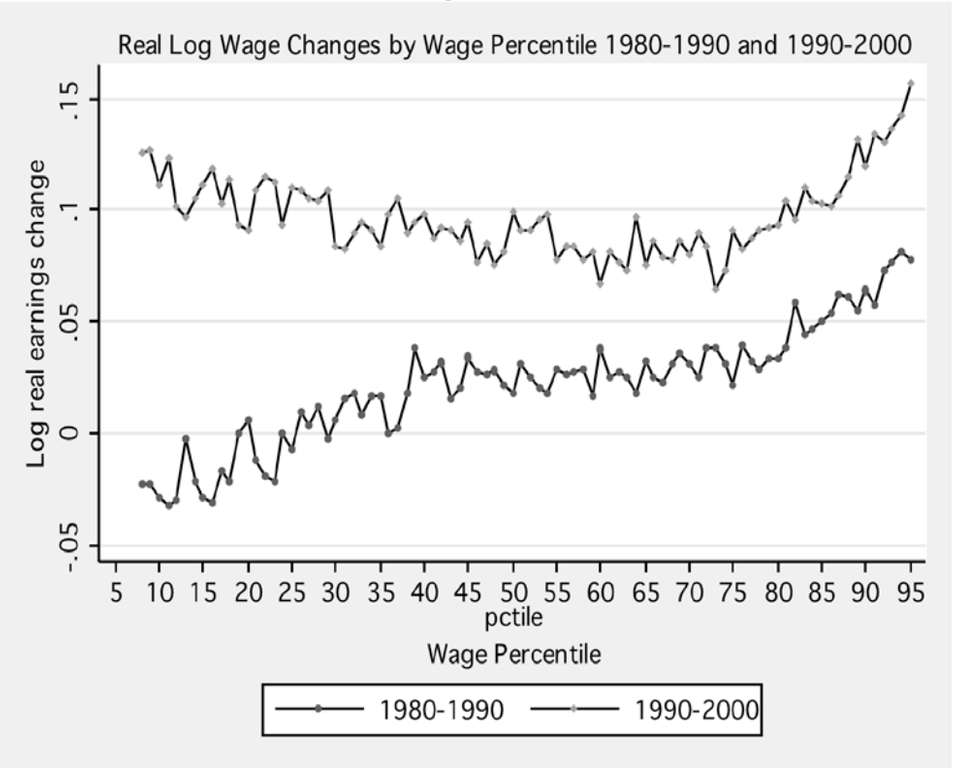

Figure 1b

Figure 1.
Changes in Real Log Hourly Wages by Wage Percentile (panel A) and Changes in Employment Shares by Occupational Skill Percentile (panel B) 1980-1990 and 1990-2000

Figure 2a

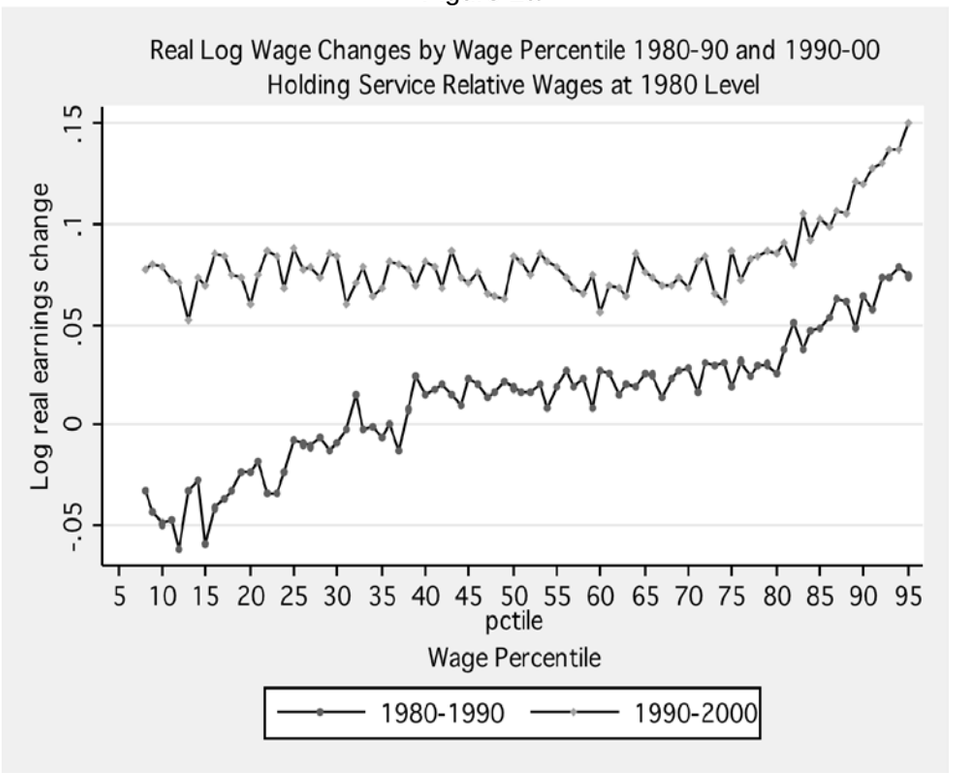

Figure 2b

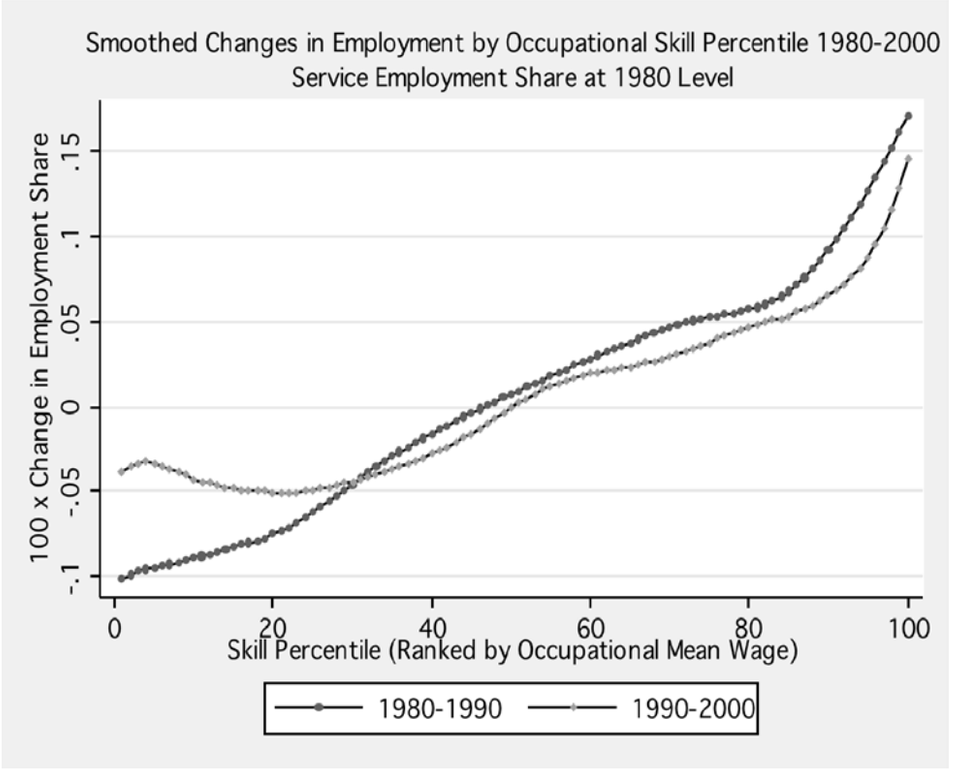

Figure 2.
Counterfactual Changes in Real Log Hourly Wages by Wage Percentile (panel A) and Changes in Employment Shares by Occupational Skill Percentile (panel B) 1980-1990 and 1990-2000, Holding Service Occupation Employment and Wages

Figure 3a

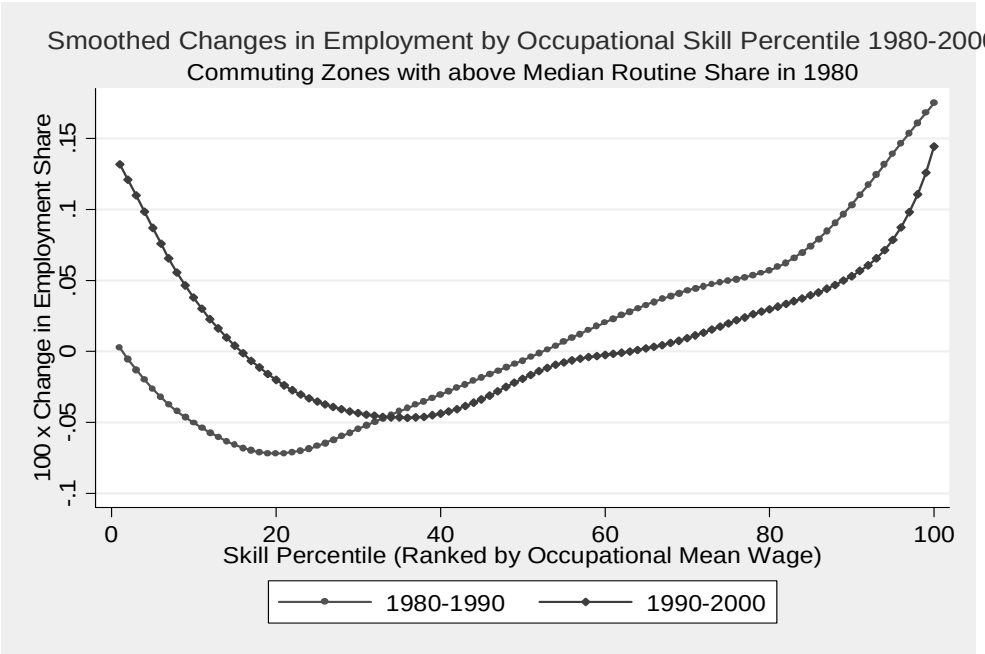

Figure 3b

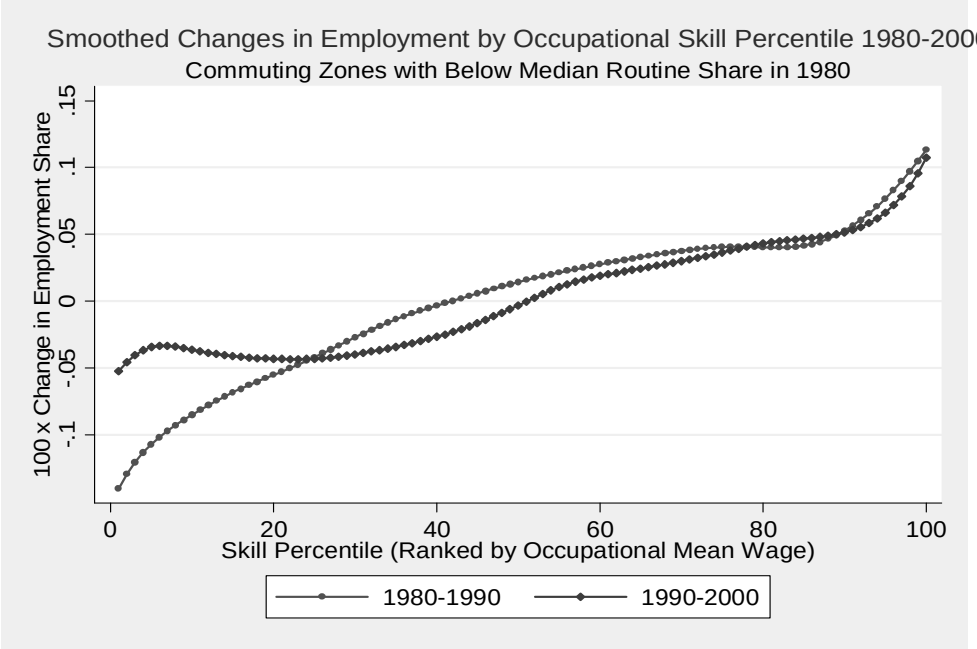

Figure 3.
Changes in Employment Shares by Occupational Skill Percentile 1980-1990 and 1990-2000: Comparing Commuting Zones with Above and Below Median Routine Occupation Share in 1980.

Figure 4a

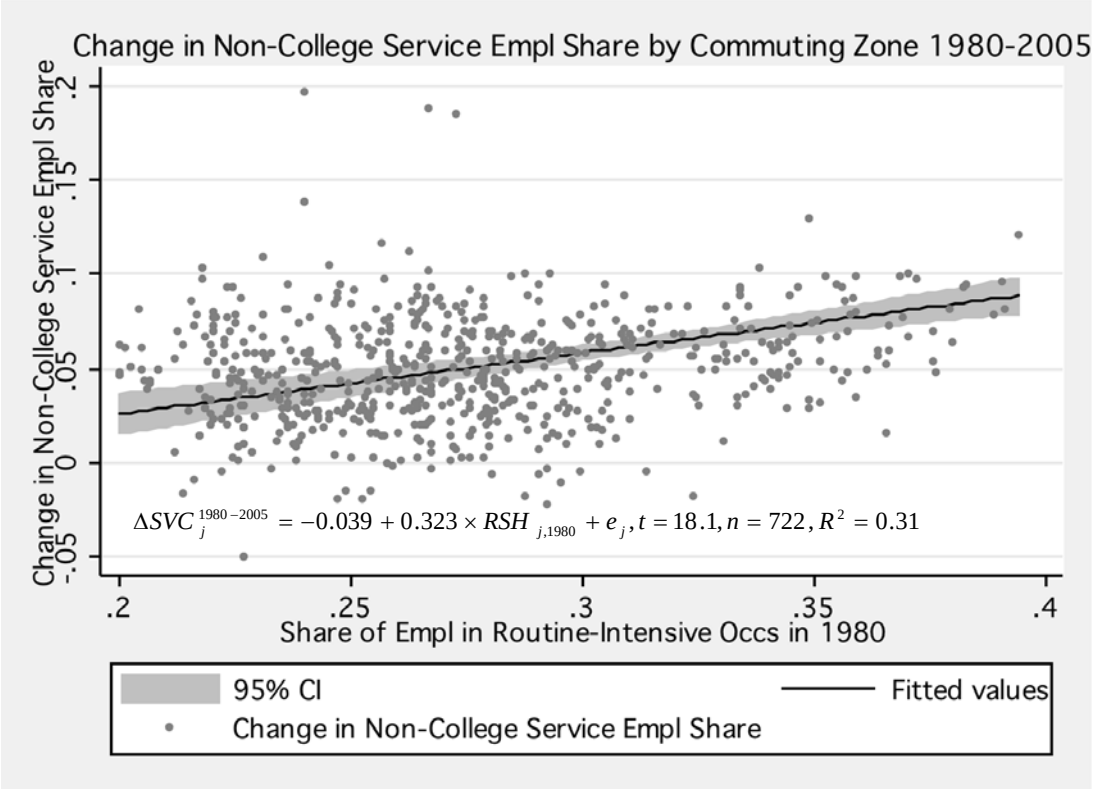

Figure 4b

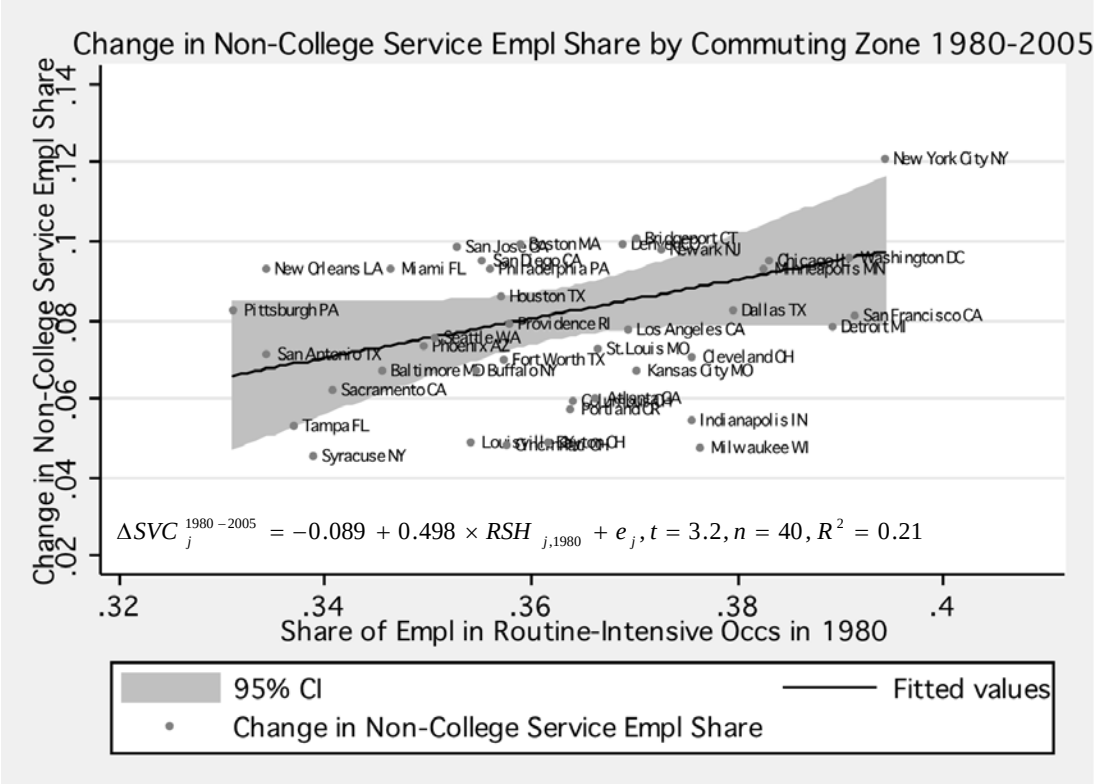

Figure 4.
Change in Non-College Employment Share in Service Occupation 1980 - 2005 Plotted Against Routine Employment Share in 1980 for Full Sample of Commuting Zones (Panel A) and the Set of Commuting Zones Containing at Least 1 Million Residents (Panel B)

Table 1. Levels and Changes in Employment Share and Mean Real Log 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	20.1	21.4	23.8	27.8	29.5	30.4	5.8	10.3
Technicians/Sales/Admin	21.7	26.6	28.9	30.8	30.1	29.5	10.1	0.8
Production/Craft/Repair	13.3	13.9	14.3	12.4	12.6	11.9	2.4	-6.9
Operators/Fabricat/Laborers	22.8	22.6	19.2	15.5	13.4	12.6	-5.5	-15.6
Farming/Fishery/Forestry	10.7	3.8	2.8	1.8	1.3	1.3	-36.3	-25.9
Service Occupations	11.4	11.7	11.0	11.8	13.0	14.3	-1.2	11.0
				B. Mean Real Log Hourly Wage (2004$)				
Managers/Professionals	2.24	2.88	2.87	2.95	3.07	3.19	0.21	0.13
Technicians/Sales/Admin	2.00	2.47	2.48	2.54	2.65	2.72	0.16	0.10
Production/Craft/Repair	2.20	2.70	2.73	2.68	2.71	2.73	0.18	0.00
Operators/Fabricat/Laborers	1.99	2.45	2.49	2.45	2.52	2.53	0.17	0.01
Farming/Fishery/Forestry	0.93	1.80	1.88	2.09	2.21	2.24	0.32	0.14
Service Occupations	1.51	2.06	2.16	2.21	2.32	2.33	0.22	0.07

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 Census 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. Computer Adoption and Task Specialization within Commuting Zones, 1980 - 2005.
Dependent Variable: 10 × Annual Change in 'Adjusted PCs per Employee' (Doms and Lewis 2006), 10 × Annual Change in Employment Share of Occupation Group

	(1)		(2)		(3)	
	A. Δ Adjusted PCs per Employee, 1980-2000					
	1980-1990		1990-2000		1980-2000	
Share of Routine Occs.$_{-1}$	0.711	**	0.529	**	0.662	**
	(0.051)		(0.058)		(0.035)	
R^2	0.653		0.375		0.455	
	B. Δ Share Routine Occupations, 1980-2005					
	All Workers		College		Non-College	
Share of Routine Occs.$_{-1}$	-0.238	**	-0.162	**	-0.277	**
	(0.013)		(0.014)		(0.018)	
R^2	0.589		0.340		0.450	
	C. Δ Share High-Skill Non-Routine Occs					
	All Workers		College		Non-College	
Share of Routine Occs.$_{-1}$	0.047	**	0.078	**	-0.034	
	(0.018)		(0.019)		(0.023)	
R^2	0.107		0.110		0.085	
	D. Δ Share Low-Skill Non-Routine Occs					
	All Workers		College		Non-College	
Share of Routine Occs.$_{-1}$	0.190	**	0.083	**	0.311	**
	(0.022)		(0.014)		(0.030)	
R^2	0.524		0.267		0.375	

Notes: N=675, N=660, and N=2166 in the three columns of Panel A, N=2166 (3 time periods x 722 commuting zones) in Panels B-D. 'Adjusted number of PCs per employee' is based on firm-level data on PC use which is purged of industry-establishment size fixed effects (Doms and Lewis 2006). The PC variable is unavailable for a small number of commuting zones with account for less than 1% of total US population. All models include an intercept and state dummies and multi-period models include time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 3. 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	
				I. OLS Estimates						
Share of Routine Occs.$_{-1}$	-0.122	**	0.032		0.082	**	0.084	*	0.321	**
	(0.020)		(0.034)		(0.024)		(0.037)		(0.087)	
Constant	0.022	**	-0.032	**	-0.014	*	-0.003		-0.042	
	(0.003)		(0.009)		(0.007)		(0.011)		(0.027)	
State dummies	Yes		Yes		Yes		Yes		Yes	
R^2	0.495		0.435		0.528		0.596		0.334	
				II. IV Estimates (2nd Stage)						
Share of Routine Occs.$_{-1}$	-0.136	**	0.063	~	0.075	**	0.153	**	0.539	**
	(0.018)		(0.032)		(0.026)		(0.043)		(0.111)	
Constant	0.025	**	-0.040	**	-0.012		-0.023	~	-0.109	**
	(0.003)		(0.009)		(0.008)		(0.013)		(0.034)	
State dummies	Yes		Yes		Yes		Yes		Yes	
R^2	0.493		0.429		0.528		0.580		0.312	
				III. IV 1st Stage						
Predicted Share of Routine Occs. 1950	1.078	**	0.704	**	0.627	**	0.456	**	0.366	**
	(0.074)		(0.060)		(0.061)		(0.052)		(0.043)	
R^2	0.820		0.732		0.689		0.613		0.548	

N= 722 commuting zones. Routine occupations are defined as the occupations with largest routine task/manual task ratios that account for one third of overall employment in 1980. IV models predict the start-of-period routine occupation share based on commuting zones' historical industry mix in 1950; see text for details. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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

	1950 - 2005					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Control Variables in First Differences					
Share of Routine Occs.$_{-1}$ × 1980-05	0.228 **	0.208 **	0.129 **	0.190 **	0.208 **	0.115 **
	(0.027)	(0.026)	(0.032)	(0.021)	(0.026)	(0.026)
Share of Routine Occs.$_{-1}$	-0.042 **	-0.069 **	-0.073 **	-0.071 **	-0.070 **	-0.064 **
	(0.012)	(0.018)	(0.016)	(0.016)	(0.019)	(0.014)
Δ College/Non-college pop			0.012 *			0.017 **
			(0.006)			(0.006)
Δ Immigr/Non-college pop			0.100 **			0.101 **
			(0.039)			(0.038)
Δ Manufact/Empl				-0.072 **		-0.094 **
				(0.024)		(0.021)
Δ Unemployment rate				0.315 **		0.390 **
				(0.044)		(0.047)
Δ Female empl/pop					-0.059 **	0.096 **
					(0.020)	(0.020)
Δ Age 65+/pop					0.064	0.170 **
					(0.053)	(0.050)
State dummies	No	Yes	Yes	Yes	Yes	Yes
R^2	0.366	0.396	0.413	0.448	0.401	0.474
	B. Control Variables in Start-of-Period Levels					
Share of Routine Occs.$_{-1}$ × 1980-05	0.228 **	0.208 **	0.141 **	0.160 **	0.203 **	0.098 **
	(0.027)	(0.026)	(0.024)	(0.021)	(0.025)	(0.018)
Share of Routine Occs.$_{-1}$	-0.042 **	-0.069 **	-0.086 **	-0.061 **	-0.023	0.002
	(0.012)	(0.018)	(0.024)	(0.015)	(0.020)	(0.023)
R^2	0.366	0.396	0.403	0.404	0.415	0.440

N=3610 (5 time periods x 722 commuting zones). Share of routine occupation variables are instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include an intercept and time dummies. Models in panel II use the same specifications as those in panel I but include start-of-period levels of the control variables instead of first differences. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 5. Routine Employment Share and Growth of Service Employment within Commuting Zones, 1950 - 2005. Dependent Variable: 10 × Annual Change in Share of Population Group's Non-College Employment in Service Occupations

	Males		Females		US Borns		Foreign Borns	
Share of Routine Occs.$_{-1}$ × 1980-05	0.168	**	0.141	~	0.058	*	0.315	**
	(0.023)		(0.080)		(0.028)		(0.091)	
Share of Routine Occs.$_{-1}$	-0.014		0.036		-0.057	**	-0.081	
	(0.015)		(0.036)		(0.018)		(0.069)	
Constant	0.005	~	-0.037	**	0.018	**	0.020	
	(0.003)		(0.010)		(0.004)		(0.015)	
State dummies	Yes		Yes		Yes		Yes	
R^2	0.236		0.512		0.283		0.052	

N=3610 (5 time periods x 722 commuting zones). Share of routine occupation variables are instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include a full set of time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 6. Predicting Changes in Service Occupation Employment using Proxies for Non-Offshorability and Income and Substitution Effects. Dependent Variables: 10 × Annual Change in Share of Non-College Employment in Service Occupations, 1980-2005

	I. Offshoring		II. Income Effects		III. Substitution Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of Routine $Occs_{-1}$		0.153 **		0.179 **		0.175 **	0.182 **	0.154 **
		(0.032)		(0.029)		(0.029)	(0.029)	(0.027)
Non-Offshorability $Index_{-1}$	-0.007	0.003						
	(0.005)	(0.005)						
Δ ln(P90) Weekly Wage			0.013	-0.019				
			(0.015)	(0.015)				
Δ Avg Annual Hours per Coll Grad / 2080					-0.111 **	-0.122 **		
					(0.032)	(0.031)		
Δ Avg Annual Hours per Male Coll Grad / 2080							-0.068 **	
							(0.018)	
Δ Avg Annual Hours per Female Coll Grad / 2080								-0.079 **
								(0.024)
R^2	0.169	0.193	0.166	0.192	0.185	0.212	0.202	0.209

N=2166 (3 time periods x 722 commuting zones). The Non-Offshorability index is standardized to a mean of zero and a standard deviation of one in 1980. Share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include an intercept, state dummies, and time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 7. Changes in Educational Composition, 1980-2005. Dependent Variable: 10 × Annual Change in Education Shares; Difference in Education Shares between Migrant Workers (Out-of-State 5 Years Ago) and Non-Migrant Workers.

	College Graduates		Some College		High Sch. Graduates		High Sch. Dropouts	
	(1)		(2)		(3)		(4)	
	A. ∆ Education Shares among Workers, 1980-2005							
Share of Routine Occs.$_{-1}$	0.359	**	-0.173	**	-0.395	**	0.209	**
	(0.044)		(0.038)		(0.067)		(0.047)	
R^2	0.423		0.779		0.516		0.630	
	B. Difference Education Shares of Migrant Workers vs. Non-Migrant Workers, 1980-2000							
Share of Routine Occs.$_{-1}$	0.557	**	-0.567	**	-0.160		0.170	
	(0.138)		(0.117)		(0.107)		(0.110)	
R^2	0.568		0.775		0.622		0.736	

N=2166 (3 time periods x 722 commuting zones) in Panel A, N=1444 (2 time periods x 722 commuting zones) in Panel B. Share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include an intercept, state dummies, and time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 8. Routine Employment Share and Wage Changes by Major Occupation Groups, 1980 - 2005.
Dependent Variable: Log Real Hourly Wage.
Microdata Estimates using Pooled 1980/2005 Census and ACS Samples

	(1) Manager / Profess.		(2) Tech / Sales / Admin		(3) Product / Craft / Repair		(4) Operat / Laborers		(5) Service Occs		(6) Service vs. Prodn/ Operat	
I. Males												
(A) Share of Routine Occs.$_{-1}$ x 2005	0.834	**	1.313	**	-0.349	*	-0.632	**	0.096		0.663	**
	(0.177)		(0.222)		(0.175)		(0.199)		(0.259)		(0.193)	
Worker X's?	No		No		No		No		No		No	
(B) Share of Routine Occs.$_{-1}$ x 2005	0.903	**	0.885	**	0.160		-0.324		0.423	~	0.610	**
	(0.175)		(0.202)		(0.190)		(0.207)		(0.246)		(0.204)	
Worker X's?	Yes		Yes		Yes		Yes		Yes		Yes	
N	987,065		858,177		1,038,589		1,304,826		528,027		2,871,442	
II. Females												
(A) Share of Routine Occs.$_{-1}$ x 2005	1.267	**	1.095	**	0.089		-0.551	**	0.087		1.084	**
	(0.162)		(0.166)		(0.319)		(0.190)		(0.186)		(0.214)	
Worker X's?	No		No		No		No		No		No	
(B) Share of Routine Occs.$_{-1}$ x 2005	1.210	**	1.106	**	0.267		-0.066		0.361	*	0.701	**
	(0.166)		(0.169)		(0.267)		(0.192)		(0.176)		(0.161)	
Worker X's?	Yes		Yes		Yes		Yes		Yes		Yes	
N	926,169		1,831,136		94,843		528,532		840,657		1,461,565	

Notes: Each cell reports the coefficient estimate from a separate IV regression. Share of routine occupations is instrumented by the 1950 industry mix instrument. All models include an intercept, a full set of commuting zone dummies, and a time dummy. Models with worker X's also include nine dummies for education levels, a quartic in potential experience, dummies for married, non-white and foreign-born, and interactions of all individual level controls with the time dummy. Column (6) pools the three major groups of low-skill occupations: Production, craft and repair occupations, operators, laborers and fabricators, and service workers. The coefficient in column (6) refers to the interaction term between the share of routine occupation variable and a dummy for service workers. Hourly wages are defined as yearly wage and salary income divided by the product of weeks worked times usual weekly hours. Robust standard errors in parentheses are clustered on commuting zones. Observations are weighted by each worker's share in total labor supply in a given year. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Appendix Table 1. Characteristics, Rankings, and Sizes of Routine and Non-Routine Occupations

A. Characteristics of Routine and Non-Routine Occupations in 1980

	Routine Occupations	High Wage Non-Routine Occs	Low Wage Non-Routine Occs
Avg Ln Hourly Wage	2.53	2.84	2.29
Share College Educ	0.45	0.54	0.27
Average Routine Task Intensity (RTI) Score	1.18	-0.56	-0.63

B. Occupations Ranked by Routine-Task-Intensity and Employment

1. Occupations with Highest RTI Scores

1	Secretaries and Stenographers
2	Bank Tellers
3	Pharmacists
4	Payroll and Timekeeping Clerks
5	Motion Picture Projectionists *
6	Boilermakers
7	Butchers and Meat Cutters
8	Accountants and Auditors
9	Actuaries
10	Proofreaders

2. 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 Transp. Attendants, Inspectors *
6	Police and Detectives, Public Service *
7	Truck, Delivery, and Tractor Drivers
8	Garbage and Recyclable Material Collector
9	Crossing Guards *
10	Railroad Coupler, Brake, Switch Operators

3. Largest High-Wage Non-Routine Occs

1	Truck, Delivery, and Tractor Drivers
2	Production Supervisors or Foremen
3	Primary School Teachers
4	Registered Nurses
5	Supervisors of Construction Work
6	Secondary School Teachers
7	Electricians
8	Engineering Technicians
9	Physicians
10	Police and Detectives, Public Service *

4. Largest Low-Wage Non-Routine Occs

1	Retail Salespersons and Sales Clerks
2	Sales Supervisors and Proprietors
3	Janitors *
4	Farmers
5	Health and Nursing Aides *
6	Carpenters
7	Automobile Mechanics and Repairers
8	Production Checkers, Graders, and Sorters
9	Waiters and Waitresses *
10	Textile Sewing Machine Operators

Notes: Asterisk denotes service occupations according to the Census occupational classification. Real hourly wages are inflated to 2004. The Routine Task Index (RTI) measures the log routine/manual task ratio for each detailled occupation. The distribution of RTI in the labor market in 1980 is standardized to a mean of zero and a standard deviation of one. For occupations with equal RTI score, ranking ties are split by giving a higher ranking to the occupation with larger share in total US employment in 1980. High and low-wage non-routine occupations are grouped by 1980 mean occupational wages. Each group contain one-third of 1980 employment, with the remaining third of 1980 employment classified as routine task-intensive. Residual occupations groups (miscellaneous, other, and not elsewhere classified) are excluded from the ranking.

Appendix Table 2. Routine Employment Share and Growth of Employment in Detailled Service Occupations 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. Regression Analysis											
Share of Routine Occs.$_{-1}$ × 1980-05	0.064	**	0.044	**	0.013		0.018		0.019	**	0.020	**	0.010	*	0.015	**	0.006	
	(0.010)		(0.012)		(0.012)		(0.011)		(0.006)		(0.005)		(0.004)		(0.004)		(0.012)	
Share of Routine Occs.$_{-1}$	-0.012	~	0.001		-0.007	~	-0.013	*	-0.006	*	-0.007	**	0.005	*	-0.008	**	-0.021	**
	(0.007)		(0.004)		(0.004)		(0.006)		(0.003)		(0.002)		(0.002)		(0.003)		(0.008)	
Constant	0.009	**	0.005	**	0.006	**	0.005	**	0.003	**	0.001	**	-0.001	**	-0.001		-0.009	**
	(0.001)		(0.001)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.001)		(0.002)	
State dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.110		0.256		0.116		0.469		0.131		0.157		0.096		0.264		0.584	
							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%		1.15%		0.44%		0.49%		0.19%		0.25%		0.28%		0.13%	

N=3610 (5 time periods x 722 commuting zones). Share of routine occupation variables are instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include a full set of time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.