The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market*

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Abstract

We offer a unified explanation and empirical analysis of the polarization of U.S. employment and wages between 1980 and 2005, and the concurrent growth of low skill service occupations. We attribute polarization to the interaction between consumer preferences, which favor variety over specialization, and the falling cost of automating routine, codifiable job tasks. Applying a spatial equilibrium model, we derive, test, and confirm four implications of this hypothesis. Local labor markets that were specialized in routine activities differentially adopted information technology, reallocated low skill labor into service occupations (employment polarization), experienced earnings growth at the tails of the distribution (wage polarization), and received inflows of skilled labor.

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

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1 Introduction

A vast literature documents a pronounced rise in wage inequality in the United States and numerous other advanced nations commencing in the 1980s, and proposes skill-biased technological change as its primary cause. The intellectual foundation of this literature is what Acemoglu and Autor (2010) refer to as the canonical model, which features two distinct skill groups—typically, college and high-school workers—performing two distinct and imperfectly substitutable occupations or producing two imperfectly substitutable goods.[1] Technology in the canonical model is assumed to take a *factor-augmenting* form, meaning that it complements either high or low skill workers and thus induces either a monotone increase or decrease in wage inequality between skill groups. The canonical model is not only tractable and conceptually attractive but has also proved empirically quite successful in accounting for the evolution of skill premia in the United States throughout the twentieth century, as well as capturing major cross-country differences in skill premia among advanced nations.[2]

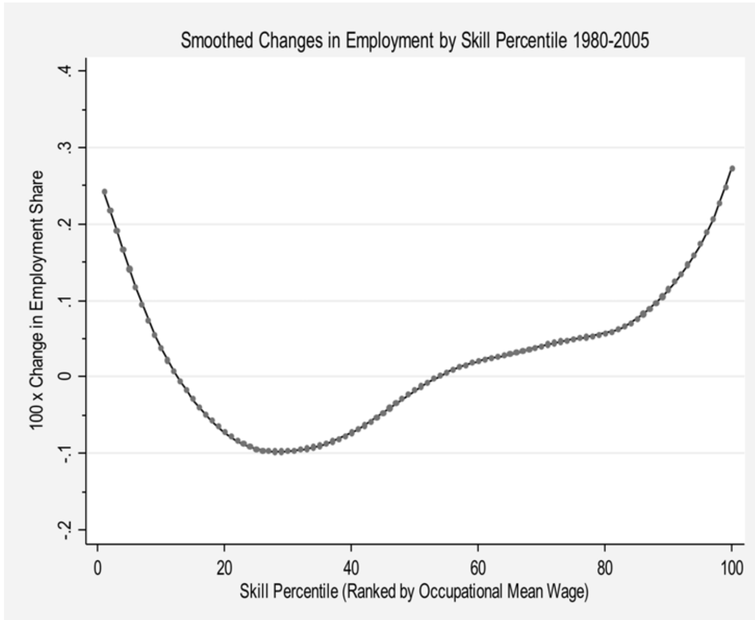
Despite its virtues, the canonical model falls short of providing a satisfactory framework for understanding two major features of the recent evolution of inequality that are the focus of this paper. A first is the strikingly non-monotone growth of employment by skill level, which is depicted in Figure 1a. This figure is constructed by using Census IPUMS and American Community Survey (ACS) data to calculate the change between 1980 and 2005 in the share of employment accounted for by 318 detailed occupations encompassing all of U.S. non-farm employment. Occupations are ranked by skill level, which is approximated by the mean log wage of workers in each occupation in 1980.[3] Consistent with the conventional view of skill-biased technological change, employment growth is differentially rapid in occupations in the upper two skill quartiles. More surprising in light of the canonical model are the employment shifts seen below the median skill level. While occupations in the second skill quartile fell as a share of employment, those in the lowest skill quartile expanded sharply. In net, employment changes in the U.S. during this period were strongly U-shaped in skill level, with relative employment declines in the middle of the distribution and relative gains at the tails.

[1] In many cases, this model is extended to more than two skill groups (see, e.g., Card and Lemieux, 2001, and Acemoglu, Autor and Lyle, 2004).

[2] See Katz and Murphy (1992) and a large subsequent literature summarized and extended by Katz and Autor (1999), Acemoglu (2002), Goldin and Katz (2008) and Acemoglu and Autor (2010).

[3] Since the sum of shares must equal one in each decade, the change in these shares across decades must total zero (except for rounding due to the locally weighted smoother applied to the series). Ranking occupations by mean years of completed schooling instead of wages, or using a base year other than 1980 for these rankings, yields very similar results.

Panel A



Panel B

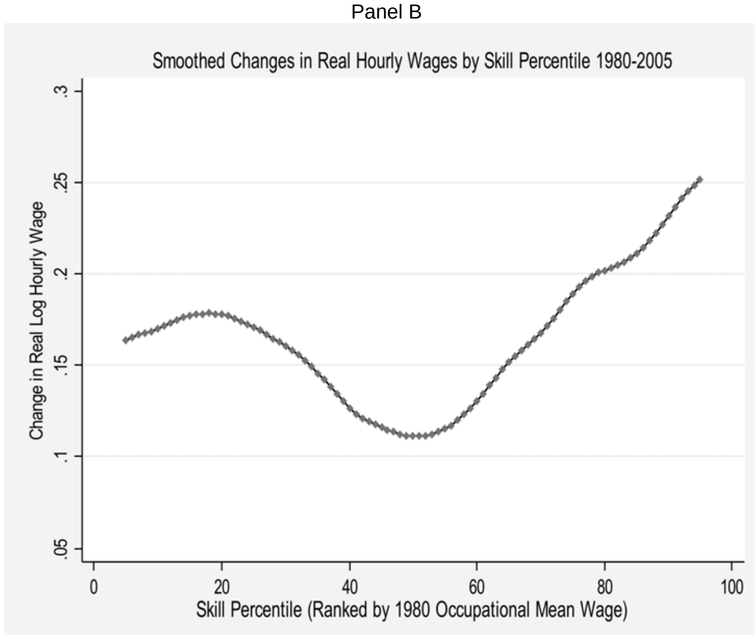


Figure 1.
Smoothed Changes in Employment (Panel A) and Hourly Wages (Panel B) by Skill Percentile, 1980-2005.

This pattern of employment polarization is not unique to the U.S. Although not recognized until recently, a similar 'polarization' of employment by skill level has been underway in numerous industrialized economies since at least the 1990s.[4] Using harmonized European Union Labour

[4]The polarization of U.S. employment was initially studied by Acemoglu (1999) while Goos and Manning (2007) provided the first rigorous analysis of polarization based on U.K. data.

Force Survey Data, Goos, Manning and Salomons (2009, 2010) find that in 15 of 16 European countries for which data are available, high-paying occupations expanded relative to middle-wage occupations in the 1990s and 2000s, and in *all 16 countries*, low-paying occupations expanded relative to middle-wage occupations.

The second key unexplained feature of the evolution of inequality on which we focus is the non-monotonicity of wage changes by skill percentile in this same period. As shown in Figure 1b, which plots smoothed changes in real hourly earnings by occupational skill percentile between 1980 and 2005, the non-montone growth of employment by skill level has a clear counterpart in the evolution of wages. As with employment growth, wage growth is strikingly U-shaped in skill percentiles, with the greatest gains in the upper tail, modest gains in the lower tail, and substantially smaller gains towards the median.[5]

This paper offers a unified explanation and detailed empirical analysis of the forces behind the changing shape of low education, low wage 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 of the employment and earnings distributions is substantially (though not entirely) accounted for by a single, proximate cause: 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.[6] 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). This rapid growth stands in contrast to declining employment in all similarly low-educated occupation groups, which include production, craft and repair occupations, operative, fabricator and laborer occupations, and agriculture, forestry and fishing occupations. The rise in service employment was even steeper for non-college workers—those with no more than a high school education—rising from 13.8 to 20.7 percent of non-college hours between 1980 and 2005 (a 50 percent increase). Accompanying their

[5]Figures 1a and 1b use the same run variable on the x-axis (1980 occupational rankings and employment shares) and are therefore directly comparable. The polarization plots in Figure 1a and 1b differ from related analyses in Autor, Katz and Kearney (2006 and 2008), Acemoglu and Autor (2010) and Firpo, Fortin and Lemieux (2009), which use occupational skill percentiles to measure employment polarization and use raw wage percentiles to measure wage polarization.

[6]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 83 percent of non-farm employment in 2005 (source: www.bls.gov). Since part-time jobs are relatively prevalent in service occupations, the share of service *jobs* in U.S. employment is even larger than their share in total labor input. Hecker (2005) reports that service occupations accounted for nearly one in five jobs in 2004 whereas our calculations in Table 1 find that service occupations contribute approximately one in seven hours of labor input.

rising employment, real wage growth in service occupations substantially outpaced that in other low skill occupations, averaging seven percent per decade between 1980 and 2005.[7]

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

	Level						10yr 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
Operator/Fabricator/Laborer	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
Operator/Fabricator/Laborer	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.

To benchmark the contribution that service occupations make to aggregate employment and wage polarization, we calculate a simple counterfactual scenario in which the employment share and relative wage level of service occupations are each held at their 1980 levels. Figure 2a shows that reweighting the distribution of employment in 2005 to hold the share of employment in service occupations constant at its 1980 level substantially reduces the upward twist of the lower tail of the employment distribution during this twenty-five year period.[8] Similarly, holding the wage differential between service occupations and other blue collar occupations constant at its 1980

[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 undercount illegal immigrants who provide a substantial share of U.S. farm labor.

[8]The figure uses data from the 1980 Census and 2005 ACS and is calculated using a simple variant of the DiNardo, Fortin and Lemieux (1996) density reweighting method. Further details are given in the figure notes.

level throughout the 1980 through 2005 period (Figure 2b) substantially dampens the upward twist of the lefthand tail of the distribution of wage changes by occupational skill in this time interval.[9] These simple plots make a critical point: to interpret the pronounced polarization of employment and wages in the U.S. and potentially in other advanced countries, it is necessary to understand the rapid rise of employment and wages in service occupations.[10]

The primary hypothesis advanced in this paper is that the secular rise in employment and wages in low skill service occupations is caused by the interaction between consumer preferences, which favor variety rather than specialization, and non-neutral technological progress, which greatly reduces the cost of accomplishing routine, codifiable job tasks but has a comparatively minor impact on the cost of performing in-person service tasks. 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—non-neutral technological progress concentrated in goods production (by which we mean non-service occupation activities) has the potential to raise aggregate demand for service outputs and ultimately increase employment and wages in service occupations.

We develop these implications formally in a simple general equilibrium model of 'routine-task' replacing technological change, building upon Autor, Levy and Murnane (2003, ALM hereafter), Weiss (2008), and in a broader sense, Baumol's (1967) model of unbalanced technological progress.[11] Technological progress in our model takes the form of an ongoing decline in the cost of computerizing routine tasks, which can be performed both by computer capital and low skill ('non-college') workers in the production of goods. The adoption of computers substitutes for low skill workers performing routine tasks. These routine tasks—such as bookkeeping, clerical work, and repetitive production and monitoring activities—are readily computerized because they follow precise, well-defined procedures. Importantly, occupations intensive in these tasks are most commonplace in the middle of the occupational skill and wage distribution.

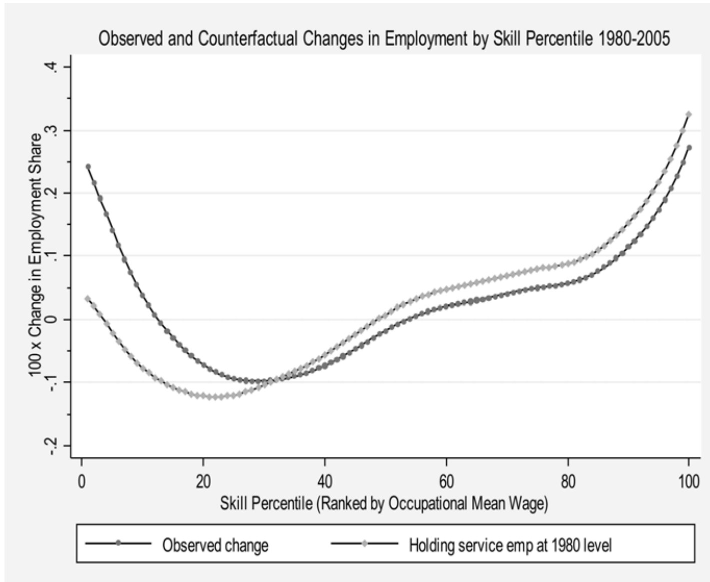
The secularly falling price of accomplishing routine tasks using computer capital complements the 'abstract' creative, problem-solving, and coordination tasks performed by highly-educated workers such as professionals and managers, for whom data analysis is an input into production.

[9] This calculation fixes the wage gap between service occupations and other blue collar occupations to its 1980 level for the entire 1980 to 2005 period. Further details are given in the figure note.

[10] The growth of employment and wages in service occupations commenced in the 1980s. Its effects on the aggregate distribution of employment and earnings did not become highly evident until the 1990s, when service occupation growth was large enough to dominate offsetting declines in other low-skilled occupations (see Acemoglu and Autor, 2010). Aggregate polarization became visible in the U.K. and Germany during the 1980s (Spitz-Oener, 2006, Goos and Manning, 2007, and Dustmann, Ludsteck and Schöenberg, 2009).

[11] In related work, Ngai and Pissarides (2007) derive a multisector model where unbalanced productivity growth leads to rising employment in sectors that have low TFP growth. Acemoglu and Guerrieri (2007) develop a model in which endogenous technological change leads to unbalanced technological progress due to differentially rapid progress in capital relative to labor intensive technologies.

Panel A



Panel B

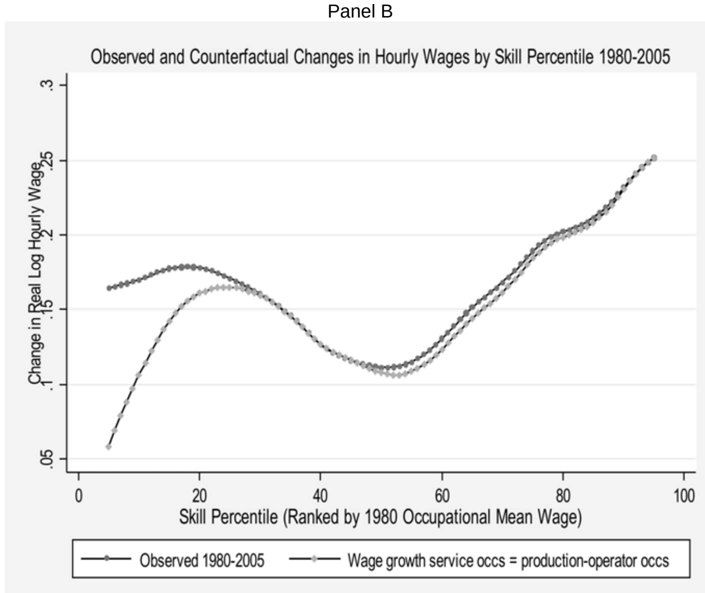


Figure 2.
Smoothed Changes in Employment (Panel A) and Hourly Wages (Panel B) by Skill Percentile, 1980-2005.

Notes: To construct the counterfactual in Panel A, we pool ACS data from 2005 with Census data from 1980 and estimate a weighted logit model for the odds that 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 2005 using the estimated odds multiplied by the hours-weighted Census sampling weight, effectively weighting downward the frequency of service occupations in 2005 to their 1980 level. Given the absence of other covariates in the model, the extra probability mass is implicitly allocated uniformly over the remainder of the distribution. We calculate the counterfactual change in service occupation wages in Panel B by assigning to each service occupation in 2005 its 1980 real log wage level plus the mean log wage change between 1980 and 2005 in production, craft and repair occupations, and operator, fabricator and laborer occupations, all of which have comparably low education levels.

Critically, automation of routine tasks neither directly substitutes for nor complements the core jobs tasks of low-education occupations—service occupations in particular—that rely heavily on 'manual' tasks such as physical dexterity and flexible interpersonal communication.[12] Consequently, as computerization erodes the wage paid to routine tasks in the model, low skill workers reallocate their labor supply to service occupations.

The theoretical analysis asks how the allocation of low skill labor between goods and services, and the inequality of wages, evolve as automation drives the price of routine tasks towards zero. A focal question is whether ongoing, skilled-labor augmenting technological change necessarily causes inequality between high and low skill workers to rise in perpetuity (unless offset by corresponding labor supply shifts). The answer supplied by the model is no. We show first that when the elasticity of substitution *in production* between computer capital and routine labor is higher than the elasticity of substitution *in consumption* between goods and services, the continuously falling price of computers ultimately causes wages for low skill labor performing manual tasks to exceed wages for low skill labor performing routine tasks. Low skill labor flows accordingly from goods to services, while all high skill labor remains in goods production, leading to *employment polarization.*

The second key result concerns *wage polarization.* Wage polarization occurs if the elasticity of substitution between goods and services in consumption does not exceed unity—that is, goods and services are at least weakly complementary. If so, the wages paid to manual tasks (and hence non-college earnings) converge to a steady growth rate that equals or exceeds the growth rate of college wages. If instead the consumption elasticity of substitution between goods and services is relatively high, then the model yields the canonical case of monotone skill biased technological change where wages and employment fall most at the bottom of the occupational skill distribution (i.e., in manual tasks). Thus, the conceptual framework nests the canonical case of monotone skill biased technological change as one polar outcome of the model, though not the one that appears to best fit the data.

Building from the observation that the output of low-skill service occupations is non-storable and non-tradeable—hence, suppliers and demanders of in-person services must collocate—we test the theoretical framework at the level of local labor markets.[13] We measure levels and changes in economic variables over 1980 through 2005 within 722 consistently defined, fully inclusive Commuting Zones using data from the Census IPUMS and from the ACS for 1980, 1990 and 2000, and

[12]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."

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

2005. To isolate pre-determined variation in the susceptibility of local labor markets to substitution of information technology for routine labor input, we combine Census data on industry and occupation mix by local labor market with data from the Dictionary of Occupational Titles (U.S. Department of Labor, 1977) on job tasks by occupation to generate a simple index measuring the share of labor employed in routine task-intensive occupations in each commuting zone (the 'routine share') at the start of the relevant time period. We document that the specialization of local labor markets in routine activities in the 1980s forward is largely pre-determined by industry structure *in 1950*—three decades prior to the era of service occupation growth—which allows us to use the 1950 industry mix to construct an instrument for local labor market specialization in routine tasks in later decades.

To guide the empirical work, we extend the conceptual model to a spatial equilibrium setting in which mobile high skill workers reallocate across geographic regions to arbitrage differential changes in real earnings induced by the interaction between a uniformly falling price of automating routine tasks and differences across regions in the ability of firms to capitalize on these advances stemming from industry specialization. This extension provides testable implications for four outcome variables at the level of local labor markets. Local markets that were historically specialized in routine task-intensive industries should differentially: (1) adopt computer technology and displace workers from routine task-intensive occupations; (2) undergo employment polarization as low skill labor reallocates into manual task-intensive in-person services; (3) exhibit larger (nominal) wage growth at both ends of the occupational skill distribution (i.e., wage polarization); and (4) experience larger net inflows of workers with both very high and very low education, driven by rising demand for both abstract labor in goods production and manual labor in service production.

Each of these implications receives robust empirical support. Commuting zones that were specialized in routine intensive occupations in 1980 (as a function of historical industry structure) experienced differential increases in workplace computer use and reductions of employment in routine task-intensive jobs over the subsequent 25 years (i.e., 1980 through 2005). Simultaneously, they experienced a sharp differential rise in low skill service occupation employment. Applying a longer sample frame, we show that the growth of service occupations in routine-intensive commuting zones was absent in the 1950s and 1960s, weakly evident in the 1970s, and then robustly present and accelerating in subsequent decades.

The differential growth of service employment in routine-intensive commuting zones was accompanied by wage polarization: relative wages rose in both low skill service occupations and high skill managerial, professional, and technical occupations, while falling across the remaining set of more routine-intensive, low-skilled occupations. Corroborating the importance of local demand shifts, we document significant differential migration of both high skill (college educated) workers and very low skill (high school dropout) workers into these initially routine intensive labor markets. In net, these results reveal a process of employment and wage polarization within regional labor markets that parallels the polarization of employment and wages observed in aggregate data..

We evaluate numerous alternative explanations, alongside unbalanced technological progress, for the striking differences in wage and employment polarization across local labor markets. Influential work by Clark (1957) finds that the income elasticity of demand for services is greater than unitary, implying that preferences are non-homothetic. If so, rising prosperity will raise the share of income devoted to services, even if productivity growth is balanced. We refer to this as the income effect hypothesis. A related idea explored in papers by Manning (2004), Ngai and Pissarides (2008) and Mazzolari and Ragusa (2008), is that rising returns to skill spur high skill workers to increase their labor supply while substituting market for home-based production of household services, thus raising employment in service occupations. We refer to this as the substitution effect hypothesis.[14] By contrast, the positive effect of computerization on service employment and wages in our model results from the interaction between productivity growth that favors goods and preferences that favor diversity over specialization in consumption.[15]

In practice, we find limited empirical support for either the income or substitution effect channels in explaining employment and wage polarization in local markets. Growth of service employment within commuting zones is *negatively* correlated with changes in the hours worked of male and female college graduates, which is inconsistent with the household substitution hypothesis. Similarly, rising high wages in commuting zones, as measured by growth in the real 90th wage percentile, are at best weakly correlated with increases in service employment, a pattern that is inconsistent with the income effect hypotheses.

We also ask whether the key findings on changes in task specialization in local labor markets are explained by the offshoring of tasks that do not require on-site performance or face-to-face contact. Using an index of the offshorability of occupations adapted from Firpo, Fortin and Lemieux (2009), we find that differences in susceptibility to offshoring account for almost none of the substantial variation in growth of service occupation employment across local labor markets

[14]Leonardi (2010) 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.

[15]Consumers in our model have homothetic preferences—hence, neither goods nor services are inferior—and do not engage in household production or leisure, so there are no substitution effects in labor supply. We shut down both income and substitution channels to highlight that polarization can arise purely from unbalanced growth absent these other forces.

between 1980 and 2005.

Other potential contributors to the growth of service occupations discussed in the literature include: 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 educational attainment, elderly population share, and female labor force participation of commuting zone residents, which may raise demand for services. Though each of these factors has the expected correlation with rising penetration of service jobs in local labor markets, controlling for these variables does not change the main inference: regions that were initially specialized in routine-intensive occupations experienced a disproportionate degree of growth in service occupation employment.[16] In summary, our results suggest a critical role for changes in labor specialization, spurred by automation of routine task activities, as a driver of rising employment and wage polarization in the U.S. and, potentially, in other countries.

In the next section, we outline a model of unbalanced productivity growth and derive implications for the evolution of occupational composition, skill allocations, 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 through 7 present empirical tests of the model's four main predictions for computer adoption, task specialization, wage polarization, and geographic mobility by skill group. Section 8 concludes.

1.1 Environment

We consider an economy with two sectors ($j = g, s$) that produce 'goods' and 'services' for consumption using four factors of production.[17] Three of these factors are labor (task) inputs: manual, routine and abstract (L_m, L_r, L_a). These labor inputs are supplied by workers of two skill levels ($i = H, U$) corresponding to high and low skill workers. The fourth factor of production is computer capital K, which is an intermediate (non-consumption) good that also provides routine task services. In each sector, a continuum of mass one of firms produces output.

Production of goods combines routine labor, abstract labor, and computer capital, measured in efficiency units, using the following technology:

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

[16] Our conclusion that automation of routine tasks is the primary explanation for observed employment polarization is also echoed by recent cross-country analyses by Goos, Manning and Salomons (2010) and Michaels, Natraj and Van Reenen (2010). Distinct from these studies, our paper documents and analyzes polarization across local labor markets rather than countries.

[17] What we specifically have in mind is that the 'service' sector provides *low skill* in-person services such as haircutting and food service. The 'goods' sector involves all other economic activities, including manufacturing industries and skilled service industries such as banking or higher education.

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

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

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

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 skill 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 skill 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 skill 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. Specifically, a low skill worker supplies routine tasks only if his earnings in goods production exceeds the (uniform) service wage (i.e., $w_r(t) \times \eta_i \geq w_m(t)$). Given the positive self-selection and attendant higher earnings of low skill workers in goods relative to service occupations, workers in service occupations tend to be at the bottom of the wage-ranked occupational skill distribution (i.e., at the left-hand side of polarization graphs) while routine occupations are towards the middle of the distribution.

To permit analytic solutions of the model, it is convenient to choose a functional form for $f(\eta)$. We assume that η is distributed exponentially on the interval $[0, \infty]$ with $f(\eta) = e^{-\eta}$. The choice of functional form is, however, innocuous since the long run equilibrium of the model (i.e., as $t \to \infty$) depends only on technology, preferences, and factor endowments (i.e., H and U).

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

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

[18] 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 substitution of computer capital for labor input of routine tasks.

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. Capital fully depreciates between periods.[19] Productivity is rising at δ, reflecting technological progress. At time 1, one unit of the consumption good Y can be used to produce one efficiency unit of computer capital:

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

Competition guarantees 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:

$$\begin{aligned} u &= \left(c_s^{\rho} + c_g^{\rho}\right)^{1/\rho}, \qquad (6) \\ \text{where } \rho &< 1. \end{aligned}$$

The elasticity of substitution in consumption between goods and services is $\sigma_c = 1/(1-\rho)$.

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

We are interested in the long-run ($t \to \infty$) 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 present the static solution of the model and its asymptotic equilibrium immediately below and then extend the model to a spatial equilibrium setting.

1.2 The planner's problem

Since there are no distortions, the equilibrium allocation can be characterized by solving the social planner's problem. In each time period, the planner chooses the level of capital $K(t)$, and the allocation of labor $L_m(t)$ to manual tasks in the service sector that maximize aggregate utility. The equilibrium at each time can be analyzed in isolation because capital fully depreciates between periods and consumption equals output. The price of computer capital falls exogenously over time, and the equilibrium prices of all factors follow from their marginal products.

[19] More precisely, the flow of services provided by computer capital is paid its rental price continually as these services are consumed.

Given $p_k(t)$ at time t, the social planner's problem at time t can be written as:

$$\begin{aligned}
& \max_{K,L_m} \left(L_m^{\frac{\sigma-1}{\sigma}} + \left(Y_g - p_k(t) K\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} && (7) \\
\text{where } Y_g &= L_a^{1-\beta} X^{\beta} \text{ and } X \equiv \left[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu} \right]^{1/\mu} \\
& L_r = g(L_m) \equiv (1 - \log(1 - L_m))(1 - L_m),
\end{aligned}$$

where X is the aggregate input of routine tasks, $g(\cdot)$ is a function with the property that $g(0) = 1$ and $g(1) = 0$, and we use σ in place of σ_c to simplify notation. Note that the social planner essentially chooses the level of capital, $K(t)$, and the allocation of labor $L_m(t)$ to manual tasks in the service sector, and thus also the allocation $L_r(t) = g(L_m(t))$ to routine tasks in the goods sector.

The first order conditions for problem (7) with respect to capital K and labor L_m respectively are given by:

$$\frac{\partial Y_g}{\partial K} = p_k(t), \tag{8}$$

$$L_m^{-1/\sigma} = (Y_g - p_k K)^{-1/\sigma} \frac{\partial Y_g}{\partial X} \frac{\partial X}{\partial L_r} \left(-\log(1 - L_m)\right), \tag{9}$$

where we have used

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

The system in (8) and (9) contains two unknowns (L_m, X) in two equations and uniquely solves for the equilibrium at any time t. We use these equations to first solve for the asymptotic allocation of low skill labor between goods and services and then to solve for equilibrium wages.

1.3 Asymptotic labor allocation

Since the price of computer capital $p_k(t)$ falls to zero asymptotically, the equation determining the equilibrium marginal product of computer capital (Eq. 8) can only hold if $K \to \infty$ as $p_k \to 0$. Hence:

$$\lim_{t \to \infty} K(t) = \infty. \tag{10}$$

Since L_r is bounded from above and 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:

$$\lim_{t \to \infty} X / \alpha_k K = 1. \tag{11}$$

Using this equation and Eq. (10), the supplementary Theory Appendix shows that the asymptotic supply of low skill labor to services, L_m^*, is uniquely determined as follows:[20]

$$L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \bar{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases} . \tag{12}$$

This equation says that the allocation of low skill labor between services (manual tasks) and goods (routine tasks) depends upon the relative magnitudes of the consumption and production elasticities (σ and $\sigma_r = 1/(1-\mu)$, respectively), scaled by the share of the routine aggregate in goods production (β).

To see the intuition for this limiting result, consider a case where $\beta = 1$, so that equation (12) simplifies to $\frac{\sigma_r}{\sigma} \gtreqless 1$. In this case, the asymptotic allocation of low skill labor to services versus goods production depends entirely on whether the elasticity of substitution *in production* between computer capital and routine labor is higher or lower than the elasticity of substitution *in consumption* between goods and services (both of which demand low skill labor). If the production elasticity exceeds the consumption elasticity, technological progress (i.e., a falling computer price p_k) raises relative demand for low skill labor in service employment. In the limit, all low skill labor flows from goods production into services production. If this inequality is reversed, all low skill labor eventually concentrates in the goods sector, where it performs routine tasks (which is opposite to the trends we see in the data).

The role played by β in this equation—that is, the share of the routine aggregate in goods production—is also intuitive. If β is low, a relatively small share of the gains to technical progress accrue to low skill labor performing routine tasks (through q-complementarity) and a correspondingly larger share accrues to high skill labor performing abstract tasks. Consequently, the lower is β, the smaller is the critical value of σ_r/σ required for low skill labor to flow into services.

1.4 Asymptotic wage inequality

Two measures of inequality relevant for this analysis. The first is the relative wage paid to routine versus manual tasks. When this ratio rises, wages in routine production occupations (in the middle of the occupational wage distribution) grow relative to wages in service occupations at the bottom of the distribution (and vice versa when the ratio falls). The second is the relative wage paid to abstract versus manual tasks, reflecting earnings inequality between occupations at the top and bottom of the occupational skill distribution. In our terminology, a monotone increase in inequality is a case where w_a/w_m rises and w_m/w_r falls. In contrast, wage polarization occurs

[20] Here, $\bar{L}_m$ is the solution to the equation $(\bar{L}_m)^{-1/\sigma} = \kappa_1^{-1/\sigma}\kappa_2 g\,(\bar{L}_m)^{\mu-1}\,(-\log(1-\bar{L}_m))$.

when w_m/w_r rises while w_a/w_m is either stable or declining. We next derive the necessary and sufficient conditions for these outcomes.

Since low skill labor necessarily flows towards the sector/task that offers the highest wage, the dynamics of w_m/w_r precisely mirror the dynamics of labor flows between goods and services (Eq. 12). Specifically:

$$\frac{w_m}{w_r} = \begin{cases} \infty \text{ if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -\log\left(1 - L_m^*\right) \text{ if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 \text{ if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}. \end{cases} \tag{13}$$

If the production elasticity exceeds the consumption elasticity (scaled by β), wages for low skill workers in the service sector rise relative to the alternative wage in goods, and low skill labor flows to service occupations at the bottom of the occupational skill distribution. Therefore, the lower tails of the wage and employment distributions 'polarize.'

This polarization is necessary but not sufficient for overall wage polarization to occur. The additional condition needed is that wages in service occupations grow at least as rapidly as high skill wages (i.e., is w_a/w_m is either constant or declining).[21] The supplementary Theory Appendix shows that this occurs if the consumption elasticity weakly exceeds unity—that is, goods and services are gross complements:[22]

$$\frac{w_a}{w_m} = \begin{cases} 0 \text{ if } \sigma < 1 \\ 1 \text{ if } \sigma = 1 \\ \infty \text{ if } \sigma > 1 \end{cases}, \text{ when } \frac{1}{\sigma} > \frac{\beta - \mu}{\beta}. \tag{14}$$

This result is of signal importance to our analysis. It underscores that despite ongoing, skilled labor augmenting technological progress and a fixed skill endowment, wage inequality need not rise indefinitely. If goods and services are at least weakly complementary, inequality between high and low skill labor either asymptotes to a constant or reverse course. Thus, consumer preferences determine whether the rising marginal *physical* product of high skill workers translates into a corresponding rise in their marginal *value* product.

1.5 Summary of closed economy model

In summary, the closed economy model gives rise to three focal cases:

1. If the elasticity of substitution in production between computer capital and routine labor is high relative to the elasticity of substitution in consumption between goods and services

[21] If by contrast, w_a/w_m were to continue to rise, wages in manual tasks would eventually become arbitrarily small *relative* to wages in abstract tasks (even while w_m is rising in absolute terms). This would not accord with our definition of wage polarization.

[22] In the supplementary Theory Appendix, we also characterize the behavior of $\frac{w_a}{w_m}$ when $\frac{1}{\sigma} < \frac{\beta-\mu}{\beta}$, which can only occur when goods and services are gross substitutes ($\sigma > 1$).

(specifically, $1/\sigma > (\beta - \mu)/\beta$), the continuously falling price of automating routine tasks ultimately causes wages in manual tasks to exceed wages in routine tasks. Low skill labor flows accordingly from goods to services (though not instantaneously since some low skill workers have strong initial comparative advantage in routine tasks). Because routine task-intensive occupations, such as clerical and repetitive production jobs, are typically found towards the middle of the occupational skill distribution, we say that employment 'polarizes.'

2. If the consumption elasticity is less than or equal to unity ($1/\sigma \geq 1 > (\beta - \mu)/\beta$), employment polarization is also accompanied by wage polarization whereby the ratio of wages paid to abstract relative to manual tasks is either constant or decreasing.

3. Finally, when the production elasticity is low relative to the consumption elasticity ($1/\sigma < (\beta - \mu)/\beta$), ongoing technological progress competes down the wage paid in routine relative to abstract tasks but does not raise demand for services sufficiently to increase the manual relative to routine wage. In this case, wages and employment fall most at the bottom of the occupational skill distribution. Notably, this case corresponds most closely to the monotone skill-biased technological setting considered by the canonical model. It does not, however, appear to be the case best supported by the data.[23]

1.6 Spatial equilibrium

We now extend the above closed economy model to consider an integrated, spatial equilibrium setting in which mobile high skill workers reallocate across regions in response to changes in real earnings that are induced by the interaction between a uniformly falling price of automating routine tasks and heterogeneity in industry specialization that affect regions' ability to capitalize on these technological advances. The spatial equilibrium framework is particularly apropos to our subsequent empirical work, which studies the determinants of employment polarization at the level of local labor markets.

A large body of work documents persistent regional patterns of industry specialization that arise from location-specific productive attributes—such as climate or access to ports—or from agglomeration economies (e.g., Krugman, 1991, Blanchard and Katz, 1992, Ellison and Glaeser, 1997, and Glaeser and Gottlieb, 2009). We take these regional differences as given and in the subsequent empirical work, we use historical measures of local area industry mix in 1950 to capture

[23] It bears emphasis that the current model is *not* isomorphic to the canonical model, even in the case where high and low skill workers are gross complements. In the present model, there are two opposing forces that affect the evolution of inequality when goods and services are complements: the migration of low skill labor from goods to services, which depresses the low skill wage; and the ongoing rise in consumer demand for services, which raises the low skill wage. These countervailing forces may generate non-monotone inequality dynamics, though their limiting behavior is always governed by the asymptotic wage ratios given in the text.

longstanding geographic differences in regional specialization. These patterns of specialization are remarkably persistent over many decades, as we document below.

We consider a large set of geographic regions, $j \in J = \{1, .., |J|\}$, each endowed with a unit mass of high skill and a unit mass of low skill labor, with labor supply as above. To introduce regional specialization, we adopt the Armington (1969) assumption that products are differentiated by origin. In each region, a continuum of competitive firms produces differentiated consumption goods $Y_{g,j}$ using the technology

$$Y_{g,j} = L_{a,j}^{1-\beta_j} \left[(\alpha_r L_{r,j})^{\mu} + (\alpha_k K_j)^{\mu} \right]^{\beta_j/\mu},$$

with $\beta_j \in (0, 1)$. A higher value of β_j implies that the differentiated good produced in that region is relatively more intensive in the routine task aggregate, while a lower level of β_j corresponds to relatively high demand for abstract tasks in goods production. To simplify the analysis, we assume also that β_j is different for each region. In particular, there exists a region $j^{\max}$ such that $\beta_{j^{\max}} = \max_j \beta_j$, and a region $j^{\min}$ such that $\beta_{j^{\min}} = \min_j \beta_j$. Competitive firms in each region use low skill labor to produce service output as per Eq. (2).

Goods are costlessly tradable across regions. Services are non-tradable since they must be performed in person. Consistent with the observation that geographic mobility is higher among college than non-college workers (Topel, 1986, Bound and Holzer, 2000, and Notowidigdo, 2010), we posit that high skill labor is fully mobile across regions while low skill labor is not. We discuss below how relaxing this assumption would affect the results.

We assume that each region admits a representative household with preferences given by:

$$u(c_s, c_{g1}, ..., c_{gJ}) = u\left(c_s^{\rho} + \tilde{c}^{\rho}\right)^{1/\rho}, \tag{15}$$

where

$$\tilde{c} = \left(\sum_{j=1}^{J} c_j^{\nu} \right)^{1/\nu}, \tag{16}$$

with $\nu > 0$, implying that the goods from each region are gross substitutes. These preferences differ from our initial setup (equation (6)) only in that we allow for consumer substitution between locally produced services and the full set of consumption good varieties.

We make two further simplifications to consumer preferences for expositional ease. First, we consider only the focal case in which the consumption elasticity σ is equal to unity. This simplification is not restrictive since, as per equation (14), the aggregate model gives rise to employment and wage polarization for any substitution elasticity less than or equal to unity.

Second, because our empirical work explores variation in employment, wages, and mobility across local labor markets but does not analyze trade in goods, we make the simplifying assumption that all regional goods varieties are perfect substitutes in consumption (i.e., $\nu \to -\infty$ in equation (16)). Perfect substitutability ensures that goods prices are equated across regional economies. In equilibrium, however, goods trade does not occur since with only one tradable commodity and perfect substitutability among varieties, there are no gains from trade.

The remainder of the model is otherwise identical to the prior section. We continue to assume that there is continuous technological progress in the production of computer capital, captured by the decreasing relative price function $p_k(t)$, and that the rate of progress is equal across regions.

1.7 Equilibrium mobility and wages of high skill labor

We summarize the main results for wages and labor mobility in this section, while the supplementary Theory Appendix derives these results in detail. The spatial equilibrium condition for the high skill labor market can be written as

$$L_{a,j}(t) > 0 \text{ only if } w_{a,j}(t)/P_j(t) = w_{a,j^{\max}}(t)/P_{j^{\max}}(t). \tag{17}$$

where

$$P_j(t) = \left(p_{s,j}(t)^{1-\sigma} + 1\right)^{1/(1-\sigma)} \tag{18}$$

is the cost of increasing the consumption aggregator in local labor market j, $\left(C_{s,j}^{\frac{\sigma-1}{\sigma}} + C_{g,j}^{\frac{\sigma-1}{\sigma}}\right)^{\sigma/(\sigma-1)}$, by one unit.[24] Eq. (17) says that region j will have non-zero abstract labor supply if its real wage for abstract tasks matches the real abstract wage in the region $j^{\max}$.

There are two forces in equation (18) that influence the decision of high skill labor to migrate. First, an increase in the skilled wage $w_{a,j}(t)$ creates an incentive for high skill labor to migrate to region j. Second, an increase in local prices $P_j(t)$ creates an incentive for high skill labor to migrate *away* from region j. The equilibrium allocation of skilled labor balances these two forces, so that high skill workers have identical real earnings across all regions.

We show in the supplementary Theory Appendix (equation A27) that the spatial equilibrium condition (17) can be rewritten as

$$\frac{\kappa_1 L_{a,j}(t)^{-\beta_j} K_j(t)^{\beta_j}}{\kappa_1^{1/2} L_{a,j}(t)^{(1-\beta_j)/2} K_j(t)^{\beta_j/2}} = \omega(t), \tag{19}$$

where

$$\lim_{t\to\infty} \frac{w_{a,j}(t)}{w_{m,j}(t)^{1/2}} = \omega(t) \text{ for each } j$$

and $\omega(t)$ is a function that is independent of region j.

[24]As in the above static economy, we normalize the good price in each region to 1, i.e., $p_{g,j}(t) = 1$ for each j.

The term $K_j(t)^{\beta_j}$ in the numerator of this expression captures the positive effect of capital growth on the share of college labor (since the two factors are complements), while the term $L_{a,j}(t)^{-\beta_j}$ in the numerator captures the effect of the scarcity of college labor on wages. The denominator of this expression captures the effect of capital growth on the price of service goods. As the economy grows, services (which are produced by a scarce factor) increase in relative price, which has a negative effect on the welfare of college workers.

In equilibrium, high skill labor flows across regions until these forces are in balance and equation (19) is satisfied for each j. This equation is satisfied only if $\beta_j < \beta_{\bar{j}}$ for each $j \neq \bar{j}$, which implies that $\bar{j} = j^{\max}$. In other words, high skill labor is attracted at a constant rate to the region with the largest β_j, which is the region that benefits most from the declining price of computer capital.

To see the intuition for this equilibrium, consider a setting in which high skill labor is initially at a positive constant level in each region. Regions with greater β_j will have faster growth of capital and goods consumption. With a unit elasticity of substitution between goods and services, this leads to a proportional effect on the price of services. Also because $\sigma = 1$, the good Y_g asymptotically has a positive share of the consumption aggregator, which implies that $P_j(t) = w_{m,j}(t)^{1/2}$ grows at a rate slower than $w_{m,j}(t)$. Hence, regions with greater β_j have faster growth of $w_{a,j}(t)$ and identical growth of $w_{m,j}(t)$, and therefore faster growth of welfare for high skill labor, $w_{a,j}(t)/w_{m,j}(t)^{1/2}$. Moreover, welfare rises equivalently for low skill workers in high β_j regions since productivity gains accrue proportionately to both skill groups given Cobb-Douglas preferences.

As skilled labor leaves other regions $j \neq \bar{j}$, the price of services decreases in these regions and the welfare of high skill workers increases. In equilibrium, the rate of skilled labor's departure from other regions ensures that in every period t, the remaining high skill workers are indifferent between their current geographic region and all alternatives.[25] In the asymptotic equilibrium, all high skill labor is attracted to the region $\bar{j} = j^{\max}$ with the highest β_j.

1.8 Empirical implications

These spatial equilibrium results provide four main empirical implications that are tested in the subsequent empirical analysis. As the price of computer capital falls, the model predicts that local labor markets with greater initial specialization in routine tasks (a higher 'routine share') will experience:

1. Greater adoption of information technology;

[25] Because the price of services and hence the low skill wage rise proportionately with the high skill wage, mobility of high skill workers across regions also equalizes the real wages of low skill workers by region.

2. Greater reallocation of low skill workers from routine task-intensive occupations to service occupations (since there is a larger share of low skill workers who are initially specialized in routine tasks and then displaced from these tasks by automation);

3. Larger increases in wages for both high skill abstract and low skill manual labor (i.e., wage polarization), driven by the q-complementarity between information technology and abstract tasks in production and the gross complementarity between goods and services in consumption. The model makes clear that these regional wage differentials are nominal, however, since real wage differentials across regions are arbitraged by high skill mobility;[26]

4. Larger net inflows of high skill labor, driven by the interaction between differentially rapid adoption of computer capital in initially routine task-intensive labor markets and q-complementarity between computer capital and high skill labor.

Two elements omitted from the model deserve discussion. A first is our stylized assumption that high but not low skill labor is mobile across regions. Clearly, allowing for low skill labor mobility in our setup would lead to qualitatively similar results in that both high and low skill workers would differentially migrate towards the region with the highest routine share given its greater rate of capital accumulation and higher labor productivity growth. Informally, we therefore anticipate that greater inflows of the most and least skilled workers should both be detected in local labor markets with a high initial routine share—a conjecture that we confirm below.[27]

A second element of realism intentionally omitted from the model is the potential for skill supplies to adjust to changes in the skilled wage differential. If we were to endogenize human capital investment decisions, changes in earnings inequality would alter the path of skills accumulation, thus preventing wage inequality from either rising without bound or collapsing.[28] We omit this consideration to emphasize that even with skill supplies held constant, ongoing skilled labor augmenting technical change need not imply ongoing growth of inequality.

We now bring these implications to the data.

[26] Although the declining price of computer capital raises real earnings in aggregate, high skill labor mobility eliminates any real geographic wage differentials, so higher nominal wages in a region are fully offset by a higher cost of living. Moretti (2008) presents evidence that the prices of housing, goods and services are all higher in high-wage, high-education cities, and that these price differentials may offset as much as 40 percent of the higher nominal wages of high skill workers in these locations.

[27] More formally, our setup does not accommodate simultaneous high and low skill migration without further assumptions because, without a locally fixed factor that becomes scarce as workers flow into high routine share regions, full mobility readily gives rise to a case where all labor relocates to the region with the highest β_j. This feature of the model can be readily amended, at some cost in complexity, by making the plausible assumption that each regional variety Y_{gj} faces a downward sloping aggregate demand curve (as in equation (16)). This demand side force would prevent the economy from fully specializing in any one regional variety.

[28] Indeed, in our data, the college share of worked hours rises from 42 to 62 percent between 1980 and 2005.

2 Data sources and measurement

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

2.1 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.[29] 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.[30]

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. 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. Two disadvantages of MSAs are that (1) they do not cover rural parts of the U.S.; and (2) their geographic definition is periodically adjusted to reflect the growth of cities, so that the MSA information available in public use Census samples does not refer to time-consistent geographic areas. This inconsistency is problematic for our analysis because the economic characteristics of suburban areas that are appended to MSAs are likely to systematically differ from the core cities.

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.[31] Our analysis includes the 722 CZs that cover the entire mainland of the US (both metropolitan and rural areas). Commuting zones have three characteristics that make them particularly suitable for our analysis of local labor markets: they cover the entire U.S.; they are based primarily on economic geography rather than incidental factors such as minimum population or state boundaries; one can use Cen-

[29]The 1960 Census lacks detailed geographic information.

[30]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.

[31]Tolbert and Killian (1987) earlier developed commuting zones using the 1980 Census. These commuting zones are largely but not fully identical to the 1990 definitions.

sus 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.

2.2 Measuring the 'routine employment share'

A crucial input into our analysis is a summary index of routine task activities within commuting zones. This measure is derived from the occupational composition of employment. We measure routine task-intensity in each occupation using data from ALM (2003), who merge job task requirements 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.[32] While our theoretical model posits that low skill workers supply either routine or manual tasks, the DOT permits an occupation to involve multiple tasks at different levels of intensity.

To identify routine-intensive occupations, we construct an index of routine task-intensity, RTI:

$$RTI_k = \ln\left(T^R_{k,1980}/T^M_{k,1980}\right), \tag{20}$$

where T^R_k and T^M_k are, respectively, the routine and manual task inputs in each occupation k in 1980, measured on a 0 to 10 scale.[33] This measure is rising in the relative importance of routine tasks within an occupation and falling in the relative importance of manual tasks. We next classify as 'routine intensive' those occupations those that fall in the top third of the distribution of the RTI measure in 1980, with occupations weighted by their share in total non-college employment. This simple definition of routine occupations 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, 4

[32] 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. 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 mean routine task score 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. Further details on these variables are found in Appendix Table 1 of ALM.

[33] 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.

are service occupations, and the remainder involve driving motor vehicles.[34]

Our subsequent analysis contrasts the evolution of computer use, employment in service occupations, earnings inequality, and labor mobility across local labor markets that differ in their initial specialization in routine task-intensive employment. To measure this cross-market variation, we assign to each commuting zone j a routine employment share measure, RSH_{jt}, equal to:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1 \left[RTI_k > RTI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{21}$$

where L_{jkt} is the employment in occupation k in commuting zone j at time t, and $1[\cdot]$ is the indicator function that takes the value of one if the occupation is routine task-intensive by our definition. Hence, RSH_{jt} measures the fraction of a commuting zone's employment at the start of a decade that falls in routine intensive occupations.[35] The mean of this measure is 0.33 in 1980 by construction, and the population weighted 80/20 percentile range is 10 percentage points (specifically, $RSH^{P20} = 0.275$ and $RSH^{P80} = 0.373$).

A challenge for our empirical approach is that the evolution of routine employment share by CZ is potentially endogenous to the labor market outcomes that we analyze. For example, if as predicted by our model, low skill workers move from routine task-intensive occupations, such as clerical and production work, into in-person services, this will reduce the routine share and hence introduces simultaneity into our RSH measure. To purge this simultaneity, we exploit historical cross-CZ differences in industry specialization. Our approach works as follows: let $E_{ij,1950}$ equal the employment share of industry $i \in 1, ..., I$ in commuting zone j in 1950, and let $R_{i,-j,1950}$ equal the routine occupation share among workers in industry i in 1950 in all U.S. states *except* the state that includes commuting zone j.[36] The product of these two measures provides a predicted value for the routine employment share in each commuting zone, which depends only on the local

[34]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 occupations in the Census. Because these occupations do not possess the strong supplier-demander collocation attribute of service occupations, they 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 fall below the median.

[35]We measure the routine share in total employment rather than the routine share among non-college workers because the former measure is more precisely measured at the CZ level. The results are not sensitive to this choice, however, since the two measures are very highly correlated ($\rho > 0.99$ in 1980). We have also considered the robustness of results to alternative commuting zone routine intensity measures including the mean RTI in each commuting zone, and the share of employment in the top 20 or top 50 percent of routine-intensive occupations (rather than the top third). All of these measures perform similarly in our analysis.

[36]Following Autor and Duggan (2003), we exclude own state employment from the construction of our instrument for local labor market conditions to remove any mechanical correlation between the instrument and the endogenous variable. Throughout the analysis, we implicitly consider commuting zones to be part of the state that contains the largest share of their population.

industry mix in 1950 and the occupational structure of industries nationally in 1950:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-j,1950}. \tag{22}$$

Appendix Table 2 implements this setup by regressing the observed routine share in each commuting zone at the start of each decade on the 1950 industry mix measure and a set of state dummies. Estimates are weighted by the national share of population in each commuting zone and year. The $\widetilde{RSH}_j$ measure proves strongly predictive of the realized routine share in each decade. The coefficient on this variable is close to unity in 1950, and secularly declines in magnitude in subsequent decades, attaining a coefficient of 0.37 in 2000.[37] This decline is to be expected since initial conditions are likely to become less relevant over the long run. Nevertheless, the power of the predictive relationship is sizable in all periods, with t-ratios that always exceed 8.5. The second row of the table presents a pooled model that includes all decades of data and adds time dummies and a full set of interactions between the $\widetilde{RSH}_j$ measure and these dummies. Point estimates for the coefficients of interest in the pooled regression are similar in magnitude and significance to the by-decade estimates. In short, location-specific, historical differences in industry structure appear to exert a large and persistent influence on contemporaneous occupational structures.

In the subsequent empirical work, we use this historical industry structure measure as an instrumental variable to isolate longstanding, predetermined geographic variation in occupational composition that is not attributable to subsequent technological and demographic developments (e.g., computerization, immigration, demographic change, migration and wage inequality). We do not claim, nor does the analysis require, that these patterns of industry specialization in 1950 are randomly assigned to commuting zones—only that they induce systematic predetermined geographic variation in the share of workplace tasks that are suitable for computerization in later decades.

3 Initial evidence: Computerization, and employment and wage polarization across commuting zones

Prior to conducting a rigorous assessment, we provide initial descriptive evidence on the first three primary predictions of the model concerning employment and wage polarization, computer adoption, and task substitution within local labor markets.

A key prediction of the analytic framework is that commuting zones specialized in routine task-intensive work will experience differential employment shifts out of routine occupations in the

[37] The predictive relationship in 1950 does not have to equal unity since only out-of-state variation in occupational composition within industries is used to predict the routine share in each commuting zone.

middle of the occupational skill distribution and into low skill service occupations as information technology substitutes for workers engaged in routine tasks. Figure 3a provides a summary evaluation of this prediction. Following the approach of Figure 1a in the Introduction, Figure 3a plots the change between 1980 and 2005 in the employment share at each skill percentile in two sets of commuting zones: those with a routine share above the grand mean in 1980 and those with a routine share below it.[38] The comparison is striking. Routine-intensive commuting zones exhibit a pronounced polarization of employment between 1980 and 2005. Polarization is clearly more subdued in the set of commuting zones with an initially low routine share. We perform the parallel exercise for wages in Figure 3b. Wage polarization is also more pronounced for high routine share commuting zones, particularly in the upper quantiles of the skill distribution (at or above the 60th percentile).

A second core precept of the model is that commuting zones with a larger initial routine share should differentially adopt information technology in response to its declining price. We explore this implication using a measure of geographic computer penetration developed by Doms and Lewis (2006). Based on private sector surveys of computer inventories, this measure counts the number of personal computers per employee at the firm level, which is a relevant, albeit 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 match the Doms and Lewis 'adjusted computers-per-worker' measure for the years 1990 and 2002 to commuting zones.[39] 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.[40]

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

$$\Delta PC_{js\tau} = \alpha + \beta \times RSH_{jst} + \gamma_s + e_{js\tau}, \tag{23}$$

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, RSH_{jst} is that commuting zone's share of routine employment in year t at the start of the decade, and standard errors are clustered at the state

[38] To facilitate a direct comparison with Figure 1, the run variable in the figure corresponds to the overall skill distribution in 1980; it is not renormalized to the skill distribution in each subset of commuting zones.

[39] 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.

[40] 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.

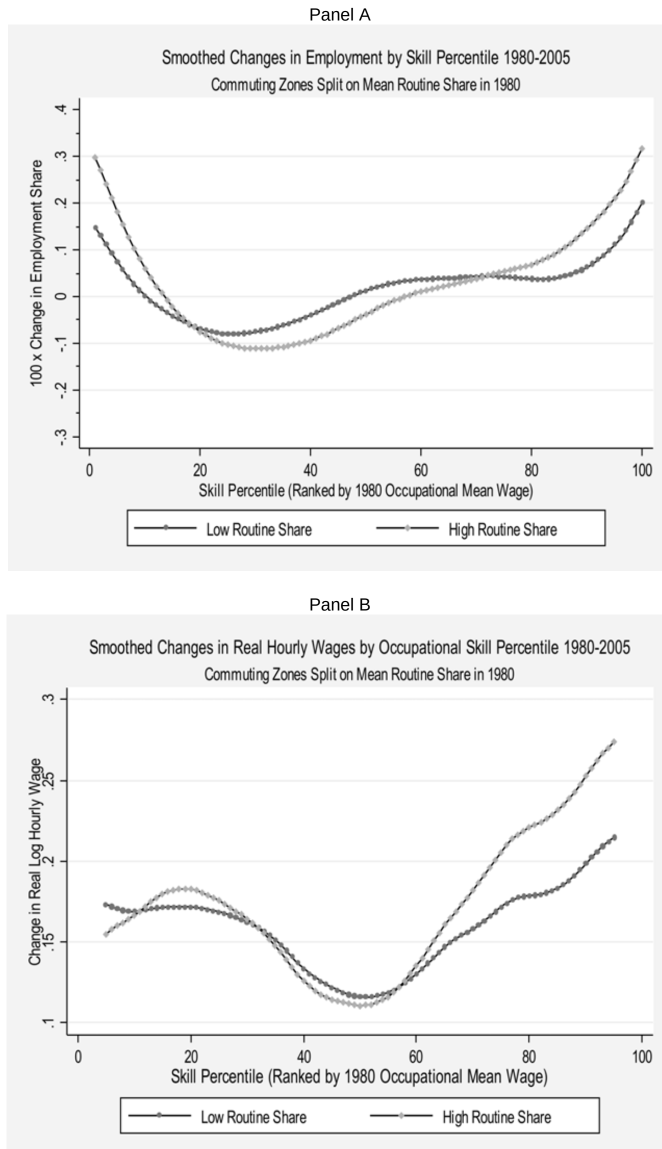


Figure 3.
Smoothed Changes in Employment (Panel A) and Hourly Wages (Panel B) by Skill Percentile in Commuting Zones with High and Low Routine Employment Shares in 1980.

level. The inclusion of a vector of state dummies, γ_s, means that the coefficient of interest, β, is identified by within-state cross-CZ variation. We estimate this model either separately by decade or pooling multiple decades as stacked first differences and adding time dummies.

Panel A of Table 2 presents OLS and 2SLS estimates. 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 80^{th} and 20^{th} percentile commuting zones is larger than one full standard deviation of the computer adoption measure in each decade. OLS and 2SLS estimates are similar in magnitude—differing by no more than 15 percent—and precision is quite high for both sets of models.

A third cornerstone of the model is that, because computer technology serves as a substitute for routine labor input, the relatively rapid adoption of computers in routine-intensive local labor markets should be accompanied by a differential decline in employment in routine-intensive occupations. We explore this prediction by regressing the change in the commuting zone share of routine employment by education group (college, non-college, and both) on the initial routine intensity of the commuting zone using a stacked-first difference variant of equation (23).

Table 2. Computer Adoption and Task Specialization within Commuting Zones, 1980 - 2005: OLS and 2SLS Estimates.
Dependent Vars: 10 × Annual Change in 'Adjusted PCs per Employee' , 10 × Annual Change in Employment Share of Routine Occupations

		(1)		(2)		(3)	
		I. Δ Adjusted PCs per Employee, 1980-2000					
		1980-1990		1990-2000		1980-2000	
(a. OLS)	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. 2SLS)	Share of Routine Occs.$_{-1}$	0.804	**	0.628	**	0.766	**
		(0.063)		(0.067)		(0.053)	
	R^2	0.648		0.371		0.450	
		B. Δ Share Routine Occupations, 1980-2005					
		All Workers		College		College	
(a. OLS)	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	
(b. 2SLS)	Share of Routine Occs.$_{-1}$	-0.247	**	-0.167	**	-0.284	**
		(0.015)		(0.018)		(0.021)	
	R^2	0.5889		0.340		0.450	

Notes: N=675, N=660, and N=1335 in the three columns of Panel I, and N=2166 (3 time periods x 722 commuting zones) in Panel II. In the IV specifications, the variable share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies. '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 that 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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The estimates in the lower panel of Table 2 confirm that commuting zones with initially higher routine task specialization saw larger subsequent declines in routine occupations. The estimate in column (1) suggests that a commuting zone at the 80th percentile of 1980 RSH experienced a 2.4 percentage points larger contraction of the routine occupation share per decade between 1980 and 2005 than did a 20th percentile commuting zone. This relationship is also highly significant when estimated separately for college and non-college workers in columns (2) and (3). 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). A plausible explanation for this pattern is that non-college workers in routine-intensive occupations perform a disproportionate share of the routine tasks that are subject to displacement.[41]

In net, we find strong initial support for the hypothesis that routine-intensive commuting zones experienced differential wage and employment polarization, greater adoption of computer technology, and a larger decrease in routine employment. We now turn to a more rigorous assessment of the mechanisms of the model.

4 Employment Polarization

A key empirical fact documented in the Introduction is the aggregate polarization of employment growth at the bottom of the U.S. occupational skill distribution is largely accounted for by rising employment in low skill service occupations (Figure 2a). Our spatial model predicts that this phenomenon should be driven by differential changes in employment composition in initially routine task-intensive labor markets where the potential for displacement of low skill labor from routine activities is greatest. We assess this prediction here.

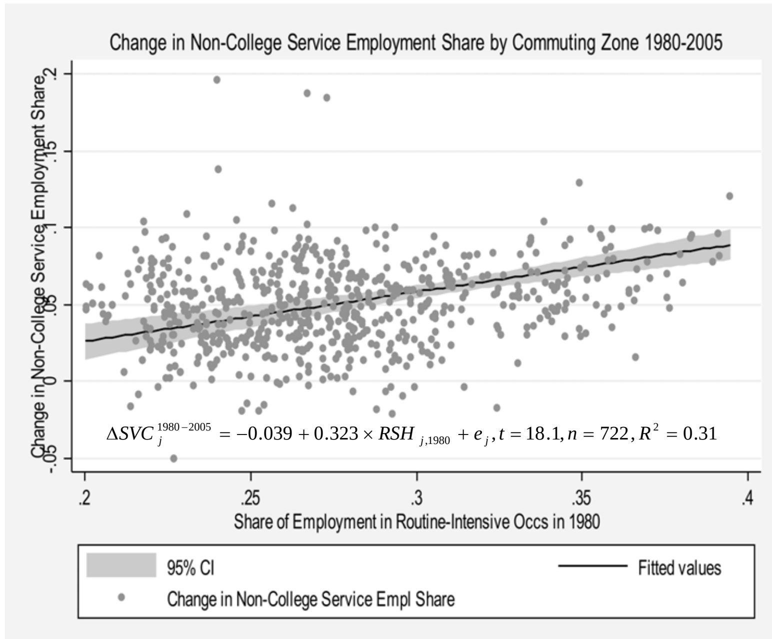
The scatter plot in the upper panel of Figure 4 depicts the bivariate relationship between initial commuting zone routine share, RSH_{1980} and the change in the share of non-college labor employed in service occupations over the subsequent 25 years. This figure offers strong initial support for the theoretical prediction. 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:

$$\Delta SVC_{j,1980-2005} = -0.039 + \underset{(t=18.1)}{0.323 \times RSH_{j,1980}} + e_{jt} \qquad R^2 = 0.31 \tag{24}$$

[41] Autor and Dorn (2009) further analyze the composition of employment *gains* in non-routine occupations. They find that declines in routine occupations within commuting zones 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 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

Panel A



Panel B

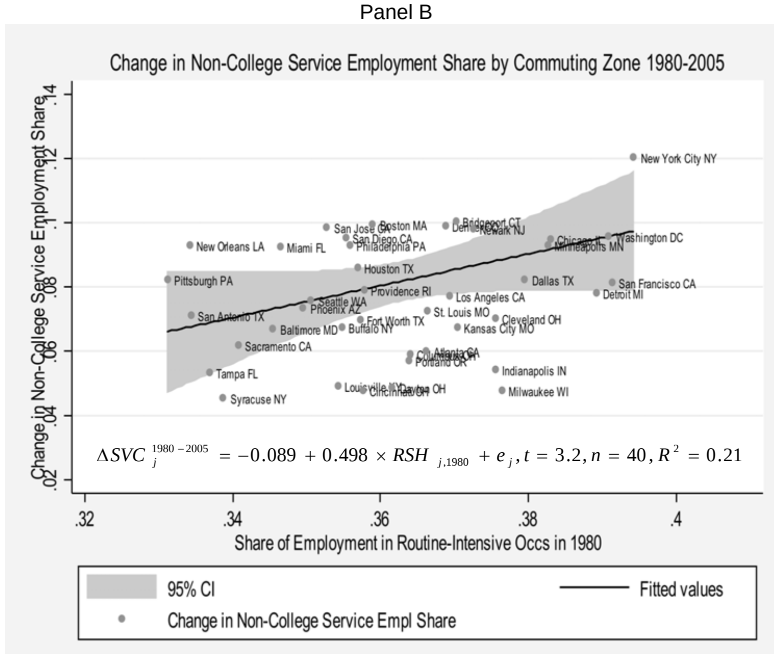


Figure 4.
Changes in Non-College Employment Share in Service Occupation, 1980-2005, vs. Routine Employment Share in 1980 for All Commuting Zones (Panel A) and Commuting Zones with at Least One Million Residents (Panel B).

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 in 1980. Each commuting zone 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 such as Washington, DC and San Francisco. Many routine-intensive occupations, such as clerical work and accounting, are commonplace in these high-skill cities because these occupations provide support services for the professions.

If the robust correlation between initial routine task intensity and growth of service employment observed since 1980 is a consequence of technological change, as our conceptual framework posits, then we would not expect it to be strongly evident in earlier decades. We verify this prediction by considering a longer timeframe in Table 3. Using a specification akin to (23), we regress the commuting zone level growth of service employment in each decade between 1950 and 2005 on the start of decade routine occupation and state dummies.[42]

A central pattern that emerges, both in OLS and 2SLS models, is that the strong, positive predictive relationship between the routine employment share and growth of service employment within commuting zones is only weakly evident prior to the 1980s, and actually has the opposite sign in the 1950 to 1970 period.[43] This relationship becomes positive and highly significant in the 1980s, and its magnitude rises in each subsequent period.

Alongside routine task-intensity, a host of factors may explain differences across commuting zones in the growth of service employment. We explore these factors in Table 4 using an augmented version of equation (23):

$$\Delta SVC_{js\tau} = \alpha + \beta_1 \times RSH_{jst} + \beta_2 \Delta X_{js\tau} + \delta_\tau + \gamma_s + e_{js\tau}. \tag{25}$$

[42]The lack of detailed geographic information in the 1960 Census prevents us from constructing commuting zones for this decade, and hence we analyze the 1950 to 1970 period as a single first difference. The dependent variable for 1950 to 1970 is divided by two and the dependent variable for 2000 to 2005 is multiplied by two to place them on the same decadal time scale.

[43]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 tended to have low levels of the RSH in 1950. Thus, the movement of labor from farm occupations into other low skilled occupations in these CZs may potentially explain the negative relationship between the RSH and growth of service employment in this period.

Table 3. Routine Employment Share and Growth of Service Employment within Commuting Zones, 1950 - 2005: OLS and 2SLS Estimates. 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. 2SLS Estimates		
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. Descriptives: Non-College Service Employment		
Mean Growth	0.006	-0.004	0.026	0.024	0.037
Std Dev Growth	(0.015)	(0.016)	(0.013)	(0.015)	(0.035)

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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

This model stacks the three time periods covering the interval 1980 through 2005, and includes a full set of time period effects, state effects, as well as measures of contemporaneous changes in a number of relevant human capital, labor market, and demographic variables. The routine share variables are instrumented with interactions between the 1950 industry mix instrument and time dummies.[44]

[44] We have estimated analogous OLS and 2SLS models that use the full 1950 through 2005 sample and include both a RSH main effect and an $RSH \times 1[t \geq 1980]$ interaction term, thus allowing for a pretrend on the RSH variable. Consistent with the results in Table 3, these five decade models indicate a sharp contrast between the pre and post 1980 time periods. We present the shorter sample frame estimates in the paper for compactness. Tables of estimates using the full time interval are available from the authors.

As a baseline, the first column presents a pooled specification with time dummies and the routine share measure only. The second column adds state dummies, which have little effect on the point estimates.

Column 3 adds two variables intended to capture shifts in the demand and supply for service occupations: the change in the ratio of college to non-college educated individuals in the population (expressed in logarithms) 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 weakly predicts a rise in service employment among non-college workers and a rise in the foreign born population share strongly predicts this growth (consistent with 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 the unemployment rate rises and weakly when manufacturing employment declines.

Column 5 considers two demand shifters: the elderly population share and the female labor force participation rate. Since the elderly have high demand for specific services such as home health assistance, a rising share of senior citizens in the population may raise 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 (Manning, 2004; Mazzolari and Ragusa, 2008). Surprisingly, increased female employment is associated with a lower growth 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 have the expected signs, and most are statistically significant. Nevertheless, the positive relationship between initial routine employment share and growth of service employment in the post-1980 period remains sizable and robust. Comparing columns (1) and (6), the point estimate on RSH is about sixty percent as large in the most inclusive model as in the bare specification in the first column. The economic magnitude of this estimate is substantial. Recall that the 80/20 range of the routine share measure is 0.10 in 1980. This translates into a difference of approximately 1.0 percentage point per decade in the growth of the non-college service employment in the 80^{th} versus 20^{th} percentile commuting zone relative to a mean decadal change of 2.9 percentage points over 1980 through 2005.

Arguably, the empirical approach used by equation (25) is unduly conservative in that it controls for contemporaneous outcomes such as unemployment and declining manufacturing that

Table 4. Routine Employment Share and Growth of Service Employment within Commuting Zones, 1980 - 2005: Stacked First Differences (2SLS Estimates).
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Share of Routine Occs.$_{-1}$	0.186 **	0.165 **	0.118 **	0.144 **	0.155 **	0.105 **
	(0.020)	(0.027)	(0.036)	(0.026)	(0.026)	(0.033)
Δ College/Non-college pop			0.009			0.012
			(0.008)			(0.008)
Δ Immig/Non-college pop			0.068 **			0.072 **
			(0.023)			(0.028)
Δ Manufact/Emp				-0.048		-0.058 ~
				(0.031)		(0.032)
Δ Unemployment rate				0.293 **		0.363 **
				(0.045)		(0.061)
Δ Female emp/pop					-0.081 **	0.075 *
					(0.025)	(0.030)
Δ Age 65+/pop					0.150 *	0.259 **
					(0.065)	(0.063)
State dummies	No	Yes	Yes	Yes	Yes	Yes
R^2	0.109	0.191	0.206	0.248	0.205	0.270

N=2166 (3 time periods x 722 commuting zones). Share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies. All models include an intercept 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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

may themselves result from automation and displacement of routine-intensive occupations. When specification (25) is re-estimated using as controls start-of-period *levels* of the six additional explanatory variables rather than contemporaneous changes, the coefficient on the routine share variable is significant and similar in magnitude.[45]

Is the relationship between routine task-intensity and growth of service employment driven by a narrow subset of service occupations? Appendix Table 3 presents 2SLS estimates of equation (25) fit separately for each of nine subgroups of service occupations. Commuting zones that were initially routine intensive saw differential employment growth in a broad set of service occupations including food service, personal appearance, child care, recreation, and building cleaning and gardening. In fact, point estimates are positive for all service occupation categories except the residual group of miscellaneous service occupations, and are statistically significant at $p \geq 0.10$ in six of nine cases. The positive relationship between RSH and service employment growth is present

[45] A table of estimates is available from the authors.

both in female-dominated service occupations that provide substitutes for home production (e.g., child care workers and hairdressers) and in typically male-dominated service jobs (e.g., janitors and security guards).

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 considered.

5 Employment Polarization: Alternative Hypotheses

This section evaluates three alternative hypotheses that could potentially explain the polarization of employment. These are: (1) offshoring rather than automation of job tasks that displaces low skill workers into non-offshorable service occupations; (2) rising incomes at the top of the wage distribution, which raise demand for in-person services among wealthy households (an income effect, as in Clark 1957); and (3) rising returns to skill, which spur college educated workers to increase labor supply and substitute market for home-based production of household services (Manning, 2004, Ngai and Pissarides, 2008, and Mazzolari and Ragusa, 2008). Though all of these mechanisms appear plausible, we find little evidence that they are empirically important drivers of polarization, at least at the level of local labor markets.

An expanding literature studies the growth of international offshoring, whereby firms carry out specific subcomponents (or tasks) of their production processes abroad (e.g., Feenstra and Hanson, 1999, Grossman and Rossi-Hansberg, 2008, Blinder, 2009, Blinder and Krueger, 2009, and Jensen and Kletzer, forthcoming). Papers in this literature argue that the occupational tasks most suitable for offshoring are those that can be performed effectively without physical proximity to customers or specific worksites. Many of the routine tasks in production and clerical occupations appear to meet these criteria.[46] In contrast, the job tasks performed in service occupations are typically poorly suited to offshoring as many require face-to-face interactions between workers and customers (e.g., hairdressers and waiters) or direct physical access to the customer's work site (i.e., cleaners and security guards). This reasoning suggests that offshoring could explain the growth of low skill service employment rather than (or in addition to) the automation of routine tasks.

Unlike trade in goods, the offshoring of job tasks has not been historically included in national

[46] Blinder (2009) notes that the clearly defined procedures of routine tasks may make them particularly prone to offshoring but argues that the overlap between routine content and offshoring potential is incomplete. Blinder and Krueger (2009) find that their survey measures of offshorability and 'routinizability' are essentially orthogonal. As discussed below, our commuting zone level offshorability and routine employment share measures are significantly positively correlated.

accounts and is thus poorly measured. We follow the standard approach in the literature by measuring the offshoring *potential* ('offshorability') of job tasks in a commuting zone rather than the actual offshoring that occurs. To operationalize offshorability, we use a simple average of the two variables *Face-to-Face Contact* and *On-Site Job* that Firpo, Fortin and Lemieux (2009) derive from U.S. Department of Labor's Occupational Information Network database (O*NET).[47] This measure captures the degree to which an occupation requires either direct interpersonal interaction or proximity to a specific work location.[48] The commuting zone level offshorability index is equal to the average offshorability score of employment in each commuting zone and year, and is further normalized to have a mean of zero and a cross commuting zone standard deviation of one in 1980. We find a moderately large correlation between routine employment shares and offshorability across commuting zones ($\rho = 0.48$).

Using a variant of equation (23), panel A of Table 5 tests whether commuting zones with higher start-of-period offshorability experienced differential growth of service employment among non-college workers between 1980 through 2005. Column (1) finds the expected positive relationship between offshorability and the subsequent growth of low skill service employment, but the point estimate is statistically insignificant and the measure has little explanatory power. Column (2) adds the routine share measure to the model. This variable is robustly predictive of service employment growth, and its magnitude is little affected by inclusion of the offshorability index (compare column (2) of Table 4). The offshorability measure remains insignificant and reverses sign when the routine share variable is added.

While we cannot exclude the possibility that a different measure of offshorability would offer stronger evidence in favor of the offshoring hypothesis, our finding is in line with other recent work that compares the explanatory power of offshoring relative to other job task measures such as routine task content in explaining cross-industry and cross-national trends in employment or wage polarization (Firpo, Fortin and Lemieux, 2009; Goos, Manning and Salomons, 2010; Michaels, Natraj and Van Reenen, 2010). A general finding of these studies is that offshorability plays a relatively minor explanatory role when considered alongside other potential causes.

In the subsequent two panels of Table 5, we explore the contribution that income and sub-

[47] O*NET data is available for download at http://online.onetcenter.org/. 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." They define *on-site job* as 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."

[48] We reverse the sign of the measure so that it is increasing rather than decreasing in offshorability. According to this metric, the five least offshorable occupations 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.

Table 5. 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

	A. Offshoring		B. Income Effects		C. 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)
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 offshorability index is standardized with a mean of zero and a cross commuting zone standard deviation of one in 1980. The 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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

stitution effects among high skill workers make to rising service employment. We augment the baseline regression model for 1980 through 2005 with two additional variables, each measured at the commuting zone level. To capture wage structure shifts that may generate income effects, we use changes in the 90^{th} percentile of the log weekly wage distribution among full-time, full-year workers.[49] To measure shifts in the labor supply of high skill workers that may generate substitution effects that increase service demand, we use changes in mean annual hours worked by college graduates.[50]

Consistent with the differential polarization of employment and wages observed in routine task-intensive commuting zones documented above (Figures 3a and 3b), we find that both top wages and high skill hours rose by significantly more over 1980 through 2005 in commuting zones with high values of RSH.[51] Nevertheless, these proxies for income and substitution effects do not

[49]This distributional statistic provides a good proxy for the market price of 'high' skills available from the Census data since it captures the wage commanded by workers with strong labor force attachment (i.e., full-time, full-year workers). Other wage measures considered yield similar results but have lower explanatory power.

[50]This labor supply measure averages market hours over working and non-working graduates and its first difference captures changes at both the intensive and extensive margin of labor supply.

[51]Regression estimates imply that the commuting zone at the 80th percentile of RSH in 1980 experienced 8 additional log points per decade rise in the 90^{th} percentile of full-time, full-year wage and 11 additional hours per

have a strong direct relationship with growth in service employment. A rise in the 90^{th} percentile of weekly wages is only weakly correlated with rising service employment, and this relationship turns negative when the routine share is included (panel B). Rising annual work hours of college graduates is *negatively* related to service employment growth, a pattern than holds whether we measure college labor overall or separately by gender (panel C). Notably, the routine share variable remains highly predictive of rising service employment in all cases, and is essentially unaffected by inclusion of these controls. In net, we find little empirical support for the income or substitution effect channels as drivers of rising service employment.

6 Wage Polarization and Labor Mobility

The final testable predictions of the conceptual framework concern wage polarization and labor mobility. The spatial model predicts that (nominal) wage polarization should occur differentially in initially routine task-intensive labor markets. This occurs through two channels that impact the wage distribution at different locations. At the upper end of the distribution, computerization directly raises the productivity of high skill labor through q-complementarity in production. Since there is greater potential for substitution of computer technology for labor in initially routine task-intensive labor markets (as the data in Table 2 confirm), top wages are predicted to rise by more in these markets. Simultaneously, rising output of goods stemming from computerization raises demand for in-person services at least equiproportionately (provided that the substitution elasticity in consumption does not exceed unity). This raises wages in low skill service occupations in unison with wages in high skill occupations.

Greater wage growth in high skill and in service occupations should attract inward labor mobility to initially routine-intensive markets, a prediction that we test below. In the equilibrium of the spatial model, this mobility arbitrages the *real* component of the geographic wage differentials. However, routine task-intensive markets will still experience a larger polarization of *nominal* wages (i.e., wages that are not indexed for *local* consumption prices which depend on the wage level of low skill service workers.)

6.1 Wage polarization

Figure 3b above provides initial evidence of differential wage polarization in routine-intensive markets. To more rigorously test the predictions for wage polarization, we pool microdata on log

decade increase in annual labor supply of college graduates relative to the 20th percentile commuting zone over the 1980 through 2005 period. Both relationships are statistically significant. The correlation between RSH and the change in the 90^{th} percentile of earnings is 0.35 while the correlation between RSH and the change in college labor supply is 0.05. A full table of results is available from the authors.

hourly wages from the 1980 Census and the 2005 American Community Survey to estimate a set of 2SLS wage equations of the following form:

$$\ln w_{ijkt} = \alpha_k + \beta_{1k}\left\{RSH_{j,1980} \times 1\left[t = 2005\right]\right\} + X'_{ijkt}\beta_{2kt} + \delta_{tk} + \gamma_{jk} + e_{ijkt}, \quad (26)$$

where i denotes workers, j denotes commuting zones, k denotes occupations, and t denotes times (1980, 2005). These equations also include time dummies, commuting-zone dummies, an interaction between the (instrumented) start-of-period routine employment share variable and the 2005 dummy, and in some specifications, a full set of worker-level covariates interacted with time dummies. Hourly wages are deflated by the national Personal Consumption Expenditure deflator, which does not account for local or regional price levels. We perform estimates separately for each of the major occupation categories of Table 1 (except for farm occupations, for which reported wages are not reliable). Standard errors are clustered at the commuting zone level since the main predictive variable, RSH, does not vary within commuting zones.[52]

Estimates in the first two columns of Table 6 show that commuting zones specialized in routine task-intensive employment in 1980 saw differential wage increases between 1980 and 2005 among workers in the two occupation groups with highest education levels. A 10 percentage point higher routine share in 1980 (equal to the gap between the 80^{th} and 20^{th} percentile commuting zone) 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 routine task-intensive low skill occupations in our conceptual framework. Opposite to the pattern for highly-skilled occupations, a higher routine share of employment in 1980 predicts significant relative wage declines in these occupations (i.e., relative to commuting zones that were less routine task-intensive). While the precision of the point estimate for wages of females in production occupations is low, the table also makes evident that only 10 percent as many females as males are employed in production occupations, whereas there are 40 percent as many females as males in operative occupations.

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

[52]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.

Table 6. Routine Emp Share and Wage Changes by Major Occupation Groups, 1980 - 2005.
Microdata Estimates using Pooled 1980/2005 Census and ACS Samples (2SLS Estimates).
Dependent Variable: Log Real Hourly Wage

		(1) Manager, Profesnl		(2) Tech, Sales, Admin		(3) Product, Craft, Repair		(4) Operator, Laborer, Fabricator		(5) Service Occs		(6) Service *vs.* Product, Operator	
								I. Males					
(A)	Share of Routine	0.834	**	1.313	**	-0.349	*	-0.632	**	0.096		0.663	**
	Occs.$_{-1}$ × 2005	(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	0.903	**	0.885	**	0.160		-0.324		0.423	~	0.610	**
	Occs.$_{-1}$ × 2005	(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	1.267	**	1.095	**	0.089		-0.551	**	0.087		1.084	**
	Occs.$_{-1}$ × 2005	(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	1.210	**	1.106	**	0.267		-0.066		0.361	*	0.701	**
	Occs.$_{-1}$ × 2005	(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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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 6 re-estimates these models, now 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. Estimates for high skill occupations are not systematically affected by these covariates. Notably, coefficient estimates for the less skilled occupations in columns (3) through (5) become less negative or more positive when these controls are included, indicating adverse changes in skill composition in these occupations in initially routine-intensive commuting zones. This pattern may suggest differential inward mobility of low skill labor into these labor markets, a hypothesis that we confirm below. After controlling for individual-level covariates, a higher initial routine share not only predicts a significant wage gain in service occupations relative to other low skill occupations but also a significantly greater wage gain in service occupations relative to other commuting zones.[53]

In net, routine task-intensive labor markets saw strongly rising relative wages in high skill occupations, stable or declining relative wages in less skilled production and operative occupations, and moderately rising relative wages in low skill service occupations. In combination with earlier results, these findings demonstrate that displacement of routine tasks within commuting zones is accompanied by relative growth in both service employment and service wages.[54] What makes this finding particularly compelling is that service occupations are the only low skill job category that appears to benefit from this process.

6.2 Labor mobility

The patterns of wage growth by occupation documented in Table 6 imply that labor markets with a relatively high routine occupation share should attract a differential inflow of labor at both ends of the skill distribution. Table 7 assesses this prediction and finds strong confirmation. A higher RSH predicts substantially greater polarization of educational attainment within local markets, with the proportions of both 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 rising local market demand for high skill workers who specialize in abstract tasks and for low skill workers who perform manual tasks in services.

The second panel of Table 7 specifically explores geographic mobility of workers as a source of changes in commuting zones' education structure in the decades 1980-1990 and 1990-2000. The dependent variable is the difference between the share of individuals with education level e among recent 'migrant' workers and the share of individuals with education level e in a commuting zone's start-of-period workforce. Migrant workers are defined as residents who moved to their current location from another state or country in the last five years of a decade (i.e., between 1986 and 1990 or between 1996 and 2000). We are not able to construct an analogous measure for 2005

[53] A recent paper by Smith (2010) demonstrates a striking state-level relationship between the movement of adults into service occupations and declining employment rates of teenagers in these jobs. Despite this trend, the results in Table 6 underscore that the rising wages in service relative to other low-education occupations in Table 1 are unlikely to be driven by the selection of relatively more skilled or experienced workers into service jobs.

[54] 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.

Table 7. Changes in Educational Composition, 1980-2005 (2SLS Estimates). 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		HS Graduates		HS Dropouts	
	(1)		(2)		(3)		(4)	
	A. Δ 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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

because the American Community Survey data do not report place of residence five years earlier.[55]

Consonant with the results in panel A, the migration models find that in routine task-intensive local labor markets, recent entrants are substantially more likely to be college graduates than incumbents, and, to a lesser degree are also more likely to be high school dropouts. In net, Table 7 confirms that geographic labor mobility contributes to increasing relative supply of workers at both ends of the educational spectrum in routine task-intensive local labor markets. In combination with the findings on wage polarization, these results suggest that mobility is driven by local demand shifts for both high and low skill occupations.

7 Conclusions

While the past 25 years have seen stagnant or declining real earnings and employment of most low skill occupations, employment and earnings in service occupations offer a striking exception.

[55]The definition of migrants based on states of residence is an imperfect proxy for migration across commuting zones. We use it because the PUMS files for the decennial Censuses report place of residence five years ago only at a relatively high level of geographic aggregation.

Between 1980 and 2005, the share of hours worked in service occupations among non-college workers 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. This phenomenon is broadly important because it offers insight into the polarization of employment and earnings in the U.S. and, potentially, other industrialized countries. Indeed, a key fact documented by this paper is that rising employment and wages in service occupations account for a substantial share of aggregate polarization and growth of the lower tail of the U.S. employment and earnings distributions between 1980 and 2005.

This paper proposes a unified explanation and conducts a detailed empirical analysis of the forces behind the changing shape of low education, low wage employment in the U.S. labor market. We hypothesize that recent computerization has substituted for low skill workers in performing routine tasks while complementing the abstract, creative, problem-solving, and coordination tasks performed by highly-educated workers. As the declining price of computer technology has driven down the wage paid to routine tasks, low skill workers have reallocated their labor supply to service occupations, which are difficult to automate because they rely heavily on dexterity, flexible interpersonal communication, and direct physical proximity. Our conceptual model shows that if the demand for these service outputs does not admit close substitutes, then substitution of information technology for routine tasks used in goods production can induce rising wages and employment in low skill service occupations. This hypothesis builds on Baumol's (1967) model of unbalanced technological progress by broadening it to the study of skill demands and wage structure (in addition to Baumol's focus on sectoral composition).

Motivated by the observation that workers in service occupations must collocate with demanders of their services, we extend the model to a spatial equilibrium setting and develop empirical implications that we test at the level of 722 consistently defined commuting zones encompassing the entirety of the U.S. mainland. The model predicts that commuting zones that were initially relatively intensive in routine job activities—that is, tasks that became cheap and easy to computerize in recent decades—should have exhibited differential changes in the structure of local production along four dimensions: (1) greater adoption of information technology; (2) greater reallocation of low skill workers from routine task-intensive occupations into service occupations (i.e., employment polarization); (3) larger increases in wages at both ends of the occupational skill distribution (i.e., wage polarization); (4) and larger net inflows of both high and low skill labor attracted by these demand shifts.

In bringing the model to the data, we measure commuting zones' specialization in routine task-intensive employment by mapping task data from the Dictionary of Occupational Titles to occupation data from the Census. We instrument this task-based measure using the interaction between commuting zones' historical industry structures and the national occupational composition of these industries (both measured in 1950). The variation in routine task intensity across commuting zones proves robustly predictive of the changes in task and wage structure implied by the model, including: reallocation of labor activity away from routine tasks; employment growth in low skill service occupations; differential adoption of information technology; polarization of earnings growth; and differential inward mobility of high and low skill labor.

Alongside our primary hypothesis of unbalanced technological progress, we consider a panoply of alternative explanations including offshoring of jobs tasks, income and substitution effects in high skill consumption and labor supply, and demographic or economic shifts including immigration, population aging, female labor force entry, and declining manufacturing employment. Many of these alternative explanations receive some empirical support but none appears to play a leading role. Moreover, none would appear conceptually suited to explain the totality of evidence presented.

The consequences of employment and wage polarization for skill demands, earnings levels, and job composition are only beginning to receive academic study (e.g., Levy and Murnane, 2004; U.S. National Research Council, 2008). Our results suggest a critical role for changes in labor specialization, spurred by automation of routine task activities, as a driver of rising employment and wage polarization in the U.S. and potentially in other countries. We believe that the conceptual and empirical tools offered in this paper have the potential to advance economic analysis and understanding of this topic.

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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 cell. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight and the weight derived from the geographic matching process that is described below.

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 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 since 1990 is the Public Use Micro Area (PUMA). 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 entire land area of the U.S. into more than 2,000 of these 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 equal 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.

The Census Public Use files for the years prior to 1990 identify subareas of states called County Groups (in 1970 and 1980) or State Economic Areas (in 1950). These geographic units have a similar structure as PUMAs except that they do not provide a detailed within-county breakdown of the most populous counties. They are matched to CZs using the same procedure as outlined for PUMAs above. The 1960 Census files are not suitable for an analysis at the detailed geographic level because they provide no geographic information other than state.

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 and a full list of the resulting 330 occupations are given in Dorn (2009).

Appendix tables

Appendix Table 1. Rankings of Occupations with Highest and Lowest Routine Intensity

A. Occupations with Highest RTI Scores	B. Occupations with Lowest RTI Scores
1 Secretaries and Stenographers	1 Parking Lot Attendants
2 Bank Tellers	2 Fire Fighting, Prevention and Inspection *
3 Pharmacists	3 Bus Drivers
4 Payroll and Timekeeping Clerks	4 Taxi Cab Drivers and Chauffeurs
5 Motion Picture Projectionists *	5 Public Transp. Attendants, Inspectors *
6 Boilermakers	6 Police and Detectives, Public Service *
7 Butchers and Meat Cutters	7 Truck, Delivery, and Tractor Drivers
8 Accountants and Auditors	8 Garbage and Recyclable Material Collectors
9 Actuaries	9 Crossing Guards *
10 Proofreaders	10 Railroad Coupler, Brake, Switch 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. Residual occupations groups (miscellaneous, other, and not elsewhere classified) are excluded from the ranking.

Appendix Table 2. First Stage Estimates of Models for Routine Occupation Share Measure. Dependent variable: Routine Occupation Share in Commuting Zones in Indicated Years

	1950	1970	1980	1990	2000
	I. Single Decade Regressions				
1950 Industry Mix Measure	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
	II. Pooled Regression, 1950-2005				
1950 Industry Mix Measure	1.106 **	0.764 **	0.642 **	0.425 **	0.304 **
	(0.064)	(0.047)	(0.045)	(0.039)	(0.032)
R^2					0.821

Panel I reports the coefficient estimates from separate regressions by decade with N=722. in each model. Panel II reports a single regression with N=3610. All models include state dummies and are weighted by the share of each commuting zone in national population in each sample year.

Appendix Table 3. Routine Employment Share and Growth of Employment in Detailled Service Occupations within Commuting Zones, 1980 - 2005: Stacked First Differences (2SLS Estimates).
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	Persnl Appear-ance	Security Guards	Recreat-ion	Misc Persnl Svcs
	A. Estimates								
Share of Routine Occs._{-1}	0.060 **	0.044 **	0.003	0.011	0.009 *	0.015 *	0.015 **	0.009 ~	-0.002
	(0.013)	(0.013)	(0.014)	(0.009)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)
Constant	-0.005	-0.005	0.004	-0.006 **	-0.002 *	-0.005 *	-0.003 **	-0.003 **	0.001
	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.103	0.282	0.128	0.102	0.166	0.103	0.083	0.236	0.122
	B. Descriptive Statistics: Employment Shares (Non-College Employment)								
Emp. share 1980	4.18%	3.11%	1.88%	1.41%	0.51%	0.75%	0.63%	0.15%	0.31%
Emp. 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=2166 (3 time periods x 722 commuting zones). Share of routine occupation variable is 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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

NOT FOR PUBLICATION

Theory Appendix for "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market"

The planner's problem

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

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

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

$$\max_{K,L_m} \left(L_m^{\frac{\sigma-1}{\sigma}} + (Y_g - p_k(t) K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{A1}$$

$$\text{where} \qquad Y_g = X^{\beta} \text{ and } L_r = g(L_m) \equiv (1 - \log(1 - L_m))(1 - L_m),$$

and $g(\cdot)$ 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 manual tasks in the service sector (and thus, also the allocation $L_r(t) = g(L_m(t))$ to routine tasks in the goods sector).

We next characterize the solution to problem (7). The first order conditions with respect to capital K and labor L_m respectively give:

$$\frac{\partial Y_g}{\partial K} = p_k(t), \tag{A2}$$

$$L_m^{-1/\sigma} = (Y_g - p_k K)^{-1/\sigma} \frac{\partial Y_g}{\partial X} \frac{\partial X}{\partial L_r} (-\log(1 - L_m)), \tag{A3}$$

where we have used

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

The system in (8) – (9) contains two unknowns (L_m, X) in two equations and uniquely solves for the equilibrium at any time t.

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

Asymptotic allocation of labor

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. Bearing in mind that L_r is bounded from above, it can be seen that equation (8) holds as $p_k \to 0$ only if $K \to \infty$. In other words, we have

$$\lim_{t\to\infty} K\left(t\right) = \infty. \tag{A4}$$

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 written as

$$X \sim \alpha_k K. \tag{A5}$$

Using Eq. (8) and Eq. (8) respectively, we further have

$$Y_g \sim \left(\alpha_k K\right)^{\beta} \text{ and } p_k K \sim \beta\left(\alpha_k K\right)^{\beta}. \tag{A6}$$

From these expressions, net output (consumption) satisfies

$$C_g = Y_g - p_k K \sim \kappa_1 K^{\beta}, \tag{A7}$$

where we define $\kappa_1 \equiv \left(1-\beta\right)\alpha_k^{\beta}$. Using these expressions in Eq. (9), it can be seen that the asymptotic manual labor choice $L_m^* \equiv \lim_{p_k\to 0} L_m\left(p_k\right)$ is the solution to:

$$\left(L_m^*\right)^{-1/\sigma} = \kappa_1^{-1/\sigma}\kappa_2 K^{\beta-\mu-\beta/\sigma} L_r^{\mu-1}\left(-\log\left(1-L_m^*\right)\right) \tag{A8}$$

where $L_r = g\left(L_m^*\right)$, and we define $\kappa_2 \equiv \beta\alpha_k^{\beta-\mu}\alpha_r^{\mu}$.

Using this equation and Eq. (A4), the asymptotic level of L_m^* is uniquely solved as follows:[56]

$$L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \bar{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases}. \tag{A9}$$

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

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

Dynamics of equilibrium in the aggregate economy case

Recall that L_r is bounded from above and K limits to ∞ (cf. Eq. (A4)). Hence, $\frac{L_r(t)}{K(t)}$ will be decreasing for sufficiently large t. Suppose that $p_k(0)$ is sufficiently small so 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 parametrization, 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. Then, in summary, we have the following dynamics:

$$X \sim \alpha_k K, \qquad Y_g \sim \alpha_k^\beta K^\beta, \qquad p_k K \sim \beta \alpha_k^\beta K^\beta, \text{ and } C_g \sim \kappa_1 K^\beta. \tag{A10}$$

The dynamics of $L_m(t)$ can be obtained by using these expressions in Eq. (9).[57]

Asymptotic wages

We normalize the price of the good g to 1 at each time t. Factors are paid their marginal products. Hence,

$$w_a = \frac{dY_g}{dL_a} = (1-\beta) Y_g \sim \kappa_1 K^\beta, \tag{A11}$$

where the last line uses the dynamics in Eq. (A10). Similarly, note that

$$w_r = \frac{\partial Y_g}{\partial X}\frac{\partial X}{\partial L_r} = \beta X^{\beta-\mu}\alpha_r^\mu g(L_m)^{\mu-1} \sim \kappa_2 K^{\beta-\mu} g(L_m)^{\mu-1} \tag{A12}$$

where we used $L_r = g(L_m)$.[58]

Finally,

$$w_m = p_s = \left(\frac{C_s}{C_g}\right)^{-1/\sigma} = (L_m)^{-1/\sigma} C_g^{1/\sigma} \sim (L_m)^{-1/\sigma} \kappa_1^{1/\sigma} K^{\beta/\sigma}. \tag{A13}$$

Asymptotic wage ratios

From these expressions, relative wages and their dynamics can be determined. We are most interested in $\frac{w_m}{w_r}$, the relative wage of low skill workers in goods versus services production. To obtain the asymptotics of this ratio, note that the first order condition (9) can also be written as:

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

[57] The dynamic analogues of Eqs. (A6) and (A7) can also be obtained.

[58] Note that, unlike w_a, the dynamic behavior of w_r is not necessarily monotonic. In particular, Eq. (A12) 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.

Then, using the characterization in (A9), we have

$$\frac{w_m}{w_r} = \begin{cases} \infty \text{ if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -\log\left(1 - L_m^*\right) \text{ if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 \text{ if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases}. \tag{A14}$$

We are also interested in the behavior of the ratio $\frac{w_a}{w_m}$. Using equations (A11) and (A13), we have

$$\frac{w_a}{w_m} \sim \frac{\kappa_1 K^{\beta}}{\left(L_m\right)^{-1/\sigma} \kappa_1^{1/\sigma} K^{\beta/\sigma}}. \tag{A15}$$

If $\frac{1}{\sigma} > \frac{\beta-\mu}{\beta}$, then equation (A15) shows that the asymptotic behavior of $\frac{w_a}{w_m}$ depends on σ. In particular,

$$\frac{w_a}{w_m} = \begin{cases} 0 \text{ if } \sigma < 1 \\ 1 \text{ if } \sigma = 1 \\ \infty \text{ if } \sigma > 1 \end{cases}, \text{ when } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta}. \tag{A16}$$

If instead $\frac{1}{\sigma} < \frac{\beta-\mu}{\beta}$ (which is greater than 1), then Eq. (A9) shows that $L_m^* = 0$. But then, Eq. (A15) shows that the ratio $\frac{w_a}{w_m}$ is indeterminate. This indeterminacy stems from a rather superficial reason. Although employment in the service sector limits to zero, the wages of the few remaining workers in this sector near the limit may be high. This suggests that the right object to consider may be the *wage bill* of manual labor. When we consider this object, 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 $\left(L_m\right)^{1-1/\sigma} = 0$).

Lastly, we derive the dynamics of the wage ratio between abstract and routine tasks. Eqs. (A11) and (A12) 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 case, the wages of routine labor are kept high for a rather superficial reason: routine tasks are not very important in production, and thus the economy allocates labor away from routine tasks; as there are very few workers remaining in routine tasks, each 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 worker might be receiving a high wage. In other words, the intuition suggests that we should instead attempt to prove the following:

$$\lim_{t\to\infty}\frac{L_a w_a}{L_r w_r}=\infty \text{ when } \frac{1}{\sigma}>\frac{\beta-\mu}{\beta}. \tag{A17}$$

That is, the share of abstract labor relative to the share of routine labor limits to infinity. To prove this, consider Eqs. (A11) and (A12) (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 limit in (A17), and completes our analysis for relative wages.

Derivation of spatial equilibrium

Let $\left\{L_{a,j}\left(t\right), L_{m,j}\left(t\right), K_j\left(t\right)\right\}$ and $\left\{w_{m,j}\left(t\right), w_{a,j}\left(t\right), w_{s,j}\left(t\right), p_s\left(t\right)\right\}$ denote the factor allocations and prices in region j in the asymptotic equilibrium. As in the above static economy, we normalize the good price in each region to 1, i.e., $p_{g,j}\left(t\right)=1$ for each j. Define also the ideal price index for the consumption aggregator, $\left(C_{s,j}^{\frac{\sigma-1}{\sigma}}+C_{g,j}^{\frac{\sigma-1}{\sigma}}\right)^{\sigma/(\sigma-1)}$, as

$$P_j\left(t\right)=\left(p_{s,j}\left(t\right)^{1-\sigma}+1\right)^{1/(1-\sigma)}. \tag{A18}$$

Here, $P_j\left(t\right)$ is the cost of increasing the consumption aggregator by one unit. The spatial equilibrium condition in the high skill labor market can be written as

$$L_{a,j}\left(t\right)>0 \text{ only if } w_{a,j}(t)/P_j(t)=w_{a,j^{\max}}(t)/P_{j^{\max}}(t). \tag{A19}$$

A geographic equilibrium at time t is a collection of factor allocations $\left\{L_{a,j}\left(t\right), L_{m,j}\left(t\right), K_j\left(t\right)\right\}$, and prices $\left\{w_{m,j}\left(t\right), w_{a,j}\left(t\right), w_{s,j}\left(t\right), p_{s,j}\left(t\right)\right\}$, such that two conditions hold:

1. Local market equilibrium: The allocations, $\left\{L_{a,j}\left(t\right), L_{m,j}\left(t\right), K_j\left(t\right)\right\}$, and prices, $\left\{w_{m,j}\left(t\right), w_{a,j}\left(t\right), w_{s,j}\left(t\right), p_{s,j}\left(t\right)\right\}$, constitute a static equilibrium of the region j given high skill labor supply $L_{a,j}\left(t\right)$ and the price $p_k\left(t\right)$ (as described in the previous section).

2. Spatial equilibrium: The market for high skill labor is in spatial equilibrium when (A19) holds for each region j, so that high skill workers have identical real earnings across all regions.

We conjecture that the asymptotic equilibrium allocations take the following form:

$$\begin{aligned}
\frac{\dot{K}_j(t)}{K_j(t)} &= g_{K,j} \text{ for some } g_{K,j} > 0, \text{ for each } j, \\
L_{m,j}(t) &\to 1, \\
L_{a,\bar{j}}(t) &\to L_a \equiv \sum_j L_{a,j}.\text{for one region } \bar{j} \text{ (in particular, } g_{L,\bar{j}} = 0). \\
\frac{\dot{L}_{a,j}(t)}{L_{a,j}(t)} &= g_{L,j} \text{ for some } g_{L,j} < 0, \text{ for each region } j \neq \bar{j}.
\end{aligned} \tag{A20}$$

The rationale behind this equilibrium conjecture is as follows: The conjecture that $K_j(t)$ grows in every region intuitively follows from the fact that $p_K(t) \to 0$. The conjecture that $K_j(t)$ grows at a constant rate follows from the analysis in the previous section, which shows that the production function is asymptotically Cobb-Douglas. The conjecture that $L_{m,j}(t) \to 1$ follows from the parametric assumption $\sigma = 1$, which ensures that each region in isolation would allocate all low skill labor to manual tasks.

The last two conjectures rely on the observation that all other factor allocations asymptotically grow at the constant rate. This suggests that high skill labor also asymptotically grows at a constant rate. However, this is only possible if all high skill labor is eventually allocated to a single region, and the rest of the regions lose high skill labor at an asymptotically constant rate (it is also possible if high skill labor is asymptotically constant in all regions, but this case can be ruled out). The identity of the region, $\bar{j}$, along with the constant growth terms $\{g_{K,j}, g_{L,j}\}$, are yet to be determined. We also conjecture that

$$g_{Y,j} \equiv g_{L,j}(1-\beta_j) + \beta_j g_{K,j} > 0 \text{ for each } j \tag{A21}$$

(which will be verified below), which ensures that $Y_{g,j}(t)$ and $C_{g,j}(t)$ asymptotically grow at a positive rate.

Under these conjectures, much of the discussion of the closed economy model also applies to each region in spatial equilibrium. In particular, it can be seen that

$$\begin{aligned}
X_j(t) &\sim \alpha_k K_j(t), \\
p_k(t) K(t) &\sim \beta L_{a,j}(t)^{1-\beta} (\alpha_k K_j(t))^{\beta}, \\
C_{g,j}(t) &\sim \kappa_1 L_{a,j}(t)^{1-\beta} (\alpha_k K_j(t))^{\beta}.
\end{aligned} \tag{A22}$$

Moreover, $C_{g,j}(t)$ and $p_k(t) K(t)$ also grow at the constant rate $g_{Y,j} > 0$ (defined in (A21)). This also implies that $g_{K,j} = g_{Y,j} + \delta$. Plugging in the definition of (A21), we can also solve for $g_{K,j}$ in terms of $g_{L,j}$:

$$g_{K,j} = g_{L,j} + \frac{\delta}{1-\beta_j}. \tag{A23}$$

This expression is intuitive. On the one hand, capital grows in response to the technological progress. On the other hand, capital growth is potentially slowed by the fact that high skill labor may be leaving a region (note that, under our conjecture, $g_{L,j}$ is negative for all regions but one).

Wages in each region may be calculated exactly as in the closed economy model. Thus we have:

$$\begin{aligned} w_{s,j}(t) &\sim \kappa_1 L_{a,j}(t)^{-\beta_j} K(t)^{\beta_j}, \\ w_{m,j}(t) &= \left(\frac{C_{g,j}(t)}{C_{s,j}(t)}\right)^{1/\sigma} \sim \kappa_1^{1/\sigma} L_{a,j}(t)^{(1-\beta_j)/\sigma} K_j(t)^{\beta_j/\sigma}, \\ w_{a,j}(t) &= \kappa_1 L_{a,j}(t)^{-\beta_j} K_j(t)^{\beta_j}. \end{aligned} \tag{A24}$$

Note that $w_{m,j}(t)$ grows at rate $g_{Y,j}/\sigma$. In particular $w_{m,j}(t) \to \infty$. Using this observation and $p_{s,j}(t) = w_{m,j}(t)$, Eq. (18) can be simplified to

$$P_j(t) \sim w_{m,j}(t)^{1/2} \text{ for each } j. \tag{A25}$$

Moreover, under the conjecture in (A20), the labor market equilibrium condition (17) will be satisfied with equality for each region. Substituting Eq. (A25), the labor market equilibrium condition can be written as follows:

$$\frac{w_{a,j}(t)}{w_{m,j}(t)^{1/2}} \sim \omega(t) \text{ for each } j \tag{A26}$$

where $\omega(t)$ is a function that is independent of region j.

The mobility of high skill labor

Using the expressions for wages in (A24), the labor market equilibrium condition in (A26) can be written as:

$$\frac{\kappa_1 L_{a,j}(t)^{-\beta_j} K_j(t)^{\beta_j}}{\kappa_1^{1/2} L_{a,j}(t)^{(1-\beta_j)/2} K_j(t)^{\beta_j/2}} = \omega(t). \tag{A27}$$

The term $K_j(t)^{\beta_j}$ in the numerator of this expression captures the positive effect of the capital growth on the share of high skill labor (since the two factors are complements). The term $L_{a,j}(t)^{-\beta_j}$ in the numerator captures the effect of the scarcity of high skill labor on wages. The denominator of this expression captures the effect of the capital growth on the price of service goods: As the economy grows faster, services (which are produced by scarce factors) become more expensive, which has a negative effect on the welfare of a high skill worker. In equilibrium, labor flows across regions until these forces are in balance and equation (A27) is satisfied for each j.

Using the conjectures that $K_j(t)$ and $L_{a,j}(t)$ grow (or shrink) at asymptotically constant rates, equation (A27) holds only if:

$$\beta_j \frac{g_{K,j}}{2} = \left(\frac{1-\beta_j}{2} + \beta_j\right) g_{L,j} + \eta \text{ for each } j,$$

where η is some constant. Recall that region $\bar{j}$ has asymptotically zero high skill labor growth (see the conjecture in (A20)). Hence, considering the previous equation for region $\bar{j}$ gives $\eta = \beta_j \frac{\sigma-1}{\sigma} g_{K,\bar{j}}$, which implies

$$\beta_j \frac{g_{K,j}}{2} - \beta_{\bar{j}} \frac{g_{K,\bar{j}}}{2} = \left(\frac{1-\beta_j}{2} + \beta_j\right) g_{L,j} \text{ for each } j.$$

Plugging in the expression (A23) and solving for $g_{L,j}$ gives:

$$g_{L,j} = \frac{\delta}{1-\beta_j} - \frac{\delta\beta_{\bar{j}}}{1-\beta_{\bar{j}}} \text{ for each } j. \tag{A28}$$

Using Eq. (A23), the growth rate of capital is also characterized as:

$$g_{K,j} = \delta\left(\frac{\beta_j}{1-\beta_j} - \frac{\beta_{\bar{j}}}{1-\beta_{\bar{j}}}\right) \text{ for each } j. \tag{A29}$$

Note that the conjecture $g_{L,j} < 0$ for each $j \neq \bar{j}$ holds only if $\beta_j < \beta_{\bar{j}}$ for each $j \neq \bar{j}$. This implies that $\bar{j} = j^{\max}$, that is, the labor is attracted at a constant rate to the region with the greatest β_j. Eqs. (A28) and (A29) completely characterize the constant growth rates in (A20). It can be checked that the constructed allocation is an equilibrium.