Figure 1. Smoothed Changes in Employment and Hourly Wages, 1980–2005

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 1, panel A. 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 US nonfarm employment. Occupations are ranked by skill level, which is approximated by the mean log wage of workers in each occupation in 1980.

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 United States 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. Notably, this pattern of employment polarization is not unique to the United States. Although not recognized until recently, a similar "polarization" of employment by skill level has been underway in numerous industrialized economies in the last 20 to 30 years.[3]

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 (Figure 1, panel B). 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 toward the median.[4]

This paper offers an integrated explanation and detailed empirical analysis of the forces behind the changing shape of low education, low wage employment in the US 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 accounted for by rising employment and wages in a single broad category of employment: *service occupation*s.

Service occupations are jobs that involve assisting or caring for others, for example, food service workers, security guards, janitors and gardeners, cleaners, home health aides, child care workers, hairdressers and beauticians, and recreation occupations.[5] Though among the least educated and lowest paid categories of employment, the share of US labor hours in service occupations grew by 30 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 and craft occupations, operative and assembler occupations, and transportation, construction, mechanical, mining, and farm occupations. The increase was even steeper among noncollege workers, by which we mean those with no more than a high school education, among whom service

[3] Using harmonized European Union Labour Force Survey Data, Goos, Manning, and Salomons (2009, 2011) 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 polarization of US employment was initially studied by Acemoglu (1999). Goos and Manning (2007) provided the first rigorous analysis of polarization based on UK data.

[4] Figure 1, panels A and B 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 1, panels A and B differ from related analyses in Autor, Katz, and Kearney (2006 and 2008); Acemoglu and Autor (2011); and Firpo, Fortin, and Lemieux (2011), which use occupational skill percentiles to measure employment polarization and use raw wage percentiles to measure wage polarization.

[5] It is critical to distinguish service *occupations*, a group of low-education occupations providing personal services and comprising 12.9 percent of labor input in 2005 (Table 1), from the service *sector*, a broad category of industries ranging from health care to communications to real estate and comprising 83 percent of nonfarm employment in 2005 (www.bls.gov). Since part-time jobs are relatively prevalent in service occupations, the share of service *jobs* in US 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.

Table 1—Levels and Changes in Employment Share and Mean Real log Hourly Wages by Major Occupation Groups, 1950–2005: Occupations Ordered by Average Wage Level

	Level						Percent growth/ (growth per 10 yrs)	
	1950	1970	1980	1990	2000	2005	1950–1980	1980–2005
Panel A. Share of employment								
Managers/professionals/technicians/ finance/ public safety	22.3	25.8	31.6	38.2	39.6	40.9	41 (13.8)	30 (11.9)
Production/craft	5.1	4.8	4.8	3.5	3.6	3.0	−5 (−1.8)	−38 (−15.1)
Transportation/construction/ mechanics/mining/farm	29.2	22.3	21.6	18.8	18.0	18.2	−26 (−8.7)	−15 (−6.2)
Machine operators/assemblers	12.6	13.2	9.9	7.3	5.7	4.6	−21 (−7.0)	−54 (−21.5)
Clerical/retail sales	20.2	23.2	22.2	21.7	21.4	20.4	10 (3.4)	−8 (−3.3)
Service occupations	10.7	10.7	9.9	10.5	11.6	12.9	−7 (−2.3)	30 (11.9)
Panel B. Mean log hourly wage (2004$)								
Managers/professionals/technicians/ finance/public safety	2.22	2.86	2.83	2.90	3.03	3.14	61 (20.4)	31 (12.5)
Production/craft	2.24	2.73	2.75	2.72	2.70	2.72	50 (16.8)	−3 (−1.2)
Transportation/construction/ mechanics/mining/farm	2.04	2.55	2.61	2.56	2.62	2.63	57 (18.9)	2 (0.9)
Machine operators/assemblers	2.04	2.46	2.48	2.46	2.52	2.54	44 (14.7)	6 (2.3)
Clerical/retail sales	2.00	2.43	2.42	2.45	2.55	2.60	42 (14.1)	18 (7.3)
Service occupations	1.48	2.01	2.10	2.14	2.24	2.26	62 (20.7)	16 (6.4)

Notes: Sample includes persons who were age 18–64 and working in the prior year. 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 work hours. Labor supply is measured as weeks worked times usual weekly hours in prior year. All calculations use labor supply weights.

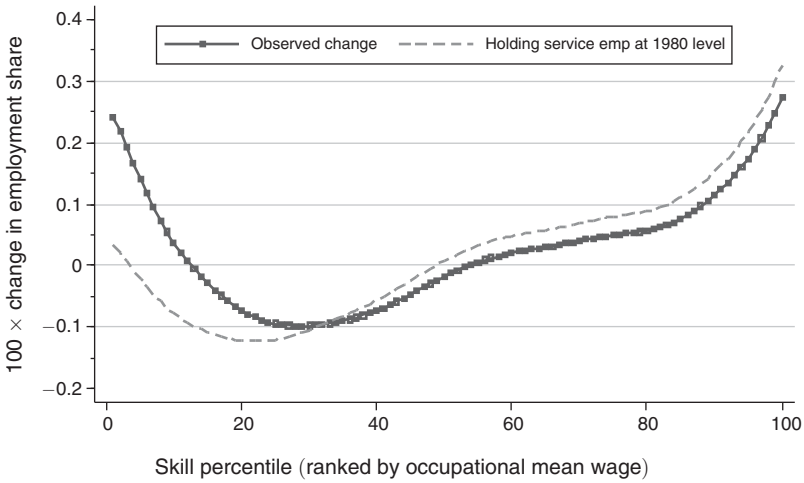
Source: Census 1 percent samples for 1950 and 1970; Census 5 percent samples for 1980, 1990, 2000; American Community Survey 2005.

occupation employment rose from 12.9 to 19.8 percent of total work hours between 1980 and 2005, a 53 percent increase (Appendix Table 1). Accompanying their rising employment, real wage growth in service occupations substantially outpaced that in other low-skill occupations, averaging 6.4 percent per decade between 1980 and 2005.

Figure 2 highlights the contribution of service occupations to aggregate employment and wage polarization by calculating a simple counterfactual scenario in which employment and wages in service occupations are held at their 1980 level. The upper panel of Figure 2 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.[6] Similarly, holding the real wage

[6] 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.

Panel A. Observed and counterfactual changes in employment by skill percentile, 1980–2005



Panel B. Observed and counterfactual changes in hourly wages by skill percentile, 1980–2005

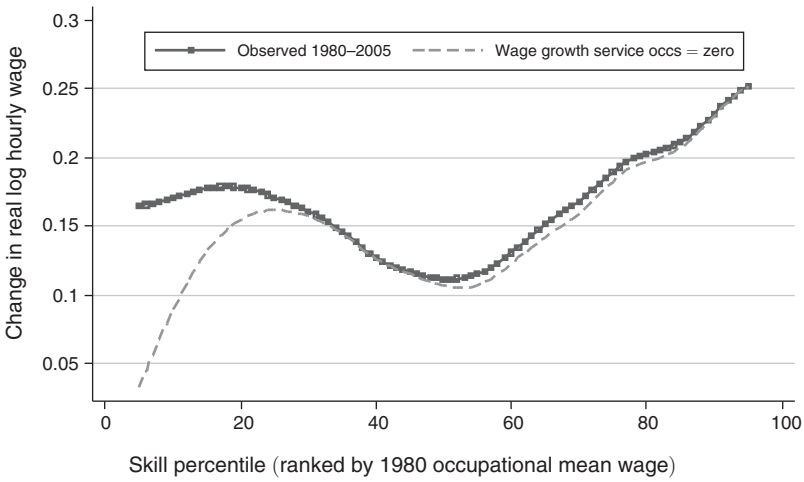


Figure 2. Observed and Counterfactual Changes in Employment and Hourly Wages, 1980–2005

Notes: The counterfactual in panel A is constructed by pooling ACS data from 2005 with Census data from 1980 and estimating 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. Observations in 2005 are reweighted 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.

Figure 3. Change in Aggregate Employment Share by Decade 1970 through 2005 in Occupations Comprising the Lowest Skill Quintile of Employment in 1980

levels of service occupations at their 1980 level throughout the 1980–2005 period (panel B) substantially dampens the upward twist of the left-hand tail of the distribution of wage changes by occupational skill in this time interval.

While the rapid growth of low-wage, low-education service occupations since 1980 may appear inconsistent with the conventional narrative in which low-skill occupations sharply contracted in the 1980s and expanded thereafter (Autor, Katz, and Kearney 2008), the reconciliation of these facts is found in Figure 3, which plots the evolution of employment in the set of occupations that comprised the lowest skill quintile of employment in 1980. This figure reveals that low-skill service and low-skill non-service occupations have exhibited strongly countervailing employment trends in every decade after the 1970s. After a contraction of employment in both service and non-service occupations in the 1970s, employment in service occupations rose consistently and with growing velocity in the 1980s, 1990s, and 2000s. Conversely, employment in low-skill non-service occupations continued to fall in each decade.[7] These divergent trends led to a *net* decline in low-skill employment in the 1980s and a net rise in the 1990s forward. Nevertheless, the growth of service occupations clearly commenced in the 1980s.

These simple exercises make a critical point: to interpret the pronounced polarization of employment and wages in the United States and potentially in other advanced countries, it is necessary to understand the rapid rise of employment and wages in service occupations. The primary hypothesis advanced by this paper is that polarization is driven by the interaction between two forces: consumer preferences,

[7] Occupational skill percentile is measured by the mean occupational wage in 1980, as in Figure 1. In 1980, 47 percent of employment in the lowest quintile was in service occupations and 92 percent of service occupation employment was in the lowest quintile. In 2005, 55 percent of employment in the lowest quintile was in service occupations and 89 percent of service occupation employment was in the lowest quintile.

which favor variety over 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 in a general equilibrium model of "routine-task" replacing technological change, building upon Autor, Levy, and Murnane (2003)—henceforth, ALM—Weiss (2008), and in a broader sense, Baumol's (1967) model of unbalanced technological progress.[8] 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 ("noncollege") workers in the production of goods. The adoption of computers substitutes for low-skill workers performing routine tasks—such as bookkeeping, clerical work, and repetitive production and monitoring activities—which 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. 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.[9] Consequently, as computerization erodes the wage paid to routine tasks in the model, low-skill workers reallocate their labor supply to service occupations.

A key implication of the model is 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, then the continuously falling price of computers ultimately causes wages for low-skill labor performing routine tasks to fall relative to wages for low-skill labor performing manual tasks. Low-skill labor flows accordingly from goods to services, while high-skill labor remains in goods production, leading to *employment polarization.* Furthermore, 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

[8] 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 differential progress in capital relative to labor-intensive technologies.

[9] 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, "[a]ssessing 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."

weakly complementary. If so, the wages paid to manual tasks (and hence noncollege earnings) converge to a steady growth rate that equals or exceeds the growth rate of college wages.

Building on the observation that the output of low-skill service occupations is non-storable and non-tradable—hence, suppliers and demanders of in-person services must collocate—we extend the conceptual model to a spatial equilibrium setting where local labor markets have differential degrees of specialization in routine-intensive industries. This extension provides testable implications for four local labor market outcomes. Specifically, it predicts that markets that were historically specialized in routine task-intensive industries should differentially (i) adopt computer technology and displace workers from routine task-intensive occupations; (ii) undergo employment polarization as low-skill labor reallocates into manual task-intensive in-person services; (iii) exhibit larger (nominal) wage growth at both ends of the occupational skill distribution (i.e., wage polarization); and (iv) 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.

We test these predictions at the level of 722 consistently defined, fully inclusive Commuting Zones (approximating local labor markets), and find robust support. Using Census data on industry and occupation mix by local labor market and data from the Dictionary of Occupational Titles (US Department of Labor 1977) on job tasks by occupation, we first document that the specialization of local labor markets in routine activities in the 1980s forward is largely predetermined by industry structure *in 1950*—three decades prior to the era of service occupation growth—which allows us to use the 1950 industry mix as an instrumental variable for local labor market specialization in routine tasks in later decades.

We find that commuting zones that were historically specialized in routine intensive occupations experienced differential increases in workplace computer use and reductions of employment in routine task-intensive jobs after 1980. Simultaneously, they experienced a sharp differential rise in low-skill service occupation employment that was accompanied by a differential growth of wages in these occupations. These patterns of growth in service occupations contribute to increased employment and wage polarization in routine-intensive local labor markets.

Alongside unbalanced technological progress, we evaluate numerous alternative explanations for the pronounced differences in wage and employment polarization across more and less routine-intensive labor markets, including deindustrialization, offshoring, rising demand for home production substitutes among households with high education and earnings, and growing low-skill immigration. None of these alternatives appears central to our findings.

Our local labor market analysis is most closely related to Beaudry, Doms, and Lewis (2010), who explore the cross-city relationship between skilled labor supply, the diffusion of information technology, and the evolution of the skilled wage premium. They document that cities that were initially relatively skill-abundant as of 1980 differentially adopted computer technology thereafter, and that this coincided with a reversal of the downward sloping city-level relationship between local skill supply and the skill premium. In addition to corroborating this complementarity between information technology and high-skill labor, the main contribution of our

paper is to document and analyze the largely unstudied relationship between the diffusion of information technology, the demand for low-skill service activities, and the polarization of employment and wages.[10]

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 II describes the data sources and details how we measure local labor markets, job tasks and, in particular, routine task-intensity. Section III presents empirical tests of the model's four main predictions for computer adoption, task specialization, wage polarization, and geographic mobility. Section IV concludes.

I. Model

We consider an economy with two sectors $(j = g, s)$ that produce "goods" and "services" for consumption using four factors of production.[11] 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 (nonconsumption) 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:

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

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.

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.

[10] Complementary research by Goos, Manning, and Salomons (2011) uses harmonized data from 16 European Union countries to study employment growth across 21 occupation groups from 1993 to 2006. Consistent with our findings, GMS conclude that declining employment in routine-intensive middle-skill occupations is the primary force behind employment polarization. Our paper capitalizes on the longer time horizon and much greater occupational and geographic detail afforded by US data sources to analyze polarization at the level of local labor markets over 55 years. Exploiting local labor market patterns of industry specialization evident in 1950, we tie historical local labor market specialization in routine activities to subsequent growth in employment in service occupations, increasing computer use, changing wage patterns, and labor mobility from 1980 through 2005.

[11] 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.

There is a continuum of mass one of high-skill workers, H, who supply abstract labor inelastically to the goods sector. There is a continuum of mass one of low-skill workers, U, who each supply either manual or routine labor.

Low-skill workers have homogeneous skills 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. Hence, a low-skill worker supplies routine tasks only if his earnings in goods production exceed the (uniform) service wage (i.e., $w_r(t) \times \eta_i \geq w_m(t)$). 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 $f(\eta) = e^{-\eta}$.[12] 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 toward the middle of the distribution.

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

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

where $Y_k(t)$ is the amount of the final consumption good allocated to production of K, $\delta > 0$ is a positive constant, and $\theta = e^{\delta}$ is an efficiency parameter. Capital fully depreciates between periods.[13] Productivity is rising at rate δ, reflecting technological progress.

At time $t = 1$, one unit of the consumption good Y can be used to produce one efficiency unit of computer capital: $1 = e^{\delta}/\theta$. Competition guarantees that the real price of computer capital (per efficiency unit) is equal to marginal (and average) cost. So, at time $t = 1$, $p_k = 1$. As time advances, this price falls, with

$$p_k(t) = \frac{Y_k}{K} = \theta e^{-\delta t}. \tag{4}$$

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

$$u = (c_s^{\rho} + c_g^{\rho})^{1/\rho}, \quad \text{where } \rho < 1. \tag{5}$$

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

[12] The choice of functional form is innocuous given that 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).

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

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 subsequently extend the model to a spatial equilibrium setting.

A. *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.[14]

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

$$\max_{K, L_m} \left(L_m^{\frac{\sigma-1}{\sigma}} + \left(Y_g - p_k(t)\, K\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{6}$$

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

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

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.

The first order conditions for problem (6) with respect to capital K and labor L_m respectively are given by

$$\frac{\partial Y_g}{\partial K} = p_k(t), \tag{7}$$

$$L_m^{-1/\sigma} = (Y_g - p_k K)^{-1/\sigma} \frac{\partial Y_g}{\partial X} \frac{\partial X}{\partial L_r} \left(-\log(1 - L_m)\right), \tag{8}$$

where we have used $g'(L_m) = \log(1 - L_m) = -\eta^*$.

The system in (7) and (8) 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.

[14] 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.

B. *Asymptotic Labor Allocation*

Since the price of computer capital $p_k(t)$ falls to zero asymptotically, computer capital limits to

$$\lim_{t\to\infty} K(t) = \infty. \tag{9}$$

Noting that 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,

$$\lim_{t\to\infty} X/\alpha_k K = 1. \tag{10}$$

Using this equation and equation (9), the online Appendix shows that the asymptotic supply of low-skill labor to services, L_m^*, is uniquely determined as follows:[15]

$$L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \overline{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases}. \tag{11}$$

This equation indicates 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 (11) 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 into services production. If this inequality is reversed, all low-skill labor eventually concentrates in the goods sector, where it performs routine tasks (opposite to what is observed in the data).[16]

[15] Here, $\overline{L}_m$ is the solution to the equation $(\overline{L}_m)^{-1/\sigma} = \kappa_1^{-1/\sigma}\kappa_2 g(\overline{L}_m)^{\mu-1}(-\log(1-\overline{L}_m))$. See the Appendix for details.

[16] The role played by β in this equation is also straightforward. 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. Hence, the lower is β, the smaller is the critical value of σ_r/σ required for low-skill labor to flow into services.

C. *Asymptotic Wage Inequality*

Two measures of inequality are relevant for our analysis. The first is the relative wage paid to manual versus routine tasks. When this ratio falls, 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. 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 when w_m/w_r rises while w_a/w_m is either stable or declining. We now derive the necessary and sufficient conditions for these outcomes.

Since low-skill labor necessarily flows toward 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 (11). Specifically,

$$\frac{w_m}{w_r} = \begin{cases} \infty & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -\log(1 - L_m^*) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta} \end{cases}. \tag{12}$$

If the production elasticity exceeds the consumption elasticity (scaled by β), wages for low-skill workers in manual tasks rise relative to the alternative wage in routine tasks, and low-skill labor flows to service occupations at the bottom of the occupational skill distribution. Therefore, the lower tails of both 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., w_a/w_m is either constant or declining).[17] The online Appendix shows that this occurs if the consumption elasticity is not less than unity—that is, goods and services are gross complements:[18]

$$\frac{w_a}{w_m} = \begin{cases} 0 \text{ if } \sigma < 1 \\ 1 \text{ if } \sigma = 1 \\ \infty \text{ if } \sigma > 1 \end{cases}, \quad \text{when } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta}. \tag{13}$$

[17] 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.

[18] The online Appendix also characterizes 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 ($\sigma > 1$).

This result is of signal importance to our analysis because 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 reverses 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.

D. *Summary of Closed Economy Model*

The closed economy model gives rise to three focal cases. First, 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 (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 toward the middle of the occupational skill distribution, we say that employment "polarizes." Note, however, that because workers who remain in the goods sector are positively selected, the ratio of wages paid to workers in goods versus service occupations need not fall as rapidly as the ratio of wages paid to an efficiency unit of routine versus manual task input. The observed change in wages per time unit may thus be smaller than the underlying change in wages per efficiency unit.

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

Third, if instead 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; wages and employment fall most at the bottom of the occupational skill distribution. 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.

E. *Spatial Equilibrium*

To guide the subsequent empirical analysis of polarization at the level of local labor markets, we extend the closed economy model to consider an integrated, spatial equilibrium setting. In this setting, mobile high-skill workers reallocate across regions in response to changes in real earnings induced by the interaction between a uniformly falling price of automating routine tasks and regional heterogeneity in industry specialization that affect regions' ability to capitalize on these technological advances.

We consider a large set of geographic regions, $j \in J = \{1, \ldots, |J|\}$, each endowed with a unit mass of high-skill labor 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.[19] 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 equation (2).

Goods are costlessly tradable across regions. Services are nontradable since they must be performed in person. Consistent with the observation that geographic mobility is higher among college than noncollege workers (Topel 1986; Bound and Holzer 2000; and Notowidigdo 2011), 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

$$u(c_s, c_{g1}, \ldots, c_{gJ}) = u(c_s^{\rho} + \tilde{c}^{\rho})^{1/\rho}, \tag{14}$$

where

$$\tilde{c} = \left(\sum_{j=1}^{J} c_j^{\nu}\right)^{1/\nu}, \tag{15}$$

with $\nu > 0$, implying that the goods from each region are gross substitutes. These preferences differ from our initial setup (equation (5)) 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 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 (13), 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,

[19] 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 here. The subsequent empirical analysis uses historical measures of local area industry mix in 1950 to capture long-standing geographic differences in regional specialization.

we make the simplifying assumption that all regional goods varieties are perfect substitutes in consumption (i.e., $\nu \to -\infty$ in equation (15)). Perfect substitutability ensures that goods prices are equated across regional economies.[20]

The online Appendix provides a detailed solution of the spatial equilibrium model, which closely resembles the closed economy model above. Its key feature is that a uniform decline in the computer price across all regions—caused by continuous technological progress in computer production—has differential effects on local labor markets whose production is intensive in routine tasks (i.e., where β_j is greater). The main predictions of the model are summarized next.

F. *Empirical Implications*

The spatial equilibrium results provide four main empirical implications that we test in Section III. 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:

(i) Greater adoption of information technology, coinciding with the displacement of labor from routine tasks;

(ii) Greater reallocation of low-skill workers from routine task-intensive occupations to service occupations;

(iii) 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;[21]

(iv) Larger net inflows of high-skill labor, driven by the interaction between differential 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 note. A first is our stylized assumption that high- but not low-skill labor is mobile across regions. 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 toward the region

[20] 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.

[21] 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 (2013) 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 some fraction of the higher nominal wages of high-skill workers in these locations.

with the highest routine share given its greater rate of capital accumulation and higher labor productivity growth—a conjecture that we confirm below.[22]

A second element of realism intentionally omitted from the model is the potential for aggregate skill supplies to respond to changes in the skilled wage differential. Allowing for endogenous skill investments would clearly temper the extremes of wage inequality that can arise in the model.[23] We omit this consideration to emphasize that even with skill supplies held constant, ongoing skilled labor augmenting technical change need not imply ever rising wage inequality.

II. Data Sources and Measurement

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

A. *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 for the years 1950, 1970, 1980, 1990, and 2000, and the American Community Survey (ACS) for 2005 (Ruggles et al. 2010).[24] The Census samples for 1980, 1990, and 2000 include 5 percent of the US population, the 1970 Census and ACS sample include 1 percent of the population, and the 1950 Census sample includes approximately 0.2 percent of the population.

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

Our analysis 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 US Office for Management and Budget for statistical purposes; they consist of a large population nucleus and adjacent communities that have a high degree of social and economic integration with the core city. Two disadvantages of MSAs are that they do not cover rural parts of the United States and their geographic definition is periodically adjusted to reflect the growth of cities. This inconsistency is problematic for our analysis because the characteristics

[22] More formally, our setup does not accommodate simultaneous high- and low-skill migration without further assumptions because, without a locally fixed factor that becomes scarcer 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 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 (15)).

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

[24] The 1960 Census lacks detailed geographic information. The 1950 sample-line subsample on which we rely is only one-fifth as large as the full 1 percent public use sample, but it contains education and occupation variables, which are key to our analysis.

of suburban areas that are appended to MSAs are likely to systematically differ from the core cities.

We pursue an alternative definition of 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 to create 741 clusters of counties that are characterized by strong commuting ties within CZs and weak commuting ties across CZs. Our analysis includes the 722 CZs that cover the mainland of the United States (both metropolitan and rural areas). Commuting zones are particularly suitable for our analysis of local labor markets because they cover the entire United States, are based primarily on economic geography rather than incidental factors such as minimum population, and can be consistently constructed using Census Public Use Micro Areas (PUMAs) for the full period of our analysis.[25] We are not aware of prior economic research that makes use of this geographic construct.

B. *Measuring the "Routine Employment Share"*

A crucial input into our analysis is a summary index of routine task activities within commuting zones. We measure routine task activities using the occupational composition of employment. Following ALM (2003), we merge job task requirements from the fourth edition of the US Department of Labor's *Dictionary of Occupational Titles* (DOT) (US Department of Labor 1977) to their corresponding Census occupation classifications to measure routine, abstract, and manual task content by occupation.[26] While our theoretical model posits that workers supply either routine, abstract, or manual tasks, the DOT permits an occupation to comprise multiple tasks at different levels of intensity. We combine these measures to create a summary measure of routine task-intensity *RTI* by occupation, calculated as

$$RTI_k = \ln(T^R_{k,1980}) - \ln(T^M_{k,1980}) - \ln(T^A_{k,1980}), \tag{16}$$

where T^R_k, T^M_k, and T^A_k are, respectively, the routine, manual, and abstract task inputs in each occupation k in 1980.[27] This measure is rising in the importance of routine tasks in each occupation and declining in the importance of manual and abstract tasks.

To illuminate the operation of the routine task-intensity measure, Table 2 provides a schematic summary of the *RTI* variable and its constituent components. Evident from the table is that the intensity of both abstract and manual task activities is roughly monotone (albeit with countervailing signs) in occupational skill

[25] 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. Further details on our construction of CZs are given in the online Appendix and in Dorn (2009). 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.

[26] Following Autor, Katz, and Kearney (2006), we collapse ALM's original five task measures to three task aggregates for abstract, routine, and manual tasks. Details of our consistent occupation scheme, which provides a balanced panel of occupations covering the 1980, 1990, and 2000 Census, and the 2005 ACS, are given in the online Appendix and in Dorn (2009).

[27] Tasks are measured on a zero to ten scale. For the 5 percent of microdata observations with the lowest manual task score, we use the manual score of the 5th percentile. A corresponding adjustment is made for abstract scores.

Table 2—Task Intensity of Major Occupation Groups

	RTI index	Abstract tasks	Routine tasks	Manual tasks
Managers/prof/tech/finance/public safety	−	+	−	−
Production/craft	+	+	+	−
Transport/construct/mech/mining/farm	−	−	+	+
Machine operators/assemblers	+	−	+	+
Clerical/retail sales	+	−	+	−
Service occupations	−	−	−	+

Notes: The table indicates whether the average task value in occupation group is larger (+) or smaller (−) than the task average across all occupations. Shaded fields indicate the largest task value for each occupation group.

while the intensity of routine task activities is highest in the middle of the skill distribution. Thus, the composite *RTI* index takes low values at the bottom of the occupational skill distribution, where manual tasks dominate, and at the top of the occupational skill distribution, where abstract tasks dominate. Service occupations stand out as the only major occupation group that combines high manual task content with low routine task content. Appendix Table 1, which enumerates the most and least routine task-intensive nonfarm occupations, contains many illustrative examples.[28]

To measure routine task intensity at the geographic level, we take two additional steps. We first use the *RTI* index to identify the set of occupations that are in the top employment-weighted third of routine task-intensity in 1980. We refer to these as routine-intensive occupations. As shown in Figure 4, routine intensity is inversely U-shaped in occupational skill. The fraction of occupations flagged as routine-intensive is lowest at the 1st and 80th percentiles of the skill distribution and rises smoothly from both locations to a maximum at approximately the 30th skill percentile.[29] A visual comparison of Figure 4 and the upper panel of Figure 1 (employment polarization) reveals, consistent with our task framework, that there is a tight correspondence between occupations' routine intensity and their growth rates: employment contracted between 1980 and 2005 at the occupational skill percentiles with highest share of routine occupations. Similarly, a comparison between Figure 4 and the lower panel of Figure 1 (wage polarization) suggests that there is also a negative relationship between occupational routine intensity and wage growth, but the correspondence is not as close as it is for employment. As we discuss further in Section IIIC, this discrepancy arises primarily from wage trends in clerical occupations, which are concentrated in the second, third, and

[28] The most routine-intensive group includes clerical occupations, accounting occupations, and repetitive-motion occupations. The least routine-intensive, low-education group includes service occupations, transportation and material moving occupations, and blue collar trades. Logically, the least routine-intensive, high-education group includes technical and scientific professions, teaching occupations, and public safety occupations.

[29] There is also a small uptick in the routine occupation share from the 80th through 95th percentiles, which in part reflects the limitations of the DOT task measures. The routine task measure is somewhat higher in technical and scientific occupations than in other high-education occupations, reflecting (in our view) a blurring of the distinction between quantitative reasoning tasks and rote procedural tasks.

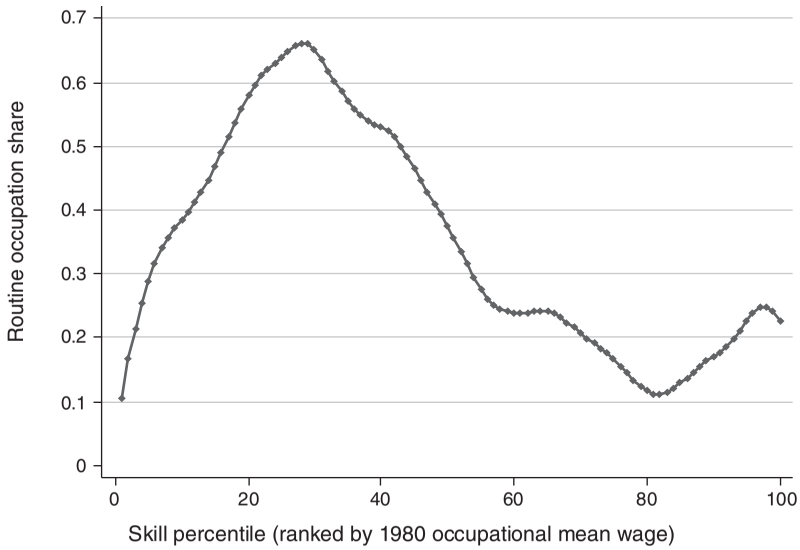


FIGURE 4. SHARE OF ROUTINE OCCUPATIONS BY OCCUPATIONAL SKILL PERCENTILE

fourth decile of the occupational skill distribution. These routine-intensive occupations experienced large declines in employment shares, as predicted by the model, but also rising relative wages from 1980 to 2005. A possible explanation for this pattern is that as traditional clerical tasks have succumbed to automation, the work content of the remaining clerical and administrative jobs has become concentrated in more skill-demanding, less routine-intensive tasks. For example, the 1976 edition of the Department of Labor's *Occupation Outlook Handbook* described the job of secretary as: "Secretaries relieve their employers of routine duties so they can work on more important matters. Although most secretaries type, take shorthand, and deal with callers, the time spent on these duties varies in different types of organizations" (US Department of Labor 1976, p. 94). In 2000, the entry for secretary reads: "As technology continues to expand in offices across the Nation, the role of the secretary has greatly evolved. Office automation and organizational restructuring have led secretaries to assume a wide range of new responsibilities once reserved for managerial and professional staff. Many secretaries now provide training and orientation to new staff, conduct research on the Internet, and learn to operate new office technologies" (US Department of Labor 2000, p. 324). This example cautions that the tasks performed within occupations are not necessarily static, and in particular, that occupations undergoing rapid computerization may differentially reduce labor input of routine tasks and increase labor input of abstract tasks.[30]

[30] This concern applies with greatest force to clerical occupations which often comprise a diverse set of tasks. Bartel, Ichniowski, and Shaw (2007) also present evidence that some precision production occupations have become less routine-intensive and more abstract-intensive as automation has advanced.

We next calculate for each commuting zone j a routine employment share measure, RSH_{jt}, equal to:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1\left[RTI_k > RTI^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \tag{17}$$

where L_{jkt} is the employment in occupation k in commuting zone j at time t, and $1[\cdot]$ is the indicator function, which takes the value of one if the occupation is routine-intensive by our definition. By construction, the mean of this measure is 0.33 in 1980, and the population weighted 80/20 percentile range is 7 percentage points ($RSH^{P20} = 0.294$ and $RSH^{P80} = 0.365$).

While its simplicity is attractive, there are many plausible ways to construct this measure, and it would be potentially problematic if our core results hinged on one particular choice. To address this concern, we have explored numerous variations of our basic measure of the concentration of routine activities in a commuting zone and have found substantially similar results across specifications.[31] Online Appendix Table 1 details these results.

III. Main Results

We now test the model's four main empirical implications concerning computer adoption and displacement of routine tasks; reallocation of noncollege labor into service occupations; wage and employment polarization; and geographic mobility.

Prior to the regression analysis, we present summary evidence on one overarching prediction of the analytic framework: commuting zones specialized in routine task-intensive jobs should experience differential employment shifts out of routine occupations in the middle of the occupational skill distribution and into low-skill service occupations as information technology substitutes for workers engaged in routine tasks. Figure 5 provides graphical evidence on this prediction. Following the approach of Figure 1, Figure 5 panel A 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.[32] 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

[31] Some of these variations include: replacing the three-factor *RTI* with a two-factor alternative, $RTI = \ln(R) - \ln(M)$; redefining the baseline *RTI* by measuring the routine task score of an occupation using either the DOT variable "Set Limits, Tolerances, or Standards" or the DOT variable "Finger Dexterity," instead of taking the average of the two; measuring the routine share in each CZ as the employment share in the top *noncollege* employment-weighted third of routine-intensive occupations; measuring the routine share using the top 25 or 40 percent of occupations rather than the top 33 percent; and using the mean *RTI* in a commuting zone as a measure of routine-intensity rather than the routine occupation share. These many variants perform quite comparably—in terms of both their effect sizes and statistical significance—in predicting the growth of noncollege service employment within commuting zones between 1980 and 2005.

[32] To facilitate comparison with Figure 1, the run variable in the figure corresponds to the overall skill distribution in 1980. Following the suggestion of an anonymous referee, we have also grouped commuting zones into terciles of initial routine share to compare employment and wage polarization between the highest and lowest terciles. Consistent with expectations, the pattern of polarization is more pronounced in this alternative split. Figures are available from the authors.

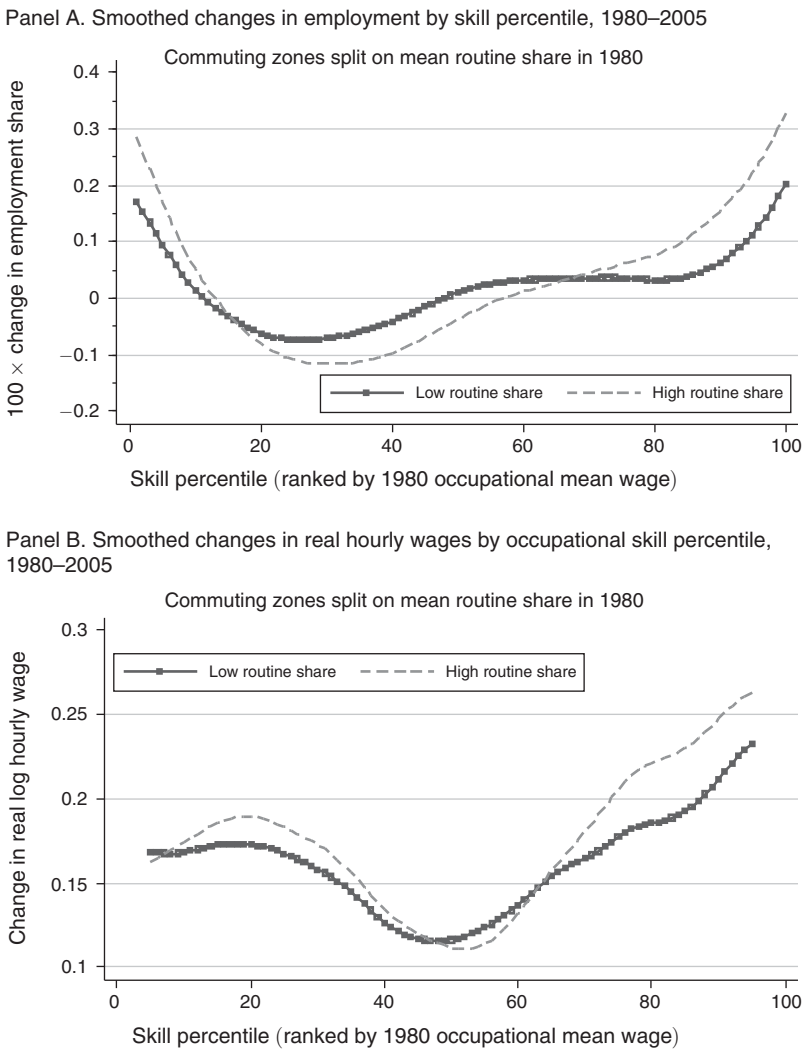


Figure 5. Smoothed Changes in Employment and Hourly Wages in Commuting Zones with High and Low Routine Employment Shares in 1980

routine share. We perform the parallel exercise for wages in Figure 5, panel B. Wage polarization is also more pronounced for high routine share commuting zones, with steeper wage growth at both tails, and shallower wage growth near the median.

The next sections present the detailed empirical analysis. Section IIIA provides evidence on technology adoption and displacement of routine labor in local labor markets. Section IIIB analyzes the determinants of rising low-skill service occupation employment within labor markets. Section IIIC provides evidence on the broader pattern of employment and wage changes among low-skill workers in occupation groups with low and high routine intensities and also discusses the ensuing effects on labor mobility.

A. *PC Adoption and Displacement of Routine Labor*

While the real cost of computing power has declined precipitously from the onset of the electronic computing era during the 1940s to the present, the rate of progress has varied substantially across decades. Nordhaus (2007, Table 8) estimates that the progress of computing decelerated in the 1960s and 1970s—when annual price declines slowed from approximately 45 percent in the 1940s and 1950s to as low as 22 percent per annum in the 1970s—and then accelerated sharply thereafter, with average cost declines averaging 60 to 70 percent per year during the period that is studied in this paper, i.e., the 1980s through the mid-2000s. The mechanism that links the declining price of computer capital to the polarization of local labor markets in our conceptual model is the substitution of information technology for labor in performing routine tasks. The model predicts that commuting zones with a greater initial routine employment share should differentially adopt information technology in response to its declining price and, by the same token, differentially displace labor from routine tasks.

We explore these implications, starting with computer adoption, by using a measure of geographic computer penetration developed by Doms and Lewis (2006) and also employed in Beaudry, Doms, and Lewis (2010). 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.[33] 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.[34]

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

$$\Delta PC_{jst} = \delta_t + \beta_0 \times RSH_{jst_0} + \gamma_s + e_{jst}, \tag{18}$$

where the dependent variable is the change in the Doms-Lewis measure of computer adoption over decade t_0 to t_1 in commuting zone j in state s, RSH_{jst_0} is that commuting zone's share of routine employment at the start of the decade, and standard errors are clustered at the state level. Due to the inclusion of a vector of state dummies γ_s, the coefficient of interest, β, is identified by within-state cross-CZ variation. We estimate this model separately by decade and by pooling multiple decades as stacked first differences with an added time dummy.

[33] 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 percent of US population.

[34] 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.

Table 3—Computer Adoption and Task Specialization within Commuting Zones, 1980–2005
(*Dependent variables: 10 × annual change in adjusted PCs per employee, 10 × annual change in employment share of routine occupations*)

	(1)	(2)	(3)
Panel A. Δ Adjusted PCs per employee, 1980–2000			
	1980–1990	1990–2000	1980–2000
Share of routine occs$_{-1}$	0.695***	0.490***	0.619***
	(0.061)	(0.076)	(0.044)
R^2	0.577	0.332	0.385
Panel B. Δ Share routine occupations, 1980–2005			
	All workers	College	Noncollege
Share of routine occs$_{-1}$	−0.254***	−0.153***	−0.295***
	(0.023)	(0.024)	(0.018)
R^2	0.433	0.206	0.429

Notes: $N = 675$, $N = 660$, and $N = 1{,}335$ in the three columns of panel A, and $N = 2{,}166$ (3 time periods × 722 commuting zones) in panel B. 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 percent of total US population. All models include an intercept, state dummies, and in multi-period models, time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Estimates of this model in panel A of Table 3 confirm that the *RSH* variable is highly predictive of computer adoption. The implied difference in computer adoption between the 80th and 20th percentile commuting zone is economically large, equal in magnitude to approximately one full standard deviation of the computer adoption measure in each decade.[35]

Panel B of Table 3 confirms that commuting zones with initially higher routine task specialization saw larger subsequent declines in routine-intensive occupations. Specifically, we regress changes in commuting zones' share of routine employment on their initial routine intensity, applying a stacked-first difference variant of equation (18) that pools three sets of changes: 1980–1990, 1990–2000, and 2000–2005. The model in column 1 suggests that a commuting zone at the 80th percentile of 1980 RSH experienced a 1.8 percentage points larger contraction of the routine occupation share per decade between 1980 and 2005 than did a 20th percentile commuting zone. Consistent with the conceptual underpinnings of the model, columns 2 and 3 find that the decline in routine employment is substantially larger for

[35] Following Beaudry, Doms, and Lewis (2010), we also estimated augmented models that control for the start-of-decade skilled labor supply in each CZ, measured as the log ratio of college to noncollege population. Consistent with their results, relative skill supply is a significant predictor of subsequent computer adoption, but the point estimate for the routine-share variable is only minimally affected by the addition of this measure. Results are available from the authors.

noncollege workers (high school or lower) than for college workers (at least one year of college).[36]

B. *The Growth of Service Occupation Employment*

As shown above, the polarization of the US employment distribution is substantially accounted for by rising employment in low-skill service occupations. A key implication of the spatial equilibrium model is that this rapid rise in service employment should be most pronounced in initially routine task-intensive labor markets since the potential for displacement of noncollege labor from routine activities is greatest in these locations.

The scatter plots in Figure 6 provide graphical evidence on this prediction. Panel A of the figure depicts the bivariate relationship between initial commuting zone routine share, RSH_{1980}, and the change in the share of noncollege labor employed in service occupations over the subsequent 25 years. Each plotted point represents one of 722 commuting zones, and the regression line corresponds to the following weighted OLS regression of the change in the service employment share on the initial RSH, where weights are equal to commuting zone shares of national population in 1980:

$$\Delta SVC_{j,1980-2005} = -0.043 + \underset{(t=16.1)}{0.336} \times RSH_{j,1980} + e_{jt} \qquad R^2 = 0.27. \tag{19}$$

The explanatory power of this bivariate relationship is substantial. The coefficient of 0.336 on *RSH* implies that a commuting zone with the mean routine share of 0.33 in 1980 is predicted to increase its share of noncollege labor in service employment by 6.9 percentage points between 1980 and 2005, while the expected increase in noncollege service employment in the commuting zone at the 80th percentile of *RSH* is 3.2 percentage greater than in the 20th percentile commuting zone.

Panel B of Figure 6 illustrates the geography of this regularity by plotting the relationship between initial routine share and the growth of service employment for the subsample of 64 commuting zones with populations over 750,000 in 1980, where each commuting zone is identified by the name of its largest city. This figure underscores an important characteristic of initially routine occupation-intensive cities: they do not only comprise industrial cities such as Detroit or Newark, but also knowledge-intensive cities such as New York City and San Francisco. This pattern is consistent with the observation that routine-intensity is high in both production and clerical occupations (Table 2). Local labor markets with relatively low routine employment tend to be specialized in such industries as hospitality and tourist services (e.g., Orlando), education and health (e.g., Raleigh), or construction and mining (e.g., Houston).

[36] Autor and Dorn (2009) further analyze the composition of employment *gains* in nonroutine occupations. They find that declines in routine occupations within commuting zones are primarily offset by relative employment gains in low-skill, nonroutine occupations—jobs that are on average significantly less skill-intensive and lower-paying than the routine occupations that are displaced. The gains in low-skill, nonroutine occupations are substantially larger for noncollege than college-educated workers relative to their displacement from routine occupations.

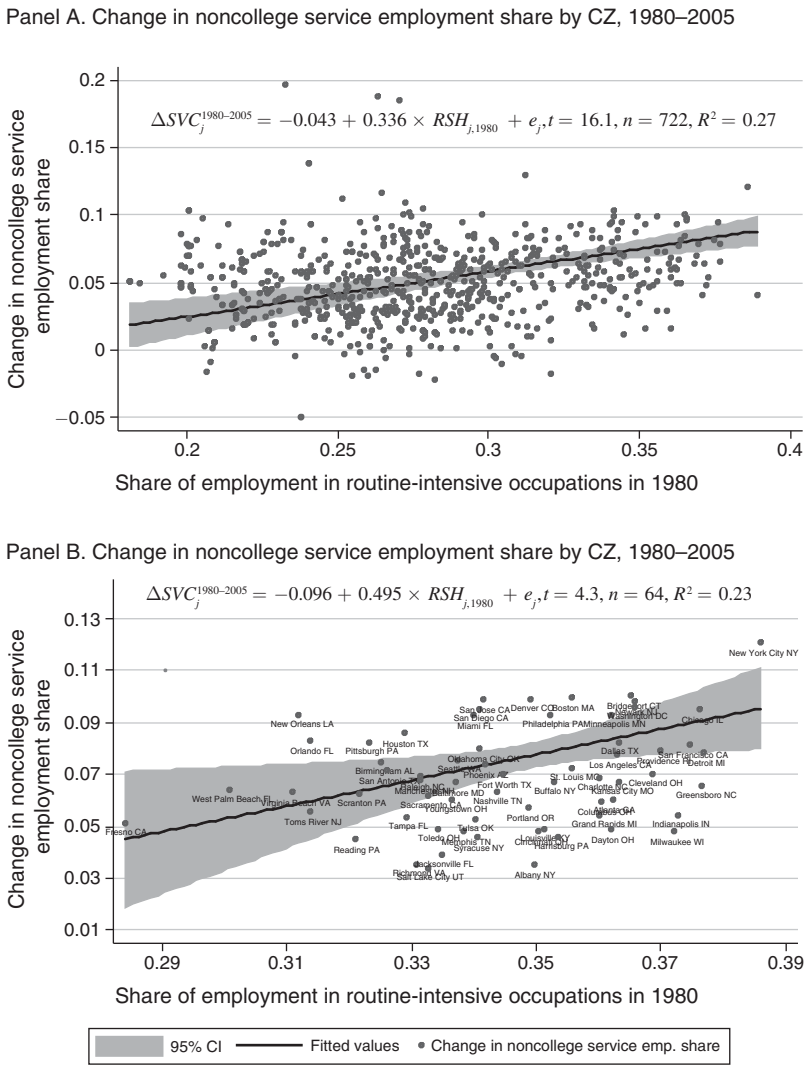


Figure 6. Changes in Noncollege Employment Share in Service Occupations, 1980–2005, versus Routine Employment Share in 1980 for All Commuting Zones (*panel A*) and Commuting Zones with > 750,000 Residents (*panel B*)

Service Employment: Detailed OLS Estimates.—Table 4 provides a longer-term perspective on the predictive relationship depicted in Figure 5 by regressing the change in the noncollege service occupation share on the start of the period routine employment share by decade for the period 1950 through 2005.[37]

The relationship between the routine employment share and growth of service employment within commuting zones is only weakly evident prior to the 1980s and

[37] 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. All models include state dummies.

Table 4—Routine Employment Share and Growth of Service Employment within Commuting Zones, 1950–2005
(*Dependent variable: 10 × annual change in share of noncollege employment in service occupations*)

	1950–1970	1970–1980	1980–1990	1990–2000	2000–2005
Panel A. OLS estimates					
Share of routine occs$_{-1}$	−0.133***	0.042	0.083***	0.084*	0.354***
	(0.020)	(0.032)	(0.028)	(0.045)	(0.110)
Constant	0.026***	−0.035***	−0.015*	−0.003	−0.051
	(0.003)	(0.009)	(0.008)	(0.014)	(0.033)
R^2	0.52	0.44	0.52	0.59	0.33
Panel B. Summary measures: noncollege service employment					
Mean growth	0.006	−0.004	0.026	0.024	0.037
SD growth	(0.015)	(0.016)	(0.013)	(0.015)	(0.035)

Notes: $N = 722$ commuting zones. Robust standard errors in parentheses are clustered on state. All models include state dummies and are weighted by start of period commuting zone share of national population.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

actually has the opposite sign during the 1950s and 1960s. The relationship becomes highly significant in the 1980s and its magnitude increases further in the 2000s.[38]

Alongside routine task-intensity, a host of human capital, demographic, and local labor market factors may explain differences across commuting zones in the growth of service employment. We consider these factors in Table 5 using an augmented version of equation (18):

$$\Delta SVC_{jst} = \delta_t + \beta_1 RSH_{jt_0} + \mathbf{X}'_{jt_0}\beta_2 + \gamma_s + e_{jst}, \tag{20}$$

where ΔSVC_{jst} is the change in the noncollege service employment share in CZ j located in state s between years t_0 and t_1, and RSH_{jt_0} is the CZ's start of period routine-share. This equation stacks the three time periods covering the interval 1980–2005, and includes a full set of time period effects, state effects, as well as the start-of-period values of seven additional explanatory variables.

As a baseline, the first column presents a pooled specification with the routine share measure, time dummies, and state dummies. Columns 2 and 3 add two variables intended to capture shifts in the demand and supply for service occupations: the ratio of college to noncollege educated individuals in the population (expressed in logarithms) and the share of the noncollege population that is foreign born. These controls enter with the expected sign. Greater relative supply of college-educated individuals predicts rising service employment among noncollege workers, as does a greater stock of foreign born residents (consistent with Cortes 2008).

[38] Farm-intensive commuting zones tended to have low levels of the *RSH* in 1950. The movement of labor from farm occupations into other low-skill occupations in these CZs may potentially explain the negative relationship between the *RSH* and growth of service employment in this period.

Table 5—Routine Employment Share and Growth of Service Employment within Commuting Zones, 1980–2005: Stacked First Differences, OLS and 2SLS Estimates
(*Dependent variable: 10 × annual change in share of noncollege employment in service occupations*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. OLS estimates: covariates specified in lagged levels							
Share of routine occs_{-1}	0.105***	0.066*	0.066**	0.110***	0.110**	0.069*	0.111***
	(0.032)	(0.036)	(0.029)	(0.031)	(0.049)	(0.035)	(0.034)
College/noncollege pop_{-1}		0.012***					0.011**
		(0.004)					(0.005)
Immigr/noncollege pop_{-1}			0.042**				0.025**
			(0.017)				(0.011)
$\text{Manufact/empl}_{-1}$				−0.056***			−0.036***
				(0.015)			(0.011)
Unemployment rate_{-1}				−0.067			−0.313***
				(0.069)			(0.068)
Female empl/pop_{-1}					−0.044		−0.200***
					(0.039)		(0.037)
Age 65+/pop_{-1}					−0.114***		−0.061***
					(0.035)		(0.020)
Share workers with $\text{wage}_t < \text{min wage}_{t+1}$						−0.134***	−0.197***
						(0.020)	(0.029)
R^2	0.179	0.189	0.196	0.195	0.191	0.196	0.233
Panel B. 2SLS estimates: covariates specified in lagged levels							
Share of routine occs_{-1}	0.192***	0.118***	0.148***	0.162***	0.218***	0.174***	0.149***
	(0.035)	(0.046)	(0.044)	(0.031)	(0.054)	(0.035)	(0.056)
R^2	0.169	0.186	0.189	0.192	0.182	0.182	0.264
Panel C. 2SLS estimates: covariates specified in ten year changes							
Share of routine occs_{-1}	0.192***	0.173***	0.152***	0.170***	0.180***	0.174***	0.112**
	(0.035)	(0.043)	(0.032)	(0.035)	(0.035)	(0.035)	(0.044)
R^2	0.169	0.174	0.188	0.232	0.186	0.182	0.265

Notes: $N = 2{,}166$ (3 time periods × 722 commuting zones). All models include an intercept, time dummies, and state dummies. In panels B and C, share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies; see text for details. Covariates in panels A and B are identical. Covariates in columns 2–5 and 7 of panel C are equal to contemporaneous decadal change in the covariates used in panels A and B. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Column 4 considers two measures of local labor demand conditions: the unemployment rate and the share of employment in manufacturing. Service employment grows less rapidly in areas with higher unemployment and a larger manufacturing employment share.

Column 5 considers a pair of potential demand shifters: the elderly share of population and the female labor force participation rate. Since the elderly have high demand for specific services such as home health assistance, a greater share of senior citizens in the population may raise service employment. Likewise, many services, such as restaurant meals or housekeeping, serve as substitutes for household production. Hence, higher female labor force participation might be expected to raise demand for these services (Manning 2004; Mazzolari and Ragusa 2013). Surprisingly, neither of these predictions is born out by the data. Service employment

appears to grow more rapidly in commuting zones with lower female labor force participation and a smaller elderly share.[39]

Since service occupations have the lowest wage levels of any major occupation group, their growth may also be affected by changes in the minimum wage. Column 6 explores the role of the minimum wage in service occupation employment by including a variable measuring the start-of-decade fraction of noncollege workers in a commuting zone whose real wage is below the minimum wage that *will be* enacted in the subsequent decade.[40] Consistent with expectations, a larger fraction of workers for whom the minimum wage will become binding significantly dampens the growth of service occupation employment.

When the full set of explanatory variables is included in the model (column 7), the point estimate on the RSH variable remains robustly significant and economically large. Recall that the 80/20 range of the routine share measure in 1980 is 0.07. This translates into a difference of approximately 0.8 percentage point per decade in the growth of the noncollege service employment in the 80th versus 20th percentile commuting zone relative to a mean decadal change of 2.9 percentage points over 1980–2005.

Instrumental Variables Estimates.—Our estimates so far explore the relationship between the routine employment share in a CZ at the beginning of a decade and subsequent within-CZ changes in computer penetration, low-skill service employment, and routine-intensive employment. This approach raises the question of what causes *RSH* to vary across commuting zones. Our theoretical model attributes this variation to stable differences in production structure across CZs, but our empirical analysis has so far been agnostic on these empirical determinants, focusing primarily on what the variation is *not* (e.g., immigration, skill supply).

To see the problem this may pose, consider an augmented version of the simple estimation equation above (20) where we replace the variable RSH_{jt_0} with two terms RSH_j^* and ν_{jt_0} where $RSH_{jt_0} = RSH_j^* + \nu_{jt_0}$:

$$\Delta SVC_{jst} = \delta_t' + \beta_1' RSH_j^* + \beta_2' \nu_{jt_0} + \gamma_2' + \epsilon_{jst}'. \tag{21}$$

In this expression, RSH_j^* represents the long-run, quasi-fixed component of industrial structure that is posited by our model to determine commuting zones' routine occupation shares. Conversely, ν_{jt_0} is any unobserved, time-varying attribute that affects CZs' routine occupation shares and also influences ΔSVC_{jst} (i.e., if $\beta_2' \neq 0$). For example, ν_{jt_0} might reflect a cyclical spike in the demand for a CZ's manufacturing outputs, which draws low-skilled workers temporarily from services into manufacturing (thus raising RSH_{jt_0} relative to RSH_j^*). If present, this type of cyclical fluctuation would lead to biased OLS estimates of β_1 in equation (20) by inducing a positive relationship between the start of period level of *RSH* and the subsequent change in *SVC* that is not caused by RSH_j^*.[41]

[39] When entered as decadal changes rather than lagged levels, both covariates enter with the expected sign: service employment grows when the elderly population share or female labor force participation rises.

[40] Statutory minimum wage levels by state and year are from Autor, Manning, and Smith (2010).

[41] Specifically, if $\beta_2' > \beta_1'$ ($\beta_2' < \beta_1'$) and Var $(\nu) > 0$, OLS estimates of β_1 will be upward (downward) biased.

To address this potential bias, we exploit historical cross-CZ differences in industry specialization to isolate the long-run, quasi-fixed component of the routine occupation share, RSH^*. Our approach is as follows: let $E_{ij,1950}$ equal the employment share of industry $i \in 1, \ldots, I$ 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 US states *except* the state that includes commuting zone j.[42] 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 industry mix in 1950 and the occupational structure of industries *nationally* in 1950:

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

This measure is a logical instrumental variable for *RSH:* because it is determined three decades prior to 1980, we expect it to be correlated with the long-run component of the routine occupation share RSH^* but uncorrelated with contemporaneous innovations to RSH reflected in ν.

Appendix Table 3 presents first-stage estimates for this instrumental variables model. The predictive relationship between $\widetilde{RSH}$ and *RSH* is sizable and highly significant, with t-ratios of six or above in each decade. The first-stage coefficient is close to unity in 1950, and takes smaller values in successive periods, obtaining a coefficient of 0.27 in 2000.[43] The decrease in magnitude is to be expected since initial conditions become less determinative over time. 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.

Using the 2SLS model, the second panel of Table 5 repeats our main estimates for the growth of noncollege service employment. These 2SLS estimates are precisely estimated and are typically somewhat larger in magnitude than their OLS counterparts. In the most complete specification (column 7), the 2SLS point estimate is 0.149 versus 0.111 in the OLS model, and both are statistically significant.

As a further test of the robustness of the predictive relationship between the routine-employment share and the reallocation of noncollege labor into service occupations, the third panel of Table 5 repeats the 2SLS estimates while entering the human capital, labor market, and demographic variables as contemporaneous changes rather than start of period levels. This approach is arguably unduly conservative in that these contemporaneous outcomes—such as unemployment and declining manufacturing—may themselves result from technological displacement of routine-intensive

[42] 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.

[43] 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.

occupations. Nonetheless, the coefficient on the routine share variable is precisely estimated and comparable in magnitude to the prior specification.[44]

We have performed many additional tests to probe the generality and robustness of the main results for computer adoption, decline of routine employment, and growth in low-skill service employment. We obtain qualitatively similar findings when estimating the models in Tables 3 and 4 using 2SLS in place of OLS, when fitting separate models for large (population $> 250K$ in 1980) and small (population $\leq 250K$ in 1980) commuting zones, and when estimating models for the decline in routine-intensive employment and growth of service employment separately by sex.[45] In addition, Appendix Table 4 fits 2SLS models for the relationship between the routine employment share and changes in noncollege employment in nine subgroups of service occupations: food service, cleaning and gardening, health support, child care, personal appearance, security guards, recreation, and miscellaneous services. The positive relationship between RSH and service employment growth is present 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). The point estimates are positive for eight of nine service occupation categories and are statistically significant at $p \geq 0.10$ in six.

Alternative Hypotheses.—In addition to the demographic and local labor market factors considered in Table 5, three other potential explanations for the rise of service employment in routine-intensive local labor markets merit careful study. These are: (i) growing offshoring (rather than automation) of job tasks, which displaces low-skill workers into non-offshorable service occupations; (ii) rising income at the top of the wage distribution, which stimulates demand for in-person services among wealthy households (an income effect, as in Clark 1957); and (iii) 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 2013). This subsection investigates these three mechanisms and finds little evidence that they are empirically important drivers of polarization—at least at the level of local labor markets.[46]

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; Jensen and Kletzer 2010; Firpo, Fortin, and Lemieux 2011; and Blinder and Krueger 2013). Papers in this literature observe 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. By contrast, the

[44] To conserve space, we do not tabulate the level or change covariates in panels B and C. The coefficients on the level controls in panels A and B are highly comparable. The coefficients on the change controls in panel C are all statistically significant and each has the expected sign: positive for college/noncollege population, immigrants/noncollege population, unemployment rate, elderly share of population, female labor force participation; negative for manufacturing employment share. Full results are available from the authors.

[45] Detailed results are available from the authors.

[46] Goos, Manning, and Salomons (2011) reach a similar conclusion in their cross-national analysis.

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 is not included in national accounts and hence is largely unmeasured. We follow the standard approach in the literature of measuring the offshoring *potential* ("offshorability") of job tasks 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 (2011) derive from the US Department of Labor's Occupational Information Network database (O*NET). This measure captures the degree to which an occupation requires either direct interpersonal interaction or proximity to a specific work location.[47] 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 substantial correlation between routine employment shares and offshorability across commuting zones ($\rho = 0.66$).[48]

The first panel of Table 6 tests whether commuting zones with higher start-of-period offshorability experienced differential growth of service employment among noncollege workers between 1980 and 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 small in magnitude. 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 1, panel B of Table 5). With this variable included, the offshorability measure reverses sign while remaining insignificant.

We have verified the robustness of this basic pattern of results to many plausible permutations of this specification: allowing the start-of-period routine occupation share and the offshorability index to each take separate slopes in the final decade of the sample; controlling for the contemporaneous change in manufacturing employment; and additionally allowing the slope on the manufacturing measure to differ in the final decade. In all cases, we find a positive, significant, and robust relationship between the routine share and the reallocation of noncollege labor into service employment.[49] Our findings here are in line with other recent work that

[47] We reverse the sign of the measure so that it is increasing rather than decreasing in offshorability. By 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. Further details are provided in the online Appendix.

[48] 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 (2013) find that their survey measures of offshorability and "routinizability" are essentially orthogonal.

[49] In these models, the offshoring variable has a marginally significant positive relationship with service employment growth in the final decade, but this is not robust to inclusion of the routine share measure. The contemporaneous decline in manufacturing employment in the final decade of the sample (an outcome variable) also predicts a significant rise in noncollege service employment, but controlling for this measure has little effect on the routine share variable. Detailed results are available from the authors.

Table 6—Predicting Changes in Service Occupation Employment with Measures of Offshorability, Income Effects, and Substitution Effects
(*Dependent variable*: *10 × annual change in share of noncollege 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$_{-1}$		0.164***		0.205***		0.209***	0.215***	0.181***
		(0.044)		(0.037)		(0.037)	(0.038)	(0.035)
Offshorability index$_{-1}$	0.007	−0.005						
	(0.005)	(0.006)						
Δ ln(P90) weekly wage			0.013	−0.017				
			(0.015)	(0.015)				
Δ Average annual hours per college grad/2,080					−0.111***	−0.127***		
					(0.032)	(0.031)		
Δ Average annual hours per male college grad/2,080							−0.069***	
							(0.018)	
Δ Average annual hours per female college grad/2,080								−0.083***
								(0.024)
R^2	0.17	0.18	0.17	0.17	0.19	0.19	0.18	0.19

Notes: $N = 2{,}166$ (3 time periods × 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.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

finds that offshorability plays a relatively minor explanatory role when considered alongside other potential causes (particularly, routine job task content) in explaining cross-industry and cross-national trends in employment or wage polarization (Goos, Manning, and Salomons 2011; Michaels, Natraj, and Van Reenen forthcoming).[50]

The next two panels of Table 6 explore the potential contribution of income and substitution effects among high-skill workers to rising service employment by augmenting the baseline regression model with two additional explanatory variables. To capture wage structure shifts that may generate income effects, we use changes in the 90th percentile of the log weekly wage distribution among full-time, full-year workers in the CZ. 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 in the CZ.[51]

Consistent with expectations, both top wages and college graduate hours per workers rose by significantly more in routine-employment intensive commuting zones between 1980 and 2005.[52] Nevertheless, these proxies for income and substitution effects do not have a strong direct relationship with growth in service employment.

[50] An exception is Firpo, Fortin, and Lemieux (2011), who estimate that offshoring contributed to wage polarization among US males between 2003 and 2009.

[51] Because this measure includes hours worked of all working-age college graduates independent of their labor force status, it captures changes at both the intensive and extensive margin of labor supply.

[52] Regression estimates imply that the commuting zone at the 80th percentile of RSH in 1980 experienced 9 additional log points per decade rise in the 90th percentile of full-time, full-year wage and 16 additional hours per decade increase in annual labor supply of college graduates relative to the 20th percentile commuting zone over the 1980–2005 period. Both relationships are statistically significant. The correlation coefficient between RSH and the change in the 90th percentile of earnings is 0.29 while the correlation between RSH and the change in college labor supply is 0.16. A full table of results is available from the authors.

A rise in the 90th 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).[53] Rising annual work hours among college graduates is negatively related to service employment growth, a pattern that 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 and is essentially unaffected by inclusion of these controls.

C. *Employment and Wage Changes in Major Occupation Groups*

The final empirical section broadens the focus of the analysis beyond service occupation employment to consider the relationship between routine employment intensity and changes in noncollege employment and wages across all six major occupation groups summarized in Table 1. The spatial model predicts that polarization of both employment and wages should be more pronounced in routine task-intensive labor markets. We have so far verified this prediction for employment in service occupations but have not considered either service occupation wages or employment and wage changes elsewhere in the occupational distribution. Table 7 takes up this task, beginning in panel A with changes in noncollege employment by major occupational category.

Although service occupations stand apart in both their low routine task content and rapid employment growth since 1980, two other major occupation groups are also characterized by relatively low routine task content: blue-collar transportation, construction, mechanical, mining, and farm occupations; and white-collar managerial, professional, technical, finance, and public safety occupations. Notably, the share of noncollege employment accounted for by these occupations expanded modestly between 1980 and 2005 (Appendix Table 1).

The first three columns of Table 7 estimate the relationship between the routine employment share and the growth of noncollege employment in these three nonroutine-intensive occupations. The first cell in column 1 repeats the earlier 2SLS estimate for noncollege service employment (compare column 1, panel B of Table 5). The next two rows highlight that the differential reallocation of noncollege labor into service occupations in CZs with high routine employment is equally pronounced for men and women. Thus, this pattern is not gender-specific. Columns 2 and 3 display analogous models for noncollege employment in the two other nonroutine-intensive occupation groups. Consistent with the pattern for service employment (though less pronounced), the noncollege employment share differentially increases in both of these occupations in routine-intensive local labor markets between 1980 and 2005.[54]

The next three columns of Table 7 repeat these estimates for three broad occupational categories that are relatively high in routine task content: clerical, administrative support, and retail sales occupations; precision production and craft occupations; and machine operator and assembler occupations. The estimates

[53] Our findings are qualitatively identical if we instead use the 75th wage percentile or the mean log weekly wage of college graduates. Results are available from the authors.

[54] Note that the white-collar nonroutine occupation category in column 3 of Table 7 is numerically small because this group of occupations employs primarily college workers.

Table 7—Routine Employment Share and Change in Occupational Employment Shares and Wage Levels within Commuting Zones, 1980–2005: 2SLS and Reduced Form OLS Estimates
(*Dependent variable: 10 × annual change in share of noncollege employment by occupation; log real hourly wage*)

		I. Occupations with low routine content			II. Occupations with high routine content		
		Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance, public safety	Administrative support, retail sales	Precision production, craft workers	Machine operators, assemblers
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in share of noncollege employment							
(i) All	Share of routine $occs_{-1}$	0.192***	0.248***	0.028	−0.277***	−0.085***	−0.107**
		(0.035)	(0.037)	(0.029)	(0.038)	(0.017)	(0.044)
(ii) Males	Share of routine $occs_{-1}$	0.210***	0.246***	−0.043	−0.055*	−0.145***	−0.213***
		(0.027)	(0.046)	(0.036)	(0.030)	(0.026)	(0.046)
(iii) Females	Share of routine $occs_{-1}$	0.253***	0.002	0.117***	−0.431***	−0.028**	0.087
		(0.073)	(0.045)	(0.030)	(0.062)	(0.012)	(0.055)
Panel B. log hourly wages of noncollege workers							
(i) All	Share of routine $occs_{80} \times 2005$	0.381***	0.023	0.433***	0.337***	−0.078	−0.388***
		(0.091)	(0.099)	(0.113)	(0.082)	(0.109)	(0.085)
(ii) Males	Share of routine $occs_{80} \times 2005$	0.346***	0.015	0.287*	0.187*	−0.075	−0.374***
		(0.132)	(0.097)	(0.149)	(0.097)	(0.140)	(0.106)
(iii) Females	Share of routine $occs_{80} \times 2005$	0.328***	0.310*	0.618***	0.468***	−0.223	−0.415***
		(0.095)	(0.183)	(0.116)	(0.092)	(0.139)	(0.105)

Notes: Panel A: Each coefficient is based on a separate 2SLS regression with $N = 2{,}166$ (3 time periods × 722 commuting zones). Models include an intercept, state dummies, and time dummies, and are weighted by start of period commuting zone share of national population. The routine occupation share is instrumented by interactions between the 1950 industry mix measure interacted with time dummies. Robust standard errors in parentheses are clustered on state. Panel B: Each row presents coefficients from one pooled OLS reduced form regression with $N = 5{,}363{,}963/2{,}844{,}441/2{,}519{,}522$ in rows i/ii/iii. Observations are drawn from the 1980 Census and 2005 ACS, and exclude self-employed and farm workers. The instrument (share of routine occupations predicted by industry structure in 1950) is interacted with a dummy for the observations of year 2005. All models include an intercept, commuting zone-occupation group fixed effects, time trends for occupation groups and states, an interaction between the time dummy and the share of workers in an occupation group whose 1980 wage was below the federal or state minimum wage of 2005, nine dummies for education levels, a quartic in potential experience, dummies for married, nonwhite, and foreign-born, and interactions of all individual level controls with the time dummy. Pooled sex models also include a female dummy and its interaction with the time dummy. 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.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

demonstrate that noncollege employment differentially contracted in all of these occupational categories in routine-intensive commuting zones between 1980 and 2005. The employment share declines were particularly pronounced in productive and operator occupations among males, and in clerical and sales occupations among females.

We next consider whether there were differential wage changes among noncollege workers in routine-intensive labor markets. We pool microdata on the log hourly wages of noncollege workers from the 1980 Census and the 2005 American Community Survey to estimate a set of 2SLS wage equations of the following form:

$$(23) \quad \ln w_{ijskt} = \gamma_{jk} + \lambda_k \{RSH_{j,1980} \times 1[t = 2005]\} + \mathbf{X}_i' \beta_t + \delta_{kt} + \phi_{st} + e_{ijkt},$$

where i denotes workers, j denotes commuting zones, s denotes states, k denotes occupations, and t denotes time (1980, 2005). The term $\lambda_k\{RSH_{j,1980} \times 1[t = 2005]\}$ interacts the (instrumented) start-of-period routine employment share variable with the 2005 dummy and thus measures, separately for each occupation group, the impact of a CZ's routine-intensity in 1980 on wage growth during 1980–2005. The wage equation also includes commuting zone and time dummies which are interacted with occupation dummies, and a set of worker-level covariates and state dummies, each interacted with time dummies.[55] Hourly wages are deflated by the national Personal Consumption Expenditure deflator, which does not account for local or regional price levels. Standard errors are clustered at the commuting zone level since the main predictive variable, *RSH*, does not vary within commuting zones.[56]

Panel B of Table 7 presents the wage estimates. For noncollege workers of both sexes, hourly wages in service occupations rise by significantly more in CZs with a relatively high routine share. A 7 percentage point higher routine share in 1980, equal to the gap between the 80th and 20th percentile commuting zones, predicts approximately 3 log points greater wage growth in service occupations between 1980 and 2005. We also find uniformly positive wage effects for the two other occupation categories with low routine task content in columns 2 and 3 of panel B, though not all individual point estimates are significant. In sum, the three occupation groups with low routine content experience differential growth in noncollege employment and wages in initially routine-intensive local labor markets.

The wage estimates for occupations with high routine content present a mixed picture. For operative and assembler occupations, the estimated wage effects are robustly negative and comparable in magnitude (but opposite in sign) to the estimates for service occupations, as predicted by the task framework. For precision production and craft occupations, wage estimates are uniformly negative but are not precisely estimated. For clerical, administrative support, and retail sales occupations, the pronounced decrease in employment found in panel A coincides with an unexpected increase in wages comparable in size and significance to the column 1 point estimates for service occupations. The fact that clerical employment and wages are moving strongly in countervailing directions in routine-intensive labor markets—opposite to the pattern for the five other occupations in Table 7—provides no conclusive evidence for falling demand for these occupations, and weakens our wage results overall.

As discussed in Section IIB, a potential interpretation of the wage trends in clerical occupations is that as traditional clerical tasks have succumbed to automation, the work content of the remaining clerical and administrative jobs has become concentrated in more skill-demanding, less routine-intensive tasks. Consistent with this observation, we note that the occupation-level correlation between employment and wage growth in 1980–2005, which is positive in the overall sample, is significantly negative among clerical and sales occupations, a pattern that is not observed for any other occupation group. This negative correlation suggests that observed wage

[55] Redundant interaction terms are dropped (e.g., with a complete set of CZ dummies, only one set of state by time dummies is retained).

[56] Wages in farm occupations are excluded because they are unreliable.

growth in clerical occupations is likely not due to rising demand for these jobs (which would tend to raise employment along with wages) but rather due to selection, i.e., the least skilled and most routine-intensive activities within clerical occupations are displaced, while more skilled and less routine-intensive clerical activities persist. This mechanism is consistent with the Roy component of our theoretical model, whereby self-selection induces the workers who are most productive in routine tasks to remain in goods production. Nevertheless, a lack of consistent time-series data on task changes within occupations prevents a full test of this hypothesis.[57]

With the caveats above, these results broadly establish that routine task-intensive labor markets saw rising employment and earnings of noncollege workers in non-routine intensive occupations combined with declining employment, and in some cases declining wages, in routine-intensive occupations.[58] Among all occupational categories, service occupations stand out for sharp gains in employment shares and wages among noncollege workers, consistent with the hypothesis that local demand has shifted in favor of this occupational category.

Complementing these findings, we show in online Appendix Table 2 that local labor markets that are intensive in routine employment also experience greater polarization of educational attainment during the same period. Specifically, the proportions of both college graduates and high school dropouts increase relative to the fractions of workers with some college or with high school education in these markets. Similarly, recent migrants into these markets are substantially more likely to be college graduates than are incumbent residents, and to a lesser degree are also more likely to be high school dropouts. In combination with the Table 7 results, this mobility evidence suggests that labor demand differentially increased between 1980 and 2005 for both the highest and lowest skilled occupations in routine employment-intensive labor markets.

IV. 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. Between 1980 and 2005, the share of hours worked in service occupations among noncollege workers rose by more than 50 percent. Simultaneously, real hourly wages of noncollege workers in service occupations increased by 11 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 United States 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

[57] Autor, Levy, and Murnane (2003, Table VI) construct measures of changes in task content within occupations using successive editions of the *Dictionary of Occupational Titles*, though, as they note, a substantial fraction of DOT occupations is not updated. Their analysis nevertheless documents a very pronounced decline in routine task content in occupations undergoing rapid computer adoption and, moreover, that this change in task content is not captured by changes in occupations' educational composition.

[58] We have estimated analogous wage models for each decade between 1980 and 2005 and obtain the same qualitative pattern of results: CZs with a higher *RSH* experienced in each decade greater relative wage gains in service, managerial, professional, and technical, and transportation and construction occupations than in production and craft and operative and assembler occupations.

of aggregate polarization and growth of the lower tail of the US employment and earnings distributions between 1980 and 2005.

This paper proposes an integrated explanation and conducts a detailed empirical analysis of the forces behind the changing shape of low education, low wage employment in the US 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 US 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: (i) greater adoption of information technology; (ii) greater reallocation of low-skill workers from routine task-intensive occupations into service occupations (i.e., employment polarization); (iii) larger increases in both employment and wages at both ends of the occupational skill distribution (i.e., wage polarization); and (iv) 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: adoption of information technology; reallocation of labor activity away from routine tasks; employment and wage growth in low-skill service occupations; and inward mobility of skilled 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 and 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 the 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; US 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 United States and potentially in other countries.

Appendix

A. *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 by 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. Top-coded 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 (which collects earnings in the prior year)

B. *Matching Census Geography to Commuting Zones (CZs)*

We matched geographic information that is available in the Census Public Use samples to 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 otherwise has no inherent economic interpretation. The 2000 Census splits the entire land area of the United States 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 allows us to compute

Appendix Table 1—Levels and Changes in Employment Share and Mean Real Log Hourly Wages by Major Occupation Groups among Workers without College Education, 1950–2005

	Level						Growth rate (%)	
	1950	1970	1980	1990	2000	2005	1950–1980	1980–2005
Panel A. Share of employment (%pts)								
Managers/prof/tech/finance/public safety	14.5	13.4	14.5	15.9	14.2	15.0	−0.1	3.9
Production/craft	5.7	5.7	6.0	4.9	5.5	4.5	6.1	−25.8
Transport/construct/mech/mining/farm	33.8	27.8	29.5	29.2	30.2	31.3	−12.7	6.2
Machine operators/assemblers	14.8	17.1	14.7	12.5	10.4	8.5	−0.8	−42.5
Clerical/retail sales	19.1	22.6	22.4	22.0	21.8	20.9	17.7	−6.6
Service occupations	12.2	13.3	12.9	15.6	17.9	19.8	5.8	53.2
Panel B. Mean log hourly wage (2004$)								
Managers/prof/tech/finance/public safety	2.16	2.69	2.63	2.59	2.68	2.76	15.8	5.3
Production/craft	2.23	2.71	2.70	2.64	2.62	2.63	15.8	−2.9
Transport/construct/mech/mining/farm	2.04	2.55	2.59	2.52	2.56	2.57	18.5	−1.0
Machine operators/assemblers	2.03	2.45	2.46	2.42	2.47	2.48	14.3	0.7
Clerical/retail sales	1.96	2.38	2.37	2.35	2.41	2.45	13.6	3.2
Service occupations	1.47	1.99	2.07	2.08	2.17	2.18	20.3	4.2

Notes: Sample includes persons who were age 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 work hours of workers without college education. Labor supply is measured as weeks worked times usual weekly hours in prior year. All calculations use labor supply weights.

Source: Census 1 percent samples for 1950 and 1970; Census 5 percent samples for 1980, 1990, 2000; American Community Survey 2005.

the probability that a resident of a given PUMA falls into a specific CZ. Many PUMAs (e.g., 81 percent 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 to PUMAs. 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 below the level of states.

C. *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 classification creates a balanced panel of 330 occupations for the years 1980–2005 that allows us 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.

Appendix Table 2—Rankings of Occupations with Highest and Lowest Routine Intensity

	Panel A. Occupations with highest RTI scores		Panel B. Low-skill occupations with lowest RTI scores		Panel C. High-skill occupations with lowest RTI scores
1	Butchers and meat cutters	1	Bus drivers	1	Fire fighting, prevention and inspection
2	Secretaries and stenographers	2	Taxi cab drivers and chauffeurs	2	Police and detectives, public service
3	Payroll and timekeeping clerks	3	Waiters and waitresses*	3	Primary school teachers
4	Bank tellers	4	Truck, delivery, and tractor drivers	4	Managers of properties and real estate
5	File clerks	5	Door-to-door/street sales, news vendors	5	Secondary school teachers
6	Cashiers	6	Carpenters	6	Electrical engineers
7	Typists	7	Telecom and line installers and repairers	7	Physicians
8	Pharmacists	8	Housekeepers, maids, butlers, and cleaners*	8	Computer systems analysts and scientists
9	Bookkeepers, accounting clerks	9	Health and nursing aides*	9	Civil engineers
10	Postal clerks, except mail carriers	10	Electricians	10	Industrial engineers

Notes: Asterisk denotes low-skill service occupations. The Routine Task Index (RTI) is defined as $\text{RTI} = \ln(\text{R}) - \ln(\text{M}) - \ln(\text{A})$ where R, M, and A are occupation-level measures for routine, manual, and abstract tasks derived from the *Dictionary of Occupational Titles* (DOT) 1977. Low-skill occupations in panel B include occupations in which the share of workers without college education is larger than in the overall workforce in 1980; high-skill occupations in panel C include occupations with a below-average share of noncollege workers. All occupations in panel A except secretaries and pharmacists are low-skill occupations according to this definition. 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. The ranking includes all occupations whose employment share is at least half as large as the employment share of the average occupation, and excludes agricultural, supervisory, and residual occupations.

Appendix Table 3—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
Panel A. Single decade regressions					
1950 Industry mix measure	1.055***	0.624***	0.521***	0.353***	0.272***
	(0.082)	(0.062)	(0.063)	(0.055)	(0.047)
R^2	0.793	0.697	0.656	0.530	0.480
Panel B. Pooled regression, 1950–2005					
1950 Industry mix measure	1.066***	0.663***	0.542***	0.328***	0.230***
	(0.082)	(0.059)	(0.060)	(0.053)	(0.047)
R^2					0.802

Notes: Panel A reports the coefficient estimates from separate regressions by decade with $N = 722$ in each model. Panel B reports a single regression with $N = 3{,}610$. All models include state dummies and are weighted by the share of each commuting zone in national population in each sample year.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Appendix Table 4—Routine Employment Share and Growth of Employment in Detailed Service Occupations within Commuting Zones, 1980–2005: Stacked First Differences (2SLS Estimates)
(*Dependent variable: 10 × annual change in share of noncollege employment in specific service occupation*)

	Food service	Building clean/ garden	Health support	House clean/ laundry	Child care	Personal appearance	Security guards	Recreation	Misc. personal services
Panel A. Estimates									
Share of routine occs$_{-1}$	0.073***	0.051***	0.003	0.012	0.009*	0.017**	0.019***	0.010*	−0.002
	(0.015)	(0.017)	(0.017)	(0.010)	(0.005)	(0.007)	(0.006)	(0.006)	(0.004)
Constant	−0.009*	−0.007	0.004	−0.006**	−0.002	−0.006***	−0.005**	−0.004**	0.002**
	(0.005)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
R^2	0.10	0.27	0.13	0.10	0.17	0.10	0.08	0.23	0.12
Panel B. Descriptive statistics: Employment shares (noncollege employment)									
Emp 2005	6.55%	4.69%	3.04%	1.86%	1.00%	0.94%	0.88%	0.43%	0.44%
Emp 1980	4.18%	3.11%	1.88%	1.41%	0.51%	0.75%	0.63%	0.15%	0.31%
Δ 1980–2005	2.37%	1.58%	1.15%	0.44%	0.49%	0.19%	0.25%	0.28%	0.13%

Notes: $N = 2{,}166$ (3 time periods × 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 state 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.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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 estheticians); 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, fire fighters, and guards. Because police officers and fire fighters have much higher educational attainment and wage levels than all other service workers, we consistently exclude them from our primary definition of service occupations. All other occupations are grouped into five broad categories that each are relatively homogeneous in their task content (see Tables 1 and 2): White-collar managerial, professional, technical, finance, and public safety occupations typically employ highly educated workers specializing in abstract job tasks; blue-collar transportation, construction, mechanical, mining, and farm occupations are rich in manual job tasks; while the three remaining occupations categories which are specialized in routine job tasks are: clerical, administrative support, and retail sales occupations; precision production and craft occupations; and machine operator and assembler occupations. Details of the construction of the occupational classification and a full list of the resulting 330 occupations are given in Dorn (2009).[59]

[59] Lefter and Sand (2011) identify several flaws in the Meyer-Osborne (2005) occupation coding scheme, implemented in the IPUMS samples, which can lead to misleading inferences about employment trends in a small number of low wage occupations. Such flaws are also identified and corrected by Dorn (2009), and the corrections are implemented in the current paper.

D. *Matching Tasks to Occupations*

Measures for abstract, routine, and manual tasks are derived from the US Department of Labor's *Dictionary of Occupational Titles* (US Department of Labor 1977; "DOT" hereafter) and matched to their corresponding Census occupation classifications. Following Autor, Katz, and Kearney (2006), we collapse the original five task measures of Autor, Levy, and Murnane (2003) to three task aggregates: the manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination"; the routine task measure is a simple average of two DOT variables, "set limits, tolerances, and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the abstract task measure is the average of two DOT variables: "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements. Further details on these variables are found in Appendix Table 1 of Autor, Levy, and Murnane (2003).

The measure for offshorability of occupations is derived from O*NET data, which are available for download at http://online.onetcenter.org/. We use a simple average of the two aggregate variables *face-to-face contact* and *on-site job*, and reverse the sign of the resulting variable so that it measures offshorability instead of non-offshorability. Firpo, Fortin, and Lemieux (2011) 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."

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