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

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PRELIMINARY AND INCOMPLETE

While employment and earnings of low-skill workers have secularly declined in the United States since the 1980s, low-skill service occupations—such as restaurant workers, health aides, cleaners, guards and hairdressers—present a striking exception to this trend. Employment in service jobs expanded persistently and rapidly between 1980 and 2005, with modest accompanying real wage gains. This paper asks why wages and employment are growing in low-skill services. Motivated by the observation that workers in service occupations must collocate with demanders of their services, we study the determinants of employment and wages in service jobs during 1980 through 2005 in 741 consistently defined commuting zones covering all of US employment. Our approach is rooted in a model of changing task specialization in which 'routine' clerical, decision-making and production tasks are displaced by automation, causing workers to reallocate labor input to relatively high-skilled 'abstract' tasks that require problem solving and discretion and to relatively low-skilled 'manual' tasks that require physical and interpersonal flexibility but little formal education. The model implies that if commuting zones differ initially in their routine task intensity, areas with higher initial routine task intensity will see higher rates of computer adoption, greater polarization of employment and earnings, and larger increases in employment and wages in service occupations. We explore these predictions using a simple measure of task intensity based on the occupational structure of commuting zones at the start of the sample period (1980). This index proves strikingly predictive of the changes in task and wage structure implied by the model, in particular: reallocation of labor activity from routine task activities to high-skilled abstract tasks and low-skilled manual tasks; differential adoption of computer technology; and wage and employment growth in service occupations but not in other low-skilled occupations. Thus, in labor markets that were initially intensive in routine tasks in 1980, employment and wages have subsequently polarized with growing employment and earnings in both high-skill occupations and in low-skill service jobs.

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I. Introduction

One of the most striking aspects of the growth of earnings inequality in the United States has been the substantial declines in employment and earnings of less-educated workers. Between 1979 and 1995, real wages of high school dropouts working full-time, full-year fell by more than 19 percent while real wages of high school graduates fell by more than 9 percent, prior to staging a modest recovery during 1995 and 2005 (Autor, Katz and Kearney 2007). Over the same two and a half decade interval, employment rates of prime-age males with high school or lower education plummeted, falling by approximately seven percentage points among whites and twice that amount among Blacks (Juhn and Potter 2006). These patterns of declining earnings and employment of low-skilled workers are broadly understood to reflect secular demand shifts favoring high over low-skilled work.

Such demand shifts are reflected in the changing occupational structure of US employment. Table 1 lists the employment shares (measured in total hours of labor input) in 1980 through 2005 of six major occupational groups, defined by the Census Bureau, covering all employment and ordered from most to least highly educated: managerial and professional specialty occupations; technicians, sales and administrative support occupations; precision production, craft and repair occupations; service occupations; operators, fabricators and laborers; and farming, fishing and forestry occupations. Workers in these occupational groups differ substantially in average human capital. In the year 2000, high school dropouts comprised 2.2 percent of employment in professional/managerial jobs, 6.7 of employment in technical, sales and administrative support jobs and 20-plus percent of employment in the four remaining categories of production, labor, service and farm jobs.

As shown in Table 1 and Figure 1a, employment growth between 1980 and 2005 has been strongly biased towards highly skilled occupations. Managerial and professional specialty occupations—the highest skilled category—experienced consistent, rapid growth between 1980 and 2005, gaining 7.1 percentage points as a share of overall employment between 1980 and 2005, a 30 percent increase. By contrast, employment in the ‘middle skill’ group of technical, sales and administrative support occupations was essentially stagnant over this period, expanding in the 1980s and then contracting to less than its 1980 level over the next 15 years. Most notably, employment shares in three of the four low-skill occupations fell sharply in each decade. Between 1980 and 2005, farming, forestry and fishery occupations contracted by more than 50 percent as a share of employment, operators, fabricators and laborers contracted by 33 percent and precision production, craft and repair occupations contracted by 19 percent.

Standing in sharp contrast to these patterns of declining employment, however, is the experience of service occupations—which include jobs such as food preparation and service, health services support, and buildings and grounds cleaning and maintenance.[1] Despite being among the least educated and lowest paid occupations in the US economy, service employment expanded in each decade between 1980 and 2005, rising from 11.0 percent of employment in 1980 to 11.8 percent in 1990, to 13.7 percent in 2000 and to 14.9 percent in 2005. This increase of 35 percent is six percentage points larger than the gain in employment shares of managerial and professional employment.[2] As shown in Figure 1b, service occupations are also the only occupational category that is growing among non-college workers (those with high school or lower education). Notably, average real wages in service occupations also grew in each decade, averaging approximately eight log points per decade between 1980 and 2005 (Table 2). Service wage growth is comparable to that of technical, sales and administrative workers, and is about two-thirds as rapid as wage growth in managerial and professional work. By contrast, wages in other low-skilled occupation categories fell sharply in the 1980s and were relatively stagnant over the entire twenty-five year period.[3] Thus, service occupations present a clear exception to the trend of stagnating or falling wages and employment in low-skill occupations.

In addition to their exceptional pattern of wage and employment growth, three attributes of service occupations are particularly intriguing. A first is that service jobs represent a type of work that is hypothesized to expand in the face of recent technological change. As Autor, Levy and Murnane (2003; ALM hereafter) observe, the first-order impact of computerization is to displace (substitute for) a set of 'middle skilled' routine cognitive and manual tasks, such as bookkeeping, clerical work and repetitive production tasks. This process potentially complements the 'abstract' tasks performed by educated professionals and managers, the productivity of which depends in part on access to abundant information and analysis. Somewhat paradoxically, computerization may have little direct impact on the

[1] It is critical to distinguish service occupations, a group of low-education occupations providing personal services and comprising 13.7 percent of labor input in 2000 (Table 1), from the service sector, a broad category of industries ranging from health care to communications to real estate and comprising 81 percent of non-farm employment in 2000 (source: www.bls.gov).

[2] Because 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. For example, Hecker 2005 reports that service occupations accounted for nearly one in five jobs in 2004 whereas our calculations based on the 2005 American Community Survey find that service occupations contribute approximately one in seven hours of labor input.

[3] An exception is farming and fishery occupations. However, wages are not likely to be measured reliably in these occupations due to both low rates of non-self-employed work among farm proprietors and substantial underreporting of work by low-paid, undocumented farm laborers. Earnings measures used in our analysis exclude self-employment earnings.

non-routine manual activities ('manual tasks') performed in many 'low-skilled' jobs because the interpersonal and environmental adaptability demanded by these jobs has proven difficult to automate (to date). As Goos and Manning (2007) discuss, this conceptual framework implies that computerization may contribute to a polarization of employment and earnings—leading to increased employment in relatively high and relatively low-skilled jobs.[4] Service occupations, which demand low levels of education but high levels of interpersonal and environmental flexibility, exemplify the type of low-skilled job predicted to grow by this framework. This is a contemporary manifestation of Baumol's (1967) classic hypothesis that relatively slow productivity growth in services leads to the long run expansion of the service sector.[5]

A second notable aspect of service employment is the central role it is hypothesized to play in the gap in employment to population rates between the US and Europe. As first highlighted by Piketty (1997), many western European countries appear to be 'missing' personal services such as retail trade and hotel and restaurant employment. Papers by Bertrand and Kramarz (2002), Freeman and Schettkat (2002), Messina (2005) and Rogerson (2007) argue that these missing services both reflect and reinforce lower rates of employment and work hours in the Europe relative to the United States.[6] In particular, these authors hypothesize that European payroll taxes and product market regulations inhibit the labor supply of high earners and simultaneously thwart the development of 'marketized' production of home services. Thus, households engage in more home-based and less market-based production, thereby depressing demand for services. It is thus noteworthy that the growth of service occupation employment in the US has accompanied a particularly pronounced growth of earnings in the upper-half of the wage distribution (Piketty and Saez 2003; Autor, Katz and Kearney 2007). One speculative interpretation of this pattern is that growth in US service employment in part reflects rising demand for

[4] Goos and Manning coined the term 'polarization' to refer to this phenomenon in their 2003 working paper. Acemoglu (1999), Spitz-Oener (2006), Autor, Katz and Kearney (2006 and 2007), Goos and Manning (2003, 2007) and Dustmann, Ludsteck and Schönberg (2007) present evidence that employment polarization has occurred during the last two decades in the UK, West Germany and US. Black and Spitz-Oener consider implications of this phenomenon for demand for female labor. Bartel, Ichniowski and Shaw (2007) present unique, plant-level evidence on the impact of technical change on work organization and productivity in the valve manufacturing industry.

[5] A foundational assumption of this argument is that the elasticity of substitution across goods is less than unity, so that the budget share of services rises with its relative price.

[6] Rogerson (2007) studies employment in the service sector rather than service occupations, but conceives of the service sector as the provider of marketized personal services (which is essentially the role played by service occupations).

market-based substitutes for household production among high earners, a process has been potentially hindered in other industrial economies.

A final relevant aspect of the growth of service employment is that economists have long hypothesized that economic development drives growth of services. Distinct from Baumol's (1967) unbalanced growth hypothesis, Clark (1957) argues that the income elasticity of demand for services is more than unitary (thus, preferences are non-homothetic). Consequently, economic growth leads to a rising share of income devoted to services, even in the case of balanced productivity growth. Supporting this view, recent work by Mazzolari and Ragusa (2007) using US consumption data finds that the fraction of household spending in non-tradable, time-intensive services increases with the household head's wage.

This study explores the link between task structures, changes in the structure of earnings and the growth of low-skilled service work in the US over the last two and a half decades. Our empirical approach builds from the observation that the output of service work is non-traded, meaning that consumers and producers of services must collocate. This makes it fruitful to study the determinants of services using a detailed geographic approach. A crucial input into our analysis is a time-consistent definition of local labor markets based on 'commuting zones' (Tolbert and Sizer 1996). Commuting zones are built from clusters of counties with strong commuting ties and are intended to approximate local US labor markets. We measure levels and changes in economic variables over 1980 through 2005 within 741 consistently defined, fully inclusive commuting zones using data from the Census IPUMS 5 percent samples for 1980, 1990 and 2000 and from the American Community Survey for 2005.

We begin by documenting that, within commuting zones, the growth of service employment is robustly correlated with increases in high wages, a finding consistent with recent work by Mazzolari and Ragusa (2007) for Metropolitan Statistical Areas. This pattern, which holds for service occupations overall and across most service sub-occupations such as food service and buildings and grounds cleaning and maintenance— is suggestive of a link between rising wage inequality and growth of service employment. But because the determinants of cross commuting zone patterns of wage inequality growth are left unexplained by this analysis, it is unclear how this correlation should be interpreted.

To overcome this conceptual hurdle, we apply an empirical approach based on a model of changing task specialization motivated by the observations above. Following ALM 2003, Goos and Manning (2004) and Autor, Katz and Kearney (2006), the model posits that the job tasks of service occupations are relatively immune to automation since they require interpersonal and environmental adaptability as well as direct physical proximity. Consequently, automation of 'routine' information processing and production tasks leaves these tasks relatively unscathed. If demand for the outputs of service occupations is relatively inelastic, the model suggests that substitution of information technology for routine tasks may lead to rising wages and employment in service occupations. The model further implies that if commuting zones differ initially in their routine task intensity, areas with higher initial routine task intensity will see higher rates of computer adoption, greater polarization of employment and earnings, and larger increases in employment and wages in service occupations.

To evaluate these broad predictions, we construct a simple index of routine task intensity (RTI) based on the occupational structure of commuting zones at the start of the sample (in 1980). This index proves strikingly predictive of the changes in task and wage structure implied by the conceptual model. In commuting zones with an initially higher RTI, we find a substantial reallocation of labor activity from routine task activities to high-skilled abstract tasks and low-skilled manual tasks. This pattern of changing task allocation occurs not only in aggregate but within major education groups: college educated workers increase their specialization in abstract tasks in the place of routine tasks; less educated workers increase their specialization in both manual and abstract tasks in the place of routine tasks. The increase in labor specialization in high RTI commuting zones is accompanied by significantly higher rates of computer adoption, consistent with the view that computerization substitutes for some of the routine tasks formerly performed by workers.

A primary implication of the conceptual framework is that employment and wages in service occupations should rise in commuting zones undergoing greater displacement of routine tasks. Consistent with this implication, we find that growth of low-skilled service occupations is substantially greater in commuting zones with higher initial routine task intensity. Moreover, real hourly wages in service occupations rise significantly in these same commuting zones while wages in other low-skilled occupations do not. In net, commuting zones with initial higher routine task intensity show a distinct pattern of rising wages in both low-skilled service occupations and in moderately and highly-skilled managerial, professional, technical, sales and administrative occupations, and yet no wage growth across the remaining set of low-skilled occupations. These preliminary results suggest a process of employment and wage polarization within regional labor markets that parallels the polarization of employment seen at the aggregate level in the US, UK and West Germany (Autor, Katz and Kearney 2006; Goos and Manning and 2007; Dustmann, Ludsteck and Schönberg 2007). What is particularly novel about these findings is that our empirical approach appears able to predict the labor markets in which these patterns of task specialization and accompanying employment and wage polarization occur.

Our study is related to papers by Manning (2004) and the independent, contemporaneous contribution by Mazzolari and Ragusa (2007). Manning (2004) develops a theoretical model and presents supporting empirical evidence from US cities suggesting that employment of low-skilled workers is increasingly dependent on the service demands of high earning households. Building on Manning's analysis, Mazzolari and Ragusa analyze the relationship between the growth of upper-tail wage inequality and employment in outsourced home production activities within MSAs during the period of 1980 through 2005. Consistent with Manning (2004), they find increased employment in non-tradable services in MSAs with greater growth in upper-half (90/50) wage inequality. We confirm this result using measures of service employment and wage inequality at the commuting zone rather than MSA level.

Our paper is also related to analyses by Doms and Lewis (2006) and Beaudry, Doms and Lewis (2007, BDL hereafter), who explore the determinants of computer adoption and changes in education returns across MSA during the period of 1980 through 2000.[7] These papers are motivated by a model of endogenous technology adoption proposed by Beaudry and Green (2003) in which geographic variation in computer adoption is driven by the relative abundance or scarcity of skilled workers, who are complemented by computer technology. Though computer adoption is not a primary focus of our paper, we do present results on this outcome and discuss their relationship to the BDL results.

The remainder of the paper is structured as follows. Section II describes our empirical strategy. A model of technical change with indirect effects on service occupations is presented in section III. Section IV describes the data, followed in section V by descriptive regressions of the relationship between wage inequality and service employment within commuting zones. Section VI introduces the Routine Task Index, explores its correlates and validates its relationship to computer adoption and changing patterns of labor specialization at the commuting zone level. Sections VII and VIII present empirical tests of our hypotheses for service employment, aggregate wage inequality and wage growth in service occupations. Section VIII concludes.

[7] The city-level computer adoption measure that we use below was developed by Doms and Lewis (2006) and generously provided to us by the authors. This measure is also used in Beaudry, Doms and Lewis (2007).

II. Empirical approach

Service occupations—that is, jobs primarily involving serving, protecting and caring for others—differ from many other low-skilled occupations in two important respects. First, the high 'manual' content of service occupations, characterized by a need for spatial, visual and verbal orientation and adaptability makes it difficult to computerize (or otherwise mechanize) the primary tasks of these occupations. Second, the services provided must be consumed at or near the place of production, therefore preventing jobs in service occupations from being outsourced out of commuting distance or overseas.[8] This latter characteristic of non-tradability is pervasive among service occupations. Service workers such as cleaners, janitors, guards and food preparation workers must be physically present to provide services at the customer's location. For service occupations such as health aides, childcare workers, and hairdressers and beauticians, this constraint is even more binding: workers must be in physical contact with their clients.

The requirement of collocation of both demanders and suppliers of services is fundamental for the empirical strategy pursued in this paper. Since service workers provide their services primarily to individuals who live within commutable distance and demanders of services will predominantly buy services from local suppliers, the services produced by low-skilled service workers will be traded in many distinct local markets within the US. We are able to exploit geographical variation across local service markets in order to test our hypotheses for service growth. As a concept for local markets, we use the geography of commuting zones, which subdivide the US into local areas that are characterized by strong commuting ties within a commuting zone and small commuting flows between these zones. The geographical measurement is described in more detail in section IV.

The second crucial observation for the empirical strategy employed here is that the service occupations' requirement of proximity between producers and end consumers is not shared by most other low-skilled occupations. Many manufacturing jobs are prone to global outsourcing since manufactured goods can often be shipped internationally. Even the perishable produce supplied by agricultural workers can be shipped over ever increasing distances. On a local level, an increasing

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[8] Blinder (2007) argues that the single most important criterion for offshorability of an occupation is whether or not a worker must be physically present at a specific work location in the US in order for a good or service to be provided to US customers. Service occupations clearly require such physical proximity.

demand for both goods and services should therefore primarily lead to increased employment growth in services, but have much less effect on workers that are engaged in the production of goods.[9]

As a tentative test for the relationship between changes in the local wage structure and local service employment, Figure 2 maps the growth of the share of service workers in a commuting zone and the growth in upper-tail wage inequality between the 90th and the 50th percentiles of the hourly wage distribution in the 1980s and 1990s. As discussed below, all our explanations for service growth predict a positive relationship between these two variables. An increase of top wages should increase upper-tail wage inequality and create a larger demand for services, therefore raising service employment. The replacement of routine workers in the middle of the wage distribution by computers and a subsequent trickle-down of such workers into service occupations will increase upper-tail wage inequality through a falling median wage and again increase service employment. Indeed, Figure 2 confirms a striking geographical correlation between service employment growth and growth of upper-tail wage inequality. Clear geographical shifts are visible particularly between the 1980s and 1990s with both service and inequality growth shifting from the center of the country to the coasts. Thus, although the locus of service growth differs between the two decades, the correlation with upper-tail inequality is apparent in each. This correlation supports the viability of the geographical identification structure to be pursued in the empirical section of this paper.

III. A model of technical change with indirect effects on service occupations

In this section, we develop a brief model of occupational change that is motivated by the analysis in ALM (2003) and Autor, Katz and Kearney (2006). Drawing on case studies that analyze the impacts of computers on the work organization of single factories or businesses, ALM observe that computers are best at executing repetitive 'routine' tasks that follow clearly defined procedures. At the same time, computers (or, more precisely, computer programmers) struggle with tasks that are less repetitive or require a large degree of environmental adaptability. These include 'abstract' cognitive and interactive tasks that are usually performed by highly skilled workers, but also 'manual' tasks such picking up irregularly scattered objects or walking through a crowd of moving people. In the ALM framework, computerization is a complement to abstract relative to manual tasks. Specifically, it complements

[9] Other non-tradable activities that may be subject to this mechanism are construction, local transportation services (such as taxis and delivery), and in-person sales jobs such as cashiers and counter clerks. We focus specifically on service occupations as defined by the US occupational classification system so as to avoid potentially ad hoc classifications.

workers engaged in abstract work by greatly reducing the cost of one of their primary inputs: information. It has only a limited direct impact of the productivity of workers engaged in manual tasks, however. To a first approximation, these tasks are neither augmented nor replaced by computerization.

In the model considered in this section, we equate manual tasks with service producing occupations and equate routine and abstract tasks with goods producing occupations. Technical advancements in routine tasks directly raise productivity in the goods sector but impact service occupations only indirectly through two forces: reallocation of labor (a supply effect) and changes in consumption patterns (a demand effect). The model predicts that technological progress in routine tasks increases employment in service occupations and raises wage inequality between high and middle-skill workers. Workers engaged in abstract tasks benefit from computerization due to greater productivity and falling prices. Workers engaged in routine tasks are potentially harmed by downward wage pressure exerted by technological progress—which in turn causes the least skilled routine workers to switch occupations to services. However, increased demand for services spurred by rising incomes causes real wages in service occupations to rise.

A. Model

Consider an economy that produces two final outputs, Goods and Services. Production of Services is Leontief:

(1) $$Y_s = \alpha_s L_M ,$$

and production of Goods is Cobb-Douglas:

(2) $$Y_g = \alpha_g (L_R + K)^{\beta} L_A^{1-\beta} ,$$

where $\alpha_s, \alpha_g > 0$ are efficiency parameters and M, R and A are Manual, Routine, and Abstract tasks respectively. The parameter $\beta \in (0,1)$ lies on the open unit interval. To reduce notation, we suppress α_s, α_g, which are constants in the model.

Abstract and manual tasks are performed by workers who supply labor inputs, L_A and L_M. Routine tasks are performed either by workers who supply L_R or by computer capital, K, measured in efficiency units.

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

(3) $$K_t = \lambda_t Y_{K_t} ,$$

where Y_{K_t} is the amount of the final consumption good allocated to production of K and λ_t is an efficiency parameter that is exogenously rising with time, reflecting advancements in information technology. Competition ensures that the real price of computer capital (in efficiency units) is $\rho_t = 1/\lambda_t$. The exogenously declining price of computer capital is the causal force in the model.

There are two types of workers in this economy, college and non-college. College workers are endowed with one unit of abstract skills, which they supply inelastically to Abstract tasks. Non-college workers are heterogeneous in their skills. Each non-college worker has one unit of Manual skills and $\eta_i > 0$ units of Routine skills. Non-college workers can freely subdivide their time between Routine and Manual tasks. In practice, however, each worker will specialize in the task in which he holds comparative advantage. Non-college workers self-select into Routine tasks iff:

(4) $$\eta_i \geq \frac{w_m}{w_r},$$

and otherwise perform Manual tasks. We can write the labor supply functions to Manual and Routine tasks as $L_M(w_m/w_r) = \theta\sum_i 1[\eta_i < w_m/w_r]$ and $L_R(w_m/w_r) = \theta\sum_i 1[\eta_i \geq w_m/w_r]$ where $1[\bullet]$ is the indicator function and θ is the non-college share of the workforce. Note that $L'_M(w_m/w_r) \geq 0$ and $L'_R(w_m/w_r) \leq 0$. We additionally assume that $L_M(\bullet)$ and $L_R(\bullet)$ are continuously differentiable.

All workers have the same preferences. We consider two cases for preferences. In the first, preferences are homothetic, implying that budget shares are independent of income and that each product (g,s) has unit elasticity of demand. This case is most simply modeled as Cobb-Douglas preferences:

(5) $$U(g,s) = Y_g^{\gamma} Y_s^{1-\gamma},$$

with $\gamma \in (0,1)$. Thus, utility maximization implies that

(6) $$\frac{Y_g p_g}{Y_s p_d} = \frac{\gamma}{1-\gamma}.$$

In the second case, preferences are non-homothetic, with the income elasticity of demand for services greater than unity and the income elasticity of demand for goods less than unity. We do not write down a specific functional form for this utility function but examine its implications heuristically.

Equilibrium in this model occurs when the economy operates on the demand curve for each factor; all factors are paid their marginal products; the labor market clears, so no worker wishes to reallocate labor input among tasks; and prices equilibrate supply and demand for Goods and Services.

We begin with by calculating an appropriate price index for consumption. Let

(7) $$Y = Y_g^{\gamma} Y_s^{1-\gamma},$$

where Y is a composite consumption good that provides one unit of utility.

Denote the prices of Goods and Services as p_g, p_s. Consumer expenditure minimization generates the following numeraire for the consumption good:

(8) $$p_y = 1 = \gamma^{-\gamma}(1-\gamma)^{\gamma-1} p_g^{\gamma} p_s^{1-\gamma} .$$

Solving for prices of Goods and Services in terms of the numeraire, we obtain:

(9) $$p_g = \gamma\left(\frac{Y_g}{Y_s}\right)^{\gamma-1},\ p_s = (1-\gamma)\left(\frac{Y_s}{Y_g}\right)^{-\gamma} .$$

Substituting these prices into the marginal productivity conditions and suppressing time subscripts yields the following expressions for wages:

(10) $$w_a = p_g \frac{\partial Y_g}{\partial A} = \gamma\left(\frac{Y_g}{Y_s}\right)^{\gamma-1}(1-\beta)R^{\beta}A^{-\beta},$$

(11) $$w_r = \rho = p_g \frac{\partial Y_g}{\partial R} = \gamma\left(\frac{Y_g}{Y_s}\right)^{\gamma-1}\beta R^{\beta-1}A^{1-\beta},$$

(12) $$w_m = p_s \frac{\partial Y_s}{\partial M} = (1-\gamma)\left(\frac{Y_s}{Y_g}\right)^{-\gamma} .$$

The societal budget constraint is:

(13) $$Y = C + Y_K ,$$

where C is the amount of the composite consumption good allocated to consumption and Y^K is the amount allocated to production of computer capital.

The main comparative statics for the impact of technical advancements in computer production ($\partial\lambda_t / \partial t$) on output, labor allocation and wages can be obtained from these expressions.

A. Due to the perfect substitutability between K and L_R, the price of computer capital pins down the Routine wage. Technological advancements in computer production therefore reduce ρ and the Routine wage one-for-one:

(14) $$\frac{\partial \ln w_r}{\partial \ln \lambda} = \frac{\partial \ln w_r}{\partial \ln \rho} \times \frac{\partial \ln \rho}{\partial \ln \lambda} = -1 .$$

B. Improvements in λ also causes a decline in the real price of Goods as may be shown by using equation (11) to obtain an expression for the goods price and then differentiating this expression with respect to ρ:[10]

(15) $\ln p_g = \ln(\rho R^{1-\beta} A^{\beta-1})$,

(16) $\dfrac{\partial \ln p_g}{\partial \ln \lambda} = (1-\beta)\dfrac{\partial \ln R}{\partial \ln \lambda} - 1 = -\beta$.

C. This result further implies that Goods output rises relative to Service output. In particular, substituting equation (16) into equation (9) yields:

(17) $\dfrac{\partial \ln(Y_g / Y_s)}{\partial \ln \lambda} = \dfrac{\beta}{1-\gamma} > 0$.

D. Equation (17) also implies that technological progress in the computing sector raises the Abstract relative to the Routine wage:

(18) $\dfrac{\partial (\ln w_a / w_r)}{\partial \ln \lambda} = -\dfrac{\partial \ln R}{\partial \ln \rho} = 1$.

Thus, inequality between Abstract and Routine worker increases.

E. A decline in ρ raises demand for Routine task input in Goods production. This demand could be met by either additional K or additional input of Routine labor. Because a fall in ρ implies a corresponding decline in w_r , labor supply to Routine tasks falls as non-college workers reallocate labor input to Services. This labor reallocation occurs until equation (4) is satisfied—that is, the marginal non-college worker is indifferent between working in Goods or Services. Hence, rising demand for Routine task input will be met by additional production of K .

F. The influx of labor into the Service sector causes Service output to expand. Despite this supply effect, the real Manual wage rises. In particular,

(19) $\dfrac{\partial \ln w_m}{\partial \ln \lambda} = \gamma \dfrac{\partial \ln(Y_s / Y_g)}{\partial \ln \rho} = \dfrac{\beta\gamma}{1-\gamma} > 0$.

This occurs because the decline in the Goods price and attendant rise in Goods relative to Service output raises real consumption of Service workers (note that the real wage impact on w_r is increasing in γ , which is the Goods share in consumption). In net, the model implies that

[10] We use the fact that own-factor input demand has a price elasticity of negative one in the Cobb-Douglass production function.

technological progress in computing raises inequality between high and medium skill workers but reduces inequality between medium and low-skill workers.

G. These implications for real wages expressed in efficiency units (w_r, w_g, w_a) are slightly different from the implications for observed wages, however. This is because positive self-selection of workers into Routine tasks means that as Routine wages falls, the average quality of Routine workers rises. Thus, it is possible for observed wage inequality between Routine and Manual workers to rise even as wage inequality between these two groups expressed in efficiency units falls.

B. Implications

This stylized model makes a set of broad predictions that we explore below. At an aggregate level, the model implies that the ongoing computerization of Routine tasks causes workers to specialize in either Abstract or Manual tasks. This process generates employment polarization, with declining employment in middle-skill clerical and routine production jobs, and rising employment in high-skill managerial and professional occupations as well as in low-skill service occupations. Simultaneously, wage inequality rises between high and middle-skill workers due to the falling market price of Routine tasks and the rising productivity of Abstract workers. Real wages of manual workers rise, however, due to rising demand for Services.

Though our model depicts price and quantity movements in a single macro-economy, the model may be usefully applied to geographic areas such as cities—or, in our case, commuting zones—if these areas can be treated as distinct labor markets. In particular, if these markets differ initially in their Routine task intensity, the model predicts that markets with higher initial Routine task intensity will see greater polarization of employment, greater growth of service employment and greater growth of wages in service occupations as routine tasks are automated.[11] This observation is central to our empirical strategy below.

After describing the data below, we begin by documenting first order descriptive relationships between growth in inequality and growth in service employment within commuting zones during 1980 through 2005. We next explore a number of candidate factors that may explain this correlation.

[11] Formally, we could rewrite equation (2) at the city (or commuting zone) level with a city-specific routine task intensity: $y_{jg} = \alpha_g R^{b_j} A^{1-b_j}$ where j denotes cities and a higher value of b_j indicates greater initial routine task intensity. If all other preference and labor supply parameters are comparable across cities (that is, uncorrelated with b_j), a uniform (common across cities) decline in the routine task price will induce greater growth in wage inequality and service employment in high b cities.

Motivated by the model, we focus on one explanatory factor, which is the 'routine task intensity' of commuting zones at the start of the study period (1980). This index is constructed using task measures from the Dictionary of Occupational Titles averaged at the commuting zone level. We find that this routine task index has large and robust predictive power for the growth of wage inequality, changes in labor specialization, and increases in service employment within commuting zones throughout 1980 through 2005. We interpret this as preliminary evidence that the growth of wage inequality and the rise in service employment are both driven (in part) by changing demand for tasks, potentially spurred by technological changes.

IV. Data and measurement

The empirical analysis draws on the Census Integrated Public Use Micro Samples (Ruggles et al. 2004) for the years 1980, 1990, and 2000 and the American Community Survey (ACS) for 2005. The Census and ACS samples cover 5 percent and 1 percent of the US population, respectively. These large sample sizes are needed for an analysis of changes in labor market composition at the detailed geographic level. The timeframe of 1980 to 2005 covers a period of rising top wages as well as the introduction and subsequent spread of desktop computing.

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

This study pursues an alternative approach for the definition of local labor markets based on the concept of Commuting Zones (CZs). Tolbert and Sizer (1996) used privileged access to 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. The CZs cover the entire area of the US, including both metropolitan and rural areas. Relative to other geographic units frequently used for analysis of local labor markets (such as Metropolitan Statistical Areas), commuting zones have two advantages: they are based primarily on economic geography rather than incidental factors such as minimum population or state boundaries; and they cover the entire US. In addition, it is possible to use Census Public Use Micro Areas (PUMAs) to consistently match Census geography to commuting zones for the full period of our analysis.[12] We are not aware of other economic research that makes use of this geographic construct.

We matched the geographic information that is available in the Census Public Use 5% samples to the CZs geography. The most disaggregated geographic unit reported in the Census samples is the Public Use Micro Area (PUMA) or, in 1980, the similarly defined county group. A PUMA is a subarea of a state that comprises a population of 100,000 to 200,000 persons but has otherwise no clearly inherent economic interpretation. The 2000 Census splits the US into more than 2,000 PUMAs. The Census Bureau reports how the population of a PUMA is distributed over counties. If a PUMA overlaps with several counties, our procedure to match PUMAs to CZs assumes that all residents of that PUMA have the same probability of living in a given county. The aggregation of counties to CZs then allows computing probabilities that a resident of a given PUMA falls into a specific CZ. In every Census year, a clear majority of PUMAs can be matched to a single CZ, while the residents of the remaining PUMAs are attributed to several CZs using probability weights based on the relative share of a PUMA's population that falls into a given CZ. This technique allows us to calculate the population characteristics of residents of each CZ consistently in each year of our data (1980, 1990, 2000 and 2005).

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

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

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

weeks worked and usual weekly hours. Topcoded yearly wages are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. Hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile. The computation of full-time full-year weekly wages is based on workers who worked for at least 40 weeks and at least 35 hours per week. Wages are deflated using the four regional indices of the Consumer Price Index.

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

To measure the intensity of Routine, Manual and Abstract task activity across commuting zones, we use a dataset assembled by Autor, Levy, and Murnane (2003) that merges data on job task requirements based upon the US Department of Labor's Dictionary of Occupational Titles (DOT) with Census occupation classifications.[13] Following Autor, Katz and Kearney (2006), we use ALM's original five task measures to construct three task aggregates for Manual, Routine and Abstract tasks. The Manual task index corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination." The Routine task measure is a simple average of two DOT variables, "set limits,

[13] These measures are also employed by Autor, Katz and Kearney (2006 and 2007), Goos and Manning (2007) and Peri and Sparber (2007) among others.

tolerances and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks. The Abstract task measure is also a simple average of two DOT variables: "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements.[14] We use these data for the geographic analysis by appending the DOT task measures by occupation to Census and ACS person records and collapsing these records to labor-supply weighted task means by commuting zone. For each commuting zone and year, we calculate overall levels of task activity for all workers as well as separate task measures for four education groups: high school dropouts, high school graduates, those with some college, and those who have completed four or more years of college.

V. Service employment growth and growth of high wages: Descriptive regressions

A robust implication of our conceptual model is that, within commuting zones, growth in high wages should accompany growth in service occupations. To provide initial evidence on this point, we plot in Figure 3 the bivariate relationship between changes real wages during 1980 through 2005 and the growth of service employment within commuting zones. We measure wage growth as the change in log real weekly earnings of full-time, full-year workers at various percentiles of the distribution. The service employment measure is the share of hours worked of non-college workers (those with high school or lower education) in service occupations.[15] The four panels of Figure 3 reveal a striking correspondence between rising wage inequality and growing service intensity within commuting zones. This correlation is highly apparent for wage changes at or above the median of the distribution (specifically, the p90, p50, and p9050). But there is no correlation between service intensity and changes in the p10.[16] These

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[14] Further details on these variables are found in Appendix Table 1 of ALM.

[15] We focus on non-college workers to avoid a possible mechanical relationship between high wages and service employment. Because the bulk of workers in the top of the earnings distribution are highly educated and because such workers are highly unlikely to work in service occupations (see Table 3), rising educational attainments within commuting zones will, all else equal, both raise high wage percentiles and reduce service employment as a share of total employment. This mechanical link is essentially absent, however, for workers with high school or lower education since few of these workers are in high wage percentiles. It bears emphasis that less than 20 percent of high school graduates and less than 30 percent of high school dropouts worked in service occupations at any point in our sample (Table 3). Thus, there was considerable scope for service employment among non-college workers to either rise or fall.

[16] The fitted lines depicted in Figure 3 correspond to the following weighted OLS regressions: $\Delta S_{j\tau} = \alpha + \Delta W_{j\tau}^{P} + \varepsilon_{j\tau}$, where the dependent variable is the 1980-2005 change in the non-college employment share in service occupations, the explanatory variable is the change in wage percentile P, and the subscript j denotes commuting zones. Estimates are weighted by the share of national population in each commuting zone at the start of period. Robust 95 percent confidence bands depicted in Figure 3 are clustered on state to allow for non-independence

results are also qualitatively comparable to the findings of Mazzolari and Ragusa (2007), who report a significant relationship during 1980 through 2005 between increases in upper-tail (90/50) wage inequality within Metropolitan Statistical Areas and growth of the share of low-skilled workers employed in non-tradable, time-intensive home production substitutes (such as food preparation and cleaning).

To probe the robustness of these bivariate relationships, Table 4 summarizes commuting-zone level regressions of the decadal change in the non-college service employment share on the contemporaneous changes in various percentiles of log weekly earnings. Panel A indicates that the conditional correlation between and a rising top wage level (measured by the p95) and growth of the non-college service occupation share is positive in each decade and in most cases significant.[17] When nine Census region dummies or fifty state dummies are added to the regression models to account for region or state specific trends (columns (4) through (9)), the precision and statistical significance of the estimates increases.[18] Panel B repeats these estimates for other wage percentiles, including the p90, p75 and p50. Although all point estimates are positive, magnitudes and significance are typically smaller for lower wage percentiles (for example, none of the coefficients for the p50 is significant). Service employment growth is therefore most strongly associated with rising wages of high earners.

In Table 5, we explore in a set of candidate variables that may explain the commuting-zone level correlation between increases in high wages and growth in service employment. We estimate stacked first difference models for changes in the non-college service share over 1980 to 2005 of the form:

(20) $$\Delta S_{j\tau} = \alpha + \delta^{90-00} + \delta^{00-05} + \beta_1 \Delta W_{j\tau}^{P} + \Delta X'_{j\tau}\beta_2 + \varepsilon_{j\tau},$$

where the time dummies, δ, serve as period-specific intercepts. To account for the fact that the third stacked first difference (2000-05) is half the length of the prior two, the dependent and independent variables are expressed as ten times annual changes. All estimates are weighted by the share of national population in each commuting zone at the start of each period, and robust standard errors are clustered

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among commuting zones in the same state. For the p90, p50, p10 and p9050 plots, respectively, the coefficients, robust t-ratios and R-squareds of the bivariate regressions are: 0.115 (t=7.11), R^2=0.28; 0.072 (t=4.15), R^2=0.09; -0.029 (t=-1.04), R^2=0.01; and 0.137 (t=4.86), R^2=0.16.

[17] We use the p95 in the by-decade analysis in Table 4, 5 and 6 but do not use the p95 for the long change (1980-2005) models in Figure 3 because the p95 is censored for approximately 20 percent of commuting zones (as a share of population) in 2005. There is no censoring of the p95 in other decades.

[18] Where commuting zone definitions cross state boundaries (due to their containing counties in multiple states), our state definitions are adjusted so that each CZ is assigned to the state that which contributes the largest share of population.

on state to allow for non-independence among commuting zones within the same state and serial correlation within commuting zones.

The first three columns of Table 5 summarize a set of stacked first-difference regressions of the change in the service employment share on the change in the p95. These estimates are highly significant (with t-ratios exceeding four in all cases) and are robust to inclusion of region or state specific trends.[19] Column (4) adds a measure of the change in the local unemployment rate in the commuting zone. The service employment share rises significantly with the unemployment rate, suggesting that service employment may be less cyclical than non-service employment and that workers may choose service occupations when higher paying work is unavailable.

Column (5) adds two variables intended to capture changes in the demand and supply for services: the change in the college-educated share of the population and the change in the share of the population that is non-college immigrants. A rising share of highly educated workers should increase consumer demand for services while a rising supply of non-college immigrants should increase labor supply to services (Cortes, 2006). Consistent with expectations, both variables predict growth in the service employment share, though only the college population share is significant.

Column (6) considers an additional two variables that may shift demand for service work: the employment to population rate of females and the population share of seniors (age 65+). If services substitute for household production, a rise in female labor supply may increase service demand (as well as potentially increase labor supply to service occupations). Contrary to expectations, increased female employment is associated with a lower growth of service employment.[20] A growing share of senior citizens in the population—who may have relatively high demand for services—is positively but insignificantly predictive of growth in service employment.

Notably, inclusion of these five additional explanatory variables (individually or as a group) has only a minor impact on the magnitude or significance on the key variable of interest. The relationship between the growth in high wages, as measured by the p95, and the service employment share remains robust. But this relationship diminishes as we consider lower wage percentiles in columns (8) through (10). The p90 is a marginally significant predictor of service employment growth, while the p75 is

[19] In a stacked first difference model, region or state specific dummies serve as trend terms. Region and state main effects are implicitly removed by first differencing

[20] But this relationship flips sign when we condition on the unemployment rate (see columns 7 through 10).

unrelated to service growth and the p50 is insignificantly negatively related to service growth. Thus, service employment growth is robustly linked to growth in high wages.

Table 6 explores which service sub-occupations drive this relationship by estimating equation (20) separately for each of nine services. Growth in the p95 is positively associated with rising employment in all service sub-occupations. Many of these relationships are statistically significant and are only slightly affected by inclusion of all explanatory variables used in Table 5. The two service occupations that contribute most substantially to service growth in commuting zones with rising top wages are Food Service occupations and Building and Grounds Cleaning and Maintenance occupations. These are also the two largest service occupations at the start of the period (1980). Personal Appearance occupations and Housekeeping and Laundry occupations also are substantial contributors.

VI. Wage inequality and service occupation growth: Why do commuting zones differ?

The robust relationship between growth in high wages and growth in service employment among non-college workers invites the question of why growth of high wages differs among commuting zones. In our conceptual model, the underlying force stimulating both wage inequality growth and changes in occupational composition is changes in the market price of tasks—specifically, displacement of routine workplace tasks formerly performed by non-college workers. At an aggregate level, this hypothesis is difficult to test since it has only aggregate (macroeconomic) implications. If, plausibly, technological changes that replace routine work are uniformly available across geographic areas within the US, the model further implies that changes in job tasks, growth in service occupations and potentially growth in wage inequality should be most pronounced in commuting zones that are initially relatively specialized in routine tasks (thus, most prone to this process of automation).

To explore whether this stylized prediction has traction in the data, we create a simple index of routine task intensity by commuting zone that is equal to the ratio of Dictionary of Occupational Titles 'Routine' to 'Manual' tasks among workers in the commuting zone at the start of the period:

(21) $$RTI_j = \hat{R}^{nc}_{j,1980} / \hat{M}^{nc}_{j,1980}.$$

Because the DOT 'task' measures have no intrinsic scale, this routine task index is standardized with a (weighted) mean of zero and variance of one.[21] In Figure 4, we plot the relationship between the routine task index (RTI) and several measures of changes in occupational composition over 1980 through 2005.

[21] We use the ratio of routine to manual tasks rather than the absolute routine tasks score because many occupations with high routine task content also have a high manual score (particularly in production occupations).

As suggested by the conceptual framework, the first (top-left) panel of Figure 4 shows a clear, positive relationship between initial routine task intensity and growth of service employment in commuting zones over the sample period. The plotted regression line in this figure has a slope of 0.0146 (t=8.66, with robust 95 percent confidence bands clustered on state). Thus, a one-standard deviation higher value of the routine task index in the base period predicts 1.46 percentage points greater growth of service employment among non-college workers over 1980 to 2005. As compared to the weighted mean change in the non-college service share of 7.5 percentage points, this a sizable relationship.

The remaining three panels of Figure 4 provide scatter plots of changes in each of the three major task activity measures (abstract, routine and manual) against initial RTI. These task activity measures are standardized in the base (1980) period, so that changes may be read as standard deviation movements relative to the initial distribution. The scatter plots indicate that patterns of occupational change (as measured by DOT variables) are much more pronounced in commuting zones with higher initial routine task intensity. Consistent with the conceptual model, commuting zones with higher initial RTI see large declines in routine task activity and sizable growth in both abstract (high-skill) and manual (low-skill) task activity.[22] The growth of manual task activity in these areas reflects their growing employment in service occupations.

Figure 5 depicts analogous scatter plots for changes in log weekly wage percentiles plotted against RTI. Higher RTI strongly predicts growth in the 90th and 50th log wage percentiles as well as increase in the log 90/50 gap. However, there is no relationship between the task index and the change in the p10.

The value of the routine task index is that it provides a summary measure of the occupational ('task') distribution within commuting zones in 1980, thus collapsing many measurable aspects of work activity in a geographic area into one salient dimension. A disadvantage of this index is that it is not immediately apparent what precisely the RTI measures—or whether an alternative index based on standard labor force and human capital measures would perform equally well (or better). To explore this possibility, Table 7 presents a series of models that explore the relationship between the RTI and a set of labor force and demographic covariates. In addition, this analysis assesses the robustness of the

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Hence, the routine/manual ratio may be useful to assess the degree to which an occupation can be classified as routine rather than manual. A subsequent revision of this paper will consider logical alternative constructions of the index.

[22] More precisely, in the model there is no scope for reallocation of labor from routine to abstract tasks, and hence displacement of routine tasks does not imply increased input of abstract tasks. In a richer framework (to be included in the next version of the paper), it would be natural to assume college workers can perform both abstract and routine tasks, but have a comparative advantage in abstract tasks relative to non-college workers. In this case, a decline in the routine task price would increase labor supply to both abstract and manual tasks.

relationship between the RTI and service employment growth to the inclusion of these covariates. These covariates, measured at the commuting zone level, include the non-college service occupation employment share, the education distribution of the population, the share of foreign born immigrants among college and non-college residents, the local unemployment rate, the female labor force participation rate, and the elderly (65+) population share. Like the RTI, each variable is measured in 1980.

The top panel of Table 7 shows that the RTI is highly correlated with a number of commuting zone level labor force and demographic measures. The RTI is higher in commuting zones with a larger share of college-educated workers (column 4), a higher p90 and p10 and a lower p50 (column 5), a larger share of college-educated immigrants (column 6), a higher female labor force participation, and a lower share of elderly residents (column 7). In combination with a complete set of state dummies, these labor force and demographic variables explain fully 90 percent of the variation in the RTI (column 8).

Despite these strong correlations, Panel B of Table 7 demonstrates that the commuting zone level relationship between the RTI and the growth of service employment over 1980 to 2005 is highly robust to inclusion of these covariates. In the first column of panel B, the bivariate relationship between the RTI and the 25 year change in the non-college service employment share is 1.46, corresponding to the linear fit for the scatter plot in the Figure 4. An increase of the RTI by one standard deviation hence predicts a rise of service employment by 1.46 percentage points. Inclusion of state dummies in column (2) reduces this point estimate to 1.21 (t=7.3). The R-squared of this bivariate regression is 0.29. Columns (3) through (8) successively add the covariates included in the corresponding columns of panel A. These additional variables variously attenuate or magnify the coefficient on the RTI. But the RTI coefficient remains highly significant in all models. When all covariates from panel A are added to the final model in panel B (column 8), the coefficient on the RTI is estimated at 1.11 (t=4.3), which is seventy-five percent as large as the bivariate relationship estimated in column (1).

Further evidence of the predictive power of the RTI for the commuting-zone level growth of service employment is found in Table 8. Here, we estimate a set of by-period and stacked first-difference estimates for the growth of service employment. These models are comparable to the estimates in Table 5, with the difference that the key explanatory variable is now the RTI instead of the p95. [23] The

[23] The RTI in these models corresponds to its start of period value in each commuting zone. Thus, the 1980-90 changes use the 1980 RTI, the 1990-2000 changes use the 1990 RTI and the 2000-05 changes use the 2000 RTI. As above, the RTI is standardized in 1980 with mean zero and variance one. Its mean and variance in 1990 and 2000

first three columns show that the Routine Task Index is highly predictive of growth in service employment in all three time periods (1980-90, 1990-2000, 2000-05). Moreover, the magnitude of this relationship increases in the third period, potentially reflecting the strong growth of service employment after 2000 (see Table 1). Stacked first difference models in columns (4) through (8) show that service growth is robustly greater in CZ's with greater growth in unemployment, with larger increases in the college-educated population share, with larger increases in the female labor force participation rate, and with greater increases in the elderly share of the population. In each of these models, the RTI remains highly significant.

From the Table 7 and 8 results, we conclude that the RTI provides a useful summary measure of the start-of-period occupational structure of commuting zones. Consistent with our conceptual model, this index is highly predictive of the growth of service employment. Yet, it is not fully captured by other standard covariates such as education, age structure, immigration, or labor force participation. It bears emphasis that the RTI measure is not intended as a unique or complete representation of the job task characteristics of commuting zones. With sufficient degrees of freedom, it clearly would be feasible to construct a multivariate index of occupational structure that is more predictive of subsequent changes in commuting zone characteristics (and in particular the growth of service employment) over 1980 through 2005.[24] Nevertheless, the RTI provides a helpful proxy measure which we employ in the subsequent analysis.

VII. Computerization, task specialization and wage levels

Our conceptual model makes four further predictions about the relationship between initial routine task intensity and subsequent changes in commuting zone level outcomes. First, the model implies that workers reduce labor supply to routine task activities because these tasks are computerized. Thus, computer adoption should be higher in commuting zones that are initially relatively routine task intensive. Second, displacement of routine tasks should lead to changes in job specialization, with highly educated workers increasingly specializing in abstract tasks in place of routine tasks, and less educated workers increasingly specializing in manual tasks in place of routine tasks. Third, changing task prices should spur rises in earnings inequality—particularly in the upper-half of the distribution—as abstract and manual task prices rise relative to the routine task price. Finally, this process should cause wages in

are 0.030 (0.709) and -0.503 (0.390), respectively. Thus, the index declines steeply after 1990, with substantial convergence in commuting-zone levels of routine task intensity (seen in the sharp fall in the variance of the index).

[24] For example, a complete set of occupation by gender measures would absorb all variation in the RTI.

service occupations to rise relative to other activities performed by less skilled workers in the same commuting zones. We explore each of these implications below.

A. Computer adoption

The second panel of Figure 4 shows that commuting zones that were particularly routine task intensive in 1980 saw substantial drops in labor input activity in routine tasks in the subsequent twenty-five years. Our conceptual framework unambiguously implies that this decline in workers' routine task input in these commuting zones should have gone hand in hand with adoption of computer technology to substitute for these routine tasks. More precisely, commuting zones with high RTI in 1980 should have seen relatively greater rates of computer adoption in subsequent decades.

We test this implication using a measure of geographic computer penetration developed by Doms and Lewis (2006). This measure is based on private sector survey data on computer inventories (number of personal computers per employee) assembled by a market research firm. Doms and Lewis aggregate this variable to the MSA level and purge it of industry times establishment size interaction effects via an OLS regression.[25] We use the Doms and Lewis measure for the years 1990 and 2002 matched to commuting zones. Approximately 50 of the 741 commuting zones do not have corresponding computer adoption data and so are dropped from the analysis. Following the approached developed by Doms, Dunne and Troske (1996), we treat the 1990 level of this variable as the 'change' from 1980 to 1990 (thus assuming that this level was close to zero in all areas in 1980). We measure the change in this variable over the subsequent decade as the 1990 to 2002 first difference.[26]

Akin to the models in Table 7 explaining growth of service employment using the RTI, we estimate models predicting computer adoption across commuting zones of the following form:

(22) $$\Delta C_{j\tau} = \alpha + \beta_1 RTI_{jt} + X'_{jt}\beta_2 + \varepsilon_{j\tau},$$

where the dependent variable is the Doms-Lewis measure of computer adoption over time interval τ in commuting zone j, RTI_{jt} is the start of period routine task index in the commuting zone, and X_{jt} is a vector of start of period covariates that may also predict computer adoption (and potentially may eliminate the conditional correlation between the task index and computer adoption—thus, these variables probe robustness).

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[25] The variable is not, however, adjusted for educational or occupational composition in a commuting zone.

[26] Because the Doms-Lewis computer adoption measure is 'residualized' as described above, its level in each period is not interpretable. However, the cross commuting zone standard deviation of this variable is 0.048 for the 1980 to 1990 change and 0.053 for the 1990 to 2000 change.

The first two columns of Table 9 present separate, by-decade OLS regressions of commuting zone level computer adoption during the 1980s and 1990s on the start of period RTI and a full set of state dummies. These models indicate that the RTI has substantial predictive power for computer adoption. In both periods, a one standard deviation higher start-of-period RTI predicts 2.2 to 2.7 additional PCs per employee) in the subsequent decade. Both estimates are highly significant, with t-ratios well over eight.

Subsequent columns of Table 9 explore the robustness of this relationship by regressing the long change (1980 to 2002) in computer adoption within commuting zones on the 1980 RTI and a number of start-of-period labor force and demographic measures. These measures include most covariates used in Table 7, including the non-college service occupation employment share, the share of foreign born immigrants among college and non-college residents, the local unemployment rate, the female labor force participation rate, and the elderly (65+) population share. In addition, we include a measure of the relative supply of skills in a region. This measure, which is used by Beaudry, Doms and Lewis (2007) as their principal predictor of computer adoption at the city level, is equal to the share of college graduates in a region plus fifty percent of the share of those with some college divided by one minus the sum of these two variables.[27]

Consistent with expectations, many of the covariates in Table 9 are significant predictors of computer adoption over 1980 to 2002. Computer adoption is greater in commuting zones that are initially more intensive in service employment, have higher levels of wage inequality, have a lower unemployment rate, and have a lower rate of female labor force participation. In addition, confirming the findings of Beaudry, Doms and Lewis (2007), computer adoption is also significantly greater in commuting zones that have a higher relative supply of skills.

In all cases, however, the RTI measure is highly robust to inclusion of these covariates (though, not surprisingly, its magnitude is reduced). In the final column, of Table 9, the RTI has a coefficient of 2.25 and a t-ratio of 3.7. Thus, the Routine Task Index appears to capture a specific component of the occupational structure that is not fully proxied by other standard covariates. Holding key features of educational and demographic structure constant, commuting zones that were initially more intensive in routine task inputs in 1980 adopted computer technology at a greater rate in the subsequent two decades—presumably to substitute physical capital for human capital in performing routine tasks.

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[27] This variable is roughly equivalent to the college/non-college relative supply measure developed by Katz and Murphy (2002).

B. Task specialization

As documented in Figure 4, commuting zones that were particularly routine task intensive in 1980 saw substantial increases in manual and abstract task activity over the next twenty-five years (as routine task activity plummeted). We explore the robustness of this pattern in Table 10 by estimating stacked first difference models for changes in task activity by commuting zone. These models are comparable to those in Table 8 for service employment growth and include identical covariates (though here the dependent variables are the standardized task measures).

The first column of Table 10 confirms the robustness of the bivariate relationships depicted in Figure 4 between the RTI in 1980 and subsequent task changes. A one-standard deviation higher initial level of the RTI predicts 0.2 standard deviations (SD) additional growth in abstract task activity, -0.3 SD's decline in Routine task activity and 0.11 SD's rise in manual task activity per decade over 1980 through 2005 (all point estimates are highly significant). These estimates may be read as confirming findings by Goos and Manning (2007) and Autor, Katz and Kearney (2006) indicating that occupation distributions are polarizing in the UK and US, with growing employment in relatively high and relatively low-skilled jobs.[28]

We next extend these models to task activity by skill levels. In columns (2) through (5) of Table 10, we replace the aggregate, commuting-zone level task activity measures with measures of task activity by each of four education groups: college, some college, high school or less than high school. We interpret these models as measuring changes in task <u>specialization</u>—that is, the degree to which workers of given education allocate labor input across task domains (ultimately measured by occupations) within commuting zones. The estimates, found in columns (2) through (5) of Table 9, strongly confirm the model's implications for task specialization. Among college graduates in commuting zones with higher RTI, we find a pronounced rise over 1980 to 2005 in abstract task specialization, a sharp decline in routine task specialization, and a small but statistically significant decline in manual task specialization. We find complementary patterns for less educated workers. A higher commuting zone RTI in 1980 predicts a sharp decline in routine task specialization for all education groups and—unlike for college graduates—a sharp rise in manual task specialization. In addition, all education groups show a rise in abstract task specialization, though this rise less pronounced for groups without a college degree.[29]

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[28] Given the aggregate patterns of polarization, it is expected that polarization would also be evident at other levels of aggregation. What is novel in Table 10 is the finding that the geographic pattern of polarization is strongly predicted by initial patterns of task specialization.

[29] In a future version of this paper, we will explore these relationships using RTIs calculated separately by education group within commuting zones.

In net, these estimates suggest that there is pervasive, differential reallocation of labor activity at all education levels within commuting zones, and that this reallocation is concentrated in commuting zones that were initially (in 1980) specialized in routine task activity. We view this evidence as supportive of the basic process of task change posited by the model.

C. Wage inequality and occupational earnings

In Table 11, we explore the relationship between task specialization and wage inequality by commuting zone. Following the format of earlier estimates, panel A summarizes stacked first-difference models for changes by commuting zone in full-time, full-year log weekly log wage levels at various percentiles. The principal explanatory variable in these models is the start of decade RTI. All models include state dummies and the full set of labor force and demographic covariates used earlier.

The Table 11 estimates indicate a strong, monotone relationship between the RTI and growth of wage percentiles by commuting zone. A one standard deviation higher RTI predicts a 14.0 log point (relative) increase per decade in the p95, a 3.4. log point increase in the p90, a 2.0 log point increase in the p50 and a 1.4 log points increase in the p10. All estimates are highly significant.[30] The lower three panels of Table 10 present separate estimates for each of the three decades of the sample. In each decade, commuting zones that are initially more specialized in routine tasks show larger rises in wage inequality, and these increases are uniformly larger at higher wage percentiles.

In our conceptual model, the underlying process driving wage inequality growth is the complementarity and substitutability among tasks. Technical advancements that lower the real costs of performing routine tasks complement workers performing abstract tasks by raising their physical productivity and indirectly complement workers performing manual tasks by raising the real value of their outputs ('services') in consumption. Thus, a testable implication of this framework is that wages in service occupations should rise in commuting zones undergoing greater displacement of routine tasks.

We explore this implication in Table 12 by regressing changes in real log hourly wages by major occupation and gender on the routine task index. We fit stacked first-difference models comparable to those in earlier tables. The first two columns of Table 12 indicate that commuting zones with initially higher routine task intensity saw relatively large real increases in hourly wages of workers in relatively highly educated occupations between 1980 and 2005. A one standard deviation higher start-of-decade RTI in a commuting zone predicts 1.5 to 3.5 log points of additional wage growth in these occupations.

[30] The extreme point estimate for the p95 is driven by the censoring (and hence imputation) of the p95 in the year 2005 for 20 percent of commuting zones (see footnote 17 and panel D of Table 10).

These results are, of course, consistent with the pattern of rising high wages in commuting zones that are initially specialized in routine tasks activities (Table 11). But this pattern does not carry to most low-skilled occupations in these same commuting zones. As shown in columns (3) through (5), commuting zones with initially higher RTI do not see differential wage growth in production, operative or farming, forestry and fishing occupations.

Service occupations present an exception to this pattern. In commuting zones that are initially specialized in routine tasks, service occupations experience significant real wage growth. This wage growth is on the order of 1 log point per decade and is present for both genders. Tables 12a and 12b present a more detailed analysis of the relationship between the RTI and growth in hourly wages in service occupations. For both genders, and all three time periods, service wage growth is typically greater in commuting zones with a higher initial RTI. In stacked first difference models presented in columns (4) through (8), the relationship between RTI and growth of service occupation wages is in all cases robust to the full set of labor market and demographic covariates introduced in prior models. Thus, the data clearly support the prediction that displacement of routine tasks within commuting zones is accompanied by growth in both service employment and service wages. What makes this finding particularly compelling is that service occupations are the only low-skill job category that appear to benefit from this process.

VIII. Conclusions [Incomplete]

While the past twenty five years have seen declining or stagnating real (and relative) earnings and employment of less educated workers, employment in low-skill service occupations presents an exception to this pattern. Between 1980 and 2005, the share of hours worked in service occupations among those with high school or lower education rose from 12.8 to 20.3 percent, a 60 percent increase. Simultaneously, real hourly wages in service occupations increased by 20 log points, which is considerably greater than wage growth in other low-skill occupations. These patterns suggest that despite a trend of widening earnings inequality between high and low-skilled workers, there have been demand shifts favoring specific types of low-skill service work.

We explore one potential explanation for the rising demand for service work based on changes in task specialization induced in part by technical change. Our conceptual framework builds from the observation that the primary job tasks of service occupations are difficult to either automate or outsource since these tasks require interpersonal and environmental adaptability as well as direct physical proximity. Thus, unlike routine low-skilled tasks that are readily substituted by computer technology, the job tasks of service occupations are relatively immune to automation—despite the fact that they are typically considered to be 'low-skilled.' If demand for the outputs of service occupations is relatively inelastic, the model suggests that substitution of information technology for routine tasks may lead to rising wages and employment in service occupations.

Motivated by the observation that workers in service occupations must collocate with demanders of their services, we study the determinants of employment and wages in services during 1980 through 2005 in 741 consistently defined commuting zones covering all of US employment. We first document that within commuting zones, the growth of service employment is robustly correlated with increases in high wages. This pattern is suggestive of a link between rising wage inequality and growth of service employment. But because the determinants of cross commuting zone patterns of wage inequality growth are left unexplained by this analysis, it is unclear how this correlation should be interpreted.

To overcome this conceptual hurdle, we developed an empirical approach motivated by the conceptual model. This model predicts that, if commuting zones differ initially in their routine task intensity, markets with higher initial routine task intensity will see greater polarization of employment, greater growth of service employment and greater increases in wages in service occupations as routine tasks are automated. These outcomes are induced by a reallocation of labor activity. As routine labor tasks are displaced by computerization, workers reallocate effort towards both abstract and manual tasks.

To bring this idea to the data, we construct a simple index of routine task intensity (RTI), which is equal to the ratio of routine to manual task activities within commuting zones at the start of our sample period. This index proves strikingly predictive of the changes in task and wage structure implied by the conceptual model. In commuting zones with an initially higher RTI, we find a dramatic reallocation of labor activity from routine task activities to high-skilled abstract tasks and low-skilled manual tasks. This pattern of changing task allocation occurs not only in aggregate but within major education groups: college educated workers increase their specialization in abstract tasks in the place of routine tasks; less educated workers increase their specialization in both manual and abstract tasks in the place of routine tasks. The increase in labor specialization in high RTI commuting zones is accompanied by significantly higher rates of computer adoption, consistent with the view that computerization substitutes for some of the routine tasks formerly performed by workers. These patterns of labor reallocation lend credence to the relevance of the task mechanism posited by the model.

Consistent with the conceptual model, we show that growth of low-skilled service employment and growth of wage inequality is substantially greater in commuting zones with higher initial routine task intensity. Most strikingly, we find that hourly wages in service occupations grow significantly in these same commuting zones but wages in other low-skilled occupations do not. In addition, a higher RTI is associated with higher wage growth in skilled occupations such as managers and professionals, and technical, sales and administrative workers. Thus, the changes in task structure that we document accompany growth in wages at the tails of the distribution but not elsewhere. These results correspond to a process of employment and wage polarization within regional labor markets that parallels the polarization of employment seen at the aggregate level in the US, UK and West Germany.

As stressed in the Introduction, we view these results as preliminary. Two clear limitations of our analysis to date are, one, that we must (for the moment) take as given the initial task structure of occupations across commuting zones—thus, we do not seek to explain why these areas are different—and two, that the task index on which we rely is based on a set of dated and imprecisely measured occupational indexes from the Dictionary of Occupational Titles. Despite these limitations, we believe the results suggest an important role for changes in labor specialization—potentially spurred by displacement of routine task activities—as a driver of rising employment and wages in service occupations.

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Table 1. Levels and Changs in the Aggregate Share of Hours Worked
by Occupation, 1980-2005

	Share of Employment				Ten Times Average Annual Change			
	1980	1990	2000	2005	1980-1990	1990-2000	2000-2005	1980-2005
Managerial and Professional Specialty	23.8%	27.8%	30.0%	30.9%	4.0%	2.2%	1.8%	2.8%
Technicians, Sales, and Administrative Support	28.9%	30.8%	29.0%	28.4%	1.9%	-1.9%	-1.1%	-0.2%
Precision, Production, Craft and Repair	14.3%	12.4%	12.1%	11.6%	-1.9%	-0.2%	-1.1%	-1.1%
Service Occupations	11.0%	11.8%	13.7%	14.9%	0.7%	1.9%	2.5%	1.6%
Operators, Fabricators, and Laborers	19.2%	15.4%	13.9%	13.0%	-3.8%	-1.6%	-1.9%	-2.5%
Farming, Fishery, and Forestry Occs.	2.8%	1.8%	1.3%	1.3%	-0.9%	-0.5%	-0.1%	-0.6%

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

Table 2. Levels and Changs in Real Mean and Median Log Houly Wages
by Occupation, 1980-2005

	Real Mean Log Wage				Ten Times Average Annual Change			
	1980	1990	2000	2005	1980-1990	1990-2000	2000-2005	1980-2005
				A. Mean Log Hourly Wage by Occupation				
Managerial and Professional Specialty	2.87 (0.64)	2.94 (0.62)	3.05 (0.64)	3.16 (0.68)	0.07	0.11	0.23	0.12
Technicians, Sales, and Administrative	2.48 (0.60)	2.53 (0.60)	2.64 (0.61)	2.71 (0.65)	0.06	0.11	0.15	0.09
Precision, Production, Craft and Repair	2.73 (0.60)	2.69 (0.56)	2.73 (0.55)	2.75 (0.56)	-0.04	0.03	0.04	0.01
Service Occupations	2.17 (0.65)	2.22 (0.60)	2.35 (0.62)	2.37 (0.63)	0.05	0.13	0.03	0.08
Operators, Fabricators, and Laborers	2.49 (0.62)	2.45 (0.56)	2.52 (0.55)	2.53 (0.55)	-0.04	0.07	0.01	0.01
Farming, Fishery, and Forestry	2.00 (0.72)	2.05 (0.60)	2.15 (0.59)	2.17 (0.58)	0.05	0.10	0.04	0.07
				B. Median Log Hourly Wage by Occupation				
Managerial and Professional Specialty	2.91 (0.64)	2.97 (0.62)	3.06 (0.64)	3.16 (0.68)	0.06	0.09	0.19	0.10
Technicians, Sales, and Administrative	2.47 (0.60)	2.53 (0.60)	2.63 (0.61)	2.69 (0.65)	0.07	0.10	0.11	0.09
Precision, Production,	2.82 (0.60)	2.75 (0.56)	2.77 (0.55)	2.78 (0.56)	-0.07	0.03	0.01	-0.02
Service Occupations	2.18 (0.65)	2.20 (0.60)	2.33 (0.62)	2.33 (0.63)	0.02	0.13	0.01	0.06
Operators, Fabricators, and Laborers	2.55 (0.62)	2.47 (0.56)	2.54 (0.55)	2.54 (0.55)	-0.07	0.07	0.01	0.00
Farming, Fishery, and Forestry	2.02 (0.72)	2.01 (0.60)	2.12 (0.59)	2.14 (0.58)	-0.01	0.11	0.05	0.05

Source: Census 5% samples for 1980, 1990 and 2000, American Community Survey 2005. Sample includes persons who were aged 18-64 and working in the prior year, except self-employed. Hourly wages are defined as yearly wage and salary income diveded by the product of weeks worked times usual weekly hours. Labor supply is measured as weeks worked times usual weekly hours in prior year. All calculations use Census sampling weights.

Table 3. Levels and Changs in the Distribution of Education Groups
Across Occupations, 1980-2005

	Share of Employment				Ten Times Average Annual Change			
	1980	1990	2000	2005	1980-1990	1990-2000	2000-2005	1980-2005
A. Managerial and Professional Specialty Occupations								
Less than High School	5.8%	4.9%	4.5%	4.5%	-0.9%	-0.4%	-0.1%	-0.5%
High School	10.8%	10.9%	10.0%	10.3%	0.1%	-0.9%	0.7%	-0.2%
Some College	23.7%	23.9%	23.7%	23.4%	0.2%	-0.1%	-0.6%	-0.1%
College Graduate	67.4%	66.2%	66.9%	65.9%	-1.2%	0.7%	-1.8%	-0.6%
B. Technicians, Sales, and Administrative Support Occupations								
Less than High School	13.9%	15.2%	15.3%	13.9%	1.3%	0.0%	-2.7%	0.0%
High School	33.4%	32.0%	29.5%	29.1%	-1.3%	-2.6%	-0.7%	-1.7%
Some College	39.9%	40.7%	38.1%	37.2%	0.7%	-2.5%	-1.7%	-1.1%
College Graduate	21.8%	24.4%	22.7%	23.0%	2.6%	-1.7%	0.5%	0.5%
C. Service Occupations								
Less than High School	17.9%	22.2%	25.2%	27.3%	4.3%	2.9%	4.2%	3.8%
High School	11.7%	14.4%	17.4%	19.3%	2.6%	3.1%	3.8%	3.0%
Some College	10.7%	11.5%	14.3%	16.2%	0.8%	2.8%	3.7%	2.2%
College Graduate	3.2%	3.6%	5.1%	5.8%	0.4%	1.5%	1.3%	1.0%
D. Low-Skill Non-Service Occupations								
Less than High School	62.4%	57.6%	55.0%	54.3%	-4.8%	-2.6%	-1.4%	-3.2%
High School	44.1%	42.7%	43.2%	41.3%	-1.4%	0.5%	-3.8%	-1.1%
Some College	25.7%	24.0%	23.8%	23.2%	-1.8%	-0.1%	-1.4%	-1.0%
College Graduate	7.6%	5.8%	5.3%	5.3%	-1.8%	-0.5%	0.0%	-0.9%

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

Table 4. Changes in Top Wage Percentiles and Growth of Service Employment among Non-College Workers within Commuting Zones, 1980 - 2005: Estimates by Decade
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	1980-1990 (1)	1990-2000 (2)	2000-2005 (3)	1980-1990 (4)	1990-2000 (5)	2000-2005 (6)	1980-1990 (7)	1990-2000 (8)	2000-2005 (9)
					A. Δ 95th Percentile				
Δ 95th wage percentile	0.023	0.073 **	0.017 **	0.035 *	0.057 **	0.016 **	0.037 *	0.046 *	0.015 **
	(0.018)	(0.023)	(0.004)	(0.014)	(0.018)	(0.004)	(0.019)	(0.019)	(0.004)
Constant	0.027	0.020	0.025	0.024	0.0252	0.029	0.009	0.023	0.049
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)	(0.001)	(0.002)	(0.002)
R^2	0.021	0.100	0.093	0.263	0.361	0.138	0.512	0.589	0.339
Region Dummies	No	No	No	Yes	Yes	Yes	No	No	No
State Dummies	No	No	No	No	No	No	Yes	Yes	Yes
					B. Δ Alternative Wage Percentiles				
Δ 90th wage percentile	0.033	0.050 *	0.053 *						
	(0.022)	(0.022)	(0.022)						
Δ 75th wage percentile				0.022	0.045 *	0.057 *			
				(0.025)	(0.019)	(0.025)			
Δ 50th wage percentile							0.024	0.007	0.032
							(0.024)	(0.017)	(0.034)
Constant	0.010	0.024	0.051	0.011	0.025	0.052	0.011	0.027	0.055
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
R^2	0.501	0.584	0.296	0.493	0.574	0.295	0.496	0.559	0.287
Region Dummies	No	No	No	No	No	No	No	No	No
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

n = 741 Commuting Zones. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Percentiles of the distribution of full-time full-year weekly wages are based on workers who worked for at least 40 weeks and at least 35 hours per week in the previous year.

Table 5. Changes in Top Wage Percentiles and Growth of Service Employment among Non-College Workers within Commuting Zones, 1980 - 2005: Stacked First-Difference Models

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ 95th wage percentile	0.017 **	0.017 **	0.015 **	0.013 **	0.014 **	0.015 **	0.012 **			
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)			
Δ 90th wage percentile								0.020		
								(0.014)		
Δ 75th wage percentile									0.004	
									(0.013)	
Δ 50th wage percentile										-0.022
										(0.016)
Δ Unemp rate				0.329 **			0.387 **	0.443 **	0.433 **	0.436 **
				(0.058)			(0.076)	(0.070)	(0.071)	(0.069)
Δ College ed/pop					0.088 **		0.085 **	0.089 **	0.098 **	0.109 **
					(0.032)		(0.033)	(0.034)	(0.034)	(0.034)
Δ Non-college immigrants/pop					0.032		0.103 ~	0.151 *	0.162 **	0.158 *
					(0.060)		(0.058)	(0.061)	(0.063)	(0.065)
Δ Female emp/pop						-0.065 ~	0.058	0.077 *	0.069 ~	0.063 ~
						(0.036)	(0.040)	(0.036)	(0.037)	(0.035)
Δ Age 65+/pop						0.026	0.118 ~	0.186 **	0.173 **	0.141 **
						(0.063)	(0.061)	(0.056)	(0.055)	(0.055)
1990-2000 dummy	0.000	0.000	0.000	0.004	0.001	-0.002	0.008 **	0.009 **	0.010 **	0.011 **
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
2000-2005 dummy	-0.002	-0.002	-0.001	0.007	-0.005 ~	0.001	0.003	0.008 ~	0.010 *	0.012 **
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Constant	0.027	0.029	0.028	0.018	0.030	0.030	0.016	0.014	0.014	0.014
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.095	0.110	0.183	0.193	0.221	0.188	0.231	0.200	0.198	0.200
Region dummies	No	Yes	No	No	No	No	No	No	No	No
State dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

n = 2,223 (741 Commuting Zones × 3 time periods). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Percentiles of the distribution of full-time full-year weekly wages are based on workers who worked for at least 40 weeks and at least 35 hours per week in the previous year.

Table 6. Changes in Top Wage Percentiles and Growth of Service Employment, 1980 - 2005: Stacked First-Difference Estimates by Detailed Service Occupation
Dependent Variable: 100 × Annual Change in Commuting Zone's Ratio of Non-College Employment in Service Sub-Occupation to Non-College Employment in Non-Service Occupations

	Food Service		Health Support	Building Cleaning/ Gardening		House Cleaning/ Laundry	Security Guards
Δ p95	0.083	*	0.017	0.097	**	0.025	0.012
	(0.038)		(0.023)	(0.026)		(0.016)	(0.009)
Δ p95 + full controls	0.072	~	0.019	0.084	**	0.018	0.012
	(0.038)		(0.021)	(0.025)		(0.011)	(0.010)

	Personal Appear-ance		Child Care	Recreat-ion		Misc. Personal Svcs	
Δ p95	0.025	*	0.022	0.010	~	0.014	~
	(0.011)		(0.021)	(0.006)		(0.007)	
Δ p95 + full controls	0.021	~	0.025	0.010	~	0.013	~
	(0.011)		(0.022)	(0.006)		(0.007)	

n = 2,123. (741 Commuting Zones × 3 time periods). Robust standard errors in parentheses are clustered on state. All models include state dummies. 'Full controls' include all additional covariates used in column (7) of Table 5. All models include an intercept and are weighted by start of period commuting zone share of national population. Percentiles of the distribution of full-time full-year weekly wages are based on workers who worked for at least 40 weeks and at least 35

Table 7. Correlates of the Routine Task Index (RTI) in 1980 and Robustness of the Relationship between RTI and Growth of Service Employment:, 1980-2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Routine Task Index in 1980 × 10^{-2}							
Non-college share in service occs			0.07 *					-0.05 *
			(0.04)					(0.02)
College+/ pop 1980				0.21 **				0.02
				(0.02)				(0.03)
Some college/ pop 1980				-0.03				0.02
				(0.02)				(0.01)
HS dropout/ pop 1980				-0.01				0.00
				(0.01)				(0.01)
Real p90 in 1980					0.07 **			0.03 **
					(0.02)			(0.01)
Real p50 in 1980					-0.07 **			-0.02 *
					(0.01)			(0.01)
Real p10 in 1980					0.09 **			0.04 **
					(0.01)			(0.01)
College immigrants/ pop						0.50 **		-0.03
						(0.09)		(0.06)
Non-college immigrants/ pop						-0.15 **		-0.03
						(0.04)		(0.07)
Unemployment rate 1980							-0.07	0.02
							(0.05)	(0.04)
Female emp/pop 1980							0.12 **	0.07 **
							(0.01)	(0.01)
Age 65+/pop 1980							-0.11 *	-0.02
							(0.05)	(0.01)
R^2		0.388	0.396	0.782	0.833	0.613	0.781	0.901
State Dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes
	B. Change in Share of Non-College Employment in Service Occupations 1980-2005							
Routine task index 1980 × 10^{-2}	1.46 **	1.21 **	1.17 **	0.66 **	0.69 **	0.66 **	1.86 **	1.11 **
	(0.17)	(0.17)	(0.15)	(0.19)	(0.25)	(0.17)	(0.27)	(0.26)
R^2	0.287	0.510	0.520	0.551	0.550	0.616	0.558	0.682
State Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

n=741 Commuting Zones. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Each column of each panel presents a separate OLS regression. All models include an intercept and are weighted by the commuting zone's share of national employment in 1980. In Panel A,the dependent variable is the standardized routine task index for year 1980. In panel B, the dependent variable is the annualized change in the share of employed non-college workers in service occupations. All covariates listed in Panel A are included in corresponding columns in Panel B.

Table 8. Routine Task Intensity and Growth of Service Employment among Non-College Workers within Commuting Zones, 1980 - 2005: Stacked First-Difference Models
Dependent Variable: 10 × Annual Change in Share of Non-College Employment in Service Occupations

	1980 - 1990	1990 - 2000	2000 - 2005	1980 - 2005				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine task index$_{-1}$ × 10^{-2}	0.331 **	0.323 **	1.335 **	0.481 **	0.314 **	0.401 **	0.431 **	0.360 **
	(0.106)	(0.104)	(0.384)	(0.094)	(0.093)	(0.097)	(0.094)	(0.090)
Δ Unemp rate					0.355 **			0.423 **
					(0.047)			(0.058)
Δ College ed/pop						0.087 **		0.074 *
						(0.034)		(0.034)
Δ Non-college immigrants/pop						0.133 *		0.086
						(0.058)		(0.065)
Δ Female emp/pop							-0.051 *	0.070 *
							(0.026)	(0.030)
Δ Age 65+/pop							0.086	0.170 **
							(0.060)	(0.058)
1990-2000 dummy				0.001	0.004 *	0.004 ~	-0.003	0.016 **
				(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
2000-2005 dummy				0.010 **	0.001	0.016 **	0.006	0.017 **
				(0.003)	(0.001)	(0.004)	(0.004)	(0.005)
Constant	0.013	0.029	0.067	0.031	0.031	0.021	0.034	0.013
	(0.001)	(0.000)	(0.003)	(0.031)	(0.001)	(0.004)	(0.003)	(0.005)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.529	0.581	0.322	0.151	0.208	0.161	0.156	0.222
n	741	741	741	2,223	2,223	2,223	2,223	2,223

Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. All models include state dummies. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade).

Table 9. Computer Adoption within Commuting Zones 1980 to 2002 and initial Routine Task Intensity.
Dependent Variable: Doms-Lewis Measure of Computer Adoption ('adjusted PCs per employee')

	1980 - 1990	1990 - 2002				1980 - 2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Routine task index$_{-1}$ × 10^{-2}	2.74 **	2.22 **	5.42 **	5.18 **	2.98 **	2.25 **	4.45 **	5.59 **	2.25 **
	(0.22)	(0.25)	(0.40)	(0.39)	(0.64)	(0.76)	(0.54)	(0.68)	(0.60)
Non-college share in service occs				1.32 **					0.83 **
				(0.19)					(0.24)
High-skill/low-skill population 1980					0.36 **				0.23 *
					(0.08)				(0.12)
Real p90 in 1980						0.46 **			0.23 **
						(0.09)			(0.08)
Real p50 in 1980						-0.23 *			-0.08
						(0.10)			(0.07)
Real p10 in 1980						0.18			0.12 ~
						(0.14)			(0.07)
College immigrants/ pop							1.50 **		-0.12
							(0.45)		(0.41)
Non-college immigrants/ pop							-0.56 **		-0.04
							(0.17)		(0.19)
Unemployment rate 1980								-0.55 ~	-0.48 *
								(0.30)	(0.20)
Female emp/pop 1980								-0.18	-0.20 ~
								(0.13)	(0.10)
Age 65+/pop 1980								-0.07	0.00
								(0.25)	(0.23)
R^2	0.637	0.371	0.611	0.652	0.655	0.665	0.628	0.614	0.701
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

n=687 Commuting Zones (n=672 in (2)). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. The Doms-Lewis measure of computer adoption measures the number of personal computers per employee, controlling for 950 industry/establishment interactions. All models include an intercept and are weighted by the commuting zone's share of national employment in 1980.

Table 10. Routine Task Intensity and Changes in Real Full-Time Weekly Log Wage Percentiles within Commuting Zones, 1980 - 2005: Stacked First-Difference Models

Dependent Variable: 10 × Annual Change in Standardized Task Measure

	All Workers (1)		College Grad (2)		Some College (3)		HS Grad (4)		HS Dropout (5)	
	A. Change in Abstract Task Measure									
Routine task index$_{-1}$	0.217	**	0.150	**	0.041	~	0.116	**	0.116	*
	(0.023)		(0.022)		(0.023)		(0.030)		(0.049)	
R^2	0.472		0.200		0.135		0.179		0.177	
Mean of dep var	0.520		-0.089		-0.130		-0.102		-0.200	
	B. Change in Routine Task Measure									
Routine task index$_{-1}$	-0.301	**	-0.217	**	-0.265	**	-0.302	**	-0.186	*
	(0.028)		(0.040)		(0.030)		(0.030)		(0.075)	
R^2	0.406		0.168		0.224		0.268		0.157	
Mean of dep var	-0.888		0.021		-0.745		-1.091		-0.390	
	C. Change in Manual Task Measure									
Routine task index$_{-1}$	0.118	**	-0.029	*	0.093	**	0.178	**	0.180	**
	(0.012)		(0.012)		(0.023)		(0.015)		(0.033)	
R^2	0.479		0.039		0.283		0.171		0.246	
Mean of dep var	0.098		0.150		0.332		0.494		0.391	

n = 2,123. (741 commuting zones × 3 time periods). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. All models include state dummies and controls for contemporaneous commuting-zone level changes in the unemployment rate, the share of college-educated (some college+) residents, the share of non-college (high school graduate or lower) immigrants, the female labor force participation rate, and the share age 65+ in the population. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade). All task measures (dependent variables) are standardized with mean zero and variance one in 1980.

Table 11. Routine Task Intensity and Changes in Real Full-Time Weekly Log Wage Percentiles within Commuting Zones, 1980 - 2005: Stacked First-Difference Models
Dependent Variable: 10 × Annual Change in Indicated Wage Percentile

	p95 (1)	p90 (2)	p75 (3)	p50 (4)	p10 (5)	p9050 (6)	p5010 (7)
				A. 1980 - 2005: Stacked first differences			
Routine task index$_{-1}$	0.140 **	0.034 **	0.026 **	0.020 **	0.012 **	0.014 **	0.008 **
	(0.016)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
R^2	0.432	0.484	0.513	0.447	0.221	0.196	0.306
n	2,223	2,223	2,223	2,223	2,223	2,223	2,223
				B. 1980 - 1990			
Routine task index$_{-1}$	0.041 **	0.035 **	0.029 **	0.028 **	0.012 *	0.008 **	0.016 **
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)
R^2	0.676	0.703	0.695	0.698	0.635	0.449	0.426
n	741	741	741	741	741	741	741
				C. 1990 - 2000			
Routine task index$_{-1}$	0.043 **	0.040 **	0.026 **	0.009 **	0.001	0.031 **	0.008 *
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.456	0.496	0.391	0.441	0.725	0.650	0.636
n	741	741	741	741	741	741	741
				D. 2000-2005			
Routine task index$_{-1}$	0.651 **	0.025 *	0.018 *	0.010	-0.012	0.015	0.023 **
	(0.083)	(0.011)	(0.007)	(0.009)	(0.009)	(0.013)	(0.007)
R^2	0.572	0.303	0.382	0.301	0.334	0.199	0.333
n	741	741	741	741	741	741	741

Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. All models include state dummies. Models in top panel include controls for contemporaneous commuting-zone level changes in the unemployment rate, the share of college-educated (some college+) residents, the share of non-college (high school graduate or lower) immigrants, the female labor force participation rate, and the share age 65+ in the population. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade).

Table 12. Routine Task Intensity and Changes in Real Hourly Wages by Occupation, 1980 - 2005: Stacked First-Difference Models
Dependent Variable: 10 × Annual Change in Indicated Wage Measure

	Manager-Profsnl (1)		Tech - Sales - Admin (2)		Opera-tives (3)	Produc-tion (4)		Farm - Fish - Forest (5)		Service Occs (6)	
					A. Males						
A. Routine task index$_{-1}$	0.014	**	0.030	**	0.004	0.001		-0.034	~	0.011	**
	(0.004)		(0.005)		(0.004)	(0.003)		(0.018)		(0.004)	
R^2	0.519		0.473		0.315	0.309		0.107		0.318	
B. Routine task index$_{-1}$ + controls	0.021	**	0.035	**	0.004	0.004		-0.014		0.014	**
	(0.005)		(0.004)		(0.003)	(0.004)		(0.014)		(0.004)	
R^2	0.532		0.489		0.328	0.332		0.122		0.329	
Mean of dep var	0.113		0.065		-0.026	-0.049		0.011		0.019	
					B. Females						
A. Routine task index$_{-1}$	0.031	**	0.028	**	0.004	0.008		0.006		0.010	**
	(0.003)		(0.003)		(0.007)	(0.007)		(0.017)		(0.004)	
R^2	0.585		0.388		0.133	0.054		0.070		0.405	
B. Routine task index$_{-1}$ + controls	0.033	**	0.024	**	0.004	0.012	*	0.013		0.010	*
	(0.003)		(0.003)		(0.006)	(0.006)		(0.019)		(0.004)	
R^2	0.594		0.431		0.148	0.060		0.074		0.418	
Mean of dep var	0.140		0.093		0.008	0.046		-0.016		0.036	

n = 2,123. (741 commuting zones × 3 time periods). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Each cell corresonds to a separate OLS regression. All models include state dummies. Specification (B) also includes measures of contemporaneous commuting-zone level changes in the unemployment rate, the share of college-educated (some college+) residents, the share of non-college (high school graduate or lower) immigrants, the female labor force participation rate, and the share age 65+ in the population. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade).

Table 13a. Routine Task Intensity and Change in the Male Log Mean Hourly Wage in Service Occupations 1980 - 2005: Stacked First-Difference Models
Dependent Variable: 10 × Annual Change in Male Log Mean Hourly Wage in Service Occupations

	1980 - 1990	1990 - 2000	2000 - 2005	1980 - 2005				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine task index$_{-1}$ × 10^{-2}	0.014 ~	0.011 *	0.010	0.011 **	0.014 **	0.013 **	0.012 **	0.014 **
	(0.008)	(0.005)	(0.019)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Δ Unemp rate					-0.654 *			-0.599 ~
					(0.274)			(0.338)
Δ College ed/pop						-0.212		-0.228
						(0.196)		(0.209)
Δ Non-college immigrants/pop						-0.442 *		-0.398
						(0.216)		(0.304)
Δ Female emp/pop							0.223 ~	0.029
							(0.123)	(0.153)
Δ Age 65+/pop							-0.509 ~	-0.738 *
							(0.299)	(0.357)
1990-2000 dummy				0.146 **	0.141 **	0.139 **	0.159 **	0.124 **
				(0.019)	(0.018)	(0.022)	(0.024)	(0.027)
2000-2005 dummy				0.073 **	0.088 **	0.059 *	0.087 **	0.058
				(0.015)	(0.018)	(0.023)	(0.027)	(0.036)
Constant	-0.054	0.094	0.021	-0.063	-0.062	-0.037	-0.075	-0.026
	(0.011)	(0.009)	(0.020)	(0.011)	(0.011)	(0.026)	(0.021)	(0.036)
State dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
R^2	0.069	0.022	0.002	0.318	0.325	0.321	0.322	0.329
n	741	741	741	2,223	2,223	2,223	2,223	2,223

Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade).

Table 13b. Routine Task Intensity and Change in the Female Log Mean Hourly Wage in Service Occupations 1980 - 2005: Stacked First-Difference Models

Dependent Variable: 10 × Annual Change in Female Log Mean Hourly Wage in Service Occupations

	1980 - 1990	1990 - 2000	2000 - 2005	1980 - 2005				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine task index$_{-1}$ × 10^{-2}	0.031 **	-0.012 *	0.007	0.010 **	0.012 **	0.010 *	0.009 **	0.010 *
	(0.007)	(0.005)	(0.014)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Δ Unemp rate					-0.385			-0.489
					(0.344)			(0.363)
Δ College ed/pop						0.126		0.083
						(0.167)		(0.174)
Δ Non-college immigrants/pop						-0.028		-0.176
						(0.196)		(0.279)
Δ Female emp/pop							0.115	-0.056
							(0.161)	(0.166)
Δ Age 65+/pop							-1.164 **	-1.273 **
							(0.388)	(0.460)
1990-2000 dummy				0.102 **	0.099 **	0.110 **	0.096 **	0.082 **
				(0.016)	(0.015)	(0.017)	(0.022)	(0.025)
2000-2005 dummy				-0.058 **	-0.049 **	-0.047 *	-0.070 *	-0.072 *
				(0.012)	(0.015)	(0.019)	(0.028)	(0.036)
Constant	0.022	0.126	-0.036	-0.012	-0.011	-0.026	-0.004	0.006
	(0.008)	(0.009)	(0.012)	(0.009)	(0.008)	(0.022)	(0.022)	(0.035)
State dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
R^2	0.170	0.025	0.001	0.405	0.408	0.406	0.414	0.418
n	741	741	741	2,223	2,223	2,223	2,223	2,223

Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. Routine task index is equal to ratio of DOT Routine to Manual task input in Commuting Zone at start of decade (1980, 1990 or 2000). This measure is standardized with mean zero and variance one in 1980 (1990 and 2000 values are in same units but are not restandardized in each decade).

Figure 1a

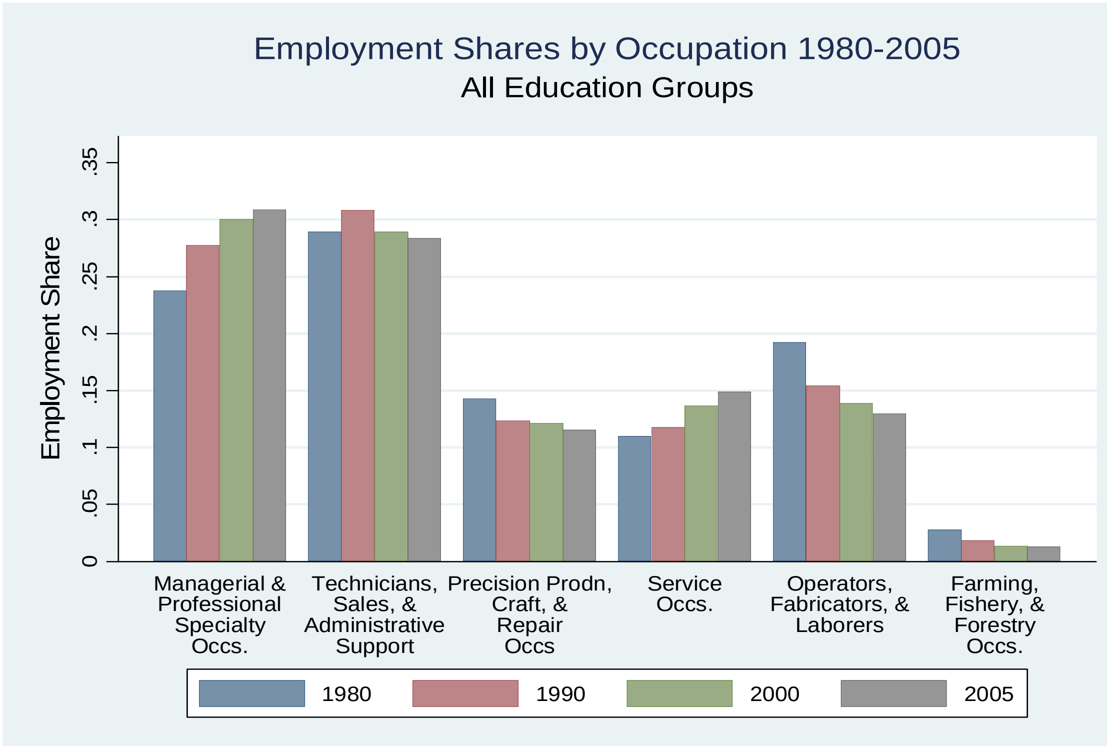


Figure 1b

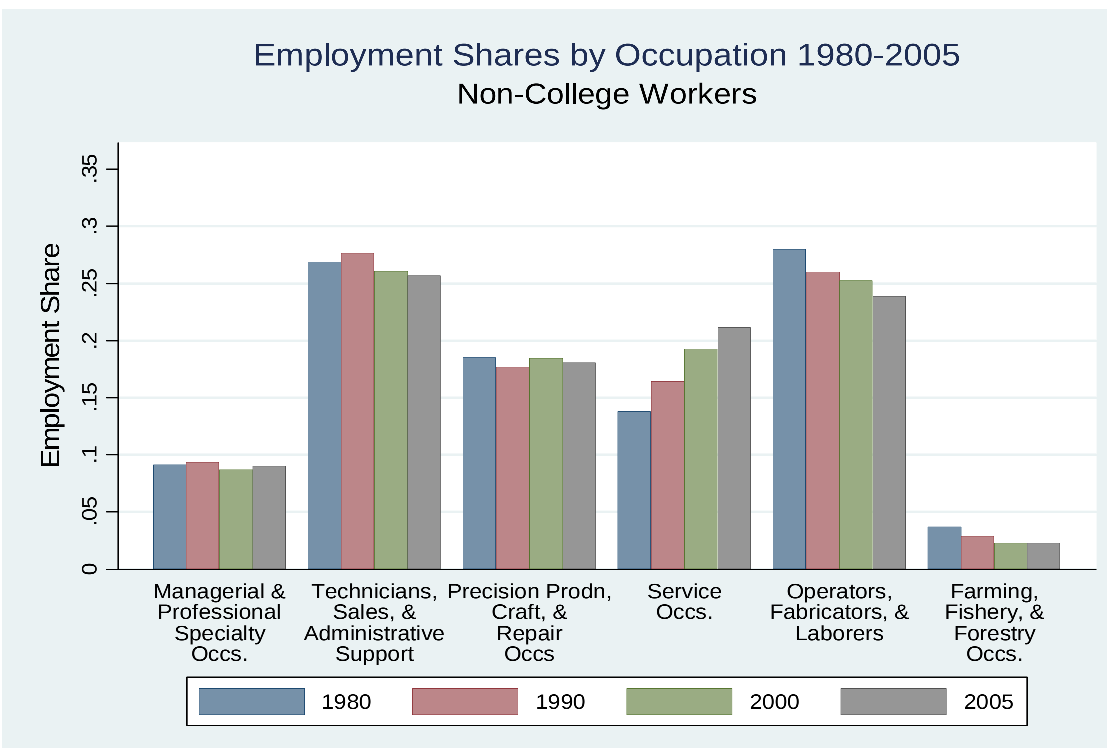
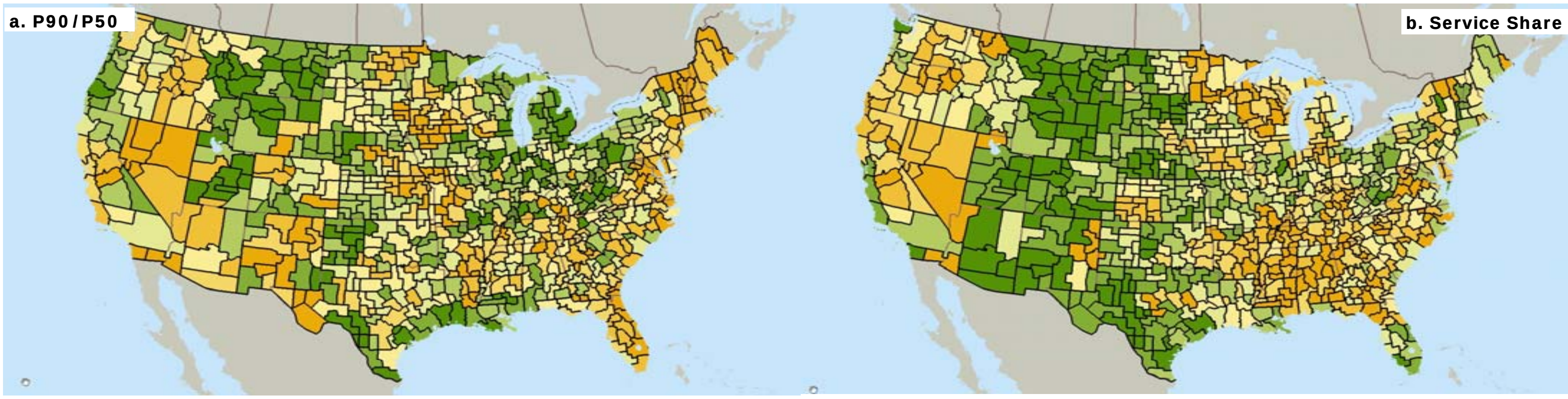
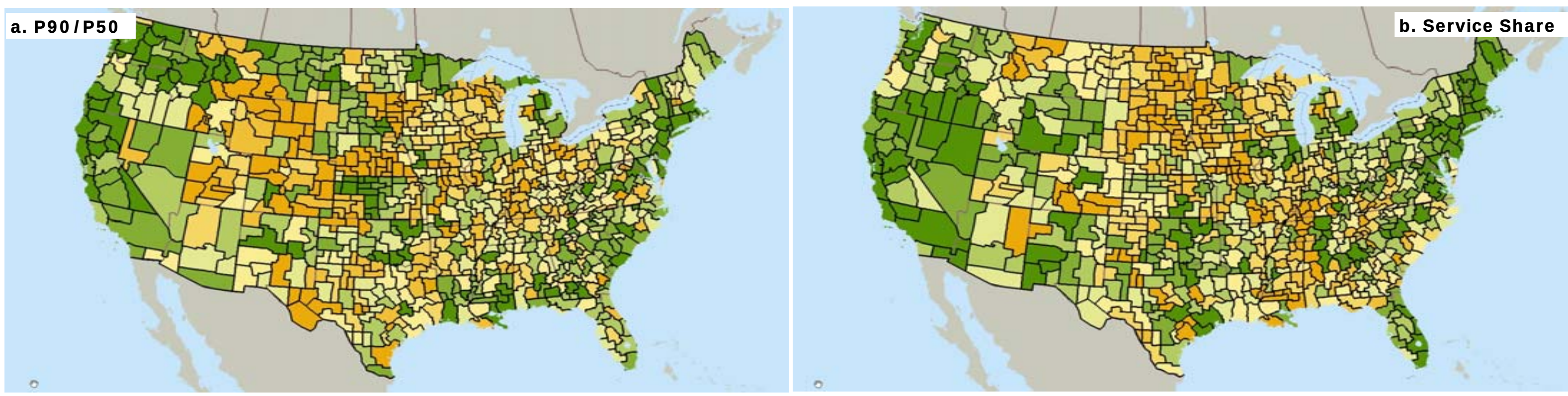


Figure 2. Changes in Log Hourly P90/P50 Inequality and
the Share of Non-College Labor in Service Occupations by Commuting Zone

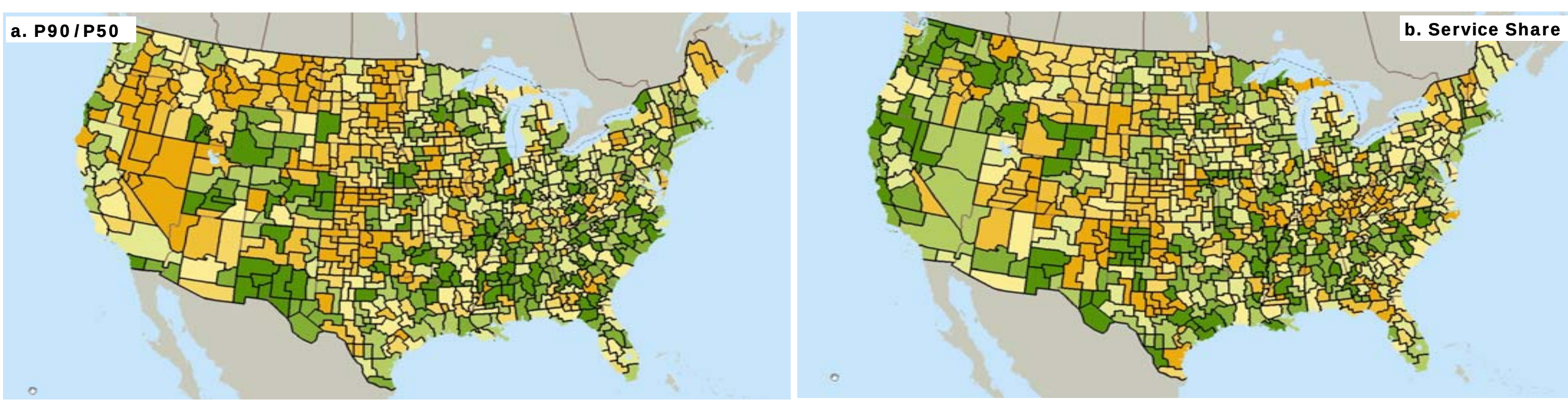
A. 1980-1990



B. 1990-2000



C. 2000-2005



Note: The color scale reflects a ranking of commuting zones according to the plotted variable. Dark green represents areas with largest growth and dark orange stands for areas with lowest growth.

Figure 3. Changes in Real Log Weekly Wage Percentiles and Growth
in the Share of Non-College Labor in Service Occupations by Commuting Zone, 1980 - 2005

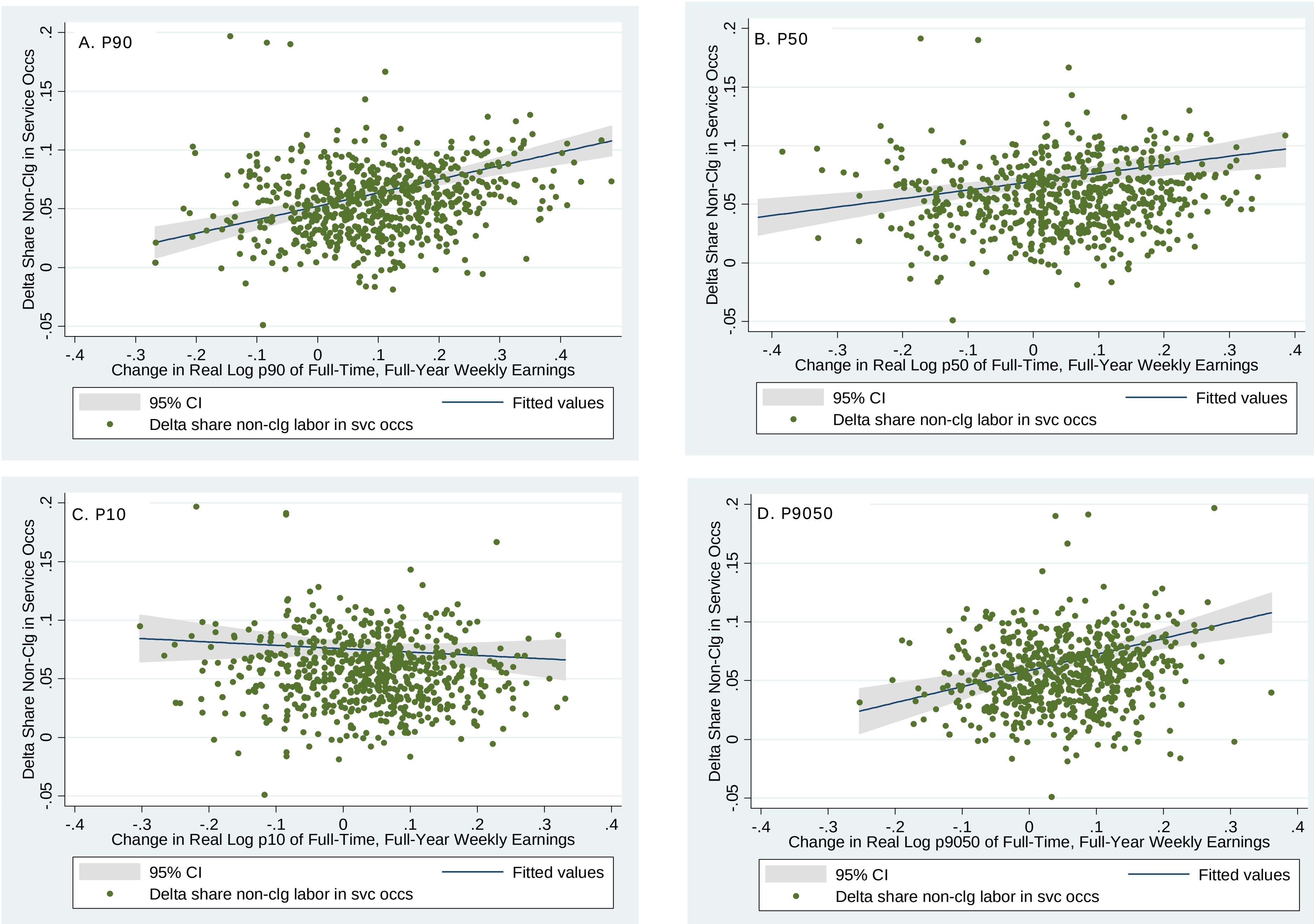


Figure 4. Initial Routine Task Intensity (1980) and Changes in Service Occupation Share and Changes Task Input by Commuting Zone, 1980 - 2005

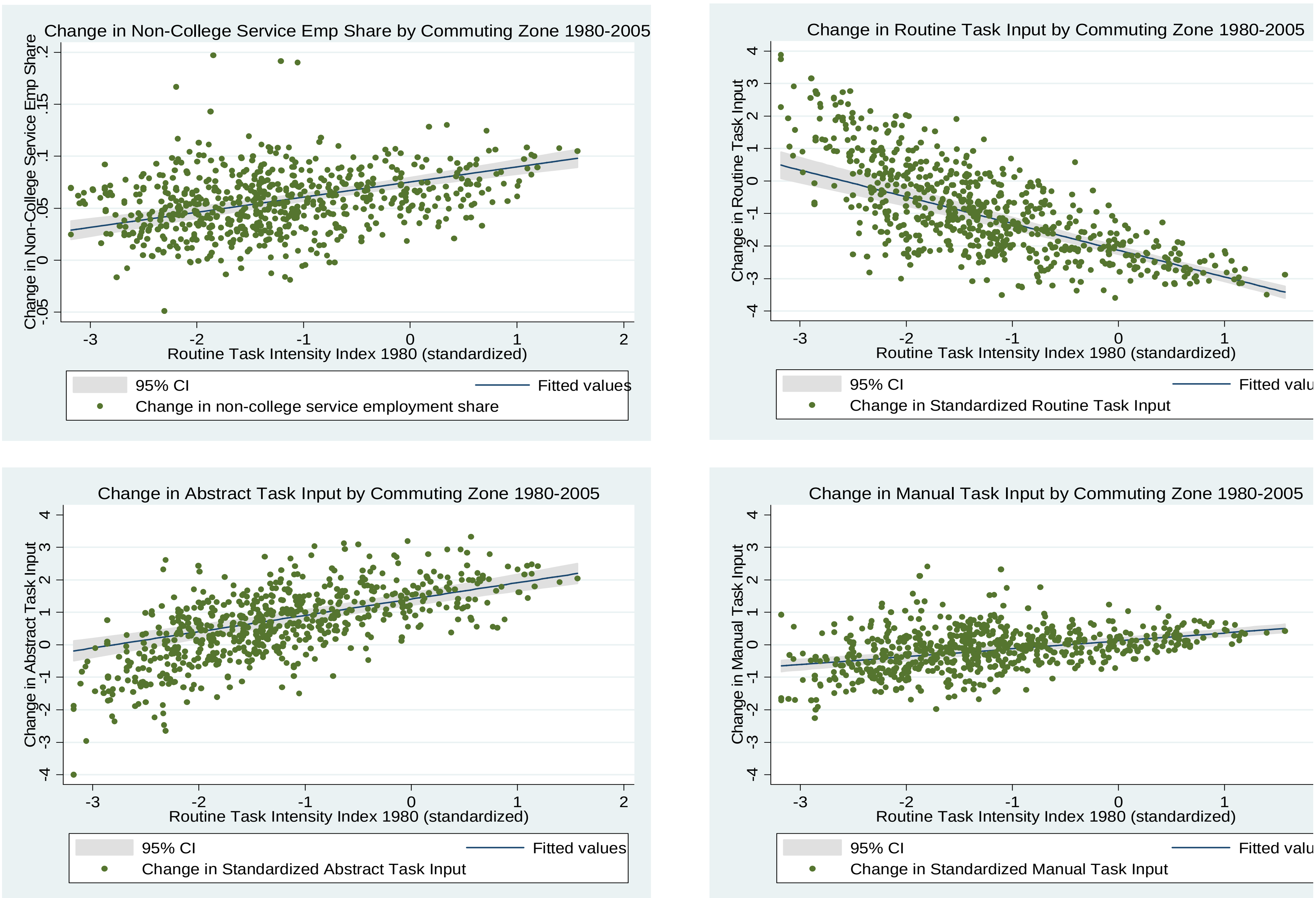


Figure 5. Initial Routine Task Intensity (1980) and Changes in log Weekly Full-Time Full-Year Wage Percentiles
by Commuting Zone, 1980 - 2005