Task Specialization in U.S. Cities from 1880-2000*

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Abstract

We introduce a new methodology for measuring the production tasks undertaken within occupations. We use this methodology to provide the first evidence on the evolution of production tasks in urban and rural areas in the United States from 1880-2000. We find that tasks involving thought, communication and intersocial activity (“interactiveness”) were more concentrated in densely-populated areas in 2000, but not in 1880. We provide evidence in support of the predictions of a model of agglomeration and the task composition of employment, in which improvements in communication technologies favor an increased concentration of interactive tasks in metro areas.

KEYWORDS: Agglomeration, Task Specialization, Urbanization.

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1 Introduction

As a large and growing share of the world’s population concentrates in cities, workers’ labor market outcomes are increasingly determined in urban labor markets. Yet we know relatively little about the tasks undertaken in urban versus rural areas and how these have changed over time. This paper combines Census of Population and Dictionary of Occupations (DOTs) data to provide novel evidence on the task composition of employment in urban and rural areas in the United States from 1880-2000. What kinds of jobs are available in urban areas? How do these differ from the jobs available in rural areas? Do large and small cities offer the same employment opportunities or does the task composition of employment differ across cities of different sizes? Are these patterns stable over time? If they have changed, what explains these changes in patterns of task specialization? What are the implications of the evolving task composition of employment for our understanding of the sources of agglomeration? This paper provides answers to these and other related questions.

We use the DOTs data to provide the first evidence on the evolution of the task composition of employment in urban and rural areas over a long historical time period. To measure the tasks undertaken by workers within occupations, we examine the occurrence of 3,000 verbs in over 12,000 occupational descriptions. We find substantial changes in the tasks undertaken within urban versus rural areas. In 1880, the tasks most concentrated in metro areas included “Braid,” “Sew,” “Stretch” and “Thread.” In contrast, in 2000, the tasks most concentrated in metro areas comprised “Analyze,” “Advise,” “Confer” and “Report.” We use Roget’s Thesaurus – the seminal reference for English language use – to interpret these changing patterns of task specialization. We find a negative and statistically significant correlation of -0.43 between the thesaurus categories most concentrated in metro areas in 1880 and 2000. In particular, we find an increase over time in the concentration in metro areas of tasks involving a combination of thought, communication and intersocial activity. We define this combination of tasks as “interactiveness,” because it captures the essence of human interaction: the generation (“thought”) and transmission (“communication”) of ideas to other humans (“intersocial activity”).

At the beginning of our sample period, metro and non-metro areas actually had similar levels of interactiveness. Over time, metro areas experienced larger increases in interactiveness than non-metro areas, making metro areas substantially more interactive today. We date the origins of this rise in the relative interactiveness of metro areas back to the early-twentieth century. We show that the observed increases in the interactiveness of employment around the turn of the twentieth century are related to the spatial diffusion of the telephone.

Understanding changes in task specialization in urban and rural areas is central to evaluating alternative theories of agglomeration. Traditionally, these theories have emphasized the costs of moving goods and people over space. In the new economic geography literature, agglomeration is explained by consumer
love of differentiated varieties, increasing returns to scale and the costs of transporting these differentiated
varieties (e.g. Fujita, Krugman and Venables 1999). In the canonical models of urban economies, agglom-
eration is driven by economies of scale in producing a single final good, while commuting costs provide a
dispersion force (e.g. Alonso 1964, Muth 1968, Mills 1967). More recently, research has focused on human
capital externalities (e.g. Moretti 2004, Davis and Dingel 2013) and the costs of exchanging ideas (e.g.
Davis and Dingel 2012, Gaspar and Glaeser 1998), which highlights the costs of moving ideas rather than
goods and people (e.g. Glaeser and Kohlhase 2003).

Whereas most of these theories our static, emphasizing a single source of agglomeration economies,
our findings suggest a view of urban and rural areas that is inherently dynamic. According to this view
the nature of the tasks undertaken in urban versus rural areas, and hence the source of agglomeration, has
changed over time. Our findings of an increased importance of interactive tasks in urban relative to rural
areas support the idea that the movement of ideas has become more important as a source of agglomeration
relative to the movement of goods and people. Even after abstracting from the agricultural sector, urban
areas are not simply scaled-up versions of rural areas that are more productive in a single production activity.
Rather urban areas perform a different set of production tasks from rural areas and these differences can
change over time with for example available communication technologies.

Since externalities in the movement of ideas are likely to differ from those in the movement of goods and
people, our findings suggest potential changes in the strength of agglomeration economies over time, with
implications for the appropriate public policy interventions to align private and social returns. Whereas most
existing empirical research has concentrated on estimating the overall strength of agglomeration economies,
our findings highlight the need to distinguish between different sources of agglomeration economies and
allow their relative importance to change over time.¹ Our results also suggest that the rapid urbanization of
developing countries such as China and India is likely to be accompanied by substantial changes in the relative
demand for different occupations, with implications for human capital and education policies designed
to influence the relative supply of skills. To the extent that differences in specialization in interactive tasks
across cities are combined with a secular reallocation of economic activity towards more interactive tasks,
our findings also contribute towards understanding differences in economic growth across cities.

To guide our empirical investigation, we develop a simple model of the organization of economic activity
across tasks and locations. The model emphasizes that the remote sourcing of tasks occurs not only across
countries (as in the literature on offshoring) but also within them (where population is mobile between
regions). Some locations (metro areas) are more productive and hence have higher population density and
wages than other locations (non-metro areas). Firms choose whether to undertake tasks locally or incur
communication costs to remote source them from other lower-wage locations. More interactive tasks are

¹Few empirical studies have sought to distinguish between different sources of agglomeration economies, a notable exception
being Ellison, Glaeser and Kerr (2010).
assumed to have higher communication costs, because their greater dependence on human interaction makes
them more costly to perform remotely. The model predicts that reductions in communication costs induce
metro areas to specialize in more interactive tasks, which raises the productivity and relative wages of metro
areas, and hence reallocates population to metro areas. Therefore, although remote sourcing displaces a
range of production activities from metro areas to non-metro areas, the resulting increase in productivity
and wages in metro areas relative to non-metro areas increases the relative population of metro areas.

Guided by these predictions, the main contribution of the paper is to develop a methodology for mea-
suring the tasks undertaken within each occupation and to provide evidence on the evolution of these tasks
in urban and rural areas over time. We show that densely-populated locations have become more interactive
relative to less-densely-populated locations – both between metro and non-metro areas and across metro
areas of different population densities. We find similar results for each of the components of interactiveness
(thought, communication and intersocial activity), suggesting that it is the combination of these activities
that is important. We provide external validation for our results using separate independent measures of in-
teractiveness that have been constructed for contemporary time periods. We establish that the concentration
of interactive occupations in metro areas is observed for both employment and wage bill shares, consistent
with an increase in the relative demand for interactive occupations.

We also provide evidence against a number of potential alternative explanations. To demonstrate that
our findings are not driven by the relocation of manufacturing from urban areas or the expansion of services
in urban areas, we show that the increased interactiveness of metro areas takes place within as well as
between sectors and is not driven by any one occupation or sector. We also find similar results when we
exclude occupations associated with headquarters, suggesting that the increased interactiveness is not driven
solely by a concentration of headquarters in urban areas. We show that our findings are not explained by an
expansion in the geographical boundaries of metro areas over time, since we find similar results when we
restrict attention to central cities. We document similar results for single and married individuals, suggesting
that the increased interactiveness of metro areas is not driven by an increased need for “power couples” to
colocate. Taken together, these results support a change in the organization of production activities within
industries to favor the concentration of more interactive tasks in cities.

Our paper is related to a number of literatures. We build on the wider literature on agglomeration
economies, as surveyed in Duranton and Puga (2004) and Rosenthal and Strange (2004). One strand of
this literature emphasizes the role of human capital, skills and the division of labor in promoting agglom-
eration, including Baumgardner (1988), Becker and Murphy (1992), Glaeser and Saiz (2003), Glaeser and
Resseger (2009), Bacolod, Blum and Strange (2009a,b), Duranton (1998), Duranton and Jayet (2011),
of this literature has contrasted specialization by sector with specialization by function (e.g. headquarters
versus plants), including Duranton and Puga (2005), Rossi-Hansberg, Sarte and Owens (2009), Ota and
Fujita (1993), Helsley and Strange (2007), and Fujita and Tabuchi (1997). In contrast to these studies, which have used relatively aggregate measures of skills and specialization, we use the disaggregated information in the DOTs to provide the first evidence on tasks undertaken in metro and non-metro areas over time. Consistent with the predictions of our model of agglomeration and the remote sourcing of tasks, we find that the increase in the interactiveness of employment is related to the diffusion of new communication technologies.

Our research also builds on the labor economics literature on the task content of employment, including Autor, Levy and Murnane (2003), Autor and Dorn (2013), Autor and Handel (2009), and Gray (2010). We develop a new approach to measuring the task content of employment, which enables us to measure the individual tasks performed by workers within each occupation (captured by the verbs in occupational descriptions) rather than being restricted to a single overall numerical score for each occupation (such as “Direction, Control and Planning (DCP”)). We use these verbs to measure the relative importance of multiple tasks for each occupation and to develop a new measure of the overall interactiveness of occupations. We thus contribute to an emerging literature in economics and the social sciences that uses textual search to quantify hard-to-measure concepts, including political influence in Gentzkow et al. (2012) and culture in Michel et al. (2011). In contrast to much of the labor economics literature, our focus is on differences in the task content of employment between urban and rural areas. Whereas this prior labor economics research has mainly concentrated on recent decades, we provide evidence over more than a century.

Our theoretical and empirical research on the remote sourcing of tasks within countries is also related to the international trade literature on offshoring, including Becker, Ekholm and Muendler (2009), Blinder (2009), Blinder and Krueger (2012), Grossman and Rossi-Hansberg (2008), and Ottaviano, Peri and Wright (2010). An advantage of our empirical setting using U.S. micro data over a long historical time period is that we can provide direct evidence on the role of improvements in communication technology (telephones) in explaining changes in interactiveness. Our work is therefore related to the literature on innovations in communication technology and urban growth (e.g. Pool 1977, Fischer 1992, Gaspar and Glaeser 1998, Leamer and Storper 2001). Our micro data enable us to explore the effects of such innovations on task specialization at a fine spatial scale and to develop instruments for their dissemination.

The remainder of the paper is structured as follows. Section 2 introduces the model. Section 3 discusses the data. Section 4 presents some initial evidence based on sectors and occupations to motivate our more detailed analysis of task specialization. Section 5 introduces our empirical methodology for measuring task specialization. Section 6 constructs our measure of interactiveness and presents our baseline results. Section 7 reports a number of robustness tests and compares our measure of an occupation’s interactiveness to other independent measures and to other occupational characteristics. Section 8 presents evidence on the determinants of changes in task specialization. Section 9 concludes.
2 Theoretical Model

To guide our empirical research, we develop a simple model of the organization of economic activity across tasks and locations. We augment the economic geography model of Helpman (1998) with the production technology featuring a continuum of tasks from Grossman and Rossi-Hansberg (2008). Allowing for the remote sourcing of tasks introduces a key new mechanism into the economic geography model: the fraction of tasks that are remotely sourced influences the relative population of locations.

The model considers two locations that differ in terms of their productivity (and hence wages). Firms in the high-wage (metro) location decide whether to perform tasks locally or to remote source them from the low-wage location (non-metro). Remote sourcing incurs communication costs, which we interpret as capturing the interactiveness of tasks. More interactive tasks are assumed to have higher communication costs, because their greater dependence on human interaction makes them more costly to perform remotely.

We use the model to examine the impact of an improvement in technology that reduces communication costs for all tasks proportionately. We show that such a reduction in communication costs leads the metro location to specialize in more interactive tasks and to remote source less interactive tasks from the non-metro location. Although this remote sourcing displaces production activities from the metro location, it increases productivity and hence wages, reallocating population from non-metro to metro areas. Therefore a key prediction of the model is that reductions in communication costs increase both the interactiveness and population of metro areas relative to non-metro areas.

2.1 Preferences and Endowments

The economy consists of two locations (metro ($M$) and non-metro ($N$)) and a single final goods sector. Each location $j \in \{M, N\}$ is endowed with an inelastic supply of land ($H_j$). The economy as a whole is endowed with an inelastic supply of workers ($L$) who are perfectly mobile across locations. The representative consumer’s preferences in location $j$ are defined over the consumption of the homogeneous final good ($C_j$) and residential land use ($H_j$):

$$U_j = C_j^\alpha H_j^{1-\alpha}, \quad 0 < \alpha < 1.$$

We assume that the final good is costlessly traded and choose it as our numeraire, such that $p_M = p_N = 1$. Expenditure on residential land in each location is redistributed lump-sum to residents of that location, as in Helpman (1998). Therefore total income in each location equals payments to labor used in production.

\[\text{In the working paper version of this paper, we considered a multi-region version of the model that incorporates stochastic productivity draws following Eaton and Kortum (2002). To reveal the central economic mechanism in the model, we focus here instead on this simpler specification of the model.}\]

\[\text{For empirical evidence using U.S. data in support of the constant expenditure share implied by the Cobb-Douglas functional form, see Davis and Ortalo-Magne (2011).}\]
plus expenditure on residential land:

\[ v_j L_j = w_j L_j + (1 - \alpha) v_j L_j = \frac{w_j L_j}{\alpha}, \]  

(1)

where \( L_j \) is the population of location \( j \), \( v_j \) is its per capita income and \( w_j \) is its wage. Equilibrium land rents in each location \( (r_j) \) are determined by land market clearing. Using utility maximization and income (1) in land market clearing, we obtain equilibrium land rents as a function of wages and population:

\[ r_j = \frac{1 - \alpha}{\alpha} \frac{w_j L_j}{H_j}. \]  

(2)

### 2.2 Production

Production occurs under conditions of perfect competition and constant returns to scale. The final good is produced from a continuum of tasks \( i \in [0, 1] \) using a Leontief technology:

\[ y_j = \min_{i \in [0, 1]} \{ x_j(i) \} \cdot \rho \]  

(3)

Tasks are produced with labor according to a linear technology:\(^4\)

\[ l_j(i) = a_j(i) x_j(i). \]

Tasks can be remotely sourced from another location subject to communication costs that depend on the interactiveness of the task. When firms in location \( j \) remotely source a task \( i \) from location \( k \), they use their own production technology with unit labor requirement \( a_j(i) \), but incur an additional communication cost of \( \beta t(i) \). The amount of region \( k \) labor required to perform task \( i \) for a firm in location \( j \) is therefore:

\[ l_k(i) = \beta t(i) a_j(i) x_j(i), \quad k \neq j, \]

where \( \beta \) parameterizes the overall level of communication costs and \( t(i) \) captures differences in communication costs across tasks. We index tasks such that higher values of \( i \) correspond to more interactive tasks characterized by higher communication costs:\(^5\)

\[ t'(i) > 0. \]

\(^4\)While for simplicity we assume a single type of worker that can produce any task, the model could be extended to incorporate heterogeneous workers that differ in terms of their comparative advantage for producing different tasks (e.g. depending on their education or human capital).

\(^5\)Although we model remote sourcing as occurring intra-nationally across locations within a country, it could also occur internationally. As long as remote sourcing eliminates a larger range of less interactive tasks in high-wage locations than in low-wage locations, it will have similar qualitative predictions for changes in the task composition of employment in metro and non-metro areas, whether it occurs intra-nationally or internationally.
2.3 Remote Sourcing Decision

As communication costs fall from their autarky values ($\beta \to \infty$) to finite values ($0 < \beta < \infty$), it becomes possible to remote source tasks from lower-wage locations. We focus on parameter values for which there is an interior equilibrium, in which both regions are populated and produce the final good. We assume that the metro area has higher productivity than the non-metro area ($a_M(i) < a_N(i)$ for all $i$), which results in equilibrium in higher metro wages and population.\(^6\) Since remote sourcing is costly, it is only undertaken by firms in the higher-wage metro area to take advantage of lower wages in the non-metro area.\(^7\) In an interior equilibrium in which some tasks are remote sourced, the marginal remote-sourced task ($I$) satisfies the following indifference condition:

$$w_M = \beta t(I) w_N. \quad (4)$$

The zero-profit condition for the final good to be produced in the metro area requires that price equals unit cost:

$$1 \leq w_M \int_I^1 a_M(i) di + w_N \int_0^I \beta t(i) a_N(i) di,$$

which using the indifference condition (4) can be re-written as:

$$1 \leq w_M \Omega_M(I), \quad \Omega_M(I) = \int_I^1 a_M(i) di + \frac{\int_0^I t(i) a_N(i) di}{t(I)}. \quad (5)$$

In the special case in which no remote sourcing occurs, the metro-area zero-profit condition reduces to $1 \leq w_M \int_0^1 a_M(i) di$. Since metro area firms only remote source tasks if production costs are lower in the non-metro area, $\Omega_M(I) \leq \int_0^1 a_M(i) di$. Therefore remote sourcing affects the metro area zero-profit condition (5) in the same way as an increase in metro area productivity. The corresponding zero-profit condition for final goods production in the non-metro area is:

$$1 \leq w_N \Omega_N, \quad \Omega_N = \int_0^1 a_N(i) di. \quad (6)$$

Using the zero-profit conditions for both the metro and non-metro areas, the indifference condition for the marginal remote-sourced task (4) can be written solely in terms of $I$:

$$\beta t(I) = \frac{\Omega_N}{\Omega_M(I)}. \quad (7)$$

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6 While we do not take a stand on the source of the higher productivity in the metro area, a natural explanation is agglomeration economies. Introducing these agglomeration economies into the model is straightforward and would introduce the possibility of multiple equilibria, in which either region could be the metro or non-metro area.

7 While we focus on parameter values for which there is an incomplete specialization equilibrium, there are parameter values for which a complete specialization equilibrium exists. In such a complete specialization equilibrium, the more productive region produces the final good and more interactive tasks, while the less productive region specializes completely in less interactive tasks. The properties of this complete specialization equilibrium are similar to those of the incomplete specialization equilibrium considered here: falls in communication costs induce the metro area to specialize in more interactive tasks.
**Proposition 1** There exists a unique marginal remote-sourced task \( \hat{I} \in (0, 1) \) for parameter values satisfying the following condition for an interior equilibrium:

\[
\beta t(0) \int_0^1 a_M(i) \, di < \int_0^1 a_N(i) \, di < \beta \int_0^1 t(i) a_M(i) \, di.
\]

**Proof.** See the web appendix.  ■

Having determined the marginal remote-sourced task, relative wages follow immediately from the indifference condition (4):

\[
\frac{w_M}{w_N} = \beta t(I).
\]  (8)

Since \( t(I) \) is increasing in \( I \), it follows that wages in the metro area relative to the non-metro area (8) are increasing in \( I \). Intuitively, the ability to remote source tasks increases productivity in metro areas, which raises wages in metro areas relative to non-metro areas. The levels of wages in each location \( \{w_M, w_N\} \) follow from the metro and non-metro zero-profit conditions, (5) and (6) respectively.

Using the condition for the marginal remote-sourced task (7), we can now characterize the impact of a reduction in communication costs (\( \beta \)) on the task composition of employment.

**Proposition 2** A reduction in communication costs from their autarkic values (\( \beta \to \infty \)) to finite values (0 < \( \beta \) < \( \infty \)) concentrates metro area employment in interactive tasks (\( I > 0 \)).

**Proof.** See the web appendix.  ■

For sufficiently high communication costs (\( \beta \to \infty \)), no tasks are remote sourced. As a result, the distribution of employment across tasks of different levels of interactiveness is determined solely by unit labor requirements in the metro and non-metro areas. Hence, for similar relative unit labor requirements across tasks, workers in the metro and the non-metro areas are employed in tasks with similar levels of interactiveness. As communication costs fall to finite values (0 < \( \beta \) < \( \infty \)), firms in the higher-wage metro area remote source less interactive tasks from the lower-wage non-metro area (\( I > 0 \)), which concentrates metro area employment in more interactive tasks. Since this remote sourcing increases productivity in the metro area, it also increases relative metro area wages \( (w_M/w_N) \), as can be seen from the indifference condition for the marginal remote-sourced task (since \( t(I) \) is an increasing function).\(^8\)

### 2.4 Population Mobility

Population mobility implies that workers receive the same real income in all populated locations

\[
V_j = \frac{v_j}{v_j^{1-\alpha}} = V_k, \quad k \neq j,
\]  (9)

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\(^8\)While in the model and our empirical work we focus on improvements in communication technology, innovations in transport technology could also facilitate the remote sourcing of tasks by making it easier to trade intermediate inputs that embody these tasks. When we provide evidence below on communication technology, we include controls for transport technology.
where we have used our choice of numeraire \((p_j = 1)\).

Using the land market clearing condition (2) in the population mobility condition (9) and invoking labor market clearing, the equilibrium population of each location can be determined as a function of relative wages and the relative supply of land:

\[
\left( \frac{w_M}{w_N} \right)^\alpha \left( \frac{\bar{H}_M}{\bar{H}_N} \right)^{1-\alpha} = \left( \frac{L_M}{L - L_M} \right)^{1-\alpha}, \quad L_N = L - L_M. \tag{10}
\]

Since a fall in communication costs increases the relative metro area wage \((w_M/w_N)\), it also increases the relative metro area population \((L_M/L_N)\) in the population mobility condition (10). Furthermore, a rise in both relative metro area wages \((w_M/w_N)\) and population \((L_M/L_N)\) in turn implies a rise in relative metro area land prices \((r_M/r_N)\) from land market clearing (2). Therefore, even though remote sourcing displaces a range of tasks from the metro area to the non-metro area, it increases the population of the metro area relative to the non-metro area. The reason is that the ability to remote source low interactiveness tasks increases metro area productivity, which raises relative wages and attracts population until land rents are bid up to restore real wage equalization. We summarize this additional comparative static as follows.

**Proposition 3** A reduction in communication costs from their autarkic values \((\beta \to \infty)\) to finite values \((0 < \beta < \infty)\) increases the population of the metro area relative to the non-metro area \((L_M/L_N\) rises).

**Proof.** The proposition follows immediately from Proposition 2 and the population mobility condition (10).

The model also highlights that reductions in communication costs \((\beta \downarrow)\) have quite different effects from common reductions in production costs for all locations \((a_j (i) \downarrow\) for some \(i\) and for all \(j \in \{M, N\}\)). Reductions in communication costs induce remote sourcing and generate differences in task specialization across locations: the metro area specializes in more interactive tasks, while the non-metro area specializes in less interactive tasks. As a result, the interactiveness of employment in metro areas increases relative to that in non-metro areas. In contrast, common reductions in production costs for low interactiveness tasks relative to high interactiveness tasks shift the composition of employment towards more interactive tasks in both locations.

We use these predictions of the model to interpret our empirical results below. Secular changes in the interactiveness of employment in both metro and non-metro areas can be explained by common changes in production technology that are non-neutral across production tasks. In contrast, improvements in communication technology increase the interactiveness of employment in metro areas relative to non-metro areas. In our empirical analysis below, we provide evidence on the evolution of the task composition of employment in urban and rural areas over time, and the extent to which it is indeed related to improvements in communication technology.
3 Data Description

Our empirical analysis uses two main sources of data. The first is individual-level records from the U.S. Population Census for twenty-year intervals from 1880-2000 from Integrated Public Use Microdata Series (IPUMS): see Ruggles et al. (2010). These census micro data report individuals’ location, occupation and sector, as well as other demographic information. We use these data to determine whether an individual is located in a metro area as well as the occupation and sector in which an individual is employed.9 We weight individuals by their person weights to ensure the representativeness of the sample. Our main dataset is a panel from 1880-2000 that uses information on the share of employment within an occupation and sector in metro areas, for which the 1 percent IPUMS samples are representative.

We use the standardized 1950 occupation classification from IPUMS, which distinguishes eleven two-digit occupations (e.g. “Clerical and Kindred”) and 281 three-digit occupations (e.g. “Opticians and Lens Grinders and Polishers”). We also use the standardized 1950 sector classification from IPUMS, which distinguishes twelve two-digit sectors (e.g. “Finance, Insurance and Real Estate”) and 158 three-digit sectors (e.g. “Motor Vehicles and Motor Vehicle Equipment”).10 Since we are concerned with employment structure, we omit workers who do not report an occupation and a sector (e.g. because they are unemployed or out of the labor force). We also exclude workers in agricultural occupations or sectors, because we compare task specialization in urban and rural areas over time, and agriculture is unsurprisingly overwhelmingly located in rural areas.11 While our baseline sample uses time-varying boundaries of metro areas to ensure that these correspond to meaningful economic areas, we also report robustness checks using administrative cities whose boundaries are more stable over time.

Our second main data source is the Dictionary of Occupational Titles (U.S. Department of Labor 1991), which contains detailed descriptions of more than 12,000 occupations. Following Autor et al. (2003), previous research using DOTs typically uses the numerical scores that were constructed for each occupation by the Department of Labor (e.g. a Non-routine Interactive measure based on the Direction, Control and Planning of Activities (DCP) numerical score). In contrast, we use verbs from the detailed occupational descriptions in DOTs to directly measure the tasks performed by workers in each occupation. We use a list of over 3,000 English verbs from “Writing English,” a company that offers English language consulting.12 This approach enables us to provide a detailed analysis of the multiple tasks undertaken by workers within each occupation without being restricted to a single numerical score for each occupation. We match the

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9Metro areas are defined in IPUMS based on Census Bureau Metropolitan Statistical Areas (MSAs).

10See IPUMS for the full concordance between two-digit and three-digit occupations and sectors. While both occupation and sector classifications are standardized by IPUMS, there are a small number of occupations and sectors that enter and exit the sample over time. All our results are robust to restricting attention to occupations and sectors that are present in all years.

11Our key findings, however, are robust to the inclusion of these agricultural workers. For further analysis of the relationship between urbanization and structural transformation away from agriculture, see Michaels et al. (2012).

DOTs occupations to the three-digit occupations in our census data using the crosswalk developed by Autor, Levy and Murnane (2003). In our baseline specification, we use a time-invariant measure of tasks based on the occupational descriptions from the digital edition of the 1991 DOTs, which ensures that our results are not driven by changes in language use over time. In sensitivity checks, we also report results using digitized occupational descriptions from the first edition of the DOTs in 1939 (U.S. Department of Labor 1939).

We complement these two main data sources with information from a variety of other sources. We use the standard reference for word usage in English (Roget’s Thesaurus) to quantify the meanings of verbs from the occupational descriptions.¹³ We use ArcGIS shapefiles from the National Historical Geographical Information System (NHGIS) to track the evolution of county boundaries over time. We also use measures of improvements in transport and communication technologies. We measure the length of roads in each county using a georeferenced 1931 road map (Gallup 1931).¹⁴ At the beginning of our sample in 1880, most U.S. roads were little more than dirt tracks (see, for example, Swift 2011) and widespread paved road construction only occurred following the Federal Aid Road Act of 1916 and the Federal Highway Act of 1921. Therefore we use the 1931 map to construct a measure of the growth of the paved road network from 1880-1930. We measure the number of residence telephones in each county in 1935 using newly-digitized data from American Telephone and Telegraph Company (AT&T 1935). The telephone was not patented until 1876 just before the beginning of our sample period and the telephone network developed rapidly from 1890 onwards (see, for example, Fischer 1992). Therefore we use the data on telephones to construct a measure of the growth of telephones from 1880-1930. To address the concern that the road network could be influenced by changes in the interactiveness of economic activity, we use an instrument based on the “Pershing” map of highway routes of military importance for coastal and border defense. To address similar concerns for the telephone, we use an instrument based on proximity to primary and secondary outlets on AT&T’s long distance trunk network, whose construction was influenced by the strategic objective of connecting the nation as a whole.

4 Specialization Across Occupations and Sectors

We begin by providing some motivating evidence of changes in specialization across occupations and sectors in metro areas relative to non-metro areas. To do so, we estimate the following regression for each year $t$ separately using data across occupations $o$ and sectors $s$:

$$ MetroShare_{ost} = \mu_{ot} + \eta_{st} + \varepsilon_{ost}, $$

¹³We use the online computer-searchable edition of Roget (1911): http://machaut.uchicago.edu/rogets.
¹⁴Recent economics research on the U.S. road network has largely concentrated on the later development of the interstate highway system, as in Baum-Snow (2007), Michaels (2008) and Duranton and Turner (2012).
where $\text{MetroShare}_{ost}$ is the share of employment in metro areas in occupation $o$, sector $s$ and year $t$; observations are weighted by person weights; $\mu_{ot}$ are occupation-year fixed effects; $\eta_{st}$ are sector-year fixed effects; and $\varepsilon_{ost}$ is a stochastic error. We normalize the sector-year and occupation-year fixed effects so that they each sum to zero in each year, and hence they capture deviations from the overall mean in each year. We estimate the above regression using a share as the left-hand side variable so that the estimated coefficients have a natural interpretation as frequencies. We also find a very similar pattern of results in a robustness test in which we use a logistic transformation of the left-hand side variable: $\text{MetroShare}_{ost}/(1 - \text{MetroShare}_{ost})$.

The occupation-year fixed effects ($\mu_{ot}$) capture the average probability of being in a metro area for workers in each occupation in each year, after controlling for differences across sectors in metro probabilities. Similarly, the sector-year fixed effects ($\eta_{st}$) capture the average probability of being located in a metro area for workers in each sector in each year, after controlling for differences across occupations in metro probabilities. The sector and occupation fixed effects are separately identified because there is substantial overlap in occupations and sectors, such that each sector contains multiple occupations and each occupation is employed in several sectors.\footnote{The average three-digit sector employs workers from 111 three-digit occupations, while the average three-digit occupation contains workers employed in 81 sectors.} We estimate this regression using both the aggregate (two-digit) and disaggregate (three-digit) definitions of occupations and sectors discussed above.

As reported in Table 1 for two-digit occupations and sectors, we find substantial changes in specialization across occupations and sectors in metro areas relative to non-metro areas over time. From Panel A, in 1880, “Clerical and Kindred” workers were the most likely to be located in metro areas. In contrast, by 2000, “Clerical and Kindred” workers were ranked only fourth, and “Professional and Technical” workers were the most likely to be located in metro areas. From 1880-2000, declines in ranks were observed for “Craftsmen” (from 2 to 6) and “Operatives” (from 3 to 7), while increases in ranks were observed for “Professional and Technical” workers (from 7 to 1) and “Managers, Officials and Proprietors” (from 6 to 3). As apparent from the first and fourth columns of the table, these changes in ranks reflect substantial changes in the probabilities of workers in individual occupations being located in metro areas over time.

Since the regression (11) includes sector-year fixed effects, these changes in the metro probabilities for each occupation are not driven by changes in sector composition, but rather reflect changes in the organization of economic activity within sectors. Nonetheless, we also observe substantial changes in sector structure in metro areas relative to non-metro areas over time. From Panel B, declines in ranks from 1880-2000 were observed for “Wholesale and Retail Trade” (from 2 to 6) and “Manufacturing” (from 4 to 10). In contrast, increases in ranks from 1880-2000 were observed for “Transportation, Communication and Other Utilities” (from 6 to 3) and “Business and Repair Services” (from 9 to 1).

In Figures A1 and A2 of the web appendix, we show the evolution of the occupation and sector coefficients across each of the twenty-year intervals in our data. While “Professional and Technical” workers
display an increased propensity to locate in metro areas from 1880-1960, the probability that “Managers, Officials and Proprietors” are located in urban areas increases particularly sharply from 1940-2000. In contrast, the likelihood that “Craftsmen” are found in metro areas declines throughout our sample period, while the probability for “Clerical and Kindred” workers declines from 1900 onwards, and the probability for “Service” workers initially rises until 1920 and later declines until around 1960.

Such changes in specialization are not limited to the aggregate categories considered so far, but are also found using more disaggregated measures of occupations and sectors. In Table A1 of the web appendix, we report the results of estimating the regression (11) including three-digit-occupation-year and three-digit-sector-year fixed effects. Panels A and B report the twenty occupations within the largest increases and decreases respectively in the within-sector probability of being located in a metro area from 1880-2000. Both the top agglomerating occupations in Panel A and the top dispersing occupations in Panel B are diverse and span multiple sectors. For example, the top agglomerating occupations include “Editors and Reporters”, “Judges and Lawyers” and “Pattern and Model Makers,” while the top dispersing occupations contain “Office Machine Operators” and “Upholsterers.” In our empirical analysis below, we measure the multiple tasks undertaken by workers within each occupation, and provide evidence on the systematic characteristics shared by occupations that agglomerate versus disperse over time.

5 Measuring the Tasks Undertaken Within Occupations

To measure the tasks undertaken by workers in each occupation, we use the detailed descriptions of more than 12,000 disaggregated occupations included in the DOTs. We use the verbs from each occupation’s description to measure the tasks performed by workers within that occupation, because verbs capture an action (bring, read, walk, run, learn), an occurrence (happen, become), or a state of being (be, exist, stand), and hence capture the task being performed. To focus on persistent characteristics of occupations and abstract from changes in word use over time, our baseline analysis uses time-invariant occupational descriptions from the 1991 digital edition of the DOTs. While the tasks undertaken within each occupation can change over time, the relative task content of occupations is likely to be more stable. To provide evidence on the extent to which this is the case, we have also digitized the occupational descriptions from the first edition of the DOTs in 1939. Although the descriptions of occupations are less detailed in the historical DOTs, we find a similar pattern of results using both sets of occupational descriptions and provide evidence below on the correlation of the relative task content of occupations over time.

The first step of our procedure uses a list of over 3,000 English verbs from “Writing English,” a company that offers English language consulting. Using this list of verbs, we search each occupational description in the 1991 DOTs for occurrences of each verb in the first-person singular (e.g. (I) talk), third-person singular (e.g. (she) talks) or present participle (e.g. (he is) talking). To take an example from first-hand experience,
the occupational description for an Economist is:

“ECONOMIST: Plans, designs, and conducts research to aid in interpretation of economic relationships and in solution of problems arising from production and distribution of goods and services. Studies economic and statistical data in area of specialization, such as finance, labor, or agriculture. Devises methods and procedures for collecting and processing data, utilizing knowledge of available sources of data and various econometric and sampling techniques. Compiles data relating to research area, such as employment, productivity, and wages and hours. Reviews and analyzes economic data in order to prepare reports detailing results of investigation, and to stay abreast of economic changes...,”

where the words detected by our procedure as capturing the tasks performed by an economist are italicized. Note that sometimes the first-person singular, third-person singular or present participle forms of a verb have the same spelling as the corresponding adjectives and nouns (e.g. “prepare reports”). In this case, our procedure treats these adjectives and nouns as verbs. To the extent that the use of the same word as an adjective or noun is closely related to its use as a verb, both uses are likely to capture the tasks performed.

From this first step, we obtain the number of occurrences of each verb for each DOTs occupation. We next match the more than 12,000 DOTs occupations to IPUMS standardized 1950 occupations using the crosswalk developed by Autor, Levy and Murnane (2003). Finally, we calculate the frequency with which each verb \( v \) is used for each IPUMS occupation \( o \):

\[
\text{VerbFreq}_{vo} = \frac{\text{Appearances of verb } v \text{ matched to } o}{\text{Appearances of all verbs matched to } o},
\]

where we focus on the frequency rather than the number of verb uses to capture the relative importance of tasks for an occupation and to control for potential variation in the length of the occupational descriptions matched to each IPUMS occupation.

We provide evidence on changes in task specialization in metro areas relative to non-metro areas over time by estimating the following regression for each verb \( v \) and year \( t \) separately using data across occupations \( o \) and sectors \( s \):

\[
\text{MetroShare}_{ost} = \alpha_{vt} \text{VerbFreq}_{vo} + \eta_{vst} + \varepsilon_{ost},
\]

where \( \text{MetroShare}_{ost} \) is again the share of employment in metro areas in occupation \( o \), sector \( s \) and year \( t \); \( \text{VerbFreq}_{vo} \) is defined above for verb \( v \) and occupation \( o \); \( \eta_{vst} \) are verb-sector-year fixed effects; and \( \varepsilon_{ost} \) is a stochastic error.

The coefficient of interest \( \alpha_{vt} \) captures a conditional correlation: the correlation between occupations’ shares of employment in metro areas and their frequency of use of verb \( v \). The verb-sector-year fixed effects

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16 As an indication of the wide coverage of our list of over 3,000 verbs, only 1,830 of these verbs appear in the 1991 DOTs occupational descriptions.
control for differences across sectors in the frequency of verb use and for differences across sectors and over time in the concentration of employment in metro areas. Since VerbFreq_{v0} is time invariant, a rise in \( \alpha_{vt} \) over time implies that employment in occupations using that verb is increasingly concentrating in metro areas within sectors over time.

In Panels A and B of Table 2, we report for each year the ten verbs with the highest and lowest standardized coefficient \( \alpha_{vt} \) (the estimated coefficient multiplied by the standard deviation of VerbFreq_{v0}).\(^{17}\) As apparent from Panel A, we find substantial changes in the tasks most concentrated in metro areas within sectors over time. In 1880, the verbs with the highest metro employment shares typically involve physical tasks such as “Braid,” “Sew,” “Stretch” and “Thread.” By 1920, the top ten verbs include an increased number of clerical tasks, such as “Bill,” “File,” “Notice,” and “Record.” By 1980 and 2000, the leading metro verbs include a proliferation of interactive tasks, such as “Analyze,” “Advise,” “Confer” and “Report.” As shown in Panel B, we also find some changes in the tasks least concentrated in metro areas, although here the pattern is less clear cut (e.g. “Tread” appears from 1880-1960 and “Turn” appears from 1960-2000).

6 Quantifying Task Specialization

The approach developed in the previous section allows us to provide a detailed characterization of the tasks performed in urban and rural areas using the 3,000 verbs and 12,000 occupational descriptions. In this section, we use the meanings of these verbs to quantify the way in which the task composition of employment has evolved over time. In particular, we use the online computer-searchable version of Roget’s Thesaurus (1911), which has been the standard reference for English language use for more than a century and explicitly classifies words according to their underlying concepts and meanings. Roget’s classification was inspired by natural history, with its hierarchy of Phyla, Classes, Orders and Families. Therefore words are grouped according to progressively more disaggregated classifications that capture ever more subtle variations in meaning. A key advantage of this classification is that it explicitly takes into account that words can have different meanings depending on context by including extensive cross-references to link related groups of words.\(^{18}\)

Roget’s Thesaurus is organized into six “Classes” that are further disaggregated into the progressively finer subdivisions of “Divisions,” “Sections” and “Categories.” The first three classes cover the external world: Class I (Abstract Relations) deals with ideas such as number, order and time; Class II (Space) is concerned with movement, shapes and sizes; and Class III (Matter) covers the physical world and mankind’s perception of it by means of the five senses. The last three classes relate to the internal world of human beings: the human mind (Class IV, Intellect), the human will (Class V, Volition) and the human

\(^{17}\)We find a similar pattern of results just using the estimated coefficients instead of the estimated coefficients times the standard deviation of VerbFreq_{v0}.

\(^{18}\)For further discussion of the genesis of Roget’s Thesaurus, see for example Hüllen (2003).
heart and soul (Class VI, Emotion, Religion and Morality).

To characterize the meaning of each verb $v$, we use the frequency with which it appears in each subdivision $k$ of Roget’s Thesaurus:

$$\text{ThesFreq}_{vk} = \frac{\text{Appearances of verb } v \text{ in subdivision } k \text{ of thesaurus}}{\text{Total appearances of verb } v \text{ in thesaurus}},$$

(13)

where our use of a frequency takes into account that each verb can have multiple meanings and provides a measure of the relative importance of each meaning. In counting the appearances of verbs we make use of the thesaurus’s structure, in which words with similar meanings appear under each thesaurus Category in a list separated by commas or semi-colons. Based on this structure, we count appearances of a verb that are followed by a comma or semi-colon, which enables us to abstract from appearances of a word in idioms that do not reflect its common usage.\(^{19}\)

Combining the frequency with which a verb appears in each occupation’s description (VerbFreq$_{vo}$ in the previous section) and the frequency with which the verb appears in each subdivision of the thesaurus (ThesFreq$_{vk}$), we construct a quantitative measure of the extent to which the tasks performed in an occupation involve the concepts from each thesaurus subdivision:

$$\text{TaskContent}_{ko} = \sum_{v \in V} \text{VerbFreq}_{vo} \times \text{ThesFreq}_{vk}.$$

We use this measure to examine changes in task specialization in metro areas relative to non-metro areas over time by estimating an analogous regression for each thesaurus subdivision $k$ and year $t$ as for each verb and year in the previous section:

$$\text{MetroShare}_{ost} = \beta_{kt}\text{TaskContent}_{ko} + \eta_{kst} + \varepsilon_{ost},$$

(14)

where $\text{MetroShare}_{ost}$ is the share of employment in metro areas in occupation $o$, sector $s$ and year $t$; TaskContent$_{ko}$ is defined above for thesaurus subdivision $k$ and occupation $o$; $\eta_{kst}$ are thesaurus-subdivision-sector-year fixed effects; and $\varepsilon_{ost}$ is a stochastic error.

The coefficient of interest $\beta_{kt}$ again captures a conditional correlation: the correlation between occupations’ shares of employment in metro areas and their frequency of use of verbs in the thesaurus subdivision $k$. The thesaurus-subdivision-sector-year fixed effects ($\eta_{kst}$) control for differences across sectors in the frequency of use of thesaurus subdivisions and differences across sectors and over time in the concentration of employment in metro areas. Since TaskContent$_{ko}$ is time invariant, a rise in $\beta_{kt}$ over time implies that employment in occupations using that subdivision of the thesaurus is increasingly concentrating in metro areas within sectors over time.

\(^{19}\)For example, the verb “Consult” appears in six thesaurus Categories. The entry followed by a comma is 695 Advice, which captures the word’s meaning. Entries not followed by a comma correspond to idiomatic uses not closely related to the word’s meaning: 133 Lateness (“consult one’s pillow”); 463 Experiment (“consult the barometer”); 707 Aid (“consult the wishes of”); 943 Selfishness (“consult one’s own pleasure”); 968 Lawyer (“juris consult [Latin]”).
In Table 3, we report the estimation results for the thirty-eight Sections of the thesaurus. We calculate the standardized coefficient for each Section of the thesaurus (the estimated coefficient $\beta_{kt}$ multiplied by the variable's standard deviation) and report the ranking of these standardized coefficients in 1880 and 2000 as well the difference in rankings between these two years (1880 minus 2000). Since the thesaurus Section with the highest standardized coefficient is assigned a rank of one, positive differences in rankings correspond to thesaurus categories that are becoming more concentrated in metro areas within sectors over time. The table highlights the top-five thesaurus Sections in 1880 in bold-italics and the top-five thesaurus Sections in 2000 in bold.

The results in Table 3 reveal a sharp change the relative ranking of thesaurus Sections involving the external world (Classes I-III) and those involving the internal world of human beings (Classes IV-VI). In 1880, the top-five thesaurus Sections most concentrated in metro areas were: Quantity (Class I), Time (Class I), Matter in General (Class III), Dimensions (Class II), and Inorganic Matter (Class III). In contrast, in 2000, the top-five thesaurus Sections were: Results of Reasoning (Class IV), Means of Communicating Ideas (Class V), Moral Affections (Class VI), Voluntary Action (Class IV) and Precursory Conditions and Operations (Class IV). The correlation between the rankings of the thesaurus sections in 1880 and 2000 is negative and statistically significant (-0.43).

This approach of using the Thesaurus Sections to capture the meanings of verbs enables us to characterize non-parametrically the way in which in the task composition of employment in metro and non-metro areas has changed over time. We find that positive changes in ranks in Table 3 are typically concentrated in thesaurus Classes IV and V, which includes Class IV, Division 1 (Formation of Ideas), Class IV, Division 2 (Communication of Ideas) and Class V, Division 2 (Intersocial Volition). Therefore the positive changes in ranks reflect an increased concentration of tasks involving thought, communication and intersocial activity in metro areas.

We define this combination of thought, communication and intersocial activity as “interactiveness.” An example of such interaction is a business meeting, presentation, seminar or conference. Each of these examples involves the creation and manipulation of ideas (thought), the expression of these potentially complex ideas (communication), and the understanding of these potentially difficult ideas by others (intersocial activity). We do not exclude some ideas being generated in isolation or some communication occurring without intersocial activity (e.g. in the form of written media such as memos and publications). But much knowledge is tacit and hard to codify; the understanding of complex ideas often requires considerable bandwidth and two-way dialogue; and face-to-face interactions can be important in conveying subtleties of emphasis and meaning. While innovations in communication technology such as the telephone and the internet can be important in reducing the costs of communicating at a distance, it remains the case that consider-

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20 Again we find a similar pattern of results using just the estimated coefficient instead of the estimated coefficient times the standard deviation of TaskContent_{ko}. 

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able amounts of time and other resources are devoted by businesses and other organizations to bringing individuals together to interact with one another.

We construct our baseline measure of the overall interactiveness of an occupation based on the frequency with which verbs appear in that occupation’s description and the frequency with which those verbs appear in Classes IV and V of the thesaurus (which includes the formation of ideas, the communication of ideas and intersocial volition as discussed above):

$$\text{Interactive}_o = \sum_{v \in V} \text{FreqVerb}_{vo} \times \text{FreqInteractive}_v,$$  

where $\text{FreqVerb}_{vo}$ is the frequency with which verb $v$ is used for occupation $o$ from above; $\text{FreqInteractive}_v$ is the frequency with which verb $v$ appears in thesaurus Classes IV and V (computed as in (13)). We also report results below for the separate components of interactiveness – thought (Class IV, Division 1), communication (Class IV, Division 2) and intersocial activity (Class V, Division 2) – and show that all three components play an important role. Finally, we compare our measure of the interactiveness of occupations based on the meanings of verbs to separate independent measures, as discussed further in subsection 7.4 below.

In Panels A and B of Table 4, we report the top ten and bottom ten interactive occupations based on our measure. While any single quantitative measure of interactiveness is unlikely to fully capture the meaning of this concept, the occupations identified by our procedure as having high and low levels of interactiveness appear intuitive. Interactive tasks are arguably more central to the set of tasks performed by “Buyers and Department Heads”, “Clergymen” and “Pharmacists” than they are to the set of tasks performed by “Blasters and Powdermen”, “Roofers and Slaters” and “Welders and Flame Cutters.” Note that each occupation is likely to perform some interactive tasks: for example, “Roofers and Slaters” can negotiate with clients and liaise with architects. A key advantage of our measure is that it captures the relative importance of interactive tasks compared to all other tasks performed by workers within an occupation, because it equals the frequency with which verbs are used for an occupation multiplied by the frequency with which these verbs appear in interactive subdivisions of the thesaurus. For example, while “Roofers and Slaters” can negotiate with clients and liaise with architects (Classes IV and V of the thesaurus), building and repairing roofs (Classes I-III of the thesaurus) is arguably more central to the set of tasks undertaken by workers within this occupation.

In Figure 1, we measure the interactiveness of metro areas, non-metro areas and the economy as a whole using the employment-weighted average of interactiveness for each occupation. In this measure, interactiveness only differs between metro and non-metro areas to the extent that they have different distributions of employment across occupations:

$$\text{Interactive}_{jt} = \sum_{o=1}^{O} \frac{E_{ojt}}{E_{jt}} \text{Interactive}_o, \quad j \in \{M, N\},$$

19
where \( j \) indexes a type of location and we again denote metro areas by \( M \) and non-metro areas by \( N \); \( E_{ojt} \) corresponds to employment in occupation \( o \) in location type \( j \in \{M, N\} \) in year \( t \).

As shown in the figure, metro and non-metro areas have similar levels of interactiveness in 1880. If anything, non-metro areas have higher interactiveness than metro areas. From the early decades of the twentieth century onwards, interactiveness increases in both sets of locations. This increase, however, is larger in metro areas than in non-metro areas, so that by the end of the sample period metro areas are substantially more interactive than non-metro areas.

7 Robustness

Having presented our baseline evidence on task specialization in metro and non-metro areas over time, we now document the robustness of these findings across a large number of different samples and specifications.

7.1 Metro Areas and Administrative Cities

Our analysis has so far used variation between metro and non-metro areas. To provide further evidence of a relative increase in the interactiveness of employment in densely-populated locations, we now present evidence using a different source of variation across metro areas of differing population densities.

In Figure 2, we display mean interactiveness for each metro area (as calculated using (16)) against log population density, as well as the fitted values and confidence intervals from locally-weighted linear least squares regressions. Panels A-C show results for 1880, 1940 and 2000 respectively. To ensure that metro areas correspond to meaningful economic units in each year, we use time-varying definitions of metro areas from IPUMS. Therefore both the boundaries of each metro area and the number of metro areas changes over time. In 1880, we find little relationship between interactiveness and log population density across metro areas, which is reflected in a negative but statistically insignificant OLS coefficient (standard error) of -0.0002 (0.0013). In 1940, the relationship between interactiveness and log population density across metro areas remains relatively flat. In contrast, in 2000, we find a strong positive and statistically significant relationship between interactiveness and log population density, which is reflected in an OLS coefficient (standard error) of 0.0018 (0.0002). We find a similar pattern of results for 2000 if we restrict the sample to 1880 or 1940 metro areas, as shown in Panel D for 1940 metro areas. The magnitude of the difference in interactiveness between metro and non-metro areas in 2000 in Figure 1 is comparable to difference in interactiveness across metro areas of different population densities in 2000 in Figure 2.

Metro areas with relatively high levels of interactiveness conditional on population density in 2000 include Boston and New York, while those with low levels of interactiveness conditional on population density in 2000 include Anniston and Mansfield. These differences in interactiveness across metro area are persistent over time: the correlation coefficient between interactiveness in 1880 and 2000 is 0.52. Metro
area interactiveness is also predictive of subsequent population growth: the correlation coefficient between 1880 interactiveness and 1880-2000 population growth is 0.33.\textsuperscript{21}

As noted above, our baseline specification uses time-varying definitions of metro areas to ensure that they correspond to meaningful economic units in each year. One potential concern is that the change in the relative interactiveness of metro areas could be driven by a change in the geographical boundaries of metro areas as they have expanded to include surrounding suburbs. To address this concern, we replicated our analysis using an alternative definition of urban areas as administrative cities, which have much more stable geographical boundaries over time. Again we find an increase in the relative interactiveness of urban areas over time, whether we compare administrative cities to all other locations (Figure A4 in the web appendix) or only to non-metro areas (Figure A5 in the web appendix). We also find an increased positive relationship over time between interactiveness and population density across administrative cities of different sizes. Therefore our findings of an increase in the relative interactiveness of employment in more-densely-populated locations reflect a change in the organization of economic activity within existing geographical boundaries.

### 7.2 Other Interactiveness Measures

Our approach of using verbs from the occupational descriptions enables us to measure the multiple tasks undertaken by workers within each occupation and to construct a measure of the interactiveness of occupations based on the meanings of these verbs. In this section, we compare this measure to independently-constructed interactiveness measures.

In Table A3 of the web appendix, we report the correlation across occupations between our interactiveness measure and seventeen subcategories of the Occupational Information Network (O*NET) work activity “Interacting with Others.” These measures were constructed by US Department of Labor/Employment and Training Administration (USDOL/ETA) based on questionnaires about detailed work activities issued to a random sample of businesses and workers. Panel A reports unweighted correlations, while Panel B reports correlations weighted by employment. The measures cover a wide range of forms of interaction, including “Assisting and caring for others” and “Resolving conflict and negotiating with others.”

We find that all of the correlations with our measure of interactiveness are positive and statistically significant. The five categories with the highest unweighted correlations correspond closely to activities involving thought, communication and intersocial activity: “Interpreting the meaning of information for others,” “Provide consultation and advice to others,” “Resolving conflict and negotiating with others,” “Establishing and maintaining interpersonal relationships” and “Performing administrative activities.” These positive correlations provide external validation that our measure of interactiveness based on the meaning

\textsuperscript{21}We find similar patterns comparing values in 1940 and 2000.
of verbs is capturing work activities thought to be interactive by businesses and their employees.

Our approach of using the verbs from the occupational descriptions has a number of advantages relative to these alternative measures. It permits an analysis of the multiple tasks undertaken by workers within each occupation (e.g. “Analyze,” “Advise,” “Confer” and “Report”), allows the data to reveal the nature of these tasks through the meanings of the verbs (without imposing a prior measure of a single occupational characteristic on the data), and can be undertaken using both historical and contemporary occupational definitions (rather than being restricted to contemporary measures).

7.3 1939 DOTs

Our baseline specification measures the task content of employment using time-invariant occupational descriptions from the 1991 DOTs. While this approach ensures that our findings are not driven by changes in language use over time, it assumes that the relative task content of occupations is persistent over time. One concern is that the interactiveness of occupations could have changed over time and these changes in interactiveness could be correlated with occupations’ shares of employment in metro areas.

To address this concern, we replicated our analysis using the first edition of the DOTs from 1939. We digitized the more than 12,000 occupational descriptions in the 1939 DOTs and implemented our procedure of searching for verbs in each occupational description. The occupational descriptions are less detailed in the 1939 DOTs, which implies that the resulting measures of the task content of employment are likely to be less precise than those using the 1991 DOTs. Nonetheless, as reported in Table A2 of the web appendix, we find similar changes in task specialization in this robustness test. The verbs most correlated with metro employment shares in 1880 include physical tasks such as “Slot,” “Thread,” “Straighten” and “Stitch.” In contrast, the verbs most correlated with metro employment shares in 2000 include interactive tasks such as “Advise,” “Present,” “Question” and “Report.”

Using the verbs from the 1939 occupational descriptions and the frequency with which these verbs appear in Classes IV and V of the thesaurus, we again find increase in the interactiveness of employment over time that is more rapid in metro areas than in non-metro areas, as shown in Figure A3 in the web appendix. This similarity of the results using both the 1939 and 1991 occupational descriptions suggests that our findings are unlikely to be driven by changes in the relative interactiveness of occupations over time. Indeed, although the layout of the occupational descriptions implies that our measure of interactiveness using the 1939 DOTs is less precise than our baseline measure using the 1991 DOTs (which by itself would induce an imperfect correlation), we find that they are positively and statistically significantly correlated. As reported in Table A4 of the web appendix, the unweighted correlation coefficient between the 1939 and 1991 measures across the sample of occupations in 2000 is 0.622.
7.4 Other Occupational Characteristics

In Table A4 of the web appendix, we also examine the correlation between our interactiveness measure and other occupation characteristics. We consider the five numerical scores for each occupation from the 1991 DOTs that were constructed by the Department of Labor and used by Autor, Levy and Murnane (2003). We find that our interactiveness measure has a negative or statistically insignificant correlation with Routine Cognitive (STS), Routine Manual (FINGER) and Nonroutine Manual (EHF). We find positive and statistically significant correlations for Non-routine Interactive (DCP) and Non-routine Analytic (GED-MATH). While both of these measures are related to the concepts of thought, communication and intersocial activity captured by our interactiveness measure, the correlations are around 0.5. Therefore our interactiveness measure captures distinctive information about the tasks performed by workers within occupations. While DCP is orientated towards top-down interactions between workers (e.g. between a manager and her subordinates), our measure captures all interactions between workers (e.g. between members of a product design team). While GED-MATH is orientated towards thought, our measure of interactiveness also captures communication and intersocial activity.

In Figure A6 in the web appendix, we show the relationship across occupations between our interactiveness measure and a measure of education based on the share of workers with a college degree. We display this relationship for each year in our sample after 1940 (the first year for which education information is available in our data). Although there is a positive correlation between our interactiveness measure and college education, high-interaction occupations can have both low and high levels of education. Repeating the analysis in Figure 1 and graphing mean interactiveness in metro and non-metro areas for low-education occupations only (those with a college-educated share of less than 0.2 in either 1940 or 2000 in Figure A6), we again find an increased interactiveness of employment in metro areas, as shown in Figure A7 of the web appendix. Therefore the concentration of interactive occupations in metro areas not simply capturing a concentration of high-education occupations in metro areas.

Nonetheless the changes in the occupational and educational composition of employment are related in interesting ways. As also shown in Figure A6, the positive correlation between interactiveness and education strengthens over time. Therefore the expansion in the share of college-educated workers is non-neutral across occupations and is more concentrated in high-interactiveness occupations. The growth in the college-educated share is also concentrated in metro areas and we find an important interaction between metro areas and interactive occupations. Between 1940 and 2000, the difference in the college-educated share between metro and non-metro areas increases from 1 to 11 percentage points, with 74 percent of this increase concentrated in occupations with above-median levels of interactiveness. Therefore changes in the interactiveness of employment in metro and non-metro areas play an important role in understanding human capital differences between cities and the growth in levels of human capital over time. The increase in
interactiveness, however, is not simply capturing an increase in human capital, because as shown above we find an increased concentration of interactive occupations in metro areas even in occupations that continue to have low levels of college education at the end of our sample period.

8 Explaining Changes in Interactiveness

Having demonstrated the robustness of the increase in the relative interactiveness of metro areas across a number of different samples and specifications, we now provide further evidence on explanations for the observed change in interactiveness. First, we decompose the overall change in interactiveness into the contributions of individual occupations and sectors, which enables us to explore explanations that emphasize particular occupations and sectors. Second, we report regression specifications using variation in interactiveness between sectors, within sectors, and within sectors and occupations over time. Using these regressions, we explore the importance of the constituent components of interactiveness (thought, communication and intersocial) and present evidence on a number of potential explanations. Third, we provide direct evidence on the role played by improvements in communication technology.

8.1 Decomposing Interactiveness

We begin by decomposing the change in the overall interactiveness of metro and non-metro areas into the contributions of each two-digit occupation and sector. Overall interactiveness for metro and non-metro areas is the employment-weighted average of interactiveness for each two-digit-sector-occupation cell:

\[
I_{jt} = \sum_{z \in \Omega} \sum_{o \in \Omega_z} \frac{E_{ojt}}{E_{jt}} I_o, \quad j \in \{M, N\},
\]

where \( z \) indexes two-digit-sector-occupation cells; \( o \) indexes disaggregated three-digit occupations within these cells; and \( t \) indexes time; \( \Omega \) is the set of two-digit-sector-occupation cells; \( \Omega_z \) is the set of three-digit occupations within each cell \( z \); the interactiveness of each three-digit occupation is measured using (15) based on the time-invariant occupational descriptions from the 1991 DOTs.

Taking differences between times \( T \) and \( t > T \), the change in the overall interactiveness of metro and non-metro areas can be decomposed as follows:

\[
\triangle I_{jt} = \sum_{z \in \Omega} \sum_{o \in \Omega_z} \left[ \triangle \left( \frac{E_{ojt}}{E_{jt}} \right) \right] I_o, \quad j \in \{M, N\},
\]

where \( \triangle I_{jt} = I_{jt} - I_{jT} \); \( \triangle \left( \frac{E_{ojt}}{E_{jt}} \right) \) is the change in the employment share of occupation \( o \) in location \( j \in \{M, N\} \); and we have used the fact that occupation interactiveness is constant over time. Taking differences again between metro and non-metro areas, we obtain an analogous decomposition of the change.
\begin{equation}
\Delta I_{Mt} - \Delta I_{Nt} = \sum_{z \in \Omega} \sum_{o \in \Omega} \left[ \frac{E_{oMt}}{E_{Mt}} - \frac{E_{oNt}}{E_{Nt}} \right] I_{oz},
\end{equation}

where the right-hand sides of the decompositions (18) and (19) are summations over the contributions from each two-digit-sector-occupation-cell. These contributions correspond to a matrix with two-digit sectors for rows and two-digit occupations for columns, where the right-hand side is a summation across both rows and columns. Metro areas display a larger increase in interactiveness than non-metro areas to the extent that they experience a greater reallocation of employment shares towards high-interactiveness occupations.

Figure 3 summarizes the results from the decompositions of the change in the relative interactiveness of metro and non-metro areas (19). Panels A and B show the contributions for each two-digit occupation (summing across sectors in the rows of the matrix of contributions) for each twenty-year interval in our sample, while Panels C and D show the corresponding contributions for each two-digit sector (summing across occupations in the columns of the matrix of contributions).\textsuperscript{22} Figures A8 and A9 in the web appendix report analogous results from the decompositions of the change in interactiveness for metro and non-metro areas separately (18).

Panels A and B of Figure 3 show that the sharp increase in the relative interactiveness of metro areas from 1880-1920 is largely driven by positive contributions from Clerks (and to a lesser extent Professionals), with Operatives, Sales Workers and Managers all making negative contributions. From 1920-1960, Professionals (and to a lesser but growing extent Managers) make the largest positive contributions, while Craftsmen and Service Workers make negative contributions. From 1960-2000, Professionals and Managers have the largest positive contributions, while Clerks have the largest negative contribution.

Panels C and D of Figure 3 show that Professional and Business services are the two sectors that make the largest contributions to the increase in the relative interactiveness of metro areas over the sample as a whole. Professional Services are more important earlier in the sample period, while Business Services become more important later on. The sector that makes the largest negative contribution over the sample period as a whole is Wholesale and Retail trade, with the absolute magnitude of its contribution diminishing over time. While the contribution from Manufacturing is initially positive (up to 1920), it becomes negative from 1940 onwards.

Taking these decomposition results together, the increase in the relative interactiveness of metro areas is not driven by any one occupation or sector. Our results are not solely explained by Managers (whose contribution only becomes positive towards the end of our sample period). Clerks and Professionals make notable positive contributions towards the beginning and end of our sample period respectively. Our results are also not simply driven by a decline of Manufacturing in urban areas (indeed Manufacturing was

\textsuperscript{22}Since the change in overall interactiveness is the sum across all elements in the matrix, adding the sums for occupations and the sums for sectors would result in double-counting (since each element would be counted twice).
expanding in the early decades of our sample when some of the largest changes in interactiveness were observed). Similarly, our findings are not simply attributable to an expansion of Services in urban areas (indeed Services was a smaller share of employment in the early decades of our sample when some of the largest changes in interactiveness were observed). Instead we find evidence of a pervasive reallocation of employment towards more interactive occupations within sectors.

8.2 Variation Within and Between Sectors

To further explore the determinants of the increase in the relative interactiveness of metro areas, we begin by examining between-sector variation. Sector interactiveness is measured as the employment-weighted mean of the interactiveness of each occupation:

\[
\text{Interactive}_{st} = \sum_o \frac{E_{ost}}{E_{st}} \text{Interactive}_o,
\]

We run a regression across sectors of the share of a sector’s employment in metro areas (MetroShare_{st}) on its interactiveness (Interactive_{st}) for each year separately:

\[
\text{MetroShare}_{st} = \alpha_t \text{Interactive}_{st} + \varepsilon_{st}, \tag{20}
\]

where \(\varepsilon_{st}\) is a stochastic error; \(\alpha_t\) captures the correlation between sectors’ shares of employment in metro areas and their interactiveness in each year. We estimate the above regression and the remaining regressions in this section using a share as the left-hand side variable so that the estimated coefficients have a natural interpretation as frequencies. But we find a very similar pattern of results in a robustness test in which we use a logistic transformation of the left-hand side variable: \(\text{MetroShare}_{st}/(1 - \text{MetroShare}_{st})\).

Panel A of Table 5 reports the results, where each cell in the table corresponds to a separate regression. The first four rows are based on metro employment shares (as in the regression above and shown in parentheses in the table), while the final row is based on metro wage bill shares (as discussed further below and shown in parentheses in the table). From the first row of the table, there is a negative but statistically insignificant correlation between a sector’s metro employment share and its interactiveness in 1880. From 1900 onwards, there is an increase in the correlation between a sector’s metro employment share and its interactiveness, which is particularly sharp from 1900-1940, and becomes positive and statistically significant at conventional critical values in 1960. Therefore more interactive sectors become increasingly concentrated in metro areas over time.

In the second to fourth rows of Panel A of Table 5, we also break out overall interactiveness into thought (Class IV, Division 1), communication (Class IV, Division 2) and intersocial (Class V, Division 2). As shown in the table, we find that the sectors increasingly concentrating in metro areas over time involve each of these components of interactiveness. Therefore the between-sector rise in the interactiveness of employment in metro areas is driven by the combination of thought, communication and intersocial activity.
These changes in patterns of specialization in metro versus non-metro areas are explained in the model by changes in the relative demand for occupations as a result of either differential changes in the relative productivity of occupations or improvements in communication technology. An increase in the relative demand for an occupation raises both its employment and its wage (and hence raises its wagebill). In contrast, an increase in the relative supply of an occupation raises its employment but reduces its wage (and hence reduces its wagebill if the demand for occupations is inelastic). To assess the relative importance of these two explanations, the final row of Panel A of Table 5 reports the results of regressions in which we use the share of the sector’s wagebill in metro areas (rather than its share of employment in metro areas) as the left-hand side variable. Although the wage data are available for a much shorter time period than the employment data, we find a similar pattern of results using this alternative left-hand side variable, which is consistent with relative demand moving relative wagebills and employment in the same direction.

Having established these relationships between sectors, we next examine within-sector variation. We run a regression across sectors and occupations of the share of a sector-occupation’s employment in metro areas (MetroShare\textsubscript{ost}) on occupation interactiveness (Interactive\textsubscript{o}) for each year separately:

$$\text{Metro}_{\text{ost}} = \alpha_t \text{Interactive}_o + \eta_{st} + \varepsilon_{ost},$$  \hspace{1cm} (21)

where $\eta_{st}$ are sector-year fixed effects and $\varepsilon_{ost}$ is a stochastic error. The sector-year fixed effects ($\eta_{st}$) control for changes in sector composition over time, so that the coefficient $\alpha_t$ is identified solely from variation within sectors. The coefficient $\alpha_t$ captures the within-sector correlation between the share of employment in metro areas and the interactiveness of occupations.

Panel B of Table 5 reports the results, where each cell in the table again corresponds to a separate regression. The first four rows are again based on metro employment shares, while the final row is based on metro wage bill shares. As shown in the first row, and in line with our previous results, the correlation between metro employment shares and interactiveness is negative in 1880. Over time, this correlation becomes more positive and becomes statistically significant by 1960. Therefore, within sectors, more interactive occupations become increasingly concentrated in metro areas over time. This finding of the same pattern of reallocation across occupations both between and within sectors is consistent with a wide-ranging secular process favoring specialization in interactive occupations in metro areas.

In the second to fourth rows of Panel B of Table 5, we also break out overall interactiveness into thought (Class IV, Division 1), communication (Class IV, Division 2) and intersocial (Class V, Division 2). Again we find that the increased interactiveness of employment in metro areas is driven by the combination of thought, communication and intersocial activity. In the final row of Panel B of Table 5, we report the results of regressions in which we use the share of a sector-occupation’s wagebill in metro areas (rather than its share of employment in metro areas) as the left-hand side variable. For the shorter period over which we have the wage data, we again find a similar pattern of results using this alternative left-hand side variable,
which is consistent with relative demand moving relative wagebills and employment in the same direction.

Finally, to use variation within sectors and occupations, we pool our sector-occupation data over time and estimate a panel data regression that facilitates the inclusion of sector, occupation and year fixed effects. We regress the share of a sector-occupation’s employment in metro areas on these fixed effects and interaction terms between time dummies and our measure of occupation interactiveness:

\[
\text{MetroShare}_{ost} = \alpha_t [\text{Interactive}_o \times \text{Year}_t] + \mu_o + \eta_s + \delta_t + \varepsilon_{ost},
\]

where \(\varepsilon_{ost}\) is a stochastic error; we choose 1880 as the excluded year from the interaction terms. The occupation fixed effects (\(\mu_o\)) control for time-invariant differences between metro and non-metro areas in the share of an occupation in employment and capture the main effect of occupation interactiveness. The sector fixed effects (\(\eta_s\)) control for time-invariant differences between metro and non-metro areas in the share of a sector in employment. The year fixed effects (\(\delta_t\)) control for changes in the shares of metro areas in employment across all occupations and sectors. The coefficients \(\alpha_t\) capture the change in the correlation between metro employment shares and interactiveness relative to 1880.

Table 6 reports the estimation results. Column (1) confirms our findings above of an increasing correlation between metro employment shares and occupation interactiveness over time, which becomes positive and statistically significant by 1960. As shown in Column (2), this increasing correlation between metro employment shares and occupation interactiveness is robust to replacing the sector and year fixed effects with sector-year fixed effects to control for changes in sector composition over time.

While the model’s explanation for the increase in the relative interactiveness of metro areas emphasizes changes in the relative demand for occupations as a result of either differential changes in the relative productivity of occupations or improvements in communication technology, Columns (3)-(4) consider an alternative explanation based on changes in female labor force participation. Over our long historical time period, female labor force participation increased substantially, which implies that more and more couples face a colocation problem where both partners are looking for work in a common location (e.g. Costa and Kahn 2000). Since solving such a colocation problem is likely to be easier in more densely-populated locations, one concern is that the movement of such “power couples” into densely-populated locations could be driving the increase in the relative concentration of employment in interactive occupations in metro areas. Although it is not necessarily the case that power couples work in interactive occupations, Columns (3) and (4) provide evidence against this concern by estimating the specification in Column (2) separately for single and married people. Comparing the two columns, we find a similar pattern of results irrespective of marital status, which suggests that our findings are not being driven by the location decisions of power couples.

In Columns (5)-(7), we provide further evidence against explanations based on individual sectors and occupations. In Column (5), we include only workers in the manufacturing sector and demonstrate a similar pattern of results, which corroborates that our findings are not simply being driven by the rise of the services
sector in urban areas. In Column (6), we include only workers in the services sector, which confirms that our findings are not simply being driven by a decline in manufacturing in urban areas. In Column (7), we exclude 22 three-digit occupations that are likely to be concentrated in headquarters (e.g. “Buyers and Department Heads,” “Clerical and Kindred Workers” and “Managers, Officials and Proprietors.”) After excluding these occupations, we continue to find an increasing interactiveness of employment in metro areas over time, suggesting that our results are not being driven by headquarters alone.

In Columns (8)-(9), we examine differences in human capital across cities. Glaeser and Resseger (2009) find that the positive average relationship between productivity and metro area population is driven by a strong positive relationship for more-skilled metro areas, whereas this relationship is almost non-existent for less-skilled metro areas. Using Glaeser and Resseger (2009)’s classification of metro areas by skill, Columns (8) and (9) re-estimate the specification in Column (2) excluding more and less-skilled metro areas respectively. In both samples, we find a positive and statistically significant increase in the relative concentration of employment in interactive occupations in metro areas over time. The size of this increase is larger in the sample excluding less-skilled metro areas. But even in the sample excluding more-skilled metro areas we find a reallocation of employment towards interactive occupations in metro areas.

8.3 Improvements in Communication Technology

To provide direct evidence on the role played by improvements in communication technology in influencing the interactiveness of employment, we combine data on employment by occupation, sector and county for 1880 and 1930 with information on the spatial diffusion of the telephone. We focus on the years 1880 and 1930 because the telephone was invented in 1876 and diffused rapidly over this period. Furthermore, 1930 is the last year for which county identifiers are available in IPUMS, and hence the last year for which we can measure changes in interactiveness by county. Since this time period also witnessed the development of the first national network of paved highways, we also control for the diffusion of this new transport technology.

In the model, the interactiveness of employment depends on the extent of remote sourcing of tasks, which in turn depends on the communication technology. We therefore examine whether changes in the interactiveness of employment are related to the diffusion of the new communication technology. Our baseline specification regresses the change in interactiveness in each county from 1880-1930 ($\triangle \text{Interactive}_c$) on a measure of log telephones per capita in the 1930s (Phonepc$_c$):

$$\triangle \text{Interactive}_c = \alpha_P \ln (\text{Phonepc}_c) + \alpha_H \text{Highwaypa}_c + X_c\alpha_X + u_c,$$

(23)

\footnote{In Glaeser and Resseger (2009)’s classification, more-skilled Metropolitan Statistical Areas (MSAs) have a share of adults with college degrees of greater than 25.025 percent in 2006. The year 1960 is omitted in Columns (8) and (9) because the IPUMS 1960 data do not contain the identifiers for individual MSAs.}

\footnote{While identifiers are available for some counties in the IPUMS data for 1940, these counties are a selected subsample of all counties.}
where \( \text{Phonepc}_c \) is 1935 residence telephones divided by 1930 population. As discussed above, the telephone was virtually non-existent in 1880. Therefore the value of our telephones variable in the 1930s captures the diffusion of this new communication technology from 1880-1930. To control for changes in transport technology, we include the length of paved highways in 1931 divided by county area (\( \text{Highwaypa}_c \)). Since paved highways were a rarity outside central business districts in 1880, the value of this variable in the 1930s again captures the diffusion of this new technology from 1880-1930; \( X_c \) are controls for other county characteristics; \( u_c \) is a stochastic error.

Telephones and highways are unlikely to be randomly assigned to counties. Therefore a concern is that changes in interactiveness and the diffusion of these technologies both could be influenced by omitted third factors that enter the error term \( u_c \) and hence induce a correlation between the diffusion of these technologies and the error term. In particular, we have already shown that more densely-populated locations experienced an increase in their relative interactiveness over time, and telephones and highways may have also diffused more rapidly to more densely-populated locations. For this reason, we include among our controls \( X_c \) each county’s initial log population in 1880 and its log area.

To further address the concern that telephones and roads are non-randomly assigned, we develop instruments based on institutional features of the development of the telephone and highway network. We include these instruments alongside our controls in the following first-stage regressions:

\[
\ln (\text{Phonepc}_c) = \beta_P Z_{Pc} + \beta_H Z_{Hc} + X_c \beta_X + \varepsilon_c, \tag{24}
\]

\[
\text{Highwaypa}_c = \gamma_P Z_{Pc} + \gamma_H Z_{Hc} + X_c \gamma_X + \omega_c, \tag{25}
\]

where \( Z_{Pc} \) is our instrument for telephones (\( P \) is mnemonic for phones) and \( Z_{Hc} \) is our instrument for highways (\( H \) is mnemonic for highways); \( \varepsilon_c \) and \( \omega_c \) are stochastic errors.

To develop an instrument for log telephones per capita, we exploit the network structure of telephone communication. Following Alexander Graham Bell’s successful filing for a patent in 1876, the Bell Telephone Company was incorporated in 1877, and the first telephone exchange was opened under license from Bell Telephone in New Haven, CT in 1878.\(^{25}\) As local telephone exchanges began to emerge in major U.S. cities, the American Telephone and Telegraph Company (AT&T) was formed in 1885 as a subsidiary of American Bell Telephone to build and operate a long distance telephone network. In these early years, there was considerable debate within American Bell Telephone about the strategic rationale for developing a long distance network and whether such a network would be profitable given that much of the initial demand for telephones appeared to be local (see for example John 2010).

By the end of 1885, the first long distance line was completed between New York and Philadelphia with an initial capacity of one telephone call, and it was not until 1892 that a long distance line to Chicago was

\(^{25}\)The electric telegraph was patented much earlier in 1837 by Samuel Morse and the U.S. telegraph network was largely complete by 1880 (see Sundage 2007).
finished again with an initial capacity of one call. Following Theodore Vail’s accession to the Presidency of AT&T in 1907, the company aggressively pursued the development of its long distance network, with the strategic goals of connecting the nation as a whole (e.g. Osbourne 1930) and pressing for nationwide monopoly powers under Vail’s slogan of “One System, One Policy, Universal Service.” Ultimately this goal was achieved in 1913 with the issuance of the Kingsbury Commitment, which established AT&T as a government-sponsored monopoly, in return for it divesting its interests in the manufacture of telephone and telegraph equipment and allowing independent telephone companies to connect with its long distance network. By 1915, the first transcontinental long distance line to San Francisco was completed.

As our instrument for county log telephones per capita, we use county proximity to AT&T’s long distance network (see Map A1 in the web appendix). We measure proximity using the log of the sum of the distances from each county’s centroid to the nearest primary and secondary outlets on this network, which captures the centrality of each county relative to the network. This instrument uses the fact that AT&T’s long distance network was developed with the strategic objective of connecting the nation rather than based on interactiveness in individual counties. Our identifying assumption is that conditional on our controls for initial population and area there is no direct effect of proximity to long distance outlets on county interactiveness other than through log telephones per capita. The locations of these long distance outlets have predictive power for log telephones per capita, because they facilitated the connection of local telephone companies to the long distance network, which increased the value of a telephone connection to local subscribers, and hence increased telephone diffusion. In this way, we exploit the network properties of the telephone, which it shares with for example distribution networks, as in Holmes (2011).

Our instrument for highways per kilometer uses the institutional development of the U.S. highways network. In 1880, paved roads were the exception and were concentrated in the immediate vicinity of central business districts. Demand for road improvements grew following the production of the first American gasoline-powered automobile in Chicopee, Massachusetts in 1893 and the rapid growth in car registrations, which reached 8,000 in 1900, nearly 33,000 in 1903 and over 10 million by 1921 (U.S. Department of Transport 1976, Lewis 1997 and Swift 2011). The federal government’s involvement in the road network dates back to the formation of the Office of Road Inquiry in 1893, which became the Office of Public Roads in 1905 and the Bureau of Public Roads in 1915. Federal government participation was stimulated in part by its responsibility for the postal service, which was a department of the federal government from 1792-1971. Thus the Federal Aid Road Act of 1916 provided federal funding for rural post roads on the condition that these roads were open to public at no charge and that states submitted plans, surveys and estimates for the approval of the Secretary of Agriculture.

The scale of federal government participation grew with the Federal Aid Highway Act of 1921, which provided 50-50 matching funds for state highway building. Each state was required to propose a system of

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26 At the end of 1909, concrete accounted for only nine miles of state and county roads (Macdonald 1928).
roads for federal aid that did not exceed 7 percent of its highway mileage, and the Department of Agriculture was authorized to publish a map of the network on which federal aid would be spent by November 1923. As part of the planning process for this network, the Bureau of Public Roads commissioned General John J. Pershing to draw up a map of roads of military importance in the event of war. This “Pershing Map” identified 75,000 miles of road as strategically important for reasons of coastal and border defense (see Map A2 in the web appendix).

More than 10,000 miles of Federal Aid Highways were laid down in 1922 and by 1929 more than 90 percent of the Federal Aid Highways (around 170,000 miles) had been improved.

We instrument the length of highways per kilometer from the Gallup (1931) map using the length of Pershing highways per kilometer within each county from the Pershing Map. Our identifying assumption is that conditional on our controls for initial population and area there is no direct effect of Pershing highways per kilometer on county interactiveness other than through actual highways per kilometer. Pershing highways per kilometer have predictive power for actual highways per kilometer, because these highways of military importance were incorporated into the final network of Federal Aid Highways in the Department of Agriculture’s 1923 map.

In Column (1) of Table 7, we begin by running an OLS regression of the change in county interactiveness from 1880-1930 on county log telephones per capita in 1935, highways per kilometer in 1931 and our controls (equation (23)). We find a positive and statistically significant coefficient for telephones and a positive but statistically insignificant coefficient for highways. In Column (2), we report our instrumental variables estimates of equations (23)-(25). We find positive and statistically significant coefficients for both telephones and highways. Therefore both the diffusion of telephones induced by AT&T’s long distance network and the development of highways for military reasons raise county interactiveness. The increase in the estimated coefficients on highways between the OLS and IV specifications is consistent with the view that conditional on our controls for population density highways are disproportionately assigned to locations with lower growth in interactiveness. This finding is in line with Duranton and Turner (2012)’s results for the later interstate highway system, in which conditional on their controls highways also appear to be disproportionately assigned to relatively less-developed locations. While these specifications control for population density through the inclusion of log population and log area, we also find a very similar pattern of results if we also include an indicator variable for whether a county is located within a metro area.

In Columns (3)-(4) of Table 7, we report the first-stage regressions for phones and highways respectively, while Column (5) reports the reduced-form regression. We find that proximity to the AT&T long distance

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27 Consistent with these objectives, the Pershing Map excluded parts of the Deep South and Florida that were considered to be sufficiently swampy as to render foreign invasion impractical.

28 As discussed in the data section above, our telephones data for 1935 are for residence telephones. Separate data for business and residence telephones are available for 1945 and we find a strong correlation between them. Regressing log residence telephones on log business telephones across counties in 1945, we find an estimated coefficient (standard error) of 0.8950 (0.0090) and a regression R-squared of 0.87.
network and Pershing highways have predictive power for the endogenous variables, with first-stage F-statistics on the excluded exogenous variables of 38.40 and 26.35 in Columns (3) and (4) respectively. Consistent with this, we reject the null hypotheses of underidentification and weak identification in the Kleibergen-Paap test statistics reported in Column (2).

Taken together, these results are consistent with the view that the increase in interactiveness from 1880-1930 is indeed related to the diffusion of the new communication technology of the telephone, and that these findings are robust to controlling for the diffusion of the paved highway network.

9 Conclusions

We introduce a new methodology for measuring the tasks undertaken within occupations. We use this methodology to provide the first evidence on task specialization in urban and rural areas in the United States over a long historical time period. We measure tasks using the verbs from occupational descriptions and interpret the meanings of these verbs using Roget’s Thesaurus. In 1880, the tasks most concentrated in metro areas were “Braid,” “Sew,” “Stretch” and “Thread.” In contrast, in 2000, those most concentrated in metro areas were “Analyze,” “Advise,” “Confer” and “Report.” Our findings suggest a dynamic view of cities in which the organization of economic activity within cities has changed over time. We find an increased concentration in metro areas of “interactive” tasks, defined as those involving thought, communication and intersocial activity. This concentration is not apparent at the beginning of our sample period and has its origins in the early decades of the twentieth century.

We organize our empirical analysis around a simple model of agglomeration with a continuum of tasks. As communication costs fall from prohibitively high levels, firms in high-wage metro areas find it profitable to remote source less interactive tasks from lower-wage non-metro areas, which shifts the composition of metro area employment towards more interactive tasks. Consistent with these predictions, we find a secular change in the organization of production within industries towards a concentration of more interactive tasks in metro areas. We show that changes in the interactiveness of employment are related to the spatial diffusion of the new communication technology of the telephone in the opening decades of the twentieth century.

While theories of agglomeration have traditionally emphasized the movement of goods and people, our findings are consistent with the view that the generation, communication and exchange of ideas are increasingly important for agglomeration. As developing countries such as China and India experience rapid urbanization, our findings suggest that these population reallocations are likely to lead to substantial changes in the relative demands for tasks and skills. Although we have used our methodology to examine task specialization in urban and rural areas, it also has a wide range of potential other applications. For example, our approach could be used to examine the extent to which occupations require narrow versus broad ranges of tasks, or it could be used to construct employment and wagebill shares for individual tasks.
and examine the extent to which they are related to trade and technology.

References


### Table 1: Metro Area Specialization for Aggregate Occupations and Sectors

#### Panel A

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<td>0.01</td>
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<tr>
<td>Professional and Related Services</td>
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<tr>
<td>Mining</td>
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<td>11</td>
<td>-0.27</td>
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Notes: Coefficients estimated from a regression of the share of employment in metro areas in an occupation-sector-year on occupation-year and sector-year fixed effects (regression (11) in the paper). Occupation-year and sector-year fixed effects are each normalized to sum to zero. A separate regression is estimated for each year. Standard errors are clustered by occupation. Occupations and sectors sorted by the rank of their estimated coefficients for 1880.
### Table 2: Verbs Most and Least Strongly Correlated with Metro Area Employment Shares

#### Panel A: Verbs Most Strongly Correlated with Metro Area Employment Shares

<table>
<thead>
<tr>
<th>Rank</th>
<th>1880</th>
<th>1900</th>
<th>1920</th>
<th>1940</th>
<th>1960</th>
<th>1980</th>
<th>2000</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Thread</td>
<td>Thread</td>
<td>File</td>
<td>File</td>
<td>Document</td>
<td>Identify</td>
<td>Develop</td>
</tr>
<tr>
<td>2</td>
<td>Stretch</td>
<td>Stitch</td>
<td>Distribute</td>
<td>Bill</td>
<td>Schedule</td>
<td>Document</td>
<td>Determine</td>
</tr>
<tr>
<td>3</td>
<td>Interfere</td>
<td>Telephone</td>
<td>Record</td>
<td>Take</td>
<td>File</td>
<td>Advise</td>
<td>Analyze</td>
</tr>
<tr>
<td>4</td>
<td>Hand</td>
<td>Sew</td>
<td>Notice</td>
<td>Compile</td>
<td>Record</td>
<td>Concern</td>
<td>Factor</td>
</tr>
<tr>
<td>5</td>
<td>Ravel</td>
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<td>Telephone</td>
<td>Distribute</td>
<td>Distribute</td>
<td>Report</td>
<td>Review</td>
</tr>
<tr>
<td>6</td>
<td>Sew</td>
<td>Assist</td>
<td>Bill</td>
<td>Pay</td>
<td>Compile</td>
<td>Schedule</td>
<td>Confer</td>
</tr>
<tr>
<td>7</td>
<td>Braid</td>
<td>Visit</td>
<td>Envelope</td>
<td>Letter</td>
<td>Notice</td>
<td>Develop</td>
<td>Advise</td>
</tr>
<tr>
<td>8</td>
<td>Visit</td>
<td>Describe</td>
<td>Document</td>
<td>Notice</td>
<td>Identify</td>
<td>Analyze</td>
<td>Report</td>
</tr>
<tr>
<td>9</td>
<td>Receive</td>
<td>Number</td>
<td>Learn</td>
<td>Record</td>
<td>Send</td>
<td>Determine</td>
<td>Concern</td>
</tr>
<tr>
<td>10</td>
<td>Sack</td>
<td>Stamp</td>
<td>Number</td>
<td>Send</td>
<td>Notify</td>
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#### Panel B: Verbs Least Strongly Correlated with Metro Area Employment Shares

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<th>1980</th>
<th>2000</th>
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<tr>
<td>1821</td>
<td>Conduct</td>
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<td>Counsel</td>
<td>Delegate</td>
<td>Accord</td>
<td>Power</td>
<td>Restrain</td>
</tr>
<tr>
<td>1822</td>
<td>Teach</td>
<td>Tread</td>
<td>Discuss</td>
<td>Enlist</td>
<td>Feed</td>
<td>Pour</td>
<td>Cut</td>
</tr>
<tr>
<td>1823</td>
<td>Channel</td>
<td>Pinch</td>
<td>Hear</td>
<td>Labor</td>
<td>Escape</td>
<td>Erect</td>
<td>Power</td>
</tr>
<tr>
<td>1824</td>
<td>Sound</td>
<td>Assign</td>
<td>Assign</td>
<td>Tread</td>
<td>Hook</td>
<td>Clean</td>
<td>Massage</td>
</tr>
<tr>
<td>1825</td>
<td>Rule</td>
<td>Settle</td>
<td>Teach</td>
<td>Assign</td>
<td>Traverse</td>
<td>Massage</td>
<td>Remove</td>
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<tr>
<td>1826</td>
<td>Matter</td>
<td>Matter</td>
<td>Matter</td>
<td>Approve</td>
<td>Tread</td>
<td>Pump</td>
<td>Feed</td>
</tr>
<tr>
<td>1827</td>
<td>Drill</td>
<td>Tunnel</td>
<td>Consolidate</td>
<td>Extract</td>
<td>Loosen</td>
<td>Cut</td>
<td>Clean</td>
</tr>
<tr>
<td>1828</td>
<td>Tread</td>
<td>Sound</td>
<td>Rule</td>
<td>Tunnel</td>
<td>Range</td>
<td>Feed</td>
<td>Pump</td>
</tr>
<tr>
<td>1829</td>
<td>Tunnel</td>
<td>Rule</td>
<td>Tunnel</td>
<td>Malt</td>
<td>Activate</td>
<td>Move</td>
<td>Move</td>
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<tr>
<td>1830</td>
<td>Pinch</td>
<td>Sole</td>
<td>Sound</td>
<td>Establish</td>
<td>Turn</td>
<td>Turn</td>
<td>Turn</td>
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</tbody>
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Notes: Coefficients estimated from a regression of the share of occupation-sector employment in metro areas on the frequency with which a verb is used for an occupation and verb-sector-year fixed effects (regression (12) in the paper). A separate regression is estimated for each verb and verbs are sorted by their estimated coefficients normalized by the standard deviation for the verb frequency. Verbs are from the time-invariant occupational descriptions from the 1991 Dictionary of Occupations (DOTs).
Table 3: Correlation of Thesaurus Sections with Metro Area Employment Shares

<table>
<thead>
<tr>
<th>Thesaurus Class</th>
<th>Thesaurus Section</th>
<th>Rank Section 1880</th>
<th>Rank Section 2000</th>
<th>Rank 1880 - Rank 2000</th>
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<td>C1, Abstract relations</td>
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<tr>
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<td>-31</td>
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<tr>
<td>C1, Abstract relations</td>
<td>SECTION IV. ORDER</td>
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<td>11</td>
<td>19</td>
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<td>SECTION V. NUMBER</td>
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<td>14</td>
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<td>SECTION VI. TIME</td>
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<td>20</td>
<td>-18</td>
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<td>SECTION VII. CHANGE</td>
<td>36</td>
<td>7</td>
<td>29</td>
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<td>21</td>
<td>7</td>
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<td>C2, Space</td>
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<td>33</td>
<td>-25</td>
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<tr>
<td>C2, Space</td>
<td>SECTION II. DIMENSIONS</td>
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<td>36</td>
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<td>31</td>
<td>-28</td>
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<td>C3, Matter</td>
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<td>15</td>
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<td>C4, Intellect</td>
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<td>23</td>
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<td>5</td>
<td>29</td>
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<td>22</td>
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<tr>
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<td>6</td>
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<td>18</td>
<td>6</td>
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<td>18</td>
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<td>13</td>
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<td>15</td>
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<td>16</td>
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<td>26</td>
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<tr>
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<td>SECTION II. PERSONAL AFFECTIONS</td>
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<td>-17</td>
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<td>SECTION IV. MORAL AFFECTIONS</td>
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<td>34</td>
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<td>SECTION V. RELIGIOUS AFFECTIONS</td>
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Notes: Coefficients estimated from a regression of the share of occupation-sector employment in metro areas on the frequency with which the verbs used for an occupation are classified within thesaurus sections and thersaurus-section-sector-year fixed effects (regression (14) in the paper). A separate regression is estimated for each thesaurus section. Verbs are from the time-invariant occupational descriptions from the 1991 Dictionary of Occupations (DOTs). Thesaurus sections ranked in terms of their estimated coefficient normalized by the standard deviation for the thesaurus section frequency, where the largest value is assigned a rank of one. Top-five thesaurus sections in 1880 highlighted in bold and italics. Top-five thesaurus sections in 2000 highlighted in bold.
Table 4: Most and Least Interactive Occupations

Panel A: Top Ten Interactive Occupations
- Economists
- Nurses, professional
- Pharmacists
- Clergymen
- Religious workers
- Accountants and auditors
- Postmasters
- Buyers and dept heads, store
- Aeronautical-Engineers
- Statisticians and actuaries

Panel B: Bottom Ten Interactive Occupations
- Brickmasons,stonemasons, tile setters
- Attendants, auto service and parking
- Painters, except construction
- Plumbers and pipe fitters
- Upholsterers
- Asbestos and insulation workers
- Welders and flame cutters
- Blasters and powdermen
- Dressmakers and seamstresses
- Roofers and slaters

Notes: The table reports the ten occupations with the lowest and highest interactivité, as measured by the frequency of verb use in Classes IV and V of Roget's Thesaurus. Verbs are from the time-invariant occupational descriptions from the 1991 Dictionary of Occupations (DOTs).
Table 5: Metro Employment and Wagebill Shares and Interactiveness

Panel A: Between sectors

<table>
<thead>
<tr>
<th>Measure</th>
<th>1880</th>
<th>1900</th>
<th>1920</th>
<th>1940</th>
<th>1960</th>
<th>1980</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interactiveness (Employment)</td>
<td>-0.130</td>
<td>-0.132</td>
<td>0.258</td>
<td>0.556</td>
<td>0.728***</td>
<td>0.901***</td>
<td>0.814***</td>
</tr>
<tr>
<td></td>
<td>(0.267)</td>
<td>(0.239)</td>
<td>(0.419)</td>
<td>(0.405)</td>
<td>(0.267)</td>
<td>(0.200)</td>
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<td>-0.649**</td>
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<td>-1.805***</td>
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<td>(0.261)</td>
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<td>Communication (Employment)</td>
<td>-0.412***</td>
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<td>(0.153)</td>
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<td>Intersocial (Employment)</td>
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<td>-0.473***</td>
<td>-0.548***</td>
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<td>0.342***</td>
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<td>(0.136)</td>
<td>(0.169)</td>
<td>(0.203)</td>
<td>(0.133)</td>
<td>(0.124)</td>
<td>(0.109)</td>
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<tr>
<td>Interactiveness (Wage Bill)</td>
<td>0.557</td>
<td>0.557*</td>
<td>0.814***</td>
<td>0.733***</td>
<td>0.557</td>
<td>0.814***</td>
<td>0.733***</td>
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<td></td>
<td>(0.366)</td>
<td>(0.283)</td>
<td>(0.215)</td>
<td>(0.201)</td>
<td>(0.136)</td>
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Panel B: Within sectors

<table>
<thead>
<tr>
<th>Measure</th>
<th>1880</th>
<th>1900</th>
<th>1920</th>
<th>1940</th>
<th>1960</th>
<th>1980</th>
<th>2000</th>
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</thead>
<tbody>
<tr>
<td>Interactiveness (Employment)</td>
<td>-0.410***</td>
<td>-0.261**</td>
<td>-0.104</td>
<td>-0.0360</td>
<td>0.190***</td>
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<td>(0.119)</td>
<td>(0.119)</td>
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<td>0.0197</td>
<td>0.105***</td>
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<td>0.281***</td>
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<td>0.043</td>
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</table>

Sector-year fixed effects: Yes Yes Yes Yes Yes Yes Yes

Notes: Each cell of each panel of the table corresponds to a separate regression. The left-hand side in the first four rows of each panel is the share of employment in metro areas; the left-hand side in the fifth row of each panel is the share of the wagebill in metro areas; the wagebill data are only available from 1940 onwards; Interactiveness is our baseline measure using the 1991 DOTs and Classes IV-V of the thesaurus; Thought uses Class IV (Division 1) of the thesaurus; Communication uses Class IV (Division 2) of the thesaurus; Intersocial uses Class V (Division 2) of the thesaurus. In Panel A, the sample is a cross-section of three-digit sectors for each year, and the standard errors are heteroscedasticity robust. In Panel B, the sample is a panel of sectors and occupations for each year; sector-year fixed effects are included; and the standard errors are clustered on occupation. See Section 8.2 for further details on the estimated equation. * significant at 10%; ** significant at 5%; *** significant at 1%.
## Table 6: Metro Area Employment Shares and Interactiveness, Within-sector and Within-Occupation

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
<td>Metro</td>
</tr>
<tr>
<td>Interactiveness x 1900</td>
<td>0.00207</td>
<td>0.104</td>
<td>0.0493</td>
<td>0.292</td>
<td>0.108</td>
<td>0.124</td>
<td>0.402</td>
<td>-0.0307</td>
<td>0.124</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.162)</td>
<td>(0.119)</td>
<td>(0.195)</td>
<td>(0.178)</td>
<td>(0.246)</td>
<td>(0.0763)</td>
<td>(0.146)</td>
<td></td>
</tr>
<tr>
<td>Interactiveness x 1920</td>
<td>0.186</td>
<td>0.187</td>
<td>0.132</td>
<td>0.525**</td>
<td>0.254</td>
<td>0.272</td>
<td>0.541*</td>
<td>-0.00455</td>
<td>0.321</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.218)</td>
<td>(0.176)</td>
<td>(0.223)</td>
<td>(0.250)</td>
<td>(0.203)</td>
<td>(0.277)</td>
<td>(0.129)</td>
<td>(0.206)</td>
</tr>
<tr>
<td>Interactiveness x 1940</td>
<td>0.399</td>
<td>0.321</td>
<td>0.287</td>
<td>0.455*</td>
<td>0.334</td>
<td>0.324</td>
<td>0.732**</td>
<td>0.0379</td>
<td>0.369*</td>
</tr>
<tr>
<td></td>
<td>(0.243)</td>
<td>(0.235)</td>
<td>(0.205)</td>
<td>(0.254)</td>
<td>(0.236)</td>
<td>(0.233)</td>
<td>(0.290)</td>
<td>(0.117)</td>
<td>(0.221)</td>
</tr>
<tr>
<td>Interactiveness x 1960</td>
<td>0.573**</td>
<td>0.485***</td>
<td>0.316**</td>
<td>0.548**</td>
<td>0.284</td>
<td>0.410*</td>
<td>0.842***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.231)</td>
<td>(0.185)</td>
<td>(0.158)</td>
<td>(0.261)</td>
<td>(0.228)</td>
<td>(0.227)</td>
<td>(0.273)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interactiveness x 1980</td>
<td>0.677***</td>
<td>0.560***</td>
<td>0.489***</td>
<td>0.627**</td>
<td>0.424*</td>
<td>0.515**</td>
<td>0.893***</td>
<td>0.233***</td>
<td>0.595***</td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td>(0.174)</td>
<td>(0.152)</td>
<td>(0.258)</td>
<td>(0.250)</td>
<td>(0.240)</td>
<td>(0.268)</td>
<td>(0.0672)</td>
<td>(0.204)</td>
</tr>
<tr>
<td>Interactiveness x 2000</td>
<td>0.672***</td>
<td>0.596***</td>
<td>0.609***</td>
<td>0.788***</td>
<td>0.552**</td>
<td>0.681***</td>
<td>0.874***</td>
<td>0.261***</td>
<td>0.823***</td>
</tr>
<tr>
<td></td>
<td>(0.253)</td>
<td>(0.174)</td>
<td>(0.141)</td>
<td>(0.233)</td>
<td>(0.276)</td>
<td>(0.221)</td>
<td>(0.275)</td>
<td>(0.0670)</td>
<td>(0.167)</td>
</tr>
<tr>
<td>Observations</td>
<td>56,760</td>
<td>56,760</td>
<td>49,108</td>
<td>41,442</td>
<td>25,105</td>
<td>30,593</td>
<td>48,210</td>
<td>35,662</td>
<td>44,128</td>
</tr>
</tbody>
</table>

**Notes:** Sample is a panel of occupation-sector-year observations for twenty-year intervals from 1880-2000; 1880 is the excluded year from the interactions; interactiveness is our baseline measure using the 1991 DOTs and Classes IV-V of the thesaurus. Married only sample includes married workers only. Single only sample excludes married workers. Manufacturing only sample includes workers in manufacturing only. Services only sample includes workers in services only. Sample excluding headquarters occupations excludes 22 three-digit occupations typically concentrated in headquarters. More and less-skilled metro areas are defined as in Glaeser and Resseger (2009) based on whether the share of adults with a college degree in a Metropolitan Statistical Area (MSA) is greater than or less than 25.025 percent in 2006. The year 1960 is omitted in Columns (8) and (9) because the IPUMS 1960 data do not contain the identifiers for individual MSAs. See Section 8.2 for further details on the estimated equation. Standard errors are clustered on occupation; * significant at 10%; ** significant at 5%; *** significant at 1%.
Table 7: Interactiveness and Improvements in Communication and Transport Technologies

<table>
<thead>
<tr>
<th></th>
<th>(1) Change in Interactiveness 1880-1930</th>
<th>(2) Change in Interactiveness 1880-1930</th>
<th>(3) Log phones per capita 1935</th>
<th>(4) Highways per km 1931</th>
<th>(5) Change in Interactiveness 1880-1930</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highways per km</td>
<td>0.007</td>
<td>0.086***</td>
<td>-0.013**</td>
<td>-0.030***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.028)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log phones per capita</td>
<td>0.022***</td>
<td>0.083***</td>
<td>0.006*</td>
<td>0.016***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.019)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
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<tr>
<td>Log area</td>
<td>0.007***</td>
<td>0.010***</td>
<td>-0.013**</td>
<td>-0.030***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log population 1880</td>
<td>0.004***</td>
<td>0.002*</td>
<td>0.006*</td>
<td>0.016***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
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<tr>
<td>Pershing highways per km</td>
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<td>-0.113**</td>
<td>0.274***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.055)</td>
<td>(0.032)</td>
<td>(0.005)</td>
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<tr>
<td>Log remoteness from long distance outlet</td>
<td></td>
<td></td>
<td>-0.063***</td>
<td>0.008**</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.001)</td>
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<td>Observations</td>
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<td>2467</td>
<td>2467</td>
<td>2509</td>
<td>2509</td>
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<td>R-squared</td>
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<td>0.12</td>
<td>0.02</td>
<td>0.19</td>
<td>0.09</td>
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<td>OLS</td>
<td>OLS</td>
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<td>Specification</td>
<td>Second-stage</td>
<td>Second-stage</td>
<td>First-stage</td>
<td>First-stage</td>
<td>Reduced-form</td>
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<tr>
<td>F-statistic instruments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Underidentification test (Kleibergen-Paap LM statistic)</td>
<td>35.63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weak identification test (Kleibergen-Papp F-statistic)</td>
<td>18.61</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: Sample is a cross-section of counties from 1880-1930; Interactiveness is our baseline measure using the 1991 DOTs and Classes IV-V of the thesaurus; Highways per km is length of highways within a county in the Gallup 1931 map divided by county area; Log phones per capita is log number of residence telephones in 1935 divided by population in 1930; Log area is log county area; Log Population 1880 is log county population in 1880; Pershing highways per km is the length of highways proposed for military reasons within a county in the Pershing 1922 map divided by county area; Log remoteness from long distance outlet is the log of the sum of the distances to primary and secondary outlets on the AT&T long distance telephone network. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.
Figure 1: Mean Interactiveness in Metro and Non-Metro Areas over Time

Note: Mean interactiveness computed using time-invariant occupational descriptions from the 1991 DOTs.
Figure 2: Mean Interactiveness Across Metro Areas

Notes: Mean interactiveness computed using time-invariant occupational descriptions from the 1991 DOTs. Thick solid line is fitted values from locally-weighted linear least squares regression. Thin solid lines are 95 percent point confidence intervals.
Figure 3: Decomposition of Difference in Change in Interactiveness Between Metro and Non-Metro Areas

Panel A
Interactiveness
-0.04  0.02  0.04  0.06
1900 1920 1940 1960 1980 2000
20-year difference

Panel B
Interactiveness
-0.04  0.02  0.04  0.06
1900 1920 1940 1960 1980 2000
20-year difference

Panel C
Interactiveness
-0.04  0.02  0.04
1900 1920 1940 1960 1980 2000
20-year difference

Panel D
Interactiveness
-0.04  0.02  0.04
1900 1920 1940 1960 1980 2000
20-year difference

Notes: Decomposition of the difference between metro and non-metro areas in the change in mean interactiveness over twenty-year intervals (equation (19) in the paper) into the contributions of two-digit occupations and sectors. Mean interactiveness based on time-invariant occupational descriptions from the 1991 DOTs.