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# Cities, Tasks and Skills

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**Abstract**

This research applies a task-based approach to measure and interpret changes in the employment structure of the 168 largest US cities in the period 1990-2009. As a result of technological change some tasks can be placed at distance, while others require proximity. We construct a measure of task connectivity to investigate which tasks are more likely to require proximity relative to others. Our results suggest that cities with higher shares of connected tasks experienced higher employment growth. This result is robust to a variety of other explanations including industry composition, routinisation, and the complementarity between skills and cities.

*Keywords:* Occupations, tasks, cities, employment
*JEL Classification:* J20, J30, O30

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# 1 INTRODUCTION

The division of labor has changed over the past two decades. Technological change and especially rapid progress in information and communication technologies (ICT) has enabled a break-up of the production process, which has had implications for the organization of work and the structure of employment in many countries (Bresnahan et al., 2002; Autor et al., 2003). ICT has changed the way individual tasks can be carried out and created new possibilities for communication between workers. Not only is this observed within and between firms, but also across space. In many cases, physical distance becomes less important for production because communication at distance can be as effective as communication in person (Bloom et al., 2009). At the same time cities flourish because of the increasing importance of human interactions in modern production processes (Glaeser and Maré, 2001). These trends have been accompanied by new research approaches to relax the implicit equivalence between workers' skills and the tasks that have to be carried out at work. The core feature of these approaches is that workers apply their skills to tasks in exchange for wages. This distinction between skills and tasks becomes important when the assignment of skills to tasks is evolving with time, because the set of tasks demanded in the economy is altered by technological change that changes the need for proximity. Recent evidence on the effects of ICT and new possibilities for offshoring suggest that certain tasks have been more vulnerable to computerization and offshoring than others (Grossman and Rossi-Hansberg, 2008) and that a task-based approach to study and understand these developments is worthwhile pursuing (Baldwin and Robert-Nicoud, 2010; Acemoglu and Autor, 2011; Autor, 2013).

This paper uses a task-based approach to document and interpret recent employment trends in the 168 largest US metropolitan areas in the period 1990-2009. These cities cover about 75 percent of total US employment in 2009. Employment trends across cities are often explained by differences in industrial structure (Ellison and Glaeser, 1997). Duranton and Puga (2001) and Desmet and Rossi-Hansberg (2009) argue that new industries clustered in expensive locations benefit from knowledge spillovers, while more mature industries relocate to less expensive places because production processes have become more standardized. The main benefit of a task-based approach is that it allows us to analyze how employment growth across cities is caused by interactions among job tasks and agglomeration forces. Understanding this mechanism is potentially important in explaining why some cities have fared well, while others have been in decline.

We first show how tasks are connected to cities. To do so, occupations are viewed as bundles of tasks. Connectivity explains to what extent tasks are benefiting from the presence of other tasks and to what extent they are clustering. Empirically, our measure of task connectivity measures the importance of proximity or co-agglomeration for 41 job tasks defined in the Occupational Information Network (ONET) database across 326 (three-digit) occupations and 142 (three-digit) industries. ONET classifies all occupations in terms of the importance of job tasks. In our empirical analysis, we present changes in employment in the period 1990-2009. We construct a database of the 168 largest US cities in which we pair representative data on job task requirements from the ONET database with samples of employed workers from the Current Population Survey and Census to form a consistent panel of industry, occupation and spatial task input. The validity and strength of our empirical analysis is addressed by presenting estimates of alternative measures of task composition and alternative divisions and slices of the sample of cities, workers and occupations.

Our main results can be summarized as follows. The measure of task connectivity explains a significant part of the changes in employment in US cities over the last two decades. We document that a one standard deviation increase in task connectivity relates to an increase in employment of 30 to 45 percent of a standard deviation in our period of analysis from 1990 to 2009. Cities with a larger share of connected tasks have grown faster relative to other cities, conditional on initial employment, location characteristics and a set of other covariates. Other measures of the task composition of cities, such as the spatial concentration of tasks, do not explain changes in employment patterns in this period in the United States. The main results of our empirical analysis are robust to the inclusion of differences in the structure of employment or industries (Glaeser et al., 1992; Ellison and Glaeser, 1997; Glaeser and Kerr, 2009), the rise in the importance of social skills (Bacolod et al., 2009), and the routinisation and computerization of some parts of employment (Autor et al., 2003). In addition, the importance of connectivity between tasks in explaining changes in employment in this period is not limited to either some manufacturing or services industries or particular skill groups.

This paper is related to a relatively new and growing body of empirical research documenting and interpreting changes in the structure of employment and wages using a task-based approach in which worker skills are allocated to job tasks. Contributions to this way of analyzing trends have been made by Autor et al. (2003), Autor et al. (2006), Borghans and Ter Weel (2006), Goos and Manning (2007), Goos et al. (2009), Firpo et al. (2009), Blinder (2006) and Criscualo and Garicano (2010). These papers show across a variety of data sources that certain types of occupations seem to be disappearing in terms of employment shares and/or seem to be paying lower wages over time, while others grow and obtain wage growth. Duranton and Puga (2005) focus on a related issue by distinguishing sectoral and functional specialization of employment. Acemoglu and Autor (2011) review these international trends and argue that a task-based approach is helpful when the assignment of worker skills to job tasks is evolving with time, either because shifts in market prices command reallocation of skills to tasks or because the set of tasks demanded in the economy is changed by technological developments, trade, or offshoring. We add to these approaches a spatial dimension because reallocation of skills to tasks changes the division of tasks across space too.[1] This helps to understand employment developments across different types of cities in the United States.

By addressing the spatial dimension of employment our work is related to the recent contributions of Glaeser and Maré (2001), Bacolod et al. (2009), Bacolod et al. (2010), Autor and Dorn (2013) and Florida et al. (2012). They document trends in regional employment and show that the structure of employment reveals path dependence. In addition, some tasks seem to be associated with employment growth, while others predict declines. Especially human capital seems to be important for employment growth. In our empirical analysis, we also use measures of human capital and obtain estimated coefficients that suggest it to be an important determinant of employment change across cities. We add to this that the structure of employment in terms of task combinations seems to be even more important. Our arguments and findings are related to the empirical work on the division of labor across space. Duranton and Jayet (2011) show, based on occupations, that the distribution of workers across occupations in dense urban areas is different relative to more rural areas. We obtain estimates that suggest that connectivity of tasks is positively correlated to employment growth.

Finally, the importance of cities in bundling tasks and occupations is also used in the approaches developed in Jensen and Kletzer (2005) and Akcomak et al. (2011). They develop and apply measures of task connectivity similar to the ones we use here. Charlot and Duranton (2004) and Bacolod et al. (2009) emphasise the importance of communication and social skills in changes in city employment. Michaels et al. (2013) empirically show a change in the nature of agglomeration over time towards an increased emphasis on human interaction driven by ICT developments. Our measure includes this mechanism but also emphasizes the combination of tasks associated with employment changes. The research by Duranton and Puga (2001), Duranton and Puga (2005) and Desmet and Rossi-Hansberg (2009) points to the complementary relationship between cities and technological change in explaining changes in employment structure. We take advantage of this argument to explain why some tasks seem to be placed at distance (i.e., outside the 168 large cities in our sample, which could be either elsewhere in the United States or abroad).

This paper proceeds as follows. In the next section both the theoretical background and the empirical strategy are presented. Section 3 documents the most salient details of the data sources. In Section 4 the main estimation results are shown. Section 5 discusses other measures of task composition and Section 6 applies the analyses to several sub-samples. Section 7 concludes.

## 2 BACKGROUND AND EMPIRICAL APPROACH

Before documenting the impact of a city's initial task structure on changes in US employment in the period 1990-2009, this section discusses the intuition behind the empirical analysis. We first discuss the division of tasks across space and present the main idea behind this paper. Next, we translate this idea into an empirical measure will be used in the analysis to investigate changes in employment.

*Main Idea*

A large number of tasks are combined to produce output. These tasks are divided across workers working for a certain firm in a certain location. Worker tasks are not carried out in isolation, but bundled in the occupations of workers in the economy. Also, the output of some tasks (e.g., planning) is the input of others (e.g., production). Tasks can be carried out by a single worker, but also by different workers. A firm can choose to produce all the tasks inside the firm but it is also possible to outsource a subset of tasks. Lastly, the production process can be located in one location, but it is also possible to produce in several locations or even worldwide. The division of tasks across workers, firms and locations depends on the trade-off between coordination and production costs. A more extensive division generates advantages in production costs: each task can be produced by the most efficient worker, in the most efficient firm and at the optimal location. Costs of the coordination between tasks do however increase with the division of labor. We measure the task content along 41 worker tasks in 326 occupations and focus on the trade-off between these costs and benefits.

The division of tasks across space is determined by a trade-off between coordination and production costs. On the one hand, carrying out tasks at one location saves on transport, communication and other coordination costs and utilizes positive agglomeration forces. Beyond the physical distribution of goods and services, production requires coordination, consultation, and planning, which are easier in close proximity. Tacit, non-codified knowledge is more easily transferred face-to-face than via other communication technologies. Face-to-face contact furthermore helps to solve incentive issues and facilitates learning and human capital externalities (Storper and Venables, 2004). On the other hand, carrying out different tasks at different locations has cost advantages in the production of specific intermediate products. The resulting division of worker tasks across space depends on these economic forces.

The spatial trade-off between coordination and production costs varies across tasks. There is a tendency for some tasks to cluster with other tasks to save on coordination costs and to benefit from agglomeration advantages. This effect is counterbalanced by the possible cost advantage of placing the performance of some tasks elsewhere. It depends on the balance between proximity and cost advantages whether or not some tasks will be placed at distance. In particular, whether or not tasks will be placed at distance depends on three facets of the division of labor.

First, it depends on the time lost with the coordination of a specific task relative to the gains of the division of tasks across space. This balance has been changing over the last decades as a result of technological change. Improved communication technologies reduce the time lost communicating when placing tasks at distance (Duranton and Jayet, 2011). In addition, technological change affects the organization of work. The division of production time might change, which changes the decision on the division of tasks across workers and space (Borghans and Ter Weel, 2006; Garicano and Rossi-Hansberg, 2006). Finally, worker skills could complement or substitute for computer technology. Some tasks could be taken over by computer technology, which also changes the performance of other tasks (Borghans and Ter Weel, 2004). Lower coordination costs induce a further division of tasks across space to those places in which it is most cost effective to carry out the work.

Second, it depends on the nature of the worker tasks. Some tasks are non-tradable and cannot be done at distance at reasonable costs (e.g., cleaning offices). Hence, in all cities we observe the presence of a certain number of basic tasks that have to be carried out in close vicinity. This is a similar argument as the one noted in Autor et al. (1998), who find that computerization has a detrimental effect on the labor-market outcomes of low-skilled workers, but not at the very low end because some low-end service occupations are unaffected by this type of technological change.

Finally, tasks are connected in cities because of the existence of agglomeration forces. Coordination costs in terms of sharing inputs and transmitting information and knowledge are lower when tasks are performed closely together (Duranton and Puga, 2004). Tasks for which input sharing and information and knowledge transmission are important complement other tasks and connect in space. This seems especially true for tasks that demand higher levels of skill (Glaeser and Resseger, 2010), tasks that require more coordination and face-to-face interactions (Gaspar and Glaeser, 1998; Blum and Goldfarb, 2006) and knowledge tasks (Von Hippel, 1994). Bacolod et al. (2009) and Florida et al. (2012) show that urban wage premiums tend to be higher for analytical and social tasks and lower for physical and technical tasks. Charlot and Duranton (2004) argue that larger and more educated cities require workers to communicate more. They find support for this hypothesis in a sample of French firms and show that workers who communicate more earn higher wages. Agglomeration disadvantages such as congestion costs limit the size of the city and benefit smaller cities.

Recent technological change affected transport, coordination and production costs and through these channels the division of tasks across space. The trade-off between the proximity advantages and production costs of cities changes with these technological developments. For certain tasks this led to a move away from (US) cities (either to the countryside or abroad). Proximity advantages of cities gained however in importance in modern production processes (Glaeser and Maré, 2001). Furthermore, some tasks are automated and no longer require labor input. The economic structure of cities adjusts only at a slow pace to these developments. Therefore, we expect cities that initially focused on tasks that complement recent technological developments to prosper relative to cities that did not.

*Measuring Connectivity*

To bring the main idea to the data, we need to measure the extent to which tasks are connected to each other. We consider the extent to which one task is performed in close vicinity of other tasks. To do so, we follow Akcomak et al. (2011) and construct a measure of task connectivity based on correlations between observed patterns of task combinations across different cities. The construction of the measure consists of two steps. First, we define a measure for the spatial pattern of task performance. This measure tells us the level of spatial connectivity for each task. Next, we employ this measure to calculate the average importance of spatial connectivity of the tasks package for each city.

To construct a measure of the spatial connectivity for each task, we proceed in three steps. First, we measure the 41 worker tasks in the economy. For all 326 occupations we observe to what extent the 41 worker tasks are carried out or not. Second, we weight the presence of a worker task with its importance. ONET contains importance weights to do so. Finally, we append this information to the composition of employment shares in terms of occupations in each of the 168 cities of our sample. Hence, we create a database with 168 rows (cities) and 41 columns (tasks). Cells represent the employment share of the task (weighted by its importance) in the overall task package of a city. The correlations between the cells in each of the rows measure the extent to which tasks are spatially connected to each other.

More formally, we measure employment shares by information about the importance of the 41 worker tasks within each of the 326 occupations. Importance of worker tasks is measured on a scale from 1 (not important at all) to 5 (extremely important).[2] Employment of task $t$ in city $l$ is measured by the sum of the score on task $t$ of all workers in city $l$. Total task employment of city $l$ is measured by the sum of all task scores of all workers in the city. Next, the employment share of a task in a city is defined to be equal to the share of the importance of that task in the total task score of the city ($\tilde{E}_l$). Task connectivity for task $t$ is constructed as follows:

$$tc_t = \sum_{t'=1}^{t'=41} c(\tilde{E}_{t,l} \mid \tilde{E}_{t',l}) \quad for \quad t' \neq t. \tag{1}$$

The measure is a task specific indicator with a value for each of the 41 tasks.[3] The term $c(\tilde{E}_{t,l} \mid \tilde{E}_{t',l})$ represents the correlation between the estimated employment shares of task $t$ and task $t'$ in city $l$. We use correlation coefficients across all pairs of tasks to measure the extent to which task $t$ is connected with the other 40 tasks. Or, in terms of the agglomeration literature, the extent to which a task co-agglomerates with others (Ellison et al., 2010). The sum of the connectivity with all other tasks generates the measure of spatial connectivity of task $t$. The higher the value of this measure, the more task $t$ is found to be performed together in space with other tasks.

Some tasks connect with many other tasks, while others only connect with a few other tasks. A high (low) value of task connectivity corresponds to a location pattern consistent with that of many (a few) other tasks. For example, the worker task of controlling machines is always carried out at the location of the relevant machines, but this task does not depend on the proximity of the performance of many other tasks. As a result, its location pattern likely matches the one of the machine operators but not the one of many other tasks. Communicating with supervisors occurs in many different environments and is more likely to co-locate with a broad spectrum of other tasks. As a result, it has a high value of task connectivity. In our dataset, the connectivity measure provides the highest levels of task connectivity for tasks such as providing consultation and advice to others and interpreting the meaning of information. Apparently, these tasks are relatively strongly correlated with other tasks in space. By contrast, tasks such as handling and moving objects and repairing and maintaining mechanical equipment have the lowest level of task connectivity according to our measure.

Table 1 shows the task connectivity measure for a sample with five cities and eight tasks. Although the differences between employment shares in these tasks are rather small, there is a spatial pattern in task connectivity. Spatially, the tasks getting information, processing information, scheduling work and activities and developing and building teams co-agglomerate. The same holds for handling and moving objects together with controlling machines and processes. The higher the employment share of the first four tasks, the lower the share of the second group of tasks. Employment seems to have a pattern such that a relatively high share of information input tasks and interacting with others tasks go along as well as a relatively high share of work output tasks. The work output tasks have a negative value on our connectivity measure as they seem to be only loosely connected to the performance of the other tasks. Especially the task developing and building teams depends on the co-location of several other tasks. Table 2 presents a list of the employment shares of all 41 tasks and their levels of task connectivity. We have grouped the tasks according to the four ONET categories. At the level of single tasks, most tasks of the group interacting with others have high connectivity levels on our measure, which is consistent with the analysis of Bacolod et al. (2009).

Finally, we use the task connectivity measure ($tc_t$) to define the spatial connectivity of the task packages for each city (l). For each task in the city, its spatial connectivity is weighted by its employment share in the city. Summing this measure for all performed tasks in the city yields an indicator for the spatial connectivity of the city's task package:

$$C_l = \sum_{t=1}^{t=41} tc_t * \tilde{E}_{t,l}. \qquad (2)$$

In particular, $C_l$ measures the average connectivity of the (estimated) employment of tasks. The last column in the example of Table 1 presents the connectivity of task employment of five cities for eight tasks. According to our measure of task connectivity, the performed worker tasks in Boston are the most connected, while in Los Angeles and Detroit worker tasks are relatively loosely connected.

# 3 DATA AND DESCRIPTIVE STATISTICS

We combine the information from several data sources to construct a database on the division of tasks in the 168 largest US cities in the period 1990-2009. The tasks in the database are broadly defined and could be performed in all occupations and industries. The construction of the database from the several sources is visualised in Figure 1.

*Data*

The main indicators for the division of labor are collected from the Current Population Survey (CPS). For about 140,000 individuals we obtain information about occupation, industry and city of residence (defined as Metropolitan Statistical Area (MSA)) in each year between 1990 and 2009.[4] We distinguish 326 three-digit occupations and 142 three-digit industries. Cities are defined as MSAs, as the classification of MSAs is based on the nature of their economic activity.[5] In 2009 MSAs were responsible for more than 85 percent of the employment, income, and production of products and services in the United States (Bureau of Economic Analysis, 2009). The MSA definitions, in terms of borders, change over time. This complicates analyses of employment developments of cities. To be able to analyze a consistent sample of cities and a sound match between several data sources, MSAs are defined as combined counties following the 1990 definition. The borders of counties are consistent over time. A dataset of 168 MSAs is obtained.

Information about job tasks is collected from the ONET Database. ONET provides information about the importance of abilities, interest, knowledge, skills, work activities, work context and work values within occupations. The work activities represent the job tasks of the worker. ONET distinguishes 41 broadly defined work activities. All tasks could be performed within all 326 occupations and are therefore not industry-related. Examples are thinking creatively, scheduling work and activities and processing information. For each occupation the importance of the 41 tasks is provided by ONET on a scale from 1 (not important at all) to 5 (extremely important). The importance of the tasks by occupation are matched to the occupations observed in the CPS. Aggregating the task information at the city level generates the division of tasks by city over time (1990-2009). Table 2 lists all tasks and presents information on type, employment shares and connectivity.

ONET categorizes the work activities into four groups: information input, mental processes, work output and interacting with others. The second column of Table 3 presents an example of a task within each group, columns (1) to (4) show the average importance of the four task groups within four broad occupational groups that cover employment in our sample. The average task importance varies between 2.24 (work output for clerical and sale occupations) and 3.58 (information input for production and operator occupations). Information input tasks define where and how the information and data are gained that are needed to perform the job. These tasks have high importance levels in all occupational groups. Mental processes tasks indicate what processing, planning, problem-solving, decision-making and innovating activities are performed in the occupation. These tasks are especially important within professional, managerial and technical occupations. The standard errors of the importance of these tasks are low within the broad occupational groups. The work output tasks refer to 'what physical activities are performed, what equipment and vehicles are operated/controlled and what complex/technical activities are accomplished as job outputs'. For production and operators occupations these tasks are relatively. Lastly, the importance of interacting with others is relatively important within professional, managerial and technical occupations.

The last two rows of Table 3 present the employment shares of the occupations in 1990 and 2009, while the last two columns present these for the task groups. Professional, managerial and technical occupations have both the highest employment share in 1990 and the highest employment growth between 1990 and 2009. Also service occupations grow in terms of employment shares, while the shares of clerical, sales, production and operators occupations seem to be in decline. These findings are consistent with the findings of Acemoglu and Autor (2011). Information input is the largest task group in terms of employment, while interacting with others and mental processes experience the largest growth. Remarkably, changes between occupational groups are larger than changes between task groups.

The division of tasks across US cities is constructed from the matching of task information to occupations. We have to assume that the task structure of jobs does not differ by city characteristics. This is a strong assumption but a necessary one because we only observe the task content of occupations once. Bacolod et al. (2009) and Autor et al. (2003) face the same problem. For example, a car mechanic in Detroit conducts the same tasks relative to a car mechanic in New York. The extent of the market might however affect the task package of workers and generate specialization possibilities (Baumgardner, 1988). If this is the case, differences are caused by the extent of the city suggesting that all the tasks are still performed within the city. This would not affect our measurement of connectivity of tasks within the city. In addition, the ONET data are based on data collected in 1998 (released in 2001). This means that we only have of a cross-section of task data at our disposal, which implies that the time variation in the division of tasks is based on the employment development of individual occupations. To deal with this issue, the task structure of cities in the initial year (1990) is used to document and interpret employment changes. This is similar to the approach taken in Autor et al. (2003), who use the Dictionary of Occupational Titles of 1977 to explain employment changes from 1963 onwards. We discuss the consequences of using this approach in Section 6, where we examine the robustness of our approach in more detail.

Next, employment figures for cities over the period 1990 to 2009 are collected from the Local Area Unemployment Statistics from the Bureau of Labor Statistics (BLS). Lastly, a city's share of high-skilled inhabitants is gathered from the Census Decennial Database. High-skilled workers are defined as those workers with at least a bachelor's degree.

The Appendix presents the features of the data sources in more detail and provides insight in the construction of the classification of cities, industries, occupations and tasks. The Appendix also includes a list of all variables, their aggregation level and their sources.

*Descriptive statistics*

The database we use for the empirical analysis contains information on the division of labor and other characteristics of the 168 largest US cities. Table 9 in the Appendix presents the raw and standardized summary statistics of the core variables used in the empirical analysis. We employ only standardized variables (with a mean of zero and a standard deviation of one) in the analyses.

Table 10 in the Appendix presents correlation coefficients of the most important variables used in the empirical analysis. Cities vary in terms of characteristics such as size, skill level and economic structure. Figure 2 shows the development of the division of the four task categories over time. The importance of tasks is measured as its share in the city's total task importance of all 41 tasks for all workers. We have set 1990 to zero. Relative to 1990, the employment share of mental processes and interacting with others has risen. This is consistent with the observations of Borghans et al. (2014), Borghans et al. (2008) and Bacolod et al. (2009) that interpersonal skills gain importance. Employment shares of information input tasks and especially work output tasks decreased during the period. The discontinuity in 2001 results from a change in definition in the CPS. Our definition of cities is not affected as we employ county information. Results are robust to different time periods.

Employment in our sample of cities grows. Urbanization seems to go along with increased city size: in 1990 about 65 percent of the US population lived in one of the 168 largest cities; in 2009 this share has risen to almost 75 percent. In addition, the relatively larger cities in our sample of 168 are growing faster than the relatively smaller cities. The rank size of cities is fairly stable with Los Angeles, New York and Chicago being the top 3 (more than 4,000,000 employees in 2009). At the bottom of the distribution the same cities turn up in both 1990 and 2009. Table 4 lists the five largest and five smallest cities in our list of 168 cities in 1990 and 2009. The next columns list the five fastest growing cities and the five slowest growing or shrinking cities in the period 1990-2009 both in absolute numbers of employees and in percentages. Phoenix, Atlanta, Houston, Washington D.C. and Las Vegas are the fastest growers, adding over 500,000 employees between 1990 and 2009. On the other hand, Detroit is shrinking in both absolute and percentage terms relatively fast.

The skill level of the largest US cities varies too. Boulder-Longmont, Washington D.C. and San-Francisco form the top 3 of high-skilled cities over the whole time period. In these cities more than 40 percent of the workforce is highly skilled, which holds for only 10 to 12 percent of the workforce in cities with the lowest skilled workforce. The average share of high-skilled workers in cities increases from 20 to 24 percent in the sample period. Computer use (in terms of average importance in occupations) varies across US cities as well. In 1990 computer use was valued the most in the occupations in Huntsville, San Jose and Washington D.C. (all with an average importance above 2 on a scale from 0 to 4). Since we only have cross-sectional information on the importance of computer use, changes in computer use over time are based on changes in the division of labor across occupations. The average importance of computer use increases slightly from 1.82 to 1.85, which indicates that occupations in which computer use is relatively important in 1990 increased in terms of employment shares.

Finally, Figure 3 shows the division of tasks across city sizes. We define three size classes. Small cities employ less than 250,000 workers, medium-sized cities have a working population in between 250,000 and 1 million, and large cities employ over 1 million workers. In larger cities mental processes and interaction with others seem to be relatively more important, while work output and information input tasks are relatively less important.

# 4 RESULTS

Because our database contains only 168 observations we first display simple graphical analyses of the task connectivity of cities and several bi-variate patterns in the data. We continue by presenting regression analyses and add several co-variates to the analysis. The sensitivity of the estimated coefficients to different sets of covariates and approaches to measure agglomeration effects is addressed in Section 5 which discusses various other measures of the task structure of cities. Section 6 shows a set of estimated coefficients for different samples.

*Graphical Analysis*

Figure 4 plots the (standardized) measures of task connectivity for all 41 tasks against changes in employment shares of these tasks in the period 1990-2009. Task connectivity is defined at the task level (see Equation (1)). Each dot represents a task. The figure displays a positive correlation between task connectivity and subsequent employment change, which suggests that more connected tasks have gained in terms of employment shares over the last two decades. The correlation coefficient equals 0.75 and is significant at the one percent level. The different markers in Figure 4 represent the four different types of tasks as defined by ONET. Task connectivity is relatively high among the different interacting with others tasks and mental processes tasks. Among most work output tasks the connectivity is relatively low, exceptions are computer use and documenting/recording information. Information input tasks reveal a more scattered pattern.

Figure 5 provides information about the characteristics of cities and consists of five panels. The horizontal axis measures the standardized task connectivity in 1990 for the 168 cities in our sample and the vertical axis the standardized log of employment in 1990. Here, task connectivity is measured at the city level (see Equation (2)). The dots in all five panels are cities, the markers define several city characteristics. Panel A presents a scatter plot of the correlation between task connectivity and city size. The correlation coefficient (standard error) between the two variables equals 0.88 (0.00). Florence, Visalia-Tulare-Porterville, Johnstown, Fort Wayne and Pueblo are the cities with the lowest task connectivity. Boston, New York, Chicago, Washington D.C. and Los Angeles have the highest connectivity in their task employment. In the four remaining panels we split the sample of 168 cities according to different characteristics.

Panel B splits the sample into different regions. We have defined four regions: the North-east, the Midwest, the South and the West. The figure does not return a clear pattern; cities with relatively high shares of connected tasks do not seem to be spatially concentrated in the United States.

Differences in the industrial structure of cities partly explain the development of cities (Glaeser et al., 1992; Henderson et al., 1995). A useful measure to account for such differences is the relative specialization index (RSI). The level of specialization measures the over-representation of an industry within a city relative to other cities. We define the RSI index using the employment shares $E$ for industry $j$ and city $l$:

$$RSI_l = max(log(E_{j,l}) - log(E_j)). \tag{3}$$

$RSI_l$ measures industry $j$'s employment share in the city ($E_{j,l}$) relative to the share of the industry in national employment ($E_j$). A high specialization level indicates that employment is relatively concentrated in a certain industry. The correlation between task connectivity and $RSI_l$ equals -0.59 (0.00).[6] In Panel C we again present the correlation between task connectivity and employment, but characterize cities by different categories of relative specialization. We have split the sample into three categories using the standardized RSI: unspecialized cities (a negative deviation from the mean), medium specialized cities (a small positive deviation from the mean) and highly specialized cities (more than one standard deviation above the mean). The picture suggests that the highly specialized cities are the ones with the lowest level of task connectivity. This seems plausible, since specialization means a strong division of labor with fewer tasks being carried out at home and more tasks being outsourced to other places. For the two measures of lower levels of specialization there is no clear pattern in the data in relation to task connectivity.

The structure of human capital in cities explains another major part of the development of cities (Glaeser and Maré, 2001; Glaeser and Resseger, 2010; Moretti, 2004; Berry and Glaeser, 2005; Venables, 2011). Glaeser and Resseger (2010) document that particularly cities with a relatively high-skilled population benefit from agglomeration economies. Connected tasks turn out to be more likely to be performed by relatively high-skilled workers. The importance of connected tasks for performing a job ranges (on a standardized scale) from 0.018 for high-school graduates to 0.125 for workers with at least a bachelor degree. In Panel D of Figure 5 we have split the sample of cities according to skill level. There are four categories defined based on the deviations from the mean: very low-skilled cities (less than 14.6 percent of the employees is skilled), low-skilled cities (between 14.6 and 20.2 percent is skilled), high-skilled cities (between 20.2 and 25.8 percent is skilled) and very high-skilled cities (more than 25.8 percent is skilled). The picture shows that cities with a more highly skilled workforce have higher levels of task connectivity. The correlation between the share of high-skilled workers and task connectivity equals 0.48 (0.00). In our regression analysis we control for the skill level of the workforce.

Finally, Panel E addresses the importance of social skills. Recent work by Charlot and Duranton (2004), Bacolod et al. (2009) and Florida et al. (2012) suggests that people skills are important in explaining the success of cities. The existence and wealth of dense areas indicates that interaction is valuable. Social or people skills ease interaction and are therefore more valued in larger cities (Bacolod et al., 2009). In terms of our analysis this could imply that our measure of connectivity picks up social skills. We define social (or people) skills by the share of the ONET social skills in city employment. The task connectivity of city employment correlates with the share of social skills (0.17 (0.03)) but much less than human capital and specialization. Panel E of Figure 5 shows no clear-cut pattern when discriminating between the importance of social skills across cities to explain the correlation between task connectivity and employment in 1990. The picture suggests that task connectivity is not only picking up the effect of social skills on employment.

We take from this graphical analysis that cities with a relatively highly connected task structure seem to be larger, less specialized and more skilled than cities with lower levels task connectivity. These cities also seem to employ workers for which social skills are relatively more important. In the next subsection we distinguish between different city characteristics and their impact on employment growth.

*Estimation Results*

We estimate a number of specifications in which we explain changes in employment across our sample of cities ($\Delta E_{90-09,l}$) by our connectivity measure in the initial year ($C_{90,l}$), location characteristics ($L_l$) and a set of covariates in the initial year ($X_{90,l}$). The equation we estimate is:

$$\Delta E_{90-09,l} = \alpha_0 + \alpha_1 E_{90,l} + \alpha_2 C_{90,l} + \alpha_3 L_l + \alpha_4 X_{90,l} + \epsilon_l, \tag{4}$$

where $l$ is an index for cities, $\alpha_0$ is a constant term, $E_{90,l}$ is the initial employment and $\epsilon_l$ an error term with the usual assumptions. The summary statistics of the variables are shown in Table 9.

Table 5 presents the results of estimating a number of straightforward regression models. We estimate the determinants of the employment growth (in logs) of cities between 1990 and 2009. It should be noted that all the presented results are not sensitive to the choice of the end year, e.g. employment effects of the crisis of 2008, and our measure of employment growth. We standardize the dependent variable for convenience of interpretation. The impact of several factors in terms of standard deviations employment growth seems to be more easily to grasp than the impact on log employment change. By doing so, the coefficients show the impact of a one standard deviation change in independent variables on employment growth (measured in standard deviations).

We find that a one standard deviation increase in task connectivity relates to an increase in employment of 30 to 45 percent of a standard deviation, that is between 1990 and 2009 (after 20 years). We include initial employment (in logs) in all models. This always returns negative and significant coefficients, which suggests a tendency towards convergence in city size in our sample. In the estimates presented in column (1) of Table 5 we show the effect of task connectivity on employment growth. The coefficient is positive and significant. The interpretation of the coefficient is that a one standard deviation increase in connectivity increases the growth of the employment by about 43 percent of a standard deviation or about 144,000 employees.

The second column of Table 5 includes common controls for location characteristics. Three main trends determined the growth of cities the last decades. First, cities with a high level of human capital grew faster than relatively low-skilled cities (Glaeser and Resseger, 2010; Eeckhout et al., 2010). Second, workers were attracted to the warmer, drier places in the US. The rise of the 'Sunbelt' is associated with capital accumulation (Caselli and Coleman, 2001), improvements in the political institutions and local policies (Besley et al., 2010) and consumption amenities (Mueser and Graves, 1995; Rappaport, 2007). And lastly, public transport routes became less important for city development (Glaeser and Shapiro, 2003). As a counterforce, density in cities often results in congestion and higher costs of living and especially housing (Moretti, 2013). To capture these main trends we add the city's share of high-skilled workers, housing prices, January and July temperature and regional dummies to the regression equation of which the results can be found in column (2). Consistent with the results obtained by Glaeser and Resseger (2010) and Eeckhout et al. (2010), cities with a one standard deviation higher share of high-skilled workers grow about 18 percent of a standard deviation faster. The cost of housing decreases the growth of cities: a one standard deviation higher housing price results in about 45 percent of a standard deviation lower employment growth. The coefficient of July temperature is significant and positive, while January temperature does not seem to affect employment growth. Given temperature, the western part of the US experienced the highest growth. Adding our measure of task connectivity to the equation with only the location variables increases the adjusted R-square from 0.418 to 0.432. The task connectivity of the employment in the city seems to have an additional and seizable impact in explaining employment growth during this period.

*Other City-structure Indicators*

Next, we add various other city-structure indicators to the analyses. Columns (3) to (8) in Table 5 present the results and the relations between these indicators and task connectivity and employment growth. We also visualize these relationships in Figures 6 and 7.

First, our results could potentially be driven by differences in industrial structure of the city (e.g., Glaeser et al. (1992), Henderson et al. (1995)). Besides the previously used relative specialization index we define the local industrial structure by labor pool suitability as in Glaeser and Kerr (2009). The labor pool suitability index measures the quality of the city's employment in terms of its industrial structure. The Glaeser-Kerr index for city $l$ is defined as follows:

$$GK_l = -\sum_j E_j \left( \sum_o |E_{j,o} - (\sum_j E_{j,l} E_{j,o})| \right). \tag{5}$$

The index measures the occupational relatedness of industries in the city or labor pool suitability. The availability of employment by occupation is measured by the industry structure of the city ($\sum_j E_{j,l} E_{j,o}$). This measure is compared with the national employment share of the occupation in the industry. Hence, $E_{j,o} - (\sum_j E_{j,l} E_{j,o})$ defines the absolute difference between the national employment share of an occupation in an industry and the local availability of employment given the industrial structure. Aggregated at the city-industry level this measure shows the suitability of the overall city employment for a certain industry. This is calculated for all industries and weighted by the importance of the industry in city employment ($\sum E_j$).

Panels A and B in Figure 6 show that the connectivity of employment correlates with the industrial specialization level (-0.59, significant at the 1 percent level) and with our measure of labor pool suitability (0.89, significant at the 1 percent level). It could be the case that our measure picks up the impact of spatial variation in industrial structure on employment growth. The correlation between the indicators for industrial structure do not correlate with employment growth (see Panels A and B in Figure 7). In column (3) we show the effect of adding the city's industrial specialization level to our baseline regression, while in column (4) we include labor pool suitability. The coefficient for industrial specialization is negative and statistically significant, while labor pool suitability does not seem to have a significant impact on employment growth. Both measures do not affect the significance or size of the connectivity coefficient. The decrease of the adjusted R-square indicates that these measures do not seem to add explanatory value in explaining employment growth in this period.[7]

Column (5) in Table 5 shows the effect of adding the importance of social skills. Bacolod et al. (2009) show that the presence of social skills positively influences employment. In terms of our analysis this could imply that our measure of connectivity indirectly measures social skills. Indeed, there is a positive and significant correlation between the relative importance of social skills and task connectivity (see Panel C in Figure 6, 0.17 (0.03)). Panel C in Figure 7 shows a positive correlation (0.20 (0.01)) between employment growth and social skills. When we control for size and local characteristics, the coefficient of social skills becomes insignificant. This suggests that task connectivity does not seem to be picking up the effect of social skills on employment growth.

Finally, we address the importance of routine and non-routine job tasks and the use of computers. Tasks that are connected seem to require more interactions. Communication technologies make these interactions easier and less costly (e.g., Gaspar and Glaeser (1998), Blum and Goldfarb (2006)). Autor et al. (2003) have carefully introduced the notion of routine and non-routine job tasks. Their analysis focuses on changes in the importance of job tasks to explain changes in wages and employment in the United States. The definitions of routine and non-routine tasks used in the analysis are based on the complementarity and substitutability of job tasks and computer technology. Routine tasks are substituted and likely to lose in terms of employment and wages, while non-routine tasks are complemented by computers. The latter set of tasks gains in terms of labor-market prospects. Autor and Dorn (2013) add a spatial dimension and show that cities with employment specialization in routine-intensive occupations in the 1960s experience employment and wage polarization after 1980. A possible concern with our results could be that non-routine tasks and tasks that require more computer use are more connected relative to routine tasks. We define the importance of routines and the importance of computer use in cities. The routines variable is defined as the ratio of the importance of routine tasks relative to the importance of non-routine tasks in city employment. Routine and non-routine tasks are defined as in Autor et al. (2003). Task importance by occupation from the DOT 1977 is matched to the CPS data in the same way the task data from ONET are matched. The importance of routine tasks ($r$) and non-routine tasks ($nr$) in US cities is defined by their average importance measured via occupation distributions, see Autor et al. (2003) for a detailed description. As in the connectivity measure, we employ the importance scores to proxy the employment shares of tasks in cities:

$$Routines_l = \frac{\tilde{E}_{r,l}}{\tilde{E}_{nr,l}}. \tag{6}$$

Computer use is defined as the ONET task 'using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.' This way of using computers does not reflect all types of uses, but forms a relatively good approximation for the analysis of clustering tasks together or placing some of them at distance (for a discussion of computer measures in analyses such as ours, see Katz (2000)). Indeed, Figure 6 shows that the share of connected tasks correlates with both the share of routine tasks (0.31 (0.00)) and the importance of computer use (0.61 (0.00)). Columns (6) and (7) of Table 5 present the results of a regression model in which we explain changes in employment between 1990 and 2009 by the importance of routines and computer use. The insignificant coefficients of both indicators suggest that this measure of routines does not add explanatory power to our estimates. The effect of task connectivity remains significant.

Lastly, column (8) includes all covariates in one regression. Both the significance and the point estimate of the connectivity coefficient remains similar, the size of the point estimate even increases a bit.

# 5 ALTERNATIVE MEASURES Of TASK COMPOSITION

The estimates documented in Table 5 suggest that task connectivity is correlated with employment growth across our sample of cities. We now analyze whether the connectivity between tasks is the appropriate measure for analysis of the task composition of cities. First, this Section defines two alternative measures of task connectivity. Second, we present estimates with the employment shares of the task groups and defines three other indicators that could capture task connectivity: the labor pool suitability of tasks and the specialization and diversity level of the task structure.

*Measures Of Task Connectivity*

Table 6 presents the results. Column (1) displays the baseline results with our measure of task connectivity, which is copied from Table 5, column (2). We first construct spatial connectivity between required job skills. ONET defines skills as 'Developed capacities that facilitate learning or the more rapid acquisition of knowledge'. Examples are speaking, writing, programming and repairing. 46 separate skills are distinguished. We measure connectivity between these 46 skills in the same way as our task connectivity measure. Connectivity between skills refers to the importance of human capital in cities (Glaeser and Resseger, 2010). Column (2) presents the results of an analysis with this indicator of skill connectivity instead of our preferred indicator. The coefficient of connectivity between worker skills is insignificant. The connectivity between worker skills does not explain employment growth of cities. If we include both the connectivity between tasks and the connectivity between skills the coefficient of task connectivity is not affected. This suggests that worker tasks seem to capture the concept of task connectivity better than required skills.

Ellison and Glaeser (1997) and Ellison et al. (2010) use an indicator to define the co-agglomeration of industries. Here, we apply their indicator at the task level. The co-agglomeration index for city $l$ is defined as:

$$CA_l = \sum_{t=1}^{t=41} \tilde{E}_{t,l} \left( \frac{\sum_{l=1}^{l=168} (\tilde{E}_{t,l} - \bar{E}_l)(\tilde{E}_{t',l} - \bar{E}_l)}{1 - \sum_{l=1}^{l=168} \bar{E}_l^2} \right). \tag{7}$$

$\tilde{E}_{t,l}$ refers to the estimated employment share of task $t$ in city $l$. $\bar{E}_l$ refers to the average employment share of tasks in city $l$. The fraction on the right-hand side calculates the co-agglomeration of task $t$. The numerator in the fraction calculates the over-representation of task $t$ in city $l$ relative to the over-representation of task $t'$. The denominator controls for city size. The left part of the right-hand side generates the average co-agglomeration of the city by multiplying task employment by task co-agglomeration. In contrast with our connectivity measure, the co-agglomeration index includes information about the diversity of the city's employment. Task connectivity and co-agglomeration strongly correlate (0.63 (0.00)). However, when co-agglomeration is included in the analysis instead of task connectivity the task composition has no significant impact on employment growth. Including both measures does not change the results. The co-agglomeration index is originally used to measure the co-agglomeration of industries. The insignificant coefficient of this index suggests that spatial concentration seem to be less important at the task level.

*Measures Of Task Composition*

We next consider the effect of the four task groups separately to investigate whether employment growth is driven by one particular set of tasks. First, we define the city's task composition by the employment share of the four task groups. Columns (4) to (7) of Table 6 present the estimates in which the employment shares of the four tasks groups are included instead of the city's task connectivity. The city's employment share of information input returns a negative coefficient (significant at the 10 percent level). A one standard deviation larger employment share of one of these task groups relates to about 14 percent of a standard deviation lower employment growth. The coefficients of the share of work output and mental processes tasks are insignificant (column (5) and (6)). Lastly, the employment share of interacting with others has a positive impact on employment growth. The coefficient is smaller than the one of task connectivity and is significant at the 10 percent level only. Table 11 in the appendix shows the estimates of regressions in which cross-terms between task groups are included. None of the cross-terms between task groups is statistically significant.

Next, we define the task structure of the city by constructing the relative specialization index, the Hirschman-Herfindahl index and the Glaeser-Kerr index at the task level. Duranton and Puga (2004) indicate three micro-foundations for the efficiency mechanism of cities; increasing the possibilities to share, match and learn. Spatial concentration of industries enhances possibilities to share facilities and suppliers, match employees to employers and learn from similar workers and firms. Empirical evidence in favour of these mechanisms is substantial (for an overview of the literature, see Glaeser and Gottlieb (2009)). Here, we test whether these mechanisms also exist at the task level using indirect measures for the benefits of sharing, matching and learning.

First, the spatial concentration of tasks could ease the possibilities to share facilities and suppliers for these tasks. Column (8) in Table 6 presents the results of an analysis including the regional specialization index at the task level. The index measures the over-representation of a task within the city relative to the importance of the task in national employment. The coefficient is insignificant and the point estimate is low. The spatial concentration of our 41 tasks does not seem to explain employment growth.

As Jacobs (1969) suggested, learning might be especially beneficial under cross-fertilization with workers with different task packages. The idea is that the combination of workers with different experiences and skills results into radical new ideas. To apply this idea at the task level, we also consider the impact of a diverse task composition. The inverse Hirschman-Herfindahl index measures the diversity of tasks in the city employment:

$$HHI_l = \frac{1}{\sum_t \tilde{E}_{t,l}^2} \quad , \tag{8}$$

where $\tilde{E}_{t,l}$ represents the estimated employment share of task $t$ in city $l$. The lower the index, the more dominant a certain task is in city employment. A high value indicates a diverse composition of employment in tasks. The results of including the inverse Hirschman-Herfindahl index is reported in column (9). The coefficient is small and shows an insignificant effect of the index on employment growth.

Lastly, the matching possibilities of workers with similar task packages is measured using the labor pool suitability measure of Glaeser and Kerr. Instead of measuring occupational suitability of industries, the index (defined in Equation (5)) now measures the task suitability of occupations. Hence, the index values the quality of the task packages of workers given the occupational structure of the city. The estimated coefficient for this index is shown in column (10). It is insignificant and small.

The three alternative indicators for task connectivity do not seem to explain employment growth. Including the measures together with our measure of task connectivity does not change the results: the coefficient of task connectivity remains positive and significant. We conclude that the spatial connectivity between tasks correlates more strongly with city growth than the level of specialization, diversity and labor pool suitability of tasks.

# 6 ALTERNATIVE SAMPLES OF OCCUPATIONS, WORKERS AND CITIES

We continue by testing whether our findings are robust across different samples of occupations, workers and cities. First, our estimates result from spatial variation in employment shares; they are not based on variation in the importance of tasks within occupations. We test the impact of this static measure of task importance and construct a sample which only considers the most important tasks within occupations. The analysis focuses on the main tasks within occupations, assuming that the main job tasks do not vary across space. Another possible concern is that the division of labor has changed because of the introduction of ICT. This technology has created new communication possibilities, which could have changed task connectivity. Second, we present estimates of our connectivity measure using two separate samples of computer intensive and computer extensive occupations. Third, we address the issue of the possible differences in tasks performance between cities that are relatively manufacturing and services intensive. Fourth, we deal with the question whether our results are driven by the importance of interactions between high-skilled workers or other subsamples of workers. Finally, we deal with possible biases in our results caused by a few successful metropolitan areas such as New York City and Los Angeles. These cities belong to the largest, most connected and fastest growing cities in our sample. Lastly, we present estimates in which we exclude these cities from the sample. Table 7 shows the regression results of these analyses.

*Spatial Variation Within Occupations*

Our analysis exploits spatial variation in occupational composition to measure variation in task input. The reason is that we only observe national task inputs. This approach suffers from the problem that it assumes that tasks carried out within occupations are static. Baumgardner (1988) and Duranton and Jayet (2011) suggest that this is unlikely to be true. A car mechanic in New York might carry out a different task package than a car mechanic in Detroit. Bacolod et al. (2009) also point at this caveat in their analysis.

To deal with this issue, we conduct an additional analysis using only the 'core' tasks of an occupation. Task connectivity is calculated across the most important tasks. The assumption is that the task composition of occupations varies across space but that the 'core' tasks do not vary. For example, the task packages of a car mechanic vary between cities but the task 'repairing' will be an important task in all car mechanic jobs. The distribution of tasks across US cities is now defined by the tasks within occupations with an importance above the mean of all 41 tasks in that same occupation. Column (1) of Table 7 shows the results of a regression analysis with task connectivity defined for the most important tasks only (instead of all 41 tasks). The coefficient of task connectivity in explaining changes in employment growth drops, but the coefficient remains significant at the 10 percent level.

*Computer Intensity*

Job tasks that need to be performed in close vicinity are likely to require more face-to-face interactions. These interactions are affected by computers. The use of computers either complements or substitutes face-to-face interactions (Ioannides et al., 2008). Acemoglu and Autor (2011) indicate a crucial distinction between the employment development of computer intensive and computer extensive occupations. In Section 4 we have shown that the importance of computer use and routine tasks is unlikely to explain the impact of task connectivity on employment growth. Here, we extend this analysis and focus on the role of computer intensive occupations. Column (2) shows estimates for the correlation between the connectivity of a city's computer intensive occupations and employment growth. For computer intensive occupations the importance of computer use is at least one standard deviation larger than the average importance. The task connectivity between tasks of computer intensive occupations has a positive and significant impact on employment growth. Column (3) presents the estimates for all other occupations. The coefficient is positive and insignificant. The size of the coefficient is comparable to the one for computer intensive occupations, but it is estimated with less precision. The coefficients of both samples are smaller than the one of the baseline sample. This suggests that the connectivity between computer intensive occupations and all other occupations relates to employment growth as well.

*Idea-producing Versus Product-producing Cities*

The changing economy and especially the de-industrialization of the US economy has been beneficial to cities, such as New York, but detrimental to others, such as Detroit. Glaeser and Ponzetto (2010) show that improvements in transport and communication technologies increased the returns to ideas. Idea-producing cities, such as New York and Boston, are favored by this trend while product-producing places, such as Detroit, are hurt. Here, we test whether task connectivity is beneficial for idea-producing cities, product-producing places or both.

Column (4) of Table 7 shows estimates for a sample of manufacturing sectors only. The correlation between task connectivity and employment growth is somewhat smaller for these sectors, relative to the estimate for connectivity in Table 5, but substantial and statically significant. Next, column (5) presents the estimates for a sample of service sectors. For service sectors, the impact of task connectivity is stronger than for manufacturing sectors. Hence, changes in the employment of both product-producing and idea-producing cities seem to be partly explained by our measure of task connectivity.

*Worker Skills*

We continue by addressing the importance of the complementary between skills and cities. High-skilled workers tend to sort into larger cities and this sorting explains spatial wage and employment differences (Combes et al., 2008; Glaeser et al., 2012). The relation between skills and cities seems to be complementary (Glaeser and Resseger, 2010; Elvery, 2010). Urban density particularly stimulates human capital spillovers Rosenthal and Strange (2008) and human capital accumulates more quickly in urban areas Glaeser and Maré (2001). Large cities are however characterized by relatively fat tails and their inhabitants are more likely to be high and low-skilled workers, while medium-skilled workers seem to sort into smaller cities (Eeckhout et al., 2010). New York and Detroit seem to employ both the best workers of the country, with degrees from the best universities, and the lowest-skilled of the nation. A possible concern with our results is that they might be driven by the strong connectivity between the tasks of high-skilled workers.

We analyze whether our findings hold for several groups of workers. Column (6) in Table 7 shows the estimates for a sample of high-skilled workers who obtained at least a bachelor degree. Second, columns (7) and (8) show the estimates for samples of medium- and low-skilled workers. In all three samples the coefficient for task connectivity is positive and significant. As expected, task connectivity of high-skilled workers has a stronger impact on employment growth than task connectivity of low-skilled workers. An increase of one standard deviation in connectivity relates to a rise in employment of about 50 percent of a standard deviation in the sample of high-skilled workers and of 36 percent of a standard deviation in the sample of low-skilled workers. In line with the work of Eeckhout et al. (2010), the connectivity between tasks of medium-skilled workers is only moderately correlated with employment growth. This finding is also consistent with the estimates presented by (Autor and Dorn, 2013). They obtain a picture suggesting complementarity between low- and high-skilled workers in US cities together with a decline in labor-market opportunities of medium-skilled workers.

As often shown in the literature (Borghans et al., 2014; Bacolod et al., 2009) different demographic groups tend to perform different worker tasks. The content of jobs substantially varies between females and males and older and younger workers. Likely, the spatial connectivity of job tasks varies as well between these demographic groups. In columns (9) to (12) we test whether our results hold for samples of demographic groups. Columns (9) and (10) in Table 7 show the estimates for a sample of males and females. The coefficient of task connectivity is similar for both samples. Second, columns (11) and (12) present the estimates for workers below and above the age of 45, i.e. 'young' and 'old' workers. The connectivity of job tasks of young workers has a stronger impact on employment growth than the connectivity of job tasks of older workers. This is in line with the findings that older workers perform more 'declining' job tasks (Autor and Dorn, 2009; Bosch and Ter Weel, 2013). We conclude that the estimated effects of connectivity on employment growth seem to hold for different sub-samples of workers.

*Excluding large metropolitan cities*

Finally, we test whether some large metropolitan cities dominate our results. The largest cities in our sample of 168 cities are the cities with the highest shares of high-skilled people, the strongest connectivity between the performed tasks and the highest employment growth. The estimates shown in column (13) are from a model in which we exclude cities with levels of employment that are more than two standard deviations above the mean. These cities are Detroit, Philadelphia, Washington D.C., Chicago, New York and Los Angeles. The coefficient of task connectivity hardly decreases and remains statistically significant. The adjusted R-square increases a bit, which seems to be caused by a stronger impact of location characteristics, such as rents and July temperature in this sample.

# 7 CONCLUSION

This paper is concerned with measuring and interpreting changes in employment across 168 US cities in the period 1990-2009. Within this period (characterized by rapid technological change) not only the division of labor between and within occupation has changed, but also the division across space. Our analysis provides a task-based approach, which allows us to investigate the relationship between task connectivity and employment growth.

Our framework relies upon the idea that employment grows when job tasks need to be performed in close vicinity and human interactions are important. The importance of vicinity and human interactions for tasks could lead to clustering of tasks or spreading to other places, which we measure by task connectivity. The extent to which tasks are spatially connected indicates whether they require face-to-face contacts or could be carried out at distance at reasonable costs. To analyze employment effects of changes in the division of tasks, we apply an empirical measure of task connectivity based on the correlation between several tasks in cities.

Our estimates suggest that differences in task connectivity contribute to explaining changes in employment growth across US cities. In particular we show that changes in employment across US cities can partially be explained by our measure of task connectivity. Higher task connectivity at the city level implies less room for placing tasks at distance. When tasks are more connected to the location (and to other tasks) cities are more likely to grow relative to cities with lower levels of task connectivity. We find that a one standard deviation increase in task connectivity relates to an increase in employment of 30 to 45 percent of a standard deviation in the period 1900-2009.

The coefficient of task connectivity is not affected by the inclusion of several other city characteristics. Furthermore, spatial connectivity between tasks seems to be more effective than spatial concentration of certain tasks and labor pool suitability to explain employment growth in this period. We investigate the sensitivity of our estimates by considering the effects of computerization of work, de-industrialization, sorting of workers and the impact of excluding large cities. We also investigate the limitations of our cross-section of task data. We find that our results do not seem to be driven by other trends and they do also not seem to be influenced by measures of spatial concentration.

This paper adds to the literature in labor economics and urban economics by offering a measure to explain employment changes across space. This complements the literature in labor economics focusing on changes in the task composition of work, see Acemoglu and Autor (2011) for a review, and to the literature in urban economics explaining changes in employment in cities, see Glaeser and Gottlieb (2009) for a review. Future work should consider deepening of the exact anatomy of task connectivity for explaining the success and decline of cities.

## Notes

[1]Rosenthal and Strange (2004) and Glaeser and Resseger (2010) extensively review the literature in urban economics. This literature mostly analyses employment changes at the level of occupations.

[2]This is the original ONET scaling.

[3]It should be noted that tasks and occupations show similar location patterns. As different occupations possess similar tasks, the connectivity measure of tasks provides additional insight in the co-location of tasks relative to a similar measure at the occupational level.

[4]We apply the Current Population Survey because this dataset provides us with information that allows for the possibility to distinguish trends of several demographic groups.

[5]The CPS contains information about the person's location of living, not on the location of work. Therefore, our data exclude workers who work within a MSA but live outside the MSA. We assume that the task-package of the workers who live in the MSA is a representative sample of all the workers in the MSA.

[6]This RSI measure defines the local level of *industrial* specialization, while the connectivity measure defines the local level connectivity between *tasks*. Therefore, the correlation does not result from the construction of the variables. The industrial and task structure of cities likely interfere. However, as Duranton and Puga (2001) note, recent changes in city structures seem to be related to occupations and functions more than to industries.

[7]When we exclude task connectivity from the regressions the coefficient of labor pool suitability becomes statistically significant.

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# A DATA APPENDIX - DATA SOURCES

*Current Population Survey / May Outgoing Rotation Group*

The Current Population Survey (CPS) is a monthly household survey of the US government. It contains information about employment and other labor-market variables. For each person it provides information on occupation, industry, hours worked, earnings, education, and unionization. The data also contain background variables such as age, sex, race, ethnicity, geographic location. We use the May Merged Outgoing Rotation Group (MORG) files in which more detailed information about earnings and working hours are available. We use the years 1990-2009 because the residence of the respondent is available in terms of Metropolitan Statistical Areas (MSA). We assume that the respondents work in the same MSA as they live. In 1990 67 percent of the respondents lives in a MSA, in 2009 this is almost 75 percent.

*ONET*

Task information is gathered from the ONET Database (www.onetcenter.org). For each occupation, this database provides information about the importance of 41 work activities. Work activities are defined as ’General types of job behaviors occurring on multiple jobs’. Initial information of the ONET database is based on data from occupation analysts. This information is supplemented and updated by ongoing surveys of each occupation’s worker population and occupation experts. The level of importance of the activities is measured by the question: How important is the work activity to the performance of the job? The importance is scaled from 1 (not important at all) to 5 (extremely important). The database consists of a cross-section, which is updated over time. The 3.0 version is used for this study.

*DOT*

Another source of information on job tasks in the United States is the Fourth (1977) version of the Dictionary of Occupational Titles (DOT). The task information in this data source matches the routine / non-routine distinction more accurate than the ONET Database. We apply the cross-walk provided by (Autor et al., 2003) between the occupation classification in the DOT, which is much more detailed, and the one in the CPS. For detailed discussions on this dataset and the difference with the ONET dataset we refer to (Autor et al., 2003; Autor, 2013).

*Local Area Unemployment Statistics*

The employment data for counties is collected from the Local Area Unemployment Statistics of the Bureau of Labor Statistics (BLS). We use county data for employment statistics instead of Metropolitan Statistical Areas (MSAs). The border definitions of MSAs change over time, so growth statistics are biased. Counties are merged into MSAs following the 1990 definition of the Census. Details on the construction of the city classifications are given below.

*Census 1990 and 2000*

The share of high-skilled people and the mean rent by MSA is gathered from the Census data. For each MSA it contains information on the number of people that have obtained at least a Bachelor's degree in 1990 and 2000. We do not have information on the share of high-skilled people or rents by city for other years.

# B DATA APPENDIX CLASSIFICATIONS

*Cities*

In 2009, MSAs were responsible for more than 85 percent of the employment, income, and production of products and services in the United States (Bureau of Economic Analysis). MSAs are defined by the nature of their economic activity. The scope of regional economic activity increases over time, which is replicated in the borders of the MSA classification. To analyze the development of economic structure within cities, we need a consistent city classification. To do so, we use MSA definitions by combining counties following the 1990 definition of the Census. Since county borders do not change over time, our MSA classification represents cities, which do not change in geographical size over time. Due to a change in classification of MSAs in 2005 we loose a small fraction of our sample. The definition of the Census is optimized for this break in classification. Our city classification consists of 168 MSAs, which are stable over time.

*Industries*

The Census industry classification changes within the period 1990-2009. We use a three-digit consistent classification provided by David Dorn and used in Autor and Dorn (2013).

The classification includes 142 industries at the three-digit level. For the two-digit level we distinguish 11 industries. We exclude the agriculture industry. To verify the CPS distribution of industries over MSAs we compare it with the County Business Pattern data. Using data from the County Business Patterns instead of the CPS does not change the results.

*Occupations*

The Census classification for occupations changes over time as well. We make use of the occupation classification in Autor and Dorn (2013). This classification includes 326 occupations, which are consistently defined over time.

Tasks are defined as 'General types of job behaviors occurring on multiple jobs'. The ONET database provides the importance of 41 work activities for occupations following the Standard Occupation Classification (SOC 2000). The SOC occupational classification scheme of the ONET database is matched to the Census 2000 occupational classification scheme. This scheme is collapsed to the 326 consistent occupations. Table 2 shows the 41 tasks, their task group and descriptive statistics.

# C TABLES

TABLE 1. Examples of task connectivity (eight tasks and five cities)

| | Information input | | Mental processes | | Work output | | Interacting with others | | Connectivity |
|---|---|---|---|---|---|---|---|---|---|
| | Getting information | Monitor, processes, materials, or surroundings | Processing information | Scheduling work and activities | Handling and moving objects | Controlling machines and processes | Assisting and caring for others | Developing and building teams | |
| Boston | 18.88 | 15.17 | 15.48 | 13.67 | 12.65 | 11.37 | 12.78 | 13.27 | 0.72 |
| Dallas | 18.87 | 15.14 | 15.37 | 13.68 | 12.72 | 11.51 | 12.71 | 13.25 | 0.43 |
| Detroit | 18.58 | 15.15 | 14.98 | 13.21 | 13.37 | 12.05 | 12.65 | 13.05 | -1.56 |
| Los Angeles | 18.80 | 15.15 | 15.19 | 13.50 | 13.01 | 11.75 | 12.60 | 13.16 | -0.42 |
| New York | 18.95 | 15.08 | 15.35 | 13.72 | 12.65 | 11.23 | 13.01 | 13.21 | 0.83 |
| Task connectivity | 2.06 | -0.04 | 2.33 | 2.16 | -2.23 | -2.02 | 0.94 | 2.33 | |

Note: Cells represent task-city employment shares (defined in Section 2). Task connectivity is measured as in Equation (1) for these eight groups in these five cities. Connectivity measures the connectivity of city employment as defined in Equation (2). Both measures are standardized with a mean of zero and a standard deviation of one.

TABLE 2. Descriptive information about the tasks used in the empirical analysis (employment and connectivity)

| Task | Employment share 1990 | 2009 | Task Connectivity |
|---|---|---|---|
| ONET task group 'Information input tasks' | | | |
| Getting Information | 3.40 | 3.38 | 0.30 |
| Monitor Processes, Materials, or Surroundings | 2.74 | 2.71 | -1.39 |
| Identifying Objects, Actions, and Events | 2.99 | 2.96 | -0.97 |
| Inspecting Equipment, Structures, or Material | 2.46 | 2.38 | -1.65 |
| Estimating the Quantifiable Characteristics of Products, Events, or Information | 2.31 | 2.29 | -0.84 |
| ONET task group 'Mental processes' | | | |
| Judging the Qualities of Things, Services, or People | 2.59 | 2.61 | -0.50 |
| Processing Information | 2.76 | 2.74 | 0.84 |
| Evaluating Information to Determine Compliance with Standards | 2.69 | 2.70 | 0.19 |
| Analyzing Data or Information | 2.48 | 2.51 | 0.97 |
| Making Decisions and Solving Problems | 3.00 | 3.02 | 0.86 |
| Thinking Creatively | 2.53 | 2.56 | 0.92 |
| Updating and Using Relevant Knowledge | 2.84 | 2.85 | 0.86 |
| Developing Objectives and Strategies | 2.26 | 2.32 | 0.98 |
| Scheduling Work and Activities | 2.45 | 2.46 | 0.89 |
| Organizing, Planning, and Prioritizing Work | 2.90 | 2.92 | 0.86 |
| ONET task group 'Work output' | | | |
| Performing General Physical Activities | 2.32 | 2.26 | -1.69 |
| Handling and Moving Objects | 2.36 | 2.25 | -1.71 |
| Controlling Machines and Processes | 2.12 | 1.99 | -1.68 |
| Operating Vehicles, Mechanized Devices, or Equipment | 1.86 | 1.80 | -1.68 |
| Interacting With Computers | 2.73 | 2.69 | 0.96 |
| Drafting, Laying Out, and Specifying Technical Devices. Parts. and Equipment | 1.51 | 1.44 | -1.00 |
| Repairing and Maintaining Mechanical Equipment | 1.63 | 1.55 | -1.70 |
| Repairing and Maintaining Electronic Equipment | 1.54 | 1.47 | -1.48 |
| Documenting or Recording Information | 2.72 | 2.72 | 0.77 |
| ONET task group 'Interacting with others' | | | |
| Interpreting the Meaning of Information for Others | 2.45 | 2.49 | 1.01 |
| Communicating with Supervisors, Peers, or Subordinates | 3.21 | 3.20 | 0.29 |
| Communicating with Persons Outside Organization | 2.68 | 2.74 | 0.82 |
| Establishing and Maintaining Interpersonal Relationships | 3.00 | 3.03 | 0.84 |
| Assisting and Caring for Others | 2.31 | 2.34 | -0.80 |
| Selling or Influencing Others | 2.08 | 2.14 | 0.31 |
| Resolving Conflicts and Negotiating with Others | 2.49 | 2.56 | 0.70 |
| Performing for or Working Directly with the Public | 2.56 | 2.63 | 0.00 |
| Coordinating the Work and Activities of Others | 2.46 | 2.49 | 0.60 |
| Developing and Building Teams | 2.39 | 2.43 | 0.41 |
| Training and Teaching Others | 2.50 | 2.51 | -0.81 |
| Guiding, Directing, and Motivating Subordinates | 2.20 | 2.26 | 0.44 |
| Coaching and Developing Others | 2.32 | 2.37 | -0.21 |
| Provide Consultation and Advice to Others | 2.13 | 2.16 | 1.02 |
| Performing Administrative Activities | 2.33 | 2.31 | 0.87 |
| Staffing Organizational Units | 1.67 | 1.70 | 0.77 |
| Monitoring and Controlling Resources | 2.04 | 2.06 | 0.62 |

Note: Summary statistics based on the task values across 326 occupations following the classification as defined in the Appendix. ONET Groups refer to the work activities groups as defined by ONET. Employment share is the average employment share in city employment as defined in Section 2. Task connectivity is defined in Equation (1).

## TABLE 3. Task importance by broad occupational groups

| | | Occupational groups | | | | Employment share | |
|---|---|---|---|---|---|---|---|
| | | Professional, managerial, technical | Clerical, sales | Production, operators | Service | 1990 | 2009 |
| Task group | Task example | (1) | (2) | (3) | (4) | (5) | (6) |
| Information input | Getting information | 3.52 | 3.09 | 3.58 | 3.37 | 28.02 | 27.89 |
| | | (0.63) | (0.73) | (0.34) | (0.41) | | |
| Mental processes | Processing information | 3.64 | 3.13 | 3.03 | 2.99 | 26.73 | 27.05 |
| | | (0.29) | (0.36) | (0.30) | (0.33) | | |
| Work output | Handling and moving objects | 2.44 | 2.24 | 3.04 | 2.51 | 21.04 | 20.46 |
| | | (0.85) | (0.89) | (0.57) | (0.61) | | |
| Interaction with others | Assisting and caring for others | 3.12 | 2.80 | 2.60 | 2.88 | 24.21 | 24.69 |
| | | (0.46) | (0.56) | (0.43) | (0.44) | | |
| Employment share 1990 | | 29.73 | 30.31 | 24.55 | 15.42 | | |
| Employment share 2009 | | 36.18 | 25.52 | 20.95 | 18.15 | | |

Note: Task groups refer to the ONET classification. Importance is measured on a scale from 1 (not important at all) to 5 (extremely important). A cell shows the average importance, and its standard deviation, of the tasks of a task group within a broad occupation group. The four broad occupational groups are defined as in Acemoglu and Autor (2011).

Table 4. The largest, smallest, fastest growing and shrinking MSAs

| Size (number of workers) | | Growth | |
|---|---|---|---|
| 1990 | 2009 | Employment (number of workers) | Percentage |
| Largest MSAs | | Fastest growers | |
| Los Angeles | Los Angeles | Phoenix-Mesa | Las Vegas |
| (4,259,705) | (4,328,589) | (814,075) | (11.42) |
| New York | New York | Atlanta | McAllen-Edinburg-Mission |
| (3,745,220) | (4,256,376) | (792,870) | (107.07) |
| Chicago | Chicago | Houston | Provo-Orem |
| (3,645,767) | (4,000,905) | (630,134) | (85.66) |
| Boston | Boston, | Washington D.C. | Fayetteville-Springdale-Rogers |
| (2,910,471) | (3,101,796) | (606,593) | (85.38) |
| Philadelphia | Philadelphia | Las Vegas | Austin-San Marcos |
| (2,355,639) | (2,454,509) | (524,178) | (81.99) |
| Smallest MSAs | | Slowest growers | |
| Pueblo | Florence | Detroit | Hickory-Morgantown |
| (48,728) | (60,580) | (-178,313) | (-12.19 ) |
| Florence | Monroe | New Orleans | Benton Harbor |
| (58,064) | (66,048) | (-50,632) | (-10.52 ) |
| Waterloo-Cedar Falls | Jackson | San Jose | Binghamton |
| (58,862) | (66,162) | (-37,472) | (-9.37) |
| Fort Walton Beach | Pueblo | Dayton-Springfield | Detroit |
| (62,143) | (67,660) | (-28,604) | (-9.15) |
| Monroe | Benton Harbor | Newark | New Orleans |
| (62,704) | (67,730) | (-21,371) | (-9.08) |

TABLE 5. The estimated effect of task connectivity on employment growth, 1990-2009

| | Employment growth 1990-2009 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Employment | -0.464*** | -0.286** | -0.339** | -0.284* | -0.264* | -0.257* | -0.297** | -0.332** |
| | [0.147] | [0.143] | [0.146] | [0.149] | [0.144] | [0.143] | [0.145] | [0.150] |
| Connectivity | 0.425*** | 0.375** | 0.318** | 0.387** | 0.344** | 0.384** | 0.400** | 0.440** |
| | [0.143] | [0.158] | [0.146] | [0.193] | [0.156] | [0.156] | [0.172] | [0.213] |
| Industrial specialization | | | -0.194** | | | | | -0.219*** |
| | | | [0.076] | | | | | [0.076] |
| Labor suitability | | | | -0.014 | | | | -0.037 |
| | | | | [0.148] | | | | [0.155] |
| Social skills | | | | | 0.046 | | | -0.017 |
| | | | | | [0.065] | | | [0.070] |
| Routine tasks | | | | | | -0.077 | | -0.121 |
| | | | | | | [0.069] | | [0.079] |
| Computer use | | | | | | | -0.042 | -0.116 |
| | | | | | | | [0.082] | [0.088] |
| High skilled | | 0.179* | 0.162 | 0.177* | 0.184* | 0.163 | 0.200* | 0.185* |
| | | [0.103] | [0.099] | [0.104] | [0.101] | [0.103] | [0.107] | [0.102] |
| Rent | | -0.450*** | -0.465*** | -0.451*** | -0.449*** | -0.464*** | -0.452*** | -0.500*** |
| | | [0.087] | [0.086] | [0.088] | [0.087] | [0.090] | [0.087] | [0.089] |
| January temperature | | -0.117 | -0.191 | -0.117 | -0.121 | -0.108 | -0.119 | -0.190 |
| | | [0.146] | [0.145] | [0.147] | [0.147] | [0.147] | [0.147] | [0.147] |
| July temperature | | 0.391*** | 0.440*** | 0.391*** | 0.389*** | 0.369*** | 0.392*** | 0.413*** |
| | | [0.128] | [0.131] | [0.129] | [0.127] | [0.127] | [0.129] | [0.130] |
| North-east | | -0.295 | -0.293 | -0.296 | -0.270 | -0.284 | -0.290 | -0.278 |
| | | [0.230] | [0.239] | [0.231] | [0.237] | [0.233] | [0.229] | [0.241] |
| Midwest | | -0.535** | -0.546*** | -0.537** | -0.533** | -0.565*** | -0.532** | -0.592*** |
| | | [0.208] | [0.207] | [0.208] | [0.208] | [0.208] | [0.207] | [0.206] |
| West | | 1.439*** | 1.518*** | 1.441*** | 1.433*** | 1.402*** | 1.441*** | 1.481*** |
| | | [0.252] | [0.249] | [0.253] | [0.247] | [0.253] | [0.252] | [0.249] |
| Constant | -0.000 | -0.193 | -0.209 | -0.192 | -0.174 | -0.179 | -0.194 | -0.201 |
| | [0.076] | [0.130] | [0.127] | [0.130] | [0.129] | [0.130] | [0.130] | [0.126] |
| Observations | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Adjusted R-squared | 0.039 | 0.432 | 0.451 | 0.428 | 0.430 | 0.433 | 0.429 | 0.449 |

Note: Variables are for 1990 and defined as in Table 8 in the Appendix, Table 9 in the Appendix displays summary statistics of these variables. All variables are standardized with a mean of zero and a standard deviation of one. There are three regional dummies, region 'South' is the reference group. Robust standard errors are in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

TABLE 6. Using different measures of task composition to explain employment growth, 1990-2009

| | Employment growth 1990-2009 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Connectivity | Skills | Co-agglomeration | Information input | Work output | Mental processes | Interacting with others | Task specialization | HHI | Labor suitability |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Employment | -0.286** | 0.011 | -0.212 | 0.014 | 0.014 | 0.029 | 0.016 | -0.004 | 0.076 | 0.025 |
| | [0.143] | [0.067] | [0.157] | [0.067] | [0.067] | [0.070] | [0.066] | [0.076] | [0.090] | [0.065] |
| Measure of connectivity | 0.375** | 0.095 | 0.256 | -0.136* | -0.075 | -0.045 | 0.131* | -0.064 | -0.083 | 0.014 |
| | [0.158] | [0.082] | [0.160] | [0.071] | [0.082] | [0.079] | [0.076] | [0.071] | [0.061] | [0.063] |
| High skilled | 0.179* | 0.207* | 0.263*** | 0.187* | 0.221** | 0.301*** | 0.201** | 0.238*** | 0.286*** | 0.271*** |
| | [0.103] | [0.109] | [0.085] | [0.099] | [0.108] | [0.098] | [0.099] | [0.087] | [0.082] | [0.084] |
| Rent | -0.450*** | -0.481*** | -0.469*** | -0.465*** | -0.485*** | -0.488*** | -0.473*** | -0.470*** | -0.525*** | -0.491*** |
| | [0.087] | [0.089] | [0.087] | [0.088] | [0.089] | [0.088] | [0.087] | [0.087] | [0.092] | [0.090] |
| January temperature | -0.117 | -0.095 | -0.095 | -0.110 | -0.085 | -0.095 | -0.101 | -0.094 | -0.087 | -0.085 |
| | [0.146] | [0.149] | [0.146] | [0.149] | [0.147] | [0.149] | [0.147] | [0.147] | [0.150] | [0.151] |
| July temperature | 0.391*** | 0.361*** | 0.391*** | 0.364*** | 0.352*** | 0.363*** | 0.350*** | 0.357*** | 0.373*** | 0.362*** |
| | [0.128] | [0.125] | [0.131] | [0.125] | [0.123] | [0.126] | [0.122] | [0.125] | [0.125] | [0.125] |
| North-east | -0.295 | -0.242 | -0.261 | -0.243 | -0.241 | -0.262 | -0.226 | -0.273 | -0.215 | -0.248 |
| | [0.230] | [0.222] | [0.220] | [0.227] | [0.221] | [0.214] | [0.225] | [0.220] | [0.207] | [0.227] |
| Midwest | -0.535** | -0.512** | -0.492** | -0.531** | -0.512** | -0.521** | -0.521** | -0.533*** | -0.488** | -0.502** |
| | [0.208] | [0.203] | [0.200] | [0.206] | [0.202] | [0.200] | [0.202] | [0.201] | [0.194] | [0.220] |
| West | 1.439*** | 1.401*** | 1.443*** | 1.377*** | 1.398*** | 1.410*** | 1.369*** | 1.392*** | 1.475*** | 1.423*** |
| | [0.252] | [0.246] | [0.255] | [0.248] | [0.245] | [0.249] | [0.236] | [0.252] | [0.256] | [0.245] |
| Constant | -0.193 | -0.199 | -0.210 | -0.187 | -0.199 | -0.197 | -0.190 | -0.187 | -0.228* | -0.207 |
| | [0.130] | [0.128] | [0.128] | [0.130] | [0.128] | [0.126] | [0.127] | [0.128] | [0.122] | [0.131] |
| Observations | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Adjusted R-squared | 0.432 | 0.409 | 0.415 | 0.416 | 0.407 | 0.405 | 0.416 | 0.406 | 0.408 | 0.404 |

Note: All independent variables are measured in 1990 values and defined in Table 8 in the Appendix. Table 9 in the Appendix displays summary statistics of these variables. All variables are standardized with a mean of zero and a standard deviation of one. There are three regional dummies, region 'South' is the reference group. In column (2) the connectivity between ONET skills is used instead of the connectivity between ONET work activities. Co-agglomeration refers to the index defined in Equation (7). The share of the task group in columns (4) to (7) represents the city's standardized employment share in the respective task group in 1990. Task specialization defines the relative task specialization and is measured as in Equation (3). HHI refers to the inverse Hirschman-Herfindahl-Index and is defined in Equation (8). Labor pool suitability is measured by the Glaeser-Kerr index using tasks instead of occupations (see Equation (5)). Robust standard errors are in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

# Table 7. Estimated coefficients for different samples and types of workers

| | Employment growth 1990-2009 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Most important tasks | Computer intensive occupations | Not computer intensive occupations | Manufacturing sectors | Services sectors | High-skilled workers | Medium-skilled workers | Low-skilled workers | Males | Females | $45^{-}$ | $45^{+}$ | Without largest cities |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
| Employment | -0.128 | -0.217 | -0.241 | -0.266* | -0.311** | -0.245* | -0.218 | -0.283** | -0.298** | -0.286** | -0.337** | -0.194 | -0.287** |
| | [0.139] | [0.135] | [0.168] | [0.140] | [0.144] | [0.131] | [0.135] | [0.142] | [0.144] | [0.141] | [0.159] | [0.130] | [0.145] |
| Connectivity | 0.238* | 0.286** | 0.291 | 0.341** | 0.402** | 0.338** | 0.297* | 0.365** | 0.382** | 0.370** | 0.412** | 0.271* | 0.370** |
| | [0.140] | [0.143] | [0.178] | [0.149] | [0.161] | [0.146] | [0.152] | [0.158] | [0.159] | [0.155] | [0.170] | [0.141] | [0.159] |
| High skilled | 0.250* | 0.240*** | 0.266*** | 0.225** | 0.214** | 0.215** | 0.225** | 0.227** | 0.218** | 0.219** | 0.218** | 0.232** | 0.170 |
| | [0.138] | [0.091] | [0.084] | [0.093] | [0.092] | [0.094] | [0.094] | [0.091] | [0.093] | [0.093] | [0.092] | [0.092] | [0.105] |
| Rent | -0.471*** | -0.460*** | -0.472*** | -0.459*** | -0.466*** | -0.495*** | -0.484*** | -0.466*** | -0.459*** | -0.465*** | -0.445*** | -0.490*** | -0.485*** |
| | [0.116] | [0.089] | [0.083] | [0.084] | [0.080] | [0.078] | [0.081] | [0.082] | [0.082] | [0.081] | [0.084] | [0.080] | [0.079] |
| January temperature | -0.113 | -0.079 | -0.089 | -0.100 | -0.087 | -0.068 | -0.070 | -0.091 | -0.093 | -0.093 | -0.097 | -0.084 | -0.091 |
| | [0.198] | [0.145] | [0.147] | [0.146] | [0.142] | [0.141] | [0.143] | [0.143] | [0.144] | [0.144] | [0.145] | [0.145] | [0.148] |
| July temperature | 0.177 | 0.360*** | 0.388*** | 0.390*** | 0.389*** | 0.377*** | 0.371*** | 0.382*** | 0.390*** | 0.388*** | 0.391*** | 0.378*** | 0.414*** |
| | [0.145] | [0.128] | [0.129] | [0.127] | [0.126] | [0.126] | [0.127] | [0.125] | [0.127] | [0.127] | [0.127] | [0.128] | [0.130] |
| North-east | -0.808** | -0.303 | -0.240 | -0.268 | -0.261 | -0.268 | -0.264 | -0.279 | -0.265 | -0.268 | -0.244 | -0.282 | -0.218 |
| | [0.369] | [0.231] | [0.223] | [0.228] | [0.224] | [0.221] | [0.223] | [0.229] | [0.226] | [0.226] | [0.227] | [0.227] | [0.231] |
| Midwest | -0.740** | -0.546*** | -0.510** | -0.531*** | -0.500** | -0.499** | -0.513** | -0.526*** | -0.515** | -0.516** | -0.528** | -0.515** | -0.450** |
| | [0.327] | [0.206] | [0.204] | [0.203] | [0.198] | [0.196] | [0.199] | [0.201] | [0.200] | [0.200] | [0.204] | [0.199] | [0.206] |
| West | 0.877*** | 1.371*** | 1.402*** | 1.414*** | 1.413*** | 1.454*** | 1.416*** | 1.411*** | 1.408*** | 1.415*** | 1.386*** | 1.442*** | 1.570*** |
| | [0.313] | [0.249] | [0.247] | [0.246] | [0.239] | [0.250] | [0.251] | [0.241] | [0.242] | [0.242] | [0.241] | [0.254] | [0.249] |
| Constant | 0.141 | -0.175 | -0.199 | -0.191 | -0.201 | -0.213* | -0.200 | -0.191 | -0.195 | -0.196 | -0.188 | -0.204 | -0.265** |
| | [0.270] | [0.131] | [0.130] | [0.129] | [0.125] | [0.123] | [0.126] | [0.128] | [0.127] | [0.127] | [0.129] | [0.126] | [0.127] |
| Observations | 86 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 163 |
| Adjusted R-squared | 0.446 | 0.423 | 0.417 | 0.427 | 0.438 | 0.425 | 0.420 | 0.433 | 0.434 | 0.432 | 0.436 | 0.418 | 0.446 |

Note: All independent variables are measured in 1990 values and defined in Table 8 in the Appendix. Table 9 in the Appendix displays summary statistics of these variables. All variables are standardized with a mean of zero and a standard deviation of one. Column (1) displays results from including core tasks only in the connectivity measure. In column (2) the measure of connectivity only includes tasks with a national employment share of more than 0.02 which results in a sample of about 75% of all tasks. Occupations for which the importance of computer use is more than one standard deviation above average are defined as 'computer intensive' (column (3)). High-skilled workers obtained at least a bachelor degree while low-skilled workers obtained at most a high-school degree, medium-skilled workers continued studying after high-school but did not obtain a bachelor degree. Lastly, column (13) excludes cities which are more than two standard deviations larger than the mean: Detroit, Philadelphia, Washington D.C., Chicago, New York and Los Angeles. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

## Table 8. Variables

| Variable | Definition | Year of measurement | Measurement | Source |
|---|---|---|---|---|
| Employment growth | MSAs employment growth 1990 - 2009 | 1990-2009 | Standardized change in logs | Local Area Unemployment Statistics |
| Employment | MSAs employment | 1990 | Standardized log | Local Area Unemployment Statistics |
| Connectivity | MSAs average task connectivity, see Equation (1) | 1990 | Standardized mean | CPS matched to ONET |
| Industrial specialization | MSAs maximum over-representation of an industry, see Equation (3) | 1990 | Standardized mean | CPS |
| Labor suitability | MSAs quality of the local labor pool relative to the industrial structure, see Equation (5) | 1990 | Standardized mean | CPS |
| Social skills | MSAs share of social skills (ONET definition) in employment | 1990 | Standardized share | CPS matched to ONET |
| Routine tasks | MSAs ratio of routine task importance versus non-routine importance. Defined as in Acemoglu and Autor (2011) | 1990 | Standardized ratio | CPS matched to DOT |
| Computer use | MSAs average importance of computer use as defined in Section 4 | 1990 | Standardized score | CPS matched to ONET |
| High-skilled | MSAs share of workers with at least a bachelor degree | 1990 | Standardized share | Census Decennial Database |
| Rent | MSAs mean rent | 1990 | Standardized rent | Census Decennial Database |
| January temperature | Average State January temperature | 1990 | Standardized temperature | Census |
| July temperature | Average State July temperature | 1990 | Standardized temperature | Census |
| Regional dummies | MSAs location dummy, defined as in the Census Regional Division | | Dummy variables | Census Regional Division |
| Skill - connectivity | MSAs average connectivity of ONET Skills, see Equation (2) | 1990 | Standardized mean | CPS matched to ONET |
| Co-agglomeration | MSAs average co-agglomeration of task employment, see Equation (7) | 1990 | Standardized mean | CPS matched to ONET |
| HHI | MSAs score on the inverse Hirschman-Hefindahl index, see Equation (8) | 1990 | Standardized score | CPS matched to ONET |

Table 9. Summary statistics

| | Raw variables | | | | Standardized | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St. dev. | Min | Max | Mean | St. dev. | Min | Max |
| Employment 1990-2009 | 0.18 | 0.17 | -0.13 | 0.79 | 0.00 | 1.00 | -1.85 | 3.60 |
| Employment | 12.46 | 0.97 | 10.77 | 15.26 | 0.00 | 1.00 | -1.74 | 2.89 |
| Connectivity | 0.10 | 0.96 | -1.69 | 2.76 | 0.00 | 1.00 | -1.87 | 2.77 |
| Industrial specialization | 3.24 | 0.76 | 1.62 | 5.14 | 0.00 | 1.00 | -2.09 | 2.90 |
| Labor suitability | 0.41 | 0.08 | 0.23 | 5.14 | 0.00 | 1.00 | -2.29 | 1.75 |
| Social skills | 13.02 | 0.30 | 12.11 | 5.14 | 0.00 | 1.00 | -4.17 | 3.14 |
| Computer use | 1.81 | 0.11 | 1.41 | 0.54 | 0.00 | 1.00 | -2.50 | 3.24 |
| Share high skilled | 20.21 | 5.65 | 10.20 | 13.88 | 0.00 | 1.00 | -1.78 | 4.02 |
| Rent | -0.08 | 0.94 | -0.99 | 2.09 | 0.00 | 1.00 | -0.99 | 4.92 |
| January temperature | 33.05 | 12.55 | 5.60 | 42.84 | 0.00 | 1.00 | -1.65 | 2.72 |
| July temperature | 75.13 | 5.15 | 66.00 | 4.92 | 0.00 | 1.00 | -1.79 | 1.34 |
| North-east | 0.12 | 0.33 | 0.00 | 1.00 | | | | |
| Midwest | 0.25 | 0.43 | 0.00 | 1.00 | | | | |
| South | 0.41 | 0.49 | 0.00 | 1.00 | | | | |
| West | 0.23 | 0.42 | 0.00 | 1.00 | | | | |

Note: $n$=168 cities. All variables are measured in 1990. Variables are measured as described in Table 8 in the appendix.

## Table 10. Correlation matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Employment growth 1990-2009 | 1.00 | | | | | | | | | | | | | | | |
| (2) Employment | -0.09 | 1.00 | | | | | | | | | | | | | | |
| | (0.23) | | | | | | | | | | | | | | | |
| (3) Connectivity | 0.02 | 0.88 | 1.00 | | | | | | | | | | | | | |
| | (0.81) | (0.00) | | | | | | | | | | | | | | |
| (4) Industrial specialization | -0.11 | -0.58 | -0.59 | 1.00 | | | | | | | | | | | | |
| | (0.17) | (0.00) | (0.00) | | | | | | | | | | | | | |
| (5) Labor suitability | 0.03 | 0.82 | 0.89 | -0.54 | 1.00 | | | | | | | | | | | |
| | (0.69) | (0.00) | (0.00) | (0.00) | | | | | | | | | | | | |
| (6) Social skills | 0.20 | 0.04 | 0.17 | -0.15 | 0.11 | 1.00 | | | | | | | | | | |
| | (0.01) | (0.62) | (0.03) | (0.05) | (0.15) | | | | | | | | | | | |
| (7) Routine tasks | -0.16 | 0.36 | 0.31 | -0.25 | 0.40 | -0.30 | 1.00 | | | | | | | | | |
| | (0.04) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | | | | |
| (8) Computer use | 0.07 | 0.43 | 0.61 | -0.40 | 0.38 | 0.11 | -0.08 | 1.00 | | | | | | | | |
| | (0.36) | (0.00) | (0.00) | (0.00) | (0.00) | (0.17) | (0.27) | | | | | | | | | |
| (9) High skilled | 0.16 | 0.35 | 0.48 | -0.34 | 0.28 | 0.06 | -0.10 | 0.69 | 1.00 | | | | | | | |
| | (0.04) | (0.00) | (0.00) | (0.00) | (0.00) | (0.45) | (0.20) | (0.00) | | | | | | | | |
| (10) Rent | -0.06 | 0.42 | 0.38 | -0.38 | 0.26 | 0.01 | -0.05 | 0.31 | 0.48 | 1.00 | | | | | | |
| | (0.45) | (0.00) | (0.00) | (0.00) | (0.00) | (0.90) | (0.55) | (0.00) | (0.00) | | | | | | | |
| (11) January temperature | 0.34 | -0.04 | -0.08 | -0.13 | -0.02 | 0.16 | -0.09 | -0.13 | -0.04 | 0.23 | 1.00 | | | | | |
| | (0.00) | (0.59) | (0.31) | (0.09) | (0.77) | (0.04) | (0.22) | (0.09) | (0.62) | (0.00) | | | | | | |
| (12) July temperature | 0.21 | -0.05 | -0.09 | -0.02 | -0.03 | 0.12 | -0.07 | -0.15 | -0.13 | -0.15 | 0.72 | 1.00 | | | | |
| | (0.01) | (0.56) | (0.24) | (0.85) | (0.68) | (0.12) | (0.40) | (0.05) | (0.08) | (0.06) | (0.00) | | | | | |
| (13) North-east | -0.30 | 0.15 | 0.14 | -0.07 | 0.10 | -0.21 | 0.23 | 0.07 | -0.02 | 0.12 | -0.33 | -0.32 | 1.00 | | | |
| | (0.00) | (0.06) | (0.07) | (0.38) | (0.20) | (0.01) | (0.00) | (0.40) | (0.79) | (0.12) | (0.00) | (0.00) | | | | |
| (14) Midwest | -0.36 | -0.01 | 0.00 | 0.10 | -0.04 | -0.04 | -0.05 | 0.03 | -0.07 | -0.24 | -0.60 | -0.31 | -0.21 | 1.00 | | |
| | (0.00) | (0.92) | (0.96) | (0.20) | (0.64) | (0.58) | (0.52) | (0.72) | (0.40) | (0.00) | (0.00) | (0.00) | (0.01) | | | |
| (15) South | 0.20 | -0.10 | -0.11 | 0.00 | -0.04 | 0.11 | 0.02 | -0.13 | -0.11 | -0.28 | 0.57 | 0.78 | -0.30 | -0.48 | 1.00 | |
| | (0.01) | (0.20) | (0.16) | (0.99) | (0.60) | (0.16) | (0.75) | (0.09) | (0.16) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | |
| (16) West | 0.37 | 0.01 | 0.01 | -0.05 | 0.01 | 0.08 | -0.15 | 0.08 | 0.21 | 0.49 | 0.21 | -0.35 | -0.20 | -0.31 | -0.45 | 1.00 |
| | (0.00) | (0.89) | (0.85) | (0.52) | (0.92) | (0.31) | (0.05) | (0.33) | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) | |

Note: P-values are in parentheses. $n = 168$ cities. All variables are measured in 1990. Definitions and sources of the variables are displayed in Table 8.

Table 11. Regression results of using task group combinations

| | Information input | Work output | Mental processes |
|---|---|---|---|
| Work output | -0.049 | | |
| | [0.043] | | |
| Mental process | 0.065 | 0.047 | |
| | [0.054] | [0.046] | |
| Interacting with others | 0.032 | 0.035 | -0.083 |
| | [0.038] | [0.039] | [0.054] |

Note: Regressions include initial employment share (1990), employment in both task groups separately and the control variables as well. Only the interaction term between employment in two task groups is presented. For instance, the cell Information input - Work output shows the coefficient of the interaction term of employment in information input and employment in work output tasks (both in 1990 while the regression furthermore includes the initial employment, the employment shares in information input and work output in 1990 and the control variables). Robust standard errors are in parentheses. The coefficients are insignificant.

# D FIGURES

Figure 1. Database construction

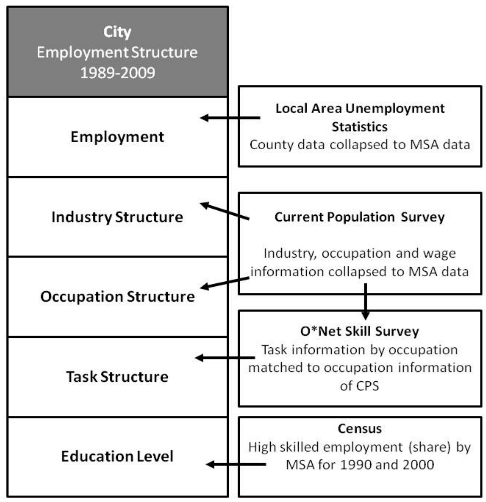
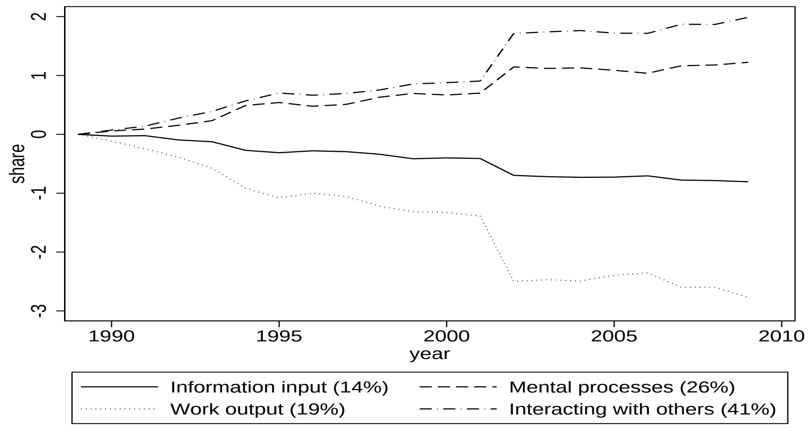
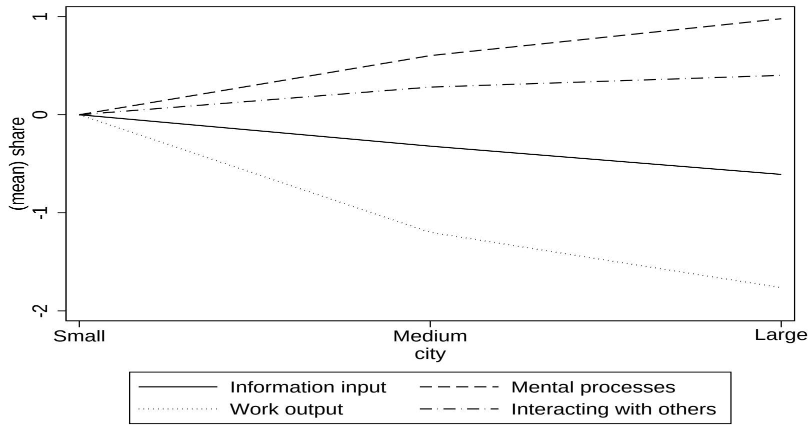


Figure 2. Employment of four broad task groups over time



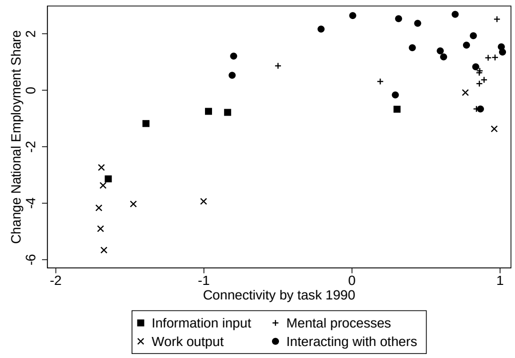

We employ occupational information to divide employment across four task groups. Lines represent the trend in the national employment share of the broad task groups. The development is normalized to the employment share in 1990. The actual employment share in 1990 is in brackets. Definition changes in the CPS cause the discontinuity in 2001. The definition of cities is not affected as we employ county information. Results are robust to different time periods.

Figure 3. Division of tasks across city sizes (1990)



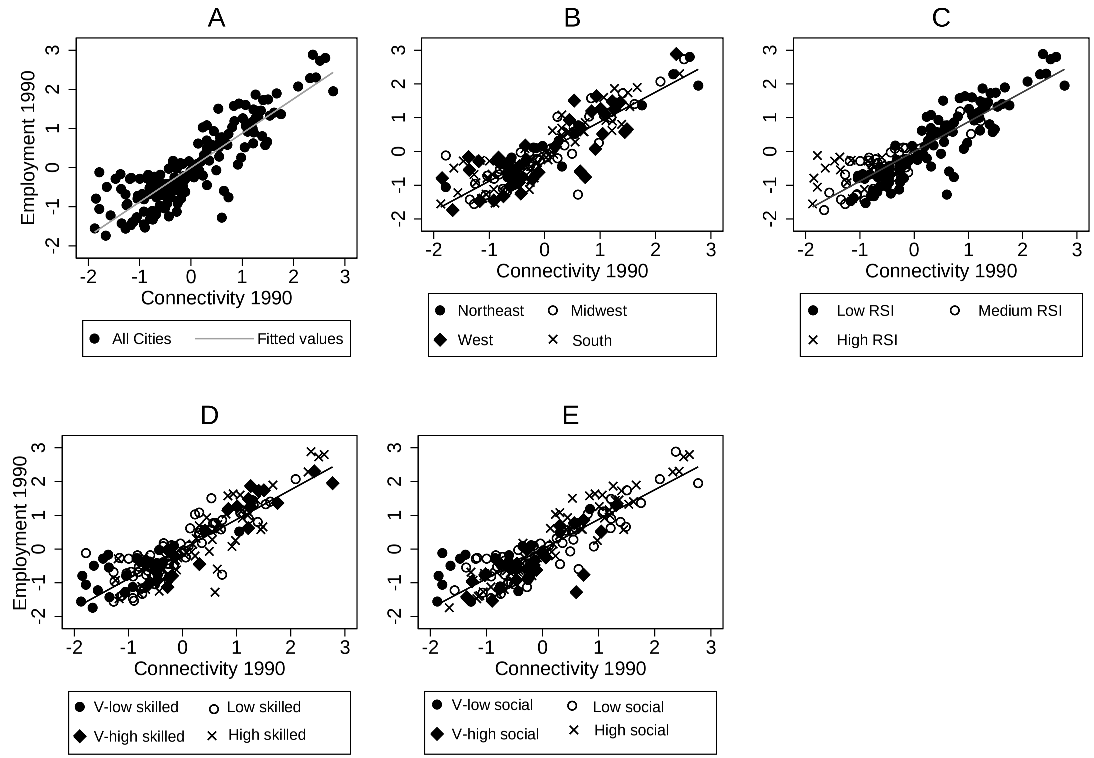

We employ occupational information to divide employment of each city across four task groups. Lines represent the relative importance of these four task groups in small, medium and large cities. The employment share of tasks is normalized to zero at the employment share in small cities. Small cities are defined to have less than 250,000 employees, medium cities between 250,000 and 1,000,000 employees and large cities more than 1,000,000 employees.

Figure 4. Task connectivity and change in employment share



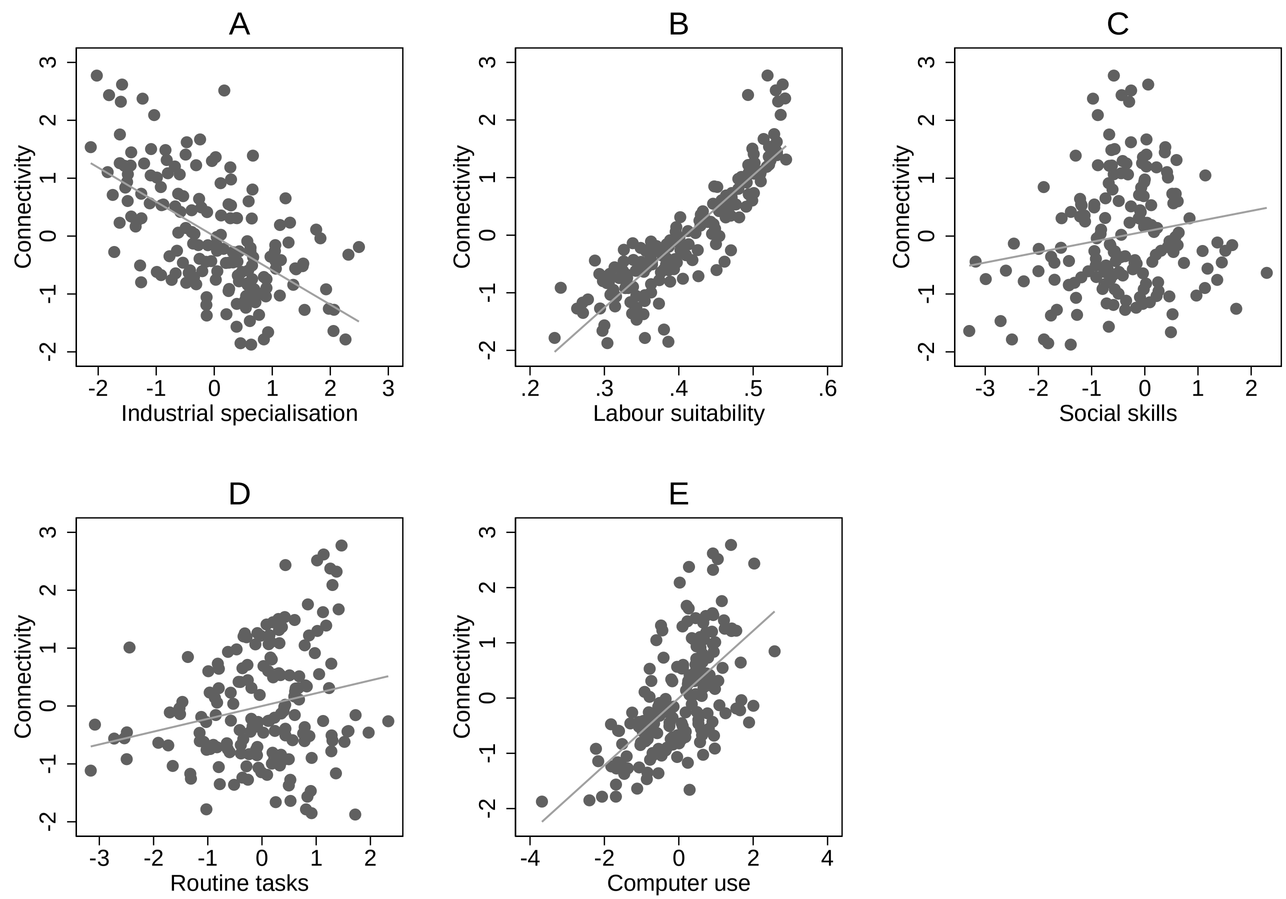

Dots represent the 41 tasks. The correlation between task connectivity and changes in employment shares is equal to 0.75 (0.00) and significant at the 1 percent level. The task connectivity measure is calculated following Equation (2). The values are standardized with a mean of zero and a standard deviation of one. The correlations differ by task group. For the information input tasks the correlation is 0.66 (0.23), for mental process tasks 0.11 (0.77), for work output tasks 0.83 (0.01) and for interacting with others tasks -0.02 (0.95).

Figure 5. The relationship between task connectivity and employment in 1990



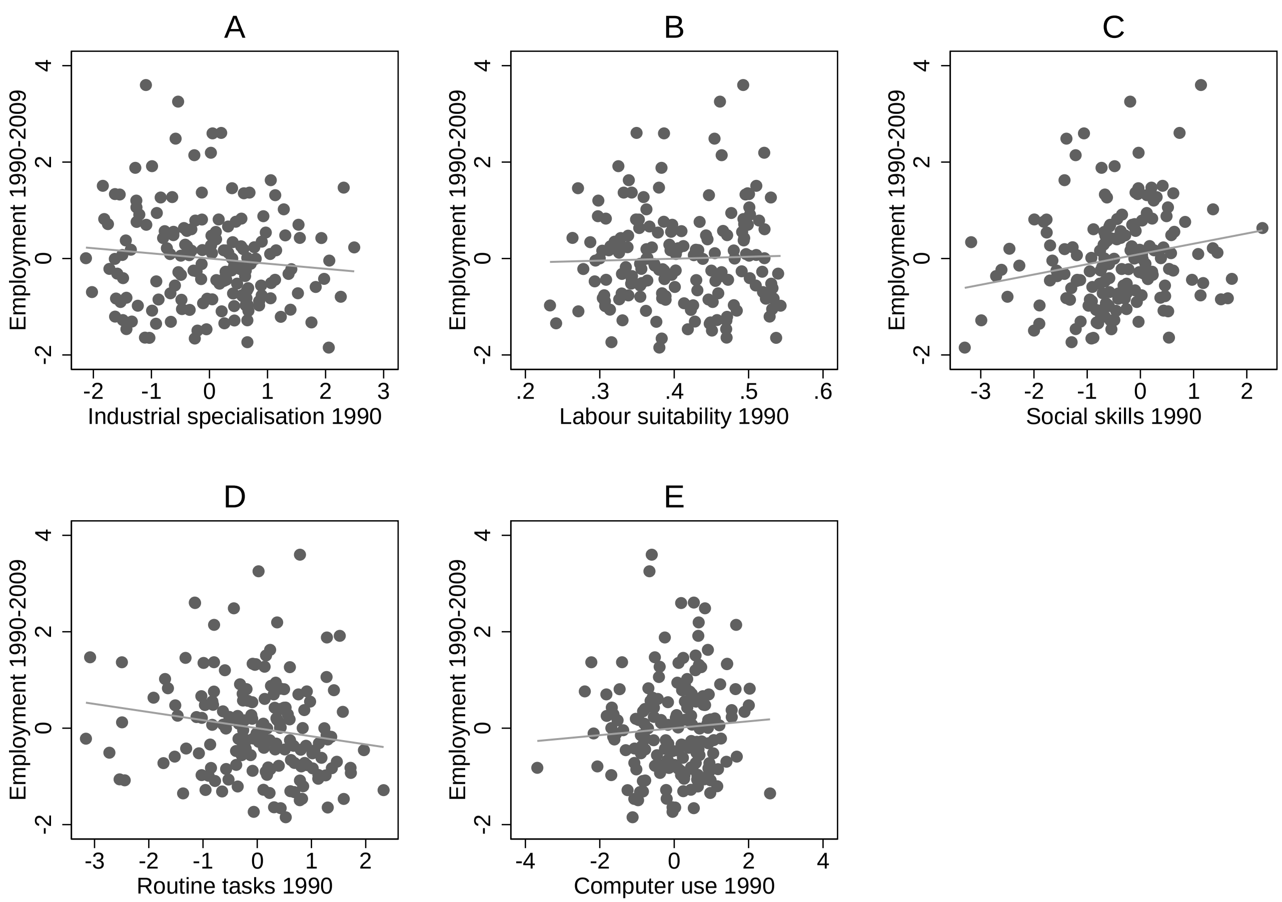

Dots represent the 168 cities in the dataset. All variables are for 1990. Table 8 in the Appendix displays measures and sources of all variables and Table 10 presents the correlations. Equation (2) defines the measure of task connectivity. Both employment and task connectivity are standardized with a mean of zero and a standard deviation of one. The regional division represents the Census regional division. $RSI$ is defined by the standardized value of Equation (3). A low $RSI$ represents a negative score, medium $RSI$ a score between 0 and 1 and high $RSI$ a score above 1. Skill categories are defined by the deviations from the mean. Very low-skilled cities have a high-skilled employment share below 14.6 (one standard deviation from the mean of 20.2 percent). Low-skilled cities have a share between 14.6 and 20.2, high-skilled cities between 20.2 and 25.8 and very high-skilled cities above 25.8. The social task categories are obtained with the same strategy. Cities with a very low social task share have a share of social tasks below 12.7, low social cities a task share between 12.7 and 13.02, high social task cities between 13.02 and 13.32 and very high social task cities above 13.32.

Figure 6. The relationship between connectivity and other factors in 1990




Dots represent the 168 cities in the dataset. The correlations are displayed in the correlation matrix (Table 10 in the Appendix). Table 8 displays measures and sources of all variables. All variables are standardized with a mean of zero and a standard deviation of one. The group of outlier cities in Panel B with a relatively higher connectivity given their labor pool suitability includes the largest metropolitan areas of the US. They will be excluded from the analysis when we address the sensitivity of our estimates in Section 6 .

Figure 7. The relationship between employment growth and other factors 1990



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