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Skill-biased agglomeration economies: a spatial perspective on demand for college graduates, Sweden 2000–2019

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Abstract: Several recent studies document that relative demand for skilled workers is becoming increasingly biased toward large cities and metropolitan regions. This development has been interpreted as suggestive evidence of increasing complementarity between skills and agglomerations of economy. We explore whether these claims extend to the Swedish labor market. By studying public income data from 2000 to 2019 through the lens of the canonical model of skill-biased technical change, enriched with factor-biased agglomeration forces, we find that annual growth in relative demand for college graduates differed 1.31 percentage points between Sweden's least and most dense municipalities. We also build further on recent literature by relating three key characteristics of municipal labor markets to economic density and growing demand for college graduates: spatial concentration of (i) non-routine tasks, (ii) business services, and (iii) job polarization. Out of the three explored mechanisms, our results suggest that local specialization in non-routine tasks best accounts for the increasing density-bias in demand for college graduates. The interpretation of our findings is however limited by data availability and we propose that future research further investigate the link between demand for college graduates and the spatial organization of economic activity.

Keywords: Skill-Biased Technical Change, Agglomeration Economies, Regional Economics, Labor Demand, Skill Differentials

JEL: J23,J24,J31,O33,R12

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1 Introduction

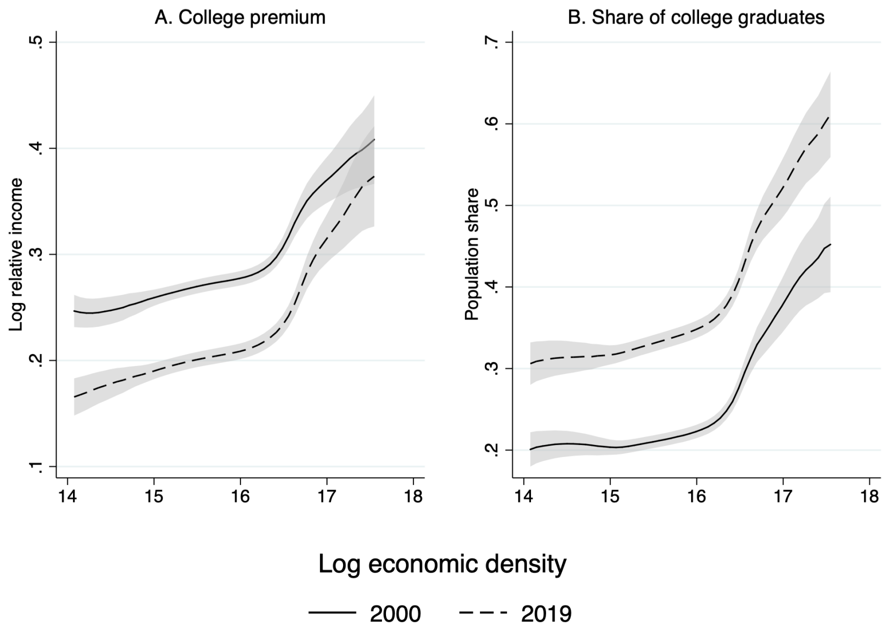
Spatially uneven economic development is a growing concern for policymakers in many economies, with potentially far-reaching economic, social, and political consequences. It is widely claimed that larger cities grow faster, and become more competitive and skill-intensive vis-à-vis smaller cities and rural areas (see e.g. Heyman & Persson, 2019; Moretti, 2012; Rossi-Hansberg, Sarte, & Schwartzman, 2019; Rubinton, 2020). Scholars often refer to this development as the Great Divergence. In the U.S., a number of regional studies document an increase in relative demand for college graduates biased toward larger cities (see e.g. Baum-Snow & Pavan, 2013; Moretti, 2013). Increasing adoption of skill-biased technologies or skill-biased technical change (SBTC) has for long served as the dominating explanation to rising relative demand for college graduates in the U.S. (Acemoglu & Autor, 2011) and in Sweden (Graetz, 2020). In light of the recent findings in regional studies, increasing complementarity between skilled labor and large cities is starting to form as an alternative explanation to increasing aggregate demand for college graduates. This is sometimes referred to as increasingly skill-biased agglomeration economies (see e.g. Autor, 2019; Baum-Snow, Freedman, & Pavan, 2018).

This thesis brings together the recent literature on agglomeration economies and SBTC to shed new light on regional differences in demand for college graduates in Sweden. The strong growth in the relative supply of college graduates since the mid-2000's parallel to a relatively constant college premium has been interpreted as suggestive evidence of SBTC or, alternatively, increasing skill–capital complementarity in the Swedish economy (see e.g. Graetz, 2020; Lindquist, 2005). In this context, we argue that the relationship between relative supply and income of college graduates, respectively, and the geographical distribution of economic activity is a so far overlooked detail.

Figure 1 provides some fresh insights that lay the foundation for our forthcoming analyses. Panel A depicts how the Swedish college premium—the average income of college graduates over that of non-college graduates—developed between 2000 and 2019 in municipalities of different economic density.[1] Firstly, we observe a clear positive relationship between the college income premium and the economic density of Swedish municipalities. Secondly, this relationship steepened between 2000 and 2019. Panel B, in turn, confirms the broad skill upgrading of the Swedish population suggested by previous literature (see e.g. Eliasson & Westerlund, 2018). The share of college graduates is substantially higher and has grown at a somewhat faster pace in economically dense municipalities. The graph prescribes a growth in the share of college graduates of about 16 percentage points between 2000 and 2019 in the densest municipalities, compared to 10 percentage points for the least dense municipalities.

[1] Throughout this thesis, we define economic density as municipal-level accessibility to total income mass in 2000. The measure is akin to Harris' (1954) classic view on market potential. Section 4.1 describes the construction of the variable in detail.

Figure 1: Relative income and supply of college graduates



Notes: Figure showing the relationship between (A) log relative income and (B) share of college graduates, respectively, and log economic density using the Kernel-weighted local polynomial smoothing command in Stata. Data include years 2000 and 2019 and working-age population (30–64). The bandwidths are obtained from Stata using the rule-of-thumb method of bandwidth selection. Bandwidths in Panel A are 0.38 for 2000 and 0.44 for 2019. Bandwidths in Panel B are 0.36 for 2000 and 0.38 for 2019. Grey areas indicate 95 percent confidence bands. Data are on the municipal level and provided by Statistics Sweden.

These trends are suggestive of increasing skill–density complementarity. They highlight the need to explore how SBTC and the organization of economic activity relate to space to fully understand the broad trends in Swedish income inequality.

Building further on these observations, our main purpose is to examine whether agglomerations of economic activity in Sweden are becoming increasingly skill-biased. We define skill-biased agglomeration economies as complementarity between college graduates and economically dense locations, translating into higher productivity and demand for college graduates. By studying geographical variation in income, education, occupations, and sectors we intend to answer the following research questions: Is relative demand for skilled labor increasingly biased toward economically dense locations? If so, what kind of local labor market characteristics, suggested by theory and literature, best account for this development?

To answer our first research question, we study publicly available Swedish income data between 2000 and 2019 through the lens of the canonical model of SBTC, enriched with factor-biased agglomeration forces. We construct a theoretically informed measure of economic density, and derive changes in relative demand for college graduates to investigate whether it has become more biased toward economically dense municipalities. To answer our second research question, we extend the analysis beyond the kind of technology adoption traditionally invoked by the SBTC literature. We sketch further on three alternative mechanisms that could rationalize an increasing skill-bias of agglomeration economies, suggested in recent literature. More precisely, we explore how (i) local specialization in non-routine tasks, (ii) local specialization in business services, and (iii) job polarization relate to economic density and growth in demand for college graduates between 2008 and 2019.

To our knowledge, we are the first to jointly study changes in relative income, supply, and demand for college graduates in relation to economic density in Sweden. The trends illustrated in Figure 1 make the country an interesting case for exploring changes in the skill-bias of agglomeration economies. Further, the Swedish economy is characterized by considerable regional variation in labor market characteristics, potentially important to the understanding of regional divergence in demand for college graduates (Heyman & Persson, 2019). Lastly, and in comparison to the U.S., the Swedish economy is characterized by a large public sector. Consequently, it also is of interest to see how well the relatively simple supply-demand framework we employ serves to study the labor market development in a country that is in many regards on the opposite side of the institutional spectrum.

Our results suggest that annual growth in relative demand for college graduates in Sweden 2000–2019 differed by approximately 1.31 percentage points between the least and most dense municipalities. The finding follows from the need to rationalize the the faster growth in the share of college graduates and a smaller decline in the college-premium of dense compared to less dense locations. The result is suggestive of ongoing regional divergence. Further, we show that in 2008, denser municipalities had a comparative advantage in non-routine tasks and business services. We also find evidence of broad job polarization across Swedish municipalities between 2001 and 2019. Out of our three labor market features, we find initial specialization in non-routine tasks to have the strongest correlation with subsequent growth in relative demand for college graduates. Yet, neither specialization in business services, non-routine tasks, nor job polarization alone provides a fully satisfactory explanation to the increasing density-bias in demand for college graduates. Our results are however likely to be biased due to limited data and should be interpreted with caution.

The thesis is structured as follows. Section 2 presents a review of theory and previous literature. In Section 3, our main theoretical model and empirical approach is developed. Section 4 describes our data and variables. Results are presented in Section 5, and discussed in Section 6. The conclusion in Section 7 completes the thesis.

2 Theoretical background

2.1 The canonical model of skill-biased technical change

Since the seminal paper by Katz and Murphy (1992), SBTC has served as the dominating explanation to the well-documented rise in the college premium observed in the U.S. since the 1980's. The core ideas were proposed by Tinbergen (1974), and has since then been developed by among others Katz and Murphy (1992) and Autor, Katz, and Krueger (1998). The canonical model of SBTC uses the following constant elasticity of substitution (CES) aggregate production function as a starting point:

$$Y_t = [A_{lt}^{\rho} L_t^{\rho} + A_{ht}^{\rho} H_t^{\rho}]^{1/\rho}. \tag{1}$$

There are two types of imperfectly substitutable workers, skilled and less-skilled labor H_t and L_t, who produce a common good with the factor-specific productivities A_{ht} and A_{lt}. The substitutability between skilled and unskilled labor is defined as $\sigma = 1/(1-\rho)$, with $\rho \leq 1$. The production is assumed to have constant returns to scale and the labor market to be perfectly competitive so that workers are paid their marginal product. In equilibrium, the canonical model prescribes relative wages of skilled and less-skilled labor as follows:

$$\frac{w_{ht}}{w_{lt}} = \left(\frac{A_{ht}}{A_{lt}}\right)^{\rho} \left(\frac{H_t}{L_t}\right)^{\rho-1}. \tag{2}$$

That is, relative wages between skilled and less-skilled labor is determined by a technology component, (A_{ht}/A_{lt}), and their relative supply, (H_{ht}/H_{lt}). The common view is that the technology component and hence relative productivity evolves over time. Given an elasticity of substitution between skilled and less-skilled labor greater than one, i.e. that the two labor types are gross substitutes, increases in the technology component prescribes an increasing skill-premium. A large number of papers seek to link relative wages and demand for college graduates to adoption of particular skill-biased technologies, of which information and communication technology (ICT) is the most common example (see e.g. Autor et al., 1998; Graetz, 2020; Krueger, 1993). Others have suggested that investments in new, more efficient capital equipment have raised the effective rate of capital inputs per skilled worker, and hence increased the relative productivity of college graduates through increasing skill–capital complementarity (Lindquist, 2005).

According to the standard view, increasing demand for college graduates in large cities could hence be understood as a consequence of SBTC being particularly oriented toward larger cities. The idea that adoption of skill-biased technologies and SBTC interacts with city size is raised in Baum-Snow and Pavan (2013) and developed in e.g. Giannone (2018) and Rubinton (2020). Consistent with this view, Rubinton (2020) documents a positive relationship between investments in ICT, city size, and demand for skilled labor in the U.S. She suggests that four mechanisms account for a greater adoption of ICT in more populated cities: market size, ex-ante comparative advantages, amenities for skilled workers, and firm selection. Similarly, Graetz (2020) finds suggestive evidence that municipal-level exposure to ICT investments is important to understand regional variation in demand for college graduates in Sweden. But distinct from Rubinton (2020), he does not find exposure to ICT to be particularly biased toward economically dense locations.

Overall, the literature lacks clear consensus on whether differential rates of technology adoption across locations drive the increasing demand for skilled labor in large cities and, in extension, the Great Divergence. A growing literature contrasts this idea with an alternative explanation that relates more directly to the specialization and character of employment of large cities, often described as increasingly skill-biased agglomeration economies (see e.g. Autor, 2019; Baum-Snow et al., 2018). The following subsections develop these ideas.

2.2 Skill-biased agglomeration economies

A stylized fact in the urban economics literature is that workers, net of sorting, are more productive and benefit from higher wages in large cities. The latter observation is generally referred to as the urban wage premium (UWP). The productivity advantage of firms and workers in large cities is often explained by technological spillovers, labor pooling and intermediate input linkages and date back to Marshall (1890/2013). Recent studies on agglomeration economies commonly refer to the typology developed by Duranton and Puga (2004). They suggest that agglomeration benefits can be divided into sharing, matching, and learning effects. Sharing relates to the pooling of indivisible resources, matching to the efficiency of labor market allocations, and learning to improved knowledge spillovers as a consequence of greater proximity between workers and firms. Separating the different mechanisms from each other is an empirically complex task (for examples, see Duranton & Puga, 2020).

There is a growing consensus in the literature that the UWP is particularly strong for workers with qualified skills, or that agglomeration economies are skill-biased. Examples include Bacolod, Blum, and Strange (2009), who suggest that the UWP in U.S. cities is higher for workers with cognitive and people skills. Further, Glaeser and Resseger (2010) find that the correlation between productivity and city size is particularly strong for cities with a high share of college graduates. In contrast, they find evidence of a UWP close to zero for less-educated U.S. cities. In Sweden, Andersson, Klaesson, and Larsson (2014) document a considerably stronger UWP for workers in occupations characterized by non-routine tasks than for workers engaged in routine-tasks. In a later study employing detailed Swedish longitudinal and spatial data, the same authors find a positive relationship between worker productivity and proximity to other workers in similar occupations, applying exclusively to employees performing advanced services or non-routine tasks (Andersson & Larsson, 2020). It is thus a common finding that agglomeration benefits are particularly strong for knowledge-intensive occupations. A general interpretation is that learning effects constitutes an important part of agglomeration benefits, in line with the third mechanism suggested in the typology of Duranton and Puga (2004).

Common to most studies on the skill-bias of agglomeration economies is that they adopt static perspectives, rather than exploring changes over time. One exception is Baum-Snow et al. (2018) who explicitly model increasing skill-bias of agglomeration forces and growing relative demand for college graduates in cities. The authors consider a neoclassical three-factor production function with capital and two types of labor. In the model, they lend from the urban economics literature by letting city size determine productivity levels. Further, they let the contribution of city-size to productivity be factor biased, i.e. vary for different worker–skill types. Baum-Snow et al. (2018) suggest that increasing factor-bias of agglomeration economies is an overlooked mechanism that could explain more than 20 percent of the aggregate increase in U.S. wage inequality since the 1980's. They argue that increasing skill–capital complementarity and SBTC alone do not suffice to rationalize the increasing divergence between U.S. labor markets.

2.3 The geography of occupational change

Common explanations to the increasing skill-bias of agglomeration economies relate to changing spatial organization of economic activity. It is easy to imagine that production externalities and relative incomes depend on the occupational composition of a city (see e.g. Glaeser & Resseger, 2010; Rossi-Hansberg et al., 2019). To the extent that spatial concentration of sectors and occupations that employ college graduates and are complementary to economic density has increased—such as occupations with a high fraction of non-routine tasks, or with high cognitive requirements—the scope for skill-biased agglomeration forces would become greater in cities.

Several studies provide evidence that sectors and functions susceptible to agglomeration forces have become more concentrated. Duranton and Puga (2005) show how decreasing costs of distance management can induce firms to separate headquarters and support services from plant operations. They suggest that firms choose to relocate their service functions to larger cities where accessibility to intermediate inputs and business service suppliers is higher. In contrast, the congestion costs of large cities induce firms to keep plant operations in more remote locations. Duranton and Puga (2005) find empirical support for increasing functional separation of firm operations in U.S. data between 1977 and 1997. A similar line of thought is developed in Eckert (2019) who argues that falling costs of ICT have magnified regional specialization in high-skill services, raising the skill premium in service-exporting regions and reducing it in service-importing regions. Analysing U.S. wage data between 1980 and 2010, Eckert (2019) documents that regions with an initially high share of business service employment grow faster and experience larger increases in the skill-wage premium. The study suggests that increasing regional specialization in high-skill business services accounted for approximately 30 percent of the aggregate rise in the U.S. college wage premium over the same period—an estimate similar to the one suggested by Baum-Snow et al. (2018).

A related strand of literature takes on a task-based perspective to study regional patterns of occupational change. Michaels, Rauch, and Redding (2019) argue that falling communication and transport costs induce urban and non-urban areas to specialize in distinct tasks. By analysing over 12,000 occupational descriptions from 1880 to 2000, they show that densely populated U.S. locations become increasingly specialized according to their comparative advantage in interactive tasks. Michaels et al. (2019) define interactive tasks as activities associated with thought, connectivity, and intersocial activity, closely related to cognitive ability. They argue that increasing specialization in interactive tasks in cities provides evidence of growing importance of human interactions in agglomerations of economic activity over time. Similar findings are presented in Rossi-Hansberg et al. (2019), who also argue that occupation-specific externalities are needed to explain why workers in cognitive non-routine occupations concentrate and earn more in places where they are already abundant. They document an increasing spatial concentration of cognitive non-routine occupations in the U.S since the 1980's. Similar results for Sweden is found in Heyman and Persson (2019). A change in nature of agglomerations toward increasing focus on interactive and cognitive non-routine tasks, thus provides another way to understand the increasing skill-bias of agglomerations.

Recently, job polarization biased toward larger cities has been suggested as another explanation to the increasing skill-bias of agglomerations. Job polarization corresponds to the simultaneous growth in the share of high-skill, high-wage occupations and low-skill, low-wage occupations that has been widely observed in the U.S. and Europe since the 1970's (for a review, see Acemoglu & Autor, 2011). The phenomenon is closely related to task-biased technical change (TBTC), which prescribes a fall in demand for middle-skill routine-character employment due to increasingly automated production processes. Autor (2019) suggests that job polarization and the accompanying fall in middle-skill occupations, concentrated to urban areas, has contributed to falling relative demand for non-college workers in densely populated U.S. cities. He documents a positive relationship between employment in middle-skill occupations and population density for non-college workers in the 1970's. In 2015, however, Autor (2019) shows that the positive relationship had disappeared. Because of the stronger job polarization in dense locations, non-college employment in large cities has become increasingly dominated by low-skill occupations rather than middle-skill occupations. Comparing the most and the least dense commuting zones in contiguous U.S., the paper documents a fall in the non-college UWP from about 65 to 18 percent between 1970 and 2015. In contrast, the corresponding college UWP remained stable at approximately 75 percent. Notably, Autor (2019) proposes job polarization biased toward larger cities as a possible explanation to the increasing skill-bias of agglomeration economies documented in Baum-Snow et al. (2018).

In line with the theory on TBTC, Adermon and Gustavsson (2015) suggest that also the Swedish labor market underwent a process of job polarization during the 1990's and 2000's. They find evidence of stronger employment growth at the tails of the skill and wage distributions parallel to declining employment numbers for middle-distribution jobs. Similar evidence is found in Heyman and Persson (2019), who also describe how job polarization has been stronger in more populated regions. More precisely, they find that the most and least paid non-routine occupations grew faster in Sweden's three metropolitan regions (Heyman & Persson, 2019). Eriksson, Hensvik, and Skans (2017) contrast this view and suggest that the employment growth in low-wage, low-skill occupations weakened from the early 2000's and on, indicating limited importance of job polarization.

3 Method

The empirical approach in this thesis is straightforward. To answer our first research question, we derive implied changes in relative demand for college graduates across Swedish municipalities employing a two-factor production function with skill-biased agglomeration forces. To answer our second research question, we quantitatively explore patterns of task- and sector-based regional specialization as well as job polarization in relation to economic density. Further, we analyze to what extent comparative advantages in sectors and tasks, and job polarization account for the growing density-bias in demand for college graduates. The following sections describe the main model and the empirical analyses in detail.

3.1 Main model

Our main model is an extension of the canonical model of SBTC presented in Section 2.1. We extend the analysis and incorporate a spatial perspective by borrowing elements from Baum-Snow et al. (2018). The starting point is the following location-specific production function:

$$Y_{ct} = [A_{lt}^{\rho} E_c^{\mu_{lt}\rho} L_{ct}^{\rho} + A_{ht}^{\rho} E_c^{\mu_{ht}\rho} H_{ct}^{\rho}]^{1/\rho} \tag{3}$$

where A_{lt} and A_{ht} denote the productivity of less-skilled and skilled labor, and L_{ct} and H_{ct} the supply of less-skilled and skilled labor in location c at time t. In contrast to the canonical model of SBTC and similar to Baum-Snow et al. (2018) we include E_c, the economic density of location c, as a productivity-enhancing component. The terms μ_{lt} and μ_{ht} allow agglomeration benefits to be factor-biased and vary over time. If $\mu_{ht} > \mu_{lt}$ agglomeration economies are biased toward skilled labor. When solving for equilibrium wages, we get the location-specific skill premium

$$\frac{w_{hct}}{w_{lct}} = \left(\frac{A_{ht}}{A_{lt}}\right)^{\rho} \left(\frac{E_c^{\mu_{ht}}}{E_c^{\mu_{lt}}}\right)^{\rho} \left(\frac{H_{ct}}{L_{ct}}\right)^{\rho-1}. \tag{4}$$

Taking logs of Equation 4 and using that $\rho = \frac{\sigma-1}{\sigma}$, we obtain the following expression

$$\ln\left(\frac{w_{hct}}{w_{lct}}\right) = \left(\frac{\sigma-1}{\sigma}\right)\left[\ln\left(\frac{A_{ht}}{A_{lt}}\right) + (\mu_{ht} - \mu_{lt})\ln E_c\right] - \left(\frac{1}{\sigma}\right)\ln\left(\frac{H_{ct}}{L_{ct}}\right). \tag{5}$$

Equation 5 highlights three mechanisms through which wage inequality within local labor markets c is determined. Under the assumption that skilled and less-skilled labor are gross substitutes, that is $\sigma > 1$, the following can be observed. Firstly, the skill premium increases with the relative productivity of the factor inputs. Secondly, the skill premium increases if the skill bias of agglomeration economies grows, that is if the difference $\mu_{ht} - \mu_{lt}$ becomes larger over time. Thirdly, the skill premium is decreasing in the relative supply of skilled labor in location c. In accordance with previous literature we choose to treat skilled and less-skilled labor as gross substitutes. Section 5.1 provides a further discussion on the treatment of σ in previous research.

3.2 Empirical implementation of main model

To answer our first research question, we apply our main model and explore how relative demand for college graduates relate to economic density and how this relationship evolved between 2000 and 2019. We return to the construction of our density measure in Section 4.1. Following the approach in Katz and Murphy (1992) we define a location-specific relative demand index as follows:

$$D_{ct} \equiv (\sigma - 1)\left[\ln\left(\frac{A_{ht}}{A_{lt}}\right) + (\mu_{ht} - \mu_{lt})\ln E_c\right]. \tag{6}$$

The advantage of the Katz-Murphy demand index is that it provides a means to study the determinants of relative income in Equation 5, net of supply-factors. In accordance with Equation 6, our extended model prescribes that changes in local relative demand occurs both due to changes in the factor-bias of agglomeration economies, and nationwide changes in relative factor productivity. By substituting our expression D_{ct} into Equation 5 and rearranging terms, we obtain the following expression:

$$D_{ct} = \ln\left(\frac{w_{hct}H_{ct}}{w_{lct}L_{ct}}\right) + (\sigma - 1)\ln\left(\frac{w_{hct}}{w_{lct}}\right). \tag{7}$$

From Equation 7 follows that the Katz-Murphy relative demand index can be derived directly from the data given observable wages, labor supply, and a common production parameter σ. Concretely, we explore to what extent the Katz-Murphy demand index has grown faster in municipalities of high economic density. Theoretically, such a development could be reflective of shifts in the term $\mu_{ht} - \mu_{lt}$.

In our analysis, we will derive D_{ct} using values of σ based on previous literature as well as a parameter deduced from our own model and data. Katz and Murphy (1992) propose a simple way of estimating the size of σ in the canonical model of SBTC, i.e. with the production function presented in Equation 1. Since SBTC is unobservable, they make the simplifying assumption that the term $\ln(A_{ht}/A_{lt})$ follows a linear trend over time. As to our model, one alternative is to assume that SBTC and the factor-bias of agglomeration economies, respectively, contributes linearly to wage inequality over our time period. That is, we assume linearity in each of the terms $\ln(A_{ht}/A_{lt})$ and $(\mu_{ht} - \mu_{lt}) \ln E_c$ in Equation 5. This would yield us the following estimating equation:

$$\ln \frac{w_{hct}}{w_{lct}} = \gamma_{0c} + \gamma_1 t + \gamma_2 t \times \ln E_c + \gamma_3 \ln \left(\frac{H_{ct}}{L_{ct}} \right) + \epsilon_{ct}. \tag{8}$$

where γ_1 reflects a productivity time trend that is uniform across locations, γ_2 captures different time trends for locations of varying economic density, and γ_{0c} denotes location fixed-effects. Comparison of Equation 5 and Equation 8 shows that σ is given by $-\gamma_3/1$. A major problem with estimating Equation 8 is that the relative supply of skilled workers is not exogenous. The coefficient of interest, γ_3, is likely to be positively biased if the inflow of skilled workers increases as a response to a growing income premium, yielding a biased elasticity of substitution. One solution to this problem—which is likely to be particularly severe when studying subnational data—is to identify exogenous variation in relative labor supply by using an instrumental variable approach (see e.g. Ciccone & Peri, 2005). Since we lack good instruments, we follow the approach in e.g. Katz and Murphy (1992) and derive σ from an aggregate national production function of the form

$$Y_t = [A_{lt}^{\rho} \bar{E}^{\mu_{lt}\rho} L_t^{\rho} + A_{ht}^{\rho} \bar{E}^{\mu_{ht}\rho} H_t^{\rho}]^{1/\rho}, \tag{9}$$

with a corresponding estimation equation of the form

$$\ln \frac{w_{ht}}{w_{lt}} = \gamma_0 + \gamma_1 t + \gamma_2 \ln \left(\frac{H_t}{L_t} \right) + \epsilon_t, \tag{10}$$

with the addition of $\bar{E}$ as a representation of time-invariant national-level economic density. The implied value of σ is given by $-\gamma_2/1$. With this approach, we instead assume linearity in the composite term $\ln(A_{ht})/(A_{lt}) + (\mu_{ht} - \mu_{lt}) \ln \bar{E}$, captured by γ_1. We claim that the endogeneity problem will be less severe when estimating the elasticity of substitution from a national production function since we expect international migration to be less responsive to changes in relative income. Further, the national approach including a linear time trend for technical change has been widely employed in the literature and proven to fit e.g. U.S. national data well (Acemoglu & Autor, 2011).

3.3 Analyzing local labor market characteristics

To answer our second research question, we draw from recent literature in urban and regional studies and explore spatial variation in key labor market characteristics. More precisely, we lend from Michaels et al. (2019) and Rossi-Hansberg et al. (2019) by constructing a measure for specialization in tasks, from Duranton and Puga (2004) and Eckert (2019) by measuring specialization in business services, and from Autor (2019) by investigating job polarization, and explore how these relate to economic density. Since the traditional SBTC literature suggests adoption of ICT as an important driver behind demand for skilled labor, we also construct a measure capturing exposure to ICT investments and investigate how it varies across municipalities. The construction of the variables is detailed in Section 4.1.

Further, we provide a straightforward regression analysis relating our three key local labor market characteristics to relative demand for college graduates. Due to limited data availability, the analysis is restricted to the years 2008–2019. The main estimation equation is:

$$\Delta Y_{c,2008-2019} = \beta_0 + \beta_1 E_c + \beta_3 S_{c2008} + \mathbf{Z}'\boldsymbol{\gamma} + \epsilon_c \tag{11}$$

where $Y_{c,2008-2019}$ denotes growth in demand for college graduates in municipality c between year 2008 and 2019, $S_{c,2008}$ denotes the relevant measure of sector- or task specialization in the base year 2008, or the degree of job polarization experienced in municipality c between year 2008 and 2019, and $\mathbf{Z}'\boldsymbol{\gamma}$ is a vector of controls. With support from the literature, we expect municipalities with an initial comparative advantage in non-routine tasks and business services, or locations that experience higher degree of job polarization, to experience stronger growth in demand for college graduates. If these same factors account for a growing density-bias in demand for college graduates, they should also capture part of correlation between E_c and $Y_{c,2008-2019}$.

In estimating Equation 11, we follow the previous literature (see e.g. Autor et al., 1998; Graetz, 2020; Katz & Murphy, 1992) and use two alternative dependent variables to proxy demand for skilled labor $Y_{c,2000-2019}$. Firstly, we study growth in the college graduate income share of total earnings in each municipality. As highlighted by Autor et al. (1998), the growth in college graduate income share is a good proxy for increases in relative demand when the elasticity of substitution is close to one. Secondly, we use growth in the share of college graduates in a municipality's working-age population as dependent variable. The main advantage of employing these outcome variables instead of, for instance, implied changes in the demand index from Equation 5 is that they have a more straightforward interpretation. The approach is also more transparent since it does not require us to assume a specific production function.

The vector $\mathbf{Z}'\boldsymbol{\gamma}$ includes four different control variables. Most importantly, we control for municipal exposure to ICT investments, highlighted by the standard SBTC literature as the primary example of a skill-biased technology. We also include a control for municipal exposure to investments in other capital. The covariate deals with the possibility that other forms of skill–capital complementarity affect municipal-level demand for college graduates. Further, we control for municipal-level unemployment and private sector employment in the base year 2008 since we expect these to be of importance to demand for college graduates. This could be the case if unemployment is biased toward non-college graduates, or if a large public sector boosts non-college income levels. Ideally, we would exclude the income of non-employed and publicly employed individuals from our data. We discuss this issue further in Section 4.2.

3.4 Methodological considerations

It is important to note that we do not consider how the relative human capital level between skilled and less-skilled labor has changed over time. Changing wages due to time-varying relative human capital levels may be confounded with SBTC (Bowlus, Bozkurt, Lochner, & Robinson, 2017). This should, however, be less of a concern in our thesis as we investigate changes over one or two decades, compared to studies investigating SBTC over several decades where within-group changes in human capital can be considerable (see e.g. Autor et al., 1998; Katz & Murphy, 1992). In our case, however, increased spatial sorting on unobservable worker characteristics could also be confounded with an increasing density-bias in demand for skilled labor. Hence, and in order to interpret our findings as as reflective of actual demand, our results hinges on the assumption that relative human capital within educational groups and across space remain rather constant.

There are several reasons to treat our estimated elasticity of substitution and, in extension, our Katz-Murphy demand indices with caution. Firstly, inherent to our CES model is that the elasticity of substitution between skilled and less-skilled labor is assumed to be constant over time and across municipalities. In theory, time-varying values of the elasticity of substitution between skilled and unskilled labor, due to for instance compositional changes within the two skill groups, could drive the observed labor market outcomes. Still, most of the literature in the field assumes a constant elasticity of substitution over time and space.

Secondly, the national production function in Equation 9 does not need to be an accurate representation of our aggregate local production functions shown in Equation 3, but merely an approximation (see e.g. Felipe & Fisher, 2003, for a further discussion on problems of aggregation in production functions). This limitation is also present in the canonical model of SBTC, where one for instance would expect factors to be less substitutable at the firm level than at the aggregate level. Similarly, we could expect college and non-college graduates to be less substitutable at the municipal level than the national, possibly leading to an upward biased σ.

Thirdly, when estimating σ, we adopt the standard approach from the traditional SBTC literature assuming a loglinear time-trend in technical change (see e.g. Autor et al., 1998; Katz & Murphy, 1992). Specifically, we assume that $\ln(A_{ht})/(A_{lt})+(\mu_{ht}-\mu_{lt})\ln \bar{E}$ grows linearly over time. As raised in Acemoglu and Autor (2011), one can also consider using alternative functional forms. One example is to include a quadratic time-trend in the estimation of Equation 8, possibly yielding other values of σ. As to the uncertainties in our estimation of the elasticity of substitution, we partly alleviate these problems by reporting results using a range of σ's, borrowed from previous literature.

Lastly, in estimating Equation 11, we do not seek to isolate exogenous variation in the independent variables of interest. The results thus represent conditional correlations rather than causal estimates. Still, we claim that these correlations are somewhat informative of whether initial specialization in tasks and sectors, as well as job polarization, are better or worse candidates in explaining why relative demand for college graduates would have become more biased toward dense municipalities.

4 Data

4.1 Data sources and variable construction

Income and education

We use publicly available labor income income data from 2000 through 2019 provided by Statistics Sweden (2021e). The full dataset consists of 278,400 year–demographic cells—one for each municipality, gender, education level, age group, and year. We use a dichotomous measure of educational attainment throughout the analysis. Individuals with at least some post-secondary education are referred to as college graduates, and individuals with upper secondary education or less are referred to as non-college graduates. As the observed income level in each demographic cell is averaged on all inhabitants, not just those part of the labor force, we restrict our sample to cells in the age interval 30–64. Excluding cells below 30 years is motivated by the relatively high age of labor market entry in Sweden (Lindberg, 2012).

The income data from Statistics Sweden are subject to the agency's standard procedures for quality assurance. The data were also inspected in Stata in order to reduce concern for erroneous reporting. As part of this exercise, we computed yearly changes in relative income between college and non-college graduates for each municipality 2000–2019 and mapped outliers. One of the year–demographic cells reported a suspiciously large change in year-to-year average income (over 300 percent). To reduce concern for skewed results due to this outlier, we imputed the mean income in the concerned demographic cell with its value from the preceding year.[2]

Economic density

Measuring economic activity or density is central to the study of agglomeration economies. A common form of economic density is the number of individuals per unit of geographical area, e.g. defined by administrative boundaries. Such naïve measures of density depend largely on the definition of spatial units. This problem is commonly referred to as the Modifiable Area Unit Problem (MAUP). More sophisticated forms of economic density include experienced density (see e.g. Duranton & Puga, 2020) or variations of Harris' (1954) classic measure of market potential. Similar to Andersson and Larsson (2020) we use a measure of labor market potential to capture variation in economic density across Swedish municipalities. In particular, we study market potential as accessibility to total income of the following form:

[2] The demographic cell corresponds to males 30-39 years with post-secondary education in the municipality Danderyd in 2019. The the reported mean income was approximately 1.6 million SEK, compared to 0.4 million SEK in the preceding years

$$E_c = \frac{I_c}{d_{cc}} + \sum_{d \neq c}^{N} \frac{I_d}{d_{cd}} \tag{12}$$

where E_c denotes economic density of municipality c, I_c denotes total income mass, and d distance. As such, the contribution of municipality d to the economic density of municipality c is inversely related to the distance d_{cd} between the two. Hence, spillovers from geographical proximity and the external economic environment of municipalities is reflected by the measure. This is important when studying labor market outcomes since we expect considerable labor commuting between municipalities. Distances are computed in Stata using centroid coordinates for each municipality. Geographical data for Swedish municipalities are retrieved from Statistics Sweden (2021a, 2021d). To compute internal distances d_{cc}, we follow the approach in Head and Mayer (2000) and treat residents as randomly distributed within each municipality. Municipalities are further assumed to be circular, and production concentrated at the center of each municipality. Under these assumptions, the average distance between residents and employers within each municipality can be approximated to

$$d_{cc} = \frac{2}{3}\sqrt{\frac{area_c}{\pi}} = \frac{2}{3}R_c \tag{13}$$

where R_c is the assumed radius of municipality c. To assure consistency when relating the variable to key outcomes over time, we treat the economic density as time-invariant and use the year 2000 municipal values throughout the thesis.[3]

We deem this form of measuring economic density to give a more correct representation of the size of the local labor market than, for instance, unadjusted municipal population density. It should however be noted that our as-the-crow-flies distances should be seen merely as a proxy for real commuting times. A potential improvement could be to include actual commuting travel times between municipalities in the computation of economic density, as done in Andersson et al. (2014). Yet, and as highlighted by Duranton and Puga (2020), different measures of economic density are often highly correlated. Hence we would not expect our measure of economic density to differ much from measures where real travel times are used. Our measure could also be improved by including the income mass of neighboring countries. This would, for instance, likely affect economic density in Southern Sweden due to its proximity to Copenhagen. Collecting and analysing data from neighboring countries is however outside of the scope of this thesis.

[3]The measure is constructed using 2021 municipal borders and areas. Borders have remained constant since year 2000 with few exceptions.

Local specialization in non-routine tasks

To measure the degree of municipal task specialization, we compute the share of non-routine tasks performed by the average employee in each municipality. We use data from Statistics Sweden (2019a) on municipal employment in the base year 2008 for 28 different occupations from the Swedish Standard Classification of Occupations (SSYK96) on the 2-digit level. For each occupation, we use data on the average share of non-routine tasks performed, provided by Becker, Ekholm, and Muendler (2013) and Hakkala, Heyman, and Sjöholm (2014). The same task descriptions are used in e.g. Andersson et al. (2014), and are reported on the 2-digit level of ISCO-88, identical to the SSYK96. The descriptions origin from German survey data on worker activities, and each task performed has been classified as either routine or non-routine. A non-routine task is defined as a tool-related task that requires training and cannot be independently performed by an apprentice during their first week of work (Hakkala et al., 2014). The definition is similar to the measure of abstract, interactive tasks used in Michaels et al. (2019). The average share of non-routine tasks for the 28 different occupations is detailed in Table A1 in Appendix A.2.

Local specialization in business services

To study sector specialization, we draw from the work by Eckert (2019) and explore the share of business service employees in each municipality. We use data from Statistics Sweden (2019a) on municipal employment in our base year 2008. The sectors used to define business services are information and communication services, financial and insurance activities, real estate activities, professional and technical services, and administrative and support service activities. These correspond to sectors J to N in the Swedish Standard Industrial Classification (SNI).

Job polarization

We follow the standard literature and study job polarization by tracking the employment shares of three broad and mutually exclusive occupational categories: low-, middle-, and high-skill occupations. Occupations are observed on a SSYK96/SSYK2012 1-digit level from 2001 through 2019, consisting of 9 major groups (Statistics Sweden, 2015, 2021b, 2021c). Military occupations are excluded as they are of non-market character. We let high-skill occupations include managers, professionals, technicians, and associate professionals (major groups 1-3). Mid-skill occupations include office clerks and workers in automated production (major groups 4 and 8). Low-skill occupations include elementary, craft and agricultural, as well as personal and protective services workers (major groups 5-7, and 9). A detailed list over occupation categories is provided in Table A1 in Appendix A.2. With this grouping of occupation categories, low-skill occupations are characterized by manual tasks with little requirement for post-secondary education, and middle-skill occupations by automated processes with little or some requirement for post-secondary education. Our division between low-, middle-, and high-skilled occupations largely follows the ideas in previous studies on job polarization such as Autor (2019) and Heyman and Persson (2019). The variable job polarization is defined as change in the municipal employment share of low- and high-skill occupations relative to total municipal employment between 2008 and 2019.

The change from SSYK96 to SSYK2012 occupational codes in 2014 entailed a break in the reporting of Statistics Sweden. As a consequence, 1-digit occupational codes are not fully comparable before and after 2014. Yet, reclassifications mainly occurred within our three broadly defined skill groups. When plotting the series for our three skill groups we only find modest shifts in employment shares between 2013 and 2014 (see Figure A1 in Appendix A.2.). Thus, we conclude that the time series before and after the break are comparable enough for our purpose.

Exposure to ICT

As previously mentioned, we focus on ICT as a potentially skill-biased technology through our analysis. Since we cannot observe ICT adoption directly, we construct a measure of local exposure to ICT investments based on municipal industrial composition. Similar to the approach in Graetz (2020), the variable is constructed as follows:

$$\text{ICT exposure}_{c,2008} = \sum_{c} \eta_{s,c,2008} \ln\left(\frac{\text{Investments}_{s,2018}/\text{Investments}_{s,2008}}{\text{Employees}_{s,2018}/\text{Employees}_{s,2008}}\right) \tag{14}$$

where $\eta_{s,c,2008}$ is the employment share of industry s in municipality c in year 2008, and $\text{Investments}_{s,t}$ and $\text{Employees}_{s,t}$ are national-level investments in ICT and number of employees in industry s in year t. The intuition behind the variable is as follows. ICT exposure in a municipality is high if employment in 2008 was dominated by sectors where ICT intensity (ICT investments per employee) grows strongly between 2008 and 2018. Data on ICT investments and employment per sector in 2008 and 2018 is obtained from Statistics Sweden (2019a, 2020). ICT investments include investments in the asset categories ICT equipment, computer programs, and databases. Table A2 in Appendix A.2 describes changes in ICT investments and employment for our 15 included industries between 2008 and 2018.

Other variables

Other municipal-level variables we use are exposure to investments in other capital, unemployment, and private sector employment in year 2008. Exposure to other capital investments is measured in the same way as ICT exposure, but with observed non-ICT investments per sector excluding investments in dwellings (Statistics Sweden, 2020). Unemployment is the share of not gainfully employed residents of a municipality of age

30–64 in year 2008 (Statistics Sweden, 2019c). Private sector's share of employment is the share of people in year 2008 and of age 25–64 employed outside the public sector (Statistics Sweden, 2019b).

4.2 Data limitations

There are several limitations concerning our data that we would like to address. Firstly, we are unable to observe hours worked. In order to interpret observed income as reflective of worker productivity we hence need to assume that hours worked do not vary too much between demographic cells. We somewhat deal with this problem by excluding young and old age groups which we expect to contain many non-working students and senior citizens. Yet, data on hourly wages and hours worked would have been preferred to properly deal with this issue. Secondly, as the data span both private and public sector, we have to assume that observed income levels are determined by market outcomes in the entire economy. Since this is unlikely for public sector employment, it would have been beneficial to isolate the income of private sector workers as done by e.g. Andersson et al. (2014). Further, it would be motivated to exclude employees from agriculture and mining since these sectors are directly linked to local natural resources. Since our income and education data are structured by demographic characteristics, and not by e.g. sector of employment, exclusion of public sector, agriculture, or mining employment is not possible. A potential robustness test could exclude female income from the analysis. This is because we expect hours worked to vary more and public sector employment to be more common for women than for men. However, since our other variables on local labor market characteristics do not allow for separating out male employment, performing a full empirical analysis only including male workers is not possible. In all, we deem that such a robustness check would still be rather limited and not add much to our present analysis.

It should be noted that our education and income data are based on the nighttime residents of each municipality. In contrast, data on sector and occupation employment are based on workplace data and hence municipal daytime populations. Ideally, we would employ workplace data also for income and education level. In order to interpret our results as reflective of our local production functions, we need to assume that the income of employees and residents in municipalities of similar economic density do not differ too much. This is an inconsistency in the data we are not able to alleviate, and that we expect to add unwelcome noise to our data.

We are in several ways restricted in our choices of time-span. Income and education data, from which we derive changes in relative demand across municipalities, are available only from 2000 to 2019. Ideally, we would have studied a more extensive period of time. When analyzing local labor market characteristics, we are forced to restrict the analysis even further and study changes between 2008 and 2019. This is due to a break in the SNI sector classifications that makes the available time-series before and after 2008 more or less incomparable. A similar break in the SSYK occupational categories in 2014 complicates the study of local labor market characteristics prior to 2008. Unbroken data series on sectors and occupations would allow us to study in detail how concentration of tasks and sectors has changes over time, and to analyze job polarization in a less rudimentary fashion.

Individual-level panel data would have solved many of the problems described above. Ideally, such data would include labor income, hours worked, sector of employment, occupation, education level, and municipality of employment. This would allow us to study incomes that more realistically reflect worker productivity and market-determined outcomes. Further, this would avoid the inconsistency in the data created from the combined use of workplace and population data described above. Data containing information on both occupation and education level would also allow us to study job polarization in more detail, for instance how it has evolved within our two educational groups.

As an answer to our limited data access, some variables are constructed using similar information. In particular, sector employment numbers in 2008 are used to compute municipal exposure to ICT investments, exposure to investments in other capital, as well as business service employment. This could potentially lead to high correlations between independent variables of interest in our regressions and, in turn, affect the precision of our estimates. Table A3 in Appendix A.2 presents correlation coefficients for our variables. We indeed observe some quite high correlations, for instance between business services and ICT exposure. This further highlights the need to treat our regression coefficients with caution.

5 Results

5.1 Estimation of the elasticity of substitution

This section presents the results from estimating the elasticity of substitution using our own model and data, as described in Section 3.2. As previously mentioned, an estimate of the elasticity of substitution between skilled and less-skilled workers, σ, is necessary in to derive the demand index defined in Equation 5. Previous studies on U.S. data have proposed a σ with an lower and upper bound of 1 and 2 respectively (Autor et al., 1998). Katz and Murphy (1992), also employing U.S. data, derive an elasticity of substitution of 1.4 and use it as as a best guess for the parameter. In a meta-analysis with parameters collected from 76 studies, Havranek, Irsova, Laslopova, and Zeynalova (2020) find an average reported estimate around 1.9. However, they suggest that the true estimate, when controlling for publication and attenuation bias, should be in the range 0.8–0.9. They further find that the elasticity of substitution tend to be higher for more developed countries. Domeij and Ljungqvist (2019) employ a richer model than ours, including capital, and propose using a lower elasticity of substitution for Swedish private sector data (1.3) than in U.S. data (1.67).

Estimation of Equation 10, in accordance with our main approach to deriving σ, yields the following result:

$$\ln\left(\frac{w_{ht}}{w_{lt}}\right) = \gamma_0 + \underset{(0.0029)}{0.0153}t - \underset{(0.0838)}{0.5076}\ln\left(\frac{H_t}{L_t}\right). \tag{15}$$

Using that $\gamma_2 = -1/\sigma$, the results suggest an estimated elasticity of substitution of $\sigma \approx 2$, which is at the upper bound of estimates suggested in previous literature using a similar approach. Further, the time trend suggests that SBTC and skill-bias in agglomeration economies jointly contributed to a yearly increase in the college premium of approximately 1.5 percent between 2000 and 2019. We let $\sigma = 2$ be the preferred estimate in the remainder of the analysis. However, to deal with the uncertainty of the estimate, we also report results for the alternative values $\sigma = 1$ and $\sigma = 1.5$.

Appendix A.1 provides the resulting elasticity of substitution from the alternative approach resting on estimation of Equation 8. That is, a fixed effects estimation using municipal-level data. As expected, we obtain a suspiciously large σ with this approach (12.5) likely reflecting severe endogeneity problems. We do not consider the resulting estimate in the remainder of the analysis.

5.2 Economic density and demand for college graduates

In this section we relate our measure of economic density to growth in relative demand for skilled labor over the period 2000–2019. As a first exercise, we compare the development across density quartiles. Panel A of Figure 2 shows how our measure of economic density varies geographically across Swedish municipalities. As expected, the economically densest quartile of municipalities largely coincides with Sweden's three metropolitan regions (Stockholm, Gothenburg, and Malmö). The third and second density quartiles are both found in the southern half of the country. In turn, the least dense quartile of municipalities is found in Northern Sweden. We note that half of our municipalities lie within a rather narrow interval, with economic density ranging from 15.46 to 15.87 log points (Quartile 2 and 3). Greater variation is found at the tails of the density distribution.[4]

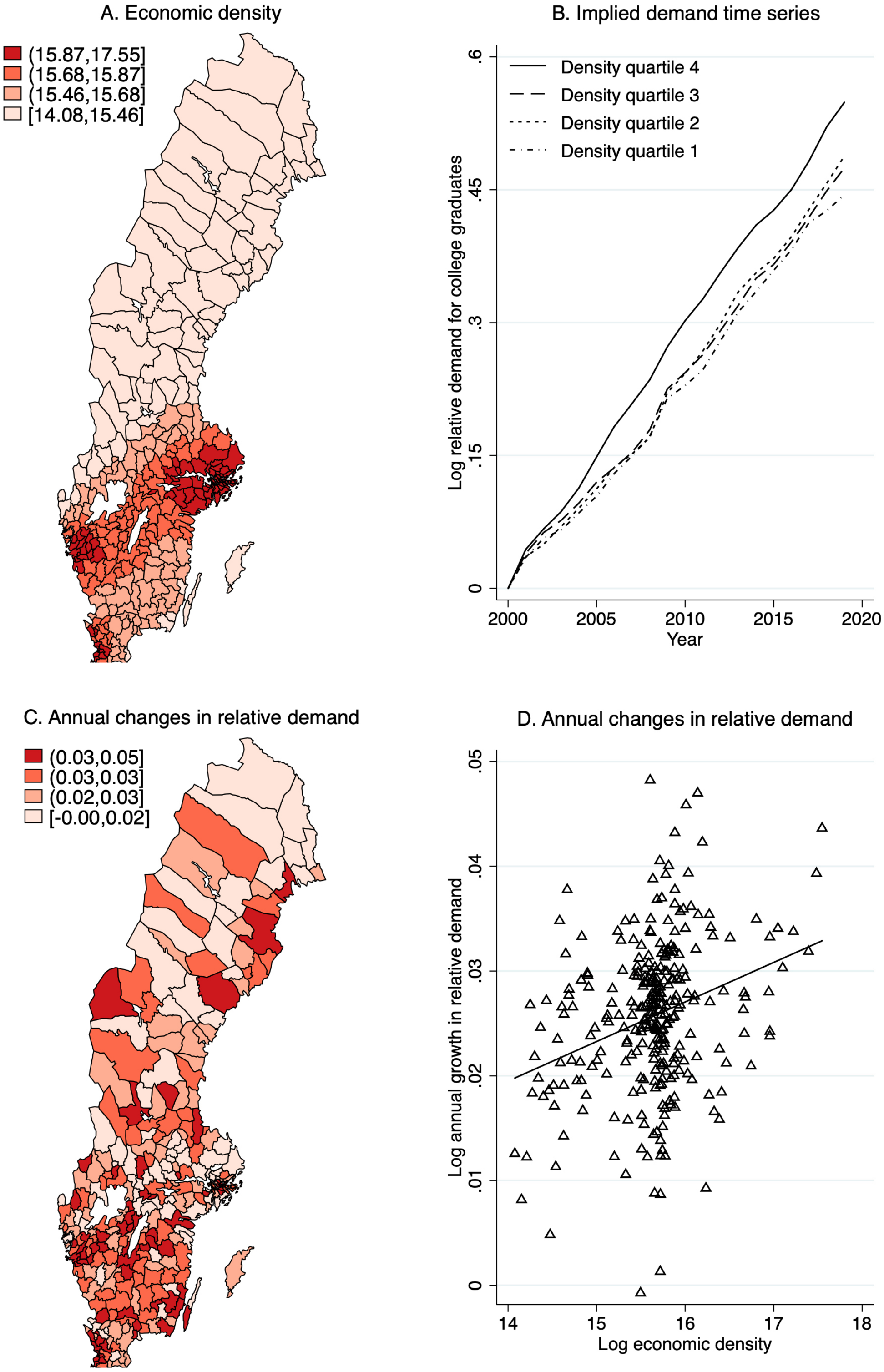
Panel B of Figure 2 plots implied time series in relative demand for the four density Quartiles 1-4. The time series are constructed as follows. The Katz-Murphy demand index is computed for each municipality and year in accordance with Equation 7 (using $\sigma = 2$). The index is then averaged and normalized to 0 in year 2000 for each quartile. We can observe that our main model prescribes a large shift in relative demand during the period for all four subsamples. Municipalities in Quartile 4 display an average increase in relative demand of about 0.55 log points over the full period (or 0.029 log points annually). This is somewhat larger than the growth in relative demand for Quartiles 1-3, ranging from about 0.44 to 0.49 log points (0.023 to 0.026 log points annually).

Next, we proceed to study changes in the Katz-Murphy demand index on the municipal level. Panel C of Figure 2 illustrates how municipal-level growth in relative demand for skilled labor is geographically distributed. The dark shade of the two metropolitan areas of Gothenburg and Malmö indicate that these pertain to the quartile with highest implied growth in relative demand. In contrast, several municipalities in the Stockholm metropolitan region display lower levels of growth in relative demand. In general, the map shows that demand for college graduates has grown somewhat faster in the southern half of the country. However, the graphical inspection of Panel C only allows for limited interpretation since, for instance, small municipalities in the Stockholm region are difficult to distinguish.

Panel D in Figure 2 explores the relationship between annual growth in relative demand and economic density for individual municipalities using our preferred value of σ. The years covered are still 2000–2019. The fitted line suggests a positive relationship between

[4] Too see how our measure corresponds to more naïve measures of density, we compare our measure with the number of residents per square kilometer in each municipality. The two measures correlate well (a correlation of 0.85), which is in line with previous literature suggesting that different measures of density often yield similar results (Duranton & Puga, 2020)

Figure 2: Economic density and implied change in relative demand for college graduates, 2000–2019



Notes: Panel A shows the geographical distribution of economic density across Swedish municipalities, computed as accessibility to total income mass in the year 2000. Panel B plots the implied time series for average relative demand for college graduates across quartiles of Swedish municipalities, from most to least dense (Q4 to Q1). Panel C and D display the implied annual log changes in relative demand for college graduates for Swedish municipalities during the period 2000–2019. Relative demand is computed using the Katz-Murphy demand index (Equation 6) using $\sigma = 2$. The line in Panel D represents a linear fit. Data are provided by Statistics Sweden.

economic density and growth in the Katz-Murphy demand index (a slope of 0.0038, significant at the 1 percent level). The following interpretation serves to get a sense of the magnitude of the correlation. A move from the least to the most dense municipality in our sample predicts an approximately 1.31 percentage points faster yearly growth in the relative demand for college graduates ($3.47 \times 0.0038 \times 100$). Panel D also shows that there is considerable variation among municipalities of similar economic density, especially at the middle of the distribution. As an example we find that Älmhult—a municipality in southern Sweden with moderate level of economic density and one of the main locations of IKEA—displays the strongest annual growth in relative demand for skilled labor during the period.

Figures A2 and A3 in Appendix A.2 present the the implied relative demand time series and municipal-level demand shifts using $\sigma = 1.5$ and $\sigma = 1$. Results are largely unaffected by the use of alternative elasticities of substitution. We note that the implied relative demand shifts increase somewhat as σ becomes smaller. This is because a lower elasticity of substitution implies a flatter relative demand curve for skilled labor and, consequently, that larger shifts in relative demand are needed to rationalize the relatively stable income premium. In large, the implied demand time series follow our expected pattern quite well, with larger shifts in relative demand for municipalities of higher economic density.

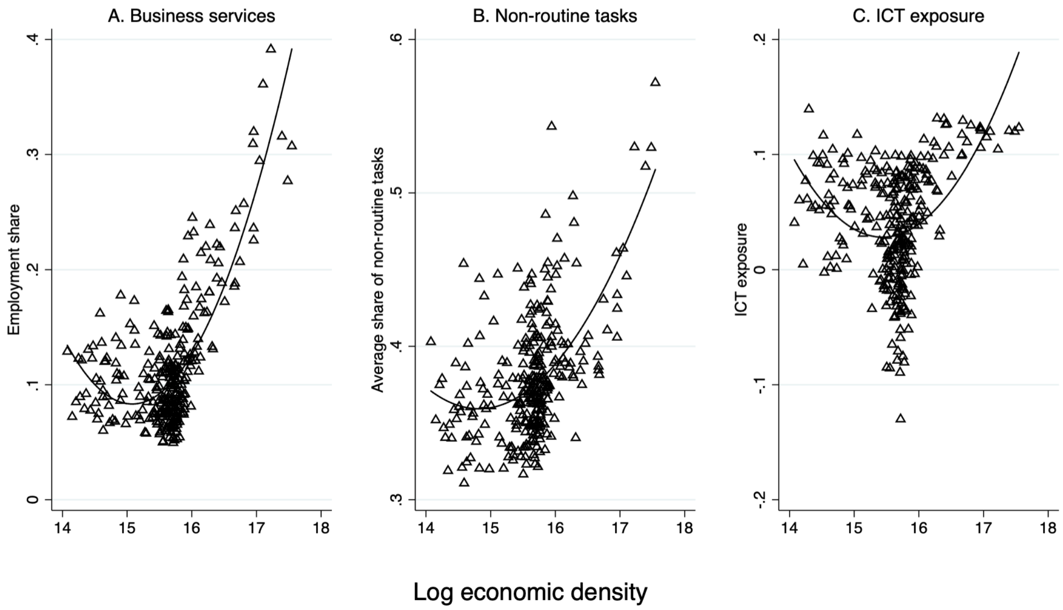
The above results suggest clear differences in the growth in relative demand for college graduates between municipalities. They further suggest that demand growth has been biased toward economically dense locations. In terms of our model illustrated by Equation 6, the result could be interpreted as positive shifts in the term $\mu_{ht} - \mu_{lt}$. This interpretation lends support to the idea of an increasing factor-bias of agglomeration economies, or that agglomerations are becoming increasingly skill-biased. The following sections explore possible explanations to this development.

5.3 Spatial variation in labor market characteristics

In this section we explore how the structure of local labor markets in terms of task and sector specialization as well as job polarization relate to our measure of economic density. Further, we investigate how exposure to investments in ICT varies across space. The purpose is to gain a better understanding of the labor market characteristics that distinguish agglomerations of economic activity in Sweden. Due to data limitations highlighted in Section 4.2, we mainly focus the period 2008–2019.

Panel A in Figure 3 presents the relationship between specialization in business services and economic density for the full sample of municipalities. Values on the y-axis denote local employment in business service sectors in the base year 2008. It can be observed that denser locations are more specialized in business services, as suggested by Duranton

Figure 3: Local labor market characteristics, 2008

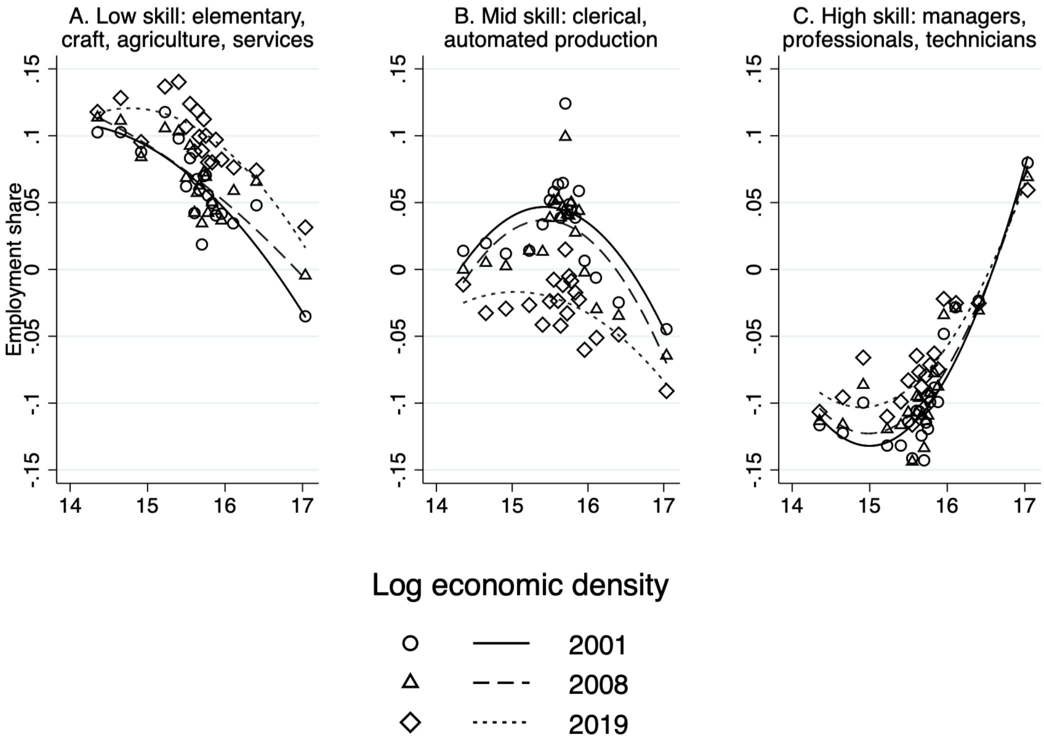


Notes: Figure showing the relationship between local labor market characteristics—–(A) share of employment in business service, (B) average share of non-routine tasks performed by workers, and (C) exposure to ICT investments—–and economic density. Lines represent quadratic fits. Variables are for 2008 and defined as in Section 4.1. Data are on the municipal level and provided by Statistics Sweden.

and Puga (2005) and in line with the findings of Eckert (2019). The quadratic fitted line suggests positive relationship between business service employment and economic density, especially for municipalities at the upper tail of the distribution. Business service employment ranges from 10 percent among the least dense to 30-40 percent for the most dense municipalities. The associated map in Panel A of Figure 5 shows that the share of business service employment is highest in Stockholm, Gothenburg and Malmö with surrounding municipalities, but also in more populated municipalities of Northern Sweden such as Sundsvall, Umeå and Luleå.

The corresponding plot for specialization in non-routine tasks is shown in Panel B of Figure 3. We notice a positive relationship between the share of non-routine tasks performed by the average worker and economic density. The relationship is in part driven by the four most dense municipalities in our sample, all displaying among the highest shares of non-routine tasks performed by workers (corresponding to Solna, Sundbyberg, Stockholm, Danderyd). The fitted line suggests a difference slightly above 10 percentage points between the most and least dense municipalities in our sample. The map in Panel B of Figure 5 shows a similar geographic distribution as for business service specialization. Employment is characterized by more non-routine work in the southern half of the country but also in a dozen of the more populated municipalities of Central and Northern Sweden. The results are in line with the finding from Michaels et al. (2019) that contemporary agglomerations are in large characterized by their focus on interactive tasks. The pattern also confirms previous findings from Swedish data suggesting that employment in the three metropolitan regions is distinguished by higher

Figure 4: Occupational employment shares: level relative to 2001 national mean



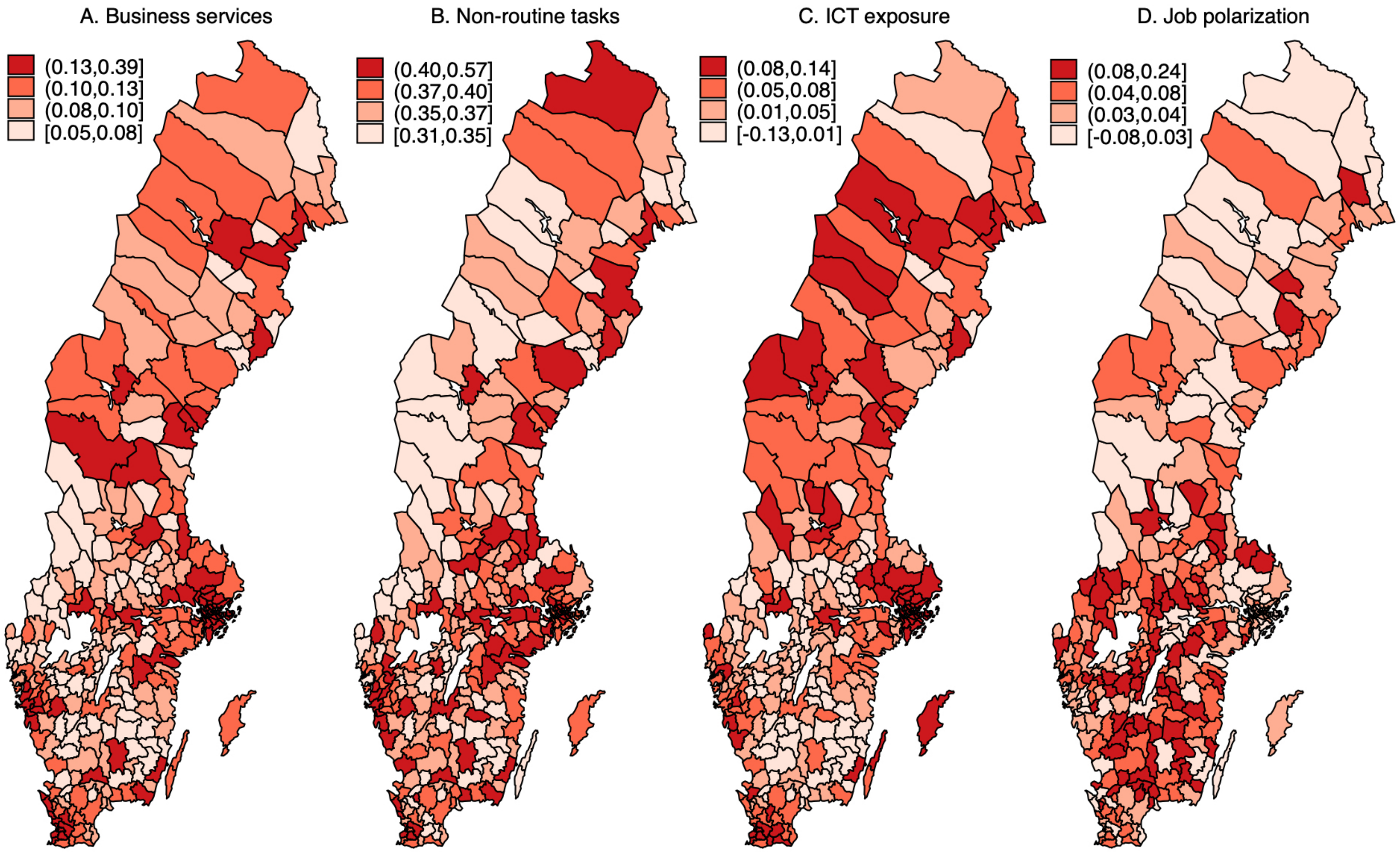
Notes: Figure presents bin-scatters depicting the relationship between municipal employment shares in (A) low-skill, (B) middle-skill, and (C) high-skill occupations relative to the 2001 national mean, respectively, and economic density for years 2001, 2008 and 2019. Each plotted point represents about 15 municipalities. Lines represent quadratic fits. Data are provided by Statistics Sweden.

levels non-routine work (Heyman & Persson, 2019).

Panel C in Figure 3 provides a corresponding analysis for municipal exposure to ICT investments. Its relationship to economic density is less clear-cut than for our measures of task-and sector specialization. The scatter displays great variation in exposure to ICT investments for municipalities at the center of the density distribution. The most dense municipalities, however, all display relatively high levels of ICT exposure. The quadratic fitted line predicts somewhat higher levels of ICT exposure for the most dense locations. The associated map in Panel C of Figure 5 does not indicate any systematic distribution of exposure to ICT investments across municipalities.

Lastly, we explore how job polarization relates to economic density. Panels A-C of Figure 4 illustrate how employment shares in low-, middle-, and high-skill occupations, respectively, relate to economic density in 2001, 2008 and 2019. Panel A illustrates a clear negative relationship between employment in low-skill occupations and economic density in year 2001. The fitted line suggests a difference corresponding to approximately 15 percentage points between the least and most dense location. The relationship flattens somewhat toward 2008 and 2019. In 2019, the difference is instead

Figure 5: Local labor market characteristics



Notes: Maps showing the geographical distribution of (A) share of business service employment, (B) share of non-routine tasks performed by the average worker, (C) exposure to ICT investments, and (D) job polarization. Job polarization is for 2008–2019 while remaining variables are for 2008. Variables are defined as in Section 4.1. Data are on the municipal level and provided by Statistics Sweden.

about 10 percentage points. The general upward shift in the urban occupation gradient reflects a broad growth in the share of low-skill jobs from 2008 to 2019. In contrast, Panel B of Figure 4 provides evidence of a broad decline in the share of middle-skill occupations between 2001 and 2019, concentrated to the period 2008 to 2019. The decline appears somewhat stronger for municipalities in the middle of the density distribution. Panel C suggests that the overall share of high-skilled occupations remained relatively constant between 2001 and 2019. There is a tendency toward faster growth in the share of high-skill occupations in locations at the middle of the density distribution. Yet if the changes are small in magnitude and reflect a limited time period of time, the above findings are line with the idea of a broad job polarization in the Swedish labor market. The following section explores how local levels of job polarization, as well as specialization in non-routine tasks, business services, and exposure to ICT investments, relate to growth in demand for college graduates.

5.4 Relating labor market characteristics to demand for college graduates

In this section, we investigate to what extent municipal labor market structure in terms of task-specialization, sector-specialization, and job polarization account for the increasing density-bias in demand for skilled labor. We estimate Equation 11 with and without controls for other local labor market characteristics. The analysis is restricted to the period 2008–2019. We consider two alternative outcome variables to proxy demand for skilled labor: the college graduate income share, and the share of college graduates in each municipality. Table 1 confirms that these measures of relative demand largely follow the same pattern as the demand indices studied in Section 5.2. Levels and changes are considerably higher for Quartile 4, while they vary little between Quariles 1–3.

Table 1: Municipal income share and supply of college graduates (percent), 2008–2019

	College graduate income share			Share of college graduates		
	2008	2019	Δ	2008	2019	Δ
All municipalities	32.84	39.68	6.84	28.20	34.97	6.76
Density quartile 4	42.89	50.61	7.72	36.33	44.39	8.06
Density quartile 3	29.65	36.42	6.77	25.43	32.10	6.67
Density quartile 2	29.55	36.40	6.86	25.62	32.10	6.48
Density quartile 1	29.35	35.39	6.04	25.51	31.36	5.85

Notes: Table showing college graduate income share and share of college graduates in 2008 and 2019. Average shares are presented for the full set of municipalities and for municipalities in each density quartile, from most to least dense (Q4 to Q1). Data are provided by Statistics Sweden.

Table 2 presents results from estimating Equation 11 using municipal growth in the college graduate income share as dependent variable. Column 1 confirms the positive relationship between growing demand for skilled labor and economic density. The size of the estimate indicates that a 100 percent increase in economic density is associated with 1.2 percentage points higher growth in the college graduate income share. In terms of our sample, this implies that a move from the least to the most dense municipality predicts a 4.17 percentage points higher growth in the college graduate income share between 2008 and 2019. This is a considerable difference given that the mean growth in our sample corresponds to 6.84 percentage points.

In Column 2 of Table 2, we add the share of business service employment in the base year 2008 as independent variable. The coefficient on share of business service employment is positive but imprecise. The estimate suggests that a 10 percentage points higher share of business services in the base year is associated with approximately 0.5 percentage points larger growth in the college graduate income share. The coefficient on economic density drops with about 24 percent compared to Column 1, reflecting a positive relationship between economic density and specialization in business services. In Column 3, we add our full set of independent variables. The coefficient on business service employment switches sign from positive to negative and becomes yet more imprecise. Thus, increasing sector-specialization seems as an unlikely explanation to the increase in demand for college graduates in dense locations.

Table 2: Local labor market characteristics on growth in college income share

	Change in college graduate income share 2008–2019 (mean: 0.068)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log density	0.0120***	0.00918***	0.00741**	0.00909***	0.00610*	0.0120***	0.00667**
	(0.00203)	(0.00234)	(0.00317)	(0.00205)	(0.00321)	(0.00203)	(0.00301)
Share business services		0.0505*	-0.0360				
		(0.0302)	(0.0522)				
Share non-routine tasks				0.0857**	0.0719		
				(0.0344)	(0.0473)		
Job polarization						0.00132	0.0610**
						(0.0268)	(0.0309)
ICT exposure			0.141**		0.0404		0.128***
			(0.0697)		(0.0525)		(0.0440)
Exposure to other capital			0.164		-0.00509		0.107
			(0.113)		(0.118)		(0.0928)
Share private sector			0.0261		0.0186		0.0131
			(0.0310)		(0.0315)		(0.0294)
Share unemployed			-0.134***		-0.136***		-0.132***
			(0.0375)		(0.0370)		(0.0365)
N	290	290	290	290	290	290	290
R^2	0.124	0.138	0.213	0.149	0.222	0.124	0.223

Notes: Regressions based on data from Statistics Sweden on the municipal level. Variables are defined as in Section 4.1. Job polarization is for 2008–2019, and remaining independent variables are for 2008. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns 4-5 of Table 2 repeat the exercise in Columns 2-3 but use the task-based measure of municipal specialization as independent variable. The coefficient on the share of non-routine tasks in Column 4 suggests a positive relationship between initial specialization in non-routine task and subsequent demand for skilled labor. The coefficient on task-specialization suggests that 10 percentage points higher initial share of non-routine tasks is associated with 0.86 percentage points larger growth in the college graduate income between 2008 and 2019. The result is somewhat suggestive of task-based specialization as a channel through which relative demand for skilled labor has increased. The same specification presents a coefficient on economic density which is about 24 percent lower compared to Column 1. When adding our full set of controls in Column 5, the coefficient on task-specialization drops slightly and loses precision. Yet, it serves as a somewhat better predictor of growing demand for college graduates than business service employment.

Columns 6-7 of Table 2 include our measure of job polarization as independent variable. The coefficient on job polarization in Column 6 is both economically and statistically insignificant, suggesting a zero-correlation between the decline in mid-skill occupations and shift in relative demand for college graduates. As could be expected, given the broad influence of job polarization described in Section 5.3, the estimate on economic density remains unchanged by the introduction of the variable. In Column 7, when adding our set of control variables, the coefficient on job polarization becomes larger and significant at the 5 percent level. The resulting estimate suggests that increasing the share of high- and low-skill jobs with 10 percentage points is associated with an increase in the college graduate income share of about 0.6 percentage points, conditional on our other covariates. Yet, due to its seemingly weak correlation with economic density, job polarization does not provide a satisfactory explanation to the increasing density-bias in demand for college graduates.

Similar to the findings in Graetz (2020), results in Table 2 suggest a positive relationship between ICT exposure and growth in relative demand for college labor. The only exception is Column 5 where the estimate close to zero. This is likely because specialization in non-routine tasks is closely related to exposure to ICT, hence capturing the same variation. The coefficient on ICT exposure (Column 3) can be interpreted as follows. If exposure to ICT had been zero instead of 0.1, as for locations with the highest exposure, growth in the graduate income share would have been 1.4 percentage points lower ($100 \times 0.141 \times 0.1$). As to the remaining controls, the coefficient on share of unemployed in 2008 indicates a negative and significant correlation with the outcome variable. The coefficients on exposure to other capital and private sector employment are imprecise and close to zero.

The specifications using the full set of control variables (Columns 3, 5, and 7, respectively) all display a statistically significant conditional correlation between economic density and growth in relative demand for college graduates. The resulting estimates are between 0.0061 and 0.0074, i.e. about 50–60 percent of the size of the coefficient on economic density in the unconditional specification in Column 1. Our interpretation is that our specifications explain only 40–50 percent of the density-bias in the growing demand for skilled labor. The failure of our other control variables to fully capture the correlation between economic density and demand for skilled labor may be due to our noisy variables, or simply because there are other measures of sectoral and occupational clustering—possibly at other spatial levels—that are more informative to the understanding of skill-biased agglomeration economies.

Table 3 presents results from estimating Equation 11 on municipal level, using growth in the college graduate share of the working age population as dependent variable. In comparison to Table 1, estimates are somewhat rescaled due to the greater variation in the outcome variable made clear by Table A4 in Appendix A.2. We note that initial share of non-routine tasks is statistically significant also after controlling for exposure to ICT investments (Column 5). The remaining coefficients of interest follow the same overall pattern.

The fit of the model is lower compared to previous research performing similar analyses (see e.g. Autor et al., 1998). The value of R-squared ranges from 0.2 to 0.39 for our specifications with the full set of independent variables. The result is likely to be driven by the fact that we only observe average incomes within demographic cells, rather than

Table 3: Local labor market characteristics and growth in share of college graduates

	Change in share of college graduates 2008–2019 (mean: 0.068)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log density	0.0150***	0.00910***	0.00606**	0.0109***	0.00472*	0.0151***	0.00586**
	(0.00179)	(0.00206)	(0.00258)	(0.00173)	(0.00257)	(0.00182)	(0.00253)
Share business services		0.105***	0.0162				
		(0.0282)	(0.0472)				
Share non-routine tasks				0.121***	0.102***		
				(0.0305)	(0.0374)		
Job polarization						-0.0318	0.0427*
						(0.0233)	(0.0248)
ICT exposure			0.138**		0.0794*		0.180***
			(0.0603)		(0.0424)		(0.0388)
Exposure to other capital			0.142		-0.000968		0.162**
			(0.0948)		(0.0954)		(0.0809)
Share private sector			0.0471*		0.0569**		0.0506**
			(0.0265)		(0.0262)		(0.0250)
Share unemployed			-0.155***		-0.160***		-0.156***
			(0.0310)		(0.0303)		(0.0305)
N	290	290	290	290	290	290	290
R^2	0.205	0.270	0.371	0.257	0.394	0.211	0.377

Notes: Regressions based on data from Statistics Sweden on the municipal level. Variables are defined as in Section 4.1. Job polarization is for 2008–2019, and remaining independent variables are for 2008. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

actual wages. Our inability to observe the education level of individuals who are actually part of of the labor force, instead of the working age population in each municipality, is also likely to drive this result.

As the base year of our regressions is 2008, one might worry about the effects of the the Global Financial Crisis. Yet, a rise in unemployment was not documented until 2009 (Statistics Sweden, 2019c). Investments in ICT year 2008 were roughly on the same levels as preceding years (Statistics Sweden, 2020) and, for the same year, we find no extraordinary jumps in average income for our demographic cells (Statistics Sweden, 2021e). Although we deem our regressions not too affected by the financial crisis, we are humble to the fact that our results can still be influenced by the choice of time period.

6 Discussion

6.1 Relating our results to previous findings

We find support for some stylized facts from the literature on SBTC and agglomeration economies in a Swedish context. Firstly, we confirm a broad skill-upgrading of Swedish population during the period 2000–2019 which has been biased toward economically dense locations. Secondly, we show that there is a positive relationship between the college income premium and economic density, and that this relationship has steepened during the last decades. While the latter is a well-established finding in the U.S. (see e.g. Autor, 2019; Baum-Snow & Pavan, 2013), it has until today been paid limited attention in Sweden. Further, the finding is consistent with the growing consensus from the urban economics literature that the UWP is generally higher for workers with more qualified skills (see e.g. Andersson & Larsson, 2020; Bacolod et al., 2009).

By studying the above trends through the lens of a canonical model of SBTC, enriched with factor-biased agglomeration economies, our results suggest that economically dense locations must have experienced faster growth in relative demand for college graduates in order to rationalize the observed labor market outcomes. The descriptive analysis predicts a difference in annual growth rate in demand for college graduates of approximately 1.31 percent when moving from the least to the most dense municipalities in our sample. Similar to Baum-Snow et al. (2018) and Autor (2019), our findings highlight the need to study labor market transformations across space to fully understand the evolution of relative incomes between demographic groups. We interpret this as suggestive evidence that agglomerations of economic activity have become increasingly skill-biased also in Sweden.

One important limitation with our results is, however, that it fails to take spatial self-selection on unobservable characteristics into account, as well as changes in human capital within skill-groups over time. Baum-Snow and Pavan (2013) suggest that sorting on unobservables is an important contributor to rising inequality within large cities in the U.S. between 1979 and 2007. To the extent that sorting on unobservable characteristics exist and is stronger for skilled workers, our implied changes in relative demand are likely to be overestimated. Similarly, it could be the case that the relative human capital level between skill-groups has changed over our studied period. Studying U.S. data, Bowlus et al. (2017) show that changes in relative human capital levels between skill-groups could explain a non-negligible portion of the changes in their relative wages. Indeed, there is a risk that these changes be confounded with SBTC and, in our case, an increasing density-bias in relative demand for college graduates.

The answer to our second research question is somewhat inconclusive. Our finding that business services are biased toward economically dense areas is in line with the previous studies such as Duranton and Puga (2005) and Eckert (2019) focusing on U.S. data. However, and distinct from Eckert (2019), we do not find initial specialization in business services to account well for the increasing skill-bias of agglomerations. We also find that non-routine tasks are concentrated to economically dense municipalities. The finding is in line with Michaels et al. (2019) and Rossi-Hansberg et al. (2019) who suggest that larger cities have a comparative advantage in such activities. Our results show that initial specialization in non-routine tasks accounts somewhat better, but far from fully, for the increasing density-bias in demand for college graduates.

Our results are somewhat suggestive that a higher degree of local job polarization increases relative demand for college graduates. But the finding that job polarization is not particularly biased toward economically dense locations makes it an implausible explanation for the increasing density-bias in demand for college graduates. The finding that job polarization is not biased toward economically dense municipalities stands in contrast to previous studies on both Swedish (Heyman & Persson, 2019) and U.S. data (Autor, 2019). Our deviating results could possibly be explained by the labor force data used. Broadly defined occupational groups forced us to make a more rudimentary categorization of occupations into low-, middle-, and high-skill occupations than in e.g. Heyman and Persson (2019).

In line with previous studies on municipal-level Swedish data Graetz (2020), we find that exposure to ICT investments is positively associated with increasing relative demand for skilled labor. But distinct from findings in U.S. data (Rubinton, 2020), we do not find any clear-cut relationship between municipal exposure to ICT investments and economic density. Hence, it does not alone provide a satisfactory explanation to the increasing density-bias in demand for college graduates. This result is possibly affected by our inability to observe actual ICT investments on the municipal level. If investments in ICT are higher in economically dense locations, holding local sector composition fixed, our measure of ICT exposure is likely to deviate considerably from actual ICT adoption. With this in mind, our results are still somewhat inconclusive on the question whether endogenously faster adoption of skill-biased technologies, as suggested by Rubinton (2020), contributes to the increasing density-bias in demand for skilled labor.

6.2 Policy implications and future research

Our results are of interest to policymakers seeking to understand the driving forces behind regional divergence, and how to mitigate its adverse effects. Continued regional income divergence risks putting stress on current systems of equalization between municipalities, intended to promote equal access to welfare and public services. Increased fiscal redistribution between municipalities could potentially threaten the system's legitimacy and create need for new policies. Firstly, and in line with our results, policies intended to increase regional connectivity (e.g. investments in transport infrastructure) could be well-motivated in order to provide thicker labor markets with greater scope for agglomeration effects. Secondly, place-based "big-push interventions"—defined by Moretti (2015) as a coordinated policy that brings skilled labor, specialized business services and employers to a new location—could become increasingly attractive to local decision makers seeking to boost regional growth. Lastly, initiatives directly incentivizing college graduates to locate in less dense municipalities, such as write-downs of student loan debts as suggested in a recent public inquiry (SOU 2020:8), could potentially help ease regional divergence and, in the long run, enable more learning effects in more sparsely populated regions.

With better data availability, it would be possible to study regional patterns of job polarization in more detail. In particular, it would be of interest to explore whether the urban occupational skill gradients for low-, middle-, and high-skilled jobs have developed differently for non-college compared to college graduates as seen in U.S. data (Autor, 2019). To assess the generalizability of our findings, it would also be valuable to study a more extensive time period to see whether our main conclusions extend to decades preceding the 2000's. Moreover, recently developed spatial data provide great opportunities to analyze geographical concentration of worker characteristics on different spatial scales (see e.g. Andersson & Larsson, 2020). Investigating how concentration of occupations and sectors has changed on different geographical levels, possibly creating greater scope for skill-biased agglomeration forces, should be a fruitful way forward to unveil the relationship between economic density and labor market outcomes. Lastly, research should further focus on welfare consequences of increased sorting of college graduates in Sweden, incorporating elements such as local rents and amenities into the analysis. Differences in housing costs and supply of amenities across municipalities are likely to be of importance both to the welfare of individuals, and to their location decisions. For this purpose, one could seek to isolate exogenous variation in labor demand through shift-share instruments (see e.g. Diamond, 2016) or presence of randomly located universities (see e.g. Moretti, 2004).

7 Conclusion

This thesis investigates whether spatially uneven growth in demand for college graduates can be understood as a consequence of increasing complementary between college graduates and agglomerations of economy. It extends the current literature by uniting the traditional framework of SBTC with fresh insights from regional and urban economics. By applying a simple supply-demand framework, we explore implied changes in relative demand for college graduates in municipalities of different economic density. We also sketch further on three ideas from the current literature—spatial concentration of tasks, sectors, and job polarization—to assess possible mechanisms behind an increasingly positive relationship between economic density and demand for college graduates.

In order to rationalize observed prices and quantities, our results predict that the economically densest municipalities in our sample experienced about 1.31 percentage points faster yearly increase in relative demand for college graduates from 2000 to 2019, compared to municipalities at the opposite of the density scale. This result is potentially reflective of increasing complementary between college graduates and agglomerations, yet if we also find considerable variation between municipalities of similar economic density.

In line with previous literature, we find that economically dense locations are particularly specialized in in non-routine tasks and business services sectors. We do not find any of these features to fully account for the increasingly positive relationship between demand for college graduates and economic density, although the task-measures is found to serve as a somewhat better predictor. We do not find job polarization to be particularly biased toward economically dense locations, hence making it an unlikely explanation for the increasing skill–density complementarity. Lastly, and in line with the traditional literature on SBCT, we find local exposure to ICT to be positively related to demand for college graduates, albeit not clearly biased toward denser municipalities. Our results are however likely to suffer from bias due to limited data availability and variables constructed on more aggregate levels compared to other literature in the field.

While the approach in this thesis is rather descriptive, and more research is needed to understand the underlying causal mechanisms, we show that the spatial dimension is important to consider when studying educational income inequality. We suggest that future studies make use of more detailed spatial labor force data to unveil the links between the geographical distribution of economic activity and regional as well as educational income disparities.

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A Appendix

A.1 Alternative estimation of the elasticity of substitution

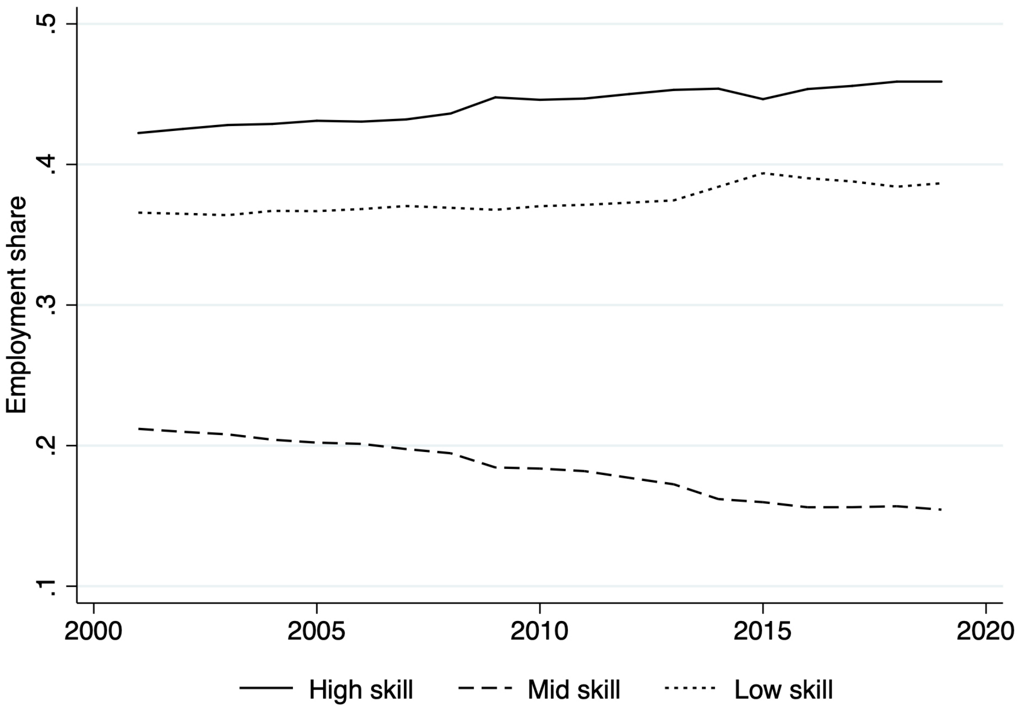
This section presents the results from our alternative approach to estimating the elasticity of substitution between college and non-college graduates using municipal-level data, i.e. estimation of Equation 8. The approach yields the following result:

$$\ln\left(\frac{w_{hct}}{w_{lct}}\right) = \gamma_{0c} - \underset{(0.0015)}{0.0103}t + \underset{(0.0001)}{0.0006}t \times E_c - \underset{(0.0085)}{0.08} \ln\left(\frac{H_{ct}}{L_{ct}}\right), \tag{16}$$

implying an elasticity of substitution of $(-1)/(-0.08) = 12.5$, well beyond the range suggested by previous literature. The result confirms our concern of an upward bias in coefficient on $\ln(H_{ct})/(L_{ct})$ stemming from domestic migration.

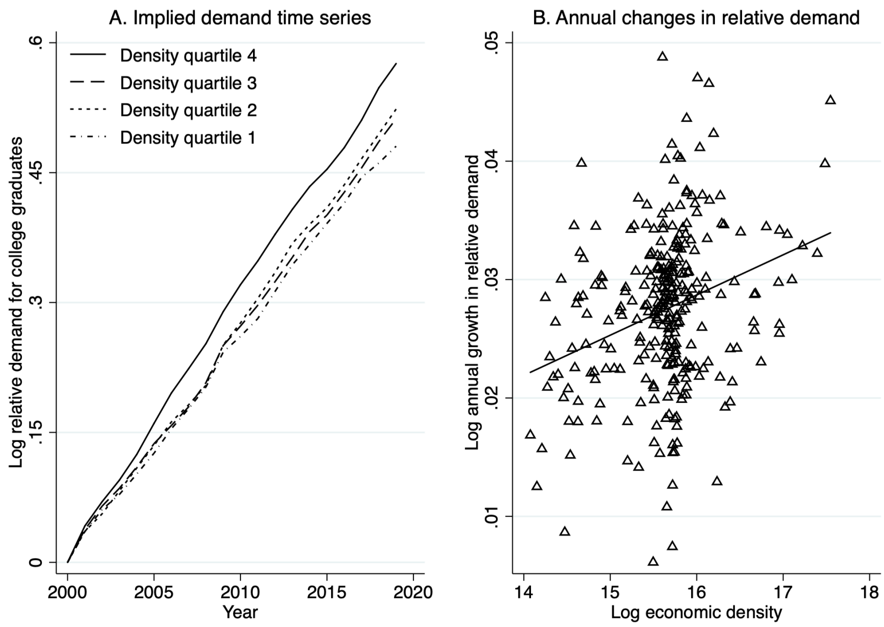
A.2 Figures and tables

Figure A1: Employment shares of occupational groups, 2001–2019



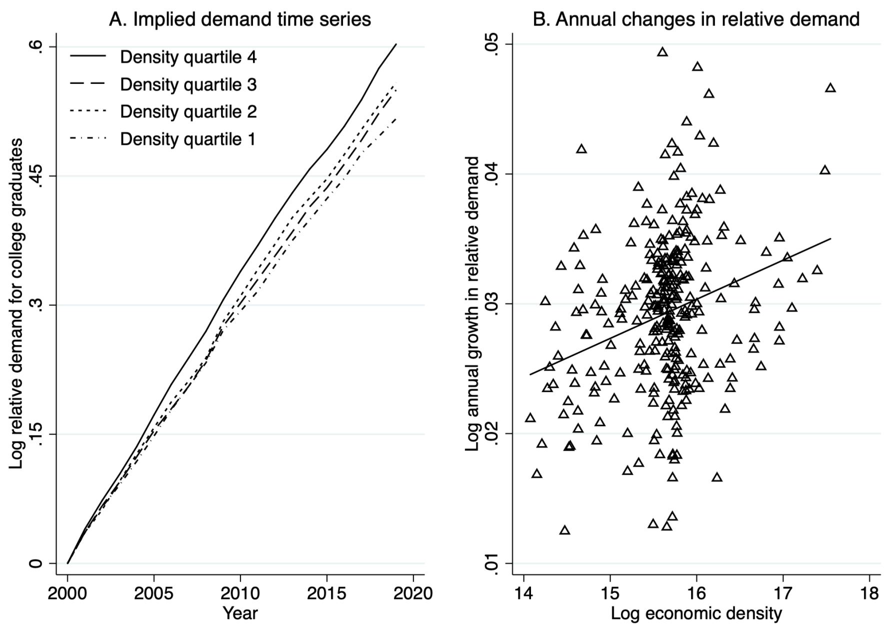
Notes: Figure showing employment shares of low-, middle- and high-skill occupations on national level for the period 2001–2019. Data are provided by Statistics Sweden.

Figure A2: Implied changes in relative demand 2000–2019, $\sigma = 1.5$



Notes: Panel A plots the implied time series for average relative demand for college graduates across quartiles of Swedish municipalities, from most to least dense (Q4 to Q1). Panel B displays the implied annual log changes in relative demand for college graduates for Swedish municipalities during the period 2000–2019. Relative demand is computed using the Katz-Murphy demand index (Equation 5) using $\sigma = 1.5$. The line in Panel B represents a linear fit with a slope of 0.034, significant at the 1 percent level. Data are provided by Statistics Sweden.

Figure A3: Implied changes in relative demand 2000–2019, $\sigma = 1$



Notes: Panel A plots the implied time series for average relative demand for college graduates across quartiles of Swedish municipalities, from most to least dense (Q4 to Q1). Panel B displays the implied annual log changes in relative demand for college graduates for Swedish municipalities during the period 2000–2019. Relative demand is computed using the Katz-Murphy demand index (Equation 5) using $\sigma = 1$. The line in Panel B represents a linear fit with a slope of 0.03, significant at the 1 percent level. Data are provided by Statistics Sweden.

Table A1: Occupations and share of non-routine tasks

Occupation	Share of non-routine tasks
High skill	
Physical, mathematical and engineering science professionals	100.0
Life science and health professionals	90.4
Physical and engineering science associate professionals	79.7
Corporate managers	78.4
Other professionals	63.0
Teaching professionals	61.2
Life science and health associate professionals	56.3
Legislators and senior officials	54.4
Other associate professionals	52.7
General managers	46.6
Teaching associate professionals	36.1
Mid skill	
Office clerks	52.1
Stationary-plant and related operators	43.6
Customer services clerks	27.1
Machine operators and assemblers	18.8
Drivers and mobile-plant operators	6.3
Low skill	
Metal, machinery and related trades workers	41.6
Precision, handicraft, printing and related trades workers	39.8
Personal and protective services workers	32.0
Extraction and building trades workers	21.4
Other craft and related trades workers	17.7
Market-oriented skilled agricultural and fishery workers	10.8
Models, salespersons and demonstrators	8.1
Laborers in mining, construction, manufacturing and transport	2.5
Agricultural, fishery and related laborers	0.9
Sales and services elementary occupations	0.0

Notes: Table showing occupations on the ISCO-88/SSYK96 2-digit level with corresponding average shares of non-routine tasks as provided by Becker et al. (2013) and Hakkala et al. (2014). The categorization into low-, middle-, and high-skill occupations follows the approach described in Section 4.1.

Table A2: Change in industry ICT intensity, 2008–2018

Industry	Δ Log ICT investments	Δ Log employment	Δ Log ICT intensity
Agriculture, forestry and fishing	0.02	0.22	-0.20
Mining, quarrying and manufacturing	-0.56	-0.17	-0.38
Electricity, water supply, sewage etc.	0.22	0.14	0.07
Construction	0.64	0.21	0.42
Wholesale and retail trade	0.23	0.08	0.15
Transportation and storage	0.07	0.01	0.05
Accommodation and food services	0.49	0.27	0.21
Information and communication	0.84	0.22	0.63
Financial and insurance activities	0.10	0.05	0.05
Real estate activities	0.52	0.21	0.31
Professional and administrative activities	0.15	0.25	-0.10
Public administration	0.34	0.24	0.10
Education	0.41	0.18	0.22
Human health and social services	0.31	0.13	0.17
Arts, other services, activities households and extraterritorial organizations	0.10	0.15	-0.05

Notes: Table showing changes in ICT investments, employment, and ICT intensity for 15 industries based on the SNI2007 classifications, 2008–2018. Data provided by Statistics Sweden.

Table A3: Corrlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Change in college income share	1.000									
(2) Change in college employment share	0.932	1.000								
	(0.000)									
(3) Log density	0.352	0.453	1.000							
	(0.000)	(0.000)								
(4) Business services	0.299	0.468	0.572	1.000						
	(0.000)	(0.000)	(0.000)							
(5) Non-routine tasks	0.307	0.417	0.479	0.703	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)						
(6) Job polarization	0.017	-0.058	0.039	-0.322	-0.154	1.000				
	(0.774)	(0.325)	(0.503)	(0.000)	(0.008)					
(7) ICT exposure	0.198	0.306	0.161	0.677	0.353	-0.595	1.000			
	(0.001)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)				
(8) Exposure to other capital	0.000	-0.045	0.213	-0.244	0.104	0.516	-0.777	1.000		
	(0.996)	(0.447)	(0.000)	(0.000)	(0.076)	(0.000)	(0.000)			
(9) Private sector	0.211	0.303	0.655	0.321	0.129	0.202	-0.153	0.260	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.001)	(0.009)	(0.000)		
(10) Unemployment	-0.320	-0.400	-0.202	-0.206	-0.110	0.011	-0.064	-0.075	-0.153	1.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.062)	(0.846)	(0.274)	(0.206)	(0.009)	

Notes: Sources and definitions of variables are presented in Section 4.1. P-values in parenthesis.