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Technology, talent and economic segregation in cities

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1. Introduction

The sharp increases in economic and spatial inequality have become of increasing interest to researchers and public policymakers. A large body of research has documented the growth of both economic inequality (Piketty, 2014) and spatial inequality across metropolitan areas (Ganong & Shoag, 2015; Giannone, 2017; Glaeser, Resseger, & Tobio, 2009; Hsieh & Moretti, 2015). Other research has also documented an increase in economic segregation within urban areas (Reardon & Bischoff, 2011; Watson, Carlino, & Gould Ellen, 2006). More recent studies have examined the connection between innovation and economic inequality across states (Aghion, Akcigit, Bergeaud, Blundell, & Hémous, 2015) and between innovation and economic segregation between and within metropolitan areas (Berkes & Gaetani, 2017).

Our research furthers this work by examining the connection between technology, talent and economic segregation. In doing this, we draw on established urban and economic theory, identifying a basic mechanism that connects human capital, economic segregation and innovation. On the one hand, innovative high-tech industries require dense spatial clusters of highly-skilled, highly-paid workers (Morretti, 2012). These affluent groups are able to buy housing in better neighborhoods with easy access to employment and transportation, and which offer better schools, better amenities and better services (Diamond, 2016; Edlund, Machado, & Sviatschi, 2015; Glaeser, Kolko, & Saiz, 2001). The demand for housing by these more advantaged workers in turn increases its cost, causing less skilled, lower-paid service and blue-collar workers to be pushed further away from these neighborhoods. This, in turn, leads to increased economic segregation.

On the other hand, such higher levels of economic segregation are likely to hinder the innovative capacity of places. A broad body of urban economic theory identifies the connection between diversity and innovation (Florida, 2002; Glaeser, 2011; Jacobs, 1969, 1984). Denser, more diverse places attract a wider range of talent or skill and human capital. But economic segregation, by definition, separates groups into different parts of the city, thereby reducing their ability to interact to generate innovative ideas and innovative companies.

Our research explicitly examines the connection between innovation and residential segregation, specifically the segregation of different socio-economic classes within metropolitan areas. We theorize that residential segregation acts to impede the human capital externalities identified by Lucas (1988) and Jacobs (1969) that are the product of dense residential clustering of people in cities, and which act as key drivers of innovation and economic development. We focus explicitly on the effects of place of residence as opposed to place of work. It is true that the clustering of industry and employment might compensate for the effects of residential segregation, by creating clusters of high-tech workers which can spur innovation. Our argument is that this is a necessary but insufficient condition for optimal innovation. Even if industry and work are clustered, we theorize that the segregation of groups of people by residence will hinder and impede the innovativeness of places. Our models test these propositions empirically.

Our research probes three key questions. First, are metropolitan areas with higher levels of technology and talent also more economically segregated? Second, do these areas become more segregated over time? And, third, do higher levels of economic segregation lead to lower levels of innovation and regional economic performance.

To explore these questions, we use structural equation models to examine the relationships between technology, talent and economic segregation, while controlling for other economic and demographic factors as well as changes in segregation over the last decade. We use a dissimilarity index of economic segregation based on income, education and occupation, and we test for determinants as well as segregation effects on regional innovative capacity and income per capita.

Our findings suggest that technology and talent are associated with higher levels of economic segregation, but not with the increases in economic segregation we have seen over time. However, we find that greater levels of economic segregation work to hinder both innovative and economic performance.

The remainder of this paper proceeds as follows. The next section outlines the key theories which inform our theory and analysis. Following that, we discuss the variables and data and structural equation modelling used in our analysis. Next, we present the results from

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our structural equation models. We then summarize our key findings about the connections between innovation, talent and economic segregation and discuss the major takeaways and implications of our research in the concluding section.

2. Concepts and theory

A wide body of research in economics, sociology, geography and regional science has documented growing economic divides between socio-economic classes across and within places. One stream of research has focused on the rise in inequality within and across nations (Atkinson, 1975, 2015). Piketty (2014) documents a significant rise in economic inequality across nations and argues that it is a function of a basic law of capitalism. A large body of studies suggests that inequality is a function of skill-biased technical change (Autor, Levy, & Murnane, 2003, 2006, 1998; Acemoglu, 1998), brought on by globalization, the deindustrialization of once high-paying manufacturing jobs and the splitting of the labor market it into a smaller cluster of high-paying, high-skill knowledge jobs and a much larger share of low-paying, low-skill routine service jobs.

Divides are not only growing between the rich and the poor, but across places. Several studies document growing spatial inequality across cities and metropolitan areas (Glaeser et al., 2009; Moretti, 2012). This is largely a result of the geographic clustering of high-skill, high-wage industries and jobs. Other research has noted the clustering of more educated and skilled people in locations that are both more productive and have access to better jobs and career networks and which offer higher levels of amenities (Albouy, 2016; Albouy & Stuart, 2014; Bishop, 2009).

Economic inequality across metropolitan areas has also been found to be closely linked to population size (Baum-Snow, Freedman, & Pavan, 2014; Baum-Snow & Pavan, 2013). Wage inequality has been found to be closely associated with both population size and technology across Canadian metropolitan areas (Breau, Kogler, & Bolton, 2014) and with levels of skill and affluence across urban areas in the U.K. (Lee et al. (2016).

Other research has also found that the higher levels of urban inequality are associated with lower rates of economic growth, after controlling for factors like education and skill levels (Glaeser et al., 2009) and that more economically unequal metropolitan areas also experienced significantly shorter spells of growth (Benner & Pastor, 2015).

Spatial inequality not only exists across cities and metropolitan areas but within them. As cities and metropolitan areas attract knowledge-based industries and more highly-skilled talent, more advantaged groups colonize the most economically advantageous and highest amenity locations, pushing the less skilled and less affluent into less well-connected and less well-served areas (Diamond, 2016).

Research has identified that economic inequality and spatial segregation within cities and metropolitan areas has been growing for decades. Income segregation has increased in all but three of the USA's 30 largest metropolitan areas between 1980 and 2010 (Taylor & Fry, 2012). Roughly 85 percent of the residents of U.S metropolitan areas lived in neighborhoods that were more economically segregated in year 2000 than they were in 1970 (Watson, 2009).

Economic segregation also has been found to have a negative effect on upward socio-economic mobility (Chetty, Hendren, Kline, & Saez, 2014). Bischoff and Reardon (2014, 2016) find that economic segregation has increased the most in more skilled, more knowledge-based and more affluent metropolitan areas, and that they have less unemployment and lower share of manufacturing industry jobs. Their research also finds economic segregation to be higher in metropolitan areas with greater levels of families with children.

Economic segregation creates significant economic penalties for disadvantaged groups (Chetty et al., 2014). Rothwell and Massey (2014) find that the difference in lifetime earnings between those raised in the richest 20 percent of neighborhoods versus those who grow up in the bottom 20 percent is about the same as the difference between just completing high school and having a college degree, adding up to nearly a million dollars in lifetime earnings. Mellander, Stolarick, and Lobo (2017) find that residential location has a bigger effect on the income of low-skilled groups than higher-skilled groups, who by definition have more locational choices.

There has long been a connection between race and economic segregation. Wilson long ago identified the concentration of racial disadvantage in cities and its effects on income and economic mobility (Morrill, 1995; Wilson, 1978, 1987). Glaeser and Vigdor (2012) found racial segregation to have declined over time, but economic segregation remains closely connected to race (see Sampson, 2012; Sharkey, 2013). Indeed, metropolitan areas have been found to be splitting into areas of racially-concentrated poverty and racially-concentrated affluence (Goetz, Damiano, & Hicks, 2015). The economic penalty for growing up in conditions of racially-concentrated poverty is considerable. Chetty et al. (2014) find race and racial segregation to be connected to lower rates of economic mobility. Rothwell and Massey (2014) find that lower rates of economic mobility among African Americans is connected to their disproportionate segregation in disadvantaged neighborhoods. Other research identifies a connection between residential segregation and employment (Andersson & Larsson, 2016; Mariassunta & Andrei, 2009; Wixe & Pettersson, 2019).

Recent studies suggest that economic inequality has worsened due to the relatively recent back-to-the-city movement among affluent and educated households (Baum-Snow & Hartley, 2016). Several factors seem to be motivating this: greater access to high-paying knowledge and professional jobs, avoidance of long commutes by car, (Edlund et al., 2015), and easier access to superior services and amenities. As the more highly-educated and affluent groups have come back to the urban center, lower-income, less-educated groups, particularly members of racial minorities, have either moved or been pushed out, exacerbating economic segregation (Baum-Snow & Hartley, 2016).

Economic segregation also appears to be associated with other factors, including the size of metros. Larger metros tend to have more segregated geographic patterns simply as a result of their size, greater number of neighborhood options, multiple commercial districts, and commuting distances. There is evidence that greater commuting distances and sprawl affects economic segregation (Chetty & Hendren, 2018; Morency, Paez, Roorda, Mercado, & Farber, 2011).

Other research suggests that the clustering of high-tech and talent are connected to the growth in spatial inequality and economic segregation. For one, cities and urban areas have become increasingly preferred locations for high-tech company startups precisely because of the increased locational preference of highly-skilled technology workers (Florida & Mellander, 2016b). A study of innovation and inequality across states found a reasonably strong connection between innovation and the increase in the share of income going to the top one percent, but little evidence of a connection between innovation and broader income inequality as measured by the Gini coefficient (Aghion et al., 2015). Indeed, this study found that states with higher levels of innovation had higher rates of economic mobility. In addition, Berkes and Gaetani (2017) found a negative relationship between economic segregation and innovation (measured as patents) across metropolitan areas.

Overall, there are good reasons drawn from urban theory to expect that economic segregation may act to hinder innovation. A broad body of research shows that innovation is the product of the clustering of diverse groups of skilled people, related economic assets and ideas (Jacobs, 1969, 1984). Lucas (1988) refers to this dense and diverse clustering of talent in urban centers as broadly providing the basic mechanism of innovation and economic development. A large body of empirical studies has found close connections between dense, diverse urban places and higher levels of innovation and income (Bettencourt, Lobo and Strumsky, 2007; Bettencourt, Lobo, Strumsky and West, 2007; Bettencourt, Lobo, Strumsky, & West, 2010; Carlino, Chatterjee, & Hunt, 2007; Florida, 2002; Glaeser, 2011). While there is still some debate on which exact measures best reflect the association between diversity and innovation – for example, levels of immigration versus measures of openness to the gay population – there is general consensus that innovation is associated with higher levels of demographic and economic diversity across places. Recent research suggests that diversity is positively associated with segregation: That is, places that are more diverse across racial, ethnic, or sexual orientation tend to have higher levels of socio-economic segregation (see e.g. Florida & Mellander, 2015). Diversity of course refers to the mix of people in general, while segregation refers to the separation of groups of people by income, race or other factors.

For these reasons, we focus on residential segregation in terms of the separation of different socio-economic groups or classes of people within metropolitan areas. As noted above, Jacobs (1969) and Lucas (1988) identify the clustering and concentration of dense and diverse human capital in cities, which Lucas dubbed human capital externalities, as the primary mechanism for innovation and economic development. Higher levels of economic segregation may impinge innovation by separating groups according to income, education, and other factors, limiting their members' ability to interact in ways that generated new ideas, technologies or enterprises. This suggests that places that are more economically segregated may grow less innovative over time.

Other research shows that economic segregation takes on different shapes and is expressed differently in different kinds of cities and metros (Delmelle, 2019; Florida & Adler, 2018). Traditionally, metropolitan areas have been segregated with more affluent classes in the suburbs and less advantaged groups concentrated in the urban center. But that pattern has changed and even been inverted in some metro areas that have seen a recent back-to- the-city movement among the affluent and educated, leading to an attendant gentrification. Florida and Adler (2018) suggest that segregation now takes on a more variegated or patchwork pattern across metro areas. The focus of our research is less on the particular expression of segregation in different kinds of cities and metros and more on the underlying factors that shape segregation across all metro areas.

In light of these broad concepts and theory, our research examines the connection between technology, talent and economic segregation across metropolitan areas. Our basic theory is that economic segregation will be greater in more technology-intensive metros with higher levels of talent. These two factors work together and independently to raise the economic performance of metros as a whole and the incomes of higher-skilled households in particular. But this leads to higher levels of inequality, thereby increasing segregation. These factors will overwhelm the increase demographic diversity of such metros, leading to higher levels of economic segregation. Thus, we also expect to find that more diverse metros to also be more economically segregated. The complicating factor of course is race. Because of the long legacy of concentrated Black poverty (Sampson, 2012; Sharkey, 2013; Wilson, 1987), we expect to find metros with higher concentrations of African Americans to be more economically segregated.

In light of this broad framing, our research is structured around three basic questions or hypotheses: (1) that metropolitan areas with higher levels of technology and talent will also have higher levels of economic segregation, (2) that these metropolitan areas are likely to become more segregated over time, and (3) that higher levels of economic segregation will also lead to lower levels of innovation and of regional income over time.

3. Model, variables and data

We use structural equation modelling to examine the connections between technology, talent and economic segregation across metropolitan areas. We build on the structure generated by Florida, Mellander, and Stolarick, (2008) which examined the connection between technology, talent and regional economic performance. The use of structural equation modelling enables us to look at the effect of technology and talent on the level and change in economic segregation on the one hand, and at the effect of economic segregation on the level of technology and talent on the other, while controlling for a range of other economic and demographic factors. We include variables for openness to diversity to take into account the effects of diversity; of universities to control for the effects of a metro's research and knowledge base; as well as variables for income, unemployment, manufacturing industry and income inequality.

Table 1
Descriptive statistics for variables.

	Mean	Minimum	Maximum	Standard Deviation
Year 2000:				
Change in Economic Segregation[a]	.074	-.086	.296	.065
Talent	.234	.110	.524	.075
Technology	.559	.000	29.956	2.179
Income Inequality	.442	.355	.542	.027
Unemployment	.037	.015	.078	.010
Black Share	.105	.002	.487	.109
Foreign-Born Share	.006	.008	.509	.068
Share under 15	.212	.128	.307	.025
Share above 65	.126	.042	.347	.032
Year 2010:				
Talent	.252	.113	.569	.077
Technology	.349	.001	11.174	1.171
Economic Segregation	.267	.161	.365	.042
Innovation	7.501	.129	106.198	9.482
Income per Capita	24,058	13,450	44,024	4084
Openness	.659	.259	2.140	.265
University	.006	.000	.033	.005
Manufacturing.	.114	.022	.366	.054
Income Inequality	.448	.385	.539	.026
Unemployment	.089	.031	.180	.002
African American	.108	.002	.519	.109
Foreign-Born	.075	.009	.365	.067
<15 Years	.198	.116	.301	.026
>65 Years	.132	.062	.335	.032

[a] 2000–2010.

Table 1 summarizes the descriptive statistics for these variables. We log these variables in our models and empirical analysis. The appendix provides fuller data on these variables for all metros with more than one million people, listing their levels of economic segregation, changes in segregation, and their level of innovation.

3.1. Key variables

Economic Segregation: This is measured as the average of three types of segregation: income segregation, educational segregation and occupational segregation. These are also three core dimensions of socioeconomic class. They are based on an Index of Dissimilarity (Massey & Denton, 1988) based on Census tract-level data across metropolitan areas for the years 2000 and 2010, and cover close to 60,000 tracts in 350-plus metropolitan regions. Income segregation is based on poor households, defined as those below the poverty level, compared to wealthy households, defined as those with incomes of $200,000 and above. Educational segregation compares adults with less than a high school degree to those with a Bachelor's degree and above. Occupational segregation compares knowledge workers, professional and creative occupations to blue-collar manufacturing and service occupations. Our overall measure of economic segregation is based on an average of these indexes. The data for year 2000 is from the IPUMS National Historical GIS (NHGIS) (Manson, Schroeder, Van Ripper, & Ruggles, 2008) for Census tracts. We have employed the NHGIS crosswalk for 2000 and 2010 to match the metropolitan area boundaries. The 2010 data comes from the American Community Survey (ACS), 5-year-estimate for

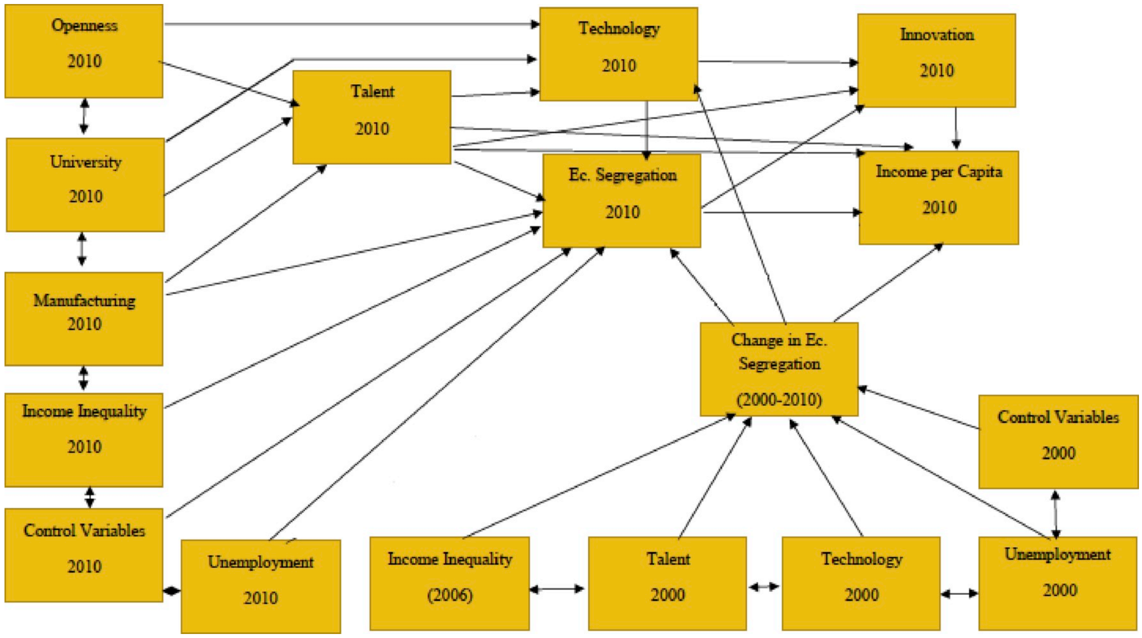

Fig. 1. System of equations.

2005–2010. For our purposes, this tract-level data is based on place of residence, not place of work.

Talent: We employ the standard measure for educational attainment or human capital based on the share of adults with a bachelor's degree or more. These data sources are from the same ACS, IPUMS, and NHGIS sources as above.

Technology: This variable measures high-tech industry concentration in terms of high-technology industrial output as a percentage of total US high-tech industrial output and the percentage of metro's total economic output from high-tech industries compared to the national share (see De Vol, Wong, Catapano, & Robitshek, 1999). This variable is for the year 2000 and 2010.

Innovation: This variable is based on patents per 100,000 people and is from the US Patent and Trademark Office (USPTO).[1]

Average Income: This is measured as income per capita 2010 from the ACS.

3.2. Control variables

Income Inequality: This is measured by the conventional measure of the Gini coefficient. This variable captures the distribution of incomes from the bottom to the top. Since the Census does not publish figures for income levels above $100,000 for metropolitan areas, we are unable to calculate the Gini coefficient, so we have to rely on the Gini coefficients provided by the Census for the years 2006 and 2010 as Gini coefficients for metropolitan areas are not available for prior years. However, these Gini Coefficients appear to be somewhat consistent over time, with a correlation coefficient 0.730 for 2006 and 2012.

Unemployment: This is the share of the labor force that is registered as unemployed based on the same ACS, IPUMS, and NHGIS sources as above.

Race: We use a variable based on ACS 2010.for the share of African-Americans to control for race.

Foreign-Born. We include a variable representing the share of adults who are foreign-born. This is from ACS 2010.

Age: We include two measures for age: share of the population under age 15 and over 65. These are again from the same ACS, IPUMS and NHGIS sources as above.

University: This is faculty per capita 2010, based on data from National Science Foundation.

Manufacturing: This is the share of employees working in the manufacturing industry. The data is for year 2010 and comes from the Census County Business Patterns.

Openness: This is a combination of the concentration of gay and lesbian households and the concentration of individuals employed in cultural occupations. The data are from the 2005–2009 Census.

3.3. Structural equation modelling

We use structural equation models to examine the relationships among these variables according to our research questions and hypotheses. Fig. 1 illustrates the hypothesized relationships we examine in our empirical models.

The regression system can be translated into six integrated equations which are as follows:

$$\begin{aligned}&\textit{Change in Economic Segregation}_{2000-2010} = \beta_{11}\textit{Talent}_{2000} + \\ &\beta_{12}\textit{Technology}_{\ 2000} + \beta_{13}\textit{Income Inequality}_{2000} + \beta_{14}\textit{Unemployment}_{2000} \\ &\quad + \sum \beta_{15}\textit{Control Variables}_{2000}\end{aligned} \tag{1}$$

$$\textit{Talent}_{2010} = \beta_{21}\textit{Openness}_{2010} + \beta_{22}\textit{University}_{2010} + \beta_{22}\textit{Manufacturing}_{\ 2010} \tag{2}$$

$$\begin{aligned}&\textit{Technology}_{2010} = \beta_{31}\textit{Openness}_{2010} + \beta_{32}\textit{University}_{2010} + \\ &\beta_{33}\textit{Talent}_{2010} + \beta_{34}\textit{Change in Economic Segregation}_{2000-2010}\end{aligned} \tag{3}$$

$$\begin{aligned}&\textit{Economic Segregation}_{2010} = \beta_{41}\textit{Talent}_{2010} + \beta_{42}\textit{Technology}_{2010} \\ &\quad + \beta_{43}\textit{Change in Economic Segregation}_{2000-2010} + \beta_{44}\textit{Unemployment}_{2010} \\ &\quad + \beta_{45}\textit{Manufacturing}_{\ 2010} + \beta_{46}\textit{Inequality}_{2010} + \sum \beta_{47}\textit{Control Variables}_{2010}\end{aligned} \tag{4}$$

$$\begin{aligned}&\textit{Innovation}_{2010} = \beta_{51}\mathrm{Talent}_{2010} + \beta_{52}\textit{Technology}_{2010} \\ &\quad + \beta_{53}\textit{Economic Segregation}_{2010}\end{aligned} \tag{5}$$

[1] We thank Dr. Deborah Strumsky for sharing data on Inventors and Patents. A more detailed description of the patent and inventor variables is available upon request.

Table 2
Correlation analysis findings.

	Eq. 1 Change in Economic Segregation	Eq. 2 Talent	Eq. 3 Technology	Eq. 4 Economic Segregation (2010)	Eq. 5 Innovation	Eq. 6 Income
Year 2000:						
Talent	-.219[a]	–	–	–	–	–
Technology	-.306[a]	–	–	–	–	–
Income Inequality	-.217[a]	–	–	–	–	–
Unemployment	-.073	–	–	–	–	–
African American	-.220[a]	–	–	–	–	–
Foreign-born	-.106[b]	–	–	–	–	–
<15 years of age	-.105[b]	–	–	–	–	–
>65 years of age	.092	–	–	–	–	–
Year 2010:						
Talent	–	–	.663[a]	.450[a]	.631[a]	.740[a]
Technology	–	–	–	.608[a]	.552[a]	.602[a]
Economic Segregation 2010	–	–	–	–	.259[a]	.254[a]
Change in Economic Segregation	–	–	-.336[a]	-.227[a]	–	-.158[a]
Innovation	–	–	–	–	–	.554[a]
Income	–	–	–	–	–	–
Openness	–	.663[a]	.742[a]	–	–	–
University	–	.498[a]	.163[a]	–	–	–
Manufacturing	–	-.255[a]	–	-.170[a]	–	–
Income Inequality	–	–	–	.489[a]	–	–
Unemployment	–	–	–	.020	–	–
African-American	–	–	–	.391[a]	–	–
Foreign-Born	–	–	–	.426[a]	–	–
<15 Years	–	–	–	.123[b]	–	–
>65 Years	–	–	–	-.371[a]	–	–

[a] indicate significance at the 1 percent level.
[b] at the 5 percent level.

$$Income_{2010} = \beta_{61} Skill_{2010} + \beta_{62} Technology_{2010} + \beta_{63} Economic\ Segregation_{2010} + \beta_{64} Change\ in\ Economic\ Segregation_{2000-2010} + \beta_{65} Innovation_{2010} \tag{6}$$

Equations (1) and (4) examine how technology and talent relate to the level and change in economic segregation while controlling for other factors such as inequality, unemployment, and demography. Equations (2) and (3) examine the factors that bear on talent and technology. These regressions also capture factors such as openness and access to universities which we assume to be directly related to talent and technology, and may be indirectly linked to segregation. Equations (5) and (6) examine the role of skill and technology on the level and change in economic segregation, and also the effect of the change in economic segregation on innovation and regional economic performance (measured as income per capita). Technically, we allow all exogenous variables in equations (1) and (4) to be correlated with one another. Equation (1) is included to partly capture path dependency and deal with endogeneity, since metropolitan areas with higher levels of economic segregation may be experiencing this due to structures that were in place already a decade earlier and therefore also had a negative impact on the change in economic segregation over time.

It is important to note that the causal relations in the model are based on theory, and what is tested is an expression of direct and indirect correlations. The estimated parameters thus capture the indirect and direct relations between a set of variables. These parameters can be expressed as standardized beta values, which will capture the variables' relative importance within that equation, while taking the indirect effects from the other regression equations into account. They can also be expressed as unstandardized beta values that capture the actual direct and indirect relation between each variable and the dependent variable.

The structural equation models are estimated by a maximum likelihood method. We are aware of possible feedback loops in this system of equations, but the modelling technique does not allow us to take them into account. The aim is to test these relations in sequences, where also indirect relations are taken into account. In summarizing the results, we report both unstandardized and standardized β-coefficients.

4. Findings

We now turn to the key findings of the analysis. We begin with the findings for a basic correlation analysis, and then turn to the findings of our structural equation models.

4.1. Correlation findings

Table 2 summarizes the key findings for the correlation analysis.[2] We organize and focus on the correlations for the dependent variables in our models.

For Equation (1), the change in economic segregation is negatively related to the variables for technology and talent as well as income inequality and race, though the correlations are rather small. For Equation (2), talent is positively related to universities, and also with higher levels of openness, and negatively related to manufacturing. In Equation (3), technology is highly related to talent and openness, more modestly associated with universities and negatively related to the change in segregation. For Equation (4), the level of economic segregation is positively related to technology and talent as well as income inequality, race and foreign-born, while being negatively associated with an older population and with higher levels of manufacturing. In Equation (5), we find innovation is positively associated with economic segregation as well as with technology and talent. Turning to Equation (6), we find that regional income is negatively associated with higher levels of economic segregation and negatively associated with the change in economic segregation. As expected, regional income is also positively associated with technology, talent and innovation. In sum, we find higher levels of technology and talent to be associated with higher levels of economic segregation, but not with a greater increase in economic segregation. Fig. 2 plots the connection between technology and

[2] We report the correlations related to each of the dependent variables in our system of equations. A full correlation table for all included variables is available from the authors upon request.

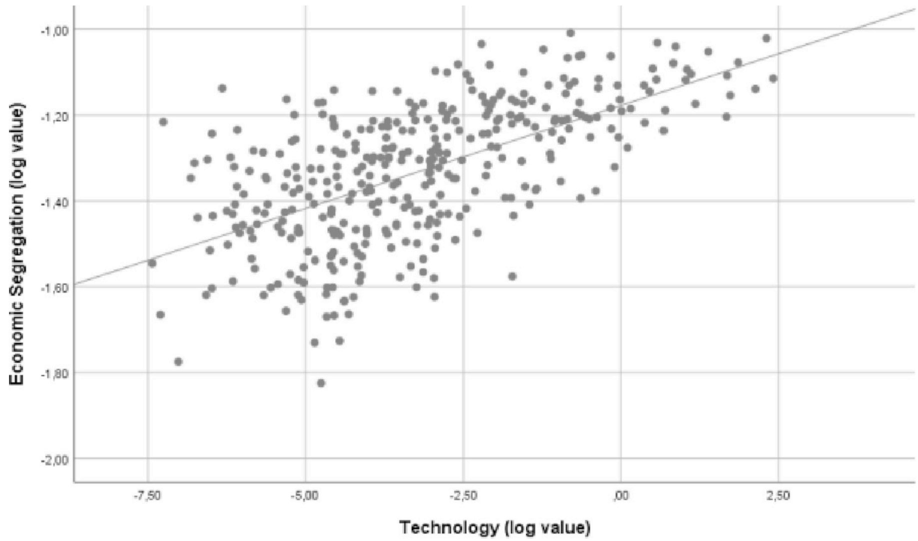

Fig. 2. Technology and economic segregation.

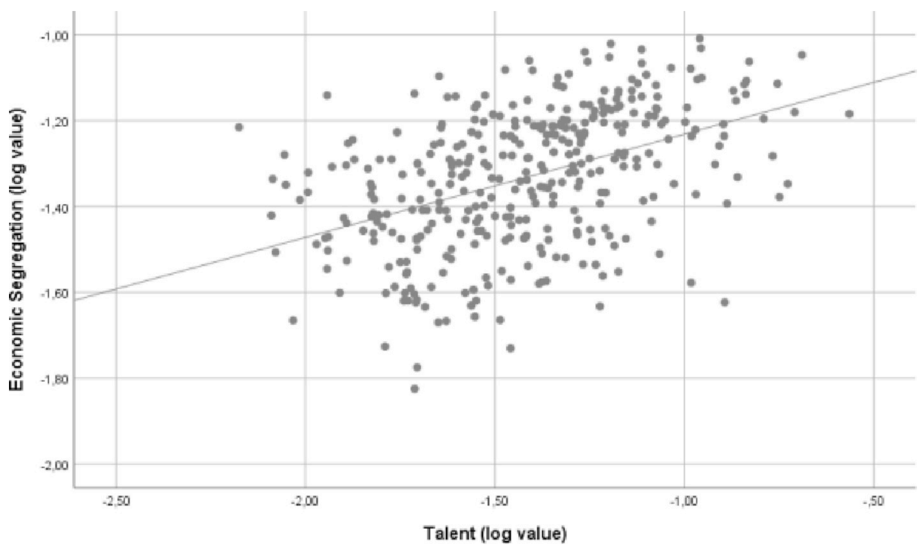

Fig. 3. Talent and economic segregation.

economic segregation, while Fig. 3 does so for talent and economic segregation:

4.2. Findings of the structural equation models

We now turn to the findings of our structural equation models, which provide a more refined test of our hypotheses regarding the relationships between technology, talent and economic segregation. Table 3 summarizes the key findings from these models. We report the squared multiple correlations which are the equivalent to R2 values from each separate regression in the system.

Starting with Equation (1) which explores the change in economic segregation over the decade 2000–2010, the R2 is just 0.181. There is a negative association for talent and technology, implying that places with more skill and larger tech industries experienced a slight decline in economic segregation between these years. The change in economic segregation was, surprisingly, also negatively associated with a larger share of African Americans and larger shares of younger and older people. That said, indirect associations between current economic segregation and technology and talent ten years earlier are captured in Equation (4) where the change in economic segregation is included as an explanatory variable.

Equation (2) looks at the determinants of talent; here the R2 is 0.624. Talent is positively associated with universities and negatively associated with manufacturing. Given the strong relationships, we could also expect more indirect relationships from universities and openness, and the level of segregation, via talent as hypothesized in Equation (4).

Equation (3) examines the factors associated with technology; this regression generates an R2 of 0.606. Technology is positively associated with talent and openness as expected, but surprisingly, it is negative and weakly associated with universities, with the lowest standardized beta value in this equation context. The result may partly be a multicollinearity effect due to the relatively strong relation with talent (as seen in Equation (2)), but the bivariate correlation (see Table 2) also suggests that the university (measured as faculty per capita) is only weakly related to technology.

Equation (4) examines the factors associated with higher levels of economic segregation. Talent and technology are explanatory variables alongside a number of control variables related to industry structures, race, demography and inequality. Economic segregation is still positively associated with both talent and even more so with technology. It is also associated with a greater change in economic segregation between

Table 3
SEM regression results.

Independent Variable	Dependent Variable	Unst. β	Stand. β	R^2
Equation (1)				
Talent (2000)	Change in Economic Segregation	−0.058[a] (0.021)	−0.278	
Technology (2000)		−0.005[a] (0.002)	−0.196	
Income Inequality		−0.131[b] (0.062)	−0.125	
African-American (2000)		−0.008[a] (0.003)	−0.168	
Unemployment (2000)		−0.020 (0.016)	−0.079	
Foreign-Born (2000)		.007 (.005)	0.085	
Under 15 (2000)		-.175[a] (049)	−0.315	
Over 65 (2000)		-.057[b] (023)	−0.214	0.181
Equation. 2				
Openness	Talent	0.497[a] (0.029)	0.599	
University		0.161[a] (0.015)	0.377	
Manufacturing		−0.047[b] (0.021)	−0.077	0.624
Equation (3)				
Talent	Technology	2.396[a] (0.373)	0.355	
Openness		2.920[a] (0.276)	0.521	
University		−0.311[a] (0.117)	−0.108	0.606
Equation (4)				
Talent	Level of Economic Segregation	0.068[a] (0.025)	0.125	
Technology		0.030[a] (0.003)	0.369	
Change in Economic Segregation		0.204[a] (0.078)	0.082	
Income Inequality		0.899[a] (0.100)	0.316	
African-American		0.035[a] (0.005)	0.268	
Unemployment		0.001 (0.022)	0.002	
Foreign-Born (2000)		.024[a] (.008)	0.118	
Under 15 (2000)		.144[a] (.054)	0.117	
Over 65 (2000)		-.084[a] (.032)	−0.116	
Manufacturing (2000)		−0.005 (0.011)	−0.014	0.655
Equation (5)				
Technology	Innovation	0.171[a] (0.030)	0.327	
Talent		1.736[a] (0.191)	0.493	
Economic Segregation		−1.044[a] (0.325)	−0.161	0.447
Equation (6)				
Technology	Income	0.024[a] (0.004)	0.299	
Talent		0.325[a] (0.028)	0.595	
Economic Segregation		−0.219[a] (0.043)	−0.218	
Change in Economic Segregation		−0.004 (0.085)	−0.001	
Innovation		0.012 (0.007)	0.076	0.598

[a] indicate significance at the 1 percent level.
[b] at the 5 percent level. N = 357 metropolitan areas.

2000 and 2010. For the control variables, we find positive relations for income inequality, as well as for the share of African-Americans. Metropolitan areas with larger shares of individuals over 65 and lower shares of children under the age of 15 are significantly less segregated. The R2 for this model is 0.655.

Equation (5) examines the factors that bear on innovation. Innovation is positively related to talent and technology, as expected, but it is negatively associated with economic segregation. This means that metropolitan areas with more talent and technology are more innovative, but if they also are more economically segregated, that innovative capacity will partly be restricted. The R2 here is 0.447.

Equation (6) looks at the factors that bear on regional economic performance broadly measured as the average income level. The R2 for this model is 0.598. Income is positively associated with talent and technology, which is in line with the broader literature and the findings of previous studies. But again, it is negatively associated with economic segregation once talent and technology are controlled for. This means that both innovative capacity and income levels will be higher in metropolitan areas with more talent and technology, but if that is combined with higher levels of economic segregation, both will be hindered to some degree.

5. Discussion and conclusions

Our research has examined the connections between technology, talent and economic segregation. It was structured around three key questions. First, do metropolitan areas with higher levels of technology and talent experience higher levels of economic segregation? Second, do metropolitan areas with higher levels of technology and talent become more economically segregated over time? And third, do places with higher levels of economic segregation negatively experience lower levels of innovative and economic performance controlling for other factors? We examined these three questions through the use of structural equation models which allowed us to examine the direct and indirect associations between technology, talent and economic segregation, while controlling for a wide range of other factors.

As noted at the start, urban theory provides good reasons why more skilled, high-tech metropolitan areas are likely to experience greater levels of economic segregation. Here, we find that both technology and talent are associated with higher levels of economic segregation, but not with increases in economic segregation over time.

Our analysis was also designed to test the notion, implied by urban economic theory, that higher levels of economic segregation may negatively impact innovation and economic performance. There is a long tradition of urban and economic theory that suggests that a key contributing factor to innovation is the ability of cities to gather together a diverse array of skilled and talented people with different backgrounds and knowledge. Thus, as cities and metropolitan areas become more segregated by income, education and occupation, the connection between diversity and innovation will be diminished.

Theory would also imply that this reduces the level of innovation and, since innovation is an input for economic performance, that it reduces economic performance as well. Our findings suggest that this is indeed the case. The level of economic segregation is negative and significant in both of our models for innovation and income. This is perhaps the novel and interesting finding of our analysis. Once we control for the effects of technology and talent which are both closely associated with innovation and regional economic performance, we find that metropolitan areas with higher levels of economic segregation are associated with lower levels of innovative and economic performance.

This is in turn suggestive of a related conundrum that may be a feature of urban economic growth. A growing body of research is noting a connection between the innovative knowledge economy and economic segregation: As metropolitan areas become hubs for talent and technology, they become more spatially sorted and segregated (Baum-Snow & Hartley, 2016; Bischoff & Reardon, 2014, 2016; Florida & Mellander, 2015). But as they become more economically segregated, this in turn negatively affects their ability to innovate and spur economic growth. In this sense, the increased sorting and economic segregation may form an additional constraint that accompanies the growth of highly-skilled urban areas.

Our research is only suggestive of this sort of counter-productive connection. We encourage further research over longer-time scales to more fully explore it. One particularly fruitful avenue of research would be to probe further the connection between place of residence and place of work. Our research shows that residential segregation dampens innovation. Future research could look more specifically at the role that place of residence and place of work play on levels of regional innovation and economic development.

CRediT authorship contribution statement

Richard Florida: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Charlotta Mellander:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing.

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Appendix

Most segregated in 2010	Most segregated in 2000	Most change in segregation 2000–2010	Most innovative in 2010
Los Angeles-Long Beach-Santa Ana, CA	Los Angeles-Long Beach-Santa Ana, CA	Nashville-Davidson–Murfreesboro–Franklin, TN	San Jose-Sunnyvale-Santa Clara, CA
Austin-Round Rock, TX	Houston-Sugar Land-Baytown, TX	Seattle-Tacoma-Bellevue, WA	San Francisco-Oakland-Fremont, CA
Houston-Sugar Land-Baytown, TX	Dallas-Fort Worth-Arlington, TX	Oklahoma City, OK	Seattle-Tacoma-Bellevue, WA
Dallas-Fort Worth-Arlington, TX	Austin-Round Rock, TX	Riverside-San Bernardino-Ontario, CA	San Diego-Carlsbad-San Marcos, CA
San Antonio, TX	Chicago-Naperville-Joliet, IL–IN–WI	Raleigh-Cary, NC	Portland-Vancouver-Beaverton, OR-WA
Columbus, OH	New York-Northern New Jersey-Long Island, NY-NJ-PA	Las Vegas-Paradise, NV	Minneapolis-St. Paul-Bloomington, MN-WI
New York-Northern New Jersey-Long Island, NY-NJ-PA	San Antonio, TX	Portland-Vancouver-Beaverton, OR-WA	Boston-Cambridge-Quincy, MA-NH
Denver-Aurora, CO	Columbus, OH	Salt Lake City, UT	Austin-Round Rock, TX
Memphis, TN-MS-AR	San Francisco-Oakland-Fremont, CA	Charlotte-Gastonia-Concord, NC-SC	Rochester, NY
Phoenix-Mesa-Scottsdale, AZ	San Diego-Carlsbad-San Marcos, CA	Memphis, TN-MS-AR	Los Angeles-Long Beach-Santa Ana, CA
Least segregated in 2010	**Least segregated in 2000**	**Least change in segregation 2000–2010**	**Least innovative in 2010**
Orlando-Kissimmee, FL	Portland-Vancouver-Beaverton, OR-WA	New Orleans-Metairie-Kenner, LA	Virginia Beach-Norfolk-Newport News, VA-NC
Portland-Vancouver-Beaverton, OR-WA	Orlando-Kissimmee, FL	Los Angeles-Long Beach-Santa Ana, CA	New Orleans-Metairie-Kenner, LA
Providence-New Bedford-Fall River, RI-MA	Tampa-St. Petersburg-Clearwater, FL	Baltimore-Towson, MD	Birmingham-Hoover, AL
Tampa-St. Petersburg-Clearwater, FL	Riverside-San Bernardino-Ontario, CA	Orlando-Kissimmee, FL	Jacksonville, FL
Virginia Beach-Norfolk-Newport News, VA-NC	Pittsburgh, PA	San Diego-Carlsbad-San Marcos, CA	Oklahoma City, OK
Minneapolis-St. Paul-Bloomington, MN-WI	Seattle-Tacoma-Bellevue, WA	Hartford-West Hartford-East Hartford, CT	San Antonio, TX
Pittsburgh, PA	Las Vegas-Paradise, NV	Chicago-Naperville-Joliet, IL–IN–WI	Louisville-Jefferson County, KY-IN
Jacksonville, FL	Virginia Beach-Norfolk-Newport News, VA-NC	San Francisco-Oakland-Fremont, CA	Richmond, VA
New Orleans-Metairie-Kenner, LA	Providence-New Bedford-Fall River, RI-MA	Miami-Fort Lauderdale-Pompano Beach, FL	Riverside-San Bernardino-Ontario, CA
Buffalo-Niagara Falls, NY	Minneapolis-St. Paul-Bloomington, MN-WI	Atlanta-Sandy Springs-Marietta, GA	Nashville-Davidson–Murfreesboro–Franklin, TN

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