SKILL-BIASED TECHNICAL CHANGE AND REGIONAL CONVERGENCE*

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Abstract

In the last century, the US witnessed the great reversal of regional convergence: between 1940 and 1980, the wage gap between poorer and richer US cities shrank at an annual rate of 1.4% but it stopped shrinking after 1980. This paper documents that this change was driven solely by highly skilled workers. Based on this evidence, I build a dynamic spatial equilibrium model with regional convergence and divergence forces. The model highlights the role of technology: convergence forces enter through spatial technology diffusion and divergence forces through a national Skill-Biased Technical Change shock interacted with local knowledge spillovers. Three main results from the quantification exercise arise: i) spatial technology diffusion is consistent with the patterns of regional convergence between 1940 and 1980 and the interaction between local knowledge spillover and a national Skill-Biased Technical Change shock explains 50% of the decline in regional convergence; ii) the same mechanism reconciles the secular decline in US migration since 1980; iii) at the national level, if technology were not skill-biased, there would be less aggregate inequality but also less growth nowadays.

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1 Introduction

There is consensus that spatial technology diffusion brings prosperity from the rich to the poor locations. It induces regional catch-up for all workers, independently of their skill level. There is also consensus that technological progress has widened the productivity gap between highly and less skilled workers starting around 1980. This process, commonly known as Skill-Biased Technical Change (SBTC), increased the skill premium between the two skill groups.[1][2] This paper adds a third observation about the technological process. I argue that not all highly skilled workers benefitted equally from SBTC. Those in cities with a higher concentration of skills and population had a larger increase in wages through knowledge spillovers. Combining these three observations, this paper rationalizes one of the most salient features of regional growth in the last century: the great reversal of regional convergence. This view also reconciles the secular decline in US migration across regions, another puzzling feature of the data.

It has been noticed that between 1940 and 1980, wages grew 1.4% per year faster in poorer US cities than in richer ones.[3] Regional convergence ended in 1980, and from then to 2010, wages grew at similar rates in cities with different income levels. Figure 1 plots the annual demeaned average wage growth against its initial demeaned wage level in logs. The β-convergence rate, given by the slope of the trend line, is 0.014 between 1940 and 1980 but goes to zero and is not statistically significant between 1980 and 2010.[4]

What has not been noticed up to now is that the end of regional convergence masks a crucial heterogeneity: the end of convergence occurred only for highly skilled workers. This is the central empirical contribution of this paper. As shown in figure 2, before 1980, the regional convergence rate was the same for both highly and less skilled workers. However, since 1980, the wages of less skilled workers have continued to converge at 1.4% annually,

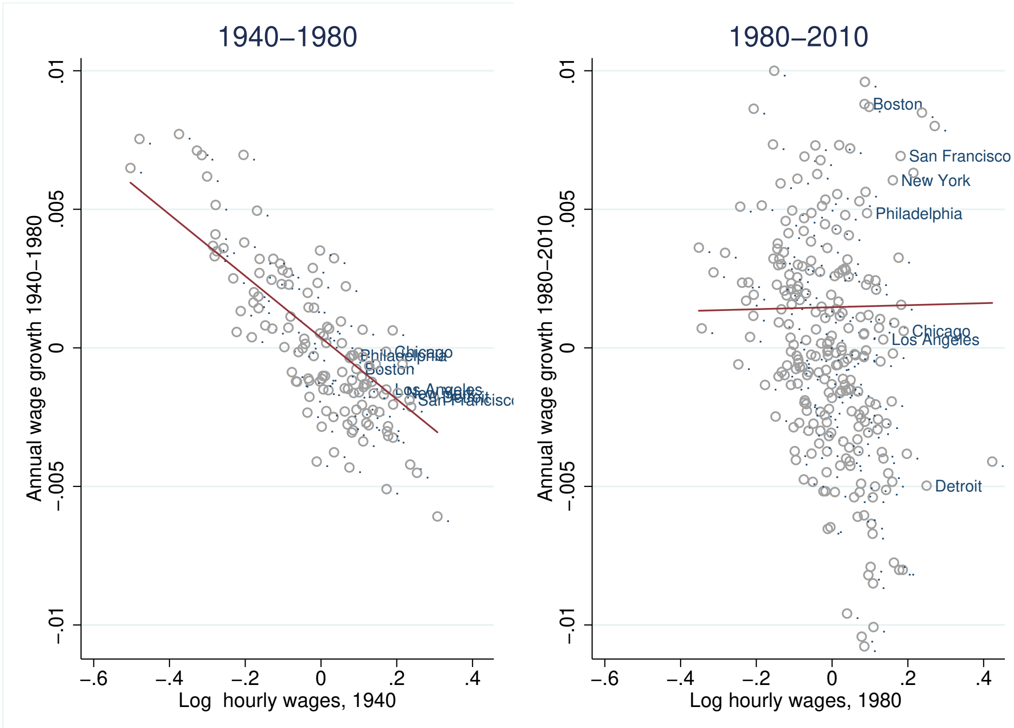
[1] I define highly skilled workers with at least a college degree and less skilled those with less than a college degree.

[2] Comin et al. (2012) and Desmet and Rossi-Hansberg (2014), among others, show how technology diffusion across space pushes regional convergence. Katz and Murphy (1992), Card and DiNardo (2002), Levy and Murnane (1992) and Bound and Johnson (1992), to cite a few, show how SBTC increased the skill premium.Skill premium is defined as the difference between the wages of the highly skilled and the less skilled workers.

[3] Throughout the paper, I use "cities" to refer to "Metropolitan Statistical Areas", the geographical unit used in this paper. A formal definition is provided in section 2.

[4] Berry and Glaeser (2005) are the first to point to this decline in convergence across cities after 1980. Ganong and Shoag (2017) show a similar reduction in convergence for income per capita across US states after 1980.

Figure 1: Regional Convergence across Cities before and after 1980



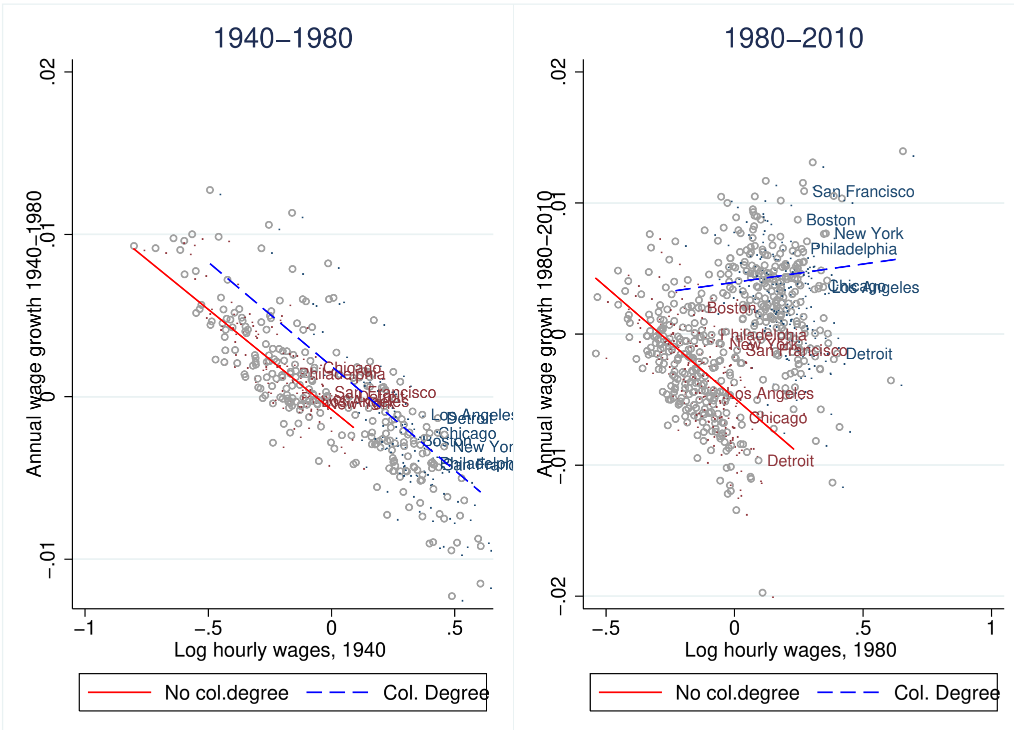
Note: This figure plots each city's (demeaned) annual average wage growth against its (demeaned) initial wage level. The left side depicts 1940-1980; the right side depicts 1980-2010. The red line depicts a weighted least square bi-variate regression. Data come from the decennial US Census and the 2010 American Community Survey.

while the regional convergence rate for highly skilled workers has been close to 0%. Thus, any account of the end of convergence must distinguish between skill groups. This, together with two other empirical regularities, support the claim that demand forces, such as knowledge spillovers, pushed highly skilled workers to already highly skilled place fostering their wages. The two other facts are that: i) after 1980, the correlation between the college ratio and the skill premium is positive across cities, contrary to what was previously observed;[5] ii) since 1980, migration destinations of highly skilled workers have shifted towards already skill-concentrated cities, opposite to what was previously observed. These three facts indicate that performance differences between highly skilled and less skilled workers played a crucial role in the cessation of the regional convergence and are also consistent with the idea that demand grew relatively more than supply in cities with a more considerable initial concentration of

[5]I define the college ratio (or skill ratio) as the share of college-educated workers to less-than college-educated workers. The skill premium is defined as the difference between the wage of the college-educated workers and the wages of the less-than college-educated workers.

highly skilled workers, benefiting from higher wage growth.

Figure 2: Regional Convergence by Skill Group across Cities before and after 1980



Note: This figure plots each MSA's annual average wage growth (demeaned) against its (demeaned) initial wage level by skill type (highly skilled and less skilled workers). The left figure depicts 1940-1980; the right depicts 1980-2010. Each MSA's circle size is proportional to its initial population size by skill group. The red solid and the blue dashed line in each graph depict a weighted least square bi-variate regression for less and highly skilled workers.

Motivated by this evidence, the two other main contributions of this paper are: i) to develop a quantitative dynamic spatial equilibrium model where technological progress rationalizes the patterns of regional convergence and its reversal for the highly skilled workers; ii) to show that the exact mechanism is consistent with the stark decline in US migration documented in the data and that at aggregate level it delivers more inequality but also more growth.[6] The model features as main ingredients spatial technology diffusion to embed convergence, a national SBTC and local knowledge spillovers that drive divergence. To get quantitatively closer to the data and compare it with other explanations, multi-industries,

[6]Other related findings suggest that technology rationalizes both the "Great Convergence" and "Great Divergence" of skills before and after 1980. Following the definition of "Great Divergence" coined by Moretti (2012), I define the "Great Convergence" of skills as the period between 1940 and 1980, where the relationship between initial college ratio and college ratio growth was negative.

housing, amenities and costly migration are included. Cities differ along with local amenities and an initial component of productivity. Specifically, labor productivity varies across local labor markets and it is determined by the endogenous knowledge spillovers that depend on city-level population and skill concentration, a national SBTC component and the city-specific technology diffusion process. Given this set of ingredients, the novelty of the model is to combine two streams in the literature. First, I follow the literature pioneered by Desmet and Rossi-Hansberg (2014) and Desmet et al. (2018) and I introduce spatial technology diffusion which makes the model dynamic. Second, in the spirit of Rosen (1979), Roback (1982), and Diamond (2016), I endogenize household location choice across heterogeneous cities and skills.

It is crucial to note that accounting for the reversion in the trends in wages, employment and migration patterns for each skill group requires a combination of the two models above. As I show in Appendix E, spatial equilibrium models with no spatial technology diffusion generate divergence rates across US cities but not the convergence rates. These models also produce a secular increase in migration rates contrary to the data. Simultaneously, adding skill heterogeneity in Desmet and Rossi-Hansberg (2014), enables me to explain the differential sorting patterns and the shift we observe in the 1980s, which is key in the reversal of regional convergence. Overall, allowing for heterogeneity in skills and spatial diffusion of technology over time produces a suitable framework to analyze the core question of this paper; that is, to explain why regional convergence reversed.

The mechanism works as follows. Spatial technology diffusion pushes for convergence equalizing the wages across cities. Instead, the national technological innovation with local knowledge spillover counterbalances the convergence before 1980. If technology were not skill-biased, the convergence forces would favor the poorer cities by pushing them toward the productivity frontier. When SBTC becomes more potent at the national level, the interaction between national SBTC and local knowledge spillover leads to a more significant skill premium in more educated locations. Highly and less skilled workers have some degree of complementarity. Thus, knowledge spillovers raise the wages of all workers, although at different speeds. This differential increase in the wages of highly skilled workers changes the relative migration returns for these two groups. Therefore, more highly skilled workers migrate to highly skilled cities than less skilled workers. Migration has a twofold effect. On the one hand, as more workers migrate to a location, the marginal productivity of each type reduces, which decreases the incentive to migrate. On the other hand, when more highly skilled workers move to a location, productivity increases because of the knowledge spillovers, which raises the wages of all the workers, especially those highly skilled.

I apply the model to the data in the third part of the paper. Given the focus on demand forces, the main goal is to estimate the parameters that govern the productivity process. A key element to proceed with the estimation is a national measure of SBTC. To do so, I average out, at the national level, the local exposure to routinization built by Autor and Dorn (2013).[7] To estimate the critical parameters of the model, I use a GMM procedure. This exercise departs from the literature that uses similar identification strategies for static model by estimating the dynamic technology diffusion process. I exploit equilibrium conditions and the technology diffusion process to construct moments interacted with local instruments such as the local exposure to routinization as in Autor and Dorn (2013) as well as housing restrictions.[8] The identifying assumption is that these proxies for SBTC shocks interacted with land unavailability and housing regulations are orthogonal to changes in local productivity. I then calibrate the model using estimated parameters, supplemented with others borrowed from the literature, and solve it numerically. Finally, I validate the model by comparing the patterns of regional convergence in the last 70 years to the data when considering a national SBTC. The model matches the data closely.

The main quantitative exercise is to "turn off" the divergence forces in the model. The **core** result is that approximately 50% of the observed decline in regional convergence among highly skilled workers is due to technology becoming more skill-biased. Once knowledge spillover and SBTC are accounted for, alternative explanations such as housing regulations and migration costs matter by a few percentage points. Overall, the quantification suggests that the interaction of SBTC and local spillover is the driving force of the reversal of regional convergence. A somewhat surprising result is that the model matches the secular decline in US migration, whis is a puzzling feature of the data. Second, it is consistent with the "Great

[7] Autor and Dorn (2013) study the effect of routinization on the polarization of employment and wages. They also argue that their shock fits the overall increase in the skill premium.

[8] I exploit the differential exposure of cities to computerization as in Autor and Dorn (2013). They analyze the effect of computer innovation on the output differences across regional labor markets. Computers' arrival primarily affects routinized occupations because machines can replace those workers. Therefore, the effect of computers is heterogeneous across locations depending on the share of highly and less skilled workers holding very routinized occupations. To capture the exogenous component in the productivity changes of the workers that do not depend on contemporaneous occupational structure, I use a 10-year lagged city's composition of routine intensive occupations by industry.

Convergence" and "Great Divergence" in the skill ratio. Third, it also matches the increase in wage dispersion across cities, as documented by Hsieh and Moretti (2015).

Finally, at the national level, the model suggests that if a national SBTC shock had not operated through this sorting channel, real wage growth and skill premium would have been smaller than they are. This significant result might have normative implications since it assesses how space impacts a trade-off between inequality and growth.

This paper speaks to three strands of the literature. The most related works are recent studies that develop dynamic quantitative spatial equilibrium models such as Desmet and Rossi-Hansberg (2014), Desmet et al. (2018), Caliendo et al. (2019), Lyon and Waugh (2019) and Nagy (2020). My paper contributes to this literature by adding divergence and convergence forces in a unified framework with rich features such as heterogeneous skills, industries, housing, and knowledge spillovers. Thus, it provides a benchmark to perform regional and aggregate long-run growth and inequality analysis within and across countries. Besides the current application, this framework can be used to address questions on the local and aggregate impact of sorting across locations within and across countries. At the same time, it is tractable enough to be fully estimated. The closest work is the seminal paper of Desmet et al. (2018) from which this model borrows the spatial technology diffusion process and the formulation of migration costs. Nevertheless, it departs from it by allowing for regional forces that push for divergence and the skill structure. This allows deepening the understanding of regional convergence, its reversal and the secular migration decline.

Furthermore, this paper also relates to the literature that studies the increase in the US spatial dispersion and the "Great Divergence" of skills, such as Berry and Glaeser (2005), Moretti (2012), Hsieh et al. (2013), Eeckhout et al. (2014), Hsieh and Moretti (2015), Diamond (2016), Ganong and Shoag (2017), Baum-Snow et al. (Forthcoming), Fajgelbaum and Gaubert (2018), Eckert et al. (2020) and Rossi-Hansberg et al. (2019). This paper complements this literature in several ways. Empirically, by finding that regional convergence only stopped for highly skilled workers and that before 1980 there was "Great Convergence" of skills. Methodologically, by embedding convergence forces through spatial technology diffusion in a spatial equilibrium model and highlighting and quantifying a mechanism consistent with both convergence and divergence and the secular decline of US migration. The most related study among these is the pioneering work of Diamond (2016) that proposes "skill-biased amenities" to explain the "Great Divergence" of skills observed after 1980. In contrast, my paper focuses on technological progress where spatial diffusion rationalizes regional convergence in wages before 1980 and "skill-biased technologies" explain the divergence in wages for high-skilled only. A model with "skill-biased amenities" but without "skill-biased technologies" cannot explain the reversal in regional convergence since more amenities put down pressure on wages rather than raising them. Also, a model with no technology diffusion cannot explain the initial convergence rates.

Additionally, this paper complements long-standing literature on regional convergence across countries and states inspired by the seminal works of Baumol (1986), Barro and Sala-i Martin (1992), and Barro and Sala-i Martin (1997); and continued by Bernard and Jones (1996), Caselli and Coleman (2001), Gennaioli et al. (2014) and Comin and Ferrer (Forthcoming). My paper complements this literature in several dimensions. First, it provides a quantitative model with real geography that can be mapped 1-to-1 to the data. Second, I propose a framework with both convergence and divergence built-in that can match the data on prices and quantities and connects the long-standing convergence literature to the one about cities.

The remainder of the paper is organized as follows. Section 2 describes the data and the empirical analysis. Section 3 proposes a theoretical framework. In Section 4, I estimate the core parameters and calibrate the model. In Section 5, I solve the model with the calibrated parameters, show how it maps to the data and conduct a counterfactual analysis. Section 6 concludes with a brief summary and future directions.

2 Data and Empirical Regularities

This paper's main new empirical finding is that regional convergence stopped only for highly skilled workers but did not for less skilled workers. This fact motivates the exploration of the skill premium and migration patterns over the last 70 years. The facts jointly point to how supply forces (such as marginal return to labor) have been dominated over time by demand forces (such as skill-biased knowledge spillovers and technological change). This pushes the skill premium up more in already skill abundant cities and more skill migrants to keep joining those same cities. This rationalizes the overall decline in regional convergence. To the best of my knowledge, facts in sections 2.2, 2.3 and 2.4 are new to the literature while fact 2.5 reproduces the previously documented "Great Divergence" and introduces the "Great Convergence".

2.1 Data

My analysis drdeparts from it, taking into account thaws on the Census Integrated Public Use Micro Samples (IPUMS) for the years 1940, 1950, 1960, 1970, 1980, 1990, and 2000; and the American Community Survey (ACS) for 2010 (Ruggles et al. (2015)).[9] To construct measures of migration, I use the March Current Population Survey (CPS) data which is a monthly US household survey conducted jointly with the US Census Bureau and the Bureau of Labor Statistics. The focus is on household and demographic questions. I use measures of geographic constraints and land use regulations from Saiz (2010). More details about the data and the definitions of the variables are in the appendix.

2.2 The End of Regional Convergence for Highly Skilled Workers

The central empirical fact of this paper shows that regional wage convergence stopped only for highly skilled workers. Figure 2 shows that the cross-MSA wage convergence rates between 1940 and 1980 were the same for highly skilled and less skilled workers. Nevertheless, they differ strongly after 1980. Between 1980 and 2010, the regional wage convergence rate occurred only among less skilled workers but not highly skilled workers.

To illustrate these patterns, I run the same "convergence" regression as in Baumol (1986):

$$\frac{w_{kjt} - w_{kj\tau}}{(t - \tau)} = \alpha + \beta^k w_{kj\tau} + \epsilon \tag{1}$$

where k is the skill group, highly skilled H or less skilled L; j is the MSA; and t is the final year of the analysis and τ is the initial year. $w_{kj\tau}$ is the log hourly wage by skill group k in MSA j at time τ. The dependent variable is the annual average wage growth of log hourly wages between τ and t. The initial population size weights all the regressions. If the estimates of β^k are negative and statistically significant, then there is regional convergence and the convergence rate is exactly β^k. If they are positive and statistically significant, then there is wage divergence. In Figure 2, I plot the observations at the MSA level by skill group k and then the line fit, where β^H and β^L-convergence rates are the slopes of the lines. The blue dashed line is the β-convergence for L, and the solid red line is the β-convergence for H. Each circle is an observation by MSA and skill group. I label the ten biggest US MSAs in red to observe the less skilled and the blue for highly skilled workers.

[9] The Census samples for 1980, 1990, and 2000 include 5% of the US population; 1970 Census and ACS sample includes 1% of the population; and 1950 Census sample includes approximately 0.2% of the population.

Between 1940 and 1980, there was no difference between cross-MSAs wage convergence rates, β^H and β^L. Between 1980 and 2010, the convergence rate β^L was still negative and statistically significant, but β^H was not. This difference means that the end of convergence was driven only by the wages of highly skilled workers because the wages of less skilled workers still converged across MSAs. In Panel B of Table 2, I report the estimates of β^L and β^H in the two different periods both for population-weighted and non-population-weighted regressions. For the population-weighted regression, β^L and β^H are, respectively, -0.0123 and -0.0143 between 1940 and 1980. Both estimates are statistically significant. However, the estimates of β^L and β^H between 1980 and 2010 are, respectively, -0.0169 and 0.000636. The estimate of β^L is statistically significant, but the estimate of β^H is not statistically different from zero. In the appendix, I run several robustness tests for this fact. First, I estimate the rolling convergence for the highly skilled and less skilled workers separately for 10- and 20-year windows. Second, I run the same regression as above for compositionally adjusted wages.[10][11]

2.3 Skill Premium By Skill Ratio Over Time

The second empirical fact shows that while skill premium used to be lower in skill abundant places, it has become higher in skill abundant places in recent years. In figure 3 I define skill premium as the difference between the wages of the highly skilled workers and the less skilled workers. I run the following regression:

$$\ln\left(\frac{\hat{w}_{Hjt}}{\hat{w}_{Ljt}}\right) = \sum_{s=1940}^{2010} \beta_s \left(\frac{H_{js}}{L_{js}}\right) + \phi_j + \phi_t + \epsilon_{jt} \tag{2}$$

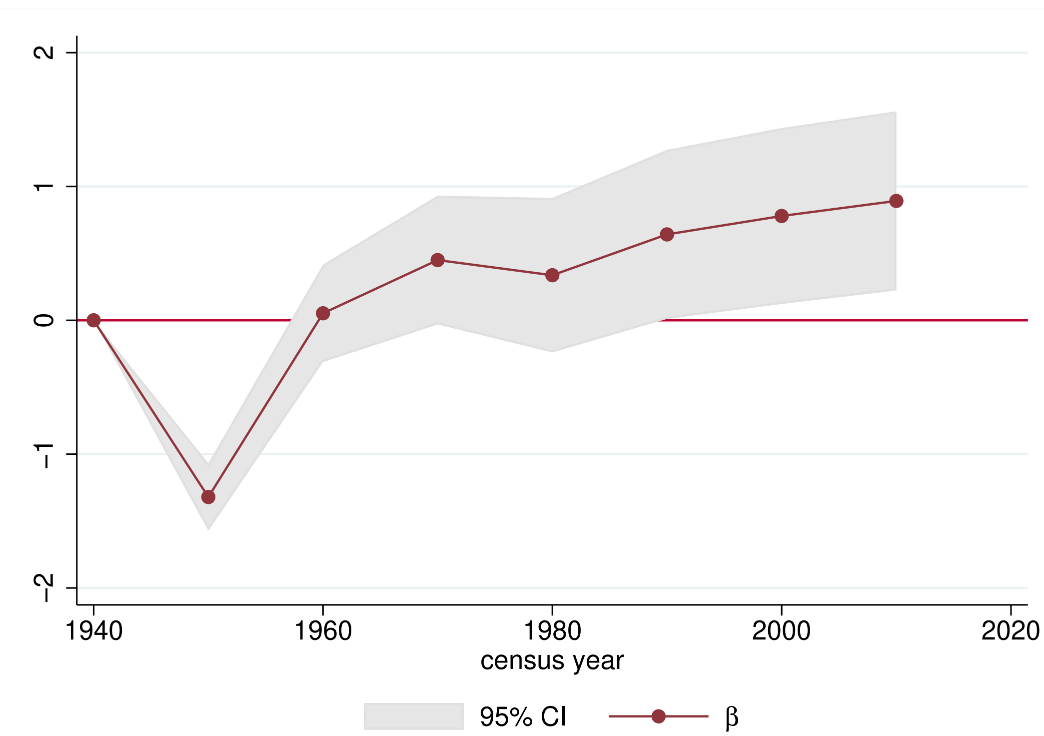
where $\hat{w}_{Hjt}$ and $\hat{w}_{Ljt}$ are the compositionally adjusted wages for MSA j at time t respectively for highly skilled and less skilled workers. ϕ_j is the MSA fixed effect, and ϕ_t is the time fixed effect. $\frac{H_{js}}{L_{js}}$ is the ratio of the total number of workers that are highly skilled to that of less skilled workers in MSA j at time s. I include in the regression every decade between 1940 and 2010. Once I run the regression for each year of the Census, I plot the estimate for the coefficient β_s for each decade. This coefficient can be interpreted as an increase of one

[10]The results are very robust to different specifications.

[11]I identified this fact in the data in the first version of this paper in September 2016. In related work, Autor (2019) notes a decline in the urban low-skill wage premium. He does not report that regional wage divergence has occurred among high but not low-skill workers

standard deviation in $\frac{H_{jt}}{L_{jt}}$ that is going to affect the skill premium by β_s standard deviations. In figure 3, there is a clear pattern for the growth of the skill premium by MSA education. In Table 3, I report the estimates of β_t that control for population. Baum-Snow and Pavan (2013) find that at least 23% of the overall increase in the variance of log hourly wages in the US from 1979 to 2007 is explained by the more rapid growth in the variance of log wages in larger locations relative to smaller locations after controlling for the skill composition of the workforce across MSAs of different sizes. This evidence reinforces the presence of growing knowledge spillovers and motivates the decision to introduce them in the theoretical framework, both for population and skill-ratio.

Figure 3: Skill Premium by MSA Education Levels



Note: This figure plots the estimate of the coefficient β for the regression 2. On the horizontal axis, I have the decades from 1940 to 2010. While on the vertical axis, I have estimates of coefficient β for each decade from 1940 to 2010. Moreover, there is a line starting at zero on the vertical axis.

2.4 The Concentration of Highly Skilled Migrants

The third fact suggests that a higher share of highly skilled workers is moving more and more to highly skilled places. The research on migration has proven that educated workers migrate more than less-educated workers. Nevertheless, where are they migrating? Are they migrating to less educated places to take advantage of the scarcity of a highly skilled labor force? To assess which type of workers migrate more to highly educated MSAs, I run a difference-in-difference analysis as in equation (3).

$$1\left(\text{Migrant}_{ijt}\right) = \alpha + \beta 1\left(H_{ijt}\right) + \gamma \frac{H_{jt}}{L_{jt}} + \sum_{s=1963}^{2013} \delta_s 1\left(\text{H}_{ijs}\right) * \left(\frac{H_{js}}{L_{js}}\right) + \Gamma X_{ijt} + \phi_j + \phi_t + \mu_{ijt} \quad (3)$$

The dependent variable in this equation is whether worker i in MSA j at time t is a migrant or not. The variable equals one if the worker is a migrant. On the right-hand side, there is an indicator variable H_{ijt} that equals one if the worker is highly skilled and zero otherwise. The second variable is the skill ratio $\frac{H}{L}$ in each MSA at each time. Third, there is the interaction between the first two variables. Regression 3 also includes MSA and time fixed effects. I use the estimated coefficient δ_s to compute the marginal effect of being a highly skilled worker and being in a more skilled MSA on the probability of being a migrant. The X_{ijt} represents the economic demographics of the workers, such as age, gender, race, and nationality.[12]

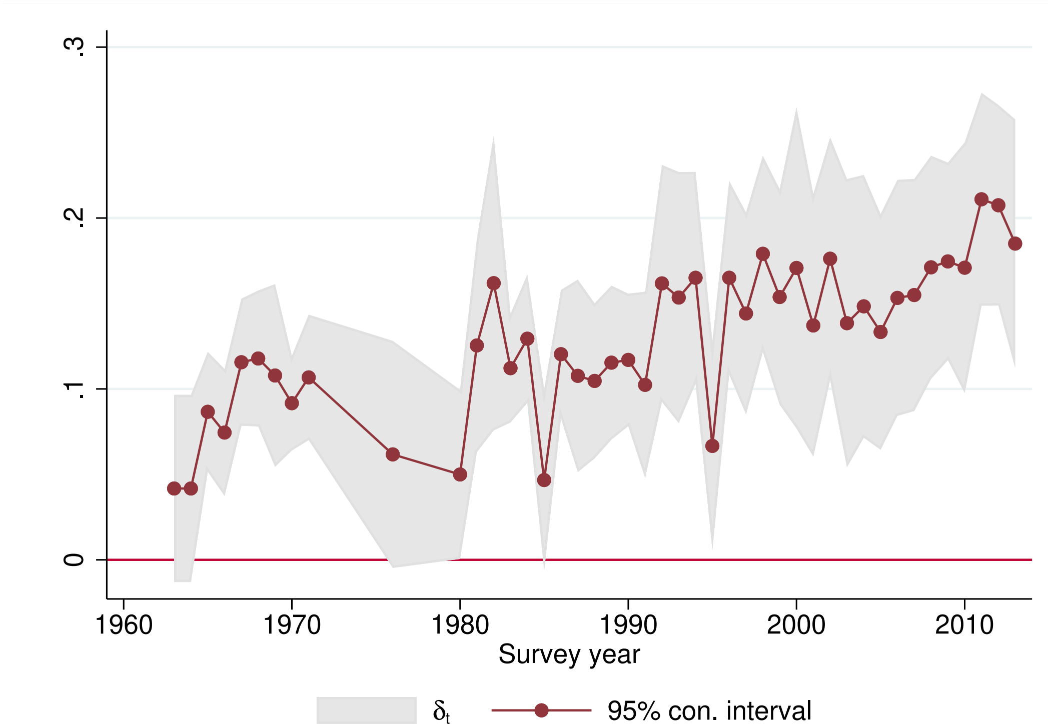
I run regression 3 both as a linear and a logit model. I focus on the marginal effect of δ_s to find the impact of the probability of worker i in MSA j at time s of being a migrant or not given MSA j's skill ratio that is interacted with the worker being highly skilled. I run the same regression with the CPS where the information about the migration status of the worker is available for the years from 1962-2010 except for 1972-1975 and 1976-1979. In the appendix, I run the same exercise using Census data extracted from the IPUMS. Each observation in figure 4 corresponds to the coefficient δ_s in regression (3). I use this as a robustness check. Then, to make evaluations consistent with the Census data and rule out potential biases because of the cycles, I take the average of the estimate for each decade for the available data. For instance, for the 1960s, I take the average of the data available up to 1965. For the 1970s, I take the average of the estimates from 1966 to 1975.

Figure 4 shows that the marginal propensity to migrate conditional on being a highly skilled worker and moving to a highly skilled MSA increases over time. Thus, in relative terms, highly skilled workers concentrate more and more over time in the more educated MSAs. This finding goes well with the hypothesis that highly skilled workers concentrate more and more on educated MSAs. Table 4 shows the evolution over time of the marginal

[12]The more detailed description is the same as the one I did for the compositionally adjusted wages.

effect of being highly skilled and being in a highly educated MSA on being a migrant.

Figure 4: Migration Rate by Destination Education Level



Note: This figure plots the estimate of the coefficient δ for the regression 3. On the horizontal axis, I have the years from 1962 to 2010. While, on the vertical axis, I have estimates of coefficient δ for each year from 1962 to 2010. Moreover, there is a line starting at zero on the vertical axis.

2.5 "The Great Convergence" and "The Great Divergence" after 1980

The last fact of this paper shows that before 1980 there was convergence in skill ratio and it replicates the "Great Divergence" of skills after 1980. Moretti (2004), Berry and Glaeser (2005), Moretti (2012) and Diamond (2016) show that the skill ratio of workers between 1980 and 2010 was diverging across MSAs. Moretti (2012) coins the term "The Great Divergence" to stress how the skills diverge over space. Nevertheless, what happened to the skill ratio before 1980? Was the skill distribution converging across MSAs when wages were converging? To answer this question, I analyze the convergence rates of the skill ratio over the last 70 years. I estimate the following specification:

$$\ln\left[\frac{H_{jt}}{L_{jt}} - \frac{H_{j\tau}}{L_{j\tau}}\right]\frac{1}{(t-\tau)} = \alpha + \beta^{HL}\ln\frac{H_{j\tau}}{L_{j\tau}} + \epsilon \quad (4)$$

where H_{jt} and L_{jt} are, respectively, the number of highly and less skilled workers living in MSA j at time t and the initial period τ. The dependent variable is the average annual growth of the skill ratio between τ and t. With this regression, I can assess how growth in the skill ratio is related to the initial skill ratio. This regression is analogous to the regressions run in Figures 1 and 2 but for quantities rather than for wages. I run this regression over different periods using the Census and ACS data. In Figure 5, I plot the observations at the MSA level and then the line fit, where β^{HL}-convergence rates are the slope of the lines. Each circle is an observation by MSA. I label the ten biggest US MSAs. Between 1940 and 1980, the β^{HL}-convergence rate was negative and statistically significant, therefore, the term "Great Convergence". However, as observed in Moretti (2004), between 1980 and 2010, the β^{HL}-convergence rate was positive and statistically significant, indicating divergence. Table 5 has the results from decomposing the years in shorter periods. The results show that the distribution of highly skilled and less skilled workers across MSAs was converging between 1940 and 1980 and then started to diverge between 1980 and 2010. Panel A shows the results when the difference between t and τ is 10 years. While in Panel B, the same difference is set at 20 years. Panel A shows that the estimated coefficients are negative and statistically significant until 1970, then they become not significant for 1970-1980 and 1980-1990. Further, between 1990-2000 and 2000-2010 they become positive and statistically significant. A 1% increase in the college share ratio increases the change in the college share by 0.07% and 0.04%, respectively, between 1990-2000 and 2000-2010. In Panel B, the results are pretty similar, but in column (1), the coefficient is positive and statistically significant. That coefficient is calculated for 1940 to 1970 since data for 1960 is not available. Therefore, in 30 years, the results should have reversed for other reasons. But, the coefficient between 1950 and 1980 is negative and statistically significant as expected. Specifically, a 1% increase in the college ratio in 1950 decreases the change in the college ratio between 1980 and 2010 by 0.32%.

Figure 5: Skill Convergence across MSAs before and after 1980

Note: This figure plots each MSA's annual average skill growth (demeaned) against its (demeaned) initial skill level. The left figure depicts 1940-1980; the right depicts 1980-2010. Each MSA's circle size is proportional to its initial population size. The red line depicts a weighted least square bi-variate regression. The line in each graph represents a weighted regression line from the bi-variate regression.

3 A Spatial Equilibrium Model with Skills and Technology Diffusion

The empirical analysis indicates that long-run changes pushing the concentration of skills and their returns in already highly skilled locations occurred. Specifically, these changes affected patterns of regional convergence, skill premium, and cross-MSA migration. These observations and the time when such changes occurred point to how a national skill-biased technology shock interacting with local knowledge spillover might rationalize the aforementioned long-term changes. To account for these effects, I develop a dynamic model of cities nesting the quantitative spatial equilibrium literature with spatial economic growth.

I start with a simple two-period and two-city setup of geography and skills to highlight the mechanism through which a national SBTC shock interacting with knowledge spillover pushes divergence over convergence forces driven by the spatial technology diffusion. Then, I present a quantitative, general equilibrium model to rationalize the empirical facts, quantify the role of the primary mechanisms, compare it with others and, finally, explore the implications for the secular migration decline and the aggregate trade-off between inequality and growth.

3.1 A Simple Two Period Model of Cities and Skills

This simple model has the goal of highlighting the mechanism. Specifically, it shows that: (i) the spatial diffusion process introduces regional convergence in a standard spatial equilibrium model; (ii) when a national skill-biased technology shock interacts with knowledge spillovers there will be a push for regional divergence.

Environment. There is a set of $J = \{\text{SF, D}\}$ locations where SF stands for San Francisco and D stands for Detroit. In the model, there are two types k of workers, highly skilled H and less skilled L. In each period t, where $t = \{1, 2\}$ they decide how much to consume and which location j to pick for living. Workers can move freely between these two locations. Each period they decide where to live and how much to consume. Each worker types k provides, inelastically, one unit of labor in the location where they live, for which they are compensated with a wage w_k. The workers move until their utilities U are equalized across locations. The labor of H and L are the only two factors of production. Firms operate in a competitive market where the only good is freely tradable and we assume the price to be equal to 1. The wage in the competitive market for the

$$w_{Hj} = \left(\frac{H_j}{L_j}\right)^{\gamma^H} MRL_{Hj} S_H \xi_j \qquad w_{Lj} = \left(\frac{H_j}{L_j}\right)^{\gamma^L} MRL_{Hj} S_L \xi_j$$

where $\left(\frac{H_j}{L_j}\right)^{\gamma^H}$ are knowledge spillovers that depend on the ratio of high-to-low skilled in location j; S_H and S_L are exogenous national-level skill-biased productivities; MRL is the marginal return to labor in the location j, and ξ_j is a productivity that depends from the previous period following a spatial diffusion process such that

$$\xi_{jt} = \xi_{jt-1}^{\gamma^2} \sum_{m \neq j} \omega \xi_{mt-1}^{1-\gamma^2} \tag{5}$$

where ω is the geographical distance between the two locations.

Proposition 1 *A spatial diffusion process as described in equation 5 increases regional convergence β as defined in equation 1.*

Proof: Suppose that initial productivity at time 0 is higher in San Francisco than in Detroit such that $\xi_{SF0} > \xi_{D0}$. Because of the spatial diffusion process in equation 5, then, $\Delta\xi_{SF-D1} < \Delta\xi_{SF-D0}$. Therefore, $\Delta w_{SF-D1} < \Delta w_{SF-D0}$, where $w = w_H * H + w_L * L$. Because the utility in this model is equal to real wage, which is equal to nominal since the price of the only good is equal to 1, then β-convergence will be given by the nominal wages. Thus, it will increase.

Now, suppose that there is a national SBTC shock that increases S_H. This might push for divergence, according to proposition 2.

Proposition 2 *A national SBTC shock (or a national increase in S_H) will decrease regional divergence β if knowledge spillovers are stronger than convergence forces such as MRL and spatial diffusion as described in equation 5.*

Proof: The proof of this statement comes from the discussion below, which highlights the core divergence mechanism of the model.

The effect of an increase in S_H on local wage of both San Francisco and Detroit high-skilled workers will be positive since it increases productivities.[13] On top of that, as shown in proposition 2, the same shock might have a larger effect in San Francisco if H is higher there. But it might differ among locations depending on the share of high-skilled workers. Specifically,

$$\frac{\partial^2 w_{Hj}}{\partial S_H \partial H_j} > 0 \qquad \text{if} \qquad \gamma^H \left(\frac{H_j}{L_j}\right)^{-1} > -\frac{1}{MRL_{Hj}} \frac{\partial MRL_{Hj}}{\partial H}$$

The expression above is key to understanding the forces in the model. If knowledge spillover forces dominate decreasing MRL, then, $\frac{\partial^2 w_{Hj}}{\partial S_H \partial H_j}$ will be positive. Therefore, more high-skill labor H is present in a region. A national skill-biased technical shock might increase the wages of high-skilled more in places where they are more concentrated (San Francisco) than where they are less concentrated (Detroit). Comparing San Francisco to Detroit where $\left(\frac{H_{SF}}{L_{SF}}\right) > \left(\frac{H_D}{L_D}\right)$, then, if

$$\left(\frac{H_{SF}}{L_{SF}}\right)^{\gamma^H} MRL_{HSF} \exp(\xi_{SF}) > \left(\frac{H_D}{L_D}\right)^{\gamma^H} MRL_{HD} \exp(\xi_D)$$

which depends on the knowledge spillover forces versus the MRL and ξ, then, H types will be more likely to move to San Francisco than to Detroit exacerbating the differences with Detroit and pushing for divergence. This is the key mechanism that drives regional divergence in the model and as well as the aggregate increase in inequality.

3.2 Quantitative Model

To quantify the effect of technological progress and compare it with other forces, I embed the mechanism described above in a quantitative spatial equilibrium model. This model departs from the above by including multiple locations, migration costs, housing sectors, amenities and industries. These features make the model more realistic and allow it to consider other potential explanations driving the data. The discussion at the end of this section explains the role of each additional feature by one. Appendix section C discusses other explanations individually. Throughout the paper, I also describe how the estimation strategy isolates the main mechanism highlighted in the paper.

13 $\frac{\partial w_{Hj}}{\partial S_H} = \left(\frac{H_j}{L_j}\right)^{\gamma^H} MRL_{Hj} \exp(\xi_j)$. Since all the elements are positive, then, a national SBTC shock will increase the wage of the high-skills differently in all locations.

Differently from the toy model, each location produces a tradable good T, a set of non-tradable intermediates, $d \in D$, and housing O. The production of tradable T employs both highly and less skilled labor. The productivity terms are different for the two sectors' production functions. The endogenous component is a function of the ratio of highly skilled workers to less skilled workers and the population. The housing supply is a function of the local rents. More details on the supply and demand of the economy are described here:

Preferences and agents' choices. In each period, agents derive utility from consuming a tradable good T and housing O according to Stone-Geary preferences with a subsistence level housing $\bar{O}$.[14] Agents also derive utility from exogenous amenities A_{kjt} and from living in more highly skilled cities with higher (H_{jt}/L_{jt}) to some exponent γ^p. The period utility of an agent i of type $k \in \{H, L\}$ who resides in location j at time t and lives in a series of locations $\bar{j}_- = (j_0, ..., j_{t-1})$ in all previous periods is given by

$$u_{ikjt\bar{j}_-} = u_{ikjt} \prod_{s=1}^{t} m_k(j_{s-1}, j_s)^{-1}$$

where u_{ikjt} is the utility which depends only on the current location j of the agents; and $m_k(j_{t-1}, j_t)$ is the migration cost of type k from moving from location j_{t-1} to location j_t, which is also a permanent utility loss for moving from j_{s-1} in $s-1$ to j_s in s. The utility u_{ikjt} is given by

$$u_{ikjt} = \theta \ln(T_{kjt}) + (1-\theta)\ln(O_{kjt} - \bar{O}) + A_{kjt} + \gamma^p \ln(H_{jt}/L_{jt}) + \zeta_{ijt}$$

where ζ is a taste shock distributed according to a Gumbel (or Type I Extreme Value) distribution. Thus,

$$\Pr[\zeta_{ijt}] = e^{-e^{(-\zeta_{ijt})}}$$

I assume that ζ_{ijt} is i.i.d. across locations, individuals, and time. Agents discount the future at rate β and so the welfare of an individual i in the first period is given by $\sum_t \beta^t u_{itj\bar{j}_-}$ where j_{it} denotes the location at time t, $\bar{j}_-$ denotes the history of previous locations, and j_{i0} is given. Agents earn a wage W_{kjt} from their work. After observing their idiosyncratic

[14] The preferences present a degree of non-homotheticity similar to Ganong and Shoag (2017). This will allow us to make a fair quantitative comparison with the housing mechanism. The main qualitative predictions of the model would not change if there was no non-homotheticity.

taste shock every period, agents decide where to live, which is subject to mobility costs m_k. These costs are paid in terms of a permanent percentage decline in utility. I use the same assumption about the separability of moving costs as in Desmet et al. (2018) such that $m_k(s, j) = m_{k1}(s)m_{k2}(j)$ with $m_k(j, j) = 1$ for all $j \in S$. This assumption turns out to be extremely useful for the feasibility of the model because it means that agents' choice of location depends only on current variables and not their location history.[15] Therefore, I rewrite the agents' problem in a recursive formulation. The value function for an agent living in location j after observing a distribution of the taste shock in all locations is given by

$$\begin{aligned} V_{kt}(j, \zeta_i') =& \max_{j'} \left[\frac{V_{ikj't}}{m_k(j, j')} + \beta E \left(\frac{V_{kt+1}(j', \zeta_i'')}{m_k(j, j')} \right) \right] \\ =& \frac{1}{m_{k1}(j)} \max_{j'} \left[\frac{V_{ikj't}}{m_{k2}(j')} + \beta E \left(\frac{V_{kt+1}(j', \zeta_i'')}{m_{k2}(j')} \right) \right] \\ =& \frac{1}{m_{k1}(j)} \max_{j'} \left[\frac{V_{ikj't}}{m_{k2}(j')} + \beta E \left(\max_{j''} \left[\frac{V_{ikj''t+2}}{m_{k2}(j'')} + \beta E \left(\frac{V_{kt+2}(j'', \zeta_i'')}{m_{k2}(j'')} \right) \right] \right) \right] \end{aligned} \tag{6}$$

From the last line of equation 6, it follows that the choice of the current location is independent of past and future locations. This independence means that the value function can be rewritten, which isolates the current component as a static problem.[16] Thus,

$$\max_{j'} \left[\frac{V_{ikj't}}{m_{k2}(j')} \right]$$

After deciding on location j', the agent solves the following static consumption problem:

$$V_{ikj't} = \max_{T_{kj't}, O_{kj't}} [\theta \ln(T_{kj't}) + (1 - \theta)(\ln(O_{kj't} - \bar{O}_{kj't}) + A_{j't} + \gamma^p \ln(H_{j't}/L_{j't}) + \zeta_{ij't}]$$

$$\text{s.t. } T_{kj't} + O_{kj't}R_{j't} = W_{kj't}$$

[15] Caliendo et al. (2019) solve the migration problem dynamically by keeping track of the distribution of workers across locations by using a "hat algebra" method. One extension of the current model would be incorporating that decision on top of the current features. However, to use their method, I would need to measure the migration flows across cities in 1940. Unfortunately, these data are not currently available to the best of my knowledge.

[16] The derivation above follows from Desmet et al. (2018).

The indirect utility of agent i of type k at time t living in MSA j can be written as

$$V_{ikjt} = \left[\theta \ln(\theta W_{kjt} - R_{jt}\bar{O}) + (1-\theta)\ln\left((1-\theta)\frac{W_{kjt}}{R_{jt}} + \bar{O}\right) + A_{kjt} + \gamma^p \ln\left(H_{jt}/L_{jt}\right) + \zeta_{ijt}\right]$$

where k is the skill group of the individual, which can be "highly skilled" H_{jt} or "less skilled" L_{jt}. w_{kjt} is the log of the wages for each skill type k in location j at time t. Using the properties of the Gumbel distribution and following McFadden (1973), I derive the number of workers of types H and L living in each location j at time t.

$$H_{jt} = \frac{\exp(\delta_{Hjt}/m_{2H}(j))}{\sum_s^S \exp(\delta_{Hst}/m_{2H}(s))} \tag{7}$$

$$L_{jt} = \frac{\exp(\delta_{Ljt}/m_{2L}(j))}{\sum_s^S \exp(\delta_{Lst}/m_{2L}(s))} \tag{8}$$

where

$$\delta_{kjt} = \theta \ln(W_{kjt} - R_{jt}\bar{O}) + (1-\theta)[\ln(1-\theta)\frac{W_{kjt}}{R_{jt}} + \bar{O}] + A_{kjt} + \gamma^p \ln\left(H_{jt}/L_{jt}\right) \tag{9}$$

Technology. In the next subsection, I describe the production technology of the final tradable sector, T; the non-tradable intermediates, $d \in D$; and the housing sector, O. The final good is produced using all the intermediates jointly in a CES fashion. The local market produces intermediates and housing. The intermediates are produced using a CES with highly skilled and less skilled labor. The housing sector is produced depending on the price of the housing sector as in Ganong and Shoag (2017). Because the tradable good T is freely tradable across locations, the price of T, $P_{Tjt} = p_{Tjt}$, $\forall j$, that means it is the same across locations and is assumed to be a numéraire.

Final Good Production. The final good is produced by combining all the intermediate d jointly in a CES fashion where the elasticity is given by α, and the share used in the production function is μ_d. Specifically,

$$T_{jt} = \big(\sum_d \mu_d Y_{djt}^{\alpha}\big)^{1/\alpha}$$

Intermediates Sector and Knowledge Spillover. The production function in equation 10 is a CES that uses two types of labor H_{djt} and L_{djt} as imperfect substitute inputs.[17]

$$Y_{djt} = [\eta_{Ldjt} L_{djt}^{\rho} + \eta_{Hdjt} H_{djt}^{\rho}]^{\frac{1}{\rho}}, \qquad \forall\, j = \{1, ..., N\} \tag{10}$$

η_{Hdjt} and η_{Ldjt} denote the productivity of H and L, respectively, in sector d at location j for time t. Productivity is divided into an exogenous and an endogenous component.[18]

Departing from the standard formulation of a CES as in Katz and Murphy (1992), I follow the recent literature on knowledge spillovers to make productivity dependent on both endogenous and exogenous components. Endogenous differences in productivity depend on the industry mix in the location. As Diamond (2016) argues, the literature on social returns to education has shown that areas with a higher concentration of college graduates are more productive due to knowledge spillover.[19] Adding knowledge spillover through endogenous productivity that derives from the skill ratio and population is also supported by my empirical findings, as in section 2. These two facts suggest that 1) the higher the skill ratio, the higher the wage premium in the location, and 2) highly skilled workers migrate to cities with a higher skill ratio more frequently than less educated workers. Together they embrace the hypothesis that knowledge spillover can be higher in cities with a higher concentration of highly skilled workers. Simultaneously, following Davis and Dingel (2014) and Baum-Snow et al. (Forthcoming), the spillover effects also appear for population, not just the skill ratio.[20] To allow for both effects, I write the expressions η_{Hdjt} and η_{Ldjt} as follows:

$$\eta_{Hdjt} = \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^H} (L_{jt}+H_{jt})^{\phi^H} S_{Ht}^{\lambda^H} \exp(\xi_{Hdjt}) \qquad \eta_{Ldjt} = \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^L} (L_{jt}+H_{jt})^{\phi^L} S_{Lt}^{\lambda^L} \exp(\xi_{Ldjt})$$

where S_{kt} is the exogenous skill-biased technology component for $k \in \{H, L\}$.[21] The

[17] I do not include physical capital in this model since my focus is on the composition of the labor force and human capital. However, the consequences of including capital might differ depending on whether capital is mobile or immobile.

[18] Applying a change in variable as in Diamond (2016), Y_{djt} can be rewritten as a function of data (w_{Ljt}, w_{Hjt}, H_{djt}, L_{djt}, H_{jt}, L_{jt}) and parameters (ρ, γ^L, γ^H, ϕ^L, ϕ^H). More details are given in the Appendix section D.2.

[19] In the latest version of Diamond (2016), spillovers are not modeled with parametric formulation but more importance is given to utility spillovers. My paper, however, benefits by modeling productivity spillovers with specific functional forms, especially for the counterfactual analysis.

[20] To guarantee the existence of a steady-state, I will need to derive sufficient conditions to be imposed on the knowledge spillovers.

[21] In the Appendix, I present a version of the model with endogenous SBTC modeled as technology adoption

exogenous productivity component is ξ_{kdjt}. ξ_{kdjt} at time 0 is given and then evolves according to:

$$\xi_{kdjt} = \xi_{kdjt-1}^{\gamma^2} \left[\int_s \omega(j,s) \xi_{kdst-1} ds \right]^{1-\gamma^2} \tag{11}$$

where $\omega(j,s)$ is a symmetric measure of distance between location j and location s and $\gamma^2 \in [0,1]$.[22] If $\gamma^2 < 1$, then the productivity in location j is dependent on the productivity of the other locations. This dependence will introduce convergence into the model through spatial knowledge diffusion.

The profits π of the firm come from the following maximization problem:

$$\pi_{djt} = \max_{l,\,h} p_{djt} [\eta_{Ldjt} l^{\rho} + \eta_{Hdjt} h^{\rho}]^{\frac{1}{\rho}} - W_{Hjt} h - W_{Ljt} l$$

where l and h are the amounts of less and highly skilled labor used by one firm that produces the intermediate good d. p_{djt} is the price at which the intermediate d is sold. A free entry condition drives profits to zero since the firms keep entering until the profits are equal to zero. Therefore, a firm choosing its production in period t knows that its current and future profits will equal zero. This result is extremely useful in solving the model. It means that the dynamic component of the model is equivalent to a repeated static model, which facilitates the numerical solution.

Since the labor markets are perfectly competitive, the wage in each location is equal to the marginal product of labor as shown in equations 12 and 13, which derive the first-order condition of the firms.

$$W_{Hjt} = p_{djt} \eta_{Hdjt} [\eta_{Ldjt} L_{djt}^{\rho} + \eta_{Hdjt} H_{djt}^{\rho}]^{\frac{1}{\rho}-1} H_{djt}^{\rho-1} \tag{12}$$

$$W_{Ljt} = p_{djt} \eta_{Ldjt} [\eta_{Ldjt} L_{djt}^{\rho} + \eta_{Hdjt} H_{djt}^{\rho}]^{\frac{1}{\rho}-1} L_{djt}^{\rho-1} \tag{13}$$

Housing Market. The supply of housing is a convex function of its price. The higher

in line with Beaudry et al. (2010). However, this version does not reproduce features that I see in the data, such as the correlation between the skill premium and the local supply of skilled labor.

[22] As a robustness test, I numerically test this productivity process, holding ω constant such that $\int_S \omega ds = 1$. The results are qualitatively unchanged.

the price of housing, the higher the supply.[23]

$$O_{jt} = R_{jt}^{\mu} \tag{14}$$

where the exponent μ represents the elasticity of housing and R is the rental rate of houses in location j at time t. This equation mimics the housing sector following Ganong and Shoag (2017). The idea behind this expression is that regulations affect the elasticity of supply as a direct cost shock. Local housing demand follows from the household problem and is given by:

$$H_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Hjt}}{R_{jt}}\right] + L_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Ljt}}{R_{jt}}\right] \tag{15}$$

The equilibrium is defined in the Appendix section A.4. I treat the existence and uniqueness properties of the model in the same session. I also report another discussion about some model assumptions, such as the spatial technology diffusion, SBTC and parameter choice. Finally, in section C, I discuss alternative explanations for regional convergence that I excluded by either looking at the data or by comparing a theoretical version of the model with moments in the data. Notice, however, that the structure of the model by inverting the wage equation and matching the productivities is already taking into account most of the potential competing explanations.

3.3 Discussion about New Features of the Quantitative Model

The toy model described in section 3.1 features only: *i)* spatial technology diffusion to embed convergence in a spatial equilibrium model; and *ii)* the interaction between SBTC and knowledge spillover forces. Instead, the full model includes several new features that serve quantification purposes and account for other potential explanations. Here, I describe what the role of the additional features is. Appendix section C details further what other explanations could be explaining the decline in regional convergence and how the existing model takes them into account in some cases.

[23] To create a fully dynamic housing model with investment decisions along the lines of Glaeser and Gyourko (2006) is a possible extension of the paper. However, to avoid moving the paper's focus away from skill-biased technology, I keep the housing market as simple as possible. This simplification also enhances comparability to Ganong and Shoag (2017). I run some simulations fluctuating the value of the parameter μ to substantial levels and trim levels to check how the housing would respond.

Housing Sector. A change in housing regulation in more expensive locations might reduce regional convergence, as pointed out by Ganong and Shoag (2017), a pioneering paper on this topic. Ganong and Shoag (2017) suggest that the US states where housing prices increased the most are also where migration declined. Hence, because migration increases convergence, the decline in migration to this area, which is also the richest, decreased the income convergence rate. Their paper suggested that housing prices and SBTC could be complementary. For this reason, to decide how to disentangle them, I add a housing sector to the model to compare the housing effects with my fundamental mechanisms. I also conduct some extra empirical tests in the Appendix section C.

Multiple Industries. I include multiple industries for two main reasons. The first reason is that the identification strategy I describe in the estimation section exploits the industry structure of MSAs. Thus, including industries in the model allows one not to go outside of the model to interpret the instrument. The second reason is that the industrial composition across US cities is very heterogeneous and highly skilled workers allocate differently through sectors across space. This directly could have impacted regional convergence. In the Appendix section C, I describe in further detail this possibility, as well as taking into account capital-skill complementarity and other tests I run to account for it.

Migration Costs. Another potential explanation is that migration costs might have reduced over time. This induces individuals to move more and allocate themselves to the richest locations faster, allowing for a faster concentration of the high-skilled workers in rich locations. To consider this mechanism, I allow migration costs to be in the model and run a counterfactual in the quantification exercise, shutting them to 0 in the period after 1980. As reported below, the results are quantitatively unchanged.

Amenities. An essential feature of geography to explain the "Great Divergence¨ of skills and several other aspects of the regional differences have been amenities as studied by Diamond (2016). Thus, I must include and estimate them since they also might have impacted regional convergence pushing for the reshuffling of high-skill to skill abundant areas. However, notice that amenities alone cannot explain the reversal of regional convergence in wages because they push down the wages of highly skilled people when they cluster in a city.

4 Estimation and Calibration of the Model

The numerical computation of the model's equilibrium involves recruiting values for all parameters used in the equations above in addition to the values for initial productivity levels, ξ_{kj0}. After obtaining these parameters, I compute the dynamic equilibrium by iterating a system of equations. In order to calibrate the model, I estimate the 10 parameters $\{\theta, \gamma^p, \gamma^L, \gamma^H, \rho, \phi^H, \phi^L, \lambda^H, \lambda^L, \gamma^2\}$ internally within the framework. The static estimation part relates to Diamond (2016). But it departs from it taking into account the dynamic aspect of the spatial technology diffusion process. There are two main reasons I choose estimation over external calibration for the core parameters. First, using parameters from the literature that studies other periods produces inaccuracies. Second, to conduct a quantitative rather than qualitative analysis, I need to disentangle the quantitative importance of each model's parameters. Specifically, I need to distinguish the effect of knowledge spillover forces from the effects produced by SBTC. Therefore, an identification procedure is necessary to clarify the individual importance of each parameter. I calibrate the remaining parameters $\{m_{2H}, m_{2L}, \mu, \bar{O}, \alpha,\ \mu_d, \forall d\}$ with data from the literature.

4.1 Estimation of the Model

To estimate the set above of 10 parameters and initial ξ_{H0} and ξ_{L0}, I exploit local exposure to SBTC. *It is crucial to notice that all the fit of the model with the data and the counterfactuals are conducted with a national change in SBTC, not local.* This aligns with the paper's main point, which is to study how the interaction between a national shift in technology and the local knowledge spillovers had local implications.

4.1.1 Skill-Biased Technical Change

Autor and Dorn (2013) rank commuting zones by the intensity of the routine occupations.[24] The authors build an index of routinization in which they categorize all occupations by their intensity of routinization. Each occupation υ is routinized if the RTI (or routine task intensity) is higher than the 66th percentile. If an occupation is routinized, the arrival of computers will significantly affect it because routine occupations and computers are substitutes. For instance, the car industry in Detroit was significantly affected by skill-biased

[24] For a full definition of commuting zones, refer to the following link from the *United States Department of Agriculture*: http://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/

technology (or routinization, specifically) because the share of laborers working in routine-intensive occupations was very high for both highly and less skilled workers. Using the same approach, I construct the RTI for both highly and less skilled workers in each occupation, as shown in equations 16 and 17.

$$\Delta S_{Ljt} = \sum_{\upsilon=1}^{\Upsilon} \left(\frac{L_{j\upsilon t}}{L_{jt}} - \frac{L_{j\upsilon t-10}}{L_{jt-10}} \right) 1\left(RTI_{\upsilon} > RTI_{P66}\right) \tag{16}$$

$$\Delta S_{Hjt} = \sum_{\upsilon=1}^{\Upsilon} \left(\frac{H_{j\upsilon t}}{H_{jt}} - \frac{H_{j\upsilon t-10}}{H_{jt-10}} \right) 1\left(RTI_{\upsilon} > RTI_{P66}\right) \tag{17}$$

Autor and Dorn (2013) find that when the price of computers starts falling, workers in routinized occupations, who are substitutable by computers, see their wages erode. Therefore, MSAs specializing in routine occupations, both for highly and less skilled workers, experience relative wage declines. ΔS_{kjt} captures this idea well through the measure of routinization. Using this same approach, I build the RTI in each occupation both for the highly skilled and less skilled workers as in equations 16 and 17. ΔS_{Hjt} and ΔS_{Ljt} are two good proxies for how SBTC affects cities differently depending on their composition.[25] Figure 6 shows the evolution over time of the aggregate measures. However, this is not a good measure of a productivity shock because it correlates with contemporary and local changes that could affect wages. Therefore, following the approach of Autor and Dorn (2013), I use national employment changes both for the highly skilled and less skilled workers that are interacted with the share of RTI for the local industry ten years ago as instruments for ΔS_{Ljt} and ΔS_{Hjt}. These instruments can be described as:

$$\Delta \tilde{S}_{Hjt-10} = \sum_{d} \left(H_{d-jt} - H_{d-jt-10}\right)\left(R_{djt-10}\right) \quad \text{and} \quad \Delta \tilde{S}_{Ljt-10} = \sum_{d} \left(L_{d-jt} - L_{d-jt-10}\right)\left(R_{djt-10}\right)$$

where $-j$ is all cities in the sample other than MSA j, d is industries in the economy, and t is time. The list of industries d used to construct the measures is reported in table

[25] While this approach provides a good proxy for the local impact of SBTC, it might not be the only one. Computer adoption might represent the arrival of computers and demonstrate how different cities are affected differently. Beaudry et al. (2010) uses this approach. However, the available data stopped in 2000. This shortfall prevents me from recreating the full analysis through 2010 and is insufficient to estimate my model. For this reason, I use Autor and Dorn (2013)'s approach, which is very flexible with data and allows me to build an index for all years in the analysis.

Figure 6: ΔS_{Hjt} and ΔS_{Ljt} aggregate over time

7.[26] H_{d-jt} and L_{d-jt} are, respectively, the number of highly skilled and less skilled workers in each industry d at the national level at time t that excludes MSA j to avoid mechanical correlations. $H_{d-jt-10}$ and $L_{d-jt-10}$ are the same lagged 10 years. R_{djt-10} is the share of routine occupations among workers in each industry in a specific MSA j. Unlike Autor and Dorn (2013), I create both the index and the instrument for highly skilled H and less skilled L. In this way, I produce extra variation in the data and use the differential impact of technological shocks on the two categories of workers. Different from Autor and Dorn (2013) that aims at capturing the polarization, here I also want to capture the skill differences. These instrumental variables, $\Delta\hat{S}_{Ljt-10}$ and $\Delta\hat{S}_{Ljt-10}$, are useful in the estimation of the parameters of the model and the construction of the moment condition.

Table 6 presents the first-stage estimates for these instrumental variables. The predictive relationship between ΔS_H and $\Delta\hat{S}_H$ is sizable and highly significant, with F-statistics of 10 or above in each decade, as shown in Panel A. The predictive relationship between ΔS and $\Delta\hat{S}_L$ is sizable and highly significant, with F-statistics of 10 or above for the decades after 1980. However, the F-statistics for the 1950s, 1970s, and 1980s are less than 10. Specifically, in the 1970s, the F-statistic is less than 7.[27]

[26] The same industries d are also used to calibrate the model for internal consistency.

[27] As a robustness test, I estimate the model without the 1950s and the parameter estimates are unchanged.

4.1.2 Labor Demand

I use moment conditions that start from the labor demand curves for highly and less skilled workers to estimate labor demand. The change in productivity levels that interact with changes in demand shocks help identify the core parameters. Using these conditions, I create moments in order to estimate the set of parameters: $\{\gamma^H, \gamma^L, \phi^H, \phi^L, \rho, \lambda^H, \lambda^L \gamma^2\}$. For this purpose, I start by taking the logs and the first differences of equations 12 and 13 which, respectively, give:

$$\Delta w_{Ljt} = (1-\rho)\Delta\ln Y_{djt}(\rho,\, \gamma^{H,}\, \gamma^L,\, \phi^{H,}\, \phi^L) + (\rho-1)\Delta\ln L_{djt} + \gamma^L \Delta\ln\frac{H_{jt}}{L_{jt}} +$$
$$+\phi^L \Delta\ln\left(H_{jt}+L_{jt}\right) + \lambda^L \Delta S_{Ljt} + \Delta\xi_{Ldjt}$$

$$\Delta w_{Hjt} = (1-\rho)\Delta\ln Y_{djt}(\rho,\, \gamma^H\, \gamma^L,\, \phi_{H,}\, \phi^L) + (\rho-1)\Delta\ln H_{djt} + \gamma^H \Delta\ln\frac{H_{jt}}{L_{jt}} +$$
$$+\phi^H \Delta\ln\left(H_{jt}+L_{jt}\right) + \lambda^H \Delta S_{Hjt} + \Delta\xi_{Hdjt}$$

Then, by using equation 11 and writing it in first differences, I can isolate $\Delta\epsilon_{kdjt}$, which is the productivity component uncorrelated with technological diffusion:

$$\Delta\xi_{Hdjt} = \xi^{\gamma_2}_{Hdjt-1}\left(\int_s \xi_{Hdst-1} ds\right)^{1-\gamma_2} - \xi^{\gamma_2}_{Hdjt-2}\left(\int_s \xi_{Hdst-2} ds\right)^{1-\gamma_2} + \Delta\epsilon_{Hdjt} \tag{18}$$

$$\Delta\xi_{Ldjt} = \xi^{\gamma_2}_{Ldjt-1}\left(\int_s \xi_{Ldst-1} ds\right)^{1-\gamma_2} - \xi^{\gamma_2}_{Ldjt-2}\left(\int_s \xi_{Ldst-2} ds\right)^{1-\gamma_2} + \Delta\epsilon_{Ldjt} \tag{19}$$

Therefore, we can replace 18 and 19 respectively into 12 and 13 isolating $\Delta\epsilon_{Hdjt}$ and $\Delta\epsilon_{Ldjt}$. In the spirit of Diamond (2016) and Suárez Serrato and Zidar (2016), the identification strategy follows from the changes in the labor supply that are uncorrelated with local productivity. Unlike previous work, this estimation strategy considers the dynamic component of the model and the fact that current local productivity is correlated with past productivity changes. Also, the interaction of SBTC shocks with the cities' housing supply elasticities leads to variation in the labor supply that is uncorrelated with the unobserved changes in local productivity. The housing supply affects the migration decisions in response to a labor demand shock. Differential housing supply elasticities generate exogenous variation in the labor supply. For example, I compare two cities, one has a very elastic housing supply and the other has a very inelastic one, both experience an increase in labor demand; and workers move to take advantage of these increases. Nevertheless, once they move, the MSA with more inelastic housing will have a higher increase in housing prices. Therefore, the rent increase will prevent more in-migration in the MSA with higher housing prices for the same level of labor demand shock that offsets the increase in wage through the labor-demand channel. Specifically, the exclusion restrictions are:[28]

$$\mathrm{E}(\Delta\epsilon_{Hdjt}\Delta Z_{jt}) = 0 \quad \text{and} \quad \mathrm{E}(\Delta\epsilon_{Ldjt}\Delta Z_{jt}) = 0$$

$$\text{Instruments}: \Delta Z_{jt} = \begin{pmatrix} \Delta\hat{S}_{Ljt}x_j^{reg} & \Delta\hat{S}_{Hjt}x_j^{reg} \\ \Delta\hat{S}_{Ljt}x_j^{unav} & \Delta\hat{S}_{Hjt}x_j^{unav} \end{pmatrix}$$

The moment conditions are jointly combined with identifying cities' supply curves and workers' labor supply to cities. Finally, they will be jointly estimated with a two-step GMM procedure.

4.1.3 Labor Supply

As specified above, the indirect utility for agent i of type k living in MSA j at time t can be written as

$$V_{ikjt} = \delta_{kjt} + \zeta_{ijt}$$

where

$$\begin{aligned} \delta_{kjt} = \Bigg[& \theta \ln(W_{kjt} - R_{jt}\bar{O}) + \\ & + (1-\theta)\left[\ln(1-\theta)\frac{W_{kjt}}{R_{jt}} + \bar{O})\right] + (1-\theta)\left[\ln((1-\theta)W_{kjt} - R_{jt}\bar{O})\right] + \\ & + \gamma^p \ln\left(H_{jt}/L_{jt}\right) + A_{kjt} \Bigg] \end{aligned}$$

The model does not rely on the agents' history and simplifies the estimation procedure by causing it to resemble a static framework. The estimation of the labor supply follows from the decision of the agents on where to live in each period. Because the utility component δ_{kjt} does not depend on individual worker characteristics, the estimates for each type k are

[28] To improve the estimation, I supplement the routinization shock with a "classic" Bartik instrument. This instrument increases the precision of the estimators.

precisely equal to the ln population of each demographic group observed living in the MSA. Therefore, this is a simplification to Berry et al. (2004). I take the difference in mean utility δ_{kjt} over time to get:

$$\Delta\delta_{kjt} = \theta \ln \frac{W_{kjt} - R_{jt}\bar{O}}{(W_{kjt-10} - R_{jt-10}\bar{O})} +$$
$$+ (1-\theta)\frac{\ln(1-\theta)\frac{W_{kjt}}{R_{jt}} + \bar{O}}{\ln(1-\theta)\frac{W_{kjt-10}}{R_{jt-10}} + \bar{O}} + (1-\theta)\frac{\ln((1-\theta)W_{kjt} - R_{jt}\bar{O})}{\ln((1-\theta)W_{kjt-10} - R_{jt-10}\bar{O})} +$$
$$+ \gamma^p \ln \Delta(H_{jt}/L_{jt}) + \Delta A_{kjt}$$

Identifying workers' preferences for wages, rent, non-traded local goods, housing, and amenities requires variation in these MSA characteristics that is uncorrelated with local unobservable amenities ΔA_{kjt}. This reasoning follows Diamond (2016). Specifically, I use SBTC shocks and their interaction with the characteristics of the supply elasticity. For the exclusion restriction to be satisfied, the set of instruments needs to be uncorrelated with unobserved exogenous changes in the MSA's local amenities. The key idea is that since national changes in industrial productivity drive SBTC shocks, these shocks are unrelated to changes in local exogenous amenities. These instruments can be supplemented with data to provide extra power in the identification process. Specifically, I obtain the share of household expenditure on non-tradable goods, θ, from the literature. I also estimate the model without using the externally calibrated data by relying only on the instruments for identification. Specifically, the moment restrictions are:

$$\mathrm{E}(\Delta A_{Hjt}\Delta Z_{jt}) = 0 \qquad \text{and} \qquad \mathrm{E}(\Delta A_{Ljt}\Delta Z_{jt}) = 0$$

$$\text{Instruments: } \Delta Z_{jt} = \begin{pmatrix} \Delta\hat{S}_{Ljt} & \Delta\hat{S}_{Hjt} \\ \Delta\hat{S}_{Ljt}x_j^{reg} & \Delta\hat{S}_{Hjt}x_j^{reg} \\ \Delta\hat{S}_{Ljt}x_j^{unav} & \Delta\hat{S}_{Hjt}x_j^{unav} \end{pmatrix}$$

All parameters are jointly estimated in a 2-stage GMM where standard errors are clustered at the MSA level and there are decade fixed effects to account for national changes. Further, I test whether the over-identification restrictions can be jointly satisfied.[29]

4.2 Migration Costs

By taking the differences in δ_{kjt}, migration costs $m_{k2}(j)$ are eliminated since they do not vary over time. Therefore, another strategy is needed to calibrate the migration costs. To do so, I rely on existing literature that has estimated migration costs using structural models. A famous work from Kennan and Walker (2011) provides estimates of large moving costs from one state to the other in the US but does not distinguish between high and less skilled workers. Notowidigdo (2011), instead, provides separate migration costs for highly and less skilled workers, closely related to what the migration costs in my settings look like. This makes his estimates applicable to my setting. Specifically, Notowidigdo (2011) uses an exponential function to estimate migration costs. The functional form he estimates is as follows:

$$m_{k2}(j) = \frac{\sigma^k exp(\beta^k x_j) - 1}{\beta^k}$$

where x_j relates to MSA characteristics such as population. This functional form is very flexible since, despite having only two parameters, it has advantageous curvature features as Notowidigdo (2011) discusses. Specifically, migration costs increase significantly when characteristics such as population are low and increase rather than at higher population levels. To check how sensitive my model is to the estimates of the migration costs, I run some sensitivity analysis. The results do change only mildly.

4.2.1 Estimation Results and Robustness

I use a GMM estimation procedure with data at the MSA level for 1940-2010 every 10 years and 14 industries. The results are reported in Table 8 where I run five model specifications to test the model's sensitivity. The main differences across the specifications are the endogenous productivity spillover of size and skill ratio and the endogenous amenity supply. The first specification only includes the endogenous spillover effect of skill. The second only includes the spillover effects on population size. The third specification adds the endogenous amenities but removes the spillover effects on population size. The fourth specification reports a "classic" model with no production spillover but only with endogenous amenities. Finally,

[29] To improve the precision of the estimates, I also add standard Bartik shocks in the instrumental set as in Diamond (2016).

the fifth and last specification reports the full model used for the rest of the analysis below. Overall, the results of the estimates are thus following the literature.

Panel A reports the estimates for the labor supply parameters. Specifically, the share of expenditure in housing, θ and the preferences for endogenous amenities γ^p. In columns (1) and column (2), the estimates of θ are between 0.618 and 0.608. This indicates that about 60% of the expenditures are on housing relative to the tradable good T. In columns (3)-(5), when we include the endogenous amenities, the estimates drop between 0.421 and 0.446. This suggests that the preference for housing shrinks when individuals assign a value to the local amenities. The second parameter of interest of the labor supply side is γ^p estimated in specifications (3)-(5). In the three specifications, the estimates are very similar. A 1% increase in the skill ratio increases the local highly and less skilled working population by 0.927% in column (5). This value is lower than that in Diamond (2016) and Albouy (2012). One explanation could be that my estimates relate to a longer period. These estimates show that workers generally prefer cities with higher wages, lower rents, and higher college shares.

Panel B, instead, reports the parameters for the labor demand such as the inverse of the elasticity of substitution ρ; the spillover effects of skill, γ^H and γ^L; the spillover effects of population size, ϕ^H and ϕ^L; the scale effects on SB^H and SB^L. Additionally, it also reports the estimate on γ^2, the spatial technology diffusion parameter. In column (1), in the model with spillover effect of skills, I estimate an elasticity of substitution of 2.5, which is the same as in Card (2009). This elasticity jumps to 3.9 when I also include the spillover effects on size. In column (3), where I remove the spillover effects on size but add the endogenous amenities, the estimate is 2.1, closer to column (1). In the model with no spillover effects, the estimates drop to 1.47. Finally, in column (5), where I estimate the entire model, the elasticity of substitution is 3.03. Overall, the estimates suggest that in a model with the spillover effects on production rather than the "classic" model, the elasticity of substitution between higher and less skilled workers increases. The estimates of γ^H in all the specifications are positive and statistically significant. In the specification of the model with no spillover effects of size (column (1) and column (3)), a 1% increase in the share of highly skilled workers raises their wages by 0.72%. Instead, in columns (2) and (5), which include spillover effects of size, a 1% increase in the share of highly skilled workers raises their wages by 0.545% and .528%, respectively. My estimates of γ^H are higher than the one in Diamond (2016) and Moretti (2004) that find an estimate of 0.322 and 0.16, respectively. This suggests that part of the positive effect of size is captured by skill composition. Overall, having a higher share of highly skilled workers increases highly skilled workers' wages by a non-negligible amount. The same cannot be told about the wages of less skilled workers. The estimates of γ^L are between 0.056 and 0.118, but they are not statistically significant in any of the specifications. The estimates of the spillover effects of size, ϕ^H for highly skilled workers are 0.271 and 0.253 in columns (2) and (5), respectively. This is equivalent to saying that in the full model, a 1% increase in the size of the city's workforce raises the highly skilled wages by 0.253%. This effect is smaller than the skill ratio effect but it is still non-negligible. For less skilled workers, the same doesn't hold. Baum-Snow and Pavan (2013) estimate that at least 23% of the overall increase in the variance of log hourly wages in the US from 1979 to 2007 is explained by the more rapid growth in the variance of log wages in larger locations relative to smaller locations. The estimates in columns (2) and (5) are around 0.210 and 0.211 but they are not statistically significant. Overall, the estimates of the production spillover suggest that being in a larger city and a more skilled city increases the wages of highly skilled workers but does not affect the wages of less skilled workers. The estimates also suggest that the spillover on the skill ratio is quantitatively more important than the size spillover. I also report the estimate for the coefficient for the SBTC measure. This estimate serves as a scale of the effect for the rest of the analysis. λ^H, the estimate on the highly skilled are slightly negative and close to 0. Instead, the estimates on λ^L are strictly negative and statistically significant ranging between -.160 and -.998. This suggests that routinization harmed the wages of the less skilled workers but not highly skilled workers.

Panel C reports the estimate of γ^2, which is the most critical parameter to regulate the degree of spatial technology diffusion. Except for specification (4), which does not have spillover effects, the estimates are between 0.934 and 0.998. In the full model, we can interpret the result as saying that technology diffuses at a rate of 4.9% every ten years. If we compare this estimate to Desmet et al. (2018), which uses a value of 0.99 per year, my estimates imply slightly lower technology diffusion.

4.2.2 Other Calibrated Parameters

To complete the calibration of the model and compute its equilibrium, I borrow the other parameters from the literature. These values are reported in Table 9. To include housing in the model with non-homothetic preferences, I also include a subsistence level of housing,

$\bar{O}$, from Ganong and Shoag (2017), which is set to match the Engel curve for housing. To complete the housing sector, I estimate a value for the elasticity of housing, μ. This elasticity is also borrowed from Ganong and Shoag (2017). I chose this elasticity to generate a one-to-one relationship between log prices and log per capita incomes to match the relationship from the data. The elasticity is equal to 0.4. This parameter decreases to 0.135 for the cities with higher regulations after 1980. The parameters of the migration cost function, which is exponential, are different for highly skilled and less skilled workers. I borrow these estimates from Notowidigdo (2011), which uses an identification strategy based on Bartik instruments. Given this functional form, it turns out that the migration costs are about 1.16, which is higher for less skilled workers than for highly skilled workers whose costs are equal to one. Another set of migration costs could have been estimated using the same approach as in Desmet et al. (2018). While Desmet et al. (2018) uses this procedure for one type of worker, the analysis could be extended to two types of workers.[30]

5 Model Simulation and Counterfactuals

In this section, I first provide more details on how I achieve the numerical computation of the equilibrium. Second, I show how the model matches the non-targeted moments in decline in β-convergence. The model correctly fits the reduction in spatial convergence for highly skilled workers. Third, I conduct a quantitative decomposition of each mechanism's effect on the decline in convergence. Fourth, I investigate whether the model matches other non-targeted moments, emphasizing the US secular migration of the last decades. I also compare important external moments such as "The Great Divergence" of skills, the secular decline in migration, and the increase in wage dispersion, among others. Fifth, I show how the increase in regional inequality fostered the trade-off between aggregate inequality and growth.

The estimation procedure obtains the values for all 10 model parameters, the initial productivity terms, and national measures of SBTC. Next, I compute the model's equilibrium by solving a system of equations for every period t that incorporates the productivity values from the previous period.

The model can be reduced to 46 equations, as shown in the appendix. The analysis

[30]Extending the migration cost algorithm is not the primary focus of this paper and, therefore, it is left for future work. The sensitivity analysis indicates that the migration costs do not change the non-targeted moments much.

includes 240 cities, so the iteration procedure contains 11,040 equations for each period t. The equilibrium conditions correspond to equations 7, 8, 12 and 13. Because of the large number of cities, the problem is highly dimensional. An extra complication to the model is the endogenous knowledge spillover effects that could induce the system of equations to explode. However, the estimates respect the restrictions imposed by the system and are stable. As a robustness test, I conduct a sensitivity analysis and check whether the parameter variation changes the results substantially and whether the system maintains regional convergence. More details about these conditions can be found in the Appendix section D.1.

5.1 Model vs. Data

In this section, I test how the model fits the data on regional convergence as shown in figure 1 and 2. Practically, I proceed in the following way:

1. I obtain the parameters estimates from the GMM estimation and recover ξ_{H0} and ξ_{L0} from inverting the model;

2. With the parameters in hand, I initialize the model for 1940 and a *national* average of S_{Ht} and S_{Lt};

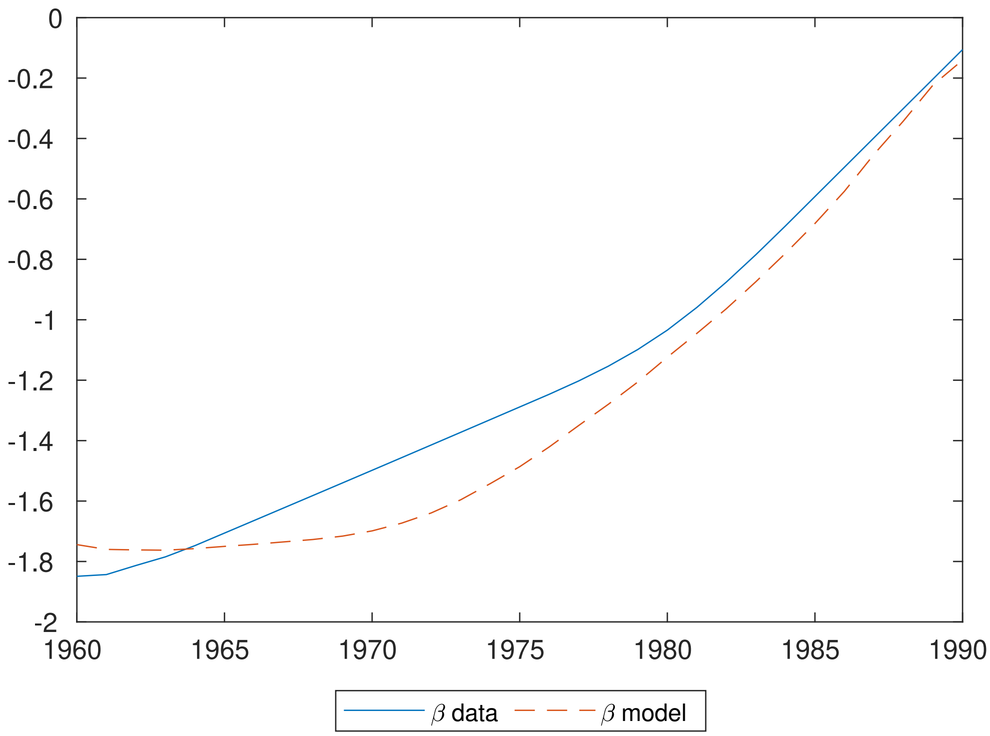
3. I solve the model forward for every 10-year until 2010;

4. With the solved model, I obtain values for high, less-skill wages, high and less skilled labor and prices in each location and run the same regression within my model as I did with the data in section 2. Specifically, with model-generated measures of average wages, wages for highly and less skilled workers since 1960, I estimate in the model the β, β^k-convergence using the specification 1 proposed in section 2, which follows from Baumol (1986).

In Figure 7, I plot the estimated β-convergence from the model and from the data to compare them. The x-axis of figure 7 report the initial year of the convergence equation 1, therefore, the analysis covers both the period since 1960. Overall, the match is satisfactory. The estimates from the data and the model differ only by 0.005% points.

The left (right) plot in figure 8 compares the $\beta^H(\beta^L)$-convergence rates over time both in the data and in the model. The estimates are very close over time. The model satisfactorily fits the regional convergence patterns in the non-targeted moment and the decline of convergence for the higher (less)-skill group.

Figure 7: Model Matching the Data on Regional Convergence



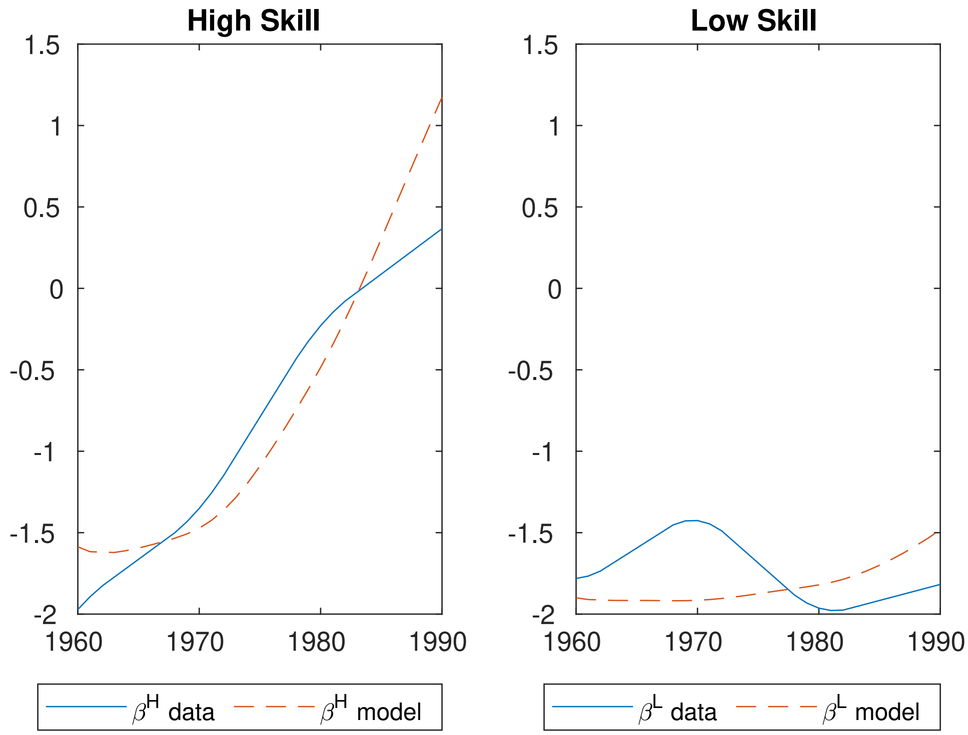
Note: This figure shows a rolling estimate of the β-convergence with a rolling window of 20 years. The solid line is the data for which we have observations every 10 years (that I smooth over time), while the dashed line is the estimate of the β-convergence from the model for which we can compute a yearly estimate.

5.2 Quantitative Decomposition

After ensuring that the model fits the data on regional convergence, I calculate several counterfactual scenarios for the β, β^H, and β^L convergence rates to assess the quantitative contributions of each of the model's mechanisms. Specifically, I proceed step-wise and sequentially "turn off" each model component that contributes to the decline in regional convergence over time.

My counterfactual of interest is comparing estimates of β, β^H and β^L over time in the baseline model with the estimates I obtain once I "turn off" the mechanisms after 1980. Table 1 reports the changes of the β, β^H and β^L estimates with 30-year rolling windows between the 1960-1990 and 1980-2010 in the full model and the counterfactuals. Each column reports

Figure 8: Model Matching the Data on High and Less Skilled Regional Convergence



Note: This figure on the left (right) shows a rolling estimate of the $\beta^H(\beta^L)$-convergence with a rolling window of 20 years. The solid line is the data for which I smooth the 20-year rolling estimate, while the dashed line is the estimate of the β-convergence from the model for which I compute a yearly estimate.

the estimates for a version of the model. Panel A shuts down the element from the full model at the time. Instead, panel B removes elements sequentially. A comparison between panel A and B tell us whether ordering matters. Column (1) reports the estimated for the full model. It suggests that the β estimate change by 100% but most of the change is due to the change in β^H and only mildly due to changes in β^L. Column (2) reports the estimates for the model without knowledge spillover forces. I set the knowledge spillover forces, γ^H, γ^L, ϕ^H, ϕ^L, to 0 starting in the year 1980. In this case, the β estimate would have dropped only by 17% mostly due to a drop in convergence in β^H while β^L would have even increased. In column (3) I report the estimates without SBTC, setting λ^H and λ^L to 0. The overall convergence would have decreased by 34%, primarily due to a decrease in β^H convergence. Finally, columns (4) and (5), respectively, show the results for the model without housing changes and the model without migration costs. Respectively, I set migration cost, m_{H2} and m_{L2}, to 0 after 1980 and housing elasticity η to be the same as in the previous period, and $\bar{O}$ to 0. In these two last cases, the β estimates change only mildly but are not very important quantitatively. Columns (1) and (2) in panel B are the same as in panel A. In column (3), the change in the β estimate would have been only 47% but it is mostly because there would have been a decrease of 74% in β^H. As in panel A, columns (4) and (5) only count marginally. The main takeaway of this decomposition exercise is that the interplay of knowledge spillover and SBTC is essential to explain the reversal of regional convergence for the highly skilled workers.

Table 1: Change in β, β^H and β^L estimates in the Model over Time

	Full	**No Agglom.**	**No SBTC**	**No Housing**	**No Migr. Cost**
Panel A: Singular Decomposition					
$\Delta\beta$	-100.37	-17.63	-34.28	-96.16	-97.50
$\Delta\beta^H$	-187.67	-76.63	-62.55	-183.03	-185.51
$\Delta\beta^L$	-23.52	35.55	-8.41	-20.30	-19.99
Panel B: Sequential Decomposition					
$\Delta\beta$	-100.37	-17.63	-47.13	-47.73	-46.35
$\Delta\beta^H$	-187.67	-76.63	-74.87	-76.68	-73.77
$\Delta\beta^L$	-23.52	35.55	-21.91	-21.64	-21.58

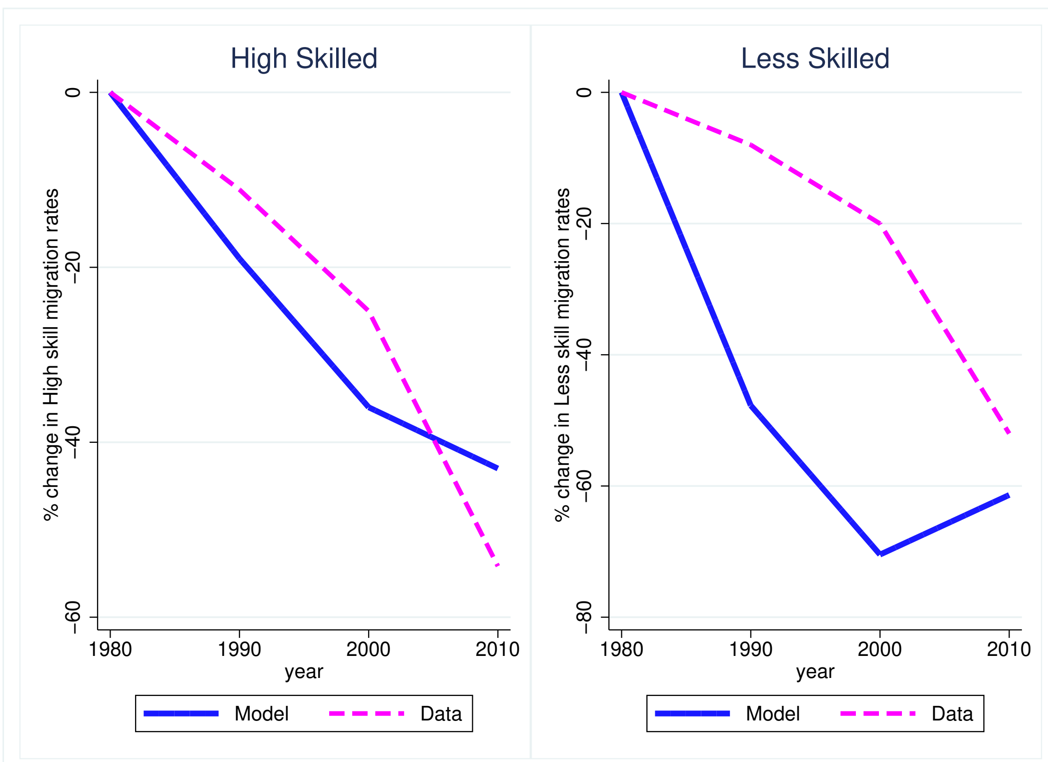
Note: This table reports the counterfactual β, β^H and β^L convergence in different settings of the model. Both in Panel A and B, the first row of the table shows the change in β overall between 1980 and 2010 in the model. The second(third) row has the results for the increase in β^H (β^L) in the model. In panel A, I remove the different channels from the model one at a time. In panel B, in each column, I vary from the full model to removing step-wise the elements of the model.

5.3 The Secular Decline in Gross Migration Flows over Time

The stark decline in geographic migration, documented by Molloy et al. (2014) is a significant structural change in the US in the last several years. In the early 1990s, about 3% of Americans moved between states each year. Nevertheless, today, that rate has fallen by half. Specifically, gross flows of people have declined by around 50% over the last 20 years. Schulhofer-Wohl and Kaplan (2017) provide and test a theory of reduction in the geographic specificity of occupations coupled with information technology and inexpensive travel. They find that these two mechanisms can explain at least half of the decline in gross migration since 1991.

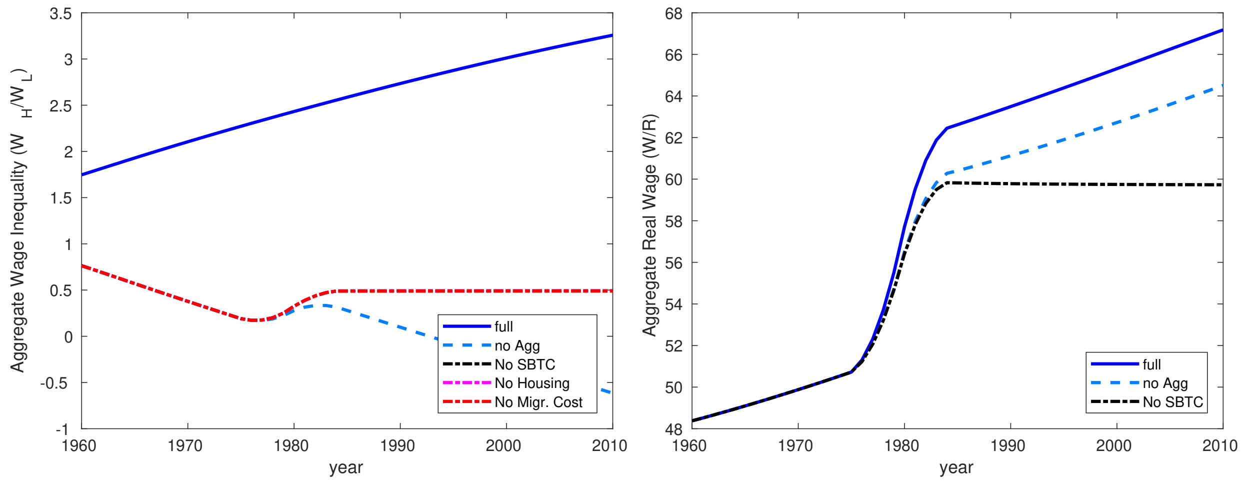
Can my framework help to rationalize the decline in gross migration flow? Figure 9 shows that the model matches the data for the trends in the migration rate over time. It shows that the decline speed is similar for the less skilled in model and data. Technological innovation increases the sorting of skilled workers into skilled cities. Once workers sort, their incentive to move will decrease since finding a city with similar wages will be harder. If the technological shock persists over time, this effect will become even more potent by decreasing migration further. For instance, suppose a highly skilled worker lived in San Francisco in the 1980s. When the technology shock arrives, the highly skilled worker would have less incentive to move because San Francisco would have the highest wages. Another highly skilled worker, who currently lives in Detroit, decides to move to San Francisco. Over time, the incentive to migrate decreases because the workers will have a better match in their current MSA. This is supported by the evidence that the variance of wages among cities went up over time, as shown in table 11.

Figure 9: Migration Rate Over Time



Note: This figure shows the evolution of the migration rates in changes for highly and less skilled workers over time for both the model and the data. On the left (right), I plot the high (less) skilled migration rates generated by the model with a blue solid line and those generated by the data with a red dashed line

Figure 10: Time Evolution of Aggregate Skill Premium and Real Wages



Note: This figure reports the evolution of aggregate wage inequality and aggregate real wage growth generated by the baseline model between 1960 and 2010, respectively. On the left (right) graph, the ratio between the national wages of high and less skill (national average yearly real wage growth) is plotted for the baseline (full) model in blue, for the model with no knowledge spillovers in light dashed blue, and with no SBTC in black small dashed, in magenta for no housing policy change and finally in red dashed or no migration costs.

5.4 A Trade-off Between Aggregate Inequality and Growth

We can use the model to quantify the nationally aggregate real wage growth predicted by the model by using the estimates of wages and prices at the local level. Then, we ask how much the national real wage growth would have been if the national SBTC shock had not happened and had not had an effect through the mechanism presented in this paper. The left panel in figure 10 shows the time evolution of skill premium. The model reproduces an increase in the national skill premium, as we see in the data with a jump around 1980. However, if knowledge spillover and SBTC had not been there, we would not have observed an increase in the skill premium. The right panel of figure 10 shows the time evolution of the national real wages. The model suggests that real wage growth would have been about .83% a year between 1960 and 2010. However, if SBTC had not happened, aggregate growth would have been only .51% a year in the same time frame. Therefore, if, on the one hand, SBTC induced more inequality both at the national and regional level, at the same time, it increased overall aggregate growth by the sorting mechanism of highly skilled workers to highly skilled cities.

Additional Moments. With data on wages and local prices generated by the model, I calculate the real wages in each city by dividing the nominal wage by the price index. In figure 13, I plot the evolution of the β estimate for real wages. Unfortunately, while historical data on local prices is minimal, this model allows a time series of prices back to 1940 by city. The slope of the decline reproduced by the model is similar to the one in the data as the left plot shows. The majority of the decline follows from the decline in the convergence of the highly skilled real wages. The real wage regional convergence for less skilled workers is around 2% a year. These findings suggest that the decline in regional convergence did not solely happen for nominal wages but also for real wages, which gives a better sense of the local purchasing power. It could have been the case that prices had adjusted across space such that the differences had shrunk. However, both data and the model suggest that it is not the case. Figure 12 shows the evolution of the variance of rents and prices across cities. For both sets of prices, the variance decreased before 1980, but the trend reverted around that time. So, despite the increase in price heterogeneity across cities, overall, it is still the case that prices are following the trends in wages.

6 Conclusions and Future Directions

In this paper, I show that the decline in regional convergence among MSAs that is observed after 1980 is primarily due to the decline in regional convergence among highly skilled workers, whereas the regional convergence among less skilled workers does not decline at all. Thus, any account of convergence and its decline must distinguish between skill groups. Motivated by this observation, I develop a quantitative spatial equilibrium model with technology diffusion to reconcile the reversal of regional convergence and other salient moments' changes in the regional data in the last 70 years and determine the aggregate growth and inequality implications of those. To the best of my knowledge, this paper is the first to point to the interaction of technology and space in the trade-off between inequality and growth. It is also the first to provide an explanation consistent with the secular migration decline.

Understanding what stopped income convergence across the US regions and increased income inequality for different skills levels might have important policy implications, especially for the regions that cannot grow like richer ones. Dealing with sustaining the growth in the richest MSAs and arresting the decline in poorer MSAs is a fundamental challenge for policymakers.

This paper plants the seeds for a broader research agenda. Specifically, how can we rationalize the regional inequality patterns across countries? The framework of this paper is flexible enough that it can be extended to perform several types of analysis, including a cross-within-country analysis. In recent work, we find that the decline in regional convergence is global feature happening for a large share of countries worldwide. In a nutshell, although poorer countries keep growing faster than rich countries, their growth rates are mainly driven by a few regions, leaving others behind (Chatterjee and Giannone, 2021). This result increases the pressure to deepen our understanding of the changing patterns of regional convergence at both the US and global levels.

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A Appendix

A.1 Definitions

MSA The geography unit is the metropolitan statistical area (MSA) which is "a region consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core." I rank the MSAs by share of highly skilled workers over less skilled workers. I define "highly skilled" MSAs as those with a concentration of highly skilled workers larger than the national average. The remainder are defined as "less skilled" MSAs. I refer to MSAs as cities in the first part of the paper for a less technical discussion. There are two main reasons why I pick MSAs over states or counties. First, MSAs are the smallest unit of analysis for which I can measure wages by skill group, number of highly and less skilled, rent by skill group back to 1940. Second, MSAs are consistent with the mechanism I want to explain in this paper. For instance, knowledge spillovers happens in San Francisco, not in California. The Census consistently includes 240 MSAs across all four decades from 1980 to 2010 but from 1940 to 1970. Following the definitions of metropolitan and micropolitan statistical areas, I try to homogenize the definitions of MSAs over time. However, this is not possible for all cites.[31]

Highly and Less skilled Workers I follow the previous work such as Acemoglu and Autor (2011) that use education as a proxy for skills. Then, I create two groups: "highly skilled" workers are the ones who have at least a 4-year bachelor's degree while "less skilled" workers are those whose education is less than that.

Composition Adjusted Wages I compute hourly wages at the individual level as annual wages divided by the number of hours worked in the last year. My estimation sample consists of individuals between 21 and 55 years of age who were employed at least 40 weeks per year and were not self-employed. However, for a robustness check, I relax the sample restrictions and, qualitatively, the results are unchanged. To conduct my analysis, I do a compositional adjustment to the wage measure reported in the Census data. This is possible thanks to the high dimensionality of the available data. I adjust the wages for age, sex,

[31] Most of my analyzes are also run at the state level, which eliminates any concern of time comparability. The results of the analysis that follow are very similar for states and MSAs. In future work, I plan to improve the time homogenization and also compare my results with those conducted at the level of commuting zones (Refer to section 4.1.1 for a definition of commuting zones).

nativity, and race. The changing composition of workers could explain some of the variation in nominal wages across MSAs over time. To account for this, I run the following regression on the Census and ACS data to create a composition adjusted wage measure (at least based on observables):

$$w_{ijt} = \gamma_t + \Gamma_t X_{it} + \epsilon_{ijt}$$

where w_{ijt} is the log of hourly wages of worker i living in MSA j at time t. The workers' characteristics are grouped in the variable that I call X_{it}. The X_{it} includes dummies for age (21-30,31-40,41-50,51-55), one dummy for gender, and a US-born dummy (whether the worker was US-born or not), and a series of race dummies with being white the omitted group. In my controls, I do not include the education status of the worker since I am going to compute the skill premium for college graduates versus less than college graduate workers.

Migration Rates I construct migration rates using data from March CPS. I take this data because they are better suited than the Census data for this task. Unfortunately, information on migration is quite sparse in the Census. My estimation sample consists of all individuals between 16 and 55 years of age for which I have observations for the years from 1962 to 2009 available in the March CPS, with the exclusion of 1972-1975 and 1977-1979. I compute the migration rate in two ways. First, I use information collected in the CPS. I code someone as a migrant if they migrated from a different MSA within the last year. I count all the workers that migrated by year, highly skilled (yes or no), and MSA weighted by their population shares in the MSA. Then, I divide this number by the population in the MSA. This procedure gives me the migration share for each MSA by education for each year in the sample available from CPS. To make sure that my approach is robust to other ways of computing the migration shares, I also calculate the number of workers living in an MSA minus the number of workers that were born in that MSA. The population in the MSA then divides everything. The results that I will show in the next section are robust to both approaches. To avoid potential biases because of the change in the composition of the labor force (besides education), I control for sex, age, race, and citizenship when I run regression 3.

A.2 Tables

Table 2: Regional Convergence Rates β

Panel A: Convergence Rate

	(1) 1940-1980	(2) 1980-2010	(3) 1980-2010-IV	(4) 1940-1980	(5) 1980-2010	(6) 1980-2010-IV
Log hourly wage, 1940	-0.0127***			-0.0159***		
	(-12.44)			(-20.54)		
Log hourly wage, 1980		-0.00122	0.00333		-0.00891**	-0.00164
		(-0.25)	(0.46)		(-2.91)	(-0.25)

Panel B: Convergence Rate by Skills: β^H and β^L

	1940-1980		1980-2010	
	No College	College	No College	College
Panel B.1				
Log hourly wage, 1940	-0.0123***	-0.0149***		
	(-14.32)	(-12.63)		
Log hourly wage, 1980			-0.0169***	0.000638
			(-9.70)	(0.30)
Panel B.2				
Log hourly wage, 1940	-0.0143***	-0.0216***		
	(-16.48)	(-21.30)		
Log hourly wage, 1980			-0.0200***	-0.00785***
			(-12.31)	(-3.87)
N	132	132	247	247

Note: This table reports the estimates of the β-convergence plotted in figures 1 and 2. In Panel A, I report the estimate of the β coefficient for the whole sample underlying figure 1. In column (1), there are β estimates for 1940-1980, and the observations are population-weighted. Column (2) has the same estimation but for 1980-2010. In columns (4) and (5), the estimations are not population-weighted. Columns (3)-(6) have the population-weighted(unweighted) estimates for the IV regression where wages in 1970 are the instrument. In Panel B.1, I report the estimates of the β-convergence corresponding to figure 2. In column (1), I report the estimate for less skilled workers between 1940 and 1980; in column (2), for college graduates in the same time period. In columns (3) and (4), the estimates are once again for the two groups, but for the 1980-2010 period. In Panel B.2, I report the same estimates as in Panel B.1, but the observations are not population-weighted. All the standard errors are robust. T-stats are in parenthesis. The ***, **, and * represent statistical significance at the 0.001, 0.01, and 0.05 levels respectively. The dependent variable in each regression is the annual average wage growth between the initial and final year reported at the top.

Table 3: Skill Premium by College Ratio of Cities over Time

	(1) Skill Premium		(2) Skill Premium	
College Ratio in 1940	-0.0631	(-0.43)	0.0775	(1.29)
College Ratio in 1950	-0.0475	(-0.51)	0.0199	(0.30)
College Ratio in 1970	-0.0505	(-0.39)	0.0132	(0.10)
College Ratio in 1980	-0.0824	(-1.08)	0.0308	(0.39)
College Ratio in 1990	-0.267***	(-3.85)	-0.138	(-1.50)
College Ratio in 2000	0.0621	(0.85)	0.186	(1.93)
College Ratio in 2010	0.217**	(2.99)	0.316***	(3.45)
Population	0.100***	(7.52)		
Time fixed effects	yes		yes	
N	1480		1480	

Note: This table reports the β_t coefficients' estimates for the OLS regression in equation 2. The dependent variable is the skill premium measured as the difference between the log wages of college graduates and less skilled workers. The only difference between column (1) and column (2) is that I control for population in column (1). The t-statistics are presented in parentheses. Observations are clustered at the state level. The ***, **, and * represent statistical significance at the 0.001, 0.01, and 0.05 levels respectively.

Table 4: Migration over Time by College Ratio of Cities by Year

	(1) Migrant		(2) Migrant	
Migrant				
Coll. Ratio*High Skill in 1964	0.0275	(1.07)	0.0136	(0.51)
Coll. Ratio*High Skill in 1965	0.0744***	(4.63)	0.0589***	(3.54)
Coll. Ratio*High Skill in 1966	0.0590***	(3.45)	0.0481**	(3.02)
Coll. Ratio*High Skill in 1967	0.102***	(5.35)	0.0926***	(5.25)
Coll. Ratio*High Skill in 1968	0.0997***	(5.41)	0.0920***	(4.87)
Coll. Ratio*High Skill in 1969	0.0918***	(3.32)	0.0799**	(2.99)
Coll. Ratio*High Skill in 1970	0.0697***	(5.61)	0.0630***	(4.81)
Coll. Ratio*High Skill in 1971	0.0886***	(5.53)	0.0770***	(4.66)
Coll. Ratio*High Skill in 1976	0.0398	(1.38)	0.0238	(0.81)
Coll. Ratio*High Skill in 1980	0.221***	(3.90)	0.212***	(3.76)
Coll. Ratio*High Skill in 1981	0.0983***	(3.54)	0.0882**	(3.07)
Coll. Ratio*High Skill in 1982	0.134**	(3.27)	0.125**	(3.00)
Coll. Ratio*High Skill in 1983	0.0779***	(5.35)	0.0728***	(4.83)
Coll. Ratio*High Skill in 1984	0.0951***	(6.03)	0.0898***	(5.10)
Coll. Ratio*High Skill in 1985	0.193***	(3.37)	0.193***	(3.31)
Coll. Ratio*High Skill in 1986	0.0897***	(6.06)	0.0854***	(5.73)
Coll. Ratio*High Skill in 1987	0.0708**	(2.85)	0.0719**	(2.96)
Coll. Ratio*High Skill in 1988	0.0688***	(3.52)	0.0693***	(3.62)
Coll. Ratio*High Skill in 1989	0.0791***	(4.23)	0.0798***	(4.29)
Coll. Ratio*High Skill in 1990	0.0795***	(4.94)	0.0813***	(5.16)
Coll. Ratio*High Skill in 1991	0.0601**	(2.70)	0.0644**	(2.82)
Coll. Ratio*High Skill in 1992	0.118***	(4.86)	0.105***	(4.33)
Coll. Ratio*High Skill in 1993	0.107***	(4.02)	0.0942***	(3.53)
Coll. Ratio*High Skill in 1994	0.115***	(5.29)	0.108***	(4.89)
Coll. Ratio*High Skill in 1995	0.0136	(0.54)	0.00593	(0.23)
Coll. Ratio*High Skill in 1996	0.123***	(6.07)	0.108***	(5.22)
Coll. Ratio*High Skill in 1997	0.0971***	(4.63)	0.0857***	(4.02)
Coll. Ratio*High Skill in 1998	0.133***	(6.66)	0.120***	(5.77)
Coll. Ratio*High Skill in 1999	0.103***	(4.69)	0.0939***	(4.21)
Coll. Ratio*High Skill in 2000	0.122***	(3.40)	0.112**	(2.97)
Coll. Ratio*High Skill in 2001	0.0817**	(2.87)	0.0757**	(2.60)
Coll. Ratio*High Skill in 2002	0.124***	(4.62)	0.116***	(4.35)
Coll. Ratio*High Skill in 2003	0.0828**	(2.62)	0.0771*	(2.38)
Coll. Ratio*High Skill in 2004	0.0927***	(3.39)	0.0863**	(3.02)
Coll. Ratio*High Skill in 2005	0.0792**	(3.22)	0.0714**	(2.87)
Coll. Ratio*High Skill in 2006	0.0974***	(3.98)	0.0915***	(3.70)
Coll. Ratio*High Skill in 2007	0.0986***	(4.23)	0.0928***	(3.95)
Coll. Ratio*High Skill in 2008	0.115***	(5.28)	0.108***	(4.87)
Time fixed effects	yes		yes	
Controls	No		yes	
N	1411802		1411802	

Note: This table reports the marginal effects for every year for the probit regressions. The dependent variable is the decision on whether to move or not. Standard errors are presented in parentheses and are clustered at the state-level. The ***, **, and * represent statistical significance at the 0.001, 0.01, and 0.05 levels respectively. Column (2) is identical to column (1), except that column (1) controls for the population.

Table 5: $\Delta\frac{H}{L}$ vs. Initial $\frac{H}{L}$ in the Data

	(1) 1940-1950	(2) 1950-1970	(3) 1970-1980	(4) 1980-1990	(5) 1990-2000	(6) 2000-2010
Panel A						
$\frac{H}{L}$	-0.218*	-0.439***	0.0355	-0.00158	0.0708***	0.0401*
	(0.115)	(0.0887)	(0.0587)	(0.0305)	(0.0238)	(0.0218)

	1950-1970	1950-1980	1970-1990	1980-2000	1990-2010
Panel B					
$\frac{H}{L}$	0.240**	-0.320***	0.0970	0.0770**	0.0797**
	(0.117)	(0.0963)	(0.0808)	(0.0390)	(0.0386)
N	103	143	119	247	238

Note: Panel A shows the estimates of running the initial $\frac{H}{L}$ on the growth over 10 years, $\Delta\frac{H}{L}$ as in specification 4. Panel B replicates the same analysis as Panel A for the growth over 20 years, $\Delta\frac{H}{L}$. Standard errors are in brackets. The ***, **, and * represent statistical significance at the 0.001, 0.01, and 0.05 levels respectively.

Table 6: First-Stage Estimates of Models for Routine Occupation Share Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dep. Variable S_{Hjt}						
$\Delta\hat{S}_{Hjt}$	3.046***	3.643***	2.852***	4.418***	3.062***	3.043***
	(0.620)	(1.024)	(0.632)	(1.118)	(0.719)	(0.737)
F	24.12	12.65	20.34	15.63	18.14	17.06
Panel B: Dep. Variable S_{Ljt}						
$\Delta\hat{S}_{Ljt}$	1.021***	0.891**	0.850***	2.483***	2.535***	2.511***
	(0.341)	(0.344)	(0.285)	(0.531)	(0.527)	(0.591)
F	8.975	6.709	8.891	21.86	23.15	18.06
N	144	119	270	249	283	283

Note: This table reports the first-stage estimates between the instrumental variable and the measure of skill bias. Standard errors are in brackets. In column (1), I run the regression for 1950 and in column (2)-(6) for 1970-2010. The sample does not contain 1960. In panel A, I report the results for highly skilled workers and in panel B for less skilled workers. The ***, **, and * represent statistical significance at the 0.001, 0.005, and 0.01 levels respectively.

Table 7: Description of industries used for estimation

Sector	Description
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)

Note: This table lists the industries used for the estimation and the calibration of the model and for the construction of the $\Delta\tilde{S}_H$ and $\Delta\tilde{S}_L$ measures. The division of the industries resembles the one from the CENSUS as 2-digit NAICS.

Table 8: Model Estimates for 1940-2010

		(1)	(2)	(3)	(4)	(5)
A. Labor Supply						
θ	Share of Housing	0.618***	0.608***	0.431***	0.446***	0.421***
		(0.102)	(0.100)	(0.117)	(0.112)	(0.116)
γ^p	Elast. w.r. t. to $\frac{H}{L}$			0.914***	0.940***	0.927***
				(0.119)	(0.113)	(0.122)
B. Labor Demand						
ρ	$\frac{1}{1-\rho}$=elast. of substitution	0.603***	0.748***	0.526***	0.319*	0.670***
		(0.226)	(0.183)	(0.165)	(0.166)	(0.194)
γ^H	Wage Elast. w.r.t. $\frac{H}{L}$ for H	0.722***	0.545*	0.723***		0.528**
		(0.280)	(0.280)	(0.252)		(0.259)
γ^L	Wage Elast. w.r.t. $\frac{H}{L}$ for L	0.073	0.056	0.118		0.113
		(0.245)	(0.262)	(0.217)		(0.223)
ϕ^H	Wage Elast. w.r.t. $(H+L)$ for H		0.271***			0.253***
			(0.080)			(0.079)
ϕ^L	Wage Elast. w.r.t. $(H+L)$ for L		0.210			0.211
			(0.133)			(0.141)
λ^H	Wage Elast. w.r.t S^H for H	-0.096	-0.048	-0.083	0.072	-0.067
		(0.109)	(0.128)	(0.105)	(0.123)	(0.113)
λ^L	Wage Elast. w.r.t S^H for L	-0.237**	-0.160	-0.228*	-0.998***	-0.160
		(0.116)	(0.143)	(0.128)	(0.236)	(0.150)
A. Diffusion						
γ^2	Tech. Diffusion	0.998***	0.934***	0.997***	1.190***	0.951***
		(0.051)	(0.067)	(0.051)	(0.035)	(0.064)
Observations		705	705	705	705	705

Note: This table reports the moments and the estimates of the model. The ***, **, and * represent statistical significance at the 0.001, 0.005, and 0.01 levels respectively.

Table 9: Externally calibrated Parameters

Parameter	Value	Literature
Subsistence level of Housing: $\bar{O}$	0.25	Ganong and Shoag (2017)
Elasticity of Supply Housing: μ	0.4	Ganong and Shoag (2017)
Migration costs: σ^L and β^L	-.065 and -.861	Notowidigdo (2011)
Migration costs: σ^H and β^H	-.066 and -1.044	Notowidigdo (2011)
Share of each Intermediate: α	0.51	Burstein et al. (2017)

Note: This table reports the parameters calibrated externally from existing literature, the value and the reference to the papers.

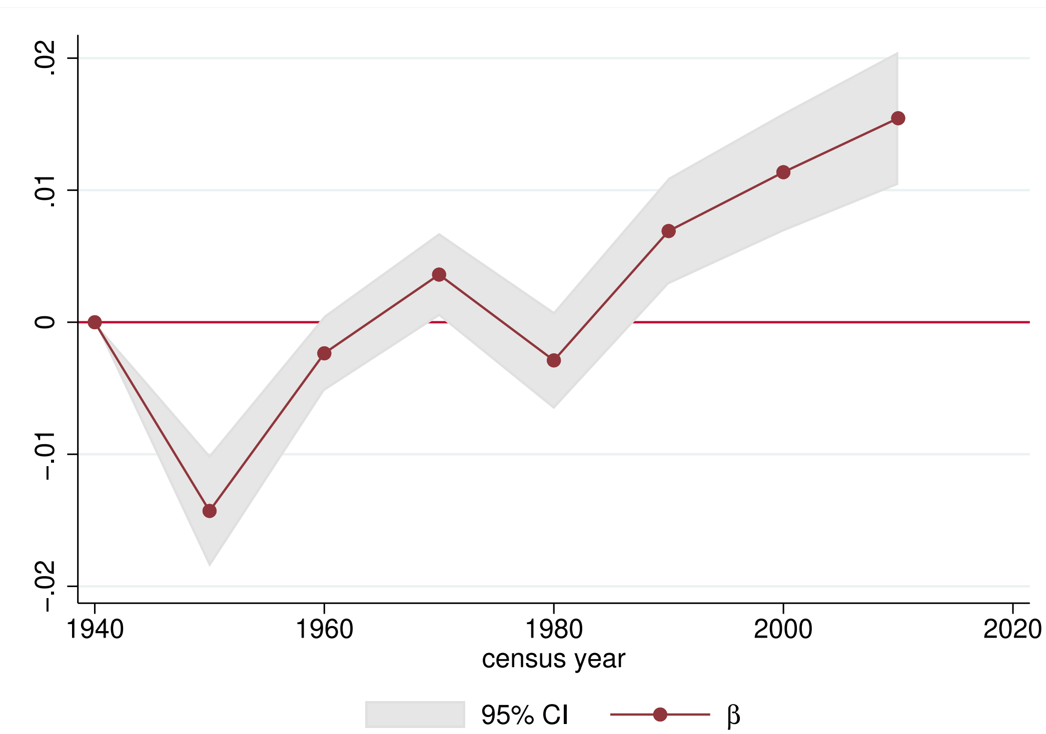
Table 10: $\Delta \frac{H}{L}$ vs. Initial $\frac{H}{L}$ in the Model

	(1) 1940-1950	(2) 1950-1960	(3) 1960-1970	(4) 1970-1980	(5) 1980-1990	(6) 1990-2000	(7) 2000-2010
$\frac{H}{L}$	-0.245***	-0.244***	-0.244***	-0.212***	0.332***	0.170***	0.0826***
	(0.00248)	(0.00259)	(0.00271)	(0.00861)	(0.0289)	(0.00983)	(0.00493)

Note: This table reports the estimates of β^{HL} convergence over time of regression 4 estimated with data generated in the baseline model. Column (1) shows the estimates of running the initial $\frac{H}{L}$ in 1940 on the growth over the 30 years, $\Delta \frac{H}{L}$ between 1940 and 1970. Columns from (2) to (7) show the estimates of running the initial $\frac{H}{L}$ on the growth over 20 years for each period from 1960-1980 until 1990-2010.

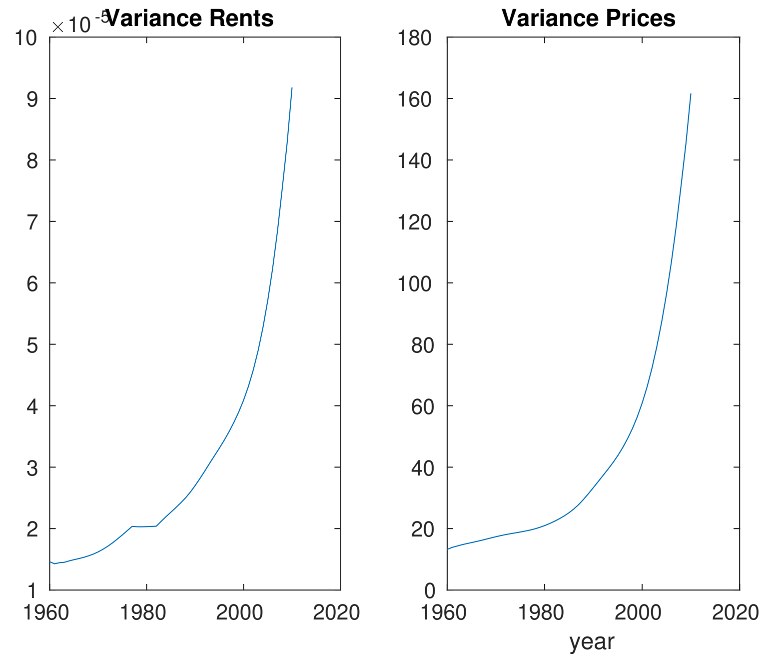
A.3 Figures

Figure 11: Skill Premium by MSA Population Levels



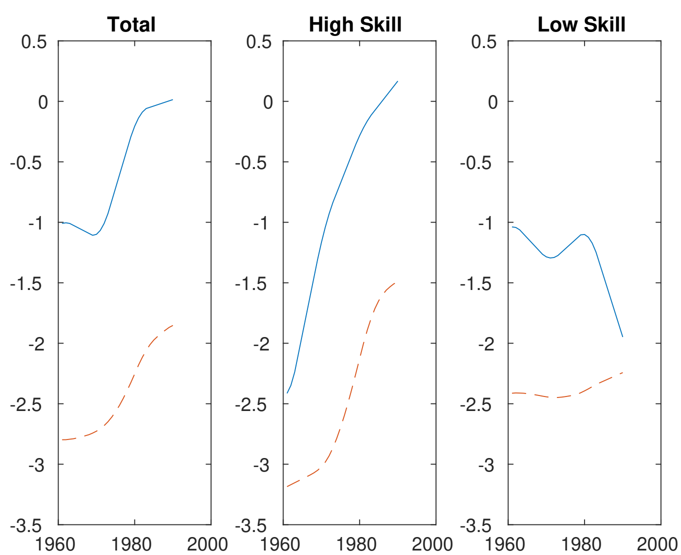
Note: This figure plots the estimate of the coefficient β for the regression 2. On the horizontal axis, I have the decades from 1940 to 2010, while on the vertical axis, I have the estimate of the coefficient β for each decade from 1940 to 2010. Moreover, there is a line starting at zero on the vertical axis.

Figure 12: Time Evolution of Rents and Prices Variance



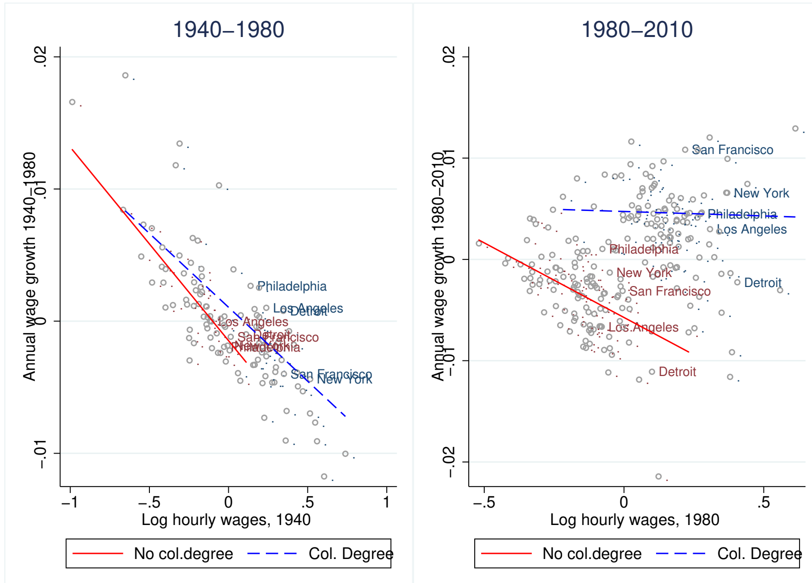
Note: This figure shows the estimated evolution of the variance of rents on the left and prices on the right generated by the baseline model between 1960 and 2010.

Figure 13: Model Matching Data on Real Wage Regional Convergence



Note: This figure on the left (center)(right) shows a rolling estimate of the $\beta(\beta^H)(\beta^L)$-convergence with a rolling window of 20 years. The solid line is the data for which I smooth the 20-year rolling estimate, while the dashed line is the estimate of the β-convergence from the model for which I compute a yearly estimate.

Figure 14: Regional Convergence across MSAs before and after 1980 by Skill Group - Low housing elasticity states



Note: This figure shows two scatter plots of log wages by MSA in the initial year against the annual average growth of wages in the final year by skill type (highly skilled and less skilled workers) in cities that are in states with low housing elasticities. Specifically, on the left-hand side (right-hand side), I plot the demeaned log wages in 1940 (1980) by MSA against the annual average growth of wages between 1940 (1980) and 1980 (2010) by skill type (highly skilled and less skilled workers). The line in each graph represents a weighted regression line from the bi-variate regression.

A.4 Equilibrium and Discussion of the Assumptions

I define the dynamic competitive equilibrium of this model as follows:

Definition The equilibrium consists of a set of allocations $\{\{L_{djt},\, H_{djt}\}_{d=1}^{D}\}_{j=1}^{J}$ and a set of prices $\{\{P_{djt}\}_{d=1}^{D},\, R_{jt}\}_{j=1}^{J}$, wages $\{W_{Hjt}, W_{Ljt}\}_{j=1}^{J}$, such that given $\{\{\xi_{Ldj0},\, \xi_{Hdj0}\}_{d=1}^{D}\}_{j=1}^{J}$, $\{\{A_{Ljt},\, A_{Hjt}\}_{t=1}^{T}\}_{j=1}^{J}$, a set of parameters normalizing $P_{jt} = P_t = 1$ and $\sum_j (L_{jt} + H_{jt}) = 1$ in each time period t:

1. Given migration costs and idiosyncratic preferences, workers choose their location and consumption to maximize the utility satisfying equations 7, 8 and 9;

2. Firms maximize profits such that equations 12, 13 hold;

3. There is free entry for firms into the tradable sector such that $\pi = 0$;

4. Labor markets clear such that 7 and 8 hold;

5. Housing markets clear such that the demand of equation 15 is equal to the supply in equation 14:

$$R^{\mu}_{jt} = H_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Hjt}}{R_{jt}}\right] + L_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Ljt}}{R_{jt}}\right]$$

6. Total labor supplies are the sum of labor demanded in each intermediate such that

$$L_{jt} = \sum_{d=1}^{D} L_{djt} \qquad \text{and} \qquad H_{jt} = \sum_{d=1}^{D} H_{djt}$$

7. Technology evolves according to 11.

A.5 Existence and Uniqueness

Because of the endogenous productivity channels, this model might allow for multiple equilibria. These equilibria might happen if the knowledge spillovers are strong enough that the workers agglomerate all together in the same locations. To avoid this problem, I must impose restrictions on the production function parameters such that the knowledge spillovers are compensated for by dispersion forces. Allen and Arkolakis (2014) prove the existence and uniqueness of equilibrium in a static model with knowledge spillovers. Desmet et al. (2018) extend the proof to a dynamic model with only one type of agent. Both studies find that the strength of knowledge spillovers and dispersion externalities is crucial in guaranteeing the uniqueness and existence of spatial equilibrium. Unfortunately, the proofs of Allen and Arkolakis (2014) and Desmet et al. (2018) do not apply and cannot be extended to a case with heterogeneous labor aggregated in a CES fashion. Therefore, I proceed with solving the model for several sets of knowledge spillovers' parameters. These simulations show that the equilibrium is unique for the range of values of the knowledge spillover parameters and starts at very different initial levels. 4.1.

A.6 Discussion

Spatial Technology diffusion: Introducing this persistent productivity formulation with spatial diffusion generates convergence directly in the model, as in Barro and Sala-i Martin (1997), Caselli and Coleman (2001), and Desmet et al. (2018). Unlike a model that compares steady-states, convergence generated with a diffusion mechanism is better suited to the explanation in Barro and Sala-i Martin (1997) that argues that a neoclassical model with friction to capital mobility reproduces the convergence rates across countries and within the US. Caselli and Coleman (2001), instead, build a dynamic model in which total factor productivity (TFP) grows faster in agriculture, there are declining costs of acquiring human capital, and farm goods are a necessary good. These two models introduce convergence through two different mechanisms. Also, Caliendo (2011) and Bajona and Kehoe (2010) show that convergence can be proven in a dynamic Hecksher-Ohlin model. The convergence produced by an idea-diffusion process is closer to a declining cost of human capital or physical capital mobility. As formerly mentioned and shown in appendix E, the model without spatial technology diffusion is not able to replicate the main results.

SBTC: I do model SBTC as an exogenous shock to productivity that differs between the two skill groups. Katz and Murphy (1992) in their seminal work think of SBTC as a residual in productivity that changed over time. In this paper, I use the routinization measures, similar to the ones developed in Autor and Dorn (2013) to distinguish technological innovation from other residuals. Autor and Dorn (2013) use similar measures to capture polarization instead. The literature on SBTC has used several approaches to model it. Krusell et al. (2000) and Beaudry et al. (2010) model it as a capital-labor relationship. In Appendix C.5, I show that a model with physical capital and a decrease in the price of computers would not reproduce some features that are present in the current setting and that are key in the data. On top of that, the current setting incorporates industrial composition while not accounting for physical capital. While physical capital is important in the production of goods, it is not crucial for this paper. But, how would physical capital bias the results of this model? This answer depends on capital mobility and the complementarity or substitutability of capital with highly skilled labor. If physical capital is freely tradable such that rental rates are equalized across locations, then the model would draw the same conclusions as it does without capital.

Parameters' set: On the production side, the spillover's parameters could be more parsimonious and reduced to three rather than four. However, the current formulation allows a closer connection to existing estimates and determines the elasticities for both groups of workers and the skill ratio and the size effect. Qualitatively, no pivotal moment would be affected. In the housing market, there are two parameters. These serve to match the Stone-Geary preferences as in Ganong and Shoag (2017). Even in the absence of the housing mechanism, the model would reproduce key moments of the data, as shown later.

B Other Results of the Model

This section reports results comparing model and data on trends in wage dispersion and the "Great Divergence" of skills.

B.1 Wage Dispersion Increase Over Time

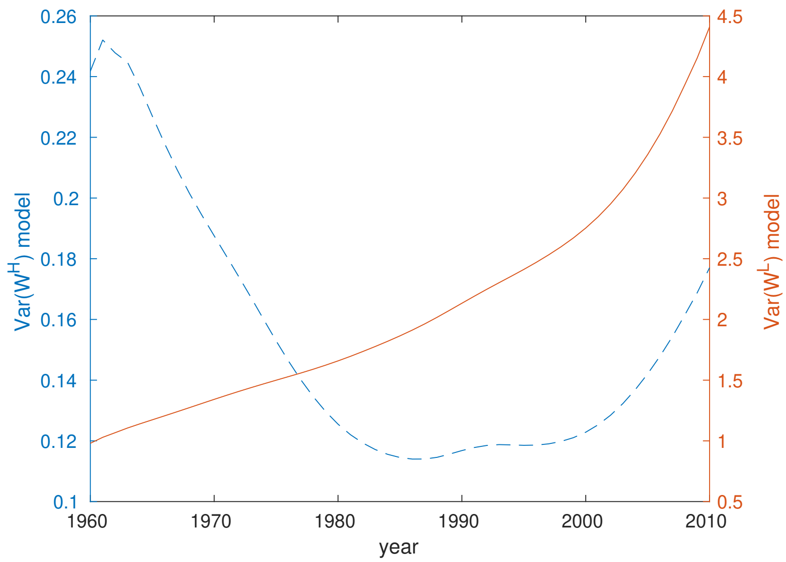
Hsieh and Moretti (2015) show that wage dispersion across US cities increased substantially between 1964 and 2009. As in table 11, the model indicates that wage dispersion in the US has increased dramatically over the last 30 years following the findings in Hsieh and Moretti (2015). My model supplements this finding by predicting differences in wage dispersion between highly skilled and less skilled workers. Figure 15 suggests that the variance in the highly skilled wages was decreasing until 1980 when it started increasing. Instead, the variance of wages for the less skilled group was constantly increasing over time. As shown in table 11, the variance between 1964 and 2009 increased by 213%. It only increased 5% for the highly skilled while it increased by 222% for the less skilled. I run some counterfactual analysis by shutting down knowledge spillovers as in section 5.2 sequentially and I find that if the knowledge spillover economies had been set to 0, then, the increase in wage variance would have gone up only by 11.43% for the whole group, but it would have decreased for highly skilled as shown in column (2) and mildly increased for the low-skilled workers. In column (3), I also shut down the SBTC finding that variance would have decreased both for the highly and less skilled workers if one of these forces had been in place. Columns (4) and (5), respectively, housing costs and migration, suggest that the contribution to variance in wages is close to null, quantitatively.

Table 11: Change in Variance of High and Less Skill Model over Time in the Model

	Full	**No Agglom.**	**No SBTC**	**No Housing**	**No Migr. Cost**
$\Delta Var(W)$	213.21	11.43	-59.50	-59.41	-59.44
$\Delta Var(W_H)$	5.10	-63.41	-47.91	-47.29	-47.88
$\Delta Var(W_L)$	222.84	21.46	-61.21	-61.19	-61.16

Note: This table reports the variance in wages by skills over time in the model. The first row of the table shows the results for the increase in wage dispersion overall between 1964 and 2009 in the model. The second (third) row describes the results for the increase in wage variance for highly and lees skilled workers between 1964 and 2009 in the model. Each column reports a step-wise variation from the baseline model.

Figure 15: Variance of High and Less Skill Model over Time

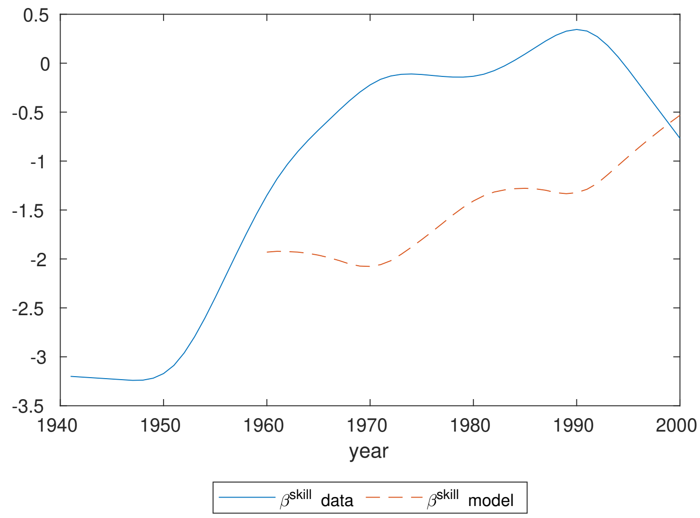


Note: This figure reports the evolution over time of the variance of high and less skilled wages across space generated by the baseline model. The blue dashed (red solid) line reports the variance of the high (less) skilled workers, respectively.

B.2 The "Great Convergence and the "Great Divergence" of Skills over Time

Using model-generated data, I estimate specification 4 and compare the outcomes in the model and the data in figure 16. The model reproduces shows a β^{HL} convergence rate going from -2.5% in 1970 to -.5% in 2010. Overall, β^{HL} declines much faster despite the last period, where it coincides with the model. Overall, this finding suggests that the model is consistent with this other non-targeted moment, which means that it reproduces features of the wage data, such as the decline in cross-MSA wage convergence, and features of employment data such as the divergence in the skill ratio. In table 10, when I compare the 10-year rolling window estimates over time, the coefficients slowly move from -.245 in 1940-1950 to 0.0826 in 2000-2010, switching signs in 1980-1990.

Figure 16: The “Great Divergence” in Skills: Data vs. Model



Note: This figure shows the evolution of the estimates of β_t^{HL} in equation 4 both in the data and in the model.

C Other Potential Explanations

Several potential explanations are complementary to the SBTC and knowledge spillovers' hypothesis. In this section, I explore the changes in policy such as housing, unionization and *Right to Work Laws*. I also discuss and show evidence about international trade together with the industry's composition, the firms' decisions on location, capital-skill complementarity and structural transformation.

C.1 Housing Regulation

Ganong and Shoag (2017) provide an explanation based on housing prices that suggests that the US states where housing prices increased the most are also the ones where migration declined. Hence, because migration increases convergence, the decline in migration to this area, which is also the richest, also decreased the income convergence rate. As suggested in their paper, the housing prices and SBTC could be complementary. For this reason, to decide how to disentangle them, I add a housing sector to the model to compare the housing effects with my key mechanisms.

Additionally, I conduct an empirical test that shows that even in the areas where the housing restrictions are high, there is a great difference in the convergence rate of wages for the highly skilled and the less skilled groups. I construct figure 2 for the MSAs in states where the housing prices went up dramatically because of housing regulations. Figure 14 shows that the effect of regulations on the decline in income convergence looks quite similar to the one without any restriction. Thus, I can conclude that there is room also for the SBTC in the group of states where housing prices are high.

C.2 Structural Transformation Towards IT Service and Communication

Another potential and complementary explanation is that technological innovation might have caused a sectoral rather than a skill-biased effect. Such an effect would cause productivity increases in highly innovative industries such as IT service and communication. Therefore, cities with a higher concentration of creative industries benefit more from technological change. To control the IT sector's importance, I estimate conditional convergence in wages between 1980 and 2010.[32] The results reported in Table 12 show that unconditional regional convergence is not statistically significant in column A. However, when I add a control for the IT sector in column B, the coefficient for wages in 1980 becomes positive and statistically significant. In column C, I add control for the highly skilled ratio, and the coefficient on initial wages in 1980 increases in magnitude and becomes negative. This evidence shows that adding sectoral differences in technological intensity does not explain regional convergence, if anything, it would increase divergence. The framework developed above takes into account these sectoral differences by including highly skilled and less skilled sectors as defined in table 7.

In addition to sectoral innovation shifts, changes in firms' relocation decisions over time can reduce regional convergence. More skilled firms might begin to move to richer places but then reverse their decision and move to poorer cities to take advantage of lower costs. To investigate whether firms' location decisions change over time requires firm-level data. Faberman and Freedman (2016) use longitudinal establishment data for the US during the years 1992-1997. They do not find that spillover is important for firms' decisions to locate in urban areas rather than other areas. Unfortunately, the data on the firms' locations back to 1940 are not available. In this regard, I use publicly available data at the industry level

[32] I define the IT sector by looking at the codes of the IND1990 variable in the IPUMS data set and select industries that are more technology-oriented.

to test whether more skilled occupations have become increasingly concentrated in more skilled cities over time. If this is the case, it might mean that in addition to the sorting of highly skilled workers into highly skilled cities, there is also sorting of highly skilled firms into highly skilled cities. To test this hypothesis empirically, I run the following regression to obtain the marginal effects by decade

$$\text{Skill concentration}_{kjt} = \alpha + \sum_{t=1950}^{T} \beta_t \left(\frac{H_{jt}}{L_{jt}}\right) + \phi_t + \phi_j + \epsilon_{kjt}$$

where k is the industry, j is the MSA, and t is time. The ϕ_t are time fixed effects, and ϕ_j are MSA fixed effects. I build the measure of "Skill concentration" by calculating the ratio between the number of skilled workers over the number of total workers that are in industry k in location j at time t. This hypothesis is confirmed in the data. In figure 17, I plot the coefficient β_t over time. The figure shows that a more skill-concentrated MSA becomes more strongly correlated with skill concentration at the industry level. This concentration is evidence of sorting not just workers but also industries and thus firms.

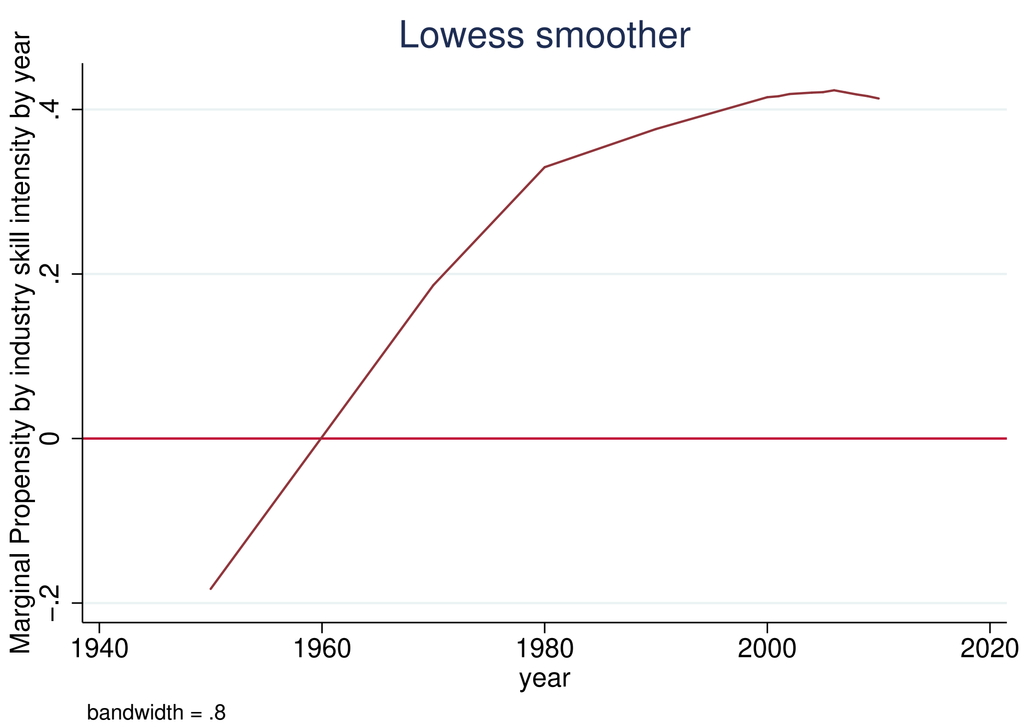
C.3 Right to Work Laws and Unions

In Southern and Western US, 26 states have passed *Right to Work Laws* since 1940. These laws permit workers to work without having to join a union. The *Right to Work Laws* might have a spatial effect of increasing the wages of less skilled workers in the states where they were implemented. Holmes (1998) shows that state policies play a role in the location of an industry. However, only 26 states have adopted right-to-work laws and figure 18 shows that the majority of the states passed these laws in the 1950s and 1960s, long before the secular decline in regional convergence. Besides the *Right to Work Laws*, union membership has gone up substantially in the US, and this growth might have directly affected the regional convergence rate. To account for this growth, I use data on unions from the CPS survey aggregated at the state level starting in 1990. Table 13 reports the estimates of regional convergence's regression at the state level between 1990 and 2010. I find that controlling for the presence of unions does not increase the β estimates. If anything, it decreases it.

C.4 International Trade

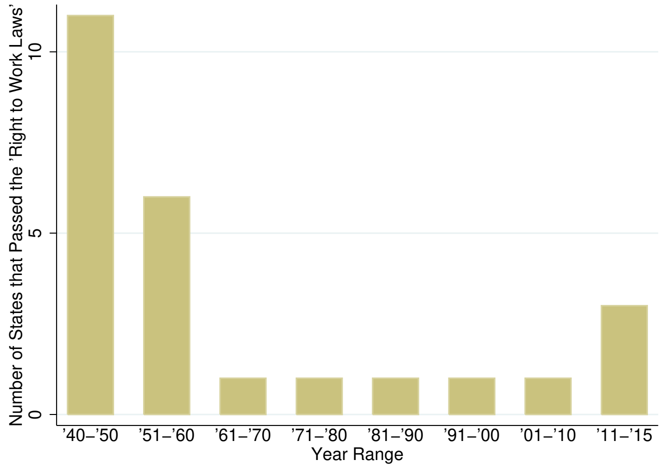
Besides SBTC, there is evidence that international trade affects the increase in the skill premium at the national level (Feenstra and Hanson 1999). Consequently, this trade might also affect the slowdown in regional convergence. However, Feenstra and Hanson (1999) finds that there is no prominent effect of international trade, such as outsourcing, on the skill premium. Instead, Autor et al. (2015) find that the increase in the import penetration from China affected employment rates in the commuting zones where the penetration from China was higher. However, outsourcing had modest effects on the skill premium and imports from China. Therefore, while this demand might also be relevant, the timeline and the magnitude of the effect do not explain the substantial slowdown in the regional convergence of wages. However, I do run the regional convergence regression at the state level while controlling for the import penetration from China as in Autor et al. (2015). The results show that controlling for the trade shock does not affect the speed at which wages converge.

Figure 17: Industry Sorting over time



Note: This figure plots the estimated effect of skill concentration at the MSA level and at the industry level. The line is computed using the estimates of the skill ratio at the MSA level (β), using specification C.2.

Figure 18: Right To Work Laws



Note: This histogram plots the number of states that passed the "Right to Work Laws" by decade starting with the 1940s.

Table 12: β Convergence Rates by Skills and IT

	(1) A	(2) B	(3) C
Log hourly wages 1980	-0.0000389	0.00593**	-0.0126***
	(-0.02)	(2.95)	(-10.58)
IT		0.00656***	0.00538***
		(13.49)	(16.54)
col_degree			0.0106***
			(19.85)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports the β convergence estimates adjusted by skills and IT. The dependent variable in this table is Δw_{jt} for location j at time t. The initial period is 1980 and the final period is 2010. In column A, I run it against wages in the initial period of 1980. In column B, I control for the IT sector dummy. In column C, I control for the college degree.

Table 13: Regional convergence with Unions Controls

	(1)	(2)	(3)	(4)
Log hourly wage, 1980	-0.00840***	-0.00723**	-0.00604**	-0.00454
	(-2.76)	(-2.31)	(-2.28)	(-1.63)
Union		-0.0413**		-0.0427**
		(-2.27)		(-2.28)
Pop. Weight	Yes	Yes		
Observation	147.00	147.00	147.00	147.00
R square	0.26	0.30	0.14	0.19

Note: This regression shows the coefficient for the decline in wage growth between 1990 and 2010 on the initial wage in 1990, conditioning on the union presence by state. All the observations are clustered at the state level.

Table 14: Regional convergence with Import Penetration from China

	(1)	(2)	(3)	(4)
	(1)	(2)	(3)	(4)
Log hourly wage, 1980	-0.00840***	-0.00760**	-0.00604**	-0.00539**
	(-2.74)	(-2.58)	(-2.26)	(-2.12)
China Import Penetr.		-0.000320		-0.000373
		(-1.34)		(-1.42)
Pop. Weight	Yes	Yes		
Observation	49.00	48.00	49.00	48.00
R square	0.26	0.27	0.14	0.16

Note: This regression shows the coefficient for a regression of wage growth between 1990 and 2010 on the initial wage in 1990, conditioning on the import penetration from China by state. All the observations are clustered at the state level.

C.5 Model with Endogenous Innovation Rate: Capital-Skill Complementarity

The model specified above provides for an exogenous SBTC and differs for each location j. However, I could allow SBTC to be modeled as "technological adoption" following Beaudry et al. (2010). When computers arrive, firms need to decide whether to adopt them (PC) or stick with their current technology (K). This new technology is assumed to be skill-biased relative to the old technology because, for the same level of prices, the latest technology uses skilled labor more intensively. Specifically, where there is a higher concentration of highly skilled workers, there is also a higher ratio of computers per worker.

The production function with the old technology K is equal to

$$Y_d = \mathrm{K}^{(1-\alpha)}[aH^\rho + (1-a)L^{1-\rho}]^{\frac{\alpha}{\rho}} \tag{20}$$

Suppose that the production function of good Y_d location j with the new technology PC is equal to

$$Y_d = \mathrm{PC}^{(1-\alpha)}[bH^\rho + (1-b)L^{1-\rho}]^{\frac{\alpha}{\rho}} \tag{21}$$

where $a < b < 1$, which are personal computers. The firms need to decide the optimal amount of PC they want to pick. However, the decision of how much PC to choose increases with $\frac{H}{L}$. Before the availability of the PC technology, location j that had higher supply of skilled labor also had relatively low wages (because of a congestion effect on skills). Therefore, the return to skill increases most in locations that choose to adopt PC most intensively. However, the relationship between skill supply and return to skill is weakly decreasing. After the arrival of the PC technology, the relationship between the supply of skill and the return to skill is given by

$$\ln\frac{W_H}{W_L} = \begin{cases} \ln\left[\frac{aH^{\rho-1}}{(1-a)L^{\rho-1}}\right] & if\ \frac{H}{L} \leq \phi^L \\ \ln\left[\frac{a\phi^{L\,\rho-1}}{(1-a)}\right] = \ln\left[\frac{b\phi^{H\,\rho-1}}{(1-b)}\right] & if\ \phi^L < \frac{H}{L} < \phi^H \\ \ln\left[\frac{bH^{\rho-1}}{(1-b)L^{\rho-1}}\right] & if\ \frac{H}{L} \geq \phi^H \end{cases} \tag{22}$$

where ϕ^H and ϕ^L are the critical values of the skill ratio such that if a location is characterized by $\frac{H}{L} < \phi^L$, then it retains the old technology. If $\frac{H}{L} > \phi^H$, then the location switches to the new technology. Equation 2 shows that when a firm keeps the old technology, the relationship between the skill ratio and skill premium is negative, as if the firm had already switched to the new technology. However, when the firm is in transition between the old and new technologies, this relationship is equal to zero. This prediction of the model goes against fact 1 in figure 3. In fact, in figure 3, the relationship between the supply of skills and the skill premium becomes positive in the decade after 2000 and, overall, there is a positive trend. Therefore, a model with exogenous technological innovation seems better able to describe the data. Complementary papers such as Rubinton (2020) and Eeckhout et al. (2021) develop quantitative papers studying the role of capital-skill complementarity on space.

D Theory Appendix

This appendix supplements the theoretical framework presented in Section 3 in several respects. In subsection D.1, I describe the algorithm for solving the system of equations and obtaining the solution to the model. And, subsection D.2 derives an alternative expression for Y_T.

D.1 Description of the Computational Algorithm

To recover the equilibrium quantities and prices for period t, it is necessary to solve the full model numerically. I can reduce the equilibrium conditions by the following six, which are reported again below for the sake of clarity:

$$W_{Hjt} = (\eta_{Hdjt})[\eta_{Ldjt} L^{\rho}_{djt} + \eta_{Hdjt} H^{\rho}_{djt}]^{\frac{1}{\rho}-1} H^{\rho-1}_{djt} \tag{23}$$

$$W_{Ljt} = (\eta_{Ldjt})[\eta_{Ldjt} L^{\rho}_{djt} + \eta_{Hdjt} H^{\rho}_{djt}]^{\frac{1}{\rho}-1} L^{\rho-1}_{djt} \tag{24}$$

$$R^{\mu}_{jt} = H_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Hjt}}{R_{jt}}\right] + L_{jt}\left[\bar{O} + (1-\theta)\frac{W_{Ljt}}{R_{jt}}\right] \tag{25}$$

All $d \in D$ intermediate market sectors clear:

$$\frac{P_{djt}}{\alpha P_{jt}} = [\eta_{Ldjt} L^{\rho}_{djt} + \eta_{Hdjt} H^{\rho}_{djt}]^{\frac{1}{\rho}}$$

From the decision on the location of the labor market, the labor market clearing becomes

$$H_{jt} = \frac{\exp(\delta_{Hjt}/m_{2H}(j))}{\sum_s^S \exp(\delta_{Hst}/m_{2H}(s))} \tag{26}$$

$$L_{jt} = \frac{\exp(\delta_{Ljt}/m_{2L}(j))}{\sum_s^S \exp(\delta_{Lst}/m_{2L}(s))} \tag{27}$$

where

$$\begin{aligned} \delta_{kjt} = \Bigg[& \theta \ln(W_{kjt} - R_{jt}\bar{H}) + \\ (1-\theta)[\ln((1-\theta)\frac{W_{kjt}}{R_{jt}} + \bar{O}] + (1-\theta)\ln((1-\theta)(W_{kjt} - R_{jt}\bar{O})] & + \\ + A_{kjt} + \gamma^p \ln\left(H_{jt}/L_{jt}\right) & \Bigg] \end{aligned} \tag{28}$$

and

$$L_{jt} = \sum_{d=1}^{D} L_{djt} \qquad and \qquad H_{jt} = \sum_{d=1}^{D} H_{djt}$$

I end up with a system of 46 equations in 46 unknowns $\{W_{Hjt},\, W_{Ljt},\, H_{djt},\, L_{djt},\, R_{jt}\ P_{djt}\, \forall j \quad \text{and} \quad \forall d\}$ for each MSA. Since the analysis includes 240 cities and 14 industries, I have a system of 46x240=11,040 equations. I solve this system using an iteration algorithm. The algorithm consists of the following steps:

1. Given the set of parameters $\{\gamma^H, \gamma^L, \phi^H, \phi^L, \rho, \gamma^2, \lambda^H, \lambda^L, \theta, \gamma^p\}$, the sequences of S_t^H and S_t^L and the sequences of A_{Hjt} and A_{Ljt}, the initial productivity ξ_{Ldj0} and ξ_{Hdj0} for all j cities and for all industries d;
2. Start by guessing an allocation of $\{H_{dj0}, L_{dj0}\}_{j=1,d=1}^{J,D}$;
3. For each location, compute an equilibrium allocation h_j, output Y_{dj} wages W_{Hj} and W_{Lj} and P_{dj};
4. Using the information on prices, compute $\{H_{j,L_j\}_{j=1}^J}$
5. Check whether the distance between the values of $\{H_j, L_j\}_{j=1}^J$ and the guesses $\{H_{j0}, L_{j0}\}_{j=1}^J$ are smaller than an exogenously given tolerance level equal to e^{-10}.
6. If so, then stop. If not, consider $\{H_j, L_j\}_{j=1}^J$ as the new guess and restart the loop. Continue the procedure until the distance is smaller than the tolerance level e^{-10}.

I solve the model for 70 periods where time t is a year. In the first 40 periods, S_{Ht} and S_{Lt} are set to zero; then I set the value of S_{Ht} and S_{Lt} from the data (at the national level) from S and λ from the model estimation. Start looking for the equilibrium at time $t = 0$ and give a value for ξ^H_{j0} and ξ^L_{j0} where $\xi^H_{j0} > \xi^L_{j0}$ for all j generated by the estimation of the residuals of the wage equations in the year 1940.

Although the complex structure of the model does not allow me to derive conditions under which the algorithm converges to an equilibrium distribution of population, simulation results indicate that the algorithm displays good convergence properties unless either knowledge spillovers or dispersion forces are very strong. Specifically, the algorithm always converges to equilibrium in a broad neighborhood around the parameter values chosen in the calibration.

D.2 Rewriting Y_T

In order to estimate the needed parameters, I compute the unobserved changes in cities' productivities, given the parameters of labor demand $\{\rho, \gamma^H, \gamma^L, \phi^H, \phi^L\}$ and the data $\{w_{Hjt}, w_{Ljt}, L_{jt}, H_{jt}, L_{djt}, H_{djt}\}$. In order to make this transformation, I follow Diamond (2016) by taking the ratio of highly skilled wages to less skilled wages in location j:

$$\frac{w_{Hjt}}{w_{Ljt}} = \frac{\xi_{Hdjt} Y_{djt}^{1-\rho} H_{djt}^{\rho-1} \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^H} (H_{jt} + L_{jt})^{\phi^H}}{\xi_{Ldjt} Y_{djt}^{1-\rho} L_{djt}^{\rho-1} \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^L} (H_{jt} + L_{jt})^{\phi^L}} \implies$$

I use a change in the variable where defining highly skilled and less skilled productivities as

$$\xi_{Hdjt} = \theta(1 - \lambda_{djt})$$

$$\xi_{Ldjt} = \theta(\lambda_{djt})$$

This definition means that the skill premium can be written as:

$$\frac{w_{Hjt}}{w_{Ljt}} = \frac{\theta^{\frac{1}{\alpha}} (1 - \lambda_{djt}) Y_{djt}^{1-\rho} H_{jt}^{\rho-1} \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^H} (H_{jt} + L_{jt})^{\phi^H}}{\theta^{\frac{1}{\alpha}} \lambda_{djt} Y_{djt}^{1-\rho} L_{djt}^{\rho-1} \left(\frac{H_{jt}}{L_{jt}}\right)^{\gamma^L} (H_{jt} + L_{jt})^{\phi^L}}$$

$$\frac{w_{Hjt}}{w_{Ljt}} = \frac{(H_{jt} + L_{jt})^{\phi^H - \phi^L} H_{jt}^{\gamma^H - \gamma^L} H_{djt}^{\rho-1} L_{jt}^{-\gamma^H + \gamma^L} (1 - \lambda_{djt})}{\lambda_{djt} L_{djt}^{\rho-1}}$$

$$w_{Hjt} L_{djt}^{\rho-1} \lambda_{djt} = (H_{jt} + L_{jt})^{\phi^H - \phi^L} H_{jt}^{\gamma^H - \gamma^L} H_{djt}^{\rho-1} L_{jt}^{-\gamma^H + \gamma^L} (1 - \lambda_{djt}) \implies$$

$$\implies \lambda_{djt} \left[w_{Hjt} L_{djt}^{\rho-1} + (H_{jt} + L_{jt})^{\phi^H - \phi^L} H_{jt}^{\gamma^H - \gamma^L} H_{djt}^{\rho-1} L_{jt}^{-\gamma^H + \gamma^L} \right] =$$
$$(H_{jt} + L_{jt})^{\phi^H - \phi^L} H_{jt}^{\gamma^H - \gamma^L} H_{djt}^{\rho-1} L_{jt}^{-\gamma^H + \gamma^L} w_{Ljt} \implies$$

$$\implies Y_{djt} = \left(\frac{(L_{jt}+H_{jt})^{\gamma pH} w_{Ljt} H^{\gamma^H} L^{-\gamma^L} H_{djt}^{\rho-1} L_{djt}^{\rho} + (L_{jt}+H_{jt})^{\gamma pH} w_{Hjt} H_{djt}^{\rho} H_{jt}^{\gamma^H} L_{djt}^{\rho-1} L_{jt}^{-\gamma^L}}{(L_{jt}+H_{jt})^{\gamma pH - \gamma pL} w_{Ljt} H_{djt}^{\rho-1} H_{jt}^{\gamma^H - \gamma^L} + L_{jt}^{\gamma^L - \gamma^H} + w_{Hjt} L_{djt}^{\rho-1} L_{jt}^{\gamma^L - \gamma^H}} \right)^{\frac{1}{\rho}}$$

This formulation of Y_{djt} is used in the estimation since it does not include the productivity terms S_H, S_L, ξ_H and ξ_L.

E Comparison with Spatial Equilibrium Models Without Technology Diffusion

One of my model's novelties is that, relative to the existing literature on spatial equilibrium, it is embedded with both convergence and divergence forces. This section aims to show how technological diffusion is key in introducing regional convergence into the model and in matching the trends in the "Great Divergence" and the secular migration decline. Precisely, in this exercise, using the estimates generated in section 4.2.1, I simulate the model without the technological diffusion process. Table 15 shows how this version performs in terms of matching over time: (i) regional convergence pre-1980 and its decline, solely for highly skilled; (ii) the "Great Convergence" and the "Great Divergence" of skills and (iii) the decline in migration rates. Row (1) and (2) report the results on the overall regional convergence in the model and the data. This model does not reproduce any convergence pre-1980 and the increase in divergence is very moderate. Overall, spatial equilibrium models have forces that help the sorting, therefore, increasing the divergence, but achieving convergence as we would see in the pre-1980 is quite hard. Consequently, we cannot explain the sharp changes observed in the data in such a model. Row (3) and (4) report the speed of the convergence rate for the highly skilled in the data and the model, respectively. The model suggests that even before 1980, there would have been divergence for highly skilled wages and this divergence would have increased over time. Similarly, rows (5) and (6) suggest that data and model do not match either for the speed of regional convergence of the less skilled wages. Despite the highly skilled wages showing even more divergence coming from the larger knowledge spillovers than the less skilled wages, both groups look similar. Row (7) and (8) compare data and model prediction on the speed of convergence of the skill ratio, or the "Great Divergence". The findings suggest that this version of the model cannot account for the "Great Convergence" pre-1980 and the decline of it is also very moderate as well. Finally, rows (9)-(10) ((11)-(12)) compare the migration rates for highly (less) skilled. The findings suggest that migration across cities would have increased over time rather than decreased, as in the data. The model would produce extra sorting over time but there is no mechanism to slow down the incentive to move.

Overall, these results suggest that static spatial equilibrium models alone that do not have a growth component cannot match the sharp changes we have observed in the data in any of the salient moments.

Table 15: A Comparison with No Technological Diffusion

	1960-1980	**1970-1990**	**1980-2000**	**1990-2010**
β **Data**	-1.85	-1.50	-1.05	-0.11
β **Model**	0.04	0.05	0.06	0.06
β^H **Data**	-1.97	-1.35	-0.23	0.37
β^H **Model**	0.06	0.08	0.10	0.11
β^L **Data**	-1.78	-1.43	-1.96	-1.82
β^L **Model**	0.01	0.01	0.01	0.01
β^{HL} **Data**	-1.16	-0.14	-0.13	0.37
β^{HL} **Model**	-0.01	-0.02	-0.02	-0.03
% **Migr. Rate H Data**	4.44	3.62	3.33	2.17
% **Migr. Rate H Model**	23.51	33.44	37.16	45.35
% **Migr. Rate L Data**	2.23	2.05	2.26	1.19
% **Migr. Rate L Model**	22.62	30.41	32.49	36.30

Note: This table reports the estimates for several moments of the data, comparing them with the equivalent estimates in the model without the technology diffusion process. The top panel compares the β-convergence in the data and the model over time. The second (third) panel compares the β^H (β^L)-convergence in the data and the model over time. The fourth panel compares the β^{HL}-convergence in the data and the model over time. The bottom two panels report high and low skilled migration rates.

F Online Data Appendix

In this subsection, I first describe in detail the data sets I use for the analysis. Second, I run several robustness checks for the decline in regional convergence.

F.0.1 Data Description

My two main data sets are the US Census data extracted from IPUMS. I use the 1% sample for 1940, 1% sample for 1950, metropolitan sample for 1970, 5% sample for 1980, 5% sample for 1990, and the 5% sample for 2000. Then, for 2010, I use information from the American Consumption Survey (ACS) extracted from IPUMS. I use the information on wages, education, age, race, ethnicity, rents, birthplace, migration, population, industries, occupation, MSA, and state. All of this information is also available in the ACS data for 2010. I collect the same information from the CPS data set. The CPS is a monthly US household survey conducted jointly by the US Census Bureau and the Bureau of Labor Statistics. I use the observation for March. The CPS data set is primarily used for the analysis of migration. My geographic unit of research is the MSA. An MSA is a "region consisting of a large urban core and surrounding communities with a high degree of economic and social integration with the urban core." I also use two more data sets, one for the measure of Wharton land use regulation index (WLURI), aggregated by Saiz (2010) at the MSA level, and the other for the measurement of RTI developed by Autor and Dorn (2013). The latter uses information on the task intensity of the occupation from the "O*NET" data set, which is available for download at http://online.onetcenter.org/.[33].

F.0.2 Robustness Checks

Before turning to the robustness tests, I provide one more time the specification for the β-convergence estimation that I use throughout the paper following the specification in 1. In most of the specifications, the observations are weighted by the initial size of the location j.

I run several robustness tests starting with the ones illustrated in figure 1 and in figure 2. I change the unit of analysis from cities to counties in figure 19. In figure 19, I plot the estimated convergence rates. The estimate uses a 10-year rolling period in plot A, while plot B uses a 20-year rolling period. The convergence rate is negative and statistically significant

[33] For a more detailed description of the RTI measure, please refer to Autor and Dorn (2013)

until 1987 in plot A, while it is negative and statistically significant until 1997 in plot B. Both estimates show that the first period in which convergence ceased to be significant was 1978. This fact aligns with the findings of Higgins et al. (2006) who finds that there was a convergence between 1970 and 1990. However, departing from this prior work, I conduct an analysis in which the period is extended and find that the convergence across counties follows the same patterns as the convergence across cities and states.

As a second robustness check, I show that the convergence rate stops being significant and robust only if the initial year is after 1980. For this reason, I compute the rolling 20- and 30-year regional convergence as shown in figure 20 from 1940 onward. Then, I decompose it by skill group. Panels ((c))-((d)) and ((e))-((f)) of figure 20 show, respectively, results for the highly skilled and the less skilled groups. The rolling convergence rate β is negative and statistically different from zero until 1980, but then, it starts becoming positive but is still not significant. Finally, between 1990 and 2010, it becomes positive and statistically different from zero. But, when I decompose by skill groups, highly skilled workers show the same patterns as the aggregate convergence rate. Instead, the convergence rate for the less skilled group remains negative independently of the period. It becomes even stronger over time.

As a third robustness check, I reproduce figures 1 and 2 with compositionally adjusted wages. I control whether after using compositionally adjusted wages, the convergence rates change. As shown in figure 22, the convergence rates do not change substantially after adjusting for skill composition. Finally, another test is to see whether real wage regional convergence changes similarly to nominal wage regional convergence. The caveat in looking at real wage regional convergence is that the data on local prices are very scarce, especially before 1980. For this reason, I use self-reported monthly rental prices as a proxy for local prices. As you can see in figure 21, real wage regional convergence decreases even more than nominal wage regional convergence after 1980. Specifically, decomposing by skill groups, the convergence rate is approximately zero in the less skilled group but becomes positive in the highly skilled group.

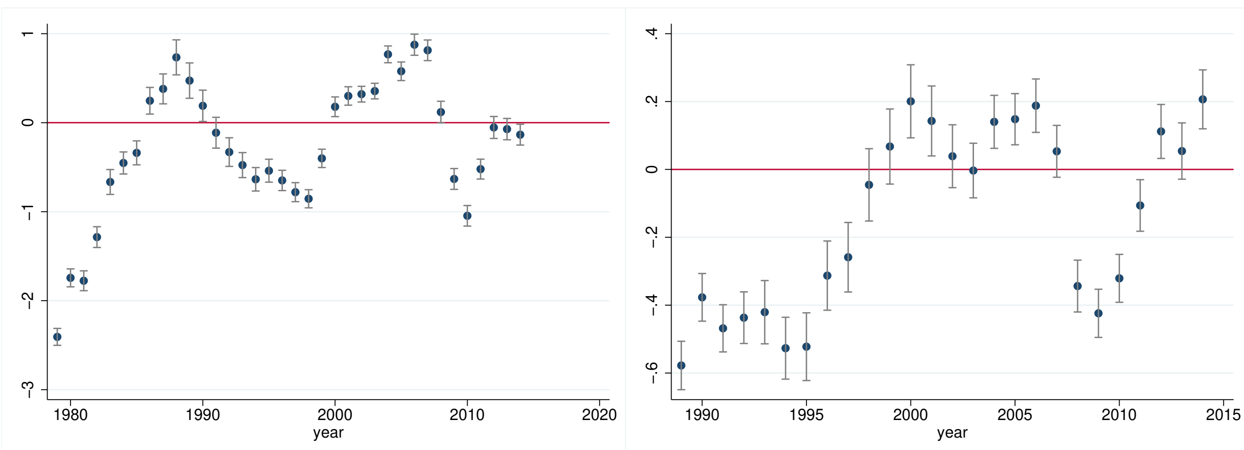
The convergence patterns might have changed because the definition of cities available between 1980 and 2010 is not perfectly identical to the one between 1940 and 1980. To ensure that these different samples are not driving the slowdown in convergence, I estimate the unconditional cities' regional convergence between 1980 and 2010 by using the 127 cities available from 1940-to 1980. Table 17 shows the convergence rate after 1940 for the reduced sample. The results show that the convergence rate is even lower if I use only cities available before 1980. Second, I look at the decline in regional convergence after adjusting for the SBTC shock. I run the following regression:

$$\Delta w_{jt} = \beta^o + \beta w_{jt-\tau} + \alpha^H \Delta S_{Hjt} + \alpha^L \Delta S_{Ljt} \tag{29}$$

where t is 2010 and tau is 30 years. After controlling for the technology shock, I get conditional convergence $=$ -1.1% a year. This rate indicates that without taking into account the mechanisms of the model, SBTC affects the decline in regional convergence.

Figure 19: Convergence by county over time

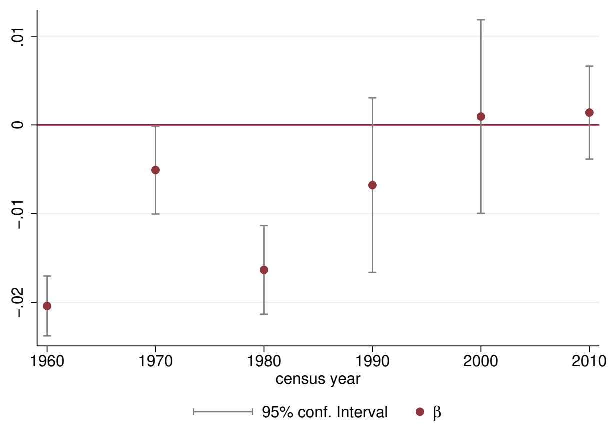
((a)) 10-year ((b)) 20-year



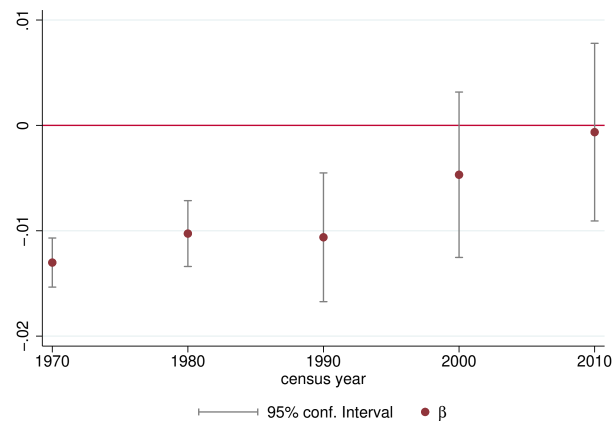
Note: This figure shows estimates of β convergence by county. Plot A shows the convergence rate at the county level for a 10-year rolling window that starts in 1969. Plot B shows the convergence rate at the county level for a 20-year rolling window that starts in 1969. Data for this analysis are from the Bureau of Economic Analysis Regional Economics Accounts. In each estimate the cities are weighted by their population. On the y-axis the coefficient is reported in percentage terms.

Figure 20: Convergence Rate Over Time - Overall and by Groups

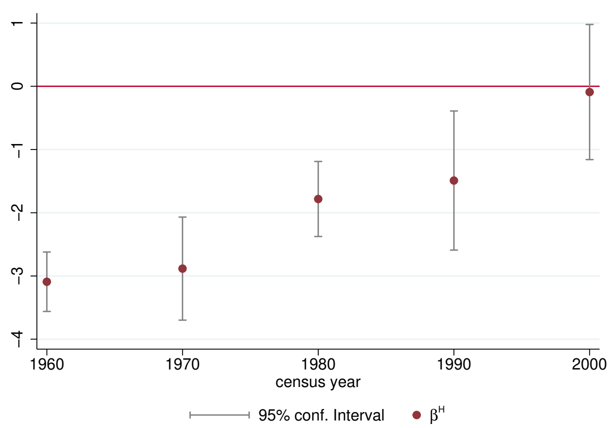
((a)) 20-year



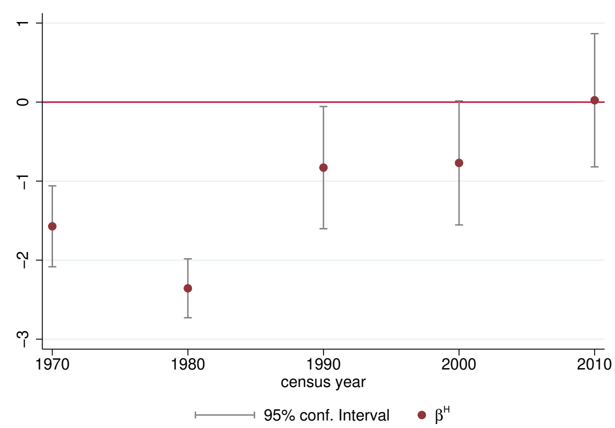
((b)) 30-year



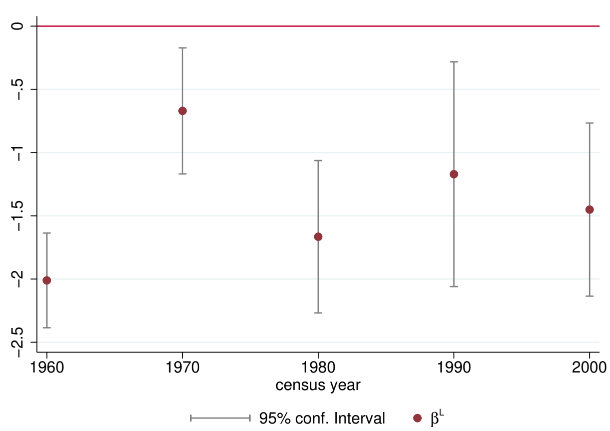
((c)) 20-year



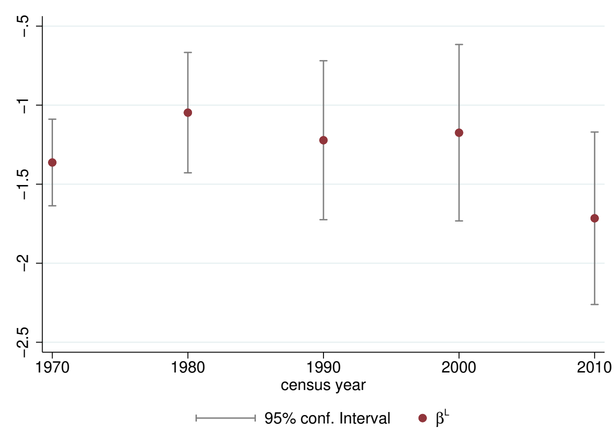
((d)) 30-year



((e)) 20-year



((f)) 30-year



Note: This figure shows the β estimates of the regression of the initial wage on the log wage changes using a 20-year and a 30-year rolling window. In each estimate the cities are weighted by their population. On the y-axis the coefficient is reported in percentage terms. Plots ((a)) and ((b)) are for the aggregate estimate of β, Plots ((c))-((d)) and ((e))-((f)) are, respectively, for β^H and β^L.

Table 16: Convergence Rates - Restricted Sample

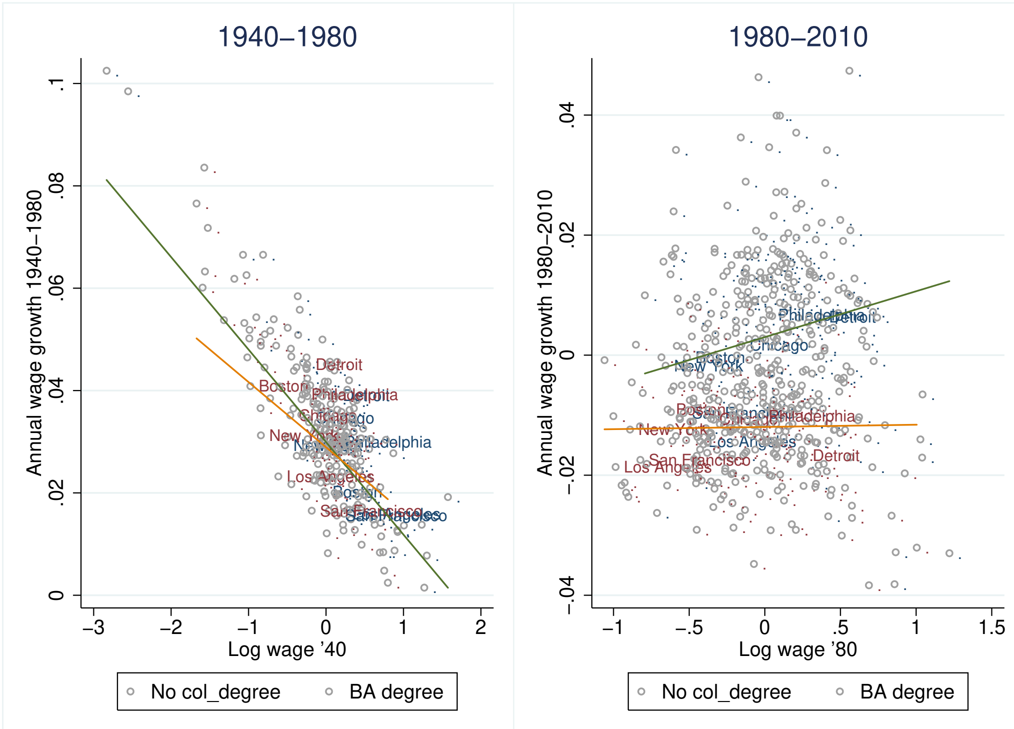
	(1) $\Delta^{1940-1980}$	(2) $\Delta\_^{80-08}$
Log($wage^{1940}$)	-0.0109***	
	(-10.53)	
Log($wage^{1980}$)		-0.00116
		(-0.25)
Constant	-0.0217***	-0.0147***
	(-137.22)	(-24.45)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

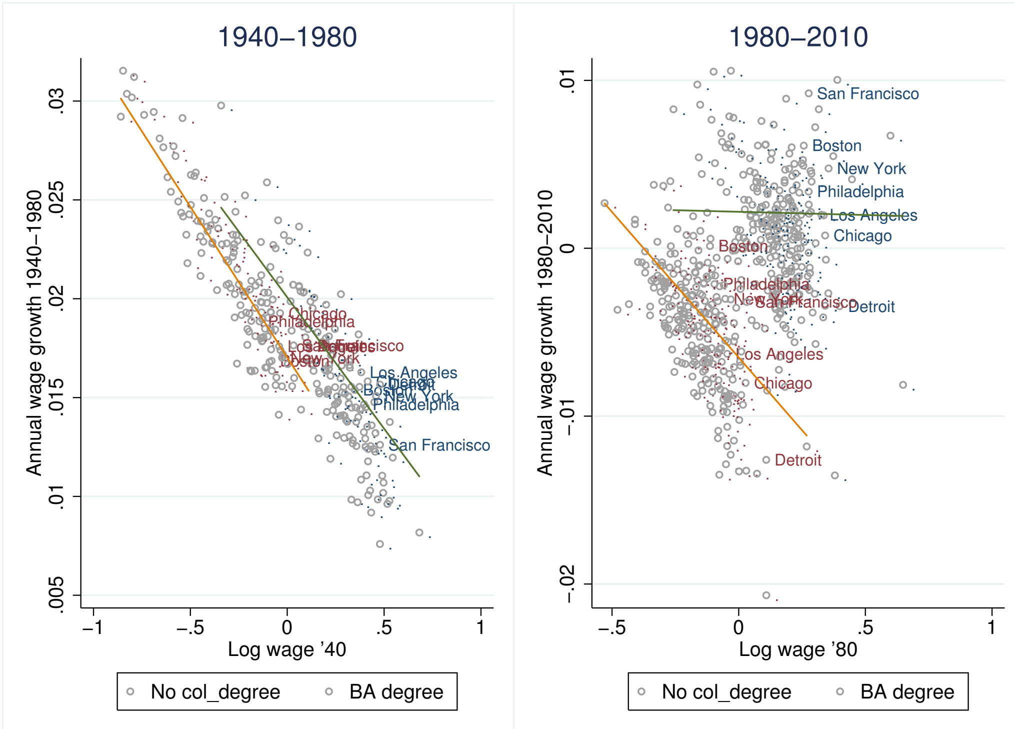
Note: This table reports the β convergence estimated for the restricted sample with only 127 cities. In column (1), estimates are reported for the 1940-1980 time period and in column (2) for the 1980-2010 time period.

Figure 21: Real Wage Regional Convergence



Note: This figure shows two scatter plots of the log wages by MSA in the initial year against the annual average growth of the wages in the final year. The wages are divided by the rental prices in the MSA. The rental price is taken from the self-reported Census data. Specifically, on the left-hand side (right-hand side), I plot the demeaned log wages in 1940 (1980) by MSA against the annual average growth of wages between 1940 (1980) and 1980 (2010). The line in each graph represents a weighted regression line from the bi-variate regression.

Figure 22: Compositionally Adjusted Regional Convergence



Note: This figure shows two scatter plots of the log wages by MSA in the initial year against the annual average growth of wages in the final year. Wages are adjusted by individual characteristics, sex, race, age, marital status, before taking the MSA average. Specifically, on the left-hand side (right-hand side), I plot the demeaned log wages in 1940 (1980) by MSA against the annual average growth of the wages between 1940 (1980) and 1980 (2010). The line in each graph represents a weighted regression line from the bi-variate regression.

Table 17: Convergence Rates - Robustness

Panel A

	(1) 1940-1980	(2) 1980-2010	(3) 1940-1980	(4) 1980-2010
Log hourly wage, 1940	-0.0185***		-0.0189***	
	(-13.21)		(-12.99)	
Log hourly wage, 1980		0.00374		-0.00423*
		(0.96)		(-2.20)

Panel B

	(1) Δw^{40-80}_pw	(2) Δw_pw^{80-10}	(3) Δw^{40-80}	(4) Δw^{80-10}
Log($wage^{1940}$)	-0.0143***		-0.0164***	
	(-16.69)		(-26.63)	
Log($wage^{1980}$)		-0.00333		-0.0101***
		(-0.72)		(-3.76)

Note: This table reports the estimate of the β-convergence of the OLS. Columns (1) and (2) show the estimates, respectively, for 1940-1980 and 1980-2010 by using population-weighted observations. Columns (3) and (4) show the estimates, respectively, for 1940-1980 and 1980-2010 by using unweighted population observations. Panel A shows the estimates of the β-convergence for local wages adjusted by the rent in each MSA. Panel B shows the estimate of the β-convergence for compositionally adjusted wages.

Table 18: Convergence Rates by Skill- Robustness

	(1) No,'40-'80	(2) Yes,'40-'80	(3) No,'80-'10	(4) Yes,'80-'10
Panel A				
Log wage '40	-0.0127***	-0.0181***		
	(-7.01)	(-11.12)		
Log wage '80			0.000369	0.00764***
			(0.36)	(3.92)

	(1) No,'40-'80	(2) Yes,'40-'80	(3) No,'80-'10	(4) Yes,'80-'10
Panel B				
Log wage '40	-0.0203***	-0.0232***		
	(-13.82)	(-19.35)		
Log wage '80			-0.00425**	-0.00584*
			(-2.94)	(-2.36)

	(1) No,'40-'80	(2) Yes,'40-'80	(3) No,'80-'10	(4) Yes,'80-'10
Panel C				
Log wage '40	-0.0152***	-0.0133***		
	(-21.13)	(-11.78)		
Log wage '80			-0.0173***	-0.000381
			(-10.65)	(-0.19)

	(1) No,'40-'80	(2) Yes,'40-'80	(3) No,'80-'10	(4) Yes,'80-'10
Panel D				
Log wage '40	-0.0163***	-0.0202***		
	(-25.22)	(-19.86)		
Log wage '80			-0.0189***	-0.0104***
			(-11.96)	(-5.52)

Note: This table reports the β-convergence estimates of the OLS regression. Columns (1) and (2) show the estimates, respectively, for "No" college degree and for "Yes" college degree workers for the years 1940-1980. Columns (3) and (4) show the estimates, respectively, for "No" college degree and for "Yes" college degree workers for the years 1980-2010. Panel A has the estimates of the β-convergence by skill for local wages adjusted by the rent in each MSA. Panel B has the same estimates as in Panel A but the observations are not weighted by local population. Panel C has the estimate of the β-convergence for compositionally adjusted wages. Panel D has the same results but the observations are not weighted by MSA population.

F.1 More Empirical Evidence on the workers' skills, wages and migration premium

Fact: Migration Premium negatively correlated with wages of local pre-1980, positively correlation afterward.

Migration Premium I define a new variable that I call the migration premium. In a nutshell, the migration premium is the difference between the wages of the migrants and the wages of the locals in a specific year and in a particular location. As above, I define migrants as all the workers who moved within the last year and locals like the ones who did not. For the worker to be a migrant, they need to have changed state in the last year. I compute the average of the compositionally adjusted wages for the workers who changed their state. Then, I compute the average of the compositionally adjusted wages for the workers that were already residing in that state before the previous year.

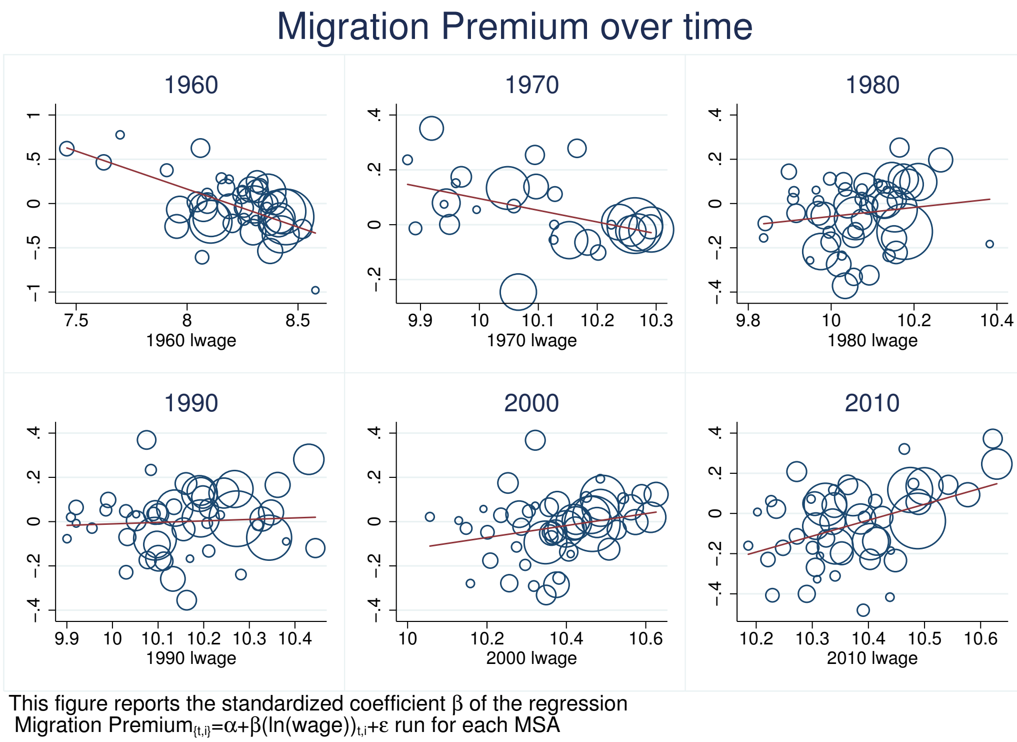
In figure 23, I look at the migration premium over time across states. For each of the years in the CPS sample, I run the following specification:

$$\ln\left(\frac{\hat{w}_{jt}^{migrant}}{\hat{w}_{jt}}\right) = \alpha_t + \beta_t \ln(\hat{w}_{jt}) + \epsilon_t$$

I run this specification for all the years of the sample in which the information on migration is available on CPS. Each regression is weighted by state population. Notice that the same results hold also for the population.

In figure 23, the migration premium is defined as the difference between the wages of the migrants and the wages of the locals. The migration premium reported in figure 23 is adjusted for age, sex, race, nativity, and marital status. This figure shows that the migration premium is negatively correlated with the wage level of the state while the relationship becomes positive in 1980. I interpret this empirical finding as showing that the advantage of migrating until 1970 was higher in poorer states. While later it became higher in the richer states.

Figure 23: Migration Premium by State over Time



Note: This figure shows a scatter plot of the log of the wages in the state in the first period t against the migration premium based on the measure of the difference between the wages of the migrants and the wages of the locals for the same year. The size of the underlying state is represented by the size of the circle in the figure. The line represents a weighted regression line from the bi-variate regression.