C 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.

C.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 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 the month of March. The CPS data set is used mainly for the analysis on migration. My geographic unit of analysis is the MSA. An MSA 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 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 measure 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/.[27].

C.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 21. In figure 21, I plot the estimated convergence rates. In plot A, the estimate uses a 10-year rolling period, while plot B uses a 20-year rolling period. The convergence rate is negative and statistically significant 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 is 1978. This fact aligns with the findings of Higgins et al. (2006) who finds that there was 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.

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

As a second robustness check, I show that the rate of convergence stops being significant and robust only if the initial year is after 1980. For this reason, I compute the rolling 20- and 30-year wage convergence as shown in figure 22 from 1940 onward. Then, I decompose it by skill group. Panels ((c))-((d)) and ((e))-((f)) of figure 22 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, the 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 actually becomes even stronger over time.

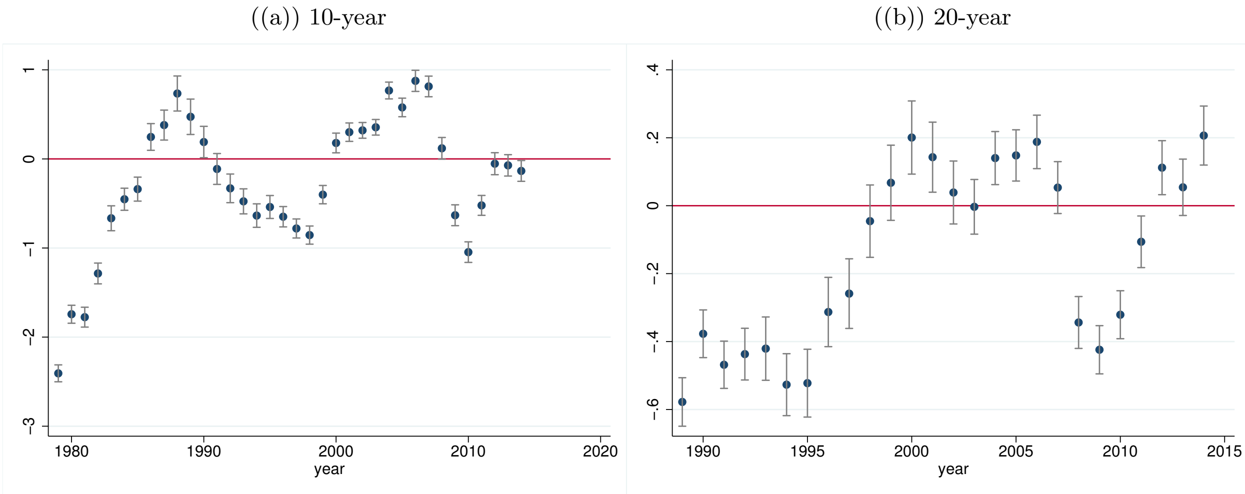
As a third robustness check, I reproduce figures 1 and 2 with compositionally adjusted wages. I control whether after using compositionally adjusted wages, the convergence rates change. As shown in figure 24, the convergence rates do not change substantially after adjusting for skill composition. Finally, another test is to see whether real wage convergence changes in the same way as nominal wage convergence. The caveat in looking at real wage 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 23, real wage convergence decreases even more than nominal wage convergence after 1980. In particular, decomposing by skill groups, the convergence rate is approximately zero in the less skilled group but becomes positive in the highly skilled group.

One reason why the convergence patterns might have changed could be because the definition of cities available between 1980 and 2010 is not perfectly identical to the one between 1940 and 1980. To make sure that it is not these different samples driving the slowdown in convergence, I estimate the unconditional cities' wage convergence between 1980 and 2010 by using the 127 cities available in 1940-1980. Table 15 shows the convergence rate after 1940 for the reduced sample. The results show that if I use only cities available before 1980, the convergence rate is even lower. Second, I look at the decline in wage convergence after adjusting for the skill-biased technical change shock. I run the following regression:

$$\Delta w_{jt} = \beta^o + \beta w_{jt-\tau} + \alpha^H \Delta S_{Hjt} + \alpha^L \Delta S_{Ljt} \tag{24}$$

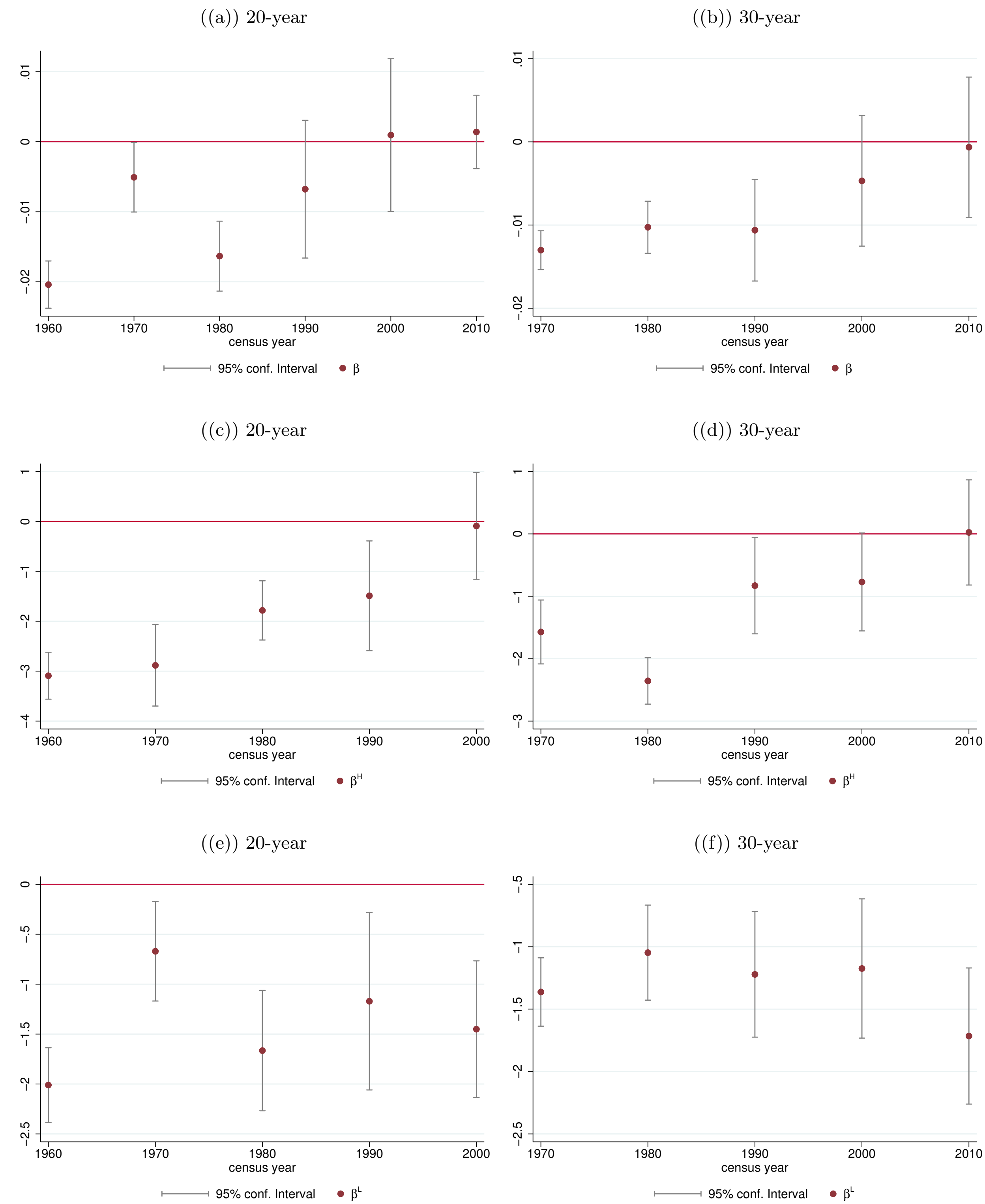
where t is 2010 and tau is 30 years. After controlling for the technology shock, I get conditional convergence $=$ -1.1% a year. This rate indicates that without taking into account the mechanisms of the model, SBTC affects the decline in wage convergence.

Figure 21: Convergence by county over time



Note: 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 22: Convergence Rate Over Time - Overall and by Groups



Note: This figure shows the beta coefficient 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 14: Convergence Rates - Restricted Sample

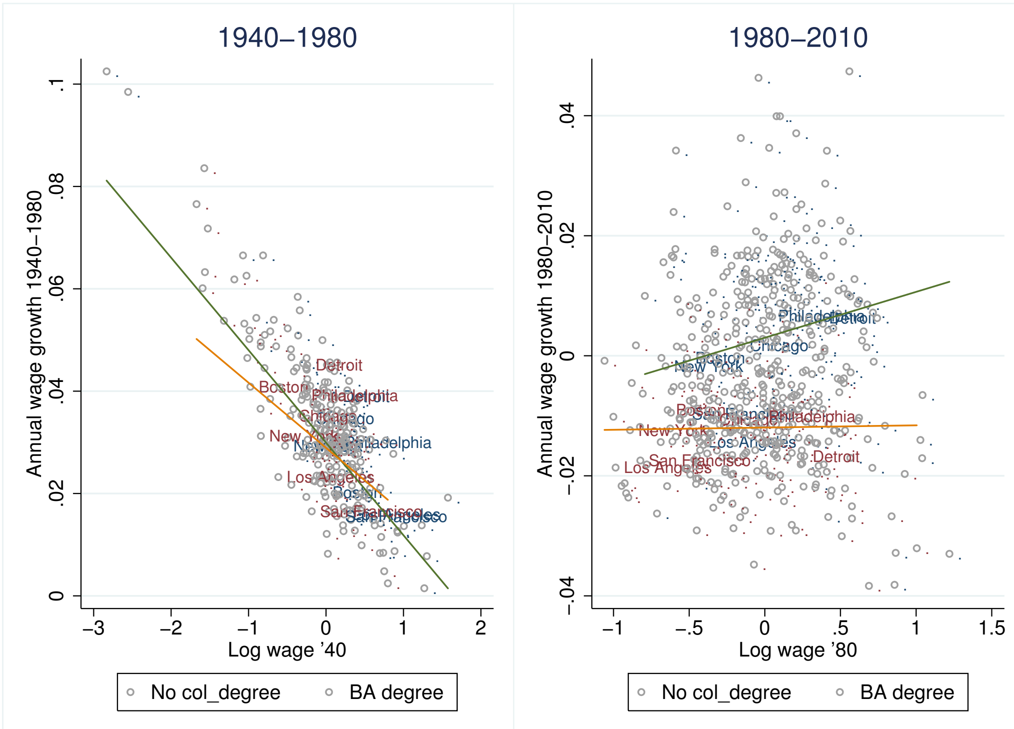
	(1) $\Delta^{1940-1980}$	(2) Δ_{-}^{80-08}
Log($wage^{1940}$)	-0.0109***	
	(-10.53)	
Log($wage^{1980}$)		-0.00116
		(-0.25)
Constant	-0.0217***	-0.0147***
	(-137.22)	(-24.45)

t statistics in parentheses

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

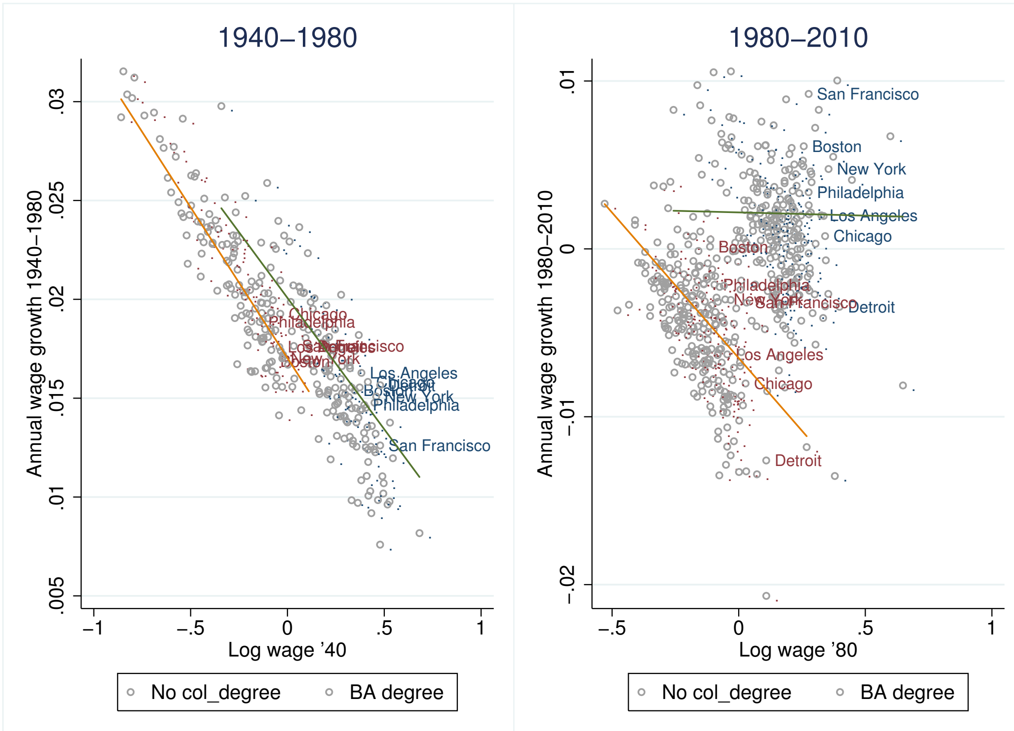
Note: I estimate the β convergence rate for the restricted sample with only 127 cities. In column (1), I estimate it for the 1940-1980 time period and in column (2) for the 1980-2010 time period.

Figure 23: Real Wage 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. In particular, 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 size of the underlying MSA is represented by the size of the circle in the figure. The line in each graph represents a weighted regression line from the bi-variate regression.

Figure 24: Compositionally Adjusted Wage 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. In particular, 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 size of the underlying MSA is represented by the size of the circle in the figure. The line in each graph represents a weighted regression line from the bi-variate regression.

Table 15: 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)

This table show 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 16: 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 shows the estimate of the β-convergence of the OLS. 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.

C.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 afterwards.

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 specific location. As above, I define migrants as all the workers who moved within the last year and locals the ones who did not. For the worker to be a migrant, he or she needs 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.

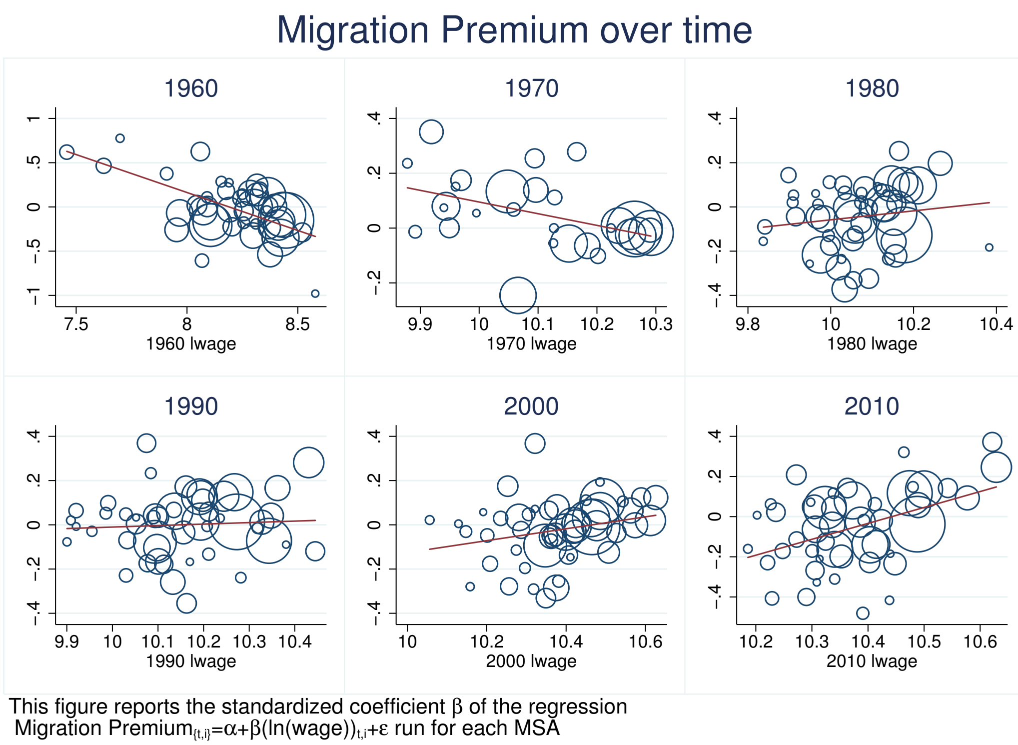
In figure 25, I look at the migration premium over time across states. For each of the years in the CPS sample, I run the following specification:

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

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 population.

In figure 25, 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 25 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 25: 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.